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Behavioural Biases in Financial Markets: The Elusive Case of Herding

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"Those who are able to see beyond the shadows and lies of their culture will never be understood, let alone believed by the masses"
Plato

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Abrégé de la thèse en langue française

Pendant bien longtemps, l'économie s'est focalisée sur l'hypothèse que les humains, et donc les agents économiques, décident et agissent de manière rationnelle afin de maximiser leur utilité espérée sous certaines contraintes (Robbins, 1932 ; Samuelson, 1938). L'incohérence de cette hypothèse avec la réalité, bien qu'identifiée et soutenue par la littérature (Rappaport, 1996), n'a pas toujours été prise en compte en économie, ni théoriquement, ni empiriquement, du moins jusque dans les années 1980.

L'économie financière ne fait pas exception à ce phénomène. L'hypothèse des marchés efficients (Fama, 1970) est un bon exemple de théorie basée sur des hypothèses de rationalité des agents et qui a été développée et très largement utilisée pour la recherche en finance de marché. Il existe une vaste littérature qui supporte ou conteste la rationalité des agents, et par conséquent, l'efficience même des marchés, tant sur le plan conceptuel (Simon, 1950 ; Rappaport, 1996) que sur le plan empirique (Ball et Brown, 1968 ; Huang, 1995 ; Lui et al., 1997). Avec l'essor de la psychologie cognitive et son application à la pensée économique grâce aux travaux de Kahneman et Tversky (1971, 1974, 1979, 1983), les économistes ont commencé à considérer le fait que les agents pouvaient être rationnels, ou irrationnels ou bien encore rationnels avec certaines limites. Les notions d'heuristique, de limites cognitives et de sentiment ont peu à peu été introduites en économie et en finance, afin d'enrichir nos connaissances sur le comportement des investisseurs, et donc sur les marchés des capitaux. Le débat sur la rationalité, l'irrationalité ou la rationalité limitée du processus de décision des agents, dans tous les aspects de la vie économique, y compris - mais pas seulement - les marchés financiers, demeure d'actualité (Hammond, 2001). Une partie de ce débat porte sur les comportements collectifs, et leurs motivations et effets. L'économie et la finance comportementales ont introduit le concept de comportement moutonnier ou mimétisme.[1]. Le mimétisme est défini comme la tendance des agents à suivre leurs pairs, en ignorant parfois certaines informations dont ils disposent (Bikhchandani et al., 1992 ; Avery et Zemsky, 1998 ; Nofsinger et Sias, 1999 ; Bikhchandani and Sarma, 2001 Hwang et Salmon, 2004 ;). Cette définition extensive du mimétisme ne précise pas si le phénomène est un choix rationnel ou s'il résulte d'un piège comportemental. De plus, il n'est pas évident que le mimétisme puisse coexister avec l'efficience de marché comme moyen de transmettre efficacement l'information ou si, au contraire, il contribue à rendre le marché inefficient et génère des cascades informationnelles. Enfin, demeure ouverte la question de la manière d'identifier le mimétisme dans le marché, que ce soit au niveau de l'intermédiaire

[1] On parle en anglais de *herding*. Dans ce résumé de thèse, nous utiliserons le terme de mimétisme pour faire référence au comportement moutonnier.

financier, de l'investisseur ou de l'analyste comme un choix d' achat ou de vente ou globalement en tant que manifestation d'un effet global résultant des choix individuels des agents.
La thèse procède à une analyse plus approfondie des approches théoriques et empiriques du mimétisme et de leur importance respective pour les marchés de capitaux, afin de mieux comprendre la nature et l'importance du mimétisme et de ses déterminants.

Cadre Théorique du Mimétisme

Le mimétisme a été étudié et décrit théoriquement afin d'examiner ses origines, qu'elles soient rationnelles ou irrationnelles, et ses effets possibles (Bikhchandani et al., 1992 ; Bikhchandani et Sarma, 2001). Tant en termes de motifs que d'effets, différents modèles considèrent le mimétisme comme un concept distinct. Ainsi, le comportement mimétique revêt de nombreuses formes et aboutit à des conséquences différentes sur l'ensemble du marché.
Les différents types de mimétisme, chez divers types d'agents - gestionnaires, investisseurs individuels, analystes financiers, etc. - peuvent être rationnels ou irrationnels. Un autre facteur important, qui nous aide à étudier la nature du mimétisme, est l'intention des agents. Le comportement mimétique rationnel est intentionnel, car l'agent décide de suivre ses pairs. Le comportement mimétique non-intentionnel est le plus souvent irrationnelle et se manifeste par des modes et des tendances, bien que des barrières informationnelles puissent conduire au mimétisme rationnel et non-intentionnel (Bikhchandani et al., 1992 ; Hirshleifer et Teoh, 2003 ; Spyrou, 2013). Une catégorie importante de mimétisme, empirique avéré, est le mimétisme fallacieux (i.e. *spurious herding*). Le mimétisme fallacieux correspond à une situation où les agents suivent collectivement un signal ou un ensemble d'informations partagés. On observe alors la convergence des comportements, mais les origines de ces comportements ne se trouvent pas dans le mimétisme *per se* (Bikhchandani et al., 1992 ; Bikhchandani et Sarma, 2001 ; Spyrou, 2013)
Depuis les recherches fondamentales de Banerjee (1992) et de Bikhchandani et al. (1992) jusqu'aux enquêtes plus récentes sur la littérature relative au comportement mimétique, comme celle de Spyrou (2013), le comportement grégaire a été divisé en plusieurs sous-catégories. Les cascades et les blocages informationnels sont éminemment importantes en ce qu'elles peuvent entraver l'efficacité du marché des capitaux (Banerjee, 1992 ; Avery et Zemsky, 1998 ; Park et Sabourian, 2011). Au cours d'une cascade informationnelle, la décision d'un agent est perçue comme un signal et peut influencer les décisions des agents par séquence, entraînant ainsi un blocage. Selon la structure du modèle et la structure de l'information, la probabilité qu'une cascade ou un blocage se produise diffère. Néanmoins, ce type de mimétisme a le pouvoir d'affecter l'efficience informationnelle, en particulier en présence de suiveurs [2], de stratégies de *momentum* et de limites à l'arbitrage (DeLong et al., 1990 ; Bikhchandani et al., 1992 ; Park et Sabourian, 2011).
D'autres motifs, qui conduisent les agents à se regrouper, sont liés à la notion de réputation et à la structure de rémunération des gestionnaires de fonds (Banerjee,

[2] Suiveur est la traduction du terme anglais *noise trader* et désigne un opérateur boursier qui suit la tendance.

1992 ; Graham, 1999 ; Dasgupta et al.,2011). Par exemple, il est souvent préférable pour un agent – et encore plus pour un analyste - d'échouer avec ses pairs que de réussir seul (Keynes, 1936). Ces types de mimétisme sont le fruit d'un choix rationnel et, à ce titre, ils conduisent à une maximisation de l'utilité pour l'agent (Dasgupta et al., 2011). La rémunération peut également être différente pour un investisseur s'il choisit de suivre les tendances ou bien s'il opte pour s'insérer dans une bulle financière (*ride the bubble*), car il a été démontré que sous certaines conditions la stratégie de suiveur peut aboutir à de meilleures performances que celles obtenues via l'analyse technique (DeLong et al., 1990). Ce type de mimétisme est lié à l'existence de bulles spéculatives et peut être lié au concept de tourmente financière (cf. Harras et Sornette, 2011).

Il existe beaucoup d'autres catégories de mimétisme qui peuvent avoir des motivations rationnelles ou irrationnelles, selon le cadre envisagé. L'une de ces catégories est le mimétisme basé sur certaines caractéristiques des actions cotées en bourse (Falkenstein, 1999). Ces caractéristiques peuvent avoir pour base le type d'investisseur ou son style d'investissement - par exemple, des titres importants pour les gestionnaires de fonds de pension - ou peuvent être irrationnelles et basées sur des motifs comportementaux - ce fut partiellement le cas pour la bulle immobilière avant la crise financière de 2008 - comme pour les modes et les gourous de la finance (Bikhchandani et Sharma, 2011). Parfois, comme ce fut le cas pour la crise des dotcoms, les actifs spécifiques et/ou les actifs financiers sont difficiles à évaluer, comme ce fut le cas pour las actions technologiques dans les années 90. L'évaluation inexacte des actions a pour conséquence d'éloigner les prix de leur valeur fondamentale. C'est ce qui se produit dans les bulles spéculatives. Les mouvements brusques dus aux modes et/ou à la myopie des investisseurs (Harras et Sornette, 2011) peuvent à la fois entraîner la création et l'éclatement de telles bulles (Dass et al., 2008 ; Bekiro et al., 2017), bien que les preuves empiriques ne soient pas concluantes à cet effet (Johansen et Sornette, 1999 ; 2010).

La richesse des approches théoriques du mimétisme pose un défi aux modèles empiriques, souvent accusés de ne pas représenter de façon adéquate la théorie (Bikhchandani et Sharma, 2001 ; Hwang et Salmon, 2004 ; Spyrou 2013). Comme cette thèse se concentre sur les aspects empiriques liés au mimétisme, nous présentons ci-dessous les principales approches empiriques.

Modèles empiriques pour le comportement mimétique : Critiques et désaccords

Le concept de mimétisme et les comportements collectifs, comme la plupart des biais comportementaux, ont été étudiés via des approches multidisciplinaires dans des environnements variés (Cipriani et Guarino, 2005 ; Drehmann et al., 2005 ; Baddeley, 2010 ; Bursztyn et Jensen, 2017) et aboutissent à des résultats relativement ambigus. De telles approches sur le mimétisme sont essentielles pour identifier le phénomène, ses déterminants et les liens possibles avec d'autres disciplines, telles que la neuroéconomie, notamment (Baddeley, 2010). Néanmoins, ces méthodes ont leurs limites, car elles sont rarement transposables dans d'autres contextes. Les raisons de ces limitations sont spécifiques à chaque contexte envisagé et incluent des questions de conception du cadre empirique ainsi que des biais liés à la nature humaine et à la

psychologie, tels que l'effet de cadrage (Gigerenzer et Hoffage, 1995 ; Cosmides et Tooby, 1996) et l'architecture de choix (Thaler et Sustein, 2008).
En partie à cause de ces limites de transférabilité et d'applicabilité, une grande partie de la recherche sur le mimétisme est basée sur des données financières, dérivées soit au niveau de l'investisseur/micro ou au niveau agrégé du marché des rendements - rendements considérés comme la manifestation agrégée des choix individuels (Chang et al., 2000). Ces deux niveaux du marché constituent la base de la recherche sur le mimétisme, avec deux catégories dominantes distinctes du modèles qui deviennent visibles. Ces catégories de méthodes empiriques sont :

- Les méthodes concernant le comportement mimétique institutionnel et individuel - souvent noté comme le mimétisme au niveau micro ou basé sur les flux d'ordres.
- Les méthodes concernant le consensus des rendements boursiers, ou le mimétisme à l'échelle de marché ou encore mimétisme global - également appelé le mimétisme au niveau macro

Pour les comportements mimétiques des institutions et des individus, il existe deux grandes mesures :

- LSV : Mesure créée par Lakoshnikov et al (1992) qui calcule la proportion excédentaire d'acheteurs pour une action donnée par rapport au marché.
- SIAS : Mesure créée par Sias (2004) qui utilise également la proportion d'acheteurs pour les actions individuelles mais dans une structure dynamique, afin de saisir le mimétisme de façon inter-temporelle.

Plus en détail, sous forme mathématique, les modèles institutionnels du mimétisme sont décrits ci-dessous :

$$H_{i,t} = |\frac{B_{i,t}}{B_{i,t} + S_{i,t}} - p_t| - AF_{i,t}$$

Pour la mesure LSV, nous indiquons $H_{i,t}$ pour chaque action i et chaque unité de temps t- souvent un trimestre. $B_{i,t}$ sont les acheteurs nets, ou en d'autres termes le nombre de gestionnaires de fonds ou investisseurs qui augmentent leurs avoirs en t et $S_{i,t}$ sont les vendeurs nets. La proportion attendue d'acheteurs nets est soustraite via pt et tient compte des décalages agrégés. $AF_{i,t}$ est un facteur d'ajustement [3].
Sous l'hypothèse nulle d'absence de mimétisme, nous supposons que la probabilité, qu'un dirigeant soit un acheteur net, suit une distribution binomiale et que la valeur absolue dans la première partie de l'équation du LSV diminuée de p_t est supérieure à zéro pour des raisons autres que le mimétisme.
En outre, pour Lakonishok et al. (1992) et la plupart des publications qui ont suivi, le mimétisme est étudié en référence aux investisseurs institutionnels. Compte tenu de la disponibilité des données, il est plus difficile d'examiner d'autres types d'investisseurs, tels que les investisseurs étrangers ou les particuliers. Certains documents étudient le mimétisme à une fréquence plus élevée (quotidienne et hebdomadaire) en utilisant les flux (cf. Hiesh(2013) qui utilise même des données intra journalières (Puckett et Yan, 2008)).

[3] Voir Lakonishok et al. (1992) pour les instructions sur AF

Lakonishok et al. (1992) ont également proposé une mesure similaire basée sur la valeur, le D-ratio. Cette mesure a ensuite été approfondie par Wermers (1999), qui a proposé la division du mimétisme en termes de sens des ordres. Le mimétisme de vente et le mimétisme d'achat sont des notions essentielles qui nous aident à examiner l'effet de la direction de l'ordre sur le comportement mimétique et son impact sur les prix et les marchés.
La méthodologie proposée par Sias (2004) tente de tenir compte des structures dynamiques - non incluses dans le LSV - comme suit :

$$RD_{i,t} = \frac{B_{i,t}}{B_{i,t} + S_{i,t}}$$

Toutes les notations restent inchangées. Ensuite, ils utilisent $D_{i,t}$, la version standardisée de RD dans une régression :

$$D_{i,t} = \beta_t D_{i,t-1} + \epsilon_{i,t}$$

Ils procèdent en décomposant le coefficient β_t en deux parties. La première partie rend compte de la corrélation qui découle du fait que les investisseurs institutionnels suivent leurs mêmes, dans et hors des mêmes décisions du commerce. La deuxième partie représente la partie de la corrélation qui résulte des investisseurs institutionnels qui suivent les autres dans et hors de certains décisions d'investissement, donc le herding.
Pour ces deux mesures, il existe de nombreuses modifications (par exemple Hsieh, 2013) et d'importantes critiques. Les deux mesures ne permettent pas de déterminer la nature du mimétisme et l'intention initiale de l'investisseur (Bikhchandani et Sarma, 2000), et elles montrent en outre que le mimétisme peut ne pas être identifié par l'une ou l'autre de ces mesures. En outre, les deux mesures ne tiennent pas compte des restrictions sur les ventes à découvert qui affectent la probabilité attribuée à un gestionnaire institutionnel dans le cadre de la négociation d'un portefeuille (Wylie, 2005). En plus, ces méthodes est généralement appliquée sur des données trimestrielles, ce qui entraîne une grande perte d'informations sur les avoirs du trimestre en cours. Enfin, la mesure LSV, qui domine la littérature, sous-estime systématiquement le mimétisme - lorsque celui-ci est présent (Frey, al, 2014). Pour le mimétisme à l'échelle du marché, qui se concentre sur les rendements, il existe deux mesures, principalement appliquées aux fréquences quotidiennes :

- CH : Mesure créée par Christie et Huang (1995) qui est basée sur l'écart-type transversal comme mesure de comportement mimétique global. La mesure examine la présence du mimétisme lors de mouvements extrêmes du marché.
- CCK : Mesure créée par Chang et al. (2000) qui utilise l'écart absolu transversal et suppose que le mimétisme se manifeste comme une relation non linéaire et négative entre la dispersion des rendements des actifs et le rendement du marché.

Ces deux méthodes sont assez similaires mais présentent des différences sensibles. Pour la méthodologie, crée par Christie et Huang (1995) on note :

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{n}(r_{i,t} - r_{m,t})^2}{N-1}}$$

Pour tester le mimétisme, la régression suivante est estimée :

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t$$

Où $r_{i,t}$ est le rendement de l'actif i, N est le nombre d'actifs, $r_{m,t}$ est le rendement du marché - souvent la moyenne des N rendements sur le marché-, D_t^L est une variable fictive qui prend la valeur 1 si, à t, le rendement du marché se situe dans la partie inférieure extrême de sa distribution ou zéro sinon, et D_t^U est une variable fictive qui prend la valeur 1 si, à t, le rendement du marché respectif se situe dans la queue supérieure extrême de sa distribution ou zéro sinon. Le critère extrême est souvent, dans les documents empiriques, fixé à 1%, 2,5% ou 5% de chaque côté. Selon les modèles traditionnels d'évaluation des actifs, les coefficients estimés de la régression ci-dessus devraient être positifs, car en cas de tensions sur le marché, on s'attend plutôt à une plus grande déviation découlant d'une plus grande volatilité de chaque actif. Si le mimétisme est présent sur le marché en question, les coefficients estimés pour β_1 et β_2 seront négatifs, indiquant une diminution de la CSSD durant un stress de marché.
Ce modèle ne tient pas compte des relations non linéaires entre la dispersion des actifs et le rendement du marché. Chang et al. (2000) ont proposé une méthodologie qui permet de saisir ces non-linéarités :

$$CSAD_t = \frac{1}{N} \sum_{1}^{N} |r_{i,t} - r_{m,t}|$$

Dans le modèle proposé par Chang et al. (2000), le rendement absolu du marché et le rendement du marché au carré sont utilisés comme variables indépendantes dans une régression comme suit :

$$CSAD_t = \alpha + \gamma_1 |r_{m,t}| + \gamma_2 r_{m,t}^2 + \epsilon_t$$

La notation est identique à la méthode CH présentée ci-dessus. Cette régression utilise l'écart absolu transversal des actifs comme variable dépendante, tandis que le rendement absolu du marché et le rendement au carré du marché sont les variables indépendantes. En particulier, le rendement du marché au carré représente la non-linéarité dont nous avons parlée précédemment.
Si le paramètre γ_2 de cette équation est négatif, alors la présence du mimétisme sur le marché est soutenue. Les auteurs eux-mêmes reconnaissent le fait que leur modèle capture certaines non-linéarités et qu'un γ_2 négatif peut indiquer d'autres types de relations non linéaires. Bohl et al. (2017) critiquent cette mesure et montrent comment cette mesure sous-estime systématiquement le mimétisme. En plus, cette méthode s'intéresse à la relation entre la mesure du mimétisme et le rendement du marché au carré, mais le rendement du marché au carré est aussi un proxy pour la variance du marché (Klein, 2013)
En ce qui concerne le mimétisme à l'échelle du marché, les méthodes ci-dessus se heurtent aux mêmes obstacles concernant l'identification de l'intention des investisseurs. L'utilisation de l'écart-type des rendements des actifs comme mesure de comportement mimétique, fait l'objet de nombreuses critiques. Tout d'abord, l'écart-type des rendements ne rend pas compte, lorsqu'il est utilisé sous une forme linéaire, de la relation entre la dispersion des actifs et le rendement du marché. La méthode

CCK de Chang et al. (2000) tente de corriger ce problème. La préoccupation, qui en découle pour la méthode CCK, est qu'elle identifie les relations négatives non linéaires comme étant du mimétisme. Ce n'est pas nécessairement le cas, comme l'admettent Chang et al. (2000). En outre, la mesure CCK sous-estime systématiquement le mimétisme (Bohl et al., 2017). Qui plus est, les deux méthodologies (CH et CCK) ne tiennent pas compte d'autres facteurs tels que la liquidité, la volatilité, les paramètres institutionnels, les conditions macroéconomiques, etc. Ce que les modèles définissent comme le mimétisme est la concentration des rendements autour du rendement du marché, lorsque celui-ci est très élevé ou très faible. Cela ne tient cependant pas compte du fait que la dispersion des actifs, lorsqu'elle est élevée, implique également une forte volatilité qui est liée à l'instabilité.
Hwang et Salmon (2004) proposent un modèle qui utilise la dispersion de la sensibilité des facteurs des rendements des actifs (MEDAF). Hwang et Salmon(2004) ont également proposé une mesure non paramétrique du mimétisme pour tenir compte de la réaction des investisseurs à de nombreux facteurs (le mimétisme du type bêta). Xie et al. (2015) ont également créé une méthode basée sur l'arbitrage des prix avec des résultats intéressants. Le problème auquel ces modèles sont confrontés est qu'ils ne sont pas applicables, dans la plupart des cas, à des fréquences quotidiennes. Mais des fréquences plus basses entraînent une perte d'information préjudiciable.
Une autre perspective importante, à travers laquelle nous avons l'intention d'étudier la littérature empirique existante, est celle des résultats empiriques obtenus. Dans la plupart des cas, le mimétisme au niveau micro est présent sur le marché (par exemple, Lakoshnikov et al.1992 ; Wermers, 1999 ; Choe et al., 1999) ; même dans le cas de marchés matures et hautement liquides tels que les marchés américains. Ceci n'est pas le cas pour le mimétisme au niveau macro qui n'est présent que dans des marchés plus petits et plus concentrés (par exemple Chang et al., 2000 ; Economou et al., 2011). En outre, le mimétisme institutionnel a un impact sur les prix à court terme mais pas à long terme. Ainsi, soit le mimétisme n'influence pas les prix à long terme, soit les spécifications utilisées ne peuvent pas saisir cet effet. Dasgupta et al. (2011) résument la littérature et offrent un soutien théorique à ce qui précède par le biais de la modélisation. Leur modèle montre comment le mimétisme ne permet de prédire les prix qu'à court terme. Ce qui est encore plus intrigant, c'est le fait que la majorité des modèles de mimétisme ne tiennent pas compte de la volatilité du marché. La volatilité créera inévitablement de l'incertitude et affectera le comportement mimétique ainsi que sa formation. La dispersion des actifs, telle que mesurée pour l'estimation du mimétisme, est directement liée à la volatilité et à la variance du marché. C'est également un facteur important, dont il faut tenir compte.
Ce sont ces questions qui seront abordées dans cette thèse. La question des mesures d'estimation et de leur cohérence en termes de résultats, ainsi que des facteurs importants qui, à notre connaissance, n'ont pas encore été étudiés en ce qui concerne le mimétisme. La structure de cette thèse, les principales méthodes utilisées, les résultats et leurs implications sont décrits ci-dessous.

La structure, les données, les principaux résultats et leurs implications

Étant donné la nature des lacunes et des problèmes liés au mimétisme dont nous avons parlés ci-dessus, cette thèse est divisée en trois grandes parties. Chaque partie recourt à des informations de différentes sources pour réaliser son objectif. Nous analyserons ci-dessous les objectifs, les principales méthodologies, les données, les principaux résultats et les implications et contributions significatives de chacune de ces parties.

Partie I

La première partie de la thèse consiste en un essai et se concentre sur la revue de la littérature concernant le comportement mimétique. Le mimétisme est un concept qui vient de la sociologie et de la psychologie dans le cadre du comportement collectif (ex. Le Bon, 1965). En tant que tel, l'identification du mimétisme sur les marchés financiers fait principalement partie de la littérature sur la finance comportementale, même si le mimétisme, lorsqu'il est rationnel, peut être expliqué par des modèles conventionnels - par exemple le mimétisme dû aux incitations à la réputation des analystes et des gestionnaires, comme dans le cadre du concours de beauté de Keynes (Keynes, 1936 ; Graham, 1999 ; Dasgupta et al., 2011).
Cette partie vise à faire le point sur la notion de mimétisme, à la fois dans le cadre de la littérature des sciences sociales et dans celui de l'économie financière, tout en se concentrant sur la définition et l'identification empirique du ce phénomène. C'est dans cette partie que les résultats incohérents et contradictoires sont discutés, afin d'identifier nos questions de recherche en cours.
L'immense littérature concernant le comportement mimétique s'intéresse à l'identification du concept même de mimétisme, sa définition théorique, comment il est empiriquement détecté, la source du mimétisme et ce qui peut l'influencer. La littérature porte aussi sur la question de l'importance du mimétisme pour les agents financiers et, dans une certaine mesure, pour les décideurs politiques. Il existe cependant une lacune importante en ce qui concerne les modèles théoriques sur le mimétisme et les outils empiriques que nous utilisons pour l'identifier. De plus, les deux principales approches empiriques concernant le mimétisme donnent fréquemment des résultats a priori contradictoires sur son existence et son étendue. Un facteur important, souvent pris en compte par les modèles financiers théoriques, concerne les mécanismes par lesquels les prix et donc les rentabilités financières, sont formés. Ces mécanismes incluent la théorie classique de l'offre et de la demande, qui a inspiré l'hypothèse des marchés efficients et les modèles classiques d'évaluation des actifs comme le MEDAF (Fama, 1970 ; Black, 1972), le risque, la volatilité et l'incertitude (Andersen, 2001 ; Bollerslev et al., 2020) et la dynamique entre différents groupes d'investisseurs, comme le désaccord et le style d'investissement (Barberis et Shleifer, 2003 ; Hong et Stein, 2007).
La revue critique de la littérature de cette thèse permet d'observer l'évolution du mimétisme en tant que concept et phénomène financier. En considérant le mimétisme à la fois comme une notion psychologique et sociologique et comme un choix révélé, nous sommes en mesure de comprendre à la fois la nature du phénomène et son mode de manifestation sur le marché. En particulier, par l'examen des moyens empiriques

d'investigation du mimétisme, cette partie parvient à examiner plusieurs questions et lacunes qui méritent d'être étudiées.
Ces questions qui définissent partiellement les rentabilités financières et le choix des investisseurs ne sont pas suffisamment étudiées par la littérature existante. Leur importance est telle qu'elles font l'objet de notre analyse empirique dans les parties de la thèse qui suivent cette partie-là.

Partie II

La première partie empirique de cette thèse comprend deux essais qui forment un tout et tentent de décrire, au moins en partie, le mécanisme de transmission - ou d'absence de transmission - du mimétisme au consensus du marché.
Le premier essai - chapitre 3 - est inspiré par les résultats contradictoires rendus par les deux différentes approches empiriques du mimétisme. Le mimétisme au niveau micro a été initialement proposé pour examiner le comportement mimétique des investisseurs institutionnels, puis étendu à d'autres groupes grâce à de petites modifications de la méthodologie (Lakonishok et al., 1992 ; Puckett et Yan, 2008 ; Hsieh, 2013). Au niveau de l'investisseur, pour la plupart des marchés - qu'ils soient organisés ou émergents, le mimétisme est systématiquement identifié pour la plupart des groupes d'investisseurs et au moins au sein d'un groupe. Par exemple, on constate que les investisseurs domestiques suivent leurs pairs au sein de leur groupe, tandis que des éléments indiquent que les investisseurs étrangers ne forment pas un groupe au niveau global mais plutôt des groupes en fonction de leur pays d'origine (Lin et Swanson, 2008 ; Lin et Lin, 2014). Inversement, la méthode CH ou CCK ne permet généralement pas d'établir une évidence en termes de mimétisme au niveau macro, à l'exception des marchés émergents (par exemple, Chang et al., 2000 ; Chiang et Zheng, 2010).
Cette controverse est également vérifiée pour le marché américain où les investisseurs institutionnels dominent le marché.[4]. Dans ce chapitre, les approches méthodologiques et conceptuelles du mimétisme sont toutes deux appliquées, avec un ensemble unique de données sur les flux d'ordres, afin d'examiner à la fois le mimétisme au niveau micro et le mimétisme au niveau macro via les rendements, en tant qu'effet global des choix des investisseurs. Il convient de noter que, sur un marché donné et à une période donnée, on peut observer l'existence de mimétisme au niveau micro mais au niveau macro. En outre, le concept relativement nouveau d mimétisme en « déséquilibres commerciaux » (trading imbalance herding) est exploré (Chung et Kim, 2017), afin de vérifier l'existence d'un tel mimétisme et d'étudier le lien avec le mimétisme de marché. Le mimétisme en « déséquilibres commerciaux », bien qu'il soit examiné globalement, est une forme du mimétisme en flux au niveau micro qui peut aider à étudier le marché avec un point de vue différent.
La dynamique entre les différents groupes d'investisseurs, avec différents niveaux de sophistication, de manière agrégée, et leur effet sur la non-transmission du mimétisme sur le marché, sont également étudiés. A cette fin, les informations saisies sur le volume par transaction sont utilisées pour déterminer le type d'investisseur et son degré de sophistication. Le volume d'une transaction est lié à la fois au type d'investisseur - l'investisseur étant plus ou moins gros dans une institution elle-même

[4] Données disponibles à cet effet via le Bureau du recensement américain (American Census Bureau) et statista.com

plus ou moins grosse - (Cready et Mynatt, 1991 ; Lee et al. ,1992 ; Lee et Radhakrishna,2000 ; Malmendier et Shanthikumar, 2007 ; Kaniel et al, 2008 ; Miller, 2010), aux asymétries possibles des ensembles d'informations détenues par les différents groupes d'investisseurs (Atiase et Bamber, 1994 ; Miller, 2010) et à la sophistication des investisseurs (Bushee, 1998 ; Bartov, 2003). De plus, différents groupes d'investisseurs ont un sentiment sur le marché qui peut être différent et ont des stratégies d'investissement différentes (Baker et Wurgler, 2007 ; Lee et Kumar, 2006 ; Hong et Stein, 2007) qui peuvent affecter le consensus des rendements (Liao et al., 2011).
La méthodologie de CCK est modifiée, pour tenir compte initialement du mimétisme au niveau micro et, dans une deuxième approche, de son état, élevé ou faible. Il est montré que le niveau de mimétisme des investisseurs affecte la convergence des rentabilités financières, mais seulement dans le cas extrême du mimétisme au niveau micro. Lorsque nous incluons la composition du marché en termes d'investisseurs, c'est le mimétisme des investisseurs plus petits, moins sophistiqués, principalement des particuliers, qui se heurte à des barrières d'information, et qui conduit à un consensus plus fort, générant plus de convergence sur le marché. D'autre part, les jours où de grands investisseurs institutionnels sophistiqués dominent le marché, la concentration des flux est liée à une plus grande variabilité à l'échelle du marché. Nos résultats impliquent que différents groupes d'investisseurs négocient en suivant des stratégies différentes. Alors que les investisseurs individuels rassemblent et créent un consensus, les investisseurs institutionnels et sophistiqués atténuent cet effet.
Mais cet effet est-il modifié par le sens de la pression en matière de transactions ou par le mimétisme ? L'achat et la vente ont-ils des effets différents sur le consensus du marché ? L'achat et la vente sont influencés par des variables et des facteurs multiples. Par exemple, les achats sont affectés de manière asymétrique à la fois par le biais d'attention (Barber et Odean, 2007) et par les informations (Chan et Lakonishok, 2003), tandis que les contraintes portant sur les ventes ont surtout un impact non seulement sur le niveau des ventes mais aussi sur le comportement des investisseurs détenant des ensembles d'informations inférieurs (Miller, 1977 ; Figlewski et Web, 1993 ; Ofek et Richardson, 2003 ; Ahn et al., 2010). Il a été démontré que le mimétisme en matière de ventes et celui en matière d'achats ont, au niveau micro, un impact différent sur le risque d'effondrement des actions individuelles, des prix et du marché, bien que les résultats soient en partie ambigus (Dasgupta et al., 2011 ; Deng et al., 2018). L'importance et l'effet de la direction des transactions et ses déséquilibres, et de la direction du mimétisme est le principal sujet du deuxième essai - chapitre 4 de la partie II.
A nouveau, une modification de la méthodologie CCK est élaborée, en utilisant les mêmes données que dans le chapitre 3, pour étudier l'effet des pressions commerciales relatives, des flux de ventes et d'achats en groupe, sur le consensus portant sur les rentabilités financières. La séparation du mimétisme en deux concepts (mimétisme d'achat et mimétisme de vente) dans l'esprit de Wermers (1999), à la fois séparément et conjointement pour les deux directions, est incorporée dans le modèle CCK, afin d'explorer l'effet du sens de la pression au niveau des ordres. Tout d'abord, on constate que la pression exercée par les déséquilibres commerciaux relatifs, parallèlement à l'ampleur du mimétisme d'achats et du mimétisme de vente n'affecte pas de manière significative le mimétisme de marché (mimétisme global). Si on considère à nouveau la composition du marché en termes d'investisseurs, une relation entre le mimétisme aux achats et aux ventes, uniquement les jours où les

échanges sont effectués par des investisseurs relativement moins sophistiqués et plus petits, et le mimétisme au niveau macro est à nouveau confirmée par les résultats empiriques. L'examen global des cas de vente et d'achat groupés n'indique pas un effet asymétrique dans l'une des deux directions sur le consensus des rentabilités financières, alors que les deux affectent le consensus et que la nature de cette influence est à nouveau liée à la dynamique entre les différents groupes d'investisseurs. Lorsque les effets des deux sens du mimétisme sur le consensus sont étudiés conjointement, on observe des différences significatives. Les résultats indiquent une fois de plus le caractère essentiel de la composition du marché en termes d'investisseurs. Le mimétisme lié aux achats d'origine institutionnelle et le mimétisme lié aux ventes provenant essentiellement d'investisseurs individuels sont tous deux liés à un renforcement du mimétisme au niveau macro.

Les résultats, combinés à la littérature existant sur le sentiment du marché, impliquent que les achats en masse par les institutions, qui agissent comme un signal, et les ventes en masse par les investisseurs de détail, affectent le sentiment de marché et les rendements. Ces différences sont essentielles pour le mécanisme de transmission des flux d'échanges vers les rendements des actifs.

Les résultats empiriques de la partie II concernent à la fois la finance comportementale et la finance traditionnelle. L'idée selon laquelle l'équilibre de marché est déterminé par l'équilibre entre les suiveurs et les arbitragistes, est un concept utilisé par les modèles financiers traditionnels. Les limites de l'arbitrage qui peuvent conduire à une inefficacité, en raison de l'ampleur du *noise trading*, peuvent également affecter le comportement grégaire. Si le mimétisme au niveau micro conduit principalement au mimétisme global, lorsqu'il est effectué par des investisseurs individuels, inexpérimentés, il est ensuite atténué par les transactions plus sophistiquées des investisseurs institutionnels. Alors les limites qui s'appliquent à la théorie de l'arbitrage s'appliquent également au mécanisme de transmission du mimétisme.

Le type d'investisseur peut également affecter à la fois la perspective conventionnelle et la perspective comportementale. Les investisseurs individuels et les petites institutions n'ont pas le même accès à l'information qu'une grande institution. En outre, le coût d'un accès, du traitement et de l'analyse efficace de l'information n'est pas le même pour tous les agents du marché.

Les différences de sentiment et de style d'investissement peuvent mis en regard des résultats de cette thèse. Étant donné que les investisseurs individuels sont affectés différemment par l'information et que les investisseurs institutionnels ont mis en place des mécanismes pour éviter cet écueil comportemental, il est logique que le sentiment des investisseurs individuels affecte le mimétisme dans le sens observé.

Si l'on considère le sens des transactions et la constitution du mimétisme au niveau micro ainsi que son effet sur le consensus des rendements, la différence entre les types d'investisseurs devient plus importante encore. Il a été montré théoriquement et empiriquement que la décision de vendre est différente de la décision d'acheter. Cette idée est soutenue par de nombreux modèles tant conventionnels que comportementaux et se fonde à la fois sur les contraintes de liquidité et les obstacles à l'information auxquels sont confrontés les différents groupes d'investisseurs, et sur les processus cognitifs différents qu'impliquent l'achat et la vente. La liquidité limitée des investisseurs individuels, les outils d'analyse plus performants utilisés par les grandes institutions, mais aussi la notion de biais d'attention et le conservatisme des investisseurs ne sont que quelques-uns des concepts qui affectent différemment

l'achat et la vente et donc le sens du mimétisme. Les données disponibles indiquent que le mimétisme lié aux ventes (investisseurs individuels) et le mimétisme lié aux achats d'origine institutionnelle sont transmis au consensus de marché, notamment lorsqu'ils sont simultanés. Là encore, les informations incluses dans les volumes unitaires de transactions sont liées au mécanisme de transmission, ce qui implique que tant le type et la sophistication des investisseurs sur le marché que leur ensemble d'informations influencent l'équilibre entre les investisseurs individuels qui forment le groupe et les investisseurs institutionnels qui vont à l'encontre du sentiment de marché. Ces conclusions sont essentielles pour la modélisation et l'analyse du comportement mimétique. Empiriquement, la notion de mimétisme n'est pas suffisamment examinée, du moins dans le cas du mimétisme au niveau macro. Les résultats de cette thèse montrent qu'un certain type de mimétisme peut fausser le marché, celui lié aux investisseurs plus petits, moins sophistiqués et moins informés qui sont plus enclins au mimétisme celui-ci pouvant créer une distorsion dans le marché. Ce fait peut, au moins en partie, expliquer pourquoi le mimétisme aux rendements se rencontre surtout sur les marchés émergents et pour les actions dont le processus d'évaluation est difficile - comme dans la crise des entreprises dot-com. Il est essentiel pour la recherche de déterminer la source du mimétisme, afin de savoir si celui-ci peut ou non avoir un impact négatif sur l'efficience du marché. En outre, il est important que les régulateurs, les participants au marché boursier et ceux qui le gèrent, de même que les décideurs politiques, aient une meilleure connaissance de qui négocie et comment. Il serait également bénéfique pour le marché et ses participants que les outils méthodologiques, utilisés tant par les décideurs et les agents économiques que dans le cadre de la recherche académique, soient améliorés afin de tenir compte de la dynamique du mécanisme de transmission du mimétisme des transactions aux rendements. Pour les besoins de la partie II, on utilise un ensemble de données unique qui est décrit ci-dessous.

Les données de la Partie II

Afin d'étudier le mimétisme à la fois dans les transactions boursières et à l'échelle du marché, il est nécessaire de disposer d'un ensemble de données comprenant des données sur les choix des investisseurs. Étant donné qu'un tel ensemble de données à l'échelle du marché est assez peu disponible et que Zhou et Lai (2009) ont déjà modifié la mesure LSV, nous pensons que les données sur les transactions (TRADES AND QUOTE DATA) pourraient également servir à estimer le mimétisme dans le niveau micro. Nous utilisons les données sur les cotations boursières de janvier 2007 à décembre 2019 pour toutes les actions composant le DJIA 30 (à tout instant). Les achats et les ventes se déduisent de façon algorithmique en utilisant la règle du tick au deuxième niveau. L'identification algorithmique des transactions entraîne une faible perte d'informations et un biais probable. Néanmoins, si l'on prend en considération la nature du mimétisme au niveau micro et la littérature existante, cette solution, bien que sous-optimale, est la plus adaptée. En plus des données sur les cotations boursières, pour cette partie, cette thèse recourt également à des données quotidiennes concernant les prix mais aussi d'autres variables importantes, comme la capitalisation boursière, de l'ensemble des 30 actions qui font partie de la composition de l'indice à chaque instant. Le DJIA 30 est un marché stable, qui comprend des actions de très grandes entreprises, souvent choisies par les gestionnaires. Les actions sont suffisamment liquides à tout moment pour répondre aux besoins de

liquidité nécessaires à l'estimation du mimétisme au niveau micro et macro.
Mentionnons également que la nature d'un marché, constitué de grandes valeurs, peut affecter les résultats empiriques. Un marché qui contient des actions représentant les sociétés industrielles de référence (*value stocks*) aux États-Unis peut exclure des informations vitales. Par construction, l'indice DJIA contient des actions solides et relativement faciles à évaluer car bien établies. Ces actions, notamment, rencontrent moins de barrières à l'arbitrage et attirent des investisseurs plus intéressés par le long terme. Ce choix de marché peut affecter la transférabilité de nos résultats vers d'autres marchés, qui contiennent des actions difficiles à évaluer comme des actions de croissance.
Cet équilibre entre les informations incluses dans l'ensemble de données et l'utilité pratique d'un ensemble de données est souvent rencontré dans les analyses à haute fréquence. Dans le cas du mimétisme à haute fréquence, c'est également le cas, non seulement dans cette thèse, mais aussi pour les études passées (Puckett et Yann, 2008). Les données dont nous disposons permettent d'étudier le mimétisme pour le même marché et la même période mais à deux niveaux. Les transactions déduites des cotations sont utilisées pour calculer le mimétisme au niveau micro, tandis que les prix de clôture quotidiens servent de base à l'examen du mimétisme au niveau macro. Notre ensemble de données, via des variables telles que le volume d'échange et le nombre de transactions, nous permet également de trouver des approximations pour le type d'investisseur et son niveau de sophistication qui nous aideront à explorer les différents déterminants du mécanisme de transmission du mimétisme aux rendements. Le choix d'une fréquence plus élevée, que les données nous autorisent à réaliser, est essentiel pour examiner le marché et ses mécanismes en limitant au maximum les pertes d'informations. Cela ne serait pas possible avec un ensemble de données traditionnelles sur les flux institutionnels trimestriels.

Partie III

Une autre variable importante qui affecte l'écart type des rendements et qui est empiriquement liée au mimétisme est le concept de volatilité. La volatilité n'est pas toujours un facteur « négatif » pour le marché (Bollerslev et al., 2020), mais elle est souvent liée aux turbulences, aux crises, ou encore à l'incertitude et à l'inefficience du marché (Bollerlev et al.,2018).
La troisième partie de cette thèse consiste en un essai qui se concentre sur cette relation entre la variabilité - variabilité spécifiquement réalisée (*realised volatility*), principalement au niveau intra-journalier - et le niveau macro du mimétisme. Le concept de volatilité est utilisé pour mettre en évidence les liens méthodologiques entre l'écart type des rendements, les mouvements de prix extrêmes et la variabilité intrajournalière. La relation entre ces variables affecte l'estimation empirique du mimétisme, principalement dans le cadre de la méthodologie CH. La méthode CCK n'échappe pas non plus à cette relation, d'autant plus qu'elle sous-estime systématiquement le mimétisme (cf. Bohl et al., 2017) et que sa structure inclut le carré du rendement du marché, qui est une approximation de la variance du marché dans certaines conditions (Klein, 2013).
Une autre question centrale concerne l'information contenue dans les mesures de volatilité estimées sur données intrajournalières - comme la variation quadratique utilisée dans notre cas - et sa moyenne en coupe concernant les conditions du marché,

le sentiment et l'incertitude. L'écart-type en coupe est analytiquement lié à la volatilité du marché (Mc Ennally et Todd, 1992, Hwang et Salmon, 2004). Cela complique la détection du dans un univers méthodologique où les outils empiriques choisissent la dispersion des actifs comme mesure du mimétisme global à l'échelle du marché. Étant donné qu'en cas de mouvements extrêmes des prix, la volatilité augmente en suivant une courbe en U par rapport à la distribution des rendements (Hamao et al., 1990), on peut se demander comment le mimétisme peut être distingué en cas de mouvements extrêmes des prix.

Cette partie est principalement axée sur la méthodologie CH, conçue pour examiner le mimétisme lors de mouvements extrêmes des prix. Afin de tenir compte de la volatilité pendant les mouvements extrêmes des prix et d'observer les éventuels changements dans les résultats du modèle, des modifications sont apportées à la méthode CH. Le type de volatilité utilisé - moyenne transversale de la variation quadratique - tient compte de la variabilité au cours d'un jour de bourse, qui peut ne pas être saisie via d'autres mesures de la volatilité qui se recourent à des données à une fréquence quotidienne. Il convient de noter que, lorsque la variation quadratique au cours de mouvements de prix extrêmes est prise en compte, les résultats sont modifiés. Initialement, le modèle CH indique un écart-type en coupe plus élevé lors des mouvements extrêmes des prix, mais lorsque la moyenne en coupe de la variation quadratique est incorporée dans le modèle, les résultats ne sont pas aussi clairs. Les preuves sont robustes à l'inclusion du sentiment et d'un indice de peur du marché et révèlent un biais d'estimation significatif.

De plus, lorsque la variation quadratique est utilisée comme variable de contrôle des états du marché - état du marché avec une variation quadratique élevée ou faible - des résultats similaires sont observés en utilisant la méthode CCK. Les jours où la variation quadratique est élevée, on observe une diminution du mimétisme global. Nos résultats indiquent que la variabilité et l'incertitude éloignent le marché du consensus. Le lien entre la variabilité au sein d'une unité de temps d'échange - par jour- et le mimétisme à travers les unités de temps- donc quotidiennement, se maintient pour les fréquences plus basses et est robuste au choix du marché.

Les résultats empiriques amènent à nouveau à la conclusion que les modèles empiriques du mimétisme agrégé et du mimétisme global ne représentent pas pleinement les modèles théoriques et n'expliquent pas suffisamment le mécanisme de formation du consensus de marché. La variabilité intrajournalière et son importance pour le marché, tant en temps normal qu'à l'occasion d'événements particuliers - tels que des mouvements de prix extrêmes ou des annonces macroéconomiques -, ne sont pas prises en compte lorsqu'il s'agit du mimétisme. La littérature existante a montré une relation entre l'arrivée d'informations, les cours des actions, la liquidité et la volatilité réalisée. Cette relation est essentielle si l'on considère pourquoi les modèles existants ne tiennent pas compte du mimétisme.

Étant donné que les choix représentent des signaux et que l'interprétation de ces signaux est influencée par les variables susmentionnées, la décision individuelle d'un agent de suivre le marché et l'effet global de ces décisions sont également affectés par la variabilité. La variabilité à haute fréquence peut ne pas être observée avec des rendements à plus basse fréquence, mais affecte pour autant les acteurs du marché et doit donc être prise en compte lors de l'étude du mimétisme. Le lien analytique entre la volatilité et l'écart-type transversal est également un facteur déterminant de l'importance de la prise en compte empirique de la volatilité réalisée.

Ces résultats pourraient être essentiels tant pour les agents du marché que pour les chercheurs. Bien que l'importance de la volatilité, sous certaines formes, ait été identifiée par les chercheurs, le lien entre le mimétisme et cette variabilité n'a pas été identifié auparavant. La simple relation linéaire entre la dispersion des actifs et le rendement du marché ou le carré du rendement du marché, utilisée pour identifier le mimétisme au consensus, n'est pas toujours adéquate pour identifier sa présence sur le marché. Cela est important, tant pour l'identification du mimétisme dans la recherche, que pour les participants au marché qui décident sur la base de signaux informationnels.
Pour les besoins de cette partie, les données sur les prix des actions sont à nouveau nécessaires pour appliquer la méthodologie empirique. Les données utilisées pour cette partie sont brièvement examinées ci-dessous.

Les données de Partie III

Pour la partie III, deux ensembles de données différents, qui servent à examiner deux marchés différents à deux fréquences distinctes, sont utilisés.
Le premier ensemble de données, dans lequel les changements méthodologiques de la CH et du CCK sont examinés, se concentre à nouveau sur l'indice Dow Jones Industrial Average 30 (DJIA 30). Contrairement à la partie précédente, les prix intrajournaliers par minute, des trente actions composant l'indice, afin de calculer à la fois la moyenne en coupe de la variation quadratique et les mesures de l'écart - bien que l'écart type en coupe (CSSD) et l'écart type absolu en coupe (CSAD)- soient utilisés. L'intervalle de temps choisi, en fonction de la disponibilité des données, se situe entre le 01/12/2005 et le 19/06/2015. L'ensemble de données comprend à nouveau la période avant, pendant et après la crise économique de 2008. Le raisonnement qui a présidé au choix du marché et les limites qu'il pose sont les mêmes que ceux exposés ci-dessus. La fréquence élevée de l'analyse impose des exigences de liquidité spécifiques. Le DJIA 30 est un choix de marché approprié qui permet d'inclure différents secteurs dans un marché liquide et de petite taille. Là encore, des limitations à la transférabilité de nos résultats peuvent s'appliquer.
Afin de tester la robustesse de la relation entre la volatilité intrajournalière et la dispersion des actifs, notre méthodologie est également appliquée à une fréquence plus basse mais à un marché plus large. À cette fin, l'indice S& P 500 a été choisi. Afin de calculer la moyenne en coupe mensuelle de la variation quadratique et les mesures de la dispersion transversale, les prix quotidiens des actions comprises dans l'indice S& P 500 de janvier 1995 à avril 2019 sont sélectionnés. Le choix d'un marché plus large, qui permet de prendre en compte des actions plus difficiles à évaluer et qui peuvent également être confrontées à des contraintes de liquidité, ne pose pas les mêmes problèmes sur la fréquence mensuelle que sur la fréquence intrajournalière et nous permet de tester la transférabilité de nos résultats sur un marché plus large et une fréquence plus faible.

Limites et recherches complémentaires

Comme toute étude empirique, cette thèse traite de certaines limites qui concernent à la fois les concepts explorés et les données utilisées. Pour commencer, le mimétisme

est un concept qui implique des détails du comportement humain, y compris mais non limité à la santé mentale de l'individu, l'état cognitif de l'individu, l'environnement spécifique du processus de prise de décision, la pression des pairs du groupe de l'individu et la place de l'individu dans ce groupe et bien d'autres caractéristiques. Toutes ces variables s'appliquent à des cas individuels et sont uniques à chaque choix singulier, de chaque individu, qu'il s'agisse d'un gestionnaire ou d'un investisseur individuel. Il est impossible d'agréger ou d'approximer toutes ces variables dans un modèle empirique, dont le but est d'examiner le consensus des rendements. Néanmoins, comme dans le cas de la composition du marché en termes d'investisseurs, certaines variables peuvent être approximées pour la moyenne du marché, surtout si l'on considère leur effet distinct sur le mimétisme. Par exemple, l'effet environnemental et le stress cognitif pourraient être approximés par des variables relatives aux crises, telles que les crises sanitaires et les épidémies (cf. COVID-19), les troubles économiques et le stress politique, tels que les périodes électorales ou de scandales politiques et/ou financiers.

Les modèles empiriques et les données utilisées pour appliquer de tels modèles ont forcément des limites qui affecteront à la fois l'interprétation des résultats et leur transférabilité. Pour commencer, les modèles empiriques choisis ici sont des modifications des modèles du mimétisme, existants et traitent donc de nombreuses limitations auxquelles ces derniers sont confrontés. La structure simple, qui permet à ces modèles d'être facilement applicables, limite à la fois la nature des relations relatives que nous souhaitons étudier et la variable que nous pourrions inclure.

Les données utilisées, pour la plus grande partie de cette thèse, sont des données intrajournalières sur les transactions boursières. Comme l'inférence est basée sur un algorithme, nos résultats présentent un biais relatif qui provient d'erreurs dans le processus d'identification. En outre, afin d'identifier la composition du marché en termes d'investisseurs, le volume moyen par transaction a été utilisé. Bien que, comme nous l'avons vu, l'utilisation de cette variable en tant qu'indicateur du type d'investisseur et de la sophistication de l'investisseur soit soutenue à la fois par des articles théoriques et des recherches empiriques, cette variable reste une variable de substitution qui ne représente pas toujours de manière parfaitement adéquate la réalité. Par exemple, si des investisseurs, qui détiennent probablement des ensembles d'informations supérieurs, décident de fractionner leur ordre dans un délai qui dépasse le jour de la transaction, il est possible qu'un grand investisseur institutionnel effectue des transactions séquentielles plus petites, même si l'ordre est fractionné. Bien que le marché du DJIA 30 soit moins sujet à ce phénomène, en raison de sa composition et du type d'investisseur qui préfère ses actions, il reste possible que le fractionnement des ordres affecte nos résultats, en ce qui concerne la composition du marché en termes d'investisseurs. De même, le choix d'une variable ou d'un concept peut souvent provoquer des discussions quant à l'interprétation et la robustesse de nos résultats. Dans le cas de la mesure de la volatilité réalisée, qui a également été examinée sur une base mensuelle, le choix de la variation quadratique intrajournalière peut limiter les résultats. D'autres formes de volatilité et d'autres concepts de celle-ci peuvent donner des résultats différents. En fonction de la disponibilité des données, d'autres mesures de la volatilité réalisée ou même d'autres concepts de celle-ci pourraient également être étudiés en relation avec l'ensemble du marché.

Chapter 1

Introduction

Economics and finance, for a vast period of time, were centred around the hypothesis that humans, and thus economic agents, decide and act rationally in order to maximise their expected utility, under certain constraints (e.g. Robbins, 1932; Samuelson, 1938). The inconsistency of this assumption with reality, although identified and supported (Rappaport, 1996), was not always accounted for in economics, neither theoretically nor empirically, at least until the 1980s.

Financial economics is no exception to that phenomenon. The efficient market hypothesis (Fama, 1970) is a clear example of such a theory based on conventional assumptions, that has been developed and employed extensively in finance, concerning capital markets. There exists vast literature trying to support or challenge rationality, and subsequently, market efficiency both conceptually (e.g. Simon, 1950; Rappaport, 1996) and empirically (e.g. Ball and Brown, 1968; Huang, 1995; Lui et al., 1997). With the rise of cognitive psychology and its application to economic thinking, through the work of Tversky and Kahneman (1971, 1974, 1979, 1983), economists began to consider the fact that agents can be rational, or irrational or even bounded rational. The notions of heuristics, cognitive limitations and sentiment were introduced to economics and finance, to enrich our knowledge about investors' behaviour, and thus capital markets. An overwhelming debate on whether the decision making process of agents, in every aspect of economic life including - but not limited to- financial markets, is rational, irrational or bounded rational is still ongoing (e.g. Hammond, 2001).

Part of this debate is collective behaviour, its motives and its effects. Behavioural economics and finance introduced the concept of mimesis and collective behaviour into financial decision making. One of the phenomena, related to mimesis and collective behaviour, is herding. Herding is defined as the tendency of agents to follow their peers, sometimes ignoring their personal information (e.g. Avery and Zemsky, 1998; Nofsinger and Sias, 1999; Hwang and Salmon, 2004). This broad definition of herding does not clarify whether herding is a rational choice or whether it stems from behavioural pitfalls. What is more, it is unclear whether herding can coexist with market efficiency, as a mean to effectively transmit information in the market, or whether it leads to informational inefficiency and cascades. Lastly, the way to identify herding in the market, shall it be via the investor, the analyst and the agent, as a choice or globally as the manifestation of the aggregate effect of individual choices of agents, is also unclear.

This introduction now proceeds to a deeper analysis of the theoretical and empirical

approaches to herding and their respective importance for capital markets, in order to better comprehend the nature and importance of herding and its determinants.

Theories about herding

Herding has been theoretically investigated and described, in order to examine its origins, those being rational or irrational, and its possible effects (e.g. Bikhchandani et al., 1992; Bikhchandani and Sharma, 2001). Both in terms of motives and in terms of effects different models, designed for different settings and environments, consider herding as a distinct concept. Thus, herding has many forms and different consequences market-wide, that stem from its relevant concepts.
Various types of herding, concerning various types of agents - managers, individual investors, financial analysts and so on - can be either rational or irrational. Another important factor, that helps us investigate the nature of herding, is intent. Rational herding is mostly intentional, as the agent decides to follow its peers. Unintentional herding is mostly irrational and it manifests in fads and fashion- although informational barriers can lead to unintentional rational herding as well (e.g. Bikhchandani et al., 1992; Hirshleifer and Teoh, 2003; Spyrou, 2013). An important category of herding, that is mostly related to evidence of empirical herding, is spurious herding. Spurious herding occurs, when agents collectively follow a shared informational signal/set. Then, empirically, we observe the convergence of behaviour but the origins of this behaviour do not lie in mimesis (e.g. Bikhchandani et al., 1992; Bikhchandani and Sharma., 2001; Spyrou, 2013), and thus the observed herding is spurious.
Beginning by the seminal research of Banerjee (1992) and Bikhchandani et al. (1992) and up until more recent investigations of the herding literature, as the one by Spyrou (2013), herding has been divided into several subcategories. One very important such category, that can impede capital market efficiency are informational cascades and blockages (Banerjee, 1992; Avery and Zemsky, 1998; Park and Sabourian, 2011 among others). During an informational cascade, the decision of an agent/investor is perceived as a signal of information and can influence the decisions of sequential agents, thus leading to a blockage. Depending on the model structure, the probability of a cascade or blockage to occur differs. Nonetheless, this type of herding has the power to affect informational efficiency, especially in the presence of noise trading, momentum strategies and limits to arbitrage (e.g. DeLong et al., 1990; Bikhchandani et al., 1992; Park and Sabourian, 2011).
Other motives, leading agents to herd are related to reputation and compensation structure (Banerjee, 1992; Graham, 1999). It is often better for an agent - especially an analyst - to fail with his peers than to succeed alone (Keynes, 1936). These types of herding are a product of rational choice and as such they lead to utility maximisation for the agent (e.g. Dasgupta et al., 2011). Similar to reputational incentives, compensation might also be higher for an investor, if he chooses to *ride the bubble* or follow the trends, as noise trading has been documented to outperform, in some cases, technical analysis (DeLong et al., 1990). This type of herding is linked to the creation of speculative bubbles and financial turmoil (Harras and Sornette, 2011).
There are many more categories of herding that can stem from rational or irrational motives, depending on the exact frame and setting. One such category is herding based on stock preferred characteristics (Falkenstein, 1999). Characteristic herding can be based on the type of investor and its investment style - for example large

securities for pension fund managers - or can be irrational and based on behavioural motives - as was the case for many groups of agents before and during the real estate market bubble of the 2008 financial crisis. Such behavioural motives can be driven by fads, fashion and financial gurus (Bikhchandani and Sharma, 2011). Sometimes, as was the case for the dotcom crisis, specific assets are difficult to evaluate, as were technological stocks in the 90s. Inaccurate valuation of equities results in prices being driven away from their fundamental value. The aggregate effect of an overwhelming overpricing of this nature often is seen in speculative bubbles. Herding due to fads and fashion and myopia (Harras and Sornette, 2011) can both result in the creation and the burst of such bubbles (Dass et al., 2008; Bekiro et al., 2017), although empirical evidence are not conclusive to that effect (Johansen and Sornette, 1999; 2010).
The vastness and richness of theoretical approaches to herding, pose a challenge for empirical models, that are often accused of not adequately representing the theory (Bikhchandani and Sharma, 2001; Hwang and Salmon, 2004; Spyrou 2013). Since this thesis focuses on investigating herding empirically, the major empirical approaches to herding are described below.

Empirical approaches to herding and gaps in the literature

Herding and collective behaviour, as most behavioural biases, has been investigated through a multidisciplinary approach in some environmental settings (Cipriani and Guarino, 2005; Drehmann et al., 2005; Baddeley, 2010; Bursztyn and Jensen, 2017) with ambiguous results. Such approaches to herding are essential to identify the phenomenon, its determinants and possible links to other disciplines, such as neurology and brain theory (Baddeley, 2010). Nonetheless, such methods come with limitations, as they are not applicable in settings different from those of the experiment. The reasons behind these limitations are specific to each setting and include issues with the environmental design and biases linked to human nature and the brain, such as the framing effect (Gigerenzer and Hoffage, 1995; Cosmides and Tooby, 1996) and choice architecture (Thaler and Sustein, 2008).
Partially due to those transferability and applicability limitations, an overwhelming research about herding is based on financial data, derived either on the investor/micro level or in the aggregate market level of returns - returns regarded as the aggregate manifestation of individual choices (Chang et al., 2000). These two levels in the market form the basis of herding research, with two distinct dominant categories of models becoming noticeable.
The micro-level empirical approach to herding was initially designed to examine herding in institutional investors, by incorporating proprietary data of institutional holdings, in order to determine whether or not managers follow each other in and out of trades (Lakonishok et al., 1992; Sias, 2004). This approach was later on extended to other type of investors and different types of data and frequencies (e.g. Hsieh). Two major empirical methodologies exist in micro-level herding literature.
The first empirical model of micro-level herding was developed by Lakonishok et al. (1992) - henceforth the LSV measure - using quarterly institutional holdings in order to infer investor behaviour. The model has a simple design and defines herd-

ing as the excess proportion of buyers of a stock, at a certain quarter, with respect to the market. The LSV measure, neither accounts for the dynamic dependencies between quarters nor follows individual investor choices concerning individual stock buys and sells. For that reason, Sias (2004) proposed a measure that distinguishes between investors following themselves into trades and following others - hereafter the SIAS measure. The latter methodology allows for dynamic dependencies in the separate choices of institutional investors.
For both these methodologies, there exist numerous modifications in order to apply these measures to distinct settings or investigate the influence of various parameters on herding. Wermers (1999), for instance, made a distinction between buy and sell herding, in order to account for the direction of trading pressures, while Zhou and Lai (2009) and Puckett and Yan (2007), among others, changed the LSV measure to apply it in trading data and high frequencies.
Although this approach to herding is widely used, important points of criticism rise regarding its validity. To begin with, when institutional proprietary data are employed, as is the case more often than not, the investor choices within a specific quarter are not observed, leading to great loss of information (Lakonishok et al., 1992; Wylie 2005; Puckett and Yan, 2007). With the rise of algorithmic trading and the high variability of prices in today's markets, this point becomes essential. What is more, various methodological issues of the use of the proportion of buyers lead to invalid results, both identifying spurious herding as mimesis (Bikhchandani and Sharma, 2001) and underestimating herding, when the latter exists (e.g. Frey et al., 2014 for the LSV measure). Other points of criticism of this approach, include, but are not limited to, the inadequacy of this measure to capture intent (Bikhchandani and Sharma, 2001) and the exclusion of important limitations posed by the market structure (e.g., Wylie, 2005 for short sale restrictions). Lastly, by construction this measure is not easily applied to individual investors and other groups in all markets. Although these type of distinctions are made in the literature (e.g. Nofsinger and Sias, 1999; Hsieh 2013) when data availability permits it, it is common for a researcher to result in modifications and the use of approximative techniques to distinguish between investor groups or to account for important market characteristics (as in Hsieh, 2013).
Another approach to herding, that attempts to include all investors and the aggregate effect of their choices, is macro-level herding or herding to the market consensus. The first methodology proposed to that effect by Christie and Huang (1995), attempts to investigate the existence of herding globally, via the linear relationship between the cross sectional deviation of stock returns from the market return and extreme market price movements - hereafter the CH method. When the cross sectional mean of individual stock deviations from the market is linearly negatively related to the state of extreme market price movements, aggregate herding exists[1]. Although, intuitively this approach seems logical, it does not investigate herding during normal market price movements and does not account for non-linear relationships between the cross sectional deviation of stock prices and the market return. Chang et al. (2000) drawing from the Capital Asset Pricing Model, create a methodology - hereafter the CCK method - to incorporate the non-linear relationship between the market return and the cross sectional standard absolute deviation of assets.

[1] When this relationship is positive, conventional pricing theories are supported

This approach - and especially the CCK method - has been modified to account for various factors that may affect the formation of consensus in the market. Liquidity (Galariotis et al., 2016), macroeconomic announcements (Galariotis et al., 2015) cultural and religious parameters (Gavriilidis et al., 2016) have all been shown to impact the formation of herding market wide. Additionally, certain markets are shown to hold influence, exceeding their borders, that is linked to herding in other markets, similarly to spill-over effects (Chiang and Zheng, 2010 for the effect of the U.S. market return).

Criticism exists regarding this approach to herding as well, as both empirical models have been proven to not properly identify and estimate herding and its extent (e.g. Hwang and Salmon, 2004; Bohl et al., 2017). Using the CH method in particular, in order to identify herding during extreme price movements, arbitrarily, points of the market return distribution are chosen as criteria of extremes (Hwang and Salmon, 2004). This is also true when the CCK method is applied, as proposed by Chang et al. (2000), for up or down markets. Furthermore, none of these measures account for the relation between market volatility, variability and the cross sectional deviation of the market return by construction (Hwang and Salmon, 2004, Yu and Sharaiha, 2007). What is more, none of these methods is designed to identify the mechanism of the formation of returns and the different dynamics, such as the disagreement of investors (disagreement as described in Hong and Stein, 2007), that affect the market globally.

By looking into the literature of empirical and theoretical herding in conjunction with the general literature of finance, several gaps and areas that require further investigation are highlighted. To begin with, models of micro-level herding, and especially for the U.S. market, identify herding to be present in the group of institutional - and sometimes other groups- investors (e.g. Lakonishok et al., 1992; Wermers, 1999; Nofsinger and Sias, 1999). The same cannot be said for macro-level herding in returns (Christie and Huang, 1995; Chang et al., 2000), apart from the case of emerging markets (e.g. Chang et al., 2000; Lin and Lin, 2014). This is even true for the U.S. market, where micro-level herding is extensively documented (Lakonishok et al., 1992; Wermers, 1999; Nofsinger and Sias, 1999 among others), institutional ownership has risen overwhelmingly and mutual funds dominate the market [2]. This observation leads to the natural question as to why this happens. Why does herding exist in the micro-level but it usually does not transfer to returns? Are the two concepts of herding incompatible? Is it possible for herding to exist in the micro-level of the market, but not transmit in returns and why? And what variables affect the mechanism of transmission of herding to the market consensus? Given that differences in investor groups sophistication (e.g. Bushee, 1998; Bartov, 2003), abilities, investment style (Barberis and Thaler, 2003; Liao et al., 2011) and opinion (Hong ans Stein, 2007; Barber et al., 2009) have been shown to play a crucial role regarding asset pricing and market efficiency, the type of investor and their sophistication as a variable may need to be considered as well. This variable could be linked to the mechanism of transmission and contagion relevant to herding, and thus it is important to be accounted for.

Furthermore, does the direction of micro-level herding affect the mechanism of transmission? Given the importance of the distinction of herding into buy herding and sell herding and the relation of each direction of herding with a different cognitive

[2] Data to this effect are available via the U.S. Bureau Census and statista.com

process, [3] there exist a vast literature - somewhat inconclusive - regarding the different origins and effects of buy versus sell herding (e.g. Dasgupta et al., 2011; Deng et al., 2018). Following our concept above, micro and macro level herding and their connection is now explored. Apart from the role of investor, the direction of trading and herding shall be examined, as possible variables of interest in the case of the mechanism of transmission of herding.
On a completely different note, methodologically the use of the cross sectional standard deviation, as a dependent variable, in herding models has been extensively criticised (Hwang and Salmon, 2004). The dependent variable, in both the CH and CCK method, is affected by variability by construction (Hwang and Salmon, 2004, Yu and Sharaiha, 2007). Especially intraday volatility has been shown to affect uncertainty, stability and investor sentiment (Bollerslev et al., 2017; Bollerslev et al., 2020). Does variability, and especially intraday volatility, affect the cross sectional standard deviation and thus herding? Does accounting for the measure or state of intraday volatility during extreme market price movements, affects the empirical results? If so, does fear and sentiment contribute to that effect in any form? Does the choice of method - albeit the CH or CCK - play a role for the effect of volatility on the cross sectional standard deviation, given that those methods are conceptually similar but methodologically distinct? What does it mean for volatility to affect the herding measure? Does this connection influence the methodology and blur the results? Or, is high intraday variability linked to disagreement that may or may not affect investor choices, resulting in the creation or not of a consensus- thus herding? These three questions, that revolve around two basic notions, are the main focus of this thesis. The data used, the method developed along with some essential results are briefly developed below.

The structure and data

Given the nature of the gaps and issues around herding identified above, this thesis is separated into three major parts. Each part draws information from different sources, in order to serve its purpose.

Part I

The first part of the thesis consists of one essay and focuses on the literature review regarding herding. Herding is a concept that comes from sociology and psychology, as part of the collective behaviour field (e.g. Le Bon, 1965). As such, the identification of herding in financial markets is mostly part of the behavioural finance literature, even if herding, when rational, can be explained by conventional models- for example herding due to reputational incentives of analysts and managers in the frame of Keynes beauty contest (Keynes, 1936; Graham, 1999; Dasgupta et al., 2011).
This part aims to review herding both as part of the social sciences literature and as part of financial economics, while focusing on the definition and empirical identification of the phenomenon. It is in this part, where the inconsistent and contraindicative results are discussed, in order to identify our proceeding research questions.

[3] For example, buying is a cognitive decision that involves attention bias and liquidity constraints (Barber and Odean, 2007), while sells do not.

The overwhelming literature concerning herding is employed and examined in order to identify what is herding, how theory frames it, how it is empirically identified, what creates and affects it and why it matters for financial agents and, to an extent, policy makers. There is a distinct gap about the theoretical models concerning herding and the empirical tools we employ to identify it. What is more, the two major empirical approaches to herding, render contraindicative results about its existence and extent, more often than not. An important factor, theoretical financial models generally consider is the mechanism through which prices and thus returns are formed. Such mechanisms include the classical supply and demand theory, that inspired the efficient market hypothesis and the conventional asset pricing models, as the CAPM (e.g. Fama, 1970; Black, 1972), risk, volatility and uncertainty (e.g. Andersen, 2001; Bollerlev et al.,2020) and the dynamics between different groups of investors, such as disagreement and investment style (e.g. Barberis and Shleifer, 2003; Hong and Stein, 2007).
Such issues that define returns and investor choice are not sufficiently explored by the existing empirical literature of herding. Their importance is such that they become the focus of our empirical analysis in the parts that follow.

Part II

The first empirical part of this thesis includes two essays, that shape a coherent continuum and attempt to describe, at least in part, the mechanism of transmission - or no transmission - of herding to the market consensus.
The first essay - noted Chapter 3 - is inspired by the conflicting results rendered by the two different empirical approaches of herding. Micro-level herding was initially proposed to examine herding by institutional investors and then expanded to other groups, via small modifications to its methodology (Lakonishok et al., 1992; Puckett and Yan, 2008; Hsieh, 2013). At the level of the investor, for most markets - either organised or emerging - herding is consistently identified - for most investor groups and at least within group. For example domestic investors are found to follow their peers in their group, while evidence indicate that foreign investors do not herd as a group but they form groups depending on the country of origin (e.g. Lin and Swanson, 2008; Lin and Lin, 2014). On the contrary macro-level herding is usually not encountered neither via the CH nor the CCK method, with the exception of emerging markets (e.g. Chang et al., 2000; Chiang and Zheng, 2010).
This distinct controversy is even true for the U.S. market, where organised trading via institutions dominates the market.[4] In this chapter, both methodological and conceptual approaches to herding are applied, in a unique trading dataset in order to examine both micro-level herding in trading and macro-level herding in returns, as the aggregate effect of investor choices. It shall be noted that, even for the same market and period, herding is found to exist on the level of trading flows but not market-wide. Additionally, the relatively new concept of herding in trading imbalances is explored (Chung and Kim, 2017), in order to verify the existence of herding in imbalances and investigate its affiliation to market-wide herding. Herding in trading imbalances, although examined market wide, is a form of micro-level herding in flows that can assist in studying the market from a different point of view.
The dynamics between different groups of investors, with different levels of sophisti-

[4] Data available to that effect via the U.S. Census Bureau and statista.com.

cation aggregately and their effect in the non-transmission of herding in the market, are also investigated. In order to do so, the information captured by the volume per trade is employed to proxy the investor type and sophistication. The volume of a trade is linked both to the investor type - the investor being small or large individual and small or large institution - (Cready and Mynatt, 1991; Lee et al. ,1992; Lee and Radhakrishna,2000; Malmendier and Shanthikumar, 2007; Kaniel and al., 2008; Miller, 2010), to possible asymmetries to the information sets held by different investor groups (Atiase and Bamber, 1994; Miller, 2010) and the investor sophistication (Bushee, 1998; Bartov, 2003). What is more, different groups of investor form different sentiment and have different investment strategies (Baker and Wurgler,2007; Hong and Stein, Hong and Stein, 2007) and this may affect the consensus of returns (Liao et al.,2011).

The CCK methodology is modified, to initially account for micro-level herding and its state being high or low. Evidence that the level of micro-level herding affects market wide herding, but only for extreme cases of herding in flows, are encountered. When we include the market composition in terms of investors, it is herding in flows combined with the strong trading presence of smaller, less sophisticated, mostly individual investors, who face informational barriers, that leads to a stronger consensus, i.e. more market-wide herding. On the other hand, on days when large institutional sophisticated investors dominate the market, herding in flows is linked to higher variability market-wide.

Our results imply that different groups of investors trade following different strategies. While individual investors herd and create a consensus, institutional and sophisticated investors mitigate that effect.

But is this effect affected by the direction of the trading pressure? Does sell and buy herding have different influence on the consensus of the market? Buys and sells are affected by different variables and factors. For example buys are asymmetrically affected both by attention bias (Barber and Odean, 2007) and information (Chan and Lakonishok, 2003), while short sale constraints mostly impact sales and investors holding inferior information sets (Miller, 1977; Figlewski and Web, 1993; Ofek and Richardson, 2003; Ahn et al., 2010). Sell and buy herding have been documented to affect the crash risk of individual stocks, prices and the market differently, although the results are ambiguous (Dasgupta et al., 2011; Deng et al., 2018). The importance and effect of the direction of trading and herding is the primary focus of the second essay - Chapter 4- of Part II.

Again a modification of the CCK methodology is developed, using the same data as in Chapter 3, to investigate the effect of relative trading pressures, sell and buy herding in flows, to the consensus of returns. The distinction of trading stocks into in sell and buy herding stocks, in the spirit of Wermers (1999), and the separate and joint introduction of sell and buy herding in models of market-wide herding, make the exploration of the effect of the direction of herding possible. To begin with, pressure stemming from relative trading imbalances, alongside sell and buy herding magnitudes, are not found to affect market-wide herding significantly, with the exception of herding measured in dollar value. When, again, the market composition in terms of investors is considered, a relation between both sell and buy herding with herding to the consensus, only in days when trading is conducted by relatively less sophisticated and smaller investors, is again supported by the empirical results. Overall examining the cases of sell and buy herding individually,

does not indicate an asymmetrical effect of one of the two directions on the consensus of returns. While both directions affect the consensus of returns, this influence and its nature are again related to the dynamics between different investor groups. When the effects of sell and buy herding to the consensus are investigated jointly, significant differences in the results arise, painting a different picture. The findings again indicate the essentiality of the composition of the market in terms of investors. Institutionally-originated buy herding and sell herding coming from retail investors are both related to stronger market wide herding. The results, combined with existing literature about market sentiment, imply that institutional buy herding, that acts as a signal, and retail investors' sell herding affect market sentiment and lead to a stronger consensus of returns. These differences are essential to the mechanism of transmission of herding from the level of trading flows to returns.
For the purposes of Part II, a unique dataset is employed that is described below.

The Data for Part II

In order to investigate herding both in trading flows and market-wide, a data set including data on investor choices is required. Given that such a data set market-wide is not easily accessible, trading data could also serve the purpose of estimating herding in trading flows[5].
Trading quote data are employed, from January 2007 to December 2019, for all stocks included in the DJIA at each point in time. Trades, albeit buys and sells, are inferred algorithmically using the tic rule in second level. The algorithmic identification of trades will result to some inevitable loss of information and some level of bias. Nonetheless, when the nature of micro-level herding and the propositions of the existing literature are taken into consideration, this solution, although sub-optimal is the most suitable. Additionally to trading quote data, for this Part, this thesis makes use of daily data regarding prices and other important stock variables, as for example market capitalisation of all 30 stocks that are part of the index composition, at each point in time. The stocks are adjusted, to fit the index composition with respect to changes in its constituents.
The choice of the DJIA 30 is not random. Given the high frequency of our analysis the number of stocks that could potentially be included in our definition of market is restricted by construction due to computational and stock related constraints.
On the other hand, the DJIA 30 is a stable market, that includes value stocks and is often chosen by managers, as it is presumably less uncertain. Value stocks are sufficiently traded to meet liquidity requirements necessary for the estimation of both micro and macro-level herding. We shall also mention that the nature of a market, consisting of large stocks may affect the empirical results. A market that contains value stocks that represent the benchmark industrial companies in the U.S., may exclude vital information. By construction the DJIA contains strong and easy to evaluate stocks of well-established equities. Such stocks, for example, face fewer barriers to arbitrage and attract investors more interested in long term investments. This choice of market might affect the transferability of our results to other markets, that contain difficult to evaluate stocks, growth stocks, more start ups and are generally more broad.

[5] There exist a modification of Zhou and Lai (2009) to the LSV measure that allows such an empirical application

This balance, of information included in the dataset versus the practical utility of a dataset, is often encountered in high frequency analysis. In the case of herding this is also the case, not just for our study, but for other studies as well (Puckett and Yann, 2008).
Apart from the limitations of the choice of market, this remains a unique dataset, that allows us to investigate herding for the same market and period, on both market levels. Trades, inferred from quotes, are used to compute micro-level herding, while daily closing prices serve as the basis of macro-level herding examination. Our dataset, via variables such as volume and total trades also permits approximations regarding the type of investor and its sophistication level, that assist the exploration of the different determinants of the mechanism of transmission of herding from flows to returns. The choice of a higher frequency, that the data allows, is essential to examine the market and its mechanisms, accounting for as much information as possible. This would not be possible via a traditional dataset of quarterly institutional flows.

Part III

Another important variable that affects the cross sectional standard deviation, by construction, and relates empirically to herding is volatility. Volatility is not always a negative factor for the market (Bollerslev et al. 2020), but is often related to turmoil, crisis, uncertainty and market inefficiency (Bollerlev et al.,2018).
Part III consists of one essay that focuses on this relation between variability - specifically realised variability mostly intraday - and macro-level herding. The concept of volatility is used to point out the methodological connections between the cross sectional standard deviation, extreme price movements and intraday variability. The relationship between these variables affects the empirical estimation of herding, mostly via the CH methodology. The CCK method is also not untouched by this relation, especially given that it systematically underestimates herding (Bohl et al., 2017) and its structure includes the squared market return , which is an approximation of market variance under certain conditions (Klein,2013).
Another important fact is the information encapsulated in measures of intraday volatility - as the quadratic variation used in our case - and its significance concerning market conditions, sentiment and uncertainty. The cross sectional standard deviation is analytically related to volatility in the market (Mc Ennally and Todd, 1992, Hwang and Salmon, 2004). This makes it impossible for herding and volatility to coexist at the same time, in the scope of methods employing the dispersion of assets as a measure of market-wide herding. Since during extreme price movements the volatility, and more so the realised volatility, is extremely high following its famous U curve, relative to the return distribution (e.g. Hamao et al., 1990), it makes us wonder how herding is even possible during extreme price movements, let alone expected.
The primary focus in this Part falls on the CH methodology, designed to examine herding during extreme price movements. Intending to account for volatility during extreme price movements and observe possible changes in the output of the model, respective modifications to the CH method are made. The type of volatility used - thus the cross sectional mean of the quadratic variation - accounts for variability within a trading day, that may not be captured when employing other measures

of volatility, that focus on a daily frequency. It should be noted that, when the quadratic variation during extreme price movements is accounted for, the output of the model changes. Initially the CH model, indicates higher cross sectional standard deviation during extreme price movements, but when the cross sectional mean of the quadratic variation is incorporated into the model, the results are not so clear. The findings are robust to the inclusion of market sentiment and fear and reveal negligible estimation bias.
What is more, when the quadratic variation is employed as a control of market states - state of the market with high or low quadratic variation - similar results are observed using the CCK method. In days with high quadratic variation, less aggregate herding is observed. Our results indicate that variability and uncertainty pull the market away from the consensus. The link between the variability within a trading time unit -per se day- and herding across time units- thus daily, holds for lower frequencies and is robust to the choice of market.
For the purposes of this part, again stock price data are needed, in order to apply the empirical methodology. The data used for this Part, are briefly discussed below.

The Data for Part III

For the purposes of part III, two different datasets, that serve to examine two different markets and two distinct frequencies, are employed.
The first dataset, in which the methodological changes in the CH and the CCK are initially applied , again focuses on the Dow Jones Industrial Average 30 (DJIA 30). Contrary to the the previous Part, intraday per minute prices, of the thirty stocks composing the index, in order to compute both the cross sectional mean of the quadratic variation and the measures of deviation - albeit the cross sectional standard deviation (CSSD) and the cross sectional absolute standard deviation (CSAD) - are used. The time range chosen, based on data availability, is between 01/12/2005 and 19/06/2015. Again the dataset includes the period before, during and after the economic crisis of 2008. The reasoning for the choice of market and the limitations this choice entails are very similar to those of the previous Part. The high frequency of the analysis forces specific liquidity requirements, while computational power also affects the type of stocks chosen. The DJIA 30 is a suitable choice of market, that allows us to include various sectors in a liquid and small market. Again limitations to the transferability of our results may apply.
In order to test for the robustness of the relationship between the intraday volatility and the dispersion of assets, the methodology is also applied, both to a lower frequency and to a broader market. For this purpose, the S & P 500 index was chosen to serve as a market. In order to compute the monthly cross sectional mean of the quadratic variation and the measures of cross sectional dispersion, daily prices for the stocks included in the S & P 500, from January 1995 until April 2019, are selected. The choice of a broader market, which allows for stocks that are more difficult to evaluate and may also face liquidity constraints, does not pose the same problems on a lower frequency and allows us to test the transferability of our results to a broader market.
Having examined the major parts of this thesis, it would be useful to also present the objectives of each essay. This introduction will now conclude by summarising the objectives of the parts to follow in a more structured manner.

Main objectives

Herding is complex phenomenon that has its roots on human behaviour and can, as such, impact the function of all social constructions, the capital markets included. The main objective of this thesis is to investigate some of the gaps in the empirical literature, regarding herding and focusing on the aggregate level.
Part I attempts to identify such gaps, by examining and analysing existing theories of herding and the empirical evidence concerning the existence and extent of mimetic behaviour. It is evident, when the literature is investigated that the theoretical depictions of herding and the empirical investigation of the phenomenon are not aligned. What is even more bizarre, is the disagreement between the main empirical approaches - albeit herding by institutional and individual investors compared to aggregate herding- relevant to the existence and extent of herding in the market.
This disagreement becomes the primary focus of part II. Micro-level and macro-level herding are investigated separately and in conjunction, in Chapter 3, that attempts to decipher the main characteristics of the mechanism of herding transmission, from the level of the investors and their flows to the consensus of returns. One of the parameters, identified by previous studies, as of high importance, for the nature of the influence of herding to the market, is the direction of herding- albeit sell and buy herding. Chapter 4 is centred around exploring the importance of the direction of micro-level herding and imbalanced trading to the consensus of returns.
Another important variable, that is linked both to market inefficiency and herding, is variability. In Part III the relationship between intraday realised volatility and the cross sectional standard deviation of assets is explored. The already established by the literature link, between the dispersion of assets and volatility, implies a structural and methodological connection that existing literature identifies but does not account for, when estimating herding. We attempt to account for the cross sectional mean of the quadratic variation, in the estimation of herding, and explore the significance of variability for the formation of a consensus in Chapter 5
Lastly, Chapter 6 concludes this thesis by displaying the main findings of this thesis and their link to existing financial theories. Additionally, the main limitations of this thesis, alongside further research that is needed to properly explore these findings, are considered.

Part I

The Literature Review: The Conceptual Relativity of Herding and its Risks

Abstract

The first part of this thesis revolves around the volume of existing literature. In the first part, the literature review is presented via the prism of methodological issues and risk. The aim of this part is to define herding as a part of the economic and financial literature. Moreover, Part I intends to focus on the empirical literature and the methods developed and study them critically. This part only contains one essay, as presented below.

Keywords— Herding, Literature Review, Herding Theories, Herding Methodologies

Chapter 2

The Curious Case of Herding:Theories and Risk

Abstract

Financial markets are complex systems, where numerous variables and mechanisms define the final picture. In such complex systems, equally complex phenomena arise. Such a phenomenon is herding. Financial herding refers to the tendency of investors to follow their peers, often ignoring their personal information. Herding due to its nature poses complications in its examination, as it can relate to various motives and it may have mixed effects. Such motives include reputational and compensational incentives, asymmetry of information and fads and fashion. The origins of herding can be either rational or irrational, making herding a part of both conventional and behavioural finance literature. By investigating the major theoretical and empirical approaches to herding, alongside the major existing findings, we identify various issues concerning the tools we have to explore herding and several factors, that affect both herding and the risk it poses for financial markets and economic systems. The nature of herding is such, that the influence it bares for the market is dependent on numerous factors, such as the market conditions, the type of financial agent, market sentiment and the exact environment in which investors operate. Thus herding- driven risk is dependent on various factors and not just the extent of herding. Lastly, the importance of the methodological approach to herding, both for the examination of herding and for the exploration of its risk, is highlighted by existing evidence. Herding is a complex phenomenon that may or may not distort the market and as such it shall be examined with caution.

Keywords— Herding, Empirical Herding, Herding Theories, Financial Risk

2.1 Introduction

Since the rise of social sciences, researchers have struggled to determine the procedure through which individuals decide. The decision-making mechanism has a central role in many scientific fields, such as psychology, sociology, neurology and cognitive studies. Economics is another field directly linked to this mechanism. In the words of Lionel Robbins (1932) "*Economics is the science which studies human behaviour as a relationship between ends and scarce means which have alternative uses.*"
The interactions between microeconomic parameters, macroeconomic variables, the banking sector and the financial markets form the ultimate economic reality, which people face every day. It is, indeed, the decision-making process of economic agents that leads to these interactions. The economic and financial settings as we know them are formed through the aggregation of these decisions and their direct and indirect effects.
For quite a while in economics and finance, the decision-making process of individuals was considered rational. The rationality assumption is a vital part for most of the theories and models of classical and neoclassical economics and finance. From Adam Smith (1776) and its assumptions about the *invisible hand* to Eugene Fama (1970) and the concept of efficient financial markets, rationality is the key underlying assumption, that allows as to model human behaviour and its economic and financial importance. Both Smith and Fama consider agents as rational decision-makers, who act to maximise their profit. In the absence of intervention and except for certain market externalities, economies and markets converge to an *optimal* equilibrium. For example, Adam Smith states that there is an invisible hand - that if we let the market free - will push the market to its optimal state. Eugene Fama states that if agents are homogenous and if the information is symmetrically distributed, the market will be efficient. Fama describes efficiency as the state when prices of assets reflect all available fundamental information about them. Fama categorises efficiency into three categories based on the level of information available in the market, as shown in Table 2.1 below.

	Past Public	Present Public	Private
Weak	Yes	No	No
Semi-strong	Yes	Yes	No
Strong	Yes	Yes	Yes

Table 2.1: Market Efficiency according to Fama (Fama,1970)

When prices include all past information, then the weak form of efficiency is validated. On the other hand, if prices reflect all past and all present information, then we refer to the market as semi-strong efficient. Lastly, a market is strongly efficient, when the prices of assets represent all past, present and private information in the market. Empirical evidence regarding the efficiency of the markets and the type of efficiency are not consistent, especially across markets.
The weak and semi-strong form of efficiency have been empirically tested, and the evidence is not conclusive. For example, Huang (1995) tests the weak form of efficiency in nine high edge markets and mostly rejects it for most markets. Chang et

al. (1996) also show that the Taiwan market is not efficient. Lui et al. (1997) find similar evidence for the majority of Chinese markets, while Phan and Zhou(2014) show that weak efficiency does not hold for the Vietnamese market.
On the contrary, some evidence of semi-strong efficiency exists in the literature, mostly regarding the U.S. market. In Gersdorff and Bacon (2009), for example, semi-strong efficiency is supported regarding U.S. market. Additionally, Ball and Brown (1968) present findings that also show that the U.S. market are semi-strongly efficient. Lastly, the literature testing the strong form of efficiency is limited, due to the difficulties of testing for private information. Jensen (1968), nonetheless, finds evidence of strong efficiency regarding the U.S. market, that is also confirmed in several other studies (Penman, 1982; Meulbroek, 1992).
So, not only efficiency is not consistently supported by empirical evidence, but it also seems to be stronger in some markets while weaker in others. The findings make one wonder how is it possible to empirically observe that some markets are strongly efficient while in some others, even weak efficiency is rejected. The answer to this question could be rooted in the assumptions behind Fama's efficiency.
Efficiency, in its core, is based on the assumptions of the homogeneity of agents and the absence of frictions. In neoclassical finance, this assumption is not unusual. Another essential variable for transactions to occur, and thus for markets to efficiently reflect information, is trust. The fact that strong and semi-strong efficiency exists in some markets, but is not present in others, could be explained either by errors in the decision-making process of agents or by the absence of trust, that creates high cost and intense uncertainty for market participants.
The cost of gathering and analysing information is, for example, considered zero by Fama in his original proposal. Then this theory was modified to account for the cost of information, as rational agents will collect information up to the point where it is marginally profitable to do so. Therefore the concept of efficiency will adjust to transaction costs and risk (Stigler 1961, Jensen 1978).
Heterogeneity of agents is another important assumption that might be linked to market inefficiency. Even in organized markets, such as the U.S., agents are not homogenous. There are institutional investors, small individual investors and large individual investors that might have different trading horizons and strategies. What is more, some of these investors are not qualified and they cannot access information properly. For example, in most markets noise traders are present and - at least in the short run - they can disrupt prices and efficiency (Black, 1986; DeLong et al., 1990, Jeanne and Rose, 2002). Neoclassical finance and efficient markets are not sufficient to explain many phenomena that are empirically observed in financial markets. One empirical observation of this form is clustered volatility. Theories of discounted dividend (Cambell and Schiller, 1988) and speculative bubbles (Zhou and Sornette, 2009; Harras and Sornette, 2011) are unable to explain the formation of clustered volatility in the market.
There are, though theoretical approaches to financial markets, that can explain more successfully market frictions, such as volatility and price disturbance, that are not based per se in the structure and informational efficiency of the market, as neoclassical finance propose. With the rise of evolutionary psychology and neuro-sciences, the field of decision making started to change. Many phobias and behavioural abnormalities are now explained through an interdisciplinary approach, whose only objective is to describe human behavior and decisions. The rise of behaviourism,

that started with Simon (1950), quickly spread over all social sciences, economics included. The ideas of cognitive failures, bounded rationality and heuristics gave researchers new tools that could explain many empirical phenomena.
In the seminal work of Tversky and Kahneman (1971, 1974, 1979, 1983), there exist many behavioural biases and heuristics, that impede optimal decision making. The aggregate effect of these biases and heuristics is evident in price distortion and financial markets as a system. A bias of this sort, for example, is conservatism (Edwards, 1968), that describes the tendency of an individual to improperly revise and judge new information, when it contradicts his de facto beliefs. This bias, in the case of financial markets, may affect the transmission of information and lead to higher weights in the distribution of prior earnings, subsequently causing underreaction to news arrival (Kadiyala and Rau, 2004). Another bias, that explains various financial phenomena, is overconfidence. Overconfidence is related to the subjective probabilities of agents and may, thus, lead to price distortions. These distortions usually manifest as overreaction and underreaction to news and information (Daniel et al., 1998; Spyrou et al., 2007; Badreddine et al., 2012; Galariotis et al., 2014). These distortions can then lead to higher scale market frictions, as, for instance, excessive volatility and deviation of the trading volume from its predicted value (Gervais and Odean, 2001; Statman, 2006; Gervais et al. 2011).
Often, one phenomenon can be linked to several biases, as these biases are interlinked. It is not easy to completely separate the behaviour, that stems from one bias, from patterns, that are derived from another. For instance, overconfidence relates to self-attribution and self-deception bias (Statman, 1999; Myers, 2015). What is more, conservatism is linked to the disposition effect, which in its roots is a form of loss aversion. [1](Shefrin and Statman, 1985).
There are numerous more biases and heuristics that impede cognitive function and may influence financial markets. These behavioural phenomena include, but are not limited to, self deception bias and endowment effect (Kahneman et al., 1990; Shogen et al., 1990), loss aversion (Tversky and Kahneman, 1983; Dawes, 2004, Koszegi and Rabin, 2006), the representativeness heuristic (Tversky and Kahneman, 1974), that can manifest in many forms [2] and last but not least the availability heuristic and adjustment from anchoring. The availability heuristic strongly relates to overreaction to information (Kliger and Kudryavtsev, 2010) and forecasts (Bradshaw, 2011), as although information is available, analysts fail to forecast successfully. Forecasts are also affected by adjusting from anchoring. To make matters even more complicated, the anchor is completely random and has nothing to do with financial markets or misperceived of probabilities and distributions(Epley and Gilovich, 2005).
All the above biases and many more serve to explain market anomalies and failures. These failures can sometimes occur due to the dual function of our brain and the way the human species evolved and not just homogeneity and informational asymmetry. Behavioural pitfalls though, are neither the sole cause of frictions in the market nor are they a constant and universal occurrence. Several phenomena cannot be classified as merely behavioural but often relate - at least partially - to cognitive factors.

[1] As agents keep stocks that have had a negative performance and prefer to sell stocks that perform well.

[2] For example the conjunction fallacy, the gambler's fallacy and the hot hand fallacy that can be observed in the short persistence, for specific stocks that have a negative performance or a positive trend, while ignoring the fundamentals (Gilovich et al., 1985; Carhart 1997, Hendricks at al; 1993)

Furthermore, there are arguments against the behavioural approach. Many of these arguments centre around the identification procedure and the design of the studies, that firstly categorised biases. For example, the experimental design and its effect on test subjects is a major point of disagreement and criticism. The experiments that led to the identification of biases and heuristics were conducted in a specific frame, and it has been shown that behavioural pitfalls do not manifest in every frame[3] (Gigerenzer and Hoffage, 1995; Cosmides and Tooby, 1996). The environment has a direct effect on our decision making process, as illustrated by choice architecture designs (Thaler and Sustein, 2008). There are cases when our brain does not assess statistical probabilities accurately. However, the environment in which we conduct such an error is crucial to the occurrence of the error. A market failure, an economic phenomenon or market friction might be a result of evolutionary psychology or a product of our brain's heuristics. It is nonetheless equally possible, that asymmetrical information, the structure of the market, the institutional and regulatory framework and many other non-behavioural factors are the cause of market failures and abnormal phenomena. A combination of all the above is also a possible explanation.
There are so many phenomena in financial markets that could be described by many different schools of thought. Many phenomena may occur in the neoclassical setting where agents are rational, and the same phenomena may occur in a behavioural setting where agents are irrational, or that rationality is bounded. One of these phenomena, whose nature is complicated, is mimetic behaviour and herding. Herding, as firstly implied in Keynes (1936) "*Beauty Contest*, describes a situation in which, a person ignores his personal information and engages in mimetic behaviour. There are many definitions and manifestations of herding, as we will see below. On the contrary, there are hardly any ways of measuring or predicting herding. The complexity of this phenomenon, its various forms and its impact on financial markets we try to investigate below.

2.2 Herding: Mimetic behaviour in Sociology Economics and Finance

Mimetic behaviour and herding were firstly explored in social sciences. Then the findings and concepts, that have already been explored, were applied and expanded in economics and finance

2.2.1 From sociology to financial markets: In a Nutshell

Sentient beings in order to survive and evolve form communities. All groups of such beings and all systems that include them, express signs of mimetic behaviour. From the creation of the first organized human communities up until now, individuals in such communities mimic one another. This mimetic tendency led to the creation of phenomena of similar collective patterns in modern societies.
Collective behaviour was primarily identified for animals, who use to form herds and follow the stronger one among their population in order to survive. Examples of herd behaviour in animals are packs such as wolves, bird flocks, fish schools and

[3] This is known as framing effect

herds of other mammals. These mammal patterns do not exclude humans. For example, intense mimesis is observed in children and young adults as an essential part of their social and cultural integration (Wulf, 2011). In this case mimesis, that has educational benefits, is socially desirable while in other instances it is not. In his book about the motives of human rebellion, Ted R. Gurr (1970) demonstrates the dynamics between humans and the motives of human rebellion, explaining how mimetism leads to spreading rebellious behaviour. In a relatively recent study by Dan Braha (2012), data from civil unrest derived by 170 countries, for an almost ninety-year period, are examined. Civil unrest is shown to be affiliated with geographic variables and mimetic behaviour.

The way crowds interact and organise has been an interesting topic during the entire history of scientific thinking. From ancient philosophers, speculating on human nature, to modern scientists, tracing the origins of human behaviour in neural experiments, a large literature has been developed concerning how people behave as part of a crowd. Particular characteristics are attributed to individuals as parts of a mass. Three very basic notions, that characterise individuals as part of a crowd are the absence of responsibility, contagion and suggestibility. Gustave Le Bon (1895) observed these three behavioural shifts in individuals who enter a critical mass. The first thing observed was that individuals conducted acts, that they would not conduct before entering the crowd, implying recklessness and loss of personal responsibility. Similar to the behavioural adaption to the crowd above, individuals adapt their beliefs to those of the crowd and thus contagion occurs. Last but not least, this adoption of the crowd mentality, that is not always beneficial for each individual, is nonetheless encountered. Since then, there have been many additions to what we call today crowd's psychology and its social implications. An example, where crowd psychology is more than evident, is that of protests, riots and any form of social demonstration and uprising (Braha, 2012). In these settings, contagion is evident between individuals who form an almost homogenous group via their interactions.

Mimetic behaviour and common neural processes in humans are basic variables, that are directly affiliated with herding formation. Scientists, in order to identify herding, either try to identify the process and mechanics of thinking or they focus on behavioural characteristics and patterns that the individuals demonstrate. Raafat et al. (2009) argue that herding shall be investigated in a multidisciplinary setting. The researchers suggest that apart from decision-making mechanisms, the structure of the market - as the *environment* - shall also be considered. New evidence from high-edge fields, such as neuroeconomics, are vary important, when we try to infer human behaviour. A neural explanation to many patterns of behaviour is implied by heuristics and is today an important part concerning decision making in economics and finance (Glimcher and Rustichini, 2004; Rustichini, 2005; Kuhnen and Knutson, 2005 ; Burke et al., 2010; Baddeley, 2012). Some manifestations of herding in the society and the three pillars of crowd psychology are demonstrated in Figure 2.1.

In financial markets, herding is a pattern that creates a risk of different forms, for many levels of the financial system. It has been affiliated with economic bubbles and asymmetrical information, but the evidence is not always strong. Below, the major types of herding and the main empirical evidence are presented, in order to shed light into the different factors, herding is affiliated with.

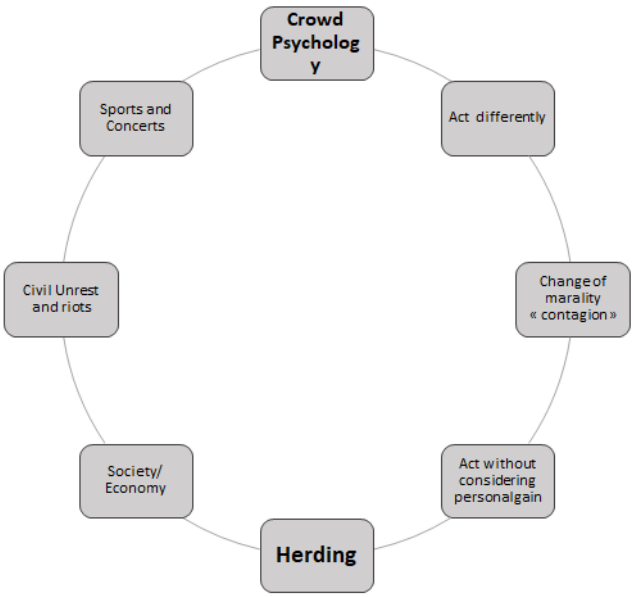


Figure 2.1: Herding and Crowd Psychology

2.2.2 Herding: Definitions and Theories

Although the concept of herding seems very straightforward, the reason behind its appearance and the form of its manifestation vary. This led to the existence of many similar but not identical definitions of herding that are briefly present below.

Definitions of Herding

Avery and Zemsky (1998) define herding as the choice of investors to ignore their own assessment and follow the trend of the previous trade, even if this choice goes against their own estimation. In the form of contagion, some types of investors and agents in the market [4] sometimes perform as a crowd, in the sense that they all base their investment strategy on previous trading and thus they follow one another, creating a distinct mass with the same *revealed* strategy in choice. Nofsinger and Sias (1999) define herding as the formation of a group of investors, who trade in the same direction simultaneously. This is the vastest definition of herding, as it only accounts for the the aggregate result of mimetic behaviour. De Bondt and Forbes (2002) base their definition of herding on analysts' predictions, as the variable that often drives herding, in the authors' frame of work. They claim that herding in trading comes as an effect of convergence of analysts' forecasts. Welch (1992, 2000) focuses on herding as a form of mimetic behaviour that investors mutually perform. On the same basis, Hwang and Salmon (2004) also focus on the mimetic nature of herding, stating that herding is a form of correlated behaviour, that manifests when those participating in the market ignore their personal information and beliefs by following either the actions of others or the movements of the market. Hirshleifer and Teoh (2003) investigate herding from the point of behavioural convergence. Bikhchandani and Sharma (2001), on the basis of information, categorise several

[4] Noise traders, under informed or under skilled investors, fund managers for reputational or compensational reasons

informational imperfections and argue that herding truly arises only when investors intentionally mimic others. In another study of informational herding, Park and Sabourian (2011) define herding in the form of a history switching behaviour in the direction of the crowd. As the authors point out, in the frame of their model herding is defined as a kind of momentum trading. The definitions described above, are based on theoretical and empirical research concerning herding and its coming to existence in some level of financial markets.
All these definitions revolve around the same concept and idea of what herding is and how it manifests. The exact fashion, in which herding manifests, varies in nature from rational to irrational, in intention from spurious to speculative and in motives from reputation to fads and sentiment. There are many different theoretical approaches and thus different models concerning herding as we discuss below.

Theories of Herding

Financial markets are a form of social creation, in the sense that they include and require observation of others in the same group (i.e. Market) and interaction with others. It is then expected of market participants to demonstrate the characteristics of crowd behaviour as they form one. Moreover, the modern world and markets, with the expansion of technology, create a setting where information is infinite. Although information is easily acquired, it is a hard task to distinguish between useful and harmful information as well as the validity of everything we learn. Apart from the cognitive load of information, there are times when investors decide to ignore their knowledge and follow the market and its tendency. So there is not only one type of herding in the market but several ones and the way investors decide in each type is motivated by a separate force.
Initially, it is important to identify the difference between intentional herding and spurious herding. Spurious herding is a situation in the market that might resemble herding, as investors seem to follow the same patterns, but investors follow fundamental information. While herding can be rational and intentional, spurious herding is the unintentional common choice of agents to follow the same information and thus it does not qualify as herding. In an attempt to quantify and examine intent, Bikhchandani and Sharma (2001), in their seminal paper about herding, they summarise the theoretical and empirical findings and categorise herding, based on the cause of its creation, defining in the same time what is known since as spurious herding. This term refers to the result of a common belief system, concerning certain occurrences in the market which investors share. Although the aggregate result of investors' decisions may resemble mimetic behaviour, it is not.
Herding, on the other hand, is intentional when investors chose to ignore their personal information and beliefs, in order to mimic other investors and their actions due to, for instance, informational cascades, reputational or compensational motives. Herding, especially when intentional, can be a product of rationale. It is though quite hard to identify intent empirically on the level of choice. Gavriilidis et al. (2013), for example, empirically define spurious herding as the tendency of investors to demonstrate the same strategy, not due to imitation but due to information (based on fundamentals), that is common in the market. Using market and sector variables to account for intent, they show that herding - on the microlevel of flows- is mostly intentional and present, especially after periods of underperformance market-wise and sector-wise as well.

Financial markets act as a place, where borrowers and lenders interact in order to create value. Information is vital to this cause, as insinuated by the efficient market hypothesis (Fama, 1970). In Bickhandani and Sharma (2001) information is a crucial factor for the creation of herding patterns in the market. Investors recognise the importance of information, in order for them to invest successfully. Many investors have limited access to information or information is too costly for them. For various reasons, not all investors have the same level of information and therefore information is not homogeneously distributed in the market causing asymmetry. Herding can be caused due to the fact that investors who do not hold sufficient information tend to follow other investors, who "probably know more". Another possible explanation, through which information causes investors to mimic, is their tendency to believe that some specific agents - experts- generally hold better or more information than others. Some investors - and especially inexperienced ones - tend to ignore their personal information to follow other investors, perceived as *financial gurus* who know better.
Banerjee (1992) creates a model of a sequential decision making process in which an agent identifies the choices made by other agents on previous terms. These investment choices are appraised as signals and they could potentially interfere with the decisions of consecutive agents, in particular in a dynamic sequential setting. The mechanism through which, information, about previous choices made by others, can rationally affect the decision making process of an agent and lead the agent to herd, is highlighted analytically. Similarly, Hirshleifer and Teoh (2003), state that an informational cascade occurs when an investor selects to follow the investment strategy of another investor, disregarding his personal information in the process. This process shall be evident in the choice of the affected investor. Informational asymmetry and the resulting cascading pose an obstacle in the market and compromise its efficiency, as prices cease to represent the totality of information and often deviate from their fundamental values. The authors describe this phenomenon as a blockage because prices fail to fully reflect the information available. These blockages can be either partial or complete and have the power to influence the market and the level of uncertainty on an aggregate level according to the authors.
Other observable consequences of informational cascades include shocks to prices, the creation of fads and fashions (ex: the internet bubble) and stampedes. In another model of sequential choice, Park and Sabourian (2011) build on the results of previously proposed sequential models and demonstrate that extreme price movements are possible, in settings less extreme and rare than existing models imply. [5]. They show how even a small number of agents can greatly affect the market and its informational efficiency. In a sequential choice setting, the order in which the agents (ie. investors) decide is important as the choice-signal of the first can affect consequent agents and their investment choices. As shown by Banerjee (1992) and Bikhchandani et al. (1992), whenever a decision is made, a signal is sent into the market and the market is formed aggregately on these signals. In extreme cases, it is only the signal of the first agent that is reflected into the market as the rest of the agents will follow the first agent, believing that the first signal reflects a supreme form of information, or just because they do not possess adequate information themselves. Of course, in true conditions, not everyone follows the first agent in order to decide. Nonetheless, often, the signals and thus the information processed by

[5] For example the setting of Avery and Zemsky, 1998

several agents is never revealed in the market due to the influence of signals - as choices - created by previous agents.
Concerning informational cascades and whether or not they are possible in the aggregate level, the results empirically are not conclusive. In Avery and Zemsky (1998) it is highlighted that a cascade is theoretically improbable to occur, if information maintains a simple structure and if there is a given price mechanism. But in today's competitive and complex markets, information very rarely maintains a simple form. Apart from being complex structure-wise, information requires analysis and inference, in order to transform into strategy. For herding to occur, in this framework, in a complicated information setting, two main conditions have to be met. Firstly, the value of the asset has to be doubted. Secondly, the information of the agent, about the market on average, has to be relatively weak.[6]. These results are further supported by experimental studies, such as the studies of Cipriani and Guarino (2005) and Drehmann et al. (2005). In both studies, subjects do not mimic the decisions of others when the structures were kept simple. Cipriani and Guarino (2005) argue that information on the decision of others, in a symmetric setting, does not lead the average subject to mimetic behaviour. Additionally, Drehmann et al. (2005) demonstrate that informational cascades, via mimesis, are not possible, when price flexibility is present in the market. These results are also statistically robust, in the sense that the big number of participants allows for generalisation. On the other hand, Park and Sabourian (2011) argue that, in a sequential choice model, the results of Avery and Zemsky (1998) shall be doubted, as the definition of the monotonic signals that are shown to prevent herding, is not robust and realistic.
The roots of these patterns are essential to identify the motives, driving informational cascades or blockages. On one hand, the motivation concerning herding may be irrational and based on appeal to wisdom and crowd psychology. On the other hand the motives of herding might be rational and intentional. As Banerjee (1992) shows, it can be rational for someone to mimic someone else, if they know that their own information is not accurate or if they suspect that there is more information available. Bikhchandani et al. (1992) also argue that the choice of following someone, as a decision unit, can be completely rational, whether or not the aggregate result is socially desired.
Another example of herding on informational motives was made by Welch (2000). Instead of focusing on the decisions of previous investors, Welch tries to identify possible explanations, based on the sources of information. In this particular setting, analysts also herd in terms of recommendations. More specifically, the recommendation of an analyst will sequentially affect the recommendations of the two proceeding analysts. He also points out the cycle between herding and the form of the market. According to his argument, lower quality and more unstable markets enhance herding behaviour due to asymmetrical information and institutional inefficiency. Empirically, these assumptions are partially validated. [7]As we will see further below herding is more intense in emerging and less organised markets.

[6] A well-informed agent would rationally follow his own information

[7] The idea that there is a causal relationship between institutions herding and market inefficiency, could be contradicted by evidence showing both that less organised markets are characterised by stronger evidence of herding (Holmes et al.,2013) and by per se literature, that showns that a rise in institutional owneship has often positive effects regarding accuracy in forecasting (Ajinkya et al. 2005) and informational symmetry, among other parameters (Healy et al. ,1999; Bird and Karolyi, 2016)

A vast part of relevant literature is devoted in herding in analysts' recommendations, along with the influence analysts have for investors' behaviour - who may herd based on these recommendations - and the market. Given that analysts affect information, the strategies of investors and market sentiment, it would be beneficial to look into motives and effects of analysts herding briefly.
Graham (1999) argues that high reputation, low ability or significant informational signals dominating the market are three parameters , that may lead analysts to herd. Kim and Zapatero (2009) show how per industry performance evaluation can result in analysts following their peers. For sufficiently large stocks, the dispersion of recommendations is negatively related with the return volatility, despite the fact that larger stocks' markets are more symmetrical in terms of information. In another study, Conrad et al. (2006) examine the sensitivity of the analysts' recommendations with respect to stock price movements. Using data from 1993 up until 1999, the authors show that large stock prices' declines are much more possible to result to an analyst downgrading a stock.
Given the above the accuracy of analysts' forecasts is a question of high importance with respect to herding. Clement and Tse (2005) suggest that prior accuracy, experience, the analyst's specialisation[8] and brokerage volume are positively related to how much bold - and not mimetic - the analysts' earnings forecast will be. Concerning accuracy of the forecast, herding forecasts, as expected are less accurate than bold forecasts and lastly herding forecasts are more incomplete, indicating that bold forecasts reflect more private information. Whether these results stem from the characteristics of analysts or the mechanism of diffusion of information is ambiguous. In their recent study Keskek et al. (2013), show how disclosure regulations affect the accuracy of analysts' forecasts, reaching the conclusion that the positive relation between the characteristics mentioned above and accuracy is mostly due to the analysts' advantage, regarding access to information. In an attempt to measure herding with respect to its motives, Huang et al. (2016) try to parametrically estimate herding propensity due to imitation and earnings' forecasts. Their findings indicate that 60% of analysts herd. The propensity to herd is high especially when non-orthogonal and more realistic informational signals are considered.
Moreover, investors face agency problems and issues regarding the accuracy and cost of information. Analysts' herding often creates frictions and leads to contagion in the market, as invesotrs are affected by analysts' recommendations. These recommendations create informational inefficiency as mentioned above, but also reputational motives to herd. An example of contagion and herding are international economic crisis and the creation of a common sentiment. For instance, concerning the crisis in Latin America in the nineties, Calvo and Mendoza (1996, 2000) investigate primarily the Mexican market. The researchers found that a cost benefit analysis picks herding as a dominant strategy rationally. They base their arguments on the domino of crisis and currency devaluation, that occurred in Latin markets, after the crisis of the Mexican peso, in the middle 1990s. They showcase the informational and behavioural contagion, that occurred as Latin countries one by one followed Mexico's road. Similar arguments can be made about the market contamination and the domino effects observed during the sub-prime market crisis, that shocked the international markets in 2008. Contagion can take place within a market- as information follows a consensus in analysts and then investors- and across markets

[8] If an analyst dos not follow many industries, he is considered more specialised.

- as herding becomes the dominant strategy and pessimism dominates the sentiment across markets. There is evidence that shows that contagion does not always take place neither within nor across markets. This does not necessarily imply that herding is absent from all markets or all market levels. It is often the case, that a part/group of the agents mitigates the effect of another part/group of the agents via arbitrage or due to investment preferences (De Long et al., 1990, Liao et al., 2011). Apart from information, there exist further reasons behind mimetic behaviour. Professional reputation and its management as an asset, by individual investors and funds alike, can be a key factor. Agents, especially less capable ones, have many career concerns that often motivate them to mimic more experienced and capable agents.

Agents, analysts and investors, who operate on the market's micro-level, take decisions that may affect their peers or other financial agents. As this consensus forms, it is often a career-wise optimal strategy, for a financial agent, to follow his peers for reasons relative to his reputation or even his compensation. In Keynes's word *it is preferable to fail with the crowd than succeed alone* (Keynes, 1936). The aggregate effect of such decisions may or may not distort prices market-wide.

There exist extensive documentation of reputational herding in financial markets. In Scharfstein and Stein (1990), when the labour market is not frictionless and thus people manage carefully reputation, individuals need to be able to "share the blame" and therefore they mimic one another. In the design of their model, the authors assume that the labour market re-evaluates a manager's ability, after taking into account the chosen investment strategies. The pressure this kind of evaluation procedure poses on managers is enormous, as every decision they make is going to have an important effect on their reputation in the market. The structure of information inside an analyst's or investor's firm is very important, especially when the level of experience of an agent is low. Opaque information environments promote herding, even when information is symmetrical, as capable investors act first and the others follow (Leece and White, 2017). However, opaque information also promotes more price discovery than disruptive herding strategies, that may cause market inefficiency. Security analysts have been also documented herding on similar strategies, but more often the consensus is based on blind mimesis and not information (Cote and Goldstein, 1999).

The setting of peer pressure and uncertainty can result in managers following other managers, especially when these other managers are highly viewed by their peers. In the setting of a game, the dominant strategy of a manager might be to follow his peers, especially in - but not limited to - cases when he has not yet established his reputation. Nicole Boyson (2009) shows that when senior managers choose to deviate from their peers' consensus, they face a significantly higher probability to fail in comparison to less senior managers. What is more, senior managers, that deviate from the herd, do not profit from higher fund flows. As the author speculates, this can be an incentive for managers to herd while their seniority expands. Even though seniority is not equivalent to reputation, senior managers that have been in the market for longer, have a higher chance of being reputationally established. In many cases, reputational and compensation-based motives co-exist and lead to managers forming a herd. The "better safe than sorry" strategy, and thus an instinct to avoid loss, leads investors to herd in order to reassure their position as part of the crowd and keep their credibility.

In the spirit of reputational motives and through sequential trade modelling, Dasgupta et al. (2011) try to identify the effect of managers' career concerns on an aggregate level. They show how career concerns lead to market inefficiency, as the information revealed in such a setting is suboptimal, although the market liquidity rises. The relationship between herding and market liquidity is also shown to be important on the market macro-level of returns (Galariotis et al., 2016), even when we examine it from the point of firm specific risk and beta herding (Krokida et al., 2016).
The assumptions of Dasgupta et al.(2011) are tested on an experimental study by Roider and Voskort (2015). They conduct a laboratory experiment to test for the existence of herding sequentially in an asset market, where salaries are determined by the participants acting as employers. Although the investor's behaviour is observed, the level of the investor's ability is not. The researchers find that trends are created without reputational motives and that reputational motives do not create significant herd behaviour themselves. This could be due to the endogeneity of reputation in the model. As stated by Rajan (2006), following other managers is a type of self-insurance, used to protect against the possibility of being wrong and the risk of underperformance. Another similar theoretical approach, in the same framework with Scharfstein and Stein (1990), is that of Ottaviani and Sorensen (2000, 2006). They model sequential investments and argue - contrary to what Scharfstein and Stein support - that better agents do not necessarily have more correlated signals, conditionally on the state of the world. In the case of binary signals especially, they demonstrate how herding rises even when signals are independent.
Apart from their reputation, agents care about their compensation as well. Very often an investor decides to "ride the bubble" and herd, as this is the most profitable strategy. Compensation-based herding is linked to the principal agent problem and to the structure of institutional investors' compensation. Compensation herding and reputation herding are linked and often pull investors toward different decisions (Massa and Patgiri, 2007). Additionally, herding may occur due to common characteristics between investors as a group. The common nature of investors includes resemblant studies and training, similar activities and ways of life, as well as common sources of information and work environments. This crowd formation, often, leads also to investors preferring the same kind of characteristics in a stock. It is shown that certain stock markers- such as size, sector and past performance - attract investors due to the investor's similarities in characteristics (Falkenstein, 1999). This type of herding is referred to as characteristic herding. Holmes et al. (2011) attribute this kind of herding mostly to cognitive parameters, as they argue that it occurs unintentionally. Herding due to common characteristics is also a big part of empirical models of micro-level herding, and precisely institutional herding (Sias, 2004). For instance, Chen et al. (2012) study qualified foreign investors - as an investor group with distinct characteristics - in Taiwan securities' market and find evidence of herding and momentum trading. The type of investor is an essential parameter to consider when approaching herding. As different types of herding are shown to have different effects (Zhang and Zhou, 2012[9]), the role of different types of investor, both in origin - foreign versus domestic - and in its nature - individual versus institutional - becomes central in our efforts to measure both herding and its effects (e.g. Barberis and Thaler, 2003; Liao, 2011).

[9] For the importance of intent

Characteristic herding, is unintentional when it occurs due to cognitive and psychological parameters. Many other financial behaviours are also occurring in a behavioural manner and many times herding and other phenomena co-exist and affect each other. For example, in the case of foreign qualified investors mentioned above, herding and momentum trading are identified jointly (Grinblatt et al., 1995 ; Wermers, 1999). So herding is also linked to many behavioural biases, through market-observed behaviours, such as over-reaction and/or under-reaction. These phenomena have the potential to distort the market affecting prices and informational efficiency. Moreover, under-reaction, over-reaction and momentum are more common in specific market settings (Galariotis, 2004; Antoniou et al., 2005; Galariotis et al., 2007; Antoniou et al. 2007; Galariotis, 2010; Galariotis, 2012; Galariotis 2013). The type of investor is once again highlighted regarding the type of investment strategy and the reaction to information. Shleifer and Summers (1990) categorise investors into noise traders, who are irrational, and rational agents, who chose with the intention of maximising their expected benefit. When market movement is not based on rational motives[10] and given the presence of noise trading, *financial gurus* - via their opinion - may influence the market and lead to herding. As stated above, arbitrageurs, being fully rational, decide against taking the risk of mitigating herding. Limits to arbitrage could potentially allow contagion and market-wide herding, as an irrational raise in demand, may drive prices away from their intrinsic values. If returns are lower than they should be, they do not properly reflect risk and informational efficiency is not achieved.

To amplify this effect, noise trading can potentially outperform technical analysis, as far as investment strategies are concerned. Contrary to common sense, DeLong et al. (1990a, 1990b) show that it is highly possible for noise traders , while being irrational and performing no technical analysis, to enjoy higher profits. Higher profits for these type of investors is a consequence of higher risk - and partially due to limitations in effective arbitrage - and thus higher returns. On top of affecting asset prices and destabilising the market, noise traders and stochastic decisions outperform in many cases rational investors and investment planning. Herding - even the irrational type - can be a profitable strategy sometimes.

Empirical evidence, of this sort, underline the importance of models, that account for behavioural patters, that relate to herding. To the support of the existence of such patterns, Barberis et al. (1998) structures a model for investors' behaviour based on sentimental factors. An important accomplishment of their analysis is that it explains phenomena such over-reaction and under-reaction to information, through the incorporation of biases and heuristics such as representativeness. [11]

Some of these behavioural biases and financial anomalies, that are linked to this model, are a variable of interest regarding collective behaviour, momentum trading and market efficiency.

Such a psychological bias , that could possibly explain mimesis, is cognitive dissonance (Festinger, 1957). Prast (2000) affiliates cognitive dissonance to herding through his seminal paper. Cognitive dissonance between two cognitive units occurs, if observing one of the two leads to observing the other. Investors often prefer

[10] Mostly fundamental information regarding assets

[11] There exist several other behavioural models that account for mispricing and patterns of trading developed by economists (Hong and Stein, 1999 ; Daniel et al., 1998 to mention a few).

to follow their peers, due to logic or dissonance. One such example is reputational herding that can either be a strategy or a manifestation of cognitive dissonance. Another behavioural concept closely linked to irrational herding is conformity. Hirshleifer (2001), identifies conformity as a parameter that drives investors to mimic one another. In this sense investors do not personally follow the actions of one peer among them, rather than, they observe the total movements of their peers and try to stay in the flow. A critical parameter, affecting the manifestation of conformity in the actions of investors, is the recent expansion of media, online networks and computer use. Information about the actions of others is more accessible now than ever. For example, Reeves and Nass (1996) argue that individuals tend to regard media like *real people*. This leads towards striking levels of conformity regarding media. In a study about facebook, herding and conformity, Egebark and M. Ekstrom (2011) used the reactions (likes, shares etc.) of users. They find evidence regarding both herding and conformity within users, showing also how social media extend these phenomena.

Last but not least, home bias (Feng and Seasholes, 2004), the effect of rumours on investors' beliefs (Buckner, 1965) and limited attention[12] are all behavioural concepts, that explain many of the herding patterns developed in, both the micro-level and the macro-level of the market. Preference to familiarity and limited attention can affect the formation of the preferences of investors. This homogeneity in preferences can lead in unintentional herding on behavioural parameters.

Home bias was initially identified by French and Poterba (1991), who investigated home bias concerning domestic and foreign equities. Tesar and Werner (1995) also identified home bias and linked it to high turnover. What is more, home bias does not exist only between counties but also regionally within the same country, as shown by Coval and Moskowitz (1999). In Feng and Seasholes (2004), we observe how geographical parameters can impact herding and the entire market system. The tendency of isolated traders, or group of traders, to herd more, alongside with the preference of investors for domestic equities, are empirically documented. The authors pose a distinction between, what they consider herding, and what they define as correlated trading. Their results indicate that observable herding measures may reflect justifiable - by fundamentals - correlated trading. The possibility of spurious results is an indication of empirical weakness concerning the methodologies for herding identifications and measurement. It is evident that behavioural factors may lead to unintentional herding. The importance of such factors is usually approached through the question of intent and is essential to the effects herding has on the market. For example, in Zhang and Zhou (2012) the importance of intent for the manifestation of momentum strategies, that will lead to inefficient markets is underlined. As the authors argue, it is extremely important to distinguish actual herding from the spurious one, if we want to assess its risk for agents and the market. Intentional herding relates to momentum trading and price distortion, while spurious herding and correlated trading do not have such effects.

Another important factor, that can cognitively impede financial decision making, are rumours. Rumours affect expectations as they are often considered a source of information - or at least a potential one. As we mentioned above, rumours can be affiliated with fads, fashions and financial gurus and can affect the market through

[12] Limited attention usually manifests in financial markets as the inclination of investors to prefer cognitively-wise familiar information

herding. Using the famous sequential model of trading with inside information created by Kyle (1985), Van Bommel (2003) shows how imprecise rumours can lead to overpricing and disturbances in the market through "stock tips". Using acquisition announcements and rumours about them as a variable, the author shows how traders, even rationally, chose to trade based on the aggregated expected overreaction. In terms of takeover rumours, they document an extravagantly high volume of trading before the announcement, indicating that rumours and uncertain information needs to be processed by the market.
We can clearly observe the complexity of herding from a theoretical point of view. In addition to that, herding is related to momentum, overreaction, informational and overall market efficiency among other factors. Herding is affected by the structure of the market and affects the market as a whole. The effects of herding in the market are dependent on the motives, the extent and the nature of herding. All these parameters determine whether herding distorts prices, or whether it assists price discovery. From a theoretical stand point, herding is quite diverse. There have been attempts to quantify this phenomenon empirically. Below we present the empirical methodologies, developed to measure herding and their performance with respect to theory. The complexity of financial markets, as we document, poses a significant obstacle in the identification and measurement of herding.

2.3 Measures of herding and empirical evidence

The empirical literature regarding herding is divided basically in three parts: the micro-data literature, that is based on flows, the macro-data literature, based on returns and a part of the literature based on theoretical models and experiments. The latter is smaller and has been criticised for its applicability and non realistic nature by design.

2.3.1 General evidence and the experimental approach

Empirically there have been attempts to test the theoretical models, that are based on the motives, the causes and the effects of herding, to verify whether or not agents herd. Especially for the initial sequential choice models, some experimental studies were conducted, to investigate herding in financial decisions in a controlled environment. Examples of such effort, are found in the aforementioned experimental work of Cipriani and Guarino (2005) and Drehmann et al. (2005). Furthermore, on a more recent note, Bursztyn and Jensen (2017) develop and test, in an ambitious field experiment, a model of social interaction and peer effect and the findings are ambiguous. Experimental and field-oriented research is generally characterised by such ambiguity as, depending on the focus of each researcher, the experimental design and the basic hypotheses change. Usually, the results of such research are applicable only for settings and frames, similar to those of the experimental design. This is partially related to framing effect, identified by cognitive psychology, and to by-necessity-posed strict parameters, throughout the process of an experiment. That being said, the results and revelations of such research are crucial for further decrypting the process, through which financial decisions are taken. What is more, the tendency of individuals to herd is highlighted by studies focused on the function of the brain. The neural approach is an important part of behavioural studies, as it

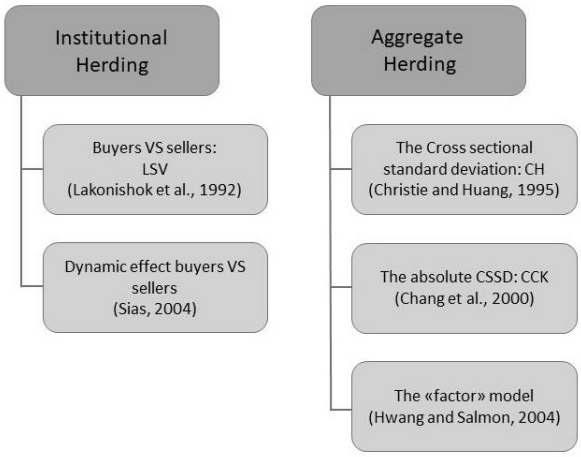


Figure 2.2: Main empirical measures of herding based on the approach

focuses on the origin of our decisions and the mechanism of our responses. Mimetic behaviour is a phenomenon that could stem from our brain function and mechanisms related to evolutionary psychology. A combined multidisciplinary study by Baddeley (2010) shows how individuality and each person's cognitive and neural processes affect the propensity to herd. The main hypothesis examines the existence of herding tendencies in financial decisions, via neural connections in the brain, that are experimentally identified. To elaborate, neural responses are displayed in a magnetic resonance, in order to quantify the effect of the decisions of others on an individual's decision to herd, regarding their financial choices. The results clearly indicate a statistically significant effect of the decisions made by others on the individual, and thus the tendency to herd is also supported by neural evidence.[13].
Although all this research is very useful concerning individually taken micro-level financial decisions, it reveals little concerning financial agents, institutions and markets. An important part of finance is the identification of parameters that affect prices, returns and volatility and the mechanism through which this happens on the individual, institutional and aggregate level, for well organised and emerging markets. In order to approach all these essential issues, empirical methodologies and studies have been developed. There are various hypotheses central to empirical approaches but the existence, the extent and the market effects of herding are primary components in all of them. This literature is generally divided into two subgroups: individual/institutional or micro-level herding and aggregate or market wide herding or herding to the market consensus or macro-level herding. In Figure 2.2 we can see the main measures of herding in the literature based on the approach and the data used. Below we analyse the basic methodologies used for micro-level data and macro-level data.

[13] As in most empirical methodologies they use Bayesian techniques to analyse their data

2.3.2 Institutional and Individual Herding : Measures and Evidence

The question of herding in financial markets was initially answered for managers. Managers may herd for their reputation, for financial gain, for misinterpreting information or out of mere incompetence. How do we observe this in their decision? How do we measure it? What consequences does it bare? These are the essential questions that micro-level herding literature tries to answer. Nonetheless, the methods designed for institutional investors - managers - have also been applied to individual investors and other investor categories. The term micro-level herding includes all of these categories[14].

Institutional Herding: Methodological Approaches

This type of empirical approach is usually used for proprietary data and centres around the existence of herding, based on the type of investor. The empirical literature of this form mostly revolves around two types of measures, one designed by Lakonishok et al. (1992) and another by Sias (2004). Both of these measures focus on herding in flows and try to identify its existence in the investment decisions of agents. Initially, both measure were applied to mutual and hedge fund managers, mostly on quarterly holdings data.
Lakonishok et al. (1992) created a measure for herding, extensively used and denoted henceforth as LSV, that attempts to capture possible extreme movements of agents. According to the authors, herding on individual stocks occurs when agents - usually managers - buy/sell a specific stock irregularly. This measure attempts to capture the concentration of trading for a certain stock, that may subsequently create an out-of-scale demand or offer for this stock. Mathematically, the LSV measure is computed as follows:

$$H_{i,t} = |\frac{B_i}{B_i + S_i} - p_t| - AF_i \tag{2.1}$$

Where B_i stands for the number of fund managers who buy a specific stock (net buyers), S_i stands for the number of fund managers who sell a specific stock (net sellers), p_t is the ratio of net buyers to the total number of active managers in the market for a certain time interval, as the expected proportion of buyers, where the term AF_i- also known as the adjustment factor - represents the expected value of $|\frac{B_i}{B_i + S_i} - p_t|$ if no herding exists in the market. The absolute value of the ratio $\frac{B_i}{B_i + S_i}$ stands for the ratio of managers, who augment their holdings of a certain stock to the total number of managers, who trade that stock, while p_t denotes the expected proportion of buyers and is usually represented by the market wide proportion of buyers - for all i at each t. The adjustment factor, AF_i represents the benchmark point of no herding and has a reverse relation with the total number of managers trading the stock in question. When the LSV is significantly greater than zero, herding is present in the market. Although this measure does not have direct dynamic properties, one could argue that if the LSV is not stable over time, then herding is also implied dynamically.

[14] We will use these terms - institutional and individual herding and microlevel herding - interchangeably.

To account for this dynamic dimension another important measure, designed to capture herding dynamically in flows, is proposed by Sias (2004). Mathematically, this starts by using the raw fraction of investors buying an asset at a certain time unit as follows:

$$RD_{i,t} = \frac{BI_{i,t}}{BI_{i,t} + SI_{i,t}} \tag{2.2}$$

Where $BI_{i,t}$ stands for the total number of institutions buying a certain asset i, at a certain period t. As it logically follows, $SI_{i,t}$ is the total number of institutions selling a certain asset i at t, while their sum $BI_{i,t} + SI_{i,t}$ is the total number of institutions trading asset i at t. Then Sias uses the statistical technique of standardisation, to adjust the scale of the variable and render it dynamically comparable. Therefore, we have:

$$D_{i,t} = \frac{RD_{i,t} - \overline{RD_{i,t}}}{\sigma(RD_{i,t})} \tag{2.3}$$

By applying a cross sectional time series regression, the author evaluates whether or not the previous term period has a significant effect on the current period, regarding the proportion of buyers to the total number of active traders of the stock as follows:

$$D_{i,t} = \beta_t D_{i,t-1} + \epsilon_{i,t} \tag{2.4}$$

The logic behind this is simple and builts on the same rationale as the LSV measure. If investors herd, then there is going to be covariance across assets, between the proportion of institutions buying at a specific quarter and the proportion of institutions buying at the previous quarter. Therefore the cross-sectional correlation between the proportion of investors buying an asset i at time t and the proportion of investors buying an asset i at time $t-1$ can be indicative of the existence and the extent of herding, relevant to this specific asset i.
Then they decompose the time dependence between two periods as follows:

$$\begin{aligned}
\beta = \quad & \rho(\Delta_{k,t}, \Delta_{k,t-1}) = \\
& \Big[\frac{1}{(K-1)\sigma(RD_{i,t})\sigma(RD_{i,t-1})}\Big] \\
& \times \\
& \frac{\sum_{k=1}^{K}\sum_{n=1}^{N_{k,t}}(D_{i,k,t} - \overline{RD_t})(D_{i,k,t-1} - \overline{RD_{t-1}})}{N_{k,t}N_{k,t-1}} \\
& + \\
& \Big[\frac{1}{(K-1)\sigma(RD_{i,t})\sigma(RD_{i,t-1})}\Big] \\
& \times \\
& \frac{\sum_{k=1}^{K}\sum_{n=1}^{N}\sum_{i=1}^{N_{k,t}-1}(D_{i,k,t} - \overline{RD_t})(D_{m,k,t-1} - \overline{RD_{t-1}})}{N_{k,t}N_{k,t-1}}
\end{aligned} \tag{2.5}$$

The equation above shows the parameter β being decomposed in two parts. The first part of the equation is the correlation that stems from agents following themselves into and out of the same trades, while the second term of this equation stands for he portion of the correlation, that results from investors following others in and out

of certain trades.

The two methodologies described above, although similar conceptually they have some significant differences. The LSV metric, although simpler to apply and interpret, does not permit dynamic comparisons, as it is not designed to capture intertemporal trading patterns (Bikhchandani and Sharma, 2000; Sias, 2004 ;Puckett and Yan 2008; Bellando, 2010). This is the most important difference between the two measures and the argument on which Sias built his methodology. Nonetheless, through empirical documentation, there is no sign of the SIAS methodology outperforming the LSV.[15]
Apart from this difference, those two methods are similar in conception. As we argue below, the results documenting herding presence on the microlevel are not in line with the macro-level approach. This indicates that the definition of herding as a relevant concept and the level we examine will partially determine our results. Moreover, both the LSV and the SIAS have been criticised for their structure. What is more, theoretical aspects of herding, such as intent are not sufficiently captured. Below some empirical findings concerning institutional and individual herding, using the above methodologies, are analysed.

Institutional and Individual Herding: Empirical Evidence

Firstly, Lakonishok et al. (1992) did not only propose the methodology, but also provided us with an empirical application for it. Quarterly data, relative to 769 tax exempt funds in the United States between 1985 and 1989 were employed, regarding 341 managers in total. Using the LSV measure, they identify herding primarily for the case of small stocks in terms of capitalisation. Pension funds, who manage funds of a certain nature and origin, trade in their majority larger stocks due to lower stock risk. Lakonishok et al. (1992), recognise the importance of regulation that limits the number of stock shares of a distinct stock, a fund can purchase. These regulations aim to limit managerial concerns and conflicts due to institutional ownership. Larger stocks, in addition to lower risk, provide a higher value per share to pension fund managers. For these type of larger stocks, the authors fail to identify strong evidence of herding. The investment strategy, that accompanies the type of fund, and thus the type of investor, is once again highlighted. Herding exists in some stock categories, that have distinct characteristics and attract a certain type of investor as well.
Staying on the same market and again for the LSV measure, Grinblatt et al. (1995), also employs quarterly data for US mutual funds for an extent eleven year period, between 1974 and 1984, in order to test for the existence of herding along with momentum trading. Their results support the existence of herding and momentum trading simultaneously for mutual fund managers. Also, there seems to be a particular type of herding regarding the size of stock and the type of fund. For example, the researchers show that income funds herd usually on larger stocks that are known for their stability and low risk. On the contrary, growth funds tend to herd on smaller stocks, that have more growth opportunities.
Another study, indicating that herding is stronger for growth funds in the US, is that of Wermers (1999), who investigates virtually the entire mutual fund industry of the

[15] To the best of our knowledge.

US for nearly 20 years, from 1975 to 1994, and encounters strong evidence of herding also correlated with high cash inflows. Again for the US market, Nofsinger and Sias (1999) investigate the behaviour of both institutional and individual investors trading in NYSE for a large period, between 1977 and 1996. They identify strong evidence of herding for both institutional and individual investors across the micro-level of the market. Institutional herding, in particular, might stem from various factors such as trading capacity, experience, peer effect, analyst recommendations, the efficacy of the transmission of information and more.
Choe et al. (1999), applied the LSV methodology on a non-US market and for a period with interesting characteristics. For the crisis that hit the Asian markets at the set of the millennium, the authors try to examine the existence or not of herding for foreign investors trading in Asian markets prior to the crisis. They concentrate on the most intense year of the Asian crisis, that being 1996/7, and examine the investing behaviour of foreign investors in Asian stock exchanges. Regarding the total sample of 419 stocks, evidence of herding for trading periods solely prior to the crisis are present. These results imply that herding may attribute to financial crisis. What is more, the question of "who herds" proves to be of high value.
More on the subject of the behaviour of foreign investors in Asian markets, Kim and Wei (2002a) encounter important evidence of herding for foreign investors in the Korean stock exchange, also during the Asian crisis, from 1996 to 1998. The time range examined is very important, as the Asian crisis occurred in 1997 and the authors examined both the year before and the year after. Holding important data on individual and institutional investors, that were either of domestic or of foreign origin, Kim and Wei manage to verify the existence of herding not just for foreign traders but for domestic traders as well with the unique exception of domestic institutional investors. Although herding is present for almost all investors' categories, the intensity of herding varies between categories with foreigners and individuals being more intense on herding. In their follow up paper, (Kim and Wei, 2002b), the authors also identify the presence of herding in onshore and offshore funds. The latter result is in line with the primary paper's results. Once more, the importance of the investor type and the intensity of herding is highlighted, especially for the impact of herding on market efficiency.
For the Jakarta stock exchange and during the same crisis period as well, Bowe and Domuta (2004) argue that for the 1997 Asian crisis both domestic and foreign investors herd significantly. Their results for the Jakarta case are on the same page with the result for the Korean case. In both markets, counter intuitively, international investors are not shown to herd more or to disproportionally disturb price efficiency. An explanation for this phenomenon can be found in the level of training and sophistication of foreign investors - that being higher - and the fact that foreign investors tend to herd within their country group, not forming a homogenous group overall. Herding in Asian markets is related to crisis formation and significant market movements. Nonetheless, the causality and direction of the relationship between herding and the crisis is harder to establish.
On a more recent study about the Asian market of Taiwan and for a more stable period, Hsieh (2013) also draws a comparison between institutions and individuals. The researcher focuses on intra-day data and finds evidence of herding, for both individuals and institutions, that trade in the Taiwan stock exchange. Funds show stronger signs of herding and tend to herd on small capitalisation firms while indi-

viduals herd less but also tend to herd on small size firms. In general, as expected, portfolio investment strategies of funds outperform those of individuals. The author attempts to identify whether or not herding is informationally driven. Institutional herding is shown to be primarily driven by information while individual herding stems mostly from sentiment. In the same spirit, Jiang and Verardo (2018) show how herding is affiliated with underperformance, as funds that herd tend to underperform. Less capable agents tend to herd more than their competent peers. The relevant incompetence of an investor, often combined with informational asymmetries, might render herding the dominant investment strategy for an investor. In this context, herding tends to contribute to deviations of prices from their intrinsic value.

For the case of Chinese markets, Feng and Seasholes (2004) find evidence concerning the effect of the geographic position on herding. Investigating the Chinese market from 1999 to 2000, they identify the impact of the location of investors on herding. Additionally, they find a severe correlation between herding and the proximity of investors to a firm's headquarters. The above indicate that herding can be caused due to the diffusion of information, usually *mouth to mouth*, and home bias. The authors also underline the importance of investor-specific characteristics, such as location, for herding.

Regarding the US market again, in the paper in which he proposed his methodology for measuring herding, Sias (2004) applied his own metric, on quarterly data between 1983 and 1997, for US fund managers. His findings provide proof for the existence of herding, concerning institutional investors in the US, along with momentum strategies. Herding does not seem to affect market efficiency in this case, as it does not cause returns to deviate from their fundamental value. Institutional herding can, thus, have stabilising effects and may also assist price discovery. This concept is also supported by arbitrage theory, the concept of noise trading, relevant to price equilibrium and empirical evidence of investors counter-trading against market sentiment and herding (De Long, 1990; Shleifer, 2000; Barberis and Shleifer, 2003).

Again for the US funds, Li and Yung (2006) provide strong evidence of institutional herding regarding the American Depository Receipt market. They empirically prove a positive relation, concerning changes in institutional ownership and returns. The results are robust to momentum tests. Institutional ownership is often a variable of high importance both for the micro-level of agents and for the macro-level market structure. Institutional ownership affect the market composition, informational symmetry and even the managers of certain stocks. This variable has the power to affect factors as prices and returns but also the type of investors participating in trading and the decisions on the management of individual stocks.

Moreover, Choi and Sias (2009), using the SIAS measure, also provide solid evidence supporting herding, along with other interesting findings. More specifically, momentum intensity is negatively related to the size of an industry and has the capacity of distorting price efficiency. In general, the above paper provides valid evidence for institutional herding per industry. A very important finding of the paper is related to reputational, compensational and agent-related herding. The authors show that it is the decisions of the managers, that result to institutional herding and argue that reputation and income are crucial to that effect.

Similarly, Popescu and Xu (2018) show that mutual fund herding is a result of managerial decisions and its intensity is higher during down markets. Again herding

is connected to the quality of the manager, as poorly performing funds herd more [16]. The evidence support the theory that career concerns motivate this kind of behaviour. Skilled managers act first and then less skilled managers act on this signal. Another important paper concerning the US market is that of Gutierrez and Kelley (2009), who display comparative evidence for the persistence of the influence of institutional buys versus institutional sells. For a twenty-six-years period starting from 1980 and resulting in 2005, the authors use the LSV methodology to demonstrate how herding on buys drives prices away from fundamentals while herding on sells acts as a mitigation means for the market. This mitigation concept could relate to the non-identification of herding in returns, while herding is present in flows. What is more, this concept indicates that herding may exist and the market may be efficient at the same time.[17] Additionally, the authors claim that the results regarding buys are of a long term nature, as they might be based on information about fundamentals. On the contrary sells-related findings can be driven from a market negative extreme and lower liquidity . Here the nature of buying and selling itself plays an important role and it might be the case that buying is a much more serious choice for an investor and entails a different decision making mechanism. Nonetheless, as this paper also demonstrates, the results, concerning the different effects of buy versus sell herding, are ambiguous.

In another paper, investigating the origins of institutional herding, Liao et al. (2011) attempt to connect herding with investor sentiment. Deviating methodologically from empirical papers about institutional herding, they use principal component analysis and they show that herding is affiliated with investor sentiment, especially when herding is on the sell-side. Institutional investors are shown to stabilise the effect of sentiment. Overall, the role of the investor type and the direction of trading are primary variables of interest. When we compare this paper with that of Gutierrez and Kelley (2009), for instance, regarding the effect of the direction of herding, we observe non converging results.

The effect of the different markets examined is another variable of importance. After the 2008 financial crisis, for instance, the real-estate market and the investor choices relevant to it became a centre of attention, concerning herding. In a study revolving around real estate mutual funds herding, momentum trading and fund performance jointly, Gallimore (2014), incorporate data for 159 real estate mutual funds,for the period 1998 – 2008, i.e. just until the beginning of the real estate crisis began. Although they identify traces of momentum, herding and a robust disposition effect, no trace of dominance in terms of strategic choice is identified.

Moving on from the US and Asian markets, there are evidence of institutional herding in a wide geographical range. In the case of the emerging polish market, Voronkova and Bohl (2005) investigate the existence of herding for institutional investors, from 1999 to 2002, regarding 17 pension funds. The authors employed semi-annual data of a unique nature, as the pension system in Poland had just transitioned to funds and Poland is an intensely concentrated market.[18]. Using several classifications, they discover significant evidence of herding, once again regarding small stocks. Additionally, in line with Choi and Sias (2009), their results also demonstrate herding on the industry level, that is also more profound for certain

[16] Also shown in Jiang and Verardo (2018)

[17] If we assume that herding is not spurious as some critics tend to argue.

[18] This is indicated by the small numbers of pension funds

industries.
More evidence on concentrated markets are provided by Holmes et al. (2011) who investigated the Portuguese market. The authors attempt to look into the nature of mimetic behaviour in-depth. They distinguish between intentional herding and spurious herding in order to examine the motives of mimetic behaviour. They argue that herding in the Portuguese market stems from reputational motives and thus it is a case of intentional rational herding. Intent can be a key factor concerning the effect of herding market-wide. For instance, in Zhang and Liu (2012), it is shown how the motivation of mimetic behaviour is a key factor regarding the destabilisation of the market. When intent is established, momentum strategies and herding coexist and disrupt the market. Momentum trading is often shown to distort prices and is more common than often speculated (Galariotis, 2013). Moreover other phenomena, such as over-reaction and under-reaction, co-exist with momentum and are, as herding, stronger in concentrated markets or in markets with thin trading (Antoniou et al., 1997; Antoniou et al., 2005; Andronikidi and Kallinterakis, 2010). In Choi and Skiba (2015), herding is examined across various markets. The importance of the market structure and transparency is again underlined. Through this study, we also observe how herding can have a stabilizing effect on prices and that herding intensity is correlated positively with informational transparency in a firm. Correlated and spurious herding is once again distinguished from intentional mimetic behaviour and behaviourally driven herding.
Special weight is given to institutional herding, for cases of markets that are dominated by mutual and hedge funds, as herding can in this case be the most crucial variable for market efficiency. For one such market, namely the UK, Wylie (2005) uses semi-annual data for 268 UK mutual funds, between 1986 and 1993. The author discovers similar evidence for the UK market, in comparison to findings for the US market for the same time range. Additionally, when the investment strategy of an agent is accounted for, differences between the US and UK markets arise. In the latter case, investors follow contrarian strategies while their colleagues on the other side of the Atlantic Ocean tend to follow market trends and momentum strategies. Similar evidence are encountered also for market-wide herding (Galariotis et al., 2015)
For yet another Asian market, Kim and Nofsinger (2005), examine the unique Japanese structure, in which many firms participate in particular establishments called *keiretsu*. A keiretsu stands for a type of intra-firm business network that exists in Japan. Their results reveal lower levels of herding for the Japanese institutional market - compared to the rest of Asia. What is interesting is the fact that herding has more persistent results for the Japanese market, although its extent and intensity are not greater. The latter result is more pronounced for firms participating in intra-firm business networks, possibly due to better information being available to them through network effects and peer pressure. The explanation, provided for the overall lower levels of herding in Japanese mutual funds, revolves around the general economic environment, the regulation and the distinct structure of the Japanese society and markets. Nonetheless, these results imply that it is not just the extent and intensity of herding that matter for the market. Herding can distort prices, even if its presence is limited, while its effect might be positive, even if its presence is strong . Consistent with the above are the evidence provided by Iihara et al. (2001). The authors investigate also the Japanese market, choosing

a slightly different methodology to account for changes in institutional ownership. Lastly for the Japanese market, Chang and Dong (2006), also demonstrate that mutual funds herding is related to idiosyncratic volatility. Idiosyncratic volatility is both a measure of uncertainty and risk and a metric related to market returns. Herding may both be affected by uncertainty and influence returns and risk in return.

Another important factor concerning empirical research in finance is the frequency of the data used. In Chen and Hong (2006) we have the chance to observe the importance of high frequency data on the examination for herding. They use daily data for managers in Taiwan, between 2001 and 2003, for institutional investors' behaviour, with respect to analyst earnings announcements. The authors verify the existence of herding along with the relation of the level of herding to specific characteristics of stocks (factors). What is more, intra-day ownership fluctuations were shown to be, at least partially, driven from herding. The role of analysts for institutional herding is an equally essential factor. Analyst recommendations often serve as a common source of information for agents - especially managers - and may contribute to herding in trading, ie. micro-level herding. What is more, such recommendations may act as the reason for the difference in investment choices of institutional investors when compared to individual agents- more so for small investors.

In the interesting case of the German market, Dorn et al. (2008) investigate whether herding is present, from 1998 to 2000, using data for 37000 accounts from a large brokerage firm in Germany. They show that although herding is not as evident, retail investors herd significantly more than the rest. The importance of the composition of trading and the market, in terms of investor type is strongly supported. Also for the German market, for a quite large period, Walter and Weber (2006) show that institutional investors herd even more than their counterparts in the US and the UK. They made use of semi-annual data for 60 mutual funds, for the period 1998 – 2002. The same conclusion applies for the Finnish case, as shown by Do et al. (2008), who examined 176 stocks between 1995 and 2004, approaching herding via institutional ownership as a proxy. When distinguishing between domestic investors and foreign investors, then the domestic investors tend to herd more, both on an institutional and on an individual level.

In the same spirit, Chang (2010), attempts to map the behaviour of international investors in emerging markets using weekly order flow data. He shows that qualified foreign investors drive herding for domestic investors. Mutual funds and other types of investors choose to invest in the same sector as international investors, for the same and proceeding periods, creating short-term price destabilisation. The importance of the perceived expertise of a specific investor group - in this case foreign investors -, combined with the market type - in this case being emerging are strongly insinuated. In the case of mutual funds in Taiwan, Hung et al. (2010) use quarterly data to validate the existence of herding institutionally, as well as the tendency of managers to choose stocks of low liquidity and book to market ratio. For the Korean case, Jeon and Moffet (2010) also show that foreign investors affect the returns. Moreover, the tendency of international investors to buy sells of domestic investors and vice versa is empirically validated.

For the case of foreign investors in the US market, Lin and Swanson (2008) use data for international investors from 38 countries, from 1990 to 2003. Apart from comparisons between the types of investors, the authors also compare methodolo-

gies. They implement both the LSV and the Sias metrics to compare between a static and dynamic approach to micro-level herding. In average, foreign investors do not mimic each other but they do form groups, that herd within countries of origin. The motivation for such behaviour, can be related to specific characteristics of investors from the same country along with certain stock characteristics - characteristic herding - ,the fact that investors from the same country share information - informational herding - and the peer pressure between investors with the same origins - reputational and cultural effects.
On a study examining the performance of portfolios of herding versus portfolios of contrarian strategies, Sarpong and Sibanda (2014) investigate the South African mutual funds, incorporating quarterly data for 41 mutual funds, for the period 2006 – 2012. They compare herding funds to contrarian funds for this concentrated market, using the LSV measure. They demonstrate how strategies against the herd outperform herding strategies. Even though herding does not seem to be the most profitable strategy, its existence is encountered and its intensity is not negligible.
Although micro-level herding is extensively documented for institutional investors, mostly domestic, its existence is not limited to managers who by definition form a group. For instance a big part of herding literature concentrates solely on hedge funds managers (Brunnermeier and Nagel, 2004; Fung and Hsieh (2000); Boyson, 2010 to name a few). The results regarding hedge fund managers are not conclusive. In some cases there exist evidence of herding, while in others not. Additionally, as some studies indicate, individual investors and foreign investors - both managers and individuals - show signs of mimetic behaviour, that may or may not be of a similar nature to that of domestic institutions. The structure of herding and the balance between the different type of agents, will contribute to the final picture on an aggregate level. What is more, the literature indicates that micro-level herding is affected by price movements, crises and extreme social and political phenomena (Shyu and Sun, 2010). The role of the informational structure, the market quality, the level of liquidity, volatility and uncertainty and risk affect the investors behaviour and often lead to herding in flows, both due to behavioural biases and because of rational motives for mimetic behaviour.
Microlevel herding and feedback trading are very important because they can destabilise the market, but also have the power to assist price discovery. The aggregate result of investors' choices is reflected, market-wide, in prices and returns. This type of herding literature examines the consensus of the market on a macro-level and not the decisions of micro-level agents. Macro-level herding or aggregate herding or herding to the market consensus or market-wide herding represents another concept of mimetic behaviour. The main methodologies and empirical results, developed to measure the consensus of the market, are presented below.

2.3.3 Aggregate Herding: Measures and Evidence

The importance of herding lies primarily in its effects for market efficiency. Given the evidence for institutional and individual herding in the agent level, a logical question arises concerning the aggregate effect of micro-level herding. In order to test herding to the market consensus, empirical literature, that focuses on whether or not herding exists in the aggregate market level, has been developed. This part of the literature investigates the consensus of returns and its relation to the market

return and extreme price movements.
Can herding create bubbles? Is it responsible for economic turmoils? Do prices reflect the tendency of investors to follow one another? How can we measure it and how do we measure the risks stemming from it? Is the cross sectional deviation of returns affected by extreme price movements and does it linearly relate to the market return? Aggregate herding or herding to the market consensus or market wide herding or macro-level herding [19] reflects and partially answers these important questions.

Aggregate Herding: Main methodological approaches.

Macro-level herding is conceptually and methodologically different from microlevel herding. Various attempts to investigate macro-level herding have been made. In empirical literature, two of these attempts dominate the methodological approach, used by empiricists, in order to examine whether investors follow the market and if this is reflected in the consensus of returns. Both of the methods we present draw their inspiration from the same concept, albeit that the consensus of the market can be approached via the cross sectional deviation of returns.
To begin with, Christie and Huang (1995) propose a structural approach - hereafter noted as CH - which begins from the cross sectional standard deviation, computed as follows:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N} (r_{i,t} - r_{m,t})^2}{N-1}} \tag{2.6}$$

where $CSSD_t$ is the cross sectional standard deviation of the N stocks in the market at time t, $r_{i,t}$ is the return of stock i at time t and $r_{m,t}$ is the market return at time t [20].
The conceptual idea behind the CH metric is that when the market is facing extreme periods, market stress arises and investors shall be more prompt to follow their peers, even by ignoring their personal beliefs and estimations. So during extreme market circumstances - market stress based on returns - the returns of the assets may deviate less from the average market return and the cross sectional standard deviation could be low.
In order to test for that, Christie and Huang (1995) use the following linear regression model:

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t \tag{2.7}$$

where α is the intercept and represents $CSSD_t$ on average, D_t^L is a dummy variable that takes the value 1 if the market return at time t lies on the extreme lower tale of its distribution or zero otherwise and D_t^U is also a dummy variable that takes the value one if the market return at t is in the extreme high range, or zero otherwise. Through these two variables we are able to distinguish between two market conditions - compared to normal market-, extreme positive and extreme negative price movements. When D_t^L is one the effect of extreme negative price movements is captured, while when D_t^U is one the effect of extreme positive price movements is revealed. During *normal* price movements the intercept captures the deviation of

[19] These terms all represent the same concept and will be used interchangeably hereafter.

[20] As market return, researchers refer to the unweighted or weighted average of the returns of N stocks. If by market we refer to the stocks included in an index then $r_{m,t}$ may also refer to the return of the index.

returns.[21] Therefore we are able to capture the choices of investors for these different settings. If the coefficients β_1 and β_2 are negative and statistically significant then an indication of herding by investors exists. If the coefficients are positive and significant then there is more disagreement during extreme market returns. It is important here to mention that according to traditional asset pricing models, that are based on the hypothesis of efficient markets, as the CAPM,[22] for example, the coefficients of the dummy variables in the regression above shall be either non-significant or positive. Traditional models can support the notion of higher diversion during extreme market returns. This methodology is widely used, as a benchmark model for the identification of market-wide herding due to its simple structure and its applicability.

Although it has been widely used by researchers, this measure of the cross-sectional standard deviation, followed by the estimation of a linear regression of dummies does not allow for non-linearities. To further elaborate, according to Chang et al. (2000), when extreme market movements occur and even given that investors tend to regress to the market average, the linearity between dispersion and the market return is not a valid assumption. This practically means that although dispersion with respect to market average can be an indication of herding, the relationship between the two is neither linear nor monotonous. The dispersion can even decrease with respect to the return of the market average portfolio. For this reason, Chang et al. (2000), hereafter CCK, use the conditional version of the CAPM and extract the expected absolute cross-section standard deviation :

$$ECSAD_t = \frac{1}{N}\sum_{1}^{N} AVD_{i,t} = \frac{1}{N}\sum_{1}^{N} |\beta_{i,t} - \beta_{m,t}| E_t(r_{m,t} - r_0) \tag{2.8}$$

Where $\beta_{i,t}$ refers to the systemic risk of the asset i at t, $\beta_{m,t}$ represents the systemic risk of the the market portfolio . The expected market premium at time t is denoted $E_t(r_{m,t} - r_0)$, $r_{m,t}$ being the average return of the market portfolio, while r_0 is the return of the portfolio with no systemic risk as designed by Black (Black, 1972), namely the zero-beta portfolio.

It is also proven mathematically that the first partial derivative of $ECSAD_t$ with respect to $E_t(r_m)$ is positive, while the second partial derivative of $ECSAD_t$ with respect to $E_t(r_m)$ is zero. They employ these properties, concerning the function of the expected cross-sectional standard deviation, to construct a measure for herding and to interpret its results. The monotony and convexity properties, mentioned above, allow the CCK measure to account for non-linear structures, regarding the relationship between the dispersion of assets' returns and the average market return. Due to the fact that the expected absolute cross sectional standard deviation between stock returns and the market return - $ECSAD_t$ - is not an observable variable, the authors attempt to find an observable proxy that could closely describe the same relationship empirically. For this purpose, they use the cross sectional absolute standard deviation as a metric and they compute it as the average absolute value of each stock relative to the return of the average market portfolio of equal weights. The cross sectional absolute standard deviation of returns is assumed to increase less or even decrease when extreme market movements occur. The cross sectional

[21] By construction D_t^L and D_t^U can be simultaneously zero but not simultaneously one.

[22] Capital Asset Pricing Model

absolute deviation was initially used as the dependent variable in equation 2.7, as a robustness test by Christie and Huang (1995), and is computed as follows:

$$CSAD_t = \frac{1}{N}\sum_{1}^{N}|r_{i,t} - r_{m,t}| \tag{2.9}$$

where $CSAD_t$ is the empirically computed cross sectional standard deviation - as shown in the right-hand part of equation 2.9 and all other notation is identical to equation 2.6 Then, they try to identify the existence and extent of herding in markets through a regression as follows:

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r_{m,t}^2 + \epsilon_t \tag{2.10}$$

If the parameter γ_2 of equation 2.10 is negative, then the presence of herding in the market is supported. The authors themselves acknowledge the fact that their model captures mainly non-linearities and a negative γ_2 may capture other types of non linear patterns. Bohl et al.(2017) criticizes this methodology, as it is shown to underestimate herding. What is more, this method assumes that the relation between herding and the squared market return - that is also an indication of variance of the market (Klein, 2013; Galariotis et al., 2016)[23] is parametric and linear.
The above equation does not focus on market stress, in the spirit of Christie and Huang (1995), but it can be modified to account for extreme price movements via a two regression process. The relevant specifications are presented below. Equation 2.11 is exactly the same as equation 2.10 implemented for the data subsample for which $r_{m,t}$ falls on the extreme right of its distribution, while equation2.12 serves the same purpose for the subsample, for which $r_{m,t}$ falls on the extreme left of its distribution as follows:

$$CSAD_t^U = \alpha_t^U + \gamma_1^U|r_{m,t}^U| + \gamma_2^U(r_{m,t}^U)^2 + \epsilon_t^U \tag{2.11}$$

$$CSAD_t^L = \alpha_L + \gamma_1^L|r_{m,t}^L| + \gamma_2^L(r_{m,t}^L)^2 + \epsilon_t^L \tag{2.12}$$

Apart from the two measures mentioned above, Hwang and Salmon (2004), henceforth HS, also defined herding and created a state-space model to capture it. In their paper, apart from the development of their model, Hwang and Salmon (2004) heavily criticise the use of any simple measure dispersion of assets' returns, as a proxy for herding. They claim that herding might be driven by fundamentals and shall be affected by the environment of the market. To properly treat such a complicated issue, they construct a methodology that captures herding in extreme market situations. In that sense, they created an alternative methodology for herding but at the same time the assumption of market extreme - via extreme price movements - is maintained.
This methodology proposes the construction of a metric in the form of the cross sectional dispersion of asset sensitivity to other important factors, that may affect

[23] The market variance is defined as the expectation of the squared market return minus the expectation of the market return squared as $Var[R_{m,t}] = E[R_{m,t}^2] - E[R_{m,t}]^2$). In an efficient market the expectation of the market return is converging to zero, the squared market return shall approximate the market variance

asset prices. The HS methodology is conceptually closer to the behavioural approach to herding, as it allows the selection of factors in the model and does not base all its results on the dispersion of assets. Also, the cross sectional dispersion of assets sensitivity better represents risk.
The authors consider that herding has a dynamic nature and that the information about herding should be based on fundamental information. One of the bases of their model, is the assumption that a biased beta - as estimated by the CAPM usually - may indicate herding and they form a method that is based on the market's biased expectations of excess returns. Furthermore, herding is allowed to vary dynamically over time, while testing for its existence and extent in relation to many factors. As far as the HS measure's performance is concerned, we should keep in mind that its application is often limited with respect to the data frequency - as it is mostly applicable monthly - and some assumptions of this method are not more realistic than the assumptions, made in the case of the CH and CCK methodologies.[24] What is more, the results this model provides do not outperform the results of the CCK model empirically (Demirer et al., 2010).
At this point, we should mention that Xie et al. (2015) also propose a new measure of herding, the weighted cross sectional variance. Their model, bares similar empirical difficulties as the HS measure, as higher frequencies are harder to estimate. In addition to that, extensive applications to this model have not yet been conducted extensively. This methodology defines herding as a deviation from an ideal state of no herding. By this, we refer to the interpretation of the distance of a computed value from its theoretical optimal as herding. This is not a straightforward conceptual leap, as such a distance could be motivated by other type of frictions.
In most empirical papers, it is either the CH or the CCK that are chosen as the principal methodological approaches. This is a result of the straightforward nature and easy application of the CH and CCK methods, along with their relative performance. All empirical measures show imperfections and fail to identify intent and intensity. Nonetheless, if we do not merely focus on empirical pitfalls, both the CH and the CCK methods approach herding - or the absence of - in an intuitive manner.
Macro-level herding is conceptualised as the aggregate result of investors' decisions, that is reflected in returns. Whether it is identified or not, macro-level herding reveals information on the market level, that may be of interest for investors, market regulators and policy-makers as well.
In the section that follows the main empirical results, for all methods, regarding macro-level herding are presented.

Aggregate Herding: Empirical Evidence

The importance of aggregate markets and price formation is such, that researchers have long tried to identify phenomena regarding the market consensus. This is also true regarding herding.
To begin with, Christie and Huang (1995), in the paper in which they propose the CH method, examine macro-level herding in the US market. Using daily data, between 1962 and 1988 and monthly data between 1925 and 1988 for firms in the US, they investigate herding to the market consensus and they compare the results

[24] The measure of herding they use is supposed to follow an autoregressive stationary process of order one and the estimation of the dispersion of time varying βs is not properly justified.

between different data frequencies. The authors find no evidence of macro-level herding during extreme price movements. Their results are robust to the choice of frequency.

Chang et al. (2000), challenging the form of the relation between the dispersion of assets and the market return, develop the CCK method. The CCK method considers that the relationship between the dispersion of assets and the market return is not linear. They test their methodology for herding in five markets - four Asian markets and the US market. For each market they employ data for different periods: for the US market from 1963 to 1997, for the Japanese market from 1976 to 1995, for the Korean market from 1978 to 1995, for the Taiwan market from 1976 to 1995 and finally for Hong Kong from 1981 to 1995. The evidence encountered is of a mixed and non conclusive nature. More specifically, there is no evidence of herding to the market consensus in the US, Japan and Hong Kong but there is evidence of intense herding in Korea and Taiwan. This indicates that herding exists in less developed and emerging markets, while it is absent in more organised and better established markets. This could be explained if one considers the type of investors in each of these markets. Emerging markets often attract opportunistic investors, individual investors with little experience and noise traders. On the contrary, well-established markets are dominated by institutional investors and better trained agents. Another interesting result of theirs, states that herding, when present, is a product of information on macroeconomic variables. The type of herding they identify is thus informational and not a product of fads and fashion.

The last of the important measures of herding, proposed in the literature, is the one by Hwang and Salmon (2004), who also point out the importance of fundamental information as well as volatility related to time series, in their effort to identify aggregate herding. The authors use their measure of factor sensitivity, in order to test for herding in the US and Korean equity markets, from 1993 to 2002. Persistent herding towards the consensus for both markets is encountered, especially before and after the periods of extreme market conditions, i.e. crisis. The latter is a result that contradicts the assumption of Christie and Huang (1995), who speculate that herding rises during extreme markets herding. Behavioural factors, such as the tendency of agents toward more individualism during critical periods, might be related to this finding. Additionally, the dispersion of assets is related to the volatility of returns and thus, the tendency of herding to be higher before and not during crisis, might be linked to the structure and nature of volatility and its effect on the informational signals. Assuming herding is prevalent during extreme market conditions and the definition of these conditions, are extremely restrictive assumptions. The CH method, and the CCK method to an extent, are often limited empirically by construction, due to such restrictive assumptions.

Remaining on the subject of herding in the US market, but for the special case of herding in Exchange trading funds, Gleason et al. (2004) use intra-day data concerning nine sectors of ETFs, to test for herding during market stress. In their methodology, they test for both market highs and lows, as well as a non-linear model in the spirit of the CCK measure. They do not find any evidence of market-wide herding for all methodologies used in this type of market.

Another important part of the literature concentrates on European markets. European markets offer a natural setting of diverse market structures with different characteristics, such as different concentration levels, liquidity structures, volume

and regulatory framework, just to name a few. For the case of the Italian market, Caparrelli et al. (2004) examine the case of macro-level herding for the period 1988 – 2001. The authors compare the CH and CCK measures and conclude that the CCK measure, accounting for non-linearity, is more suitable for the Italian market, that belongs to the category of concentrated and less organised markets. Herding is identified only when the CCK methodology is applied, while using the CH method the authors do not encounter evidence of aggregate herding during extreme price movements.

In another case of a market with high concentration, Caporale et al. (2008) find evidence of herding concerning the Greek market. The authors examine the existence of herding for different frequencies of data, i.e. daily, weekly and monthly data. Their results indicate that herding is more profound in the case of high frequency data. The period they examined, from 1998 to 2007, covers both the 1999 crisis and the period before the Greek sovereign debt crisis, that is still ongoing. Herding is evident during the whole sample period, before, during and after the 1999 crisis and only starting to decline after the regulatory changes of the Athens Stock Exchange in 2002.

Staying on the case of concentrated markets, Goodfellow et al. (2009) conduct a study for the polish market, dividing the market into two categories, one dominated by institutional investors and another dominated by individual investors. They have access to data in the two separate platforms, one for institutions and another for individuals, that exist in the polish stock exchange. The authors have thus the opportunity to distinguish institutionally originated trades from trades conducted by individual investors. They suggest that informational asymmetry in the market, along with the quality of investors - i.e. heterogeneity, investor training, access to information and capacity to analyse information - play an important role in terms of market volatility and herding. This is implied by the presence of significantly stronger evidence of herding and volatility, in the platform devoted to individuals, in comparison to the platform regarding institutions. Moreover, herding and market volatility seem to rise at greater scale in negative market extremes, when compared to positive market extremes. This result seems to be affiliated with the level of confidence, experience and training, as well as the abilities and career concerns of the investors. Poland has a very peculiar trading system and allows the authors to test for the effect of the type of investor for the case of market wide herding.

In their paper examining southern European countries, Economou et al. (2011) attempt to identify whether there is herding and contagion in countries that are connected via geographical proximity. For the case of the Greek, Spanish, Portuguese and Italian market they use a unified methodology, on daily data, between 1998 and 2008, controlling for spillover effects across countries. The authors examine whether the dispersion of returns in one of these countries, affects the dispersion in other countries. The overall presence of herding is weak, but between 2007 and 2008, during the sovereign and financial crisis in the south of Europe, they find that herding becomes more intense. This result supports the methodological assumption that herding is more profound during a turmoil and negative market extremes. Given the results for the polish market demonstrated above, we shall note how the concentration of the southern markets and the existence of less skilled investors in these markets could also relate to these results.

Certain characteristics and factors in the market seem to have an effect on herding,

similar to what was pointed out by Hwang and Salmon (2004). An important market characteristic affiliated with many frictions is liquidity. Concerning the effect of liquidity on herding, Galariotis et al. (2016) investigate the effect of liquidity on the existence of herding. Using equity price data and the CCK methodology, they show that the outcome of the empirical analysis varies when controlling for liquidity. No evidence of herding is found in the initial analysis of the data via the CCK method. On the contrary, when liquidity is accounted for, significant herding for the case of disproportional liquidity levels is encountered ,for four out of the five markets in the sample. In addition to that, in extreme periods, if an investor wishes to trade more he will choose more liquid securities. This is also shown in Barber et al. (2009a and 2009b), where liquidity is affiliated with noise trading. We shall not forget that in the case of mutual funds, Hung et al. (2010) showed that certain managers tend to herd on low liquidity stocks, indicating their preference for a more stable investment. Another important market variable, that is affiliated to risk and uncertainty is volatility.[25] In an attempt to measure the effect of herding on volatility, Blasco et al. (2012) show that there is a direct relationship between herding and volatility. Their study concerns the Spanish stock exchange and employs the herding intensity measure by Patterson and Sharma (2006). Herding not only contributes to the rise of market volatility but can also be used to improve forecasts of volatility. The relationship between herding and volatility is also underlined by efforts to use volatility in a regime switching context relevant to herding. In Schmitt and Westerhoff (2017) we note how intense uncertainty for market agents tends to lead to closer observation of other agents and stronger mimetic patterns in decisions. In Bacilar et al. (2014), we observe the impact of volatility in an oil rich environment. The level of uncertainty, in a regime switching environment, directly affects the impact other variables have on herding. There are many papers that link herding to uncertainty, risk and some forms of volatility (e.g. Messis et Zapranis, 2014; Blasco,2017), mostly attempting to explain consistently persistent volatility levels and improve its estimation (BenSaida, 2017).

In another comparative study examining the existence of herding for multiple markets - the US, the UK, Japan, France, Germany, Spain and Mexico - Blasco and Ferreruela (2008) identified herding only for the Spanish market, and for all market conditions. The authors used data from 10 different stocks in each market, between 1998 and 2004. Their results are not representative of the markets they try to investigate. The limited number of stocks - only ten - in addition to the failure of the CH methodology to account for non-linearity could affect the robustness.

On a more recent comparative study, Galariotis et al. (2015) test for herding in the US and the UK markets introducing spillover effects in the spirit of Chiang and Zheng (2010). They use macroeconomic announcements to examine the behaviour of US investors, in comparison to their counterparts in the UK. Their results are very interesting, both regarding herding and concerning market-specific findings. The authors show that US investors herd both on fundamental and non-fundamental information, while the UK investors herd primarily on fundamental information. This is in line with what we mentioned above, regarding the tendency of UK investors to follow contrarian strategies, while US investors focus on momentum trading. Aggregate herding in the US market, on the day when important information on macro

[25] Volatility can be defined differently regarding the frequency and the setting, i.e. realised volatility, idiosyncratic volatility etc.

level variables is released, is identified. Lastly, they examine and encounter contagion from the US to UK market, only during the financial crisis. As the authors note, their results are an indicator that certain characteristics regarding the market and the period considered, affect the type and extent of herding.
For the case of herding in the Chinese markets, Tan et al. (2008) conduct an extent study, including two stock exchanges over a long period. They incorporate data for a ten-year period - 1994 to 2003 - for both the Shanghai and the Shenzhen stock exchanges and find evidence of intense aggregate herding, yet only in higher frequencies. Comparing between daily, weekly and monthly data they are able to determine the persistence of herding in the market. The frequency of the data is very important, as it is affiliated with different informational settings and various types of investing styles.
Again for the Chinese equity market and for a range of time from 2004 to 2009, Fu and Lin (2010) examine herding in Chinese stocks, using both the CH and the CCK approach. The authors conclude that although, in general, the existence of herding is weak, there is a significant difference regarding the conditions of the market that we examine. It is suggested that herding is more evident for down-market conditions compared to up-market conditions.
Although some studies identify some extent of macro-level herding in Chinese markets, others do not. No herding for Chinese markets was identified by Demirer and Kutan (2006), who looked into a market of 375 stocks, from 1999 to 2002. This difference in empirical findings, concerning the same market, can be a result of the empirical design or the stocks considered. The inconsistency in results indicates that various parameters, some methodological and other empirical, influence the estimation of herding.
For example, up until now, it becomes evident that in both a micro and a macro level setting, information and market structure are important determinants for herding and investor behaviour. A less organised system, with fundamental obstacles in its construction, a market structure that does not allow transparency as well as unstable macroeconomic conditions create an unfriendly environment for long term investment and stability. This kind of setting, on the contrary, attracts noise traders, promotes momentum strategies and makes *riding the bubble* the most profitable option, in many cases. This is evident for the Chinese market where contrarian profits from overreaction exist (Jiang et al., 2018).
On the important matter of herding in the Asian markets, Yang et al. (2015) test for herding in East Asian markets towards the US market and find evidence of herding in the spot of major events. Also regarding Asian markets, Cheriyan and Lazar (2016) test the effect of herding on contagion in emerging markets, using multivariate dynamic conditional correlation GARCH models, and find only partial evidence of contagion due to herding. These results imply that herding sometimes might, to some extent, be the driving force behind international domino crises.
Concerning the Russian market, with respect to the Ukrainian crisis, Indārs et al. (2019) find evidence of herding and contagion. During the Ukrainian political crisis, herding is mostly driven by fundamental information, while in periods of unexpected crises herding is not based on information. Macroeconomic announcements are affiliated with both types of herding. The authors conclude that market structure and market conditions - liquidity, market return, oil price etc.- are vital to determine the existence, the extent and the type of herding.

In the case of the Australian market, Henker at al. (2006) use data between 2000 and 2001, for the two hundred larger stocks in Australia. An interesting fact about this study is the usage of intraday data, in comparison to daily observations. The high frequency of the data is a relatively new approach in this literature. Traders tend to exploit market frictions on a very short time frame and thus it is important to test for intraday herding. The rise of computer power and algorithmic trading only enhances this fact. Testing for herding, using both the CH and the CCK methodologies, the authors do not encounter evidence of herding regarding market wide and across industries. As they underline, this could be due to limitations related to both the CH and the CCK methodology.

On a massive study regarding 156 industries in the US, the UK, Germany, Japan and Hong Kong, for a twenty-one-year period, ranging from 1987 to 2007, Chiang and Zheng (2010) attempt to identify the existence of herding and across country contagion. Using daily data and accounting for non-linearity through the CCK measure, they demonstrate that herding exists in most markets examined. Contagion, from the US market to other markets in the sample, plays also a significant role.

Another significant part of the literature tries to relate herding to bubbles and assets' crises. Intuitively, it is easy to resort to herding to describe financial crises and bubbles. A speculative bubble occurs, when asset prices are excessively high, in a manner that prices do not reflect the intrinsic value of assets. Researchers linked herding, both to the creation and to the burst of such bubbles (Dass et al., 2008; Bekiro et al., 2017). These empirical findings are additionally supported by theoretical frames that consider myopic behaviour and mimesis (Harras and Sornette, 2011). Weirdly enough, there exist evidence that link herding to anti-bubbles, especially when overcaution and aversion to risk, that manifest in investors behaviour, drive prices to a level lower than the intrinsic value (Johansen and Sornette, 1999; 2010). Empirical evidence are not conclusive regarding the role of herding for speculative bubbles. Many examples of contradictory findings exist. For example, as shown by Galariotis et al. (2016), who examine the bond markets with relation to the recent European financial crisis, we cannot conclude that the behaviour of bond prices of European states is a result of herding. Thus, even in cases, where herding is linked to a crises, it is difficult to show that herding was a driving force for this specific crisis.

From all the above, we can conclude that the literature does not show clear results, on whether aggregate herding exists or not. The variables that affect herding are often also a subject of disagreement in the literature. Moreover, some empirical specifications and modifications of the CH and CCK methods are more efficient than others. Furthermore, empirical findings of herding highlight the role of many market-specific and investor-specific variables, for the formation of herding and the nature of its effects.

Empirically, data-driven methods have also been employed to test for herding. The data-driven approach aspires to overcome the specification problems of the CH and CCK methodology, related to the structure and the variables included in the models analytically. Examples of such attempts are semi-parametric and non-parametric measures. In an effort to identify behavioural variables in herding, Hwang and Salmon (Hwang and Salmon, 2007; Hwang, 2007) create a non-parametric measure of herding to explain herd behaviour in the US, the UK and the Korean market, that they had already identified in their previous paper (Hwang and Salmon, 2004).

Using factor models, the authors conclude that herding is more possible to arise when investors believe that they can predict the market movements. This implies that extreme market movements may not coexist with intense herding, but might be a product of investors' expectations about these movements - the curse of a self-fulfilling prophecy.
Many studies underline the importance of herding as a social phenomenon, as in the case of the Japanese keiretsus (Kim and Nofsinger, 2005). In this spirit, Gavriilidis et al. (2016) also investigate cultural and religious factors, that might impact the formation of mimetic behaviour. They investigate the effect of Ramadan on herding behaviour, in addition to domestic and international market state indicators and find a positive Ramadan effect on herding.
It is not just the existence of herding that bares importance for market efficiency. The nature of the effects of herding is equally important. A variable that is linked to the distortion of prices is the intensity and persistence of herding. Concerning this variable, Patterson and Sharma (2006) attempt to create a measure that can capture intra-day order sequence. For their study, they state that an informational cascade occurs, when in the presence of sequential negotiations that began by traders, sequences are higher than what we would have expected, if traders were trading on information only. The authors also underline the importance of intra-day herding. Statistically, this paper proposes the incorporation of bootstrapping techniques, that are shown to be more efficient. Also on intra-day trading, Vieira and Pereira (2014) apply the Patterson and Sharma measure of herding intensity along, with a slightly different index proposed also by Patterson and Sharma (2006). The results concerning herding intensity differ depending on the index used. This is yet another indication that herding is sensitive to the methodology we chose to employ. On the importance of testing for herding using intra-day data, the authors argue that the time constraint, that a trader faces when he trades on an intra-day level, restricts the analysis of information that can be conducted. It becomes thus, possible for sentimental variables to affect the investor's behaviour. Lastly, the authors highlight the importance of the market characteristics, both as a factor in general and for the case of the Portuguese market examined in particular.
The major literature regarding herding in financial markets, theoretically and empirically, raises a lot of questions regarding herding, as a concept in theory and practically markets. It is time now, to explore the limitations of the literature, along with some important risks herding bares, financially-wise.

2.4 Herding: The measurement problem and why it is so important

Herding is an important phenomenon in financial markets, the extent, intensity and nature of which, we are yet to comprehend. It is a phenomenon that has the power to impede the efficiency of the market and sometimes it is *caused by* and is *the cause of* informational asymmetry.
If we cannot successfully measure herding, then we definitely cannot measure its impact. Below we will present some of the risks of mimetic behaviour, in actual financial settings and we will summarise the imperfections in the existing empirical literature.

2.4.1 Herding and Risk: Why does it matter?

To begin with, it is important to emphasize the different concepts regarding herding, as well as its dichotomised nature. Herding can be rational and irrational, intentional and unintentional. It can vary, from being a simple sentimental response to being the dominant strategy of an experienced agent. As shown in Table 2.2, specific forms of herding are affiliated with different intent origins. This leads to herding manifesting in many levels of the financial system. The existence of herding in the micro-level of trading flows does not necessarily affect market returns. The structure of the market itself - in terms of investors, liquidity and regulations - is expected to influence the form of herding, its effect on prices and its persistence.

There are many cases where mimetic behaviour is not employed to explain neither

Type of Herding	Intent	Source of Herding
Spurious	Unintetional	Not Herding
Informational	Both	Both
Reputational	Intentional	Mostly Rational
Compensational	Intentional	Rational
Sentiment-driven	Unintentional	Irrational
Fads and Fashion	Unintentional	Irrational
Characteristics-driven	Unintentional	Mostly Irrational
Rumours-driven	Unintentional	Irrational

Table 2.2: Types of Herding from a Theoretical Perspective

trading not returns. The tendency to follow our peers - rational or not - can manifest in other types of financial decisions. For example, herding is present in the decision of institutions to enter a certain market, open a new branch or even start financing a new sector or industry. For the case of microfinance institutions in Pakistan, Monne et al. (2016), show how herding affects the decisions concerning the geographical locations of microfinance establishments. The structure of competition, the nature of micro-finance and sunk costs also affect the geographical distribution of such nature. The examples of herding, in various types of decisions, are numerous and relate to the nature and environment one wishes to explore.

Regarding financial markets, there are many parameters, within a market and an economy, that may affect the formation of collective behaviour. Herding is linked to the structure of the market, uncertainty, volatility and macroeconomic announcements, both due to the informational signal and the decision environment that such variables partially shape. Additionally, herding is often transmitted form one market/country to another, as spillover effects between regions, especially when their economies are connected (Economou et al.,2011; Galariotis et al., 2015), are quite common. In the case of volatility we have evidence that there is an empirical connection between the two phenomena. There have been attempts to use herding to explain the consistently higher volatility in the market as other theories fail to do so (Litimi et al., 2016).

Additionally, regime switching models based on volatility reveal evidence of herding (Blasco, 2017), that conventional methods do not. The type of volatility considered is relevant to the risks and uncertainty that is investigated, as for example idiosyncratic risk is represented by idiosyncratic volatility (Huang et al., 2015).

Furthermore, measures of intra-day volatility can capture variability within a day, while volatility computed on closing prices may fail to do so. Other important parameters, that may influence the formation of mimetic behaviour include, but are not limited to, news and information, cultural variables (Chang et Lin, 2015) [26] and the existence of strong commodities in the market (Balcilar et al., 2014; Balcilar et al. 2017). Whether or not herding is linked to excessively high or low volatility is a question that interests investors and regulators alike, as such a link could relate to mispricing and market failure. All the above, possibly enhanced by the natural human tendency to mimic, could lead to market distortion and informational inefficiency. In an unstable environment, herding could be more possible to occur as information is neither easily identified nor trustworthy.
Herding also relates to numerous types of risks on various levels of the market. For funds, herding can lead to a higher crash risk (Xu et al., 2017). Regarding stock prices, herding might augment the risk of a crash but might also have a stabilising effect. The nature of herding, the informational patterns, the level of transparency and behavioural pitfalls influence the intensity of herding and the effects herding might have for stocks, institutions and the market.
The nature, the intensity and the impact of herding, also vary between market levels and different group of agents. Herding is linked to a higher crash risk and lower performance for individual investors (Blake et al., 2017). Herding also influences the banking system and many of the risks affiliated with this sector come from herding (e.g. Jain and Gupta, 1987; Acharya and Yorulmazel, 2008). Such types of risk include liquidity banking risks (Bonfim and Kim, 2012) and contagion effects, which could potentially affect global economies. In the special case of banks, banking regulation, that enhances prudence, is of high significance (Kremer and Dieter, 2013).
Additionally, herding is affiliated with feedback trading, momentum and noise trading (e.g. Ginblatt et al., 1995; Yan et al., 2012; Galariotis, 2013; Demirer et al., 2014; Demirer and Balcilar, 2015 to name a few). This relationship between herding and momentum strategies is often blamed for the formation of speculative bubbles, but the evidence is not conclusive (Spyrou, 2013). As mentioned before the models about myopic trading and the formation of bubbles (Harras and Sornette, 2011) are not always verified and there is evidence of the opposite effect -ie. herding may stabilise the market (Johansen and Sornette, 1999).
In general, empirical findings indicate that microlevel herding is strong and has a negative relation to investors' abilities. Equally important is the effect of institutional and individual herding on stock prices. Micro-level herding has an effect on short term individual stock prices, but this effect does not usually persist on the long run. Aggregate herding on the other hand is not usually identified. Empirically, we observe aggregate herding in concentrated markets, inadequately organised and structurally flawed, as documented above. Herding may destabilise the market and it may affect the "trust" in the system. The trust in the system and its participants is what allows transactions to occur, not just in financial markets, but in everyday life as well. Some of the important variables to consider are the market structure and the market concentration, market volatility and uncertainty, the liquidity (or il-liquidity), the efficiency and transparency of information and the institutional framework (e.g. Chang et al., 2000; Chiang and Zheng, 2010; Liao et al., 2011; Lin and Lin, 2014; Galariotis et al. 2015; Galariotis et al., 2016). Then,

[26] Variables that are also affiliated to specific regions that have more in common than culture

there are many variables affiliated with the investors and their characteristics, as their sensitivity to newly arrived information, their risk preferences, their experience, motives and profit incentives (e.g. De Long et al., 1990; Falkenstein, 1996; Liao et al., 2011; Holmes et al., 2011) determine, to a point, their decisions. More variables of a general nature, that we may be of high interest, when estimating herding are herding spillover effects (Chiang and Zheng, 2010), macroeconomic announcements (Galariotis et al., 2015), the efficiency of arbitrage (De Long et al., 1990), the effect of the data frequency and market sentiment (Barberis and Thaler 2003; Liao et al. 2011). These variables set the frame, in which agents operate and influence the total system, via their decisions. It is thus necessary to examine these variables and their dynamics in order to distinguish true herding, its determinants and the level of its complexity.
Risks, that are generated or influenced by herding, bare also a high level of complexity. There is not sufficient proof to generally call herding a disruptive phenomenon in the market. Some papers even find contrarian effects and attribute stabilising properties to herding, as it sometimes assists the efficient distribution of information. Nonetheless, there are potential risks originating from mimetic behaviour. Herding may impede informational efficiency and lead to cascades, could result to bubbles and anti-bubbles alike, due to myopic trading, affects and is affected by volatility, has an effect on prices in a quarterly time range and is related to fads and gurus. Regarding the banking system, herding affects the liquidity and may initiate contagion between banks that may impact the overall economic system. For example, herding in the banking system often leads to inefficient credit allocation and instability for the banking system as a whole. Furthermore, herding compromises the validity of analysts' recommendations. As analysts herd, their recommendations sometimes misrepresent fundamental information and distort the relationship of trust between analysts and investors. Investors may follow an analyst into herding, without knowing that this analyst herds or may decide to follow their peers into herding, believing that the information provided by analysts is not valid and thus herding is the dominant strategy. Problems of moral hazard and adverse selection often impede the function of the market, especially when information is not transparent and the information structure is complex.
What makes herding so important is the way it interacts with other parameters. Sometimes it affects and is affected by the same variables. It is very important to measure herding efficiently in order to estimate its existence and intensity, as well as the nature of its influence on other variables.

2.4.2 Herding: The measurement Problem

All the above risks and limitations, all the variables that affect herding and all the variables that herding affects are connected to each-other and to the market as a whole. The theoretical literature about herding has provided us with many insights, ideas and models about herding that are not adequately examined by the empirical literature.
In Table 2.3 we summarise the main empirical measures of herding and their overall evidence regarding the micro and macro level herding existence. As we can clearly

Microlevel Herding	Macrolevel Herding
Institutions and Individuals	Consensus of returns
LSV Measure	CH Measure
Sias Measure	CCK Measure
	HS Measure
Evidence of herding	Some weak evidence of herding

Table 2.3: Types of Herding from an Empirical Perspective

observe the existence, extent and intensity[27] of herding, identified by the two different approaches, are quite different. This disagreement, between these two relative concepts of herding, might have its roots in the methodologies used, the structure of the market or the trading mechanisms, through which the aggregate effect of many agents' decision impacts - or not - the market as a system in the level of returns.
Regarding institutional and individual herding, none of the measures used, properly identifies the nature of herding, in a manner that adequately represents the theory (Bickichandani and Sharma, 2000). Moreover, regarding the more extensively used LSV measure, we observe that it does not have a dynamic structure. Although the LSV is quite a simple straightforward measure, it does not permit dynamic comparisons, as it is not designed to capture inter-temporal trading patterns (Bikhchandani and Sharma, 2000; Sias, 2004; Pucket and Yan 2008; Bellando, 2010). This does not allow us to observe the evolution of herding and the dynamic dependence in trading. The SIAS measure has a dynamic structure but it has not been used as extensively. For both of them valid critique has been developed in the literature. Bikhchandani and Sharma (2000), point out the obvious fact that these empirical measures fail to identify the nature and determinants of herding, e.g. whether it is intentional or not. In addition, they state that herding identified via the LSV could be spurious. It is easily observable that similar critique applies in the case of the methodology designed by Sias. Another important disadvantage of both measures is documented by Wylie (2005), regarding short sales. When short sales restrictions apply the probability assigned to a manager, regarding the trading of a portfolio, is affected. Both methodologies do not account for this fact, that changes the probability that the fund manager will buy or sell a certain asset. Another dubious choice is that of the benchmark index and its composition. Walter and Weber (2006), for the case of the German market, show that a big part of herding, identified in the German market, is dependant on the benchmark index composition. This is an indication, that the choice of empirical measures and methods can affect the results, regarding herding. Moreover, Frey at al. (2014), empirically demonstrate, by using Monte carol simulations, that the LSV index in particular underestimates the existence of herding when herding exists. The authors then create a new measure of herding, that is accurate only for symmetrical and integral herding (Bellando, 2010). This measure, slightly modified as proposed by Bellando (2010), permits us to concentrate also on different types of herding and market conditions. Both these indices seem to be empirically more robust than the LSV metric but the issue concerning the intention of the investors still holds.

[27] About the intensity of herding we can find some measures in the literature (Patterson and Sharma, 2007) but they have not been sufficiently tested and they examine very specific data and situations.

Regarding the effect of institutional and individual herding on prices, we can see a clear tendency in the literature. Microlevel herding predicts short term but not long term prices. This empirical result might be the product of various circumstances. Firstly, it is possible that neither institutional nor individual herding influence prices in the long run (Dasgupta et al., 2011). Another possible explanation may be driven by empirical evidence, that show that institutional investors have different trading strategies from individual investors, as managers often trade against sentiment (e.g. Liao et al., 2011). Equally important is the methodology chosen. If the methodology is not appropriate, then the long term effect of herding cannot be captured, due to misspecification and possible biases.[28]. Dasgupta et al. (2011) summarise the literature and offer theoretical support to the tendency of herding to impact only the short run, via modelling.

For the case of aggregate herding or herding to the market consensus, the models have exactly the same difficulty identifying intent, as the models of microlevel herding do. There is valid criticism, relative to the utilisation of the cross sectional standard deviation of assets as a measure of herding. To begin with, the CSSD cannot capture a non-linear form of relationship between the dispersion of assets and the market return. Chang et al. (2000) propose another methodology - the CCK - of herding, using the cross sectional absolute standard deviation, in order to account for a non linear structure between the market return and the deviation of stock returns from the consensus. The aggregate result of investors' behaviour captured by this methodology might not actually be herding, as the authors themselves recognise. What is more, both the CH and the CCK methodology fail to account for other factors, such as liquidity, volatility, institutional parameters, macroeconomic conditions and more, without resorting to modifications. What the models define as herding is the concentration of the returns around the market return. This though, does not account for the fact that the dispersion of assets, when high, implies also high volatility which is affiliated with instability that might or might not relate to herding.

Hwang and Salmon (2004, 2007) propose a model that uses the cross sectional dispersion of factor sensitivity of assets. This way they try to incorporate important factors to their model. They also proposed a non parametric measure of herding, to account for the reaction of investors in many factors (beta herding). In both their papers, the authors pose a valid critic about the use of the cross sectional standard deviation, that could be extended to the cross sectional absolute standard deviation. Firstly, the choice of the market high and market low dummy variables[29] is arbitrary. If we assume that market conditions are to have an effect on herding, how do we define what an extreme market condition is? Different investors, with different definitions of extremes, may have different definitions of what is a "market extreme" - and consequently when market stress occurs. Additionally, herding may take place during normal periods as well, depending on the type of market and other variables already analysed above. If herding took place before a market extreme, then the CSSD or the CSAD will not encounter herding during extreme market conditions.

[28] Econometric biases such as mispecification, endogeneity, missing variables and inappropriate model structure etc.

[29] The CCK method does not require a dummy variable for extreme price movements, but the methodology is often applied only in extreme market returns, to test for the effect of market stress on herding

For the case of the CCK, though, this problem can be avoided. The examination of herding during up and down markets is not a pre-requirement as far as the CCK method is concerned, as the method can be applied to normal periods as well, with or without distinction. So, the use of extreme price movements, as a variable for herding, could be problematic for many reasons. Moreover, in both methods fundamental information is not taken into account. This means that, when herding is encountered, it might be spurious. Fundamental information could be the reason behind the behaviour of the dispersion of assets, as it represents the aggregation of investors' decisions. These investors come from many different backgrounds. Herding may exist, and still the CSSD and CSAD models may fail to capture it. Lastly, time series volatility is not considered although volatility and dispersion are mathematically linked (Goyal and Santa Clara, 2003). Especially during extreme price movements, volatility may rise. It is thus possible that any change in the dispersion might be a result of time series volatility or uncertainty. The methodologies for aggregate herding seem to define macro-level collective behaviour as the opposite of variability in returns. Both analytically and empirically though, these methodologies are proven inadequate, as they are often doomed, by their structure and its properties, to underestimate herding (e.g. for the CCK case, Bohl et al., 2017).
Moving on to the models proposed by Hwang and Salmon (HS)(2004; 2007), we observe that the herding measure is usually applicable to a lower frequency. Furthermore, the choice of factors used is not sufficiently justified and time series volatility is not accounted for. Lastly, the HS measure also suffers from the same issue concerning herding and intent. The CCK and HS measures are very close in the core of their idea. Although the HS measure accounts for many variables, it is not clear why it is supposed to outperform the CCK measure, that is more data-driven. Furthermore, the CCK methodology can be - and often has been (e.g. for liquidity Galariotis et al., 2016) - modified to account for several factors as well. Empirical evidence that support that the superiority of the HS measure does not exist. On the contrary, the two measures often render similar results (e.g. Demirer et al., 2010)
Another important issue is the inconsistency in the results of herding. There are numerous evidence of herding with a short term effect on prices, more so concerning trading decisions by institutions and individuals. On the other hand, the evidence of herding to the market consensus are weak, especially in well organised markets. So, how come that in organised markets we have evidence of institutional herding and no evidence of aggregate herding for the same period. Is the institutional herding spurious? Does it have, as some literature suggests, anti-bubble effects on prices? Is it linked to momentum, bubbles, crashes, overreaction and underreaction? Is there a possibility, that it is not all microlevel herding created equal, in terms of cause and effect? If so, then is the type of investor, the structure of the market, the macroeconomic environment or the regulation of the market the main determinants of this phenomenon? There is another aspect to this inconsistency. If institutional herding is not spurious - i.e. assisting price discovery and being based on fundamentals - then the methodology, that we have, may not capture its market effect properly. It is equally possible that herding's effect on prices, even in the short run, is not distorting or that it spreads evenly across prices and thus the dispersion does not capture it. Additionally, different classes of investors, may trade to different directions, leading to the observed reality. Questions about the concept of herding empirically are also essential. How do we define macro-level herding? Is herding

in trading imbalances, when examined market-wide, a form of micro or macro level collective behaviour? Should returns, absolutely, converge to the market return, for market-wide herding to exist? Is the frequency - regarding institutional and individual flows being mostly quarterly - inadequate to capture the effect of micro-level herding on market-wide returns?
In order to clarify the above phenomenon, we should consider the nature of the models and what they intend to test for. Empirical (Wermers, 1999) and theoretical (Dasgupta et al., 2011) findings, support the assumption that when investors and institutions herd into a stock [30], then this stock is characterised by abnormally positive returns in the imminent future. The long run horizon is not affected by herding. When the stock returns are abnormal and do not represent the company's fundamental value, then both per stock and the market-wide volatility may subsequently rise. Due to the mathematical connection between volatility and dispersion we know that during micro-level herding, the dispersion is very possible to rise. This will lead to a deviation of the market consensus and not a convergence to it. So, testing for herding using the deviation of returns from the market return, does not represent the true aggregate effect of investors decisions. Then again, which investor shall we consider? Is it institutional investors or individual investors that have the power to distort the market?
Given the empirical problems and obstacles in identifying herding, it is also hard to identify the nature of its impact on the market. Herding is a phenomenon that may change risk and market structure, whose nature has not yet been adequately explored.

2.5 Conclusion: The Road so far and Limitations

There is an ongoing debate in economics and finance, concerning whether or not people are rational or irrational. Most of the times the situation is neither black nor white. It is grey. Herding is one of these grey phenomena, that exist in everyday life, in schools, hospitals, economies and financial markets.
Humans have the tendency to mimic each other, in order to be able to integrate into societies. This evolutionary instinct stays with us until today and dictates many of our choices. Fads and fashion are a manifestation of this cognitive bias.
Nonetheless, there are settings where mimetic behaviour occurs rationally and intentionally. These settings are usually characterised by asymmetrical information and institutional/regulatory imperfections [31] in financial and economic terms.
It is a very hard task to measure herding empirically and to test for all the different categories of herding, that theory has implied. The gap in empirical literature is evident. The results are inconclusive as to whether or not herding exists in both the micro and the macro level. The methodologies employed for different levels are not compatible with each other and they are often proven incompatible with theory. Phenomena as liquidity and volatility should be taken into account. Causality between the dispersion of returns and herding behaviour shall also be examined. Is herding the driving force behind extreme price movements or does it exist simultaneously with them? Does herding cause higher clustered volatility or is it the state of

[30] The opposite is true for the case of herding out of a stock
[31] An example of this sort is market concentration

volatility, that causes agents to (not) herds? Can we observe herding in the market returns, or is microlevel herding only affecting the market in the short run? What are the variables that affect the transmission of herding from trading to returns? Is the market structure and its informational efficiency essential variables, that we should focus on?
All these questions are still to be answered for the most part. The risks, herding bares for the market may be severe. As every phenomenon it does have origins and these origins are directly related to the nature of the risk. What drives herding behaviour is directly related to what herding will cause. An example of that is herding and momentum trading. Herding and momentum trading are correlated mostly when herding is intentional. Another example is informational herding. The type herding to the market consensus we are able to observe is mostly driven by information, as Chang et al. (2000) state.
We shall also consider the sensitivity to measurement. As shown both in microlevel and in macro-level herding, the methodology chosen might affect the results. When for example we use returns to test for herding during market extremes, we should account for whichever factor may affect these returns. Returns, represent the aggregate effect of investors' choices and as such, will be affected by all variable relevant to the investors' decision making process, including herding existing prior to these decision being made. If prices, and thus returns, deviate from their fundamental value, herding might be responsible. How will we observe herding if we consider prices then? Lastly, do all methods, used to identify herding, have the same principles? Are they comparable and what story do they tell us about the risk and uncertainty herding may add - or not - to the market?
All in all, herding is a part of the financial markets and we should treat it as such. The dynamic system, i.e. the market, will interact with its constituents and their characteristics and we are, but to observe the "final composition".

Part II

Essays on the Empirical Approaches to Herding: Microlevel Herding and its Effect on the Market Consensus.

Abstract

Below, two essays regarding the relation between microlevel herding and market wide herding are developed in two parts. For both essays included in this part, the same data are used. Nonetheless, each essay presents a different aspect. For the first part we will focus on the intensity of microlevel herding and the origins of trading that may or may not affect the consensus of returns. For the second part we will investigate the effect of the direction of trading.

Chapter 3

Why the Empirical Models of Herding Disagree: The Aggregate Effect of Microlevel Herding and the Importance of the Investor Type on Market Wide Herding

Abstract

Herding is an important and controversial phenomenon in financial markets. There are two major empirical approaches to herding: herding in the level of investor choice and herding to the market consensus. Although there is evidence of collective behaviour, both for managers and for individual investors, herding to the market consensus is not identified. The two approaches to herding do not agree concerning both the existence and the extent of herding in the market. This *disagreement* indicates either conceptual differences in the definition of herding in these models or the ineptitude of these models to fully capture herding and its effects. In this essay, we investigate these two approaches and their results. We attempt to account for the effect of micro-level herding to the consensus of returns, the mechanism of transmission of herding and the role of the investor. We encounter evidence that micro-level herding affects the consensus of returns. The composition of trading, in terms of investor type and sophistication level is also essential for the mechanism of transmission of herding. Evidence support the assumption that individual herding relates positively to herding to consensus while institutions mitigate the effect.

Keywords— Herding, Trading Imbalance, Cross sectional absolute deviation of returns, DJIA 30, Financial Markets

3.1 Introduction

Financial markets are complex systems, shaped by the interactions of agents participating in them. The majority of conventional financial models consider these agents rational or at least somewhat rational (e.g. Lintner, 1965; Fama, 1970; Black, 1972; Tseng, 2002), while most recent behavioural contributions claim that agents' effectiveness is compromised by cognitive pitfalls and psychological factors. There are many phenomena, that can be driven either by failures described by conventional models or by behavioural issues. Herding is such a phenomenon, defined as the rational or irrational tendency of investors to follow their peers, often ignoring their own personal information (Avery and Zemsky, 1998; Banerjee, 1998; Hwang and Salmon 2004, Bikhchandani and Sharma,2001 among others).
From a conceptual point of view, regarding the rationality criterion, herding can be categorised into three major groups (Devenow and Welch, 1996). Rational herding occurs, when investors chose herding as their strategy. This choice is a product of a rational decision making process. Motives lie in the compensation structure, in reputation management, or even in informational asymmetries, that render information costly to obtain or untrustworthy to interpret. Irrational herding, on the contrary, stems from behavioural pitfalls and sentiment. Loss aversion, hyperoptimism and fallacies related to the human ability to access risk under pressure are some of the behavioural factors, that lead to the rise of financial gurus, fads and fashion (e.g. Bikchandani and Sharma, 2001; Spyrou, 2013). Lastly, investors often have to respond quickly to changes. For that reason, they have to develop heuristics and rules of thumb in order to function under time constraints. Almost rational herding is driven by these heuristics and rules. An important final note concerns spurious herding, that occurs as observed herding, and is sometimes driven by changes in intrinsic and fundamental values (Bikhchandani and Sharma,2001; Spyrou, 2013; Boortz et al., 2013). This type of herding assists price discovery and market efficiency, through more effective distribution of information across market agents (Walter and Weber, 2006, Boehmer and Kelley, 2009; Dasgupta et al. 2011a and b). Theoretical models often focus on identifying herding in a particular setting or environment[1], such as characteristic herding (Falkenstein, 1996), reputational herding (Scharfstein and Stein, 1990), informational cascades and blockages (Banerjee, 1998, Park and Sabourian, 2011) or herding-driven mispricing and speculative bubbles (Johansen and Sornette, 2010).
Empirically, herding proves to be a demanding task. The extensive concept of herding, including its various origins and ambiguous impact on the market, cannot be easily identified empirically (Bikchandani et al., 1992; Bikchandani and Sharma, 2001, Spyrou, 2013). Herding is identified empirically in two major market levels, micro-level herding and macro-level herding.
Micro-level herding focuses on investors and their choice to buy or sell a certain stock. Two main approaches have been developed to test for herding in the level of investor, the LSV measure that defines herding as the excess proportion of buyers (Lakonishok et al., 1992) and the SIAS measure that incorporates a dynamic structure through the proportion of buyers (Sias, 2004). Initially, these models were used

[1] The motives, the type of agent- investor, manager, analyst etc.-, the market conditions, the type of stocks and much more create a unique setting in which herding can be explicitly modelled by theory.

on data from institutional holdings to examine herding by institutional investors on a quarterly frequency (Lakonishok et al., 1992; Sias, 2004). Nonetheless, the measures of micro-level herding can be -and have been- used for individual investors, foreign investors as well as higher frequencies (e.g. Puckett and Yan, 2007; Zhou and Lai, 2009; Hsieh 2013).
Correlated trading is present in many cases, regarding the U.S. market (Lakonishok et al., 1992, Nofsinger and Sias, 1999, Sias, 2004) and internationally as well (Holmes et al., 2011; Hsieh, 2013; Lin and Lin, 2014). Herding by institutional investors is extensive both in established and stable markets and in emerging and concentrated markets for multiple periods, including but not limited to, economic turmoils, sanitary crises and election periods (Shyu and Sun, 2010). Peer pressure, reputational motives and career concerns (Dasgupta et al.,2011a and b, Khan et al., 2012), the firm environment (Leece and White, 2017) for the managers and analyst recommendations (Coval and Stafford, 2009; Dasgupta et al, 2011a; Brown et al., 2014) are all essential variables regarding micro-level herding, especially performed by institutional managers. The nature of the impact of herding is not explicitly clear. On one hand, herding is shown to predict short term prices (Dasgupta et al., 2011b) and to increase the crash risk of individual stocks (Edelen et al., 2016; Deng et al., 2018). On the other hand, institutional investors have been shown to herd against sentiment (Liao at al., 2011) and to act as arbitrageurs to stabilise prices. Aggregately, the antibubble effect of herding is rendered possible, as investors might act collectively as arbitrageurs to correct mispricing (Johansen and Sornette, 1999). It seems that the effect of herding on efficiency is also not concrete. Herding can enhance informational efficiency but it can also relate to momentum trading and market imperfections. Intent and investor type seem to be important variables concerning the determination of the nature of the micro-level herding effect (e.g. Zhang and Liu, 2012; Hsieh 2013).
The importance of micro-level herding and its effect for individual stocks is outlined by literature, that identifies herding for many investor groups on different stocks (Hsieh, 2013; Shyu and Sun, 2010), concerning different markets (Choi and Skiba, 2015) and various information settings (Jiang and Sun, 2014). Especially in the case of institutional investors in the U.S., with the rise of institutional ownership, herding by managers, and its distinct nature from other micro-level herding categories, is of vital significance.
In recent years, institutional trading occupies an important part of the overall market. An important demonstrative example of this fact is found in the American Economy . Most funds in the U.S. are open-end funds. At the end of 2016, there were 8,066 open-end mutual funds with 16,3 trillion assets active in the U.S. market. These numbers represent roughly 86% of the U.S. industry. Just a year later in 2018, there were 9599 funds in the U.S. with 17,71 trillion U.S. dollars worth of assets. [2]. The rise of power of institutions, in the U.S. market, is behold doubt as, since 1980, the equity holdings of mutual funds alone have risen from 2,84 % to 26,61 % in 2009 [3].
The importance of institutions is also highlighted in literature, focusing on both financial markets and herding. Institutional ownership often serves as a proxy for loanable shares (Nagel, 2005; Jiang and Sun, 2014), is positively correlated to stock

[2] Data sourced directly from statista.com
[3] Data sourced directly by the U.S. Bureau Census

prices (Nofsinger and Sias, 2004) and has a direct effect to market structure and liquidity (Poon et al., 2013). On a different note, in various studies, higher institutional ownership is affiliated with higher forecast frequency, accuracy and objectivity of forecasts (Ajinkya et al. 2005) as well as better disclosure practices (Healy et al., 1999; Bird and Karolyi, 2016).

Another part of the herding literature approaches the phenomenon form a broader perspective. Macro-level herding or aggregate herding or herding to the market consensus focuses on herding in stock returns. Herding in returns intends to approach collective behaviour as the aggregate effect of investors' choices (Chang et al., 2000). The use of the cross sectional dispersion of assets is employed either in a linear relation with the market return (Christie and Huang, 1995) or in a non-linear manner (Chang et al., 2000) to investigate the existence of consensus market wide. These methods enable us to approach herding during extreme price movements (Christie and Huang, 1995) and can be modified to account for other important factors, such as macro-economic announcements (Galariotis et al., 2015), liquidity (Galariotis et al., 2016) and spillovers from other markets (Chiang and Zheng, 2010). Other methods, conceptually similar, that attempt to integrate factor sensitivity (Hwang and Salmon, 2004) or employ measures of weighed variance (Xie et al., 2015,) have been developed but are not shown to perform more efficiently than the cross sectional deviation and cross sectional absolute deviation of returns (Demirer et al., 2010).

Empirical evidence of market wide herding vary between different markets. There does not exist evidence of market wide herding in most developed markets, neither overall nor during extreme price movements (e.g. Christie and Huang; 1995; Chang et al., 2000; Chiang and Zheng, 2010 among others). The evidence indicates that in more organised and diversified markets, there is no evidence of aggregate mimetic behaviour through returns. Nonetheless, herding is often present in emerging markets, concentrated environments and settings characterised by informational asymmetries, liquidity fluctuations and noise trading (e.g. DeLong et al., 1990; Chang et al., 2000; Economou et al., 2011; Lin and Lin, 2014; Galariotis et al., 2016).

Reflecting upon herding and existing evidence regarding collective behaviour gives birth to many interesting questions, considering herding conceptually and even more methodologically. Why does empirical evidence regarding the mere existence of herding disagree? How is it possible that in a market dominated by managers, managers herd but returns do not follow? Do the models, by construction, define herding differently, or is the mechanism of trading what drives the empirical disagreement? These are the main questions of this chapter. By examining both micro-level and macro-level herding independently, we are able to investigate their separate concepts. Then, we attempt to integrate herding by institutional and individual investors in market-wide herding, to account for the mechanism of transmission from trading flows to returns. The level of micro-level herding and the underlying variable of measurement - herding in trades or in value- is an important factor to account for. What is more, given the importance of the type of investor, the composition of the market in terms of investors will also be accounted for. Large institutional investors have different objectives, strategies and limitations in comparison to smaller institutions, large individuals and small individuals in the market, both due to access to different information sets (Atiase and Bamber, 1994; Miller, 2010) and due to sentiment disagreement between the two groups (Baker and Wurgler,2007; Hong and

Stein, Hong and Stein, 2007). The information captured by the volume per trade daily contains such important information[4](Mynatt and Cready, 1991; Lee, 1992; Lee and Radhakrishna,2000; Malmendier and Shanthikumar, 2007; Kaniel and al., 2008; Miller, 2010).
In the following sections we attempt to answer these questions for a small fragment of the U.S. market, the Dow Jones Industrial Average 30. What is more, we will use the emerging concept of herding in trading imbalances (Chung and Kim , 2017) to examine the validity of our results.
In section 3.2 the data and their description are presented, as they are vital to this essay's purpose. The empirical analysis is developed in three distinct parts in section 3.3, beginning by the independent examination of the two empirical concepts, in subsection 3.3.1 followed by subsection 3.3.2, where the role of aggregated micro-level herding along with measures of trading is explored and subsection 3.3.3 where the origin and type of investors in the market are accounted for in the estimation of macro-level herding. Lastly, the conclusion and limitations of this paper are presented in section 3.4

3.2 Data and Descriptive Statistics

The data used in this chapter are not the occasional data used to examine either micro-level or macro-level herding. For this reason, it is essential to examine the data and their basic properties.

3.2.1 Data

In order to test for both micro-level and aggregate herding, we need to consider a market that has specific parameters. The measures used for herding on these two levels are constructed on distinct concepts. Part of this essay is focused on identifying whether the results rendered by these methodologies agree, regarding the existence and extent of herding. The primary concern is whether these two approaches identify the *same herding*. If we find herding on the micro-level but not on the macro-level for the same market during the same time spam, then it is clear that these measures do not capture the same behaviour or that micro-level herding is not transmitted to market returns.
For this empirical analysis, we chose the Down Jones Industrial Average 30 market, henceforth DJIA 30. To begin with, the DJIA 30 is a stable market, that includes value stocks and is often chosen by managers, as it is presumably less uncertain. It is though a small market, as it only contains thirty constituents at each point in time [5]. The choice of a smaller number of stocks is compatible with the high frequency of the analysis. Since we are going to test for micro-level herding daily, we need to make sure that the stocks chosen are sufficiently traded. What is more, stocks included in DJIA 30 are stable, liquid, less volatile and less speculative (Baker and Wurgler, 2007). If we included stocks not sufficiently traded or difficult to evaluate,

[4] The volume of a trade is a proxy for the type and size of investor. Although investors splitting their trades may compromise the results (due to investors splitting their trades to exploit their superior information set (Kyle, 1985; Glosten and Milgrom, 1985))

[5] The index composition changes over time to include the evolution of the market and of course the rise and fall of individual stocks.

we might have risked outliers affecting the results. This liquidity constraint is met by the DJIA 30 a priori due to its composition.
On the other hand, a smaller number of stocks may not provide sufficient information. Value stocks tend to be less speculative and attract investors interested in more stable, long-term investments. Also, limits to arbitrage are fewer for these stocks, as the risk of arbitrage is low and more easily assessed. Additionally, since the DJIA 30 is part of a larger market and traded among other stocks, there might be interactions that our model might not capture. This dilemma when dealing with higher frequencies of herding, conducted by institutions and individuals, have been identified in the literature of high-frequency herding (Puckett and Yann, 2008).
Similar to the argument made above, when considering herding to the market consensus, we need to take into consideration the liquidity parameter. In order to be able to estimate the effect of market stress on the standard deviation of returns we need to be able to have liquid stocks.
We use trading data ranging from January 2007 to December 2019, for all stocks included in the index, and we infer trades, being buys and sells, using the tick rule in second level. Given that we infer trades via an algorithm, a particular bias may occur. We also use daily closing prices to compute the stock returns as it is shown to be the method containing the smaller bias[6]. The market return is computed as the unweighted average of the returns included in the market portfolio.

3.2.2 Main Descriptive Measures

We used the intra-day data to infer sells and buys daily using the tick rule in the second level, as mentioned above. Then daily closing prices were employed in order to compute daily returns and the corresponding market return. Initially, we performed an Augmented Dickey-Fuller (Dickey and Fuller,1979) test for unit roots [7] - for all series used in this paper. We managed to reject the null hypothesis of non-stationarity at 1% significance level for all series on four lags. For the market return, the cross sectional standard deviation and the cross sectional absolute deviation of assets the test indicates no drift and no trend. For the micro-level herding -both measured as the excess proportion of buys and the dollar based proportion of buys- we cannot reject the hypothesis of a drift for more than four lags included in the test. Descriptive measures and graphic illustration of the data and the measures computed are presented below.
The distribution of the market return, as the unweighted average of the stock returns in the market, is presented below in Figure 3.1 as an initial point of analysis. As expected, the distribution of returns is leptokurtic and centred around zero. The standard deviation, as a measure of dispersion, is 0.01257218. The shape of the market return distribution indicates higher potential for outliers, enhancing the importance of investigating these outliers and their importance for herding. The mean market return is central to the concept of macro-level herding. In its own right, the market return represents the consensus, and its distribution is used to determine extreme price movements as a proxy for market stress in many herding concepts.

[6] For example using closing prices allows us to avoid bias due to trading noise via continuous trading sessions (Kudryavtsek, 2015)

[7] For the test specification we used three alternatives, that include separately and jointly a drift and a trend.

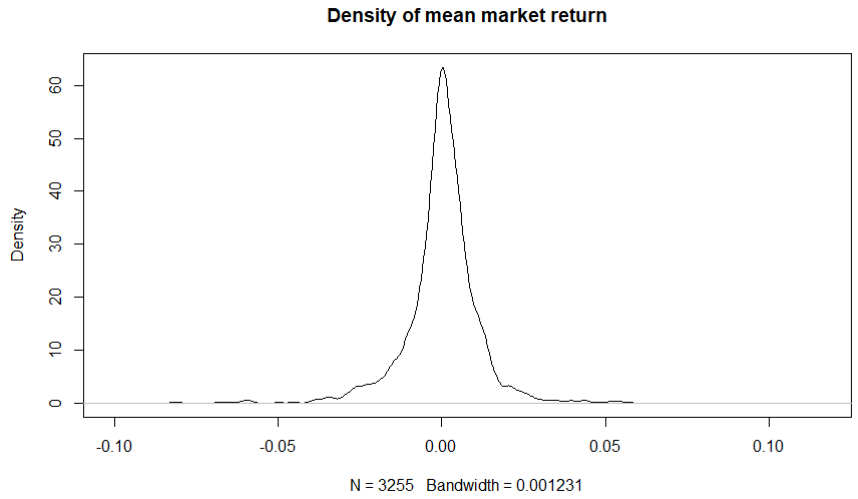


Figure 3.1: Density of the mean market return: All sample

The summary of descriptive statistics for the market return can be seen in Table 3.1. From Table 3.1, we can observe a slight asymmetry in the distribution, as the median

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.0970	-0.0040	0.0006	0.0001	0.0052	0.1128

Table 3.1: Mean, Median and Quantiles: Market return r_m

is higher than the mean, indicating higher left side concentration or more outliers in the left side of the distribution, something not visible in Figure 3.1. This can result in negative price shocks, being more common than positive shocks. The results are also affected by the 2007/8 financial crisis. In Figure 3.2, which presents the time series evolution for the market return, the effect of the crisis becomes clearer. The violent fluctuations of the market return until the end of 2009 are probably related to the financial crisis, which also affected value stocks, as those composing the DJIA 30. We can also see that the market return varies generally and shows signs of the economic cycle.

If we split the market into portfolios, based on the market value of a stock we also observe that the evolution of the portfolio return [8]for all portfolios is similar. There is overall high variability during and after the crisis of 2008 and then fluctuations become less intense. In Figure 3.3 we present the mean portfolio return - noted as market return- for four portfolios created, based on the four quantiles of the distribution of market value. The value based portfolios are similar to the overall market, again due to the composition of the index we examine. We can see that the variability of the lower market value portfolios is higher and the effect of the economic cycles is stronger. This is in line with theories that expect higher value stocks to fluctuate less, be less volatile and less affected by shocks - as shocks persist less due to effective arbitrage(Baker and Wurgler, 2007). Nonetheless, overall the difference in market value of stocks, in this particular case, does not seem to affect excessively

[8] The return of the portfolio is computed as the mean unweighted average of the returns of all stocks.

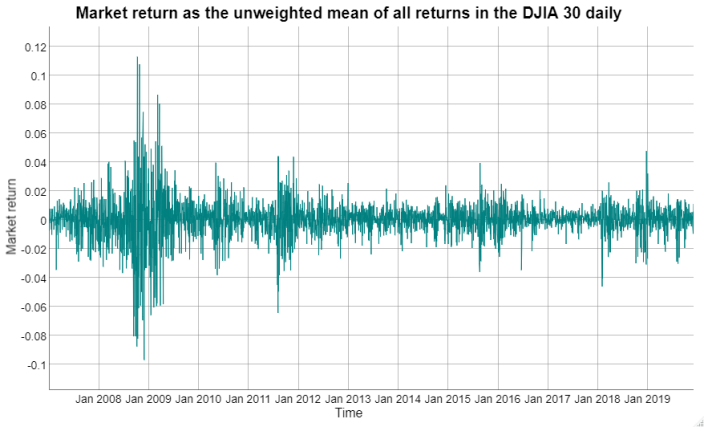


Figure 3.2: The evolution of the market return time series

the returns of stocks as the DJIA is a market composed of sector-leaders and high value stocks.

The measures of market-wide herding use the market return to compute the disper-

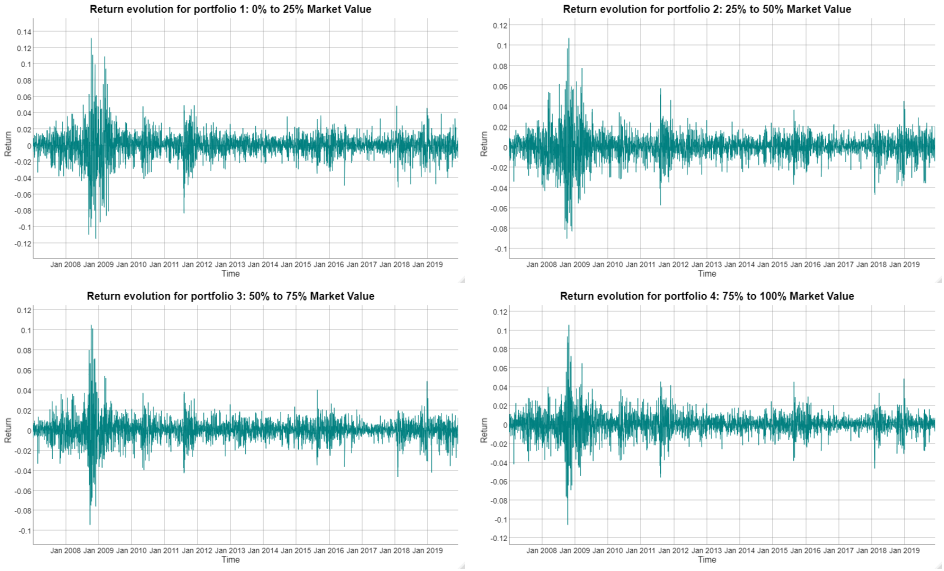


Figure 3.3: Market return evolution of four different portfolios based on the distribution of market value

sion and evaluate the consensus. The cross-sectional standard deviation - denoted CSSD - and cross-sectional absolute deviation - denoted CSAD - are measures of dispersion of returns, employed to identify herding to the consensus of returns.[9]. In Figure 3.4 the time series for the CSSD and CSAD are displayed. As we can see the two measures are quite similar. During the 2008 financial crisis, a rise in both measures is highlighted, indicating higher dispersion of returns, more volatile markets and a weaker consensus. It is important to note that herding during crises, if present, is often spurious as it may be based on the common set of information

[9] They are computed as follows: $CSSD_t = \sqrt{\frac{\sum_{i=1}^{n}(r_{i,t} - r_{m,t})^2}{N-1}}$ and $CSAD_t = \frac{1}{N}\sum_{1}^{N}|r_{i,t} - r_{m,t}|$

available to investors and dubious signals in the market (Boortz et al., 2013). On the other hand, panic developed during a crisis and the burst of a bubble, in addition to noise, may cause contagion and herding or high variability in investors choices, depending on the type of market and the investor that dominates it (Chang et al., 2000; Chiang and Zheng, 2010; Laih and Liau, 2013). In this case, the simple examination of the time series of $CSSD$ and $CSAD$ implies higher variability during the 2008 crisis. As far as micro-level herding is concerned, in our analysis, we employ

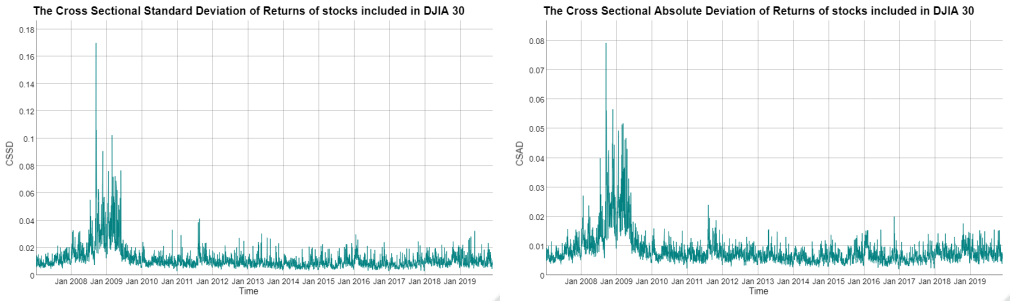


Figure 3.4: Time series evolution of the CSSD and CSAD for the whole sample

a modification of the LSV measure (Lakonishok et al., 1992; Zhou and Lai, 2009) , thus the excess proportion of buys and the dollar-based excess buys (Lakonishok et al.,1992; Wermers, 1999). Our computations are based on trades that are inferred from intraday quote data[10]. The measures used here have been used by other studies focusing on high frequency herding as well (e.g. Zhou and Lai, 2009; Hsieh, 2013). Below, measures of trading and microlevel herding are briefly described.

In Table 3.2 we can see the mean - for all series - number of stocks that have been

	Mean	Std
Value Based Buys	16.8286	5.7604
Value Based Sells	13.1702	5.7602
Trade Based Buys	21.7472	5.6097
Trade Based Sells	8.2399	5.6064

Table 3.2: Mean and standard deviation: Stocks identified as buys and sells based on the number of trades and value daily.

identified as buys and sells each day. We present the results for trades identified via value and counts of trades. To identify a stock as a buy stock, via trade, the number of buys is higher than the number of sells. In the case of the value criteria if the total dollar value of buys is higher than the value of sells, then we have a buy stock. So for example, in our whole dataset, the mean of *"stock identified as a buy via value"* is 16.8286 out of total 30.

If we now observe the distribution of the trading imbalances graphically, as displayed in Figure 3.5 ,the form differs based on the underlying variable used to define imbalance. Trading imbalance based on the counts of buys and sells are skewed to the left. Nonetheless, buys represent a higher percentage than sells with the mean being positive. Volume imbalance is slightly asymmetrical to the right, with more extreme buys than sells. The mean though is also positive. Value imbalance is even

[10] The original LSV and D-Ratio employ buyers and sellers and not buys and sells.

more leptokurtic with a higher concentration around the centre. This is an indication of asymmetries in trading, as the data indicates more outliers in value based imbalances compared to the trade-based equivalent. Asymmetries may be a result of big trades affecting the distribution. These differences may relate to differences between the trade-based and the value-based metrics of herding, both as measures in their own right and as variables of interest in the transmission of herding from flows to returns.

The asymmetries, described above, imply that micro-level herding shall be exam-

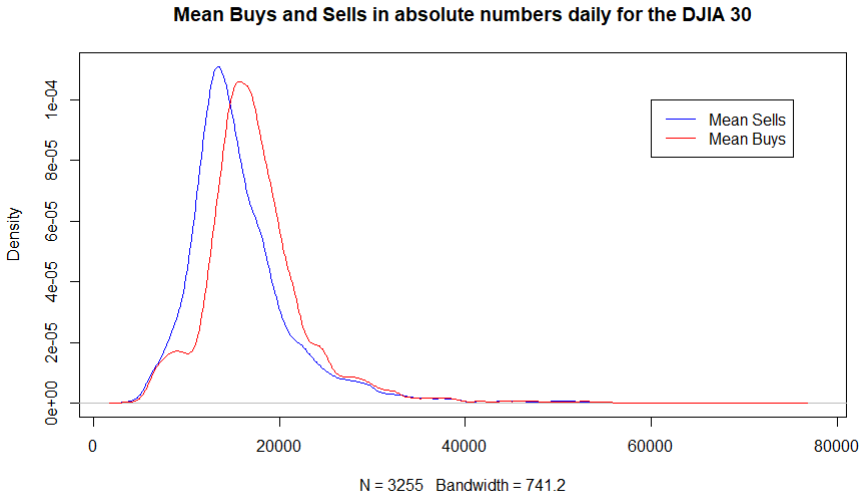


Figure 3.5: Density of the mean buys and sells in absolute numbers for the DJIA 30

ined employing both trade-counts and value as underlying variables. Using buys and sells, in counts and value we compute the two major micro-level herding static measures. Here we noted as the LSV the trade based measure and as D-ratio the value based measure. Their computation is presented in the following chapter. Given the results of the Augmented Dickey Fuller test performed, it is useful to look into the time series graphically.

In Figure 3.6 we observe that both the LSV and the D-ratio are consistently higher

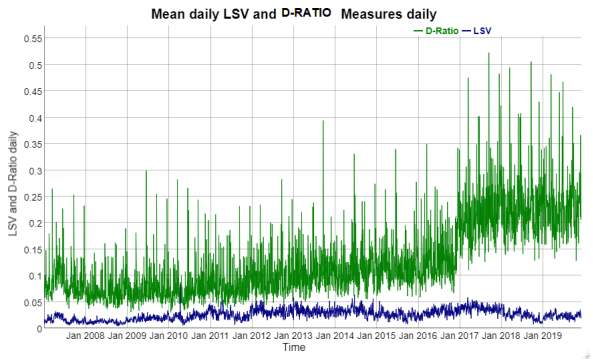


Figure 3.6: Mean LSV and D-ratio for the market portfolio daily

than zero. Especially, for the dollar based measure, and as indicated from the stationarity ADF test we can observe a break around January 2017, that is not visually

observable in the series of the LSV. Given that the D-ratio is measured using the dollar-based value this may be a result of monetary, macroeconomic or even political conditions that do not affect the number of trades. Additionally, such differences may occur due to high per trade volume, that indicates larger traders in the market.

We shall now focus on the correlation matrix between trading variables. In Table 3.3 we include the mean total number of trades, the mean total volume, the mean total value and the mean trading imbalance based on trades, volume and value.

	Trades	Imb(tr)	Imb(vol)	Volume	Imb($)	Value ($)
Trades	1.0000					
Imb (tr)	-0.1017	1.0000				
Imb(vol)	-0.0278	0.3773	1.0000			
Volume	0.6580	-0.2484	0.1220	1.0000		
Imb($)	-0.0744	0.2653	0.7599	-0.0084	1.0000	
Value ($)	0.5535	-0.0828	-0.0090	0.2804	0.0750	1.0000

Table 3.3: Correlation matrix of basic trading measures all shown in means for the DJIA market

As we can see in Table 3.3 the correlation between different imbalance means is not always strong. What is more, mean total volume, which is a proxy for liquidity, has a negative effect on the trading imbalance, measured on trade and even value. Below we look into the correlation between measures of return, measures of the cross sectional deviation of returns and trading imbalances.

	$r_{m,t}$	$CSSD_t$	$CSAD_t$	Imb (tr)	Imb(vol)	Imb($)	D_t^L	D_t^U
$r_{m,t}$	1.0000							
$CSSD_t$	-0.0773	1.0000						
$CSAD_t$	-0.0581	0.9662	1.0000					
Imb(tr)	0.3668	-0.2086	-0.2391	1.0000				
Imb(vol)	0.4032	0.0376	0.0375	0.3773	1.0000			
Imb(val)	0.2292	-0.0381	-0.0422	0.2653	0.7599	1.0000		
D_t^L	-0.5900	0.3229	0.3596	-0.3161	-0.2247	-0.1347	1.0000	
D_t^U	0.5153	0.2664	0.3216	0.0757	0.2133	0.0837	-0.0527	1.0000

Table 3.4: Correlation matrix between trading measures, the market return and herding to the consensus measures

In Table 3.4 we demonstrate the correlation matrix between the market return, the cross-sectional standard deviation - CSSD -, the cross-sectional absolute deviation - CSAD -, trading imbalances based on trade counts, volume and value along with the two dummy variables that stand for extreme returns. The dummy variables D_t^L and D_t^U account for extreme markets conditions, through the market return and thus large positive and negative price movements. Here we consider the case of 5%, as a benchmark for the identification of extremes. If the market return falls below the 5% low of its distribution then D_t^L takes the value one; otherwise it is zero. If the market return falls in the upper 5% then D_t^U takes the value one and otherwise

zero. The percentage we define, in order to denote such dummy variables of similar structure for all underlying variables, will be called henceforth *criterion*.
In Table 3.4, we observe that all trade imbalances have a negative correlation with meagre market returns, while volume imbalance has a stronger correlation to extremely high returns. All imbalance measures have a significant positive correlation to the market return indicating that high trading activity is positively correlated to the market return. Only trading imbalances measured on trades have a significant negative correlation with both cross-sectional deviation measures.
Given all the above, a clear connection between trading imbalance measured on trades and herding to the market consensus is documented. Measures of micro-level herding are computed using these imbalances and are also linked to the market consensus. In addition to the above, the nature of trading seems to be of high importance for the empirical results as well. Having looked into the data and some non parametric metrics related to them, in the following section the empirical results are being presented and analysed.

3.3 Empirical Analysis: Methodology and Empirical Findings

The section regarding the empirical results, with the respective methodology, is partitioned in three subsections. In subsection 3.3.1 the results concerning micro-level and macro-level herding are presented while in subsection 3.3.2 the aggregated effect of micro-level herding on market wide herding is investigated. A special part of this subsection is centred around the recent measure of herding in trading imbalances (Chung and Kim, 2017). Lastly in subsection 3.3.3 the type of investors and its importance are explored. All estimations in this section are performed via Ordinary Least Squares(OLS). All t -statistics and P-values shown are corrected for heteroskedasticity using the White method [11]. All inference results are robust to the choice of error correction. The significance of the coefficients is not affected by the choice of error correction.

3.3.1 Micro-level and Macro-level herding: Are the results regarding the existence of herding consistent regarding the choice of approach?

In order to present a comparison between methodological approaches to herding, we divide the results into micro-level herding and macro-level herding.
For the case of micro-level herding the LSV and D-Ratio are used, while for macro-level herding the CCK method is employed. The results are similar using the CH methodology for the simple case. These estimations can be found in the Appendix of the present chapter.

[11] The White method is compatible to our number of observations (¿250). We performed as a robustness test the Cribari-Neto (2004) method and the Newey-West method (1987; 1994) and the results were similar.

Micro-level herding

The empirical analysis begins by exploring the case of herding performed in trading by institutional and individual investors. The empirical measures developed focus on institutional investors as buyers and sellers. In this section we use the methodology proposed by Lakonishok et al. (1992) for managers, known as LSV, modified by Zhou and Lai(2009) and Hsieh (2013) to replace traders with trades. We further modify the measure by excluding the adjustment factor. The adjustment factor included in the original model accounts for the bias occurring when the proportion of buys systematically exceeds its expected value even when no herding occurs. For large enough number of trades the adjustment factor approaches zero (Lakonishok et al., 1992; Jones et al., 1999; Lin and Lin, 2014) as shown in the literature. Given the number of trades in our data - 33351.72 trades on average per stock per day- the adjustment factor approaches zero, as it declines on the number of N,[12] and is unnecessary. We define herding as:

$$H_{i,t} = |\frac{B_{i,t}}{B_{i,t} + S_{i,t}} - p_t| \tag{3.1}$$

where $B_{i,t}$ and $S_{i,t}$ stand for the total number of buys and sells per stock per day respectfully. The mean proportion of buys for all stocks p_t is used as a proxy for the expected proportion of buys $Exp(\frac{B_{i,t}}{B_{i,t}+S_{i,t}})$ that has to be subtracted from the proportion of buys of each stock. Initially, Lakonishok et al. (1992) and later on Wermers (1999) argued that a measure based on value is useful when considering herding in trading. Given the nature of our data it is essential to use both measures. We compute the dollar based ratio-DR as Wermers (1999) below:

$$DR_{i,t} = \frac{|\$B_{i,t} - \$S_{i,t}|}{\$B_{i,t} + \$S_{i,t}} \tag{3.2}$$

According to these methods herding occurs when the mean H_t and mean DR_t for the market- or a part of the market- are significantly different from zero. The higher the measure, the stronger the herding phenomenon. In Table 3.5 the results for the whole market portfolio are presented. Herding is stronger when computed in value and smaller when computed in counts of trades. Nonetheless, herding is significant- as indicated by the t-statistic- in both cases.

Measures	Mean	Std	t-statistic	Degrees of freedom
$\overline{H_t}$	0.0255	0.0099	147.73	3254
$\overline{DR_t}$	0.1249	0.0697	102.26	3254

Table 3.5: Herding by institutional and individual investors

So, although metrics of herding are small, and the market examined contains only 30 stocks at each t, the significance of the existence of micro-level herding is empirically supported. What is more, it is essential to note that the stocks included in the DJIA index do not suffer from insufficient liquidity, that may affect herding

[12] Regarding the modification employed, N stands for the number of trades, whereas in the original LSV measure N noted the total number of traders.

(Galariotis et al.,2016). Additionally, DJIA due to its construction and composition, contains stocks that represent specific sectors of the US market and are sector leaders, thus high value stocks. Although herding is not strong, it is present even within such large, established and stable stocks.
Now, we need to also examine macro-level herding, using the dominant methodologies existing in the literature.

Macro-level Herding

In order to estimate macro-level herding, the model designed by Chang et al. (2000) and the modified version for asymmetry by Chiang and Zheng (2010) are employed. The methodology proposed by Christie and Huang (1995), along with the robustness test proposed by the authors can be found in the Appendix.
The CCK method- that is more widely used- accounts for non linear structures via the squared market return. Below we briefly present the model.

$$CSAD_t = \frac{1}{N}\sum_{1}^{N}|r_{i,t} - r_{m,t}| \tag{3.3}$$

In the model proposed by Chang et al.(2000), the absolute market return and the squared return are used as independent variables in a regression as follows:

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r_{m,t}^2 + \epsilon_t \tag{3.4}$$

The $CSAD$ denotes the cross sectional absolute deviation, $r_{i,t}$ is the return of asset i, N is the number of assets in the dataset and $r_{m,t}$ is the market return, as the unweighted cross sectional average of N returns in the market. If the parameter γ_2 of equation 3.4 is negative then the presence of herding in the market is supported. The authors themselves acknowledge the fact that their model captures mainly non-linearities and a negative γ_2 may capture other types of non linear patterns. This measure assumes that the relation between herding and the squared market return - that is also an indication of market variance (Klein, 2013; Galariotis et al., 2016)[13] is non-significant or positive in the absence of herding.
The above equation does not focus on market stress but it can be modified to account for market extremes via a two regression processes. Note, additionally, that the CCK method does not account for the asymmetric effect of the market return, so the results for a modification of the CCK by Chiang and Zheng (2010) are also presented. They include the market return $r_{m,t}$ as an independent variable in their model to capture possible asymmetry of investors' behaviour given various market conditions. The modification is described below in equation 3.5.

$$CSAD_t = \alpha + \gamma_0 r_{m,t} + \gamma_1|r_{m,t}| + \gamma_2 r_{m,t}^2 + \epsilon_t \tag{3.5}$$

Chiang and Zheng (2010) present the meaning of the coefficients of equation 3.5 as follows:

[13] The market variance is defined as the expectation of the squared market return minus the expectation of the market return squared as $Var[R_{m,t}] = E[R_{m,t}^2] - E[R_{m,t}]^2$). In an efficient market the expectation of the market return is converging to zero, the squared market return shall approximate the market variance, Klein (2013)

- $\gamma_0 + \gamma_1$: form of relation between $CSAD$ and r_m when $r_{m,t} > 0$
- $\gamma_0 - \gamma_1$: form of relation between $CSAD$ and r_m when $r_{m,t} < 0$
- $asym = \frac{\gamma_0+\gamma_1}{\gamma_0-\gamma_1}$: asymmetry between $CSAD$ and r_m.

According to both Chiang and Zheng (2010) and (Duffee, 2001) the ratio above- $asym$ - reveals the relative asymmetry, if present, of the effect of a positive versus a negative market return.
Below we present the results of these methods in Table 3.6, which includes in distinct Panels the results for equations 3.4 and 3.5. As we can see in Table 3.6 no herding

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0060	0.0001	38.5800	0.0000
A	$\|r_m\|$	0.2618	0.0377	6.942	0.0000
Eq. 3.4	r_m^2	1.9496	0.9861	1.9770	0.0481
Panel	(Intercept)	0.0060	0.0002	38.5890	0.0000
B	r_m	0.0014	0.01559	0.0920	0.9268
Eq. 3.5	$\|r_m\|$	0.2620	0.0369	7.0990	0.0000
	r_m^2	1.9478	0.9832	1.9810	0.0477

Table 3.6: Herding to the market consensus: The CCK method. Results presented in two separate Panels: Panel A for equation 3.4 and Panel B for equation 3.5

is found using the CCK method and its modification by Chiang and Zheng (2010). The sign of γ_2, being positive and weakly significant - at 5% level or more - indicates higher variability in the market, while a strong consensus is not identified. What is more, the parameter γ_0 is not significant indicating no asymmetry. This is also true when we look into the parameter of asymmetry in Table 3.7 following the suggestion of Chiang and Zheng (2010). There is no significant change in the relation between the CSAD and the market return when we account for asymmetry.

Measure	Asymmetry
$\gamma_1 + \gamma_0$	0.2635
$\gamma_1 - \gamma_0$	0.2606
$\frac{\gamma_1+\gamma_0}{\gamma_1-\gamma_0}$	1.0110

Table 3.7: Asymmetry by Chiang and Zheng (2010): Coefficient estimates for equation 3.5

All in all, there is no evidence of herding to the market consensus using measures of return deviation. On the other hand, we find evidence of herding regarding trades both in trading value and in the number of trades. [14]
In the following subsection we try to account for the aggregated effect of micro-level herding and trading in the estimation of market-wide herding. This way we hope to investigate the existence and nature of a mechanism of transmission or no-transmission of herding from trading flows to the aggregate level.

[14] As shown via the examination of individual stocks, this evidence exists both regarding the whole market and in individual cases.

3.3.2 Macro-level herding revised: The aggregated effect of micro-level herding and trading imbalances on the consensus of returns

In this part, the aggregate effect of institutional and individual herding is accounted for in the estimation of market wide herding. Additionally, we will refer to imbalances as a way to estimate herding in their own right (Chung and Kim,2017) in order to test the validity of our results concerning the aggregate market level. We will begin by the more extensively examined micro-level herding, as a variable of interest for the consensus of returns.

The aggregated effect of institutional and individual herding on the consensus of returns

In order to account for micro-level herding, when estimating market wide herding, we focus on the CCK measure. The CCK measure is the most widely used, especially regarding alterations to the original variables. We follow the structure chosen by most researchers regarding modifications of the CCK measure (Chiang and Zheng,2010, Demirer et al., 2010, Galariotis et al., 2016 among others) in order to account for microlevel herding. [15]
We account for institutional and individual herding using both the mean trade-based and the mean value-based measures of micro-level herding -$\overline{H_t}$ and $\overline{DR_t}$ accordingly. We estimate the following two regressions, to investigate the effect of the whole spectrum of micro-level herding to the consensus.

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r^2_{m,t} + \gamma_3 \overline{H_t} r^2_{m,t} + \epsilon_t \tag{3.6}$$

and

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r^2_{m,t} + \gamma_3 \overline{DR_t} r^2_{m,t} + \epsilon_t \tag{3.7}$$

where again $\overline{H_t}$ stands for to the mean excess proportion of buys and $\overline{DR_t}$ for the mean D-ratio. Below in Table 3.8 the results are presented in two distinct Panels.

The coefficient γ_3 is significant only in the case of micro-level herding based on value. This indicates that micro-level herding based on the excess proportion of buys does not affect the consensus of returns as a whole.
We now continue to investigate the effect of micro-level herding extremes [16] and the consensus of returns. We apply the following regressions:

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r^2_{m,t} + \gamma_3 DH^L_t r^2_{m,t} + \gamma_4 DH^U_t r^2_{m,t} + \epsilon_t \tag{3.8}$$

and

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r^2_{m,t} + \gamma_3 DDR^L_t r^2_{m,t} + \gamma_4 DDR^U_t r^2_{m,t} + \epsilon_t \tag{3.9}$$

[15] Modifications to the CH measure to account for micro- level herding with similar implications as the ones presented below can be found in the Appendix

[16] Extreme micro-level herding based on value indicates that the mean D-ratio takes an extreme value, thus buys or sells differ greatly. Extreme micro-level herding based on trades indicate that the excess proportion of trades of individual stocks is very close(on the low case) or very far (on the high case) from its expected value(ie. the market average across t)

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0060	0.0002	39.0810	0.0000
A	$\|r_m\|$	0.2671	0.0035	7.5000	0.0000
Eq. 3.6	r_m^2	2.1701	1.3960	1.5550	0.1200
	$\overline{H_t} * r_m^2$	-25.1193	79.5700	-0.3160	0.3377
Panel	(Intercept)	0.0061	0.0001	37.3500	0.0000
A	$\|r_m\|$	0.2678	0.0377	7.1020	0.0000
Eq. 3.7	r_m^2	1.3880	0.4112	3.7020	0.0002
	$\overline{DR_t} * r_m^2$	-35.0004	10.3300	-3.3380	0.0007

Table 3.8: The aggregate effect of micro-level herding for the consensus of returns. Results presented in two Panels: for equation 3.6 (Panel A) and for 3.7 (Panel B)

Measures DH_t^L and DH_t^U are dummy variables that take the value one if $\overline{H_t}$ falls below and above a certain percentage of the distribution respectfully. The same principles apply to the dummy variables DDR_t^L and DDR_t^L regarding the case of $\overline{DR_t}$. [17] Here we display the results for both equation 3.8 and equation 3.9 for

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0061	0.0001	38.5080	0.0000
A	$\|r_m\|$	0.2679	0.0357	7.4880	0.0000
Eq. 3.8	r_m^2	1.7444	0.9238	1.8870	0.0592
	$r_m^2 * DH_t^L$	0.1984	0.9238	0.2150	0.8300
	$r_m^2 * DH_t^U$	-10.8418	2.3720	-4.5710	0.0000
Panel	(Intercept)	0.0061	0.0001	39.8780	0.0000
B	$\|r_m\|$	0.2635	0.0348	7.562	0.0000
Eq. 3.9	r_m^2	1.8093	0.9495	1.9060	0.0568
	$r_m^2 * DDR_t^L$	1.4965	0.7710	1.9400	0.0525
	$r_m^2 * DDR_t^U$s	-5.7124	0.7547	-7.5690	0.0000

Table 3.9: Herding to the consensus and micro-level herding at extremes. Results for the 12.5% criterion presented in two Panels: for equation 3.8 (Panel A) and for equation 3.9 (Panel B)

the 12.5% criterion on each side of the distribution in table 3.9. As shown in the Appendix the results are robust to the choice of criterion. [18]
The results indicate that when herding by institutional and individual investors is high - both using counts of trades and value- then herding exists market-wide as well. The coefficient γ_4 is negative and significant for the case of both $\overline{H_t}$ and $\overline{DR_t}$. Furthermore, interestingly when the D-ratio is very low- indicating lower levels of

[17] Here, we account only for the case of micro-level herding being in the extremes as a state and not the combined effect of microlevel herding in the extremes. We could add the level of microlevel herding in the extremes as follows:

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 DH_t^L * \overline{H_t} r_{m,t}^2 + \gamma_4 DH_t^U * \overline{H_t} r_{m,t}^2 + \epsilon_t$$

and similarly for equation 3.9 for the case of the Dratio. Doing so does not affect the nature and the interpretation of the results. To that effect this approach is included in the Appendix.

[18] The 20% criterion is presented as a robustness test.

value herding, then herding in the consensus is also smaller. This may be a result of the origin of high value trading coming from informed or more qualified investors. This is a weak result as the corresponding p-value is 0.0525. The results are similar when we also include micro-level herding in extremes, apart from the state of micro-level herding being extreme. These results are available in the Appendix as well.
We will now use the concept of trading imbalance herding, as explored by Chung and Kim (2017), to test the effect of trading pressure and herding in imbalances on market-wide herding in returns.

Trading Imbalance as a measure of herding and its effect on market wide herding

Trading imbalance is a vital notion and may affect the market as a whole. Chordia and Subrahmanyam (2004) show how autocorrelated trade imbalances affect daily returns, causing pressure in prices. The origin of these imbalances is also essential, as institutional traders split their large trades. This often happens when a group of investors has access to a superior information set (Glosten and Milgrom, 1985; Kyle, 1985) and decide to split the trades to prolong the period of gains and hide their trading signal from other investors. What is more, Lee et al. (2012), for the case of Taiwan, argue that order imbalances affect market efficiency as investors- all of them but mostly domestic institutions- are *"de facto"* market makers. Furthermore, order imbalances have an impact on important market characteristics such as liquidity and the - essential for aggregate herding- market return.
Regarding the case of herding, Chung and Kim (2017), developed a model using intraday data and measures inspired by literature on return commonality. These measures, that already exist regarding return commonality (e.g. Roll, 1988) can be modified to include the effect of the industry (Durnev et al.,2003). An important note, concerning herding in trading imbalances is the fact that herding stocks have been shown to have lower returns during crisis and higher returns during positive markets. Additionally, when Chung and Kim (2017) apply the CH and CCK measure no herding is discovered for the same market and period. There again herding is found in flows/imbalances, but not market-wide in returns. It becomes, thus, clear that herding in trading imbalances is an original concept that may affect the consensus of returns in a similar manner as concentrated trading.
We aspire from their measure and employ the residual of the commonality in trading imbalances regression, to test for the effect of herding in trading imbalances on the consensus of returns, while also examining their concept of herding using their measure of R-squared. Chung and Kim (2017) consider that a high R-squared is equivalent to high herding in trading imbalances.[19]. This type of herding is similar conceptually to micro-level herding, as it examines flows and trading behaviour but also allows to investigate the phenomenon of herding in trading market-wide, via the structure of the regression employed.
For the purpose of this essay, we will not use industries, as the market we use contains only 30 stocks, all of which are industry leaders. We will only examine the relationship between trading imbalances of individual stocks with the market-wide

[19] They regress the trading imbalance of each stock on the market and sector trading imbalance, inspired by literature of commonality in returns

trading imbalance. We present the main equation:

$$TI_{i,t} = \kappa_0 + \kappa_i TI_{m,t} \tag{3.10}$$

where $TI_{i,t}$ is the trading imbalance[20] of stock i at t and $TI_{m,t}$ is the market trading imbalance, as captured by the unweighted mean of all stock imbalances in the market.
Chung et Kim (2017) consider the R^2 as a measure of herding, based mostly on the literature of return commonality. We run regression 3.10 for each stock, for the whole period. The mean R^2 for the whole sample is 0.2073 and is statistically significant with a standard deviation of 0.1271 and the resulting t-statistic being 10.802 at 42 degrees of freedom.
Figure 3.7 presents graphically the R^2 for all 43 regressions. The higher the R-

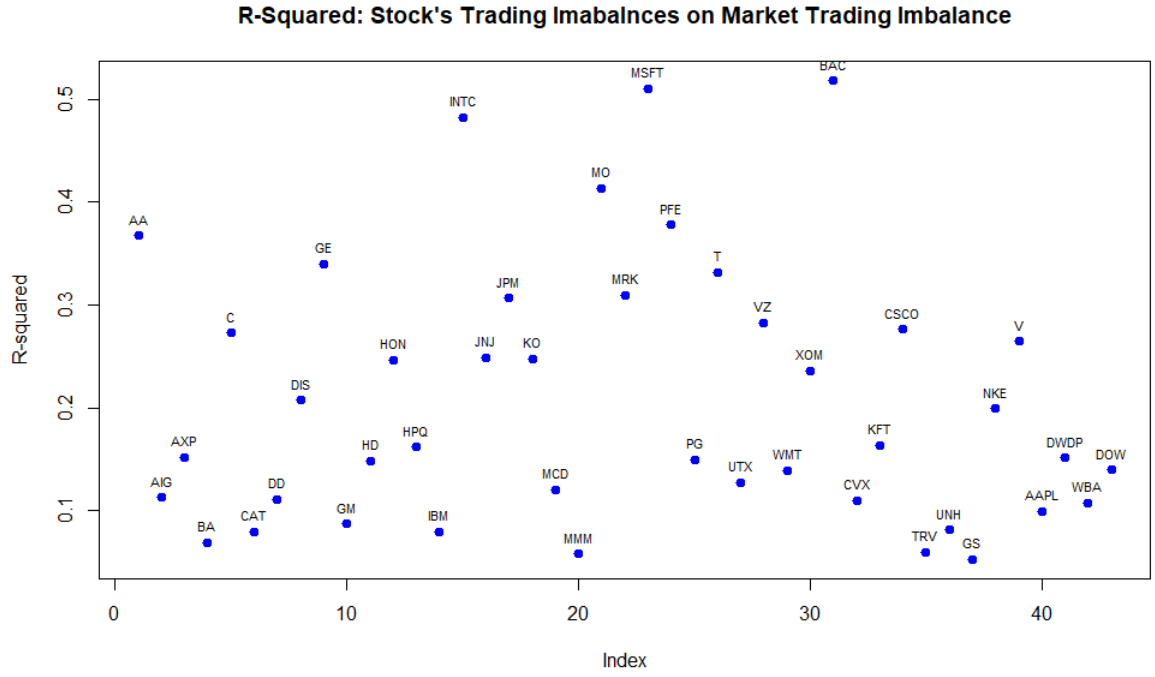


Figure 3.7: R-squared of regression 3.10 for each stock i for the whole time period

squared, the stronger the herding. We should also note that all κ_i coefficients are significant and positive, indicating also the existence of herding in individual stock trading imbalances. The table of all the coefficients κ_i can be found in the Appendix. We underline that in this case, herding is perceived as a form of commonality in trading imbalances. In the case of micro-level herding, in H_t measure for example, collective behaviour is perceived as the absolute excess percentage of buys. In Chung and Kim (2017) herding in imbalances, indicates herding in trading market-wide, as the average R-squared is computed for all stocks in the market.
We use the residuals of the regression 3.10 for each stock to account for deviations of imbalances from the market[21]. For example, if we consider that the market imbalance affects linearly the trading imbalance of a stock i, then the residual of this

[20] All measures of imbalance measured on counts of trade
[21] More information regarding this matter is available in the appendix

regression captures the trading imbalance deviation from the market. The cross-sectional mean of the absolute residual can be used to proxy the average dispersion of trading imbalances from the trading imbalance of the market. Although the form of the relation, is not established as linear theoretically, a relation between the stocks' trading imbalances and the market wide trading imbalances is supported by the results of regression 3.10 empirically. The choice of the cross -sectional average of the residuals of equation 3.10 allows as to account for herding in trading imbalances market wide, as a form of micro-level herding or herding in trading. Herding in trading imbalances occurs in the micro-level of the market and imbalances are potentially manifestations of herding in their own right (Scharfstein and Stein, 1990). When the residual is big at t then, the market imbalance does not explain the imbalance of stock i at t. We will use a dummy variable, that will take the value 1 when the absolute residual at t is below the median (50%) of its distribution and zero otherwise. In this form we can examine whether small deviation in trading imbalances relates to herding market-wide in returns.
We employ the following regression:

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 DRES_t^L r_{m,t}^2 + \epsilon_t \tag{3.11}$$

where $DRES_t^L$ is the dummy variable mentioned above and every other notation is identical to equation 3.4. Note that for multicollinearity issues we do not account for the case when the absolute residual at t is above the median. The results are inverse for this case. Table 3.10 displays the results for equation 3.11. In Table 3.10

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0061	0.0001	40.9530	0.0000
$\|r_{m,t}\|$	0.2976	0.0399	7.4420	0.0000
$r_{m,t}^2$	1.8389	0.9003	2.0430	0.0412
$DRES_t^L r_{m,t}^2$	-0.0863	0.028	-3.0480	0.0023

Table 3.10: Results for equation 3.11: Market wide herding and the dispersion of trading imbalances.

we can see that when the dispersion of trading imbalance is below the median, there is more market wide herding. In addition to this, in the opposite case of higher dispersion in absolute trading imbalances we observe that the coefficient is positive. The results indicate that the dispersion of trading imbalances is important for market wide herding, as the absolute excess proportion of buys was.
In general, measures of herding in flows, either in the form of imbalances or in the form of micro-level herding, are related to the the formation of returns market-wide. The evidence indicates that the concepts of herding are related, although their results differ. It is implied that the mechanism of transmission is not adequately incorporated in either concept and this might be one of the reasons the empirical approaches to herding render ambiguous results.
An important factor is the type of investor in the market. Especially in the case of market-wide herding, the investor and its type is often ignored by empirical models. While micro-level herding measures often incorporate the type of investor - being institutional or individual, domestic or foreigner etc. - as a way to examine who herds. The importance of this variable for market wide herding has not been sufficiently highlighted, although the type of investor is vital for the formation of returns.

Given that different expectations arise between the different type of investors due to unequal access to private information (Atiase and Bamber, 1994; Miller 2010) and that institutional and individual investors may have different trading strategies and investment styles (e.g. Barberis and Thaler 2003; Liao et al., 2011), it is possible that herding is not transmitted in returns due to investors trading in opposite directions. This is also implied by evidence of the existence of market-wide herding in "noisy" and emerging markets mostly. In the following subsection, we attempt to account for the effect of the market composition in terms of investors for all the reasons above.

3.3.3 The importance of the type of investor for herding

The composition of the market in terms of investors is a critical parameter. Institutional and individual investors don't have the same access to information, means of research, funds and more. It is logical to assume that institutional investors and individual investors will have different trading strategies. What is more, trades performed both by mutual fund managers and by retail investors contain information about sentiment (Baker and Wurgler, 2007). Sentiment is vital to the formation of speculative bubbles and the crash that usually follows (Barberis and Thaler, 2003; Shefrin, 2005; Baker and Wurgler, 2007). The disagreement of investors and agents is an important variable when we try to examine stock returns (Hong and Stein ,2007). Macro-level herding may be affected by the difference in sentiment, between different investor groups.
For this, we seek to incorporate the type of investor and its effect on market-wide herding. We speculate that an institutional investor who herds, may have a distinct impact compared to an individual investor who herds. Institutional and individual herding, in the micro-level of flows, is affected by different parameters, as these two investor groups have been found to herd on different type of stocks (e.g. Hsieh, 2013). For this, we try to incorporate the importance of investor type for the effect of aggregated micro-level herding on the consensus.
Given that our dataset does not contain information about the origin of the trade and thus the type of investor, we attempt to use a proxy variable for the composition of the market. By composition of the market, we refer to whether the market is dominated by institutional or individual investors, nad therefore the origin of trading. Mynatt and Cready (1991) argue that the volume of a trade, being high, is an indicator that the trade comes from an institution. Volume is a strong proxy of the type of investor conducting a trade (Lee, 1992; Lee and Radhakrishna, 2000; Kaniel et al., 2008; Miller, 2010 among others). Additionally, trading volume is associated with variables regarding the accounting framework in which firms operate. Atiase and Bamber (1994) show that trading volume is associated to the level of pre disclosure information asymmetry. What is also very interesting, is that volume has a significant relationship with returns, independent from the direction of trading (Brailsford, 1996).
For the purposes of this chapter, the mean volume per trade daily for the market is computed as shown in equation 3.12:

$$VpT_t = \frac{\overline{TVol_t}}{\overline{TTr_t}} \tag{3.12}$$

where $\overline{TVol_t}$ denotes the mean total volume at day t and $\overline{TTr_t}$ the total number of trades. Equation 3.12 describes the mean volume per trade in the market daily. We argue that this measure is a proxy for the composition of the market investor-wise. We will begin our analysis by using the per trade volume as a variable in the CCK method as:

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r^2_{m,t} + \gamma_3 ln(VpT_t) r^2_{m,t} + \epsilon_t \tag{3.13}$$

We use the natural logarithm of volume per trade to avoid scaling problems. Furthermore, the logarithm captures the changes of volume per trade and its effect. [22] As we can see the natural logarithm of volume per trade is negatively correlated to

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0061	0.0001	50.8370	0.0000
$\|r_{m,t}\|$	0.2768	0.0256	10.7890	0.0000
$r^2_{m,t}$	-38.6328	9.2060	-4.197	0.0000
$ln(VpT_t) * r^2_{m,t}$	6.0797	1.4160	4.2920	0.0000

Table 3.11: Herding to the market consensus and the type of investor in the market: Results for equation 3.13

herding. The results indicate that when trading is dominated by larger investors-thus institutions- there is no market wide herding. What is more, the coefficient γ_2 affiliated with the market return is negative indicating that there is market wide herding when accounting for volume per trade. When larger investors hold a larger part of the trades, then there is more variability in the market.
What is also essential, is the relation of micro-level herding and its effect on market wide herding, when we account for investor type overall in the market. The evidence in Table 3.11, regarding both γ_2 and γ_3, indicates that the type of trader is crucial concerning the mechanism which forms market-wide herding. Additionally, herding exists in the micro-level of trading and no herding is found market wide. We believe that the origin of the trader is essential in understanding the mechanism that leads to this result.
We again apply our model, including micro-level measures of herding based both on counts of trades - thus $\overline{H_t}$ and on value- thus $\overline{DR_t}$. We employ the following regressions for each case:

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r^2_{m,t} + \gamma_3 \times 100\% DVol^L_t \overline{H_t} r^2_{m,t} + \gamma_4 \times 100\% DVol^U_t \overline{H_t} r^2_{m,t} + \epsilon_t \tag{3.14}$$

and

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r^2_{m,t} + \gamma_3 \times 100\% DVol^L_t \overline{DR_t} r^2_{m,t} + \gamma_4 \times 100\% DVol^U_t \overline{DR_t} r^2_{m,t} + \epsilon_t \tag{3.15}$$

where $DVol^L_t$ and $DVol^U_t$ are dummy variables that take the value one if at t volume per trade is low and high accordingly- and zero otherwise. To define if volume per trade is low or high we use the distribution of volume per trade. If, for example, at t, VpT_t falls bellow a point of the distribution - x%- then volume per trade is low.

[22] The results are similar in nature if we use the VpT_t variable without the logarithm and are presented in the appendix

To avoid scaling problems, caused by the nature of the variables and their range, we adjust $\overline{H_t}$ and $\overline{DR_t}$ as displayed analytically above. This specification allows as to investigate the effect of micro-level herding when trades are performed mostly by institutional investors in comparison to individual investors. This way we are able to incorporate both the access to information and the sentiment of the two groups in the estimation of aggregate herding in returns.
The results for the 15%, 20% and 50% criterion for the case of $\overline{H_t}$ are presented in Table 3.12. The results, for the same choice of criteria, for $\overline{DR_t}$ are presented in Table 3.13

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0061	0.0001	46.597	0.0000
A	$\|r_{m,t}\|$	0.2624	0.0297	8.8310	0.0000
15%	$r^2_{m,t}$	1.2576	0.8518	1.4760	0.1400
	$DVol^L_t \overline{H_t} r^2_{m,t}$	-2.7282	0.3481	-7.8360	0.0000
	$DVol^U_t \overline{H_t} r^2_{m,t}$	2.2503	0.5544	4.0590	0.0000
Panel	(Intercept)	0.0061	0.0001	49.4420	0.0000
B	$\|r_{m,t}\|$	0.2589	0.0276	9.380	0.0000
20%	$r^2_{m,t}$	0.9669	0.6633	1.4580	0.1450
	$DVol^L_t \overline{H_t} r^2_{m,t}$	-2.7920	0.3656	-7.64	0.0000
	$DVol^U_t \overline{H_t} r^2_{m,t}$	2.5048	0.1544	16.22	0.0000
Panel	(Intercept)	0.0061	0.0001	48.310	0.0000
C	$\|r_{m,t}\|$	0.2665	0.0293	9.0850	0.0000
50%	$r^2_{m,t}$	0.7058	0.6904	1.0220	0.3070
	$DVol^L_t \overline{H_t} r^2_{m,t}$	-3.0003	0.4027	-7.4510	0.0000
	$DVol^U_t \overline{H_t} r^2_{m,t}$	2.2099	0.4481	4.9320	0.0000

Table 3.12: Herding to the market consensus, the effect of micro-level herding and the type of investor. Results for equation3.15 regarding the $\overline{H_t}$ presented in three panels: for the 15% (Panel A), for the 20% (Panel B) and for the 50% (Panel C) criterion

Both Table 3.12 and Table 3.13 tell a similar story. When volume per trade is low, indicating trading by individual investors is strong, micro-level herding results in more herding in returns. On the contrary, when volume per trade is high, and thus institutional investors dominate trading, micro-level herding reduces the non - linearities affiliated with herding. Moreover, in most cases introducing the cross term, renders the market squared return insignificant. The findings indicate that herding formation and the consensus of returns are more related to micro-level herding and volume per trade. The results support the hypothesis that, it is herding by individual investors , which leads to herding to the consensus. Institutional investors seem to consistently take opposite positions either preying on the individual investors or mitigating the effect of herding in trading. These results are also supported by previous empirical evidence about the optimistic sentiment, noise and managers (De Long, 1990, Shleifer, 2003) as well as managers strategically trading to counter sentiment (Liao, 2011). Moreover, retail investors have also been shown to affect mispricing and returns (Kumar and Lee, 2007). Sentiment by retail investors affects market returns and efficiency (Greenwood and Nagel, 2006; Kumar

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0060	0.0001	44.6410	0.0000
A	$\|r_{m,t}\|$	0.270	0.0311	8.6960	0.0000
15%	$r^2_{m,t}$	1.2620	0.8782	1.4370	0.1500
	$DVol^L_t\overline{DR_t}r^2_{m,t}$	-0.2437	0.0424	-5.7450	0.0000
	$DVol^U_t\overline{DR_t}r^2_{m,t}$	0.3322	0.1232	2.6960	0.0070
Panel	(Intercept)	0.0060	0.0001	48.6240	0.0000
B	$\|r_{m,t}\|$	0.2716	0.0276	9.8330	0.0000
20%	$r^2_{m,t}$	0.8068	0.6456	1.250	0.2115
	$DVol^L_t\overline{DR_t}r^2_{m,t}$	-0.2703	0.0421	-6.4270	0.0000
	$DVol^U_t\overline{DR_t}r^2_{m,t}$	0.4017	0.1033	3.8880	0.0001
Panel	(Intercept)	0.0060	0.0001	43.471	0.0000
C	$\|r_{m,t}\|$	0.2897	0.0319	9.0970	0.0000
50%	$r^2_{m,t}$	0.5033	0.6937	0.7260	0.4682
	$DVol^L_t\overline{DR_t}r^2_{m,t}$	-0.3112	0.0511	-6.0890	0.0000
	$DVol^U_t\overline{DR_t}r^2_{m,t}$	0.2977	0.0104	2.8650	0.0042

Table 3.13: Herding to the market consensus, the effect of micro-level herding and the type of investor. Results for equation3.15 regarding the $\overline{DR_t}$ presented in three panels: for the 15% (Panel A), for the 20% (Panel B) and for the 50% (Panel C) criterion

and Lee, 2007), while managers' sentiment does not always lead to contagion and herding (e.g. for mutual funds flows as a measure of sentiment Frazzini and Lamont, 2006). Lastly, our results are in line with evidence supporting that more organised and institutionally dominated markets are characterised by less irrational herding and more informationally driven aggregate behaviour - ie. informational or spurious herding (Holmes et al., 2013; Liao, 2011 among others.).

3.4 Conclusion: Main Findings and Limitations

In this chapter we examine two different empirical concepts of herding, their disagreement and the mechanism that connects them. We approach both micro-level and macro-level herding integrally, as the manifestation of individual herding at an aggregate scale. We suspect that different investor groups, their disagreement in sentiment and different information sets may affect the mechanism of transmission of micro-level herding to the consensus. This essay, deals with certain limitations, as most empirical studies do, that are briefly discussed. We shall though begin by summarising the main findings of this essay and subsequently proceed to the limitations.

3.4.1 Main Empirical Findings

In this essay, we attempt to investigate the connection between the different empirical approaches to herding, in order to examine the mechanism of transmission or contagion of herding from one market level - flows - to another - returns.
By approaching herding by investors, in flows, trading imbalances and globally in re-

turns, we are able to establish a connection between the different empirical methodologies conceptually and empirically. Micro-level herding focusing on trading flows (Lakonishok et al.,1992; Wermers, 1999; Zhou and Lai, 2009) and macro-level herding examined via the dispersion of returns (Chang et al., 2000; Chiang and Zheng, 2010), when examined separately render conflicting results regarding the existence and intensity of herding. Herding in trading imbalances, investigated through a methodology (Chung and Kim, 2017) heavily inspired by commonality (Roll, 1988), is also present in the market. A concentration of trading imbalances around its market mean is present regarding both individual stocks and the entire market aggregately.

Attempting to account for micro-level herding when examining the consensus of returns, we find evidence that herding by institutional and individual investors affects the manifestation of aggregate herding in returns, especially when the value based and extreme cases are considered. Not only that, but the residual trading imbalance - when considering herding in trading imbalances - is also significant, suggesting that trading imbalance herding also affects the consensus of returns.

All the above, lead to confusion as to why micro-level herding is not transmitted market wide. We attempt to incorporate micro-level herding and the type of investor and its size in order to examine the mechanism of transmission of herding from flows to returns. By using the mean volume per trade, the composition of trading in terms of investors is examined. This way, information about the type, size and sophistication of investors trading(e.g. Mynatt and Cready, 1991; Lee, 1992; Bushee, 1998; Kaniel et al., 2008; Miller, 2010) along with certain variables that affect differently the trading choices of different investor groups are explored. For example, the size and type of investors will affect both his access to information, its cost (Atiase and Bamber,1994; Miller, 2010) and the investor's sentiment (Kumar and Lee, 2006; Baker and Wurgler, 2007). Additionally, volume per trade reveals information about the investor sophistication. Institutional ownership in individual stocks is an indication of investor sophistication and is related to a more accurately priced stock (e.g. Bushee, 1998; Bartov, 2003). Given that higher volume per trade implies that a greater part of trading is conducted by institutions, it also implies higher investor sophistication of in the market to n extent.

We discover that, micro-level herding combined with the type of investor are essential variables, in our attempt to decipher the transmission of herding from the micro to the macro level of the market. Micro-level herding, when the presence of retail investors in the market is strong, leads to higher levels of macro-level herding as well. Herding in returns is directly related to the market composition in terms of investors and to microlevel herding. On the contrary, collective behaviour in flows, when trading is dominated by institutional investors, does not result in herding in returns. What is more, extreme levels of micro-level herding in the presence of institutional traders, leads to higher variability in the market.

All in all, the evidence support the notion that individuals herd and managers systematically take the opposite position to either profit or stabilize the market - in the spirit of arbitrage theory. Our results imply that retail investors are affiliated with trading based on sentiment, as some theories about the preferences of individual investors indicate (Barber and Odean, 2008). Also, as argued by existing literature, retail investors affect the returns and the market as a whole (Kumar and Lee, 2006; Barber et al., 2009). Institutional investors seem to herd against retail

investor sentiment (Liao et al., 2011) to mitigate the effect and/or profit from individual investors (Barber et al.,2009). The disagreement in the sentiment, between the different investor groups, may also affect the transmission of herding from flows to the market (as in Hong and Stein (2007)).
This study, due to the nature of the questions posed and the distinct structure of the data employed, encounters certain impediments and limitations . The main findings of this essay need further exploration. These issues are discussed below.

3.4.2 Limitations and Further Research

This study faces significant limitations, both regarding the nature of the data and the concept of herding itself. Firstly, the dataset contains only thirty stocks that are a part of a larger market, namely the U.S. market. Interactions with the rest of the U.S. market might affect our results. Furthermore, stocks constituting the DJIA 30 are large value stocks, industry leaders, that usually pay dividends, are not volatile and render relatively low returns. Being "less" speculative, these stocks may attract more sophisticated investors or investors interested in long-run investing - as pension funds (Baker and Wurgler, 2007). Limits to arbitrage are also low for this type of stocks (Shleifer and Vishny, 1997; D'Avolio, 2002), that implies higher informational efficiency. It would be enlightening for our findings to be tested for a larger market, containing more difficult-to-value stocks.
Additionally, trading is inferred by intraday trading data, leading to possible bias in the estimation of buys and sells - and thus trading imbalances. The original choice of the investor is not observable in our setting. We are unable to identify the trader and its nature. This leads to problems in identification of trades that have been split into multiple orders as well. Additionally, we are not able to distinguish directly the type, size and origin of the investor.
The use of proxy variables, such as the volume per trade, is necessary for the purposes of this essay, but the information, as it is not direct, may contain biases. For example, institutional investors might split their trades to persist in exploiting a superior information set (Glosten and Milgrom, 1985; Kyle, 1985). The size of a certain trade is also an indicator of the information contained in the trade (Kyle, 1985; Easley and O'Hara, 1987). This implies that the information contained in the volume of a trade, concerning the type of investor, might not be completely accurate. Higher volume trades might be a sign of investors holding a superior information set as well. This is a bias to consider when interpreting our results.
Apart from the limitations above, the findings of this essay enrich the existing knowledge, regarding the formation and transmission of herding. Herding exists in the micro-level and transmits in returns, in specific settings, when retail investors dominate the market. additionally, these results provide a partial explanation, as to why macro-level herding is identified in emerging and more noisy markets. These environments, for example, are more attractive for speculative investors and investors of lower sophistication, whose trading transmits collectively to returns and is linked to a stronger consensus. It is implied, by the findings of this essay, that when investors disagree, herding is relatively contained in the micro-level. Agreement in investor sentiment or informational cascades, might thus be the factor that leads herding to be transmitted in returns, even in well-organised and relatively efficient markets. This is an essential concept for economic crashes and financial shocks and enhances

the importance of diversification for investors and of informational efficiency for the markets.

Chapter 4

Herding to the Market Consensus and the Direction of Trading: Directional Trading alongside Sell and Buy Herding for the Consensus of Returns

Abstract

Herding is empirically defined, either as micro-level or macro-level herding. The latter examines herding through the dispersion of returns, while the former revolves around measures of trading and its concentration. Micro-level herding is then often split into two categories, sell and buy herding. In this essay, the importance of the direction of trading and micro-level herding for aggregate investor behaviour and the consensus of returns is examined. The type of investor trading in the market, and the resulting market composition in terms of investors are also accounted for market-wide herding. Evidence, that different types of investors herd in distinct manners and influence the consensus on a different way, is encountered. Our results are in line with institutional investors counter-trading against individual investors, in the spirit of arbitrage. Although trading is composed more of buys, it is sell micro-level herding that has a more intense effect on the consensus of returns. Additionally, high institutional dominance results in buy herding leading to a stronger consensus, while sell herding combined with the strong presence of retail investors also leads to a stronger consensus in returns.

Keywords— Herding, Trading Direction, Sell Herding, Buy Herding, Classes of investors, DJIA 30, Financial Markets

4.1 Introduction

Trading flows and imbalances are an important variable in determining asset prices and market efficiency, in various different settings. For example, pressure induced by trading imbalances could result in mispricing temporarily (Chordia, 2005; Narayan et al., 2015) and is related to market efficiency, stock returns and market liquidity (e.g. Chordia et al., 2002; Chordia and Subrahmanyam, 2004).
Herding is closely related to trading imbalances, as it can be collective behaviour that leads to fluctuations in trading imbalances in the market. Consequently, herding can be intensified by these order imbalances and their persistence (Scharfstein and Stein, 1990), as these imbalances are perceived as information. As documented in the previous chapter, pressures from trading and its concentration are related also to the formation of a consensus in returns. But, are order imbalances and trades all equally made? Does order imbalances and thus micro-level herding affect the consensus in the same way, independently of the direction of the pressure? Is it possible that buys and sells affect the consensus of returns asymmetrically? Is the directional effect, as in the previous essay, related to the type of investor, their sophistication and the information included in their trades?
The importance of systematic buys and sells, for the equity market and its informational efficiency, has been documented in many studies (e.g. Chan and Lakonishok, 1993; Ahn et al., 2005). What is more, sells and buys are affected by different parameters, such as liquidity constraints for buys and short selling restrictions for sells. For instance, short-sales constraints in the equity market, and the informational asymmetries these limitations enhance, influence both stock prices and the expectations and risk preferences of investors. This is extensively documented for the case of investors holding inferior information sets (Miller, 1977; Figlewski and Web, 1993; Ofek and Richardson, 2003; Ahn et al., 2010). Additionally, investors when conducting portfolio choices, buy stocks often driven by information, while sales are not necessarily motivated this way (Chan and Lakonishok, 2003).
Since herding can cause and be intensified by the persistence of trading imbalances, especially when order splitting does not occur (Scharfstein and Stein, 1990), the direction of trading is an essential variable. Moreover, the type of investor- albeit institutional versus retail or domestic versus foreign- influences, not only the formation of trading pressures and imbalances, but their directions and effects as well. For example, trading imbalances are shown to affect returns for all types of investors, but evidence indicate that returns affect mostly the trading decisions of individual investors in the market (e.g. for the Australian market Colwell et al., 2008).
The behavioural and informational parameters that affect investment choices are not the same for all types of investors. Neither are these parameters equal for buys and sells. The decision to buy is different cognitively from the decision to sell, for different investor groups. For instance, individual buys are affected by attention bias and *fancy* stock rumours (Barber and Odean, 2009). This cannot be said for retail sells, as investors can only sell stocks they already possess.
Since micro-level herding is based on imbalances and trading, it is only logical that the distinction between buys and sells will also matter. In the case of herding in flows, we indeed again observe the importance of the distinction between pressures induced by buys versus sells for the market. Wermers (1999) speculates that due to a variety of reasons, from short sale constraints to informational motives and

behavioural factors, buy herding and sell herding differ significantly in terms of motivation and effects. In the setting of buy and sell herding, the two coexist in the market, which is divided into stocks with sell herding and stocks with buy herding. Different from the overall direction of trading, this measure permits both for buy and for sell pressures to coexist at the same time. Their separate and combined effect on the market might reveal the type of herding pressure, that affects both the macro-level of the market and the mechanism of transmission of herding to the consensus.

Indeed, empirically, numerous studies identify different results of sell herding versus buy herding. For example, buy herds are followed by short term positive returns and then by reversals (Dasgupta et al., 2011). Furthermore, stocks persistently bought by institutions underperform stocks persistently sold (Dasgupta et al., 2011b). According to Deng et al. (2018) sell herding is more frequent in smaller capitalisation firms while buy herding in smaller size assets. In the same study, the authors underline that buy herding has a more reliable predictive power of crashes. The responsibility of buy herding for mispricing and the formation of speculative bubbles, compared to sell herding, is not without contradiction. In other studies, buy herding facilitates price discovery while sell herding is speculative and more intense (e.g. Li et al., 2019 for the bond market).

It is possible that short sales constraints, informational trading and investor sentiment affect differently buys and sales, creating different dynamics in different environments between trading flows and the market. This ambiguity is a possible outcome of the difference in market structure and financial products, the determinants of herding or/and even the types and groups of investors, their sophistication and their access to information. For example, block trading, i.e. large volume trades, are shown to affect stock prices and the structure of the market (e.g. Kraus and Stoll, 1972). On the other hand, retail investor sentiment is affected both by buys and sells, but the distinction between the two is important (Lee and Kumar, 2006). The sentiment of different types of investors and their disagreement play an important role for herding, as we documented in the previous chapter. For instance, buy herding may facilitate price discovery, due to its spurious nature - if buy herding is based on fundamental information. This informational asymmetry might be the reason, institutional trading is not often shown to lead to high and abnormal returns (e.g. Franzinni and Lamont, 2006) . Moreover, trading by institutions is not affected by the same sentiment as individual trading (Hong and Stein, 2007). Often managers are sophisticated investors who gain from individual losses, trading against market sentiment (e.g. Barber et al. 2009; Liao et al. 2011; Boyed et al. ,2016). Retail investors and their sentimental trading, based heavily on past returns can affect the market, via noise and informational cascades (e.g. De Long et al., 1990; Barber et al., 2009; Li et al., 2017). It is, thus, possible that buy and sell herding have different results, if we consider the composition of the market in terms of investors. As both buys and sells are distinct decision making processes that differ for different investor groups, both due to cognitive and due to practical issues- for instance liquidity- their effects might also differ. For example, buy herding is more feasible for institutions that hold more capital while sell herding is often driven by liquidity constraints and sentiment for retail investors. We expect these differences to affect the empirical findings of this essay.

In this chapter, we attempt to investigate the importance of the direction of micro-

level herding and trading for aggregate herding. Given that, as explained above, trading and herding pressures and their direction are defined differently, in this essay measures of both are employed. Both the direction of the market in a day and the pressures of sell and buy herding that co-exist, are studied as separate concepts. Several measures concerning the direction- sells and buys, negative and positive imbalances- are calculated and integrated into the CCK methodology. The type of investors trading - institutional and individual - and their role for the importance of the direction of herding on an aggregate level is also examined.
We begin by describing the data used for the empirical estimation of this essay, along with some essential observations coming directly from the data in Section 4.2. In Section 4.3 our empirical findings, along with the respective methodology are presented while Section 4.4 summarises the results and provides a conclusion.

4.2 Data and Descriptive statistics

For the purposes of this paper we employ the same data we used in the previous chapter. A combination of intraday trading data and daily variables - such as prices - for the Down Jones Industrial Average 30, from January 2007 to December 2019, are included. In order to infer trades from intraday data, the tick rule at second level is chosen. All returns were computed logarithmically from closing prices. For all measures of micro-level herding we again use the modification of Zhou and Lai (2009), employing trades instead of traders in the LSV measure and the specification of Wermers (1999) and Lakonishok et al. (1992) for the D-Ratio based on value.
For all series used, we performed an Augmented Dickey Fuller test (Dickey and Fuller,1979) for unit roots, including both a trend and a drift. For all measures of trading pressure based on the number of trades, we were able to reject the null hypothesis of the existence of unit roots only for 5 lags. For separate tests using a trend or a drift stationarity holds for more lags. Regarding measures based on value, we manage to reject non-stationarity for 8 lags. Again, individual tests do not indicate the presence of a trend or a drift. For all other series used, as in the previous chapter, no unit roots were identified. [1]
Below we present some basic descriptive measures in order to properly present our data. Figures 4.1 and 4.2 display the density and time series of the market return - as the unweighted average of the returns of stocks included in the DJIA 30. As we can see the market return fluctuates highly during the 2008 crisis. Even excluding this crisis, there is a circular fluctuation of smaller range. The distribution of the market return is leptokurtic and asymmetrically affected by extreme values, as its measures of centre indicate in Table 4.1.

Regarding trade imbalances, there are three major ways to define trades and respective imbalances: the number/counts, the volume and the value in $ of trades.

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-0.0970	-0.0040	0.0006	0.0001	0.0052	0.1128

Table 4.1: Mean, Median and Quantiles: Market return r_m

[1] Note that some of the graphs and tables shown below were also presented in Chapter 3. Since they are vital to both essays, we chose to include them here for the reader's convenience

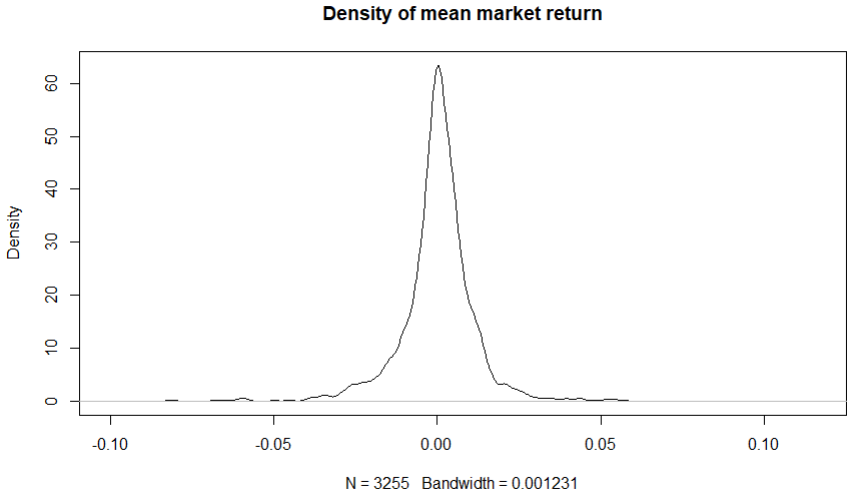


Figure 4.1: Density of the mean market return: All sample

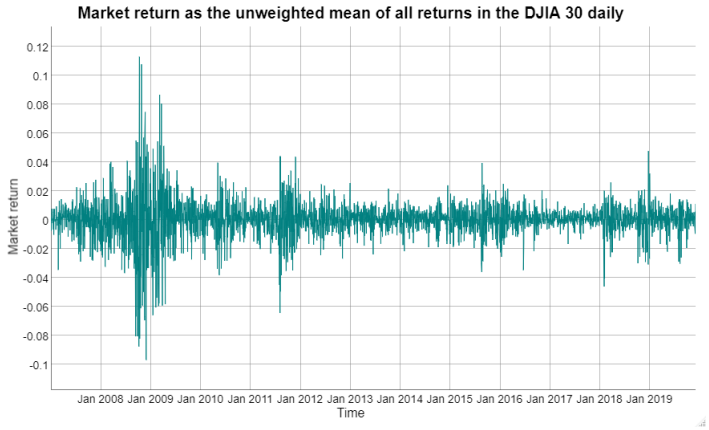


Figure 4.2: The evolution of the market return time series

Here, the respective distributions of these measures and their time series evolution are presented graphically.

The distribution of trading imbalances using trades, volume and value have dis-

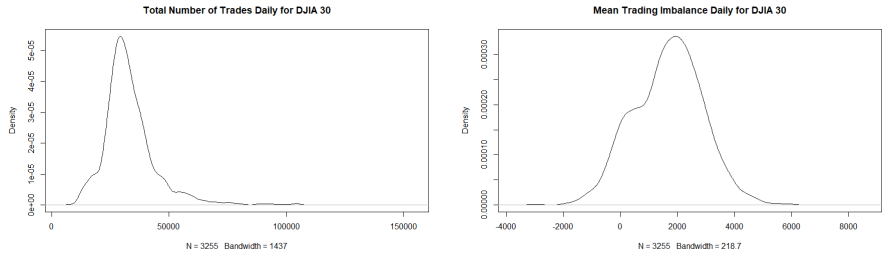


Figure 4.3: Density of the mean of total trades and mean trading imbalance based on counting trades for the DJIA 30

tinct forms, as we can note in Figures 4.3 and 4.4. Trading imbalance computed on counts of trades is described by a distribution skewed to the left. In general, buys represent a higher percentage than sells, with the mean of trading imbalance being

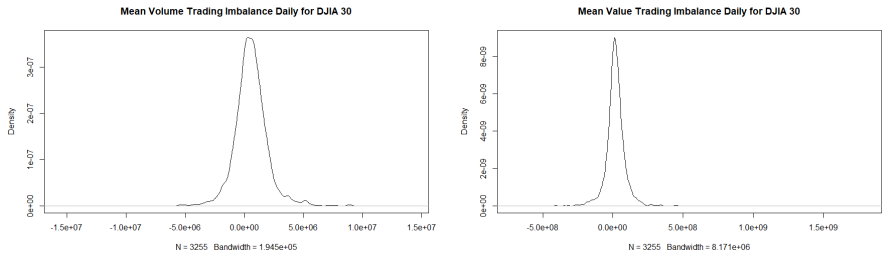


Figure 4.4: Density of the mean volume and mean value trading imbalance for the DJIA 30

	Trade Imbalance	Volume Imbalance	Value Imbalance
Min.	-3121.6000	-15129582.7000	-697718409.200
X1st.Qu.	804.7300	-178930.0000	-12426000.000
Median	1747.2670	525913.1670	16793547.910
Mean.	1672.3490	590758.7080	19352992.012
X3rd.Qu..	2493.3330	1280831.1330	48897675.8590
Max.	8009.0000	13825000.0000	1790900000.0000

Table 4.2: Mean, Median and Quantiles: Mean daily trade imbalance based on the number of trades, volume and value for all stocks in the market.

positive. Volume imbalance is slightly asymmetrical to the right. This indicates that buys are disproportionally large compared to sells. The mean is also positive indicating more buys in volume as well. This can also be observed in Table 4.2, which contains information about the mean and quantiles of the trading imbalances. Value imbalance is more centred and has a leptokurtic form. The different forms of the distribution are partially due to the determinants of the underlying variables. For example, the value imbalance, being computed in dollars, is also affected by the exchange rates, relevant to the dollar, overall monetary policies and the U.S. economy. The volume imbalance is also a sign of the type of investors trading and is directly affected, along with value imbalance, by liquidity. Regarding the number of trades, market structure - and its mechanisms set by the regulator/the stock exchange - will have a more profound influence than, per se liquidity. All the above and more, drive distributional differences between the three types of imbalances. The differences in the trading imbalances' distributions indicate a different level of sensitivity to outliers for the underlying variables. For example, trading imbalances based on volume and value have more leptokurtic distributions. This indicates that the underlying process is affected more by extreme values within the sample. What is more, stronger dynamic dependence is a possible characteristic of the underlying process of trading imbalances based on volume and value. Both by Table 4.2 and from the form of the distributions, we assume that it is important to account for different types of imbalances in our empirical analysis.

Another important factor is the direction of imbalance and its distribution. In Table 4.3 we can see the number of days of positive versus negative trading imbalances using again the three different ways to define them. Given that the identification of an imbalance as negative and positive and the number of days with positive and negative trading imbalance differ from measure to measure, it is logical to believe that they entail different information regarding herding.

Type of Imbalance	#Days Positive Imb	#Days Negative Imb
Number of Trades	2942	313
Volume	2265	990
Value	2128	1127

Table 4.3: Number of days with positive and negative trading imbalances in average in our sample for the whole period.

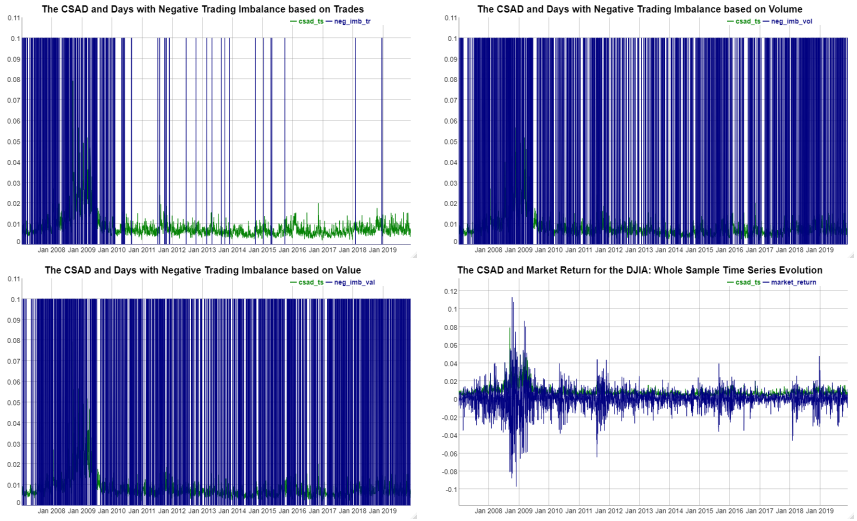


Figure 4.5: Time series evolution for the CSAD, the market return and the days with negative trading imbalance based on based on trades, volume and value, computed using mean values for all stocks in DJIA 30

In Figure 4.5 we demonstrate the evolution of the CSAD and the market return, along side trading imbalances. The three first graphs contain vertical blue lines in days with negative trading imbalances based on trades, volume and value. Clearly, the CSAD is higher during the 2008 financial crisis and all measures of trading imbalance contain negative values before the CSAD reached its peak high value. During *normal* periods, trading imbalances based on the number of trades stay somewhat positive, while the measures based on volume and value take more negative values throughout the whole time range. This is a parameter that we expect to affect the results.

Another important factor is the relative trading imbalance, as it is expressed via the mean trading imbalance based on trades, volume and value to total trades, total volume and total value respectively. This variable adjusts imbalance to the market condition by construction. For example, if trading activity is generally low due to a period of recession or if the total volume is low due to liquidity issues, or if total value is low due to dollar exchange rate fluctuations then the denominator - being total trade - will capture these factors.[2]

From Figures 4.6 and 4.7, we can clearly see that both the distribution and the time series of the relative trading imbalance based on trades is very different than the relative trading imbalance based on volume and value. This might be affiliated

[2] This variable may also include information for informational trading based on the aggregation of informational signals of buys and sells (O'Hara, 1995). This is partially why in the empirical section we use its absolute value.

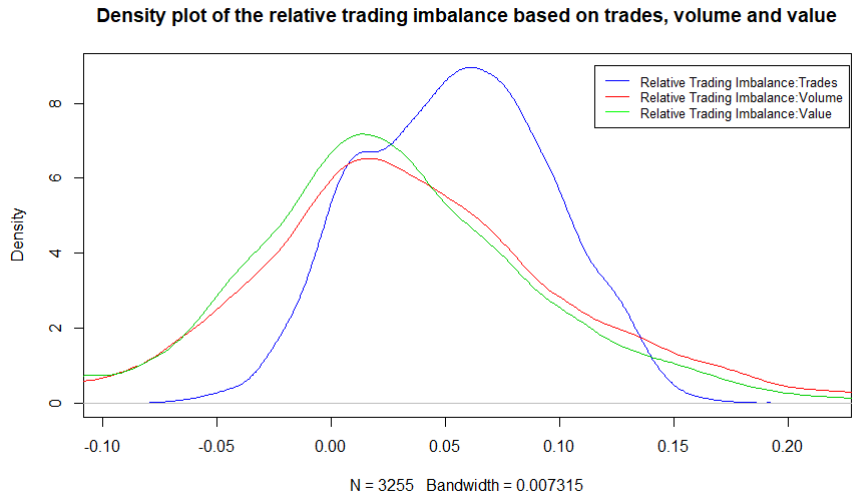


Figure 4.6: Density of the relative mean trading imbalance based on the number of trades, volume and value for the DJIA 30

with the increase of institutional investors during recent years[3], that may affect the volume imbalance and total volume, as trades with a higher volume are considered institutionally originated (Cready and Mynatt, 1991). During the crises, we see that the trading relative imbalance is smaller indicating a form of trading consensus. The graphical representation implies, that the load of trade may affect trading imbalances and that using the relative trading imbalance accounts for trading activity as whole.

We now employ another variable, the mean volume per trade which accounts for the composition of the market in terms of investors. When the volume per trade is high the market is dominated by institutional investors, relative to when volume per trade is low [4]. The series evolution and its distribution are displayed in Figure 4.8.

The distribution of volume per trade is multimodal indicating two points of concentration for the variable. The distribution is clearly asymmetrical to the right. The shape of the distribution shows the concentration of the variable around two peaks and supports the hypothesis of the formation of two groups of investors, possibly with different sentiment, access to information and investment styles. The time series of volume per trade is dominated by two different patterns: one before -roughly- January of 2013 and one after. After January 2013, volume per trade is lower, indicating a swift in the variable possibly related to regulation, changes in the market composition in terms of investors or strategies such as trade splitting. The level of investor sophistication, the use of algorithmic trading and access to information may also play a role on the evolution of volume per trade (e.g. Atiase and Bamber, 1994; Bushee, 1998; Bartov, 2003; Miller, 2010).

Equally important to the trading imbalance are buys and sells and their respective

[3] Holdings of equity of mutual funds increased form 2,84 % to 26,61 % in 2009 (US. Bureau Census)

[4] Trades of a high volume are institutionally derived according to literature (Cready and Mynatt, 1991). Small individual investors trade from 0- 200 shares, large individual investors up to 900, while above to 2000 trades are thought to be institutionally originated.

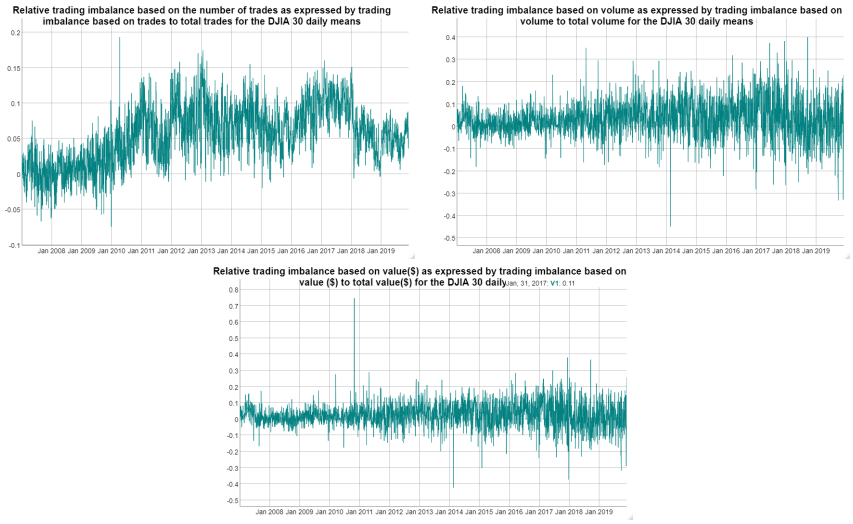


Figure 4.7: Time series evolution for relative trading imbalances based on trades, volume and value, computed using mean values for all stocks in DJIA 30

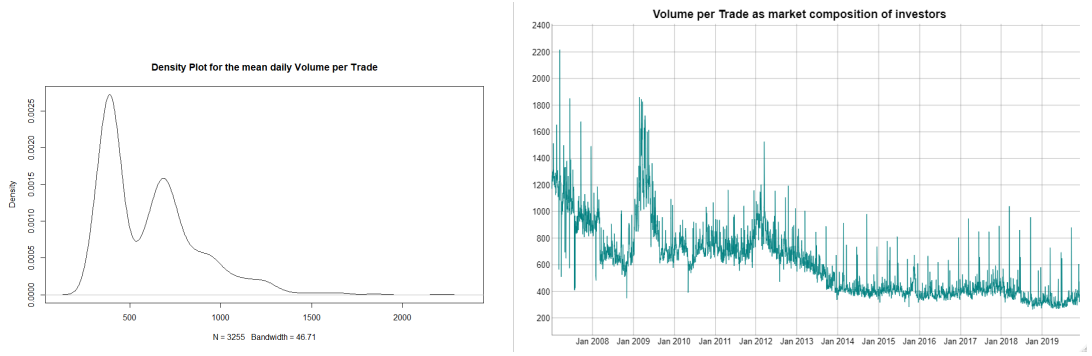


Figure 4.8: Volume per Trade ($\frac{\overline{TVol_t}}{\overline{TTr_t}}$): The density plot and time series evolution of mean daily volume per trade.

differences, as they do not affect prices and returns, as well as market risk, in an equal manner. Buys and sells are, by definition, related to trade imbalances and to market sentiment (e.g. Lee and Kumar, 2006). They are also the variables we use to compute buy and sell herding on the micro-level. Below we also present the distribution of absolute mean buys and sells for the DJIA 30 in Figure 4.9.

In Figure 4.9 it is clearly shown that mean buys exceed mean sells. In Figure 4.10 the evolution of the ratio of mean daily buys to mean daily sells is presented. Buys exceed sells for the majority of the days in the sample, as the ratio stays above one for the majority of the period reviewed here. Sells exceed buys clearly during the financial crises of 2008. This ratio is computed using the number of trades.

As noted above, there is a connection between trades and returns. Returns are based in prices and prices are - at least to an extent - based on demand and supply mechanisms [5] that are dominated by trading. For example during the crisis period or in emerging markets, mean sells exceed mean buys, due to panic and an urge of investors to get rid of dangerous assets or due to informational asymmetries (Kaminsky et al., 2004, Chiu et al., 2018). The type of investor and its access to in-

[5] Clearly the institutional and organisational framework, such as policies in the stock exchange, are also important factors.

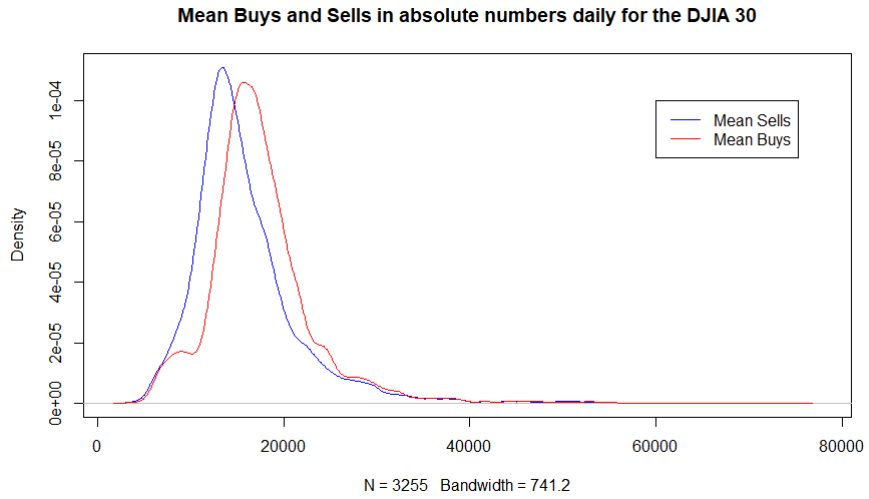


Figure 4.9: Density of the mean buys and sells in absolute numbers for the DJIA 30

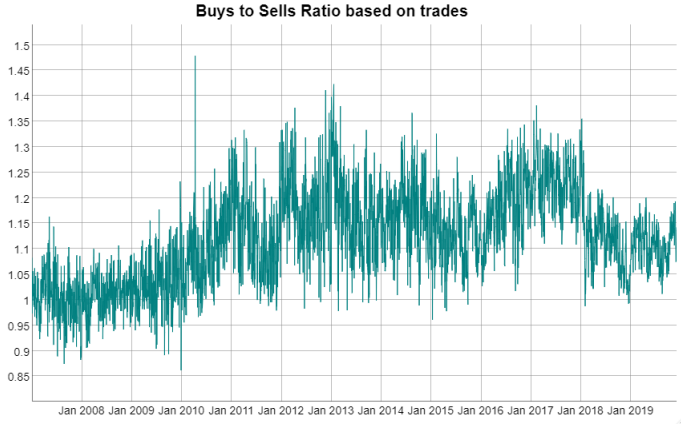


Figure 4.10: Mean buys to mean sells ratio for the DJIA 30 daily.

formation will inevitably affect his trading choices (Kim and Wei, 2002; Hoffman et al., 2013). These asymmetrical preferences of investors both affect and are affected by important market characteristics such as liquidity (Chiu et al., 2018; Galariotis et al., 2016).

Given that measures of herding in the microlevel will also be employed, we briefly present here the time series evolution, as presented in the previous chapter.

Both measures, indicate that herding exists in the market, with the value based measure showing a structural break around January 2017. If we decompose the measures, according to previous empirical methodologies, into buy herding and sell herding [6] then we get one measure of sell herding and one for buy herding per measurement choice and day.

As we can see in Figure 4.12, the trade based measures follow a more cyclical pattern, probably due to the subtraction of the market's proportion of buys. During the crisis, we observe very low buy herding probably, as speculated above, due to market sentiment, panic and informational asymmetries. Sell herding is significantly higher than buy herding throughout the sample, indicating that sell pressures may

[6] Details on the decomposition can be found in the next section.

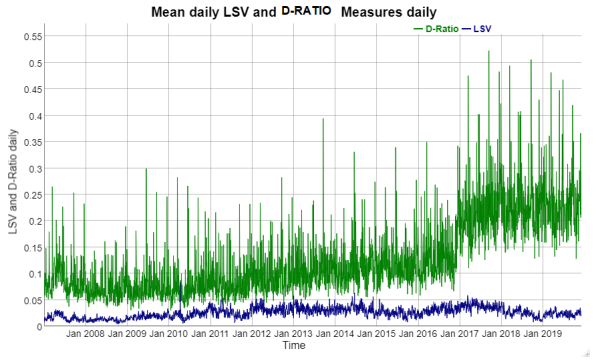


Figure 4.11: Mean LSV and D-ratio for the market portfolio daily

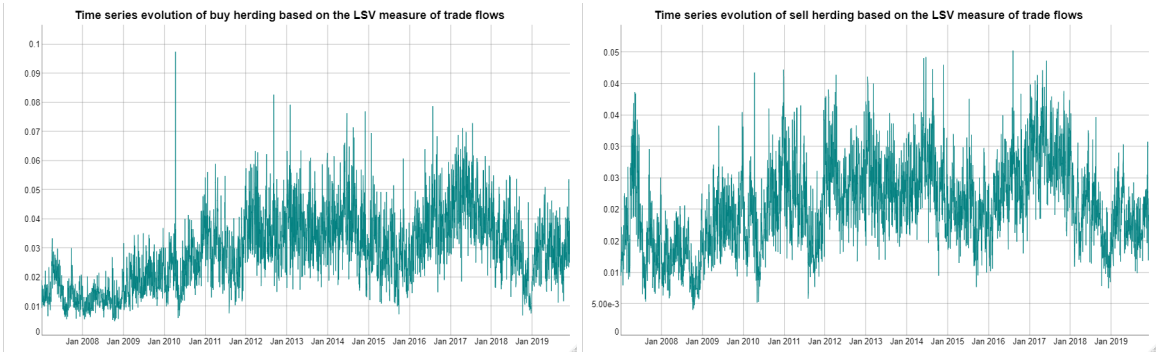


Figure 4.12: Time series evolution of Sell and Buy herding using the LSV measure based on trades for the DJIA 30 daily.

lead to more contagion and herding.
Using the measure based on value in Figure 4.13, we observe a different picture. Sell herding and buy herding using the D-Ratio are very similar, while buy herding is higher overall. What is more, buy herding seems to be more volatile, with more extreme values. Given that the D-ratio is affected by the value of the dollar and the market liquidity, this image might also include both information about market liquidity fluctuations and macroeconomic conditions. Additionally, the dollar-based microlevel herding measure accounts, by construction, for the magnitude of trades, while the trade-based measure attributes equal weights to all trades, independently of their size. These preliminary results, thus, imply that herding in trades and value is affected by the differences in the volume between trades. We expect this asymmetry, to reflect the dynamics between different investor groups, that face different informational, emotional and liquidity constraints.
Given all the above the correlation between different variables may also assist us, in identifying relations between our different variables and thus concepts.

In Table 4.4 a correlation matrix of the market return, the squared market return, the cross sectional standard deviation of returns (CSSD), the cross sectional absolute deviation (CSAD), the number of sells, the number of buys, the proportion of stocks with positive trading imbalance based on the number of trades, the proportion of stocks with positive trading imbalance based on value and the market stress dummy variables from Christie and Huang (1995) are displayed. The two measures that capture the dispersion of returns, CSSD and CSAD, are computed as

	$r_{m,t}$	$r^2_{m,t}$	$CSSD_t$	$CSAD_t$	Sells	Buys	PR^{tr}	$PR^{\$}$	D^L_t	D^U_t
$r_{m,t}$	1.0000	-0.0695	-0.0773	-0.0581	-0.1685	-0.0957	0.3639	0.5016	-0.5900	0.5153
$r^2_{m,t}$	-0.0695	1.0000	0.5680	0.6179	0.4714	0.4522	-0.0575	-0.1856	0.4268	0.3412
$CSSD_t$	-0.0773	0.5680	1.0000	0.9662	0.5967	0.5658	-0.0389	-0.2647	0.3229	0.2664
$CSAD_t$	-0.0581	0.6179	0.9662	1.0000	0.6491	0.6130	-0.0346	-0.2876	0.3596	0.3216
Sells	-0.1685	0.4714	0.5967	0.6491	1.0000	0.9790	-0.1237	-0.3018	0.3845	0.2376
Buys	-0.0957	0.4522	0.5658	0.6130	0.9790	1.0000	-0.0658	-0.1439	0.3267	0.2584
PR^{tr}	0.3639	-0.0575	-0.0389	-0.0346	-0.1237	-0.0658	1.0000	0.3189	-0.1764	0.1650
$PR^{\$}$	0.5016	-0.1856	-0.2647	-0.2876	-0.3018	-0.1439	0.3189	1.0000	-0.4320	0.1166
D^L_t	-0.5900	0.4268	0.3229	0.3596	0.3845	0.3267	-0.1764	-0.4320	1.0000	-0.0527
D^U_t	0.5153	0.3412	0.2664	0.3216	0.2376	0.2584	0.1650	0.1166	-0.0527	1.0000

Table 4.4: Correlation matrix of market return, squared market return, CSSD, CSAD, number of sells, number of buys, proportion of stocks with positive trading imbalance based on the number of trades,, proportion of stocks with positive trading imbalance based on value and the market stress dummy variables from Christie and Huang for the 5% criterion (1995)

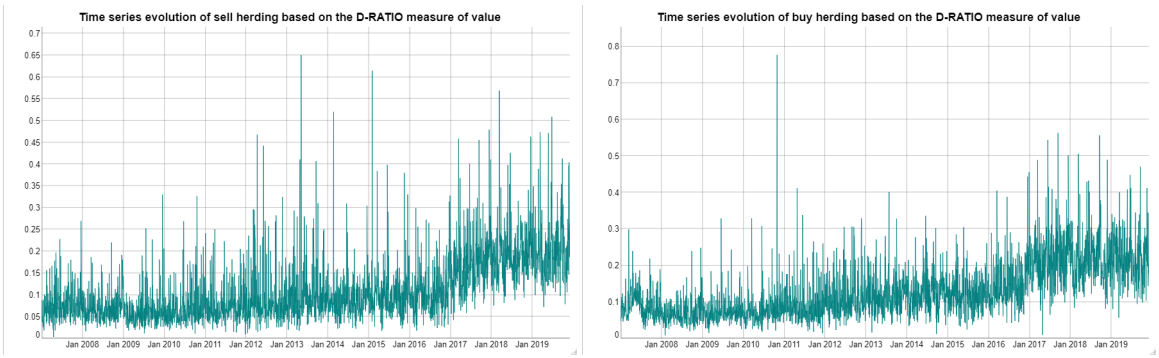


Figure 4.13: Time series evolution of Sell and Buy herding using the D-RATIO measure based on value ($) for the DJIA 30 daily

in the CH and CCK methodologies accordingly. The dummy variables, D_t^L and D_t^U represent market stress, as extreme price movements in the market. If the market return - the unweighted average of all stocks returns in the market portfolio - falls below - for D_t^L - or above - for D_t^U - a certain point of its distribution at t then the variables take the value one. The criterion used for Table 4.4 is that of 5% below or above. We notice that the number of sells and buys is positively correlated to the squared market return, the measures of dispersion of returns -$CSSD_t$ and $CSAD_t$- and extreme price movements. This indicates that there is a connection between sells and buys and all variables in the models of aggregate herding. What is more, the proportion of stocks with positive trading imbalance in the market, especially in the case of value, are negatively correlated to the measures of dispersion and the dummy variables for extreme negative price movements.
We now proceed to the empirical part of this essay. We concentrate on direction both in herding and in trading and its effect on market wide herding.

4.3 Methodology and Empirical Results

This section is divided into three subsections. The first subsection revolves around measures of direction directly extracted from the data, such as the relative trading imbalance, while subsection 4.3.2 investigates the direction of total micro-level herding in the market and the role of the type of investor to that effect. In subsection 4.3.3 micro-level herding is divided into sell herding and buy herding and their impact on the consensus of returns is explored. Lastly, subsection 4.3.4 explores the role of the type of investor, in relation to sell and buy herding, for the consensus of returns.

4.3.1 The Direction of Trading and its Effect on Aggregate Herding

Through this section we employ and modify the method proposed by Chang et al. (2000), the CCK. This method was also the primary focus of the previous chapter, as it accounts for non-linear structures between the market return and the cross-sectional absolute deviation of returns. The CCK method uses the following

regression :

$$CSAD_t = \alpha + \gamma_1 |r_{m,t}| + \gamma_2 r_{m,t}^2 + \epsilon_t \tag{4.1}$$

where $CSAD_t = \frac{1}{N}\sum_1^N |r_{i,t} - r_{m,t}|$ and $r_{m,t}$ is the market return, computed as the unweighted average of all stock returns in DJIA 30. Herding is implied when the coefficient γ_2 is negative and significant. When we apply this method to our data, no herding is found [7].

We now incorporate to this model measures that account for trading pressures and their directions. This process shall begin by incorporating the relative trading imbalance as a measure of trading pressure. Given that all variables in the CCK model are positive, we include the absolute value of the trading imbalance and we use a dummy variable for its direction as described in the equations below.

$$RTI_t^T = \frac{\overline{TI}_t^G}{\overline{TT}_t^G} \qquad G = Tr, Vol, \$ \tag{4.2}$$

where RTI_t^T is the relative trading imbalance when $\overline{TI}_t^G$ is the mean trading imbalance in day t and $\overline{TT}_t^G$ is the mean trading activity for all stocks based on trades, volume or value. Then we specify:

$$CSAD_t = \alpha + \gamma_1 |r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 \times 100\% D_{B,t}^G |RTI_t^G| r_{m,t}^2 + \gamma_4 \times 100\% D_{S,t}^G |RTI_t^G| r_{m,t}^2 + \epsilon_t \tag{4.3}$$

where $G = \{tr, \quad vol, \quad \$\}$, $D_{B,t}^G$ is a variable that takes the value one if the relative trading imbalance is positive or zero otherwise and $D_{S,t}^G$ takes the value one if the relative trading imbalance is negative or zero otherwise. The absolute relative trading imbalance is then modified $\times 100\%$ to avoid scaling issues.[8] The results are presented in three separate panels for imbalances counted on trades, volume and value in Table 4.5.

The results for equation 4.3 are mixed. For the relative trading imbalance counted by number of trades and both during negative and positive imbalances , the magnitude of the imbalance is positively related to aggregate herding. High relative imbalance measured on trades, either negative or positive, leads to higher consensus in returns. More so, for the case of negative imbalances. The difference between the two directions is significant.[9] When the relative trading imbalance is negative and high, the consensus is higher. The results insinuate that aggregate level herding is affected from excessive number of sells asymmetrically. On the other hand, there is no significance of volume based trading imbalance. Volume imbalances do not affect market wide herding neither in direction nor in magnitude. The same applies to value based imbalances. Trade counts-based imbalance seems to be the only variable for which the direction is significant, as negative imbalances have a stronger effect. The results indicate that the number of trades and their imbalance is a stronger signal for aggregate herding. Pressures from orders of small and large size trades have an impact on the relationship between the squared market return and the dispersion of assets. These trades are perceived as signals of information, and this relative trading imbalance might affect returns and the market via its informational

[7] As shown in Chapter 3

[8] The product of the relative trading imbalance and the squared market return is very small.

[9] Performing a Wald test, the F-statistic indicates that there is a significant difference between the two coefficients γ_3 and γ_4

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0061	0.0001	39.4360	0.0000
A	$\|r_{m,t}\|$	0.2832	0.0352	8.0380	0.0000
$G = tr$	$r^2_{m,t}$	3.5016	1.1880	2.9480	0.0032
	$\|RTI^{tr}_t\| * D^{tr}_{B,t} r^2_{m,t}$	-0.7417	0.1870	-3.9660	0.0000
	$\|RTI^{tr}_t\| * D^{tr}_{S,t} r^2_{m,t}$	-1.5169	0.4557	-3.3290	0.0008
Panel	(Intercept)	0.0061	0.0001	33.3160	0.0000
B	$\|r_{m,t}\|$	0.2593	0.0435	5.9660	0.0000
$G = vol$	$r^2_{m,t}$	2.6038	1.4910	1.7470	0.0080
	$\|RTI^{vol}_t\| * D^{vol}_{B,t} r^2_{m,t}$	-0.0689	0.1062	-0.5930	0.5535
	$\|RTI^{vol}_t\| * D^{vol}_{S,t} r^2_{m,t}$	-0.1837	0.1185	-1.5500	0.1211
Panel	(Intercept)	0.0061	0.0001	31.972	0.0000
C	$\|r_{m,t}\|$	0.2557	0.0454	17.77	0.0000
$G = \$$	$r^2_{m,t}$	2.6623	1.7360	1.5330	0.1250
	$\|RTI^{val}_t\| * D^{val}_{B,t} r^2_{m,t}$	-0.0794	0.1349	-0.5880	0.5560
	$\|RTI^{val}_t\| * D^{val}_{S,t} r^2_{m,t}$	-0.1660	0.1698	-0.9780	0.3280

Table 4.5: Herding to the market consensus and the direction of relative trading imbalance: Results for equation 4.3 presented in three Panels: Panel A($G = tr$), Panel B ($G = vol$) and Panel C($G = \$$)

effect (Easly et al., 2002). The findings thus imply that, in the case of the DJIA 30, the trade itself has a stronger effect on the formation of collective behaviour than the trade's size or value. Another variable that may lead to the results observed in Table 4.5 is the relationship between both volume and value to investor and market liquidity. The DJIA 30 is a liquid market, with enough trading per day for returns not to stagnate. Investors may adjust their behaviour to this fact. Furthermore, investors based on these market characteristics form expectations about the choices of their peers that might lead them to assign different importance to information coming from the number of trades. All the above, partially explain the ambiguous results we observe in Table 4.5.

All in all, trading direction does not have a strong effect on herding when raw trading and directional measures are investigated. The case of measures counted on trades is the only significant measure, indicating that it is direct trading decisions - regarding the number of shares- taken by investors that affect herding. Similar results we obtain when we employ other measures of trading pressure, as the proportion of stocks with a positive trading imbalance in a day. These results can be found in the Appendix of this chapter.

We shall now examine institutional and individual herding and its separation into sell and buy herding. We investigate both the impact of micro-level herding direction's and the impact of sell herding and buy herding jointly on the consensus of returns.

4.3.2 The Aggregate Directional Effect of Micro-level Herding and the Role of Investor in the Market for the Daily Consensus of Returns

We firstly consider the direction of micro-level herding without splitting it in two categories in a day. We define two measures of microlevel herding, based on counts of trades and value. We follow the methodology of the previous chapter as follows:

$$CSAD_t = \alpha + \gamma_1 |r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 \times 100\% D_{B,t}^{tr} \overline{H_t} r_{m,t}^2 + \gamma_4 \times 100\% D_{S,t}^{tr} \overline{H_t} r_{m,t}^2 \epsilon_t \quad (4.4)$$

$$CSAD_t = \alpha + \gamma_1 |r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 \times 100\% D_{B,t}^{val} \overline{DR_t} r_{m,t}^2 + \gamma_4 \times 100\% D_{S,t}^{val} \overline{DR_t} r_{m,t}^2 \epsilon_t \quad (4.5)$$

where $\overline{H_t}$ is the mean excess proportion of buys in a day and $\overline{DR_t}$ is the mean D-Ratio, as computed in the previous Chapter. The dummy variables $D_{B,t}^{tr}$ ($D_{S,t}^{tr}$) takes the value one if at day t the trading imbalance based on counts of trades in the market is positive (negative) or zero otherwise, as in the previous subsection. For equation 4.5 the dummy variables are defined similarly, considering the value-based trading imbalance.
The results for both equations are presented in Table 4.6. The results contradict

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0060	0.0001	40.56	0.0000
A	$\|r_{m,t}\|$	0.2679	0.0349	7.6800	0.0000
Eq.	$r_{m,t}^2$	2.2147	1.5152	1.4600	0.1439
4.4	$D_{B,t}^{tr}\overline{H_t}r_{m,t}^2$	-0.2496	0.8003	-0.3100	0.7552
	$D_{S,t}^{tr}\overline{H_t}r_{m,t}^2$	-0.4194	1;1871	-0.3500	0.7239
Panel	(Intercept)	0.0061	0.0002	35.9000	0.0000
B	$\|r_{m,t}\|$	0.2680	0.0400	6.7000	0.0000
Eq.	$r_{m,t}^2$	4.9443	1.5133	3.2700	0.0011
4.5	$D_{B,t}^{val}\overline{DR_t}r_{m,t}^2$	-0.3508	0.1059	-3.31	0.0009
	$D_{S,t}^{val}\overline{DR_t}r_{m,t}^2$	-0.3476	0.1378	-2.5200	0.0117

Table 4.6: The Direction of Micro-level Herding for the Daily Consensus of Returns. Results are presented in Panels for equation 4.4 (Panel A) using $\overline{H_t}$ and equation 4.5 (Panel B) using $\overline{DR_t}$ as micro-level herding herding.

the indications we had from the previous subsection. The micro-level measure of herding based on counts of trades does not affect the consensus neither on days with buying, nor in days with selling pressures. In the previous part, we observed that relative trading imbalances based on trades had a directional effect on the consensus of returns. The measure used here subtracts the expected proportion of buys - via the market average - to measure herding for each stock. Similar results were also observed, without accounting for the direction in the previous Chapter. Measures of microlevel herding include herding for each stock, while relative imbalances represent the mean market pressure. For example, the relative trading imbalance on value can be small, even if the relative imbalances for each stock are high. Micro-level herding though, will be high when individual imbalances are high, even if their direction is opposite. The results insinuate the significance of herding in each stock for the consensus of returns. What is more, our findings for the case of herding measured in

value, are in line with our observations in the previous Chapter. Herding pressure in value affects the market consensus. Regardless of the direction of the pressure, both in days when buys exceed sells and during higher selling pressures, micro-level herding is related to herding to the consensus. The effect of micro-level herding during buying days is higher but the difference is not significant. [10].
As already mentioned the type of investor is vital for market efficiency, and thus the formation of consensus. In this chapter, we will also employ the mean volume per trade daily to proxy the composition of the market in terms of investors (e.g. Cready and Mynatt, 1991; Kaniel et al., 2008) computed as follows:

$$VpT_t = \frac{\overline{TVol_t}}{\overline{TTr_t}} \tag{4.6}$$

We distinguish between two different scenarios regarding the market composition concerning the investors:

- Volume per trade is on a relative high - thus $DVol_t^U = 1$ - and trading is dominated by institutional investors or
- Volume per trade is on a relative low - thus $DVol_t^L = 1$ - and trading is dominated by individual investors.

We split the sample in two subsamples using the median of the mean volume per trade. For these two categories, we apply the regressions described by equations 4.4 and 4.5 for both types of micro-level herding. The results are reported in four panels in Table 4.7.

The findings indicate that there exists a significant difference between days with high buy pressures versus days with high sell pressures only when the market is composed by retail, less sophisticated investors. When the VpT_t is below the median, both $\overline{H_t}$ and $\overline{DR_t}$ seem to affect herding. Days with sell pressures have a significantly higher effect[11] than days in buys, only in the case of $\overline{H_t}$. In the case of high VpT_t, when a substantial part of trading activity originates from institutional investors, neither sell nor buy originated pressures influence asymmetrically the relation between micro-level herding and the consensus of returns. Overall, micro-level herding has an effect only when the investor in the market is small and less sophisticated, but the direction of micro-level herding pressure does not seem to play a significant role. We now proceed to examine, buy herding and sell herding, as identified in the relevant herding literature, its effect for the consensus of returns, as well as the role of investor type to that effect.

4.3.3 Sell Herding and Buy Herding in the DJIA 30

We define micro-level herding via both the LSV measure and the D-ratio, as in the previous chapter. We distinguish between buy herding and sell herding as in Wermers (1999). Whenever the proportion of buys for stock i is smaller than the market proportion of buys - at each t - then this stock demonstrates sell herding at

[10] Performing a Wald test comparison, using the finite sample F statistic for inference, we do not manage to reject the null hypothesis of $\gamma_3 = \gamma_4$.

[11] We perform a Chow Test (Chow, 1960) to test for differences in coefficients in two regressions. The F-statistic indicates significant differences for both measures used.

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0059	0.0001	60.6577	0.0000
A.1	$\|r_{m,t}\|$	0.1605	0.0303	5.3012	0.0000
Eq.	$r^2_{m,t}$	3.5292	0.3691	9.5613	0.0000
4.4	$D^{tr}_{B,t}\overline{H_t}r^2_{m,t}$	-1.8200	0.6304	-2.8868	0.0039
$VpT \leq median$	$D^{tr}_{S,t}\overline{H_t}r^2_{m,t}$	-2.7405	0.5613	-4.8825	0.0000
Panel	(Intercept)	0.0065	0.0002	28.1929	0.0000
A.2	$\|r_{m,t}\|$	0.3256	0.0426	7.6463	0.0000
Eq.	$r^2_{m,t}$	1.0663	1.7634	0.6047	0.5455
4.4	$D^{tr}_{B,t}\overline{H_t}r^2_{m,t}$	0.2350	0.9463	0.2483	0.8040
$VpT > median$	$D^{tr}_{S,t}\overline{H_t}r^2_{m,t}$	-0.2000	0.1361	-0.1469	0.8833
Panel	(Intercept)	0.0060	0.0001	61.6762	0.0000
B.1	$\|r_{m,t}\|$	0.1224	0.0247	4.9491	0.0000
Eq.	$r^2_{m,t}$	3.5314	0.8060	4.3816	0.0000
4.5	$D^{val}_{B,t}\overline{DR_t}r^2_{m,t}$	-0.1170	0.4932	-2.3718	0.0178
$VpT \leq median$	$D^{val}_{S,t}\overline{DR_t}r^2_{m,t}$	-0.1553	0.0701	-2.2153	0.0269
Panel	(Intercept)	0.0065	0.0003	24.3911	0.0000
B.2	$\|r_{m,t}\|$	0.3193	0.0532	6.0042	0.0000
Eq.	$r^2_{m,t}$	2.6769	2.2891	1.1694	0.2424
4.5	$D^{val}_{B,t}\overline{DR_t}r^2_{m,t}$	-0.1889	0.1727	-1.0932	0.2745
$VpT > median$	$D^{val}_{S,t}\overline{DR_t}r^2_{m,t}$	-0.1400	0.2187	-0.6403	0.5221

Table 4.7: The direction of micro-level herding and the role of investor for the daily consensus of returns. Results are presented in Panels: for equation 4.4 and low Volume per Trade (Panel A.1) and high Volume per Trade (Panel A.2) using $\overline{H_t}$ and for equation 4.5 and low Volume per Trade (Panel B.1) and high Volume per Trade (Panel B.2) using $\overline{DR_t}$ as micro-level herding herding.

t. When the proportion of buys for a stock i is bigger than the market equivalent, then stock i demonstrates buy herding at t. Analytically we define:

$$BH_{i,t} = H_{i,t}|p_t < \frac{B_{i,t}}{B_{i,t}+S_{i,t}} \qquad \text{and} \qquad SH_{i,t} = H_{i,t}|p_t > \frac{B_{i,t}}{B_{i,t}+S_{i,t}} \tag{4.7}$$

denoting $BH_{i,t}$ as buy herding and $SH_{i,t}$ as sell herding. This measure does not account for directional trading, but distinguishes between sell and buy herding stocks in a certain market. By construction, for each day, buy and sell herding co-exist and impose separate pressure on the market. For the purposes of this paper we also employ this distinction among others.
Additionally, we define the dollar-based measure of herding in the spirit of Lakonishok et al. (1992), as in the previous chapter. We also differentiate this measure to account for sell and buy herding:

$$BDR_{i,t} = DR_{i,t}|\$B_{i,t} > \$S_{i,t} \qquad \text{and} \qquad SDR_{i,t} = DR_{i,t}|\$B_{i,t} < \$S_{i,t} \tag{4.8}$$

where $DR_{i,t}$ is the D-ratio measured in dollar value as in Equation 3.2 and $BDR_{i,t}$ and $SDR_{i,t}$ are the mean daily D-ratios for stocks with positive and negative value imbalance respectfully.
The results regarding total, buy and sell herding, performed by institutions and individuals, along with their t-statistic are presented in Table 4.8. For one observation

in our data, on 10/03/2009, all stocks in the market had a positive value imbalance and thus in the computation of the mean SDR we will exclude this date.

Buy and sell herding co-exist and are significantly different from zero. What is

	Total Market	t value	Sell	t value	Buy	t value
LSV	0.0255	147.7300	0.0207	171.0700	0.0290	128.2300
D-Ratio	0.1249	102.2600	0.1085	87.3670	0.1287	96.6830

Table 4.8: Microlevel herding: Mean LSV and D-Ration for the total sample, mean sell herding and mean buy herding

more, buy herding is significantly higher than sell herding, for both measures chosen. Now, we try to account for the direction of micro-level herding in the CCK to investigate its effect and then examine the importance of the type of investors as well.

4.3.4 The Effect of Buy Herding and Sell Herding and the Role of Investors in the Market on the Consensus of Returns

As already mentioned above, the effects of micro-level herding may vary depending on the sources and the motives behind it. These motives are related to the variables that affect the choice of investors and the information set the investor faces. Moreover, there are various existing empirical results in the literature, that also underline the importance of the distinction of different investor groups for the formation of collective behaviour (e.g.Choe et al., 1999; Kim and Wei ,2002).

We begin by focusing only in the direction of herding pressures and their effect. We use the categories of sell herding and buy herding as defined above. As mean buy herding we refer to the unweighted mean of herding for all buy herding stocks in the market at t. The same logic is applied to sell herding. This allows as to include both sell herding and buy herding pressures for the same day in our analysis. The dynamics between these two measures are essential simultaneously and individually. We will approach the issue from both perspectives.

For the case of herding measured as the proportion of buys, we define the following equations to identify separately the effect of buy herding and sell herding:

$$CSAD_t == \alpha + \gamma_1|r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 * 100\%\overline{BH_t} * r_{m,t}^2 + \epsilon_t \tag{4.9}$$

$$CSAD_t == \alpha + \gamma_1|r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 * 100\%\overline{SH_t} * r_{m,t}^2 + \epsilon_t \tag{4.10}$$

Equation 4.9 modifies the CCK measure to account for buy herding while equation 4.10 incorporates sell herding into aggregate herding.

The mean volume per trade is again utilised to approximate the effect of the composition of the market in terms of investors, as computed in equation 4.6. When this measure is low, more individual investors are present in the market, while when this measure is high, there is a higher concentration of institutions in trading. Investor sophistication (e.g. Bushee, 1998; Bartov, 2003), their access to information (Kyle, 1985; Easley and O'Hara, 1987) and their sentiment (Kumar and Lee, 2006; Barber et al., 2009) are also accounted for via the this variable. All these notions are related

to the investor group itself as well, as the group forms the sentiment and individual's decision making processes and information set form the group.
We partition the market for buy herding and sell herding as follows:

$$CSAD_t == \alpha + \gamma_1|r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 \times 100\%\overline{BH_t}DVol_t^L r_{m,t}^2 + \gamma_4 \times 100\%\overline{BH_t}DVol_t^U r_{m,t}^2 + \epsilon_t \quad (4.11)$$

$$CSAD_t == \alpha + \gamma_1|r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 \times 100\%\overline{SH_t}DVol_t^L r_{m,t}^2 + \gamma_4 \times 100\%\overline{SH_t}DVol_t^U r_{m,t}^2 + \epsilon_t \quad (4.12)$$

where $DVol_t^L$ takes the value one at t, if volume per trade falls below a percentage of its distribution and zero otherwise and $DVol_t^U$ takes the value one if at t volume per trade falls above a point of its distribution or zero otherwise. $\overline{BH_t}$ and $\overline{SH_t}$ denote mean buy herding and sell herding at t. The results for buy herding for equations 4.9 and equation 4.11 for the 15%, 20% and 50% criterion are presented in four distinct panels in Table 4.9.

In the first panel of Table 4.9, we observe that the effect of buy herding in the

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel A	(Intercept)	0.0060	0.0002	39.1113	0.0000
All	$r_{m,t}$	0.2694	0.0349	7.7275	0.0000
Sample	$r_{m,t}^2$	2.2761	1.3742	1.6563	0.0978
	$\overline{BH_t}r_{m,t}^2$	-0.3336	0.6602	-0.5054	0.6133
Panel B	(Intercept)	0.0061	0.0001	48.6600	0.0000
15%	$\|r_{m,t}\|$	0.2611	0.0279	9.37	0.0000
Criterion	$r_{m,t}^2$	1.0438	0.7041	1.4824	0.1383
	$\overline{BH_t}DVol_t^L * r_{m,t}^2$	-2.3465	0.3168	-7.4000	0.0000
	$\overline{BH_t}DVol_t^U * r_{m,t}^2$	2.2920	0.4562	5.0245	0.0000
Panel C	(Intercept)	0.0061	0.0001	49.2100	0.0000
20%	$\|r_{m,t}\|$	0.2591	0.0279	9.3000	0.0000
Criterion	$r_{m,t}^2$	1.0238	0.6890	1.4900	0.1374
	$\overline{BH_t}DVol_t^L r_{m,t}^2$	-2.4789	0.3014	-8.2200	0.0000
	$\overline{BH_t}DVol_t^U r_{m,t}^2$	2.2430	0.4214	5.3200	0.0000
Panel D	(Intercept)	0.0060	0.0002	37.4000	0.0000
50%	$\|r_{m,t}\|$	0.3213	0.0385	8.3500	0.0000
Criterion	$r_{m,t}^2$	1.1556	1.3311	0.8700	0.3854
	$\overline{BH_t}DVol_t^L r_{m,t}^2$	-3.0670	0 .7365	-4.1600	0.0000
	$\overline{BH_t}DVol_t^U r_{m,t}^2$	0.2149	0.6846	0.3100	0.7536

Table 4.9: Buy herding, market wide herding and different percentages of volume to trade. Results are presented in Panels for equations 4.9 (Panel A) and equation 4.11: for the 15% (Panel B),for 20% (Panel C) and 50% (Panel D) for the use of $\overline{H_t}$ as herding.

institutional and individual level is negative, but not statistically significant. We then use the mean volume per trade, to investigate the importance of the market composition in terms of investors. We observe that when the presence of individual

investors is strong, then buy micro-level herding is positively related to the presence of aggregate herding for all criteria. On the other hand, when managers dominate the market, buy herding is related to higher variability in returns. This result, tough, is weaker, as for lower concentrations of institutions in the market (50% criterion) buy herding is non significant.
We subsequently apply the same methodology for sell herding, measured also as defined above by $\overline{SH_t}$.

The effect of micro-level sell herding on market-wide herding is similar to that

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel A	(Intercept)	0.0060	0.0002	38.6558	0.0000
All	$r_{m,t}$	0.2638	0.0356	7.4060	0.0000
Sample	$r^2_{m,t}$	2.0514	1.3341	1.5377	0.1242
	$\overline{SH_t} r^2_{m,t}$	-0.1233	0.7422	-0.1662	0.8680
Panel B	(Intercept)	0.0061	0.0001	48.5127	0.0000
15%	$\|r_{m,t}\|$	0.2609	0.0279	9.3653	0.0000
Criterion	$r^2_{m,t}$	1.0962	0.7076	1.5493	0.1214
	$\overline{SH_t} DVol^L_t r^2_{m,t}$	-3.0249	0.5931	-5.1005	0.0000
	$\overline{SH_t} DVol^U_t r^2_{m,t}$	2.5521	0.6020	4.2394	0.0000
Panel C	(Intercept)	0.0061	0.0001	48.8248	0.0000
20%	$\|r_{m,t}\|$	0.2586	0.0281	9.2053	0.0000
Criterion	$r^2_{m,t}$	1.0793	0.6916	1.5606	0.1187
	$\overline{SH_t} DVol^L_t r^2_{m,t}$	-3.2632	0.5979	-5.4577	0.0000
	$\overline{SH_t} DVol^U_t r^2_{m,t}$	2.5323	0.5719	4.4279	0.0000
Panel D	(Intercept)	0.0059	0.0002	37.5600	0.0000
50%	$\|r_{m,t}\|$	0.3250	0.0369	8.8200	0.0000
Criterion	$r^2_{m,t}$	1.4204	1.3579	1.0500	0.2956
	$\overline{SH_t} DVol^L_t r^2_{m,t}$	-4.7860	0.9204	-5.2000	0.0000
	$\overline{SH_t} DVol^U_t r^2_{m,t}$	0.0332	0.7334	0.0500	0.9636

Table 4.10: Sell herding, market wide herding and different percentages of volume to trade. Results are presented in Panels for equations 4.10 (Panel A) and equation 4.12: for the 15% (Panel B),for 20% (Panel C) and 50% (Panel D) for the use of $\overline{H_t}$ as herding.

of buy micro-level herding. We observe, again, that the coefficients for sell herding when volume per trade is low are all negative and significant. The effect of sell herding when volume per trade is above its median is not significant. What is intriguing, is the fact that sell herding has a stronger effect on non linearities -than buy herding- when individual investors are dominant, while this is not the case when institutional investors constitute greater parts of the market. Nonetheless, this asymmetric effect of sell herding pressures is only significant for high volume per trade.[12] The results imply that sell herding has a significant difference to buy herding when the market is composed of more sophisticated and better informed investors. Given that herding is measured in counts of trades and every trade has the same weight, market participants may conclude that institutional trades have

[12] We performed a Chow test (Chow, 1960) and the difference between the coefficients of sell herding and buy herding have a significant difference only for the case of high VpT

a stronger informational content. Thus, we see a difference in the significance of sell and buy herding, when the trading reflects the choices of more better informed, better trained, larger traders. Both in Table 4.10, that contains the results for sell herding, and in Table 4.9 we notice that the coefficient γ_2 is not significant in most cases. This indicates that the non-linearities are captured by the cross- terms effectively.
The findings, regarding the use of the D-Ratio instead of the LSV to compute directional herding, are presented in Tables 4.11 and 4.12. The corresponding regressions are similar to the ones used for directional herding based of the LSV, as follows:

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 * 100\%\overline{BDR_t} r_{m,t}^2 + \epsilon_t \tag{4.13}$$

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 * 100\%\overline{SDR_t} r_{m,t}^2 + \epsilon_t \tag{4.14}$$

Using a dummy variable for mean volume per trade, we attempt to investigate the effect of the investor type and we define:

$$\begin{aligned} CSAD_t == \alpha + \gamma_1|r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 \times 100\%\overline{BDR_t} DVol_t^L r_{m,t}^2 \\ + \gamma_4 \times 100\%\overline{BDR_t} DVol_t^U r_{m,t}^2 + \epsilon_t \end{aligned} \tag{4.15}$$

$$\begin{aligned} CSAD_t == \alpha + \gamma_1|r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 \times 100\%\overline{SDR_t} DVol_t^L r_{m,t}^2 \\ + \gamma_4 \times 100\%\overline{SDR_t} DVol_t^U r_{m,t}^2 + \epsilon_t \end{aligned} \tag{4.16}$$

where all notation is equal to the case of $\overline{BH_t}$ and $\overline{SH_t}$, while $\overline{BDR_t}$ and $\overline{SDR_t}$ stand for buy and sell herding, as measured via the D-Ratio.

The results using a value based measure for the directional herding indicate that $\overline{BDR_t}$ and $\overline{SDR_t}$ are significant and negative. This was not the case for the trade-based measures. Buy herding has a bigger effect on market wide herding. When dividing the effect to consider the composition of trading, regarding the type of investor, we observe some differences from the trade-based measure. For the criteria of 15% and 20% each side, we remark that the results are similar with the trade-based case. The effect for low volume per trade is negative, while the effect of high volume per trade is positive. We note that when the market is dominated by institutions, there exist a significant difference between the effect of sell and buy herding. Sell herding pressures, on days when trading is dominated by sophisticated, well informed larger investors, creates pressures against the consensus leading to higher variability. For the case of the median of the volume per trade distribution as a criterion, we detect a weak negative effect of buy herding - only significant for 10% - implying that buy herding on value has a positive relation to market wide herding, when the market composition is split. Again, statistical analysis indicates that the difference between sell herding and buy herding is significant only for high volume per trade. The results indicate, that the directional pressure of sell herding is significantly different from that of buy herding, on days when trading is composed by large investors. Directional pressure affects also herding, in all cases, but the direction itself does not affect the results greatly. It is implied, that well informed investors trade against sentiment using more sells than buys. This result may be derived by liquidity constraints that investors face and the decision specific notions, that we mentioned in the case of trade-based measures above. The evidence is in

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel A	(Intercept)	0.0061	0.0002	38.7870	0.0000
All	$r_{m,t}$	0.2621	0.0361	7.2598	0.0000
Sample	$r^2_{m,t}$	4.5225	1.2444	3.6342	0.0003
	$\overline{BDR_t} * r^2_{m,t}$	-0.3067	0.0964	-3.1833	0.0015
Panel B	(Intercept)	0.0060	0.0001	45.4565	0.0000
15%	$\|r_{m,t}\|$	0.2758	0.0300	9.1974	0.0000
Criterion	$r^2_{m,t}$	1.0998	0.7775	1.4145	0.1573
	$\overline{BDR_t} * DVol^L_t * r^2_{m,t}$	-0.2997	0.0480	-6.2458	0.0000
	$\overline{BDR_t} * DVol^U_t * r^2_{m,t}$	0.3248	0.1239	2.6210	0.0088
Panel C	(Intercept)	0.0060	0.0001	45.8191	0.0000
20%	$\|r_{m,t}\|$	0.2758	0.0300	9.2014	0.0000
Criterion	$r^2_{m,t}$	1.0446	0.7568	1.3802	0.1676
	$\overline{BDR_t} * DVol^L_t * r^2_{m,t}$	-0.3251	0.0525	-6.1949	0.0000
	$\overline{BDR_t} * DVol^U_t * r^2_{m,t}$	0.3305	0.1211	2.7296	0.0064
Panel D	(Intercept)	0.0060	0.0002	37.2207	0.0000
50%	$\|r_{m,t}\|$	0.3036	0.0376	8.0823	0.0000
Criterion	$r^2_{m,t}$	3.1939	1.3179	2.4234	0.0154
	$\overline{BDR_t} * DVol^L_t * r^2_{m,t}$	-0.5454	0.0890	-6.1276	0.0000
	$\overline{BDR_t} * DVol^U_t * r^2_{m,t}$	-0.1851	0.9984	-1.8539	0.0639

Table 4.11: Sell Herding, market wide herding and different percentages of volume to trade. Results are presented in Panels for equations 4.13 (Panel A) and equation 4.3.4: for the 15% (Panel B),for 20% (Panel C) and 50% (Panel D) for the use of $\overline{DR_t}$ as herding.

accordance with our findings in the previous chapter.
Since we identify that both buy and sell herding, in some cases, have an asymmetrical effect on the consensus of returns, it is important to examine their influence when employed jointly. For each day there exist both buy and sell herding pressures that may interact and jointly affect the consensus. It is essential to investigate this joint effect, both when directional pressures are in normal values and in cases of high concentration in buys and sells. For this reason, we examine the effect of buy and sell herding, both throughout the sample and in extreme cases of buy and sell pressures. This way, we will be able to identify whether there exist contradicting directional effects simultaneously in the market. We employ two equations including buy and sell herding, both measured via the number of trades and via value as shown below.

$$CSAD_t == \alpha + \gamma_1|r_{m,t}| + \gamma_2 r^2_{m,t} + \gamma_3 \times 100\% \overline{BH_t} * r^2_{m,t} + \gamma_4 \times 100\% \overline{SH_t} * r^2_{m,t} + \epsilon_t \quad (4.17)$$

$$\begin{aligned} CSAD_t == \alpha + \gamma_1|r_{m,t}| + \gamma_2 r^2_{m,t} + \gamma_3 \times 100\% D^L_{BH_t,t} \overline{BH_t} * r^2_{m,t} \\ + \gamma_4 \times 100\% D^U_{BH_t,t} \overline{BH_t} * r^2_{m,t} \\ + \gamma_5 \times 100\% D^L_{SH_t,t} \overline{SH_t} * r^2_{m,t} \\ + \gamma_6 \times 100\% D^U_{SH_t,t} \overline{SH_t} * r^2_{m,t} \\ + \epsilon_t \end{aligned} \quad (4.18)$$

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel A	(Intercept)	0.0061	0.0002	38.1002	0.0000
All	$r_{m,t}$	0.2651	0.0364	7.2788	0.0000
Sample	$r^2_{m,t}$	4.6723	1.6906	2.7637	0.0057
	$\overline{SDR_t} * r^2_{m,t}$	-0.13352	0.1564	2.1437	0.0321
Panel B	(Intercept)	0.0061	0.0001	49.3601	0.0000
15%	$\|r_{m,t}\|$	0.2570	0.0273	9.4282	0.0000
Criterion	$r^2_{m,t}$	1.0552	0.6792	1.5535	0.1204
	$\overline{SDR_t} * DVol^L_t * r^2_{m,t}$	-0.2500	0.0417	-5.9857	0.0000
	$\overline{SDR_t} * DVol^U_t * r^2_{m,t}$	0.5765	0.0987	5.8432	0.0000
Panel C	(Intercept)	0.0061	0.0001	50.3147	0.0000
20%	$\|r_{m,t}\|$	0.2524	0.0268	9.4089	0.0000
Criterion	$r^2_{m,t}$	1.0190	0.6514	1.5643	0.1178
	$\overline{SDR_t} * DVol^L_t * r^2_{m,t}$	-0.2603	0.0409	-6.3601	0.0000
	$\overline{SDR_t} * DVol^U_t * r^2_{m,t}$	0.5564	0.0856	6.5032	0.0000
Panel D	(Intercept)	0.0060	0.0002	35.2515	0.0000
50%	$\|r_{m,t}\|$	0.2982	0.0399	7.4775	0.0000
Criterion	$r^2_{m,t}$	2.9785	1.9190	1.5521	0.1207
	$\overline{SDR_t} * DVol^L_t * r^2_{m,t}$	-0.4542	0.1107	-4.1049	0.0000
	$\overline{SDR_t} * DVol^U_t * r^2_{m,t}$	-0.1558	0.1853	-0.8405	0.4007

Table 4.12: Sell Herding, market wide herding and different percentages of volume to trade. Results are presented in Panels for equations 4.14 (Panel A) and equation 4.3.4: for the 15% (Panel B),for 20% (Panel C) and 50% (Panel D) for the use of $\overline{DR_t}$ as herding.

where $\overline{BH_t}$ and $\overline{SH_t}$ stand for buy and sell herding. The dummy variables examine cases of low and high buy and sell herding. For example, for the case of buy herding we define $D^L_{BH_t,t}$ ($D^U_{BH_t,t}$)m as a dummy variable that takes the value one when buy herding is low (high), given a certain criterion. For sell herding, the dummy variables $D^L_{SH_t,t}$ and $D^L_{SH_t,t}$ are defined similarly.
Using the same mindset, for the case of the D-Ratio we employ the following equations:

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r^2_{m,t} + \times 100\% \gamma_3 \overline{BDR_t} r^2_{m,t} + \gamma_4 \times 100\% \overline{SDR_t} r^2_{m,t} + \epsilon_t \quad (4.19)$$

$$\begin{aligned} CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r^2_{m,t} &+ \gamma_3 \times 100\% D^L_{BDR_t,t} \overline{BDR_t} * r^2_{m,t} \\ &+ \gamma_4 \times 100\% D^U_{BDR_t,t} \overline{BDR_t} * r^2_{m,t} \\ &+ \gamma_5 \times 100\% D^L_{SDR_t,t} \overline{SDR_t} * r^2_{m,t} \\ &+ \gamma_6 \times 100\% D^U_{SDR_t,t} \overline{SDR_t} * r^2_{m,t} \\ &+ \epsilon_t \end{aligned} \quad (4.20)$$

where $\overline{BDR_t}$ and $\overline{SDR_t}$ denote buy and sell herding respectfully, measured in dollar-based value at t. The dummy variables are computed as in the case of the trade-based measures of buy and sell herding, using the value based measures as the underlying variables.

In Tables 4.13 and 4.14 the results for the case of herding measured on trades are presented. For the entire market, neither sell nor buy herding seem to asymmet-

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0060	0.0002	39.9777	0.0000
A	$\|r_{m,t}\|$	0.2740	0.0340	8.0689	0.0000
Eq.	$r^2_{m,t}$	2.1677	1.4233	1.5230	0.1279
4.17	$\overline{BH_t} * r^2_{m,t}$	-0.5497	0.7242	-0.7590	0.4479
	$\overline{SH_t} * r^2_{m,t}$	0.2373	0.7746	0.3063	0.7594
Panel	(Intercept)	0.0060	0.0002	38.2493	0.0000
B	$\|r_{m,t}\|$	0.2890	0.0353	8.1815	0.0000
Eq.	$r^2_{m,t}$	0.2828	0.9049	0.3125	0.7547
4.18	$D^L_{BH_t,t}\overline{BH_t} * r^2_{m,t}$	0.8930	0.9200	0.9708	0.3317
12.5%	$D^U_{BH_t,t}\overline{BH_t} * r^2_{m,t}$	-1.0307	0.4503	-2.2891	0.0221
Criterion	$D^L_{SH_t,t}\overline{SH_t} * r^2_{m,t}$	1.1645	0.8701	1.3383	0.1809
	$D^U_{SH_t,t}\overline{SH_t} * r^2_{m,t}$	-3.5647	1.1944	-2.9844	0.0029
Panel	(Intercept)	0.0061	0.0002	39.3112	0.0000
C	$\|r_{m,t}\|$	0.2801	0.0367	7.6370	0.0000
Eq.	$r^2_{m,t}$	-0.5911	1.2702	-0.4653	0.6417
4.18	$D^L_{BH_t,t}\overline{BH_t} * r^2_{m,t}$	2.1727	0.5783	3.7568	0.0002
20%	$D^U_{BH_t,t}\overline{BH_t} * r^2_{m,t}$	-1.7414	0.3765	-4.6251	0.0000
Criterion	$D^L_{SH_t,t}\overline{SH_t} * r^2_{m,t}$	0.7373	0.8120	0.9082	0.3639
	$D^U_{SH_t,t}\overline{SH_t} * r^2_{m,t}$	-1.4867	0.9761	-1.5230	0.1278

Table 4.13: Sell and Buy Herding - measured on trades - and market wide herding. Results are presented in Panels for equations 4.17 (Panel A) and equation 4.18 for the 12.5% (Panel B) and 20% (Panel C) criterion of extreme buy and sell herding.

rically affect the consensus. This is also the case when the measures are examined individually. On the other hand, when we split the sample using the volume per trade, we note that only sell herding, on days of high retail investor concentration, affects the consensus of returns, via higher market wide herding. Sell and buy pressures do not affect the consensus using either direction of herding in the case of high institutional concentration in trading.

When we examine micro-level herding in extreme cases, we discover mixed results. Extreme buy herding, regarding the entire sample, consistently relates to higher levels of aggregate herding, while only during very extreme cases of sell herding, the consensus is affected. What is more, extreme sell herding influences the consensus of returns in the case of retail, less sophisticated investors. This is not the case for extreme buy herding in this case. The findings imply that buy herding pressures, by individual investors, do not affect the consensus of returns. Given that this measure of herding does not account for the volume of trades, small trades by retail investors have the same weight as larger trades by institutions. Nonetheless, not both cases influence returns on the same manner. Given that retail investors can sell stocks they already own but can buy stocks restrained due to liquidity, these results make sense. Indeed, when extreme buy herding and sell herding coincides with the presence of large, sophisticated and institutional investors, extreme buy herding, acts as a signal and leads to the formation of consensus. The informative power of institutional trades is higher compared to this of retail investors, leading to institutional buys and retail sells affecting the market-wide consensus asymmetrically.

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0059	0.0001	60.9815	0.0000
A.1	$\|r_{m,t}\|$	0.1785	0.0288	6.1974	0.0000
Eq.	$r^2_{m,t}$	4.7291	0.5259	8.9928	0.0000
4.17	$\overline{BH_t} * r^2_{m,t}$	0.7173	0.6430	1.1155	0.2648
$VpT \leq median$	$\overline{SH_t} * r^2_{m,t}$	-4.7228	1.4081	-3.3541	0.0008
Panel	(Intercept)	0.0065	0.0002	27.6869	0.0000
A.2	$\|r_{m,t}\|$	0.3300	0.0429	7.7000	0.0000
Eq.	$r^2_{m,t}$	1.1756	1.6596	0.7083	0.4788
4.17	$\overline{BH_t} * r^2_{m,t}$	-0.2118	0.8464	-0.2502	0.8025
$VpT > median$	$\overline{SH_t} * r^2_{m,t}$	0.1560	0.7564	0.2058	0.8369
Panel	(Intercept)	0.0060	0.0001	61.0967	0.0000
B.1	$\|r_{m,t}\|$	0.1200	0.0271	4.4325	0.0000
Eq.	$r^2_{m,t}$	1.3014	1.1508	1.1309	0.2583
4.18	$D^L_{BH_t,t}\overline{BH_t} * r^2_{m,t}$	1.3330	0.8791	1.5164	0.1296
12.5%	$D^U_{BH_t,t}\overline{BH_t} * r^2_{m,t}$	0.4086	0.6817	0.5994	0.5490
Criterion	$D^L_{SH_t,t}\overline{SH_t} * r^2_{m,t}$	0.2118	0.9307	0.2276	0.8200
$VpT \leq median$	$D^U_{SH_t,t}\overline{SH_t} * r^2_{m,t}$	-4.1276	1.7859	-2.3113	0.0209
Panel	(Intercept)	0.0065	0.0002	26.3639	0.0000
B.2	$\|r_{m,t}\|$	0.3506	0.0455	7.7088	0.0000
Eq.	$r^2_{m,t}$	-0.2449	0.9432	-0.2597	0.7952
4.18	$D^L_{BH_t,t}\overline{BH_t} * r^2_{m,t}$	0.6492	0.9342	0.6949	0.4872
12.5%	$D^U_{BH_t,t}\overline{BH_t} * r^2_{m,t}$	-1.2996	0.5384	-2.4138	0.0159
Criterion	$D^L_{SH_t,t}\overline{SH_t} * r^2_{m,t}$	1.0417	0.8529	1.2213	0.2221
$VpT > median$	$D^U_{SH_t,t}\overline{SH_t} * r^2_{m,t}$	-3.9821	1.4422	-2.7611	0.0058
Panel	(Intercept)	0.0060	0.0001	59.5685	0.0000
C.1	$\|r_{m,t}\|$	0.1232	0.0288	4.2778	0.0000
Eq.	$r^2_{m,t}$	1.1043	1.4380	0.7679	0.4426
4.18	$D^L_{BH_t,t}\overline{BH_t} * r^2_{m,t}$	0.7746	0.8276	0.9359	0.3494
20%	$D^U_{BH_t,t}\overline{BH_t} * r^2_{m,t}$	-0.4340	0.4033	-1.0907	0.2756
Criterion	$D^L_{SH_t,t}\overline{SH_t} * r^2_{m,t}$	0.6984	0.9058	0.7710	0.4408
$VpT \leq median$	$D^U_{SH_t,t}\overline{SH_t} * r^2_{m,t}$	-2.0694	1.0674	-1.9387	0.0527
Panel	(Intercept)	0.0066	0.0002	27.0886	0.0000
C.2	$\|r_{m,t}\|$	0.3350	0.0470	7.1209	0.0000
Eq.	$r^2_{m,t}$	-1.0253	1.3799	-0.7430	0.4576
4.18	$D^L_{BH_t,t}\overline{BH_t} * r^2_{m,t}$	1.7808	0.6097	2.9206	0.0035
20%	$D^U_{BH_t,t}\overline{BH_t} * r^2_{m,t}$	-2.3265	0.5373	-4.3298	0.0000
Criterion	$D^L_{SH_t,t}\overline{SH_t} * r^2_{m,t}$	0.7969	0.8527	0.9346	0.3502
$VpT > median$	$D^U_{SH_t,t}\overline{SH_t} * r^2_{m,t}$	-1.4212	1.1359	-1.2511	0.2111

Table 4.14: Sell and Buy Herding - measured on trades - and market wide herding and the role of investor. Results are presented in Panels for equations 4.17 (Panels A.1 for low VpT and A.2 for high VpT) and equation 4.18 for the 12.5% (Panels B.1 for low VpT and B.2 for high VpT) and 20% (Panels C.1 for low VpT and C.2 for high VpT) criterion of extreme buy and sell herding.

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0061	0.0002	39.2754	0.0000
A	$\|r_{m,t}\|$	0.2663	0.0356	7.4876	0.0000
Eq.	$r^2_{m,t}$	5.5106	1.5854	3.4758	0.0005
4.19	$\overline{BDR_t} * r^2_{m,t}$	-0.2330	0.1086	-2.1443	0.0321
	$\overline{SDR_t} * r^2_{m,t}$	0.2071	0.1740	-1.1899	0.2342
Panel	(Intercept)	0.0062	0.0001	42.7395	0.0000
B	$\|r_{m,t}\|$	0.2323	0.0336	6.9243	0.0000
Eq.	$r^2_{m,t}$	1.7252	0.8384	2.0577	0.0397
4.20	$D^L_{BDR_t,t}\overline{BDR_t} * r^2_{m,t}$	0.5811	0.2592	2.2421	0.0250
12.5%	$D^U_{BDR_t,t}\overline{BDR_t} * r^2_{m,t}$	-0.0448	0.0802	-0.5588	0.5763
Criterion	$D^L_{SDR_t,t}\overline{SDR_t} * r^2_{m,t}$	0.6374	0.3471	1.8362	0.0664
	$D^U_{SDR_t,t}\overline{SDR_t} * r^2_{m,t}$	0.0382	0.1671	0.2285	0.8193
Panel	(Intercept)	0.0063	0.0001	47.0874	0.0000
C	$\|r_{m,t}\|$	0.2120	0.0307	6.9090	0.0000
Eq.	$r^2_{m,t}$	1.7018	0.7725	2.2029	0.0277
4.20	$D^L_{BDR_t,t}\overline{BDR_t} * r^2_{m,t}$	0.6335	0.1781	3.5573	0.0004
20%	$D^U_{BDR_t,t}\overline{BDR_t} * r^2_{m,t}$	-0.1112	11.9363	-0.9315	0.3517
Criterion	$D^L_{SDR_t,t}\overline{SDR_t} * r^2_{m,t}$	0.5297	0.2243	2.3612	0.0183
	$D^U_{SDR_t,t}\overline{SDR_t} * r^2_{m,t}$	0.0656	0.1637	0.4005	0.6888

Table 4.15: Sell and Buy Herding - measured on value - and market-wide herding. Results are presented in Panels for equations 4.19 (Panel A) and equation 4.20 for the 12.5% (Panel B) and 20% (Panel C) criterion of extreme buy and sell herding.

In Tables 4.15 ans 4.16 the results of buy and sell herding measured via the dollar value are displayed. The results differ significantly concerning this measure. Buy herding measured on value does affect the consensus of returns, while in the case of the LSV measure above, that was not the case. However when we split the sample in days with high and low institutional trading the results change. It is retail sells again that highly relate to herding. The effect is quite strong and significantly different form the effect of buy herding.
For the case of extreme microlevel herding, we again note the essential nature of sell herding pressures in cases where retail investors dominate the market. Buy herding again, as in the case of the LSV, combined with the presence of less informed and less sophisticated investors, does not affect aggregate herding. Institutional buy herding seems to relate to herding market wide. The results for institutional sell herding are not conclusive, as they vary depending of the criterion of the extreme. Our results imply that extreme institutionally-driven buy pressures and extreme individually-driven sell pressures lead to the formation of market wide herding, both when pressures are defined in trades and in value. It is insinuated that retail investors sells and institutional investors buys relate to the aggregate manifestation of collective behaviour in returns.

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0060	0.0001	63.2298	0.0000
A.1	$\|r_{m,t}\|$	0.1259	0.0243	5.1715	0.0000
Eq.	$r^2_{m,t}$	3.6027	0.7825	4.6043	0.0000
4.19	$\overline{BDR_t} * r^2_{m,t}$	-0.0697	0.0728	-0.9572	0.3386
$VpT \leq median$	$\overline{SDR_t} * r^2_{m,t}$	0.0930	0.7396	-1.2573	0.2088
Panel	(Intercept)	0.0066	0.0003	25.0630	0.0000
A.2	$\|r_{m,t}\|$	0.3079	0.0507	6.0680	0.0000
Eq.	$r^2_{m,t}$	3.9435	2.4633	1.6009	0.1096
4.19	$\overline{BDR_t} * r^2_{m,t}$	-0.2099	0.1227	-1.7111	0.0873
$VpT > median$	$\overline{SDR_t} * r^2_{m,t}$	-0.1029	0.2327	-0.4424	0.6582
Panel	(Intercept)	0.0061	0.0001	62.2814	0.0000
B.1	$\|r_{m,t}\|$	0.0966	0.0248	3.8901	0.0001
Eq.	$r^2_{m,t}$	2.3084	0.8738	2.6418	0.0083
4.20	$D^L_{BDR_t,t}\overline{BDR_t} * r^2_{m,t}$	-0.0987	0.1551	-0.6360	0.5249
12.5%	$D^U_{BDR_t,t}\overline{BDR_t} * r^2_{m,t}$	0.0598	0.3833	1.5613	0.1186
Criterion	$D^L_{SDR_t,t}\overline{SDR_t} * r^2_{m,t}$	1.0021	0.2920	3.4322	0.0006
$VpT \leq median$	$D^U_{SDR_t,t}\overline{SDR_t} * r^2_{m,t}$	-0.0184	0.0342	-0.5384	0.5903
Panel	(Intercept)	0.0067	0.0002	29.4828	0.0000
B.2	$\|r_{m,t}\|$	0.2792	0.0425	6.5751	0.0000
Eq.	$r^2_{m,t}$	1.1500	0.9188	1.2517	0.2108
4.20	$D^L_{BDR_t,t}\overline{BDR_t} * r^2_{m,t}$	0.5593	0.2785	2.0080	0.0448
12.5%	$D^U_{BDR_t,t}\overline{BDR_t} * r^2_{m,t}$	0.0166	0.0515	0.3223	0.7473
Criterion	$D^L_{SDR_t,t}\overline{SDR_t} * r^2_{m,t}$	0.5200	0.3687	1.4105	0.1586
$VpT > median$	$D^U_{SDR_t,t}\overline{SDR_t} * r^2_{m,t}$	0.3520	0.1287	2.7352	0.0063
Panel	(Intercept)	0.0061	0.0001	63.8521	0.0000
C.1	$\|r_{m,t}\|$	0.1001	0.0235	4.2563	0.0000
Eq.	$r^2_{m,t}$	2.3419	0.8212	2.8517	0.0044
4.20	$D^L_{BDR_t,t}\overline{BDR_t} * r^2_{m,t}$	-0.2259	0.1493	-1.5131	0.1304
20%	$D^U_{BDR_t,t}\overline{BDR_t} * r^2_{m,t}$	-0.0015	0.0368	-0.0412	0.9671
Criterion	$D^L_{SDR_t,t}\overline{SDR_t} * r^2_{m,t}$	1.3105	0.2979	4.3991	0.0000
$VpT \leq median$	$D^U_{SDR_t,t}\overline{SDR_t} * r^2_{m,t}$	-0.0103	0.0404	-0.2549	0.7988
Panel	(Intercept)	0.0068	0.0002	32.3517	0.0000
C.2	$\|r_{m,t}\|$	0.2465	0.0387	6.3651	0.0000
Eq.	$r^2_{m,t}$	1.2489	0.8384	1.4897	0.1365
4.20	$D^L_{BDR_t,t}\overline{BDR_t} * r^2_{m,t}$	0.6531	0.1883	3.4679	0.0005
20%	$D^U_{BDR_t,t}\overline{BDR_t} * r^2_{m,t}$	0.0019	0.0782	0.0242	0.9807
Criterion	$D^L_{SDR_t,t}\overline{SDR_t} * r^2_{m,t}$	0.3928	0.2283	1.7207	0.0855
$VpT > median$	$D^U_{SDR_t,t}\overline{SDR_t} * r^2_{m,t}$	0.3285	0.1498	2.1932	0.0284

Table 4.16: Sell and Buy Herding - measured on value - and market wide herding and the role of investor. Results are presented in Panels for equations 4.19 (Panels A.1 for low VpT and A.2 for high VpT) and equation 4.20 for the 12.5% (Panels B.1 for low VpT and B.2 for high VpT) and 20% (Panels C.1 for low VpT and C.2 for high VpT) criterion of extreme buy and sell herding.

4.4 Conclusion: Main Findings and Limitations

In this essay we attempt to further investigate the findings of Chapter 3. After establishing a connection between micro-level herding, trading and the market composition in terms of investors, the literature indicates that it is important to examine also the direction of trading. The main findings and the major limitations of this essay, alongside some propositions for further research are examined below.

4.4.1 Main Findings

The direction of trading and herding are key variables, that may or may not affect stock returns asymmetrically, as existing conflicting results in the literature indicate. In this essay, we attempt to distinguish the effect of the direction of trading and herding for market wide herding, emphasizing on the role of the investor.
The direction of trading generally, does not seem to affect the consensus of returns. A weak effect exists for directional trading, when we consider the counts of trade. Both negative and positive trading pressures are related to more herding in returns, while the effect for selling pressures is stronger. To that effect, we shall also consider, that the results may be influenced by sell pressures during the 2008 crisis. The results indicate, that generally market wide herding is not affected neither by the magnitude nor by the direction of trading imbalances. The findings are robust to the choice of measure used as the proportion of stocks with a positive trading imbalance again does not affect the consensus.
Observing that trading pressure in itself, does not affect market wide herding, leads us to question, whether the direction of herding affects the returns. Microlevel herding, both during selling and during buying days, is related to the consensus of returns. It is shown that the market consensus is not driven by institutional herding but it is stronger when smaller investors constitute a larger part of the total trading activity, both regarding trade and value herding measures.
By dividing micro-level collective behaviour into buy and sell herding, we are allowed to investigate the effect of the direction of the pressure for each day. Given that for every specific market, sell and buy herding pressures co-exist, it is important to investigate these phenomena both separately and jointly. Our results indicate that both buy and sell herding affect the consensus of returns. The investor type is again critical.
In line with theories supporting that the volume per trade includes information for the type of investor (e.g. Cready and Mynatt, 1991; Kaniel et al., 2008; Miller, 2010), the investors' sophistication and abilities (e.g. Bushee, 1998; Bartov, 2003), their access to information (Kyle, 1985; Easley and O'Hara, 1987) and their sentiment (Kumar and Lee, 2006; Barber et al., 2009), we use the mean volume per trade to account for all the investor characteristics mentioned here. We find evidence that support the conclusion of the previous chapter. It is herding by less informed, retail investors, especially in sells but also in buys, that leads to the formation of consensus. On the contrary institutional herding does not lead to market wide herding.
When we consider the effect of buy and sell herding and their extreme values jointly, interesting observations arise. It is sell herding by retail investors that relates to market wide herding. Measuring herding in trades, and thus giving equal weights to all trades and investors, assists us in distinguishing between retail investor buy

herding and sell herding. Given that retail investor trades are smaller, and buy herding requires the investor to have liquidity, the different nature of sells and buys, as choices, may influence this result. Institutional investors are more flexible in terms of liquidity and may buy a stock more easily, whereas retail investors may chose to herd in sells due to liquidity constraints. Indeed, the results indicate that buy herding combined with the presence of larger investors in the market, when sell herding is also accounted for, is linked to a stronger consensus. The same effect is found for sell herding pressures, when smaller investors' presence is stronger.
These results are in line with and can be explained by both behavioural and conventional models. Institutional buys constitute an informational signal in the market. Institutional buys, as information that may affect returns (e.g. Easley et al. ,2002), can lead to herding via informational cascades (e.g. Banerjee, 1998; Park and Sabourian, 2011). Simultaneously, retail investors driven both by the institutions superior information set (e.g. Kyle, 1985) and by attention bias (Barber and Odean, 2007) also buy stocks with high recent past returns.
The findings of this essay, also relate to literature regarding the connection between different liquidity constraints encountered by different investor groups and stock returns. For example, according to theories related to attention bias, in order to buy popular stocks, retail investors sell the stocks they recently bought, leading to sentiment-based trading losses (Barber et al., 2009) and systematic noise (Barber et al., 2009). This situation could potentially lead institutions to trade against sentiment and buy the stock retail investors sold or even succumb to selling pressures in order to avoid losses from a market crash (as in 2008). This might also be the reason why, in high concentration of institutions in trading, only for the most extreme case of sell herding examined, we find an important relation between sell herding and aggregate herding.
The results indicate that the direction of herding pressures are important for the consensus of returns. More so, when we examine the composition of the market in terms of investors, we find that it is sell herding by individuals and buy herding by institutions that affect the consensus of returns. These findings, also relate to the smart money effect indicating that the origin and direction of trading matter for market efficiency (e.g. Keswani and Stolin, 2008; Akbas et al., 2015). This chapter faces limitations similar to those of the previous chapter that are briefly discussed below.

4.4.2 Limitations and Further Research

There exist several limitations to what, this essay can explain. Many of those limitations are related to the nature of our data and our variables. As such, they exist both for the current and for the previous chapter. For instance, given that trades are self-inferred from quotes, there is a percentage of error during the identification process. In addition to that, the market composition in terms of investor type is proxied via volume per trade. Although efficient, there is a possible bias to this variable - particularly as many small trades or a few large trades could skew the results. This is particularly true for the case, when some investors hold superior information sets and split their trades into multiple orders to maximise their expected gains. Also, there are many types of investors in the market, as small individuals, large individuals, small institutions, huge institutions and so on. The extent of the

heterogeneity of investors in today's setting, exceeds the groups defined here. All these investors have different levels of competence and different trading strategies. Firstly, in the aggregation process - through which we examine the market- loss of information is expected. Additionally, it is not possible to differentiate between all types of investors and strategies in our framework.
Given all that, the findings of this essay, could assist in a better understanding of herding and its mechanism of transmission - or better said non-transmission- from the level of the trader to the level of the return. These findings are in line with the literature supporting that trading, when conducted by individuals or noise traders, impedes market efficiency and that managers act to mitigate this effect - or to prey on the less capable smaller institutions and individuals (De Long, 1990; Lee et al. ,1991, Liao et al.,2011). Moreover, the evidence provide a new insight to directional herding that relates to both behavioural and conventional models and follows the logic of investor competence, education and sophistication - thus the term "smart money". Lastly, these findings may be useful in order to understand why market-wide herding is present in concentrated, "noisy" and smaller markets, while in markets that are organised and dominated by institutions - as the U.S.- we do not find herding in returns.
As in the previous chapter, it would be useful to test the multiple hypotheses of this essay for a larger market, or using information about specific investors trading. Furthermore, investigating the questions posed in this chapter for other type of markets, with a different organisational structure, a different macroeconomic environment and a different informational setting, such as emerging markets or culturally distinct markets -as Japan- may shed light into different aspects of directional herding and the consensus of returns.
Given all the above, this chapter extends the findings of the previous chapter of this thesis. The directional aspect of trading and herding in flows is examined in conjunction with the consensus of returns. The evidence supports the notion that the effect of directional pressures relate heavily to the composition of trading in terms of investors, as the type of trader and the size of the trade is linked to herding both in their own right and possibly as informational signals.

Part III

More Methodological Issues with Herding: The Case of the CSSD and Variability

Abstract

The second part of the thesis aims to investigate the effect of price variability, as a variable and concept, to market-wide herding. Focusing, now, mostly on the methodology created by Christie and Huang (1995), we aim to examine the effect of the cross sectional quadratic variation on herding. This part contains one essay that serves this cause.

Keywords— Herding and variability, cross sectional mean quadratic variation, cross sectional standard deviation

Chapter 5

The cross sectional standard deviation of assets as a measure of herding under uncertainty: The case of the quadratic variation

Abstract

Herding is a phenomenon that has been linked to mispricing of assets and the formation of speculative bubbles. A commonly used measure of aggregate herding is the cross sectional standard deviation (CSSD), which is not an adequate measure of herding. Time series volatility - in the form of quadratic variation - is correlated with CSSD and thus herding is not adequately captured by empirical models. We use intraday and daily price data of stocks in the DJIA 30, to show that when we account for mean intraday volatility, during extreme price movements, the results concerning herding are not so clear. By employing both the measure created by Christie and Huang (1995) and the methodology by Chang et al. (2000), we underline the importance of intraday volatility, both as a measure of dispersion and as a measure of uncertainty for herding.

Keywords— Herding, Realised Volatility, Cross Sectional Standard Deviation, Financial Markets

5.1 Introduction and Motivation

Herding is an essential phenomenon in financial markets that has been linked to the mispricing of assets and the formation of speculative bubbles (Dass et al., 2008). Also, herding has been linked to informational cascades and blockages (Bikhchandani and Sharma, 2001). There is a vast literature on theoretical models for the identification of herding and its effect on the market.
Empirically, when we try to identify herding in the behaviour of financial agents, we follow two primary approaches. The first is to investigate herding on an institutional or/and individual level. Another part of the literature attempts to look for herding patterns in the market as a whole, i.e. herding to the market consensus.
The practical tools we have, lack the complexity and diversity of the theory that we try to test (Spyrou, 2013). Moreover, there is inconsistency in the empirical results. For example, many empirical papers find evidence of herding on an institutional level for a specific period in the US market, while no indication of herding to the consensus exists.[1] What is more, the aggregate empirical measures we employ, such as the cross-sectional standard deviation, the absolute cross-sectional standard deviation and factorial models are not sufficient to capture the dynamics of asset pricing.
Two primary methodologies employ the dispersion of returns to measure herding. The first methodology, that approached market-wide herding via the dispersion of assets, is the one created by Christie and Huang (1995), the CH method. Later on,Chang et al. (2000) choose to use the cross sectional absolute deviation of returns and to account for a non linear relation between the dispersion and the market return in the CCK method. This non -linear relation between the dispersion of returns and market return - captured by the squared market return - is also, depending on the results, the indication of herding or higher variation.
The first model for market-wide herding, extensively used, is the cross-sectional standard deviation model for extreme price movements by Christie and Huang, 1995 - CH henceforth. This measure uses the cross sectional standard deviation to test for herding during extreme market returns that, in this certain concept account for market stress. Although the idea is intuitively correct, there are many issues with a measure formed this way.
One of these issues is that the measure does not account for time series volatility in the returns, which affects both returns and their dispersion (Mc Ennally and Todd, 1992; Hwang and Salmon, 2004). Furthermore, this measure takes arbitrary limits as benchmarks to determine market extremes, based on the distribution of the market return. The results may differ dramatically when different criteria of extreme are considered. For instance, quantile regressions approaches indicate that herding is not present in lower quantiles (Blasco et al., 2017). Other papers modify this measure to account for non-linearity (Chang et al., 2000) between dispersion and returns. Even with modified measures[2] the dispersion of assets underestimates herding (Bohl et al., 2017), when the latter is present in the market. Using regime switching, with volatility regimes, showed more accurate results for herding to the consensus (Kabir and Shakur, 2018). In the same paper, market sentiment and information are crucial variables for herding formation. Information and market sentiment influence herd-

[1] This could happen if there was institutional/individual herding in opposite directions.
[2] Chang et al. use the cross sectional absolute standard deviation to account for non linearities.

ing in many manners. For instance, macroeconomic announcements (Galariotis et al. 2015), periods of crisis and turmoil (Calvo and Mendoza, 1996), pandemics and political events (Shyu and Sun ,2010) are all shown to affect collective behaviour in financial markets in some level.
The relationship between volatility and the dispersion of assets (Yu and Sharaiha, 2007) is also substantial theoretically. Volatility and dispersion are linked as the expected cross sectional dispersion can be decomposed into two major parts. The first part consists of the average stock volatility and market volatility, while part two represents the dispersion of expected stock returns. Additionally, volatility can be defined in various manners to capture different types of uncertainty and risk. In the framework of CCK, for example, market variance, via the squared market return, is a form of market variability (Klein, 2013), accounted for in the CCK model. This form of market variance does not capture the intraday variation of stocks and the uncertainty this variation entails. The importance of intraday variation, when examining herding daily is highlighted by both theoretical and empirical literature. Volatility could be seen as the opposite of herding but can also contribute to its creation. As shown by Bollerslev, Li and Xue (Bollerslev et al., 2017) there is often high volatility around news announcements and this [3] is in line with agents that agree-to-disagree. This is an indication of the importance of volatility for market price formation, especially in higher frequencies. Additionally, not all measures of volatility are created equal. The nature of volatility and its denotation as good and bad, regarding the cross section of returns is highlighted in Bollerslev et al. (2020). In this essay, we rely on intraday volatility in market extremes and account for it when we intend to identify herding. This way we can distinguish between market variance and the formation of herding, which may exist, but is is not identified by traditional models. We use the "naive estimator" (Andersen et al. 2001a; Andersen et al.,2003) of intraday volatility to control for the effect of time series volatility, and the uncertainty this entails, for the estimation of macro-level herding. In section 5.2 we present the major theories and empirical approaches to herding along with our main methodological approach, in Section 5.3 the data used both for the main results and the robustness test are presented. In Section 5.4 we present our main results and expand them to the CCK method, while in Section 5.4.2 several modifications and tests help to determine the robustness and value of our results, including an application on a different frequency, incorporating sentiment and fear and bootstrapping tests. Lastly Section 5.5 concludes this essay.

5.2 Methodology

We examine the effect of intraday volatility on market wide herding and the methodological issues it includes, both for the CCK and the CH measure. We will begin with the latter.

[3] The volume-volatility elasticity is systematically below 1 on days of public announcements

5.2.1 The CH measure and Intraday Volatility: An approach on extreme market price movements

We will focus on the methodology developed by Christie and Huang (1995) in order to determine whether or not volatility has an effect on herding during extreme price movements. Christie and Huang (1995) use the cross sectional standard deviation of assets to test for herding.
The methodology is analytically presented below, as follows:

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t \tag{5.1}$$

and

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{n}(r_{i,t} - r_{m,t})^2}{n-1}} \tag{5.2}$$

where $CSSD_t$ is the dispersion of assets, $r_{i,t}$ is the return of asset i, n is the number of assets, $r_{m,t}$ is the market return -usually as the cross sectional average of n returns-, D_t^L is a dummy variable that takes the value 1 if at time t the market return falls in the extreme lower tail of the return distribution or zero otherwise and D_t^U is a dummy variable that takes the value 1 if at time t the market return falls in the extreme upper tail of the return distribution or zero otherwise. According to traditional asset pricing models the estimated coefficients of the regression 5.1 should be positive or non significant, while if herding is present the estimates of β_1 and β_2 should be negative.
In order to account for volatility we will use the mean of the quadratic variation, for all stocks at each t, only during extreme market movements.[4]
The specification that is employed, is described below:

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \beta_3 vol_t \chi D_t^L + \beta_4 vol_t \chi D_t^U + \epsilon_t \tag{5.3}$$

where vol_t is the cross sectional average of the square root of the quadratic variations for all stocks daily computed as:

$$vol_t = \frac{\sum_{i=1}^{n}(\sqrt{\sum_{dt=1}^{T} r_{i,dt}^2})}{n} \tag{5.4}$$

where n is the number of stocks in each day, dt is the time unit [5], and $\sum_{dt=1}^{T} r_{i,dt}^2$ represents the quadratic variation for each stock daily.[6]
The β parameters reveal whether uncertainty during a trading day affects the dispersion of returns and whether this happens during extreme price movements. The cross-sectional quadratic variation captures the effect of uncertainty and allows us to see how β_1 and β_2 behave without uncertainty. We also modify the CCK measure for uncertainty as presented in the following subsection.

[4] For a daily frequency we will use the mean intraday realised volatility for day t for all stocks. For a monthly frequency we will use the daily realised volatility to compute the mean of all stocks over a trading month and then use monthly stock returns to determine herding.

[5] Day t when we measure intraday realised volatility or month t when we measure daily realised volatility

[6] The number of intraday variations or daily variations depending on frequency.

5.2.2 The CKK measure and Intraday Volatility: An approach of extreme uncertainty

Another important measure - widely used - is the CCK method, which applies a non-linear relation between the market return and the dispersion of returns, while attempting to capture herding. Analytically the methodology is described below.

$$CSAD_t = \alpha + \gamma_1 |r_{m,t}| + \gamma_2 r_{m,t}^2 + \epsilon_t \tag{5.5}$$

where $CSAD_t = \frac{1}{n}\sum_1^n |r_{i,t} - r_{m,t}|$ and $r_{m,t}$ is the market return, computed as the unweighted average of all stock returns or the daily index return. We modify this measure to account for states of uncertainty via the level of the cross sectional mean of the quadratic variation. We, thus define states of the market that are characterised by extreme high uncertainty, extreme low uncertainty or stability as follows:

$$CSAD_t = \alpha + \gamma_1 |r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 D_t^{L_{rv}} r_{m,t}^2 + \gamma_4 D_t^{U_{rv}} r_{m,t}^2 + \epsilon_t \tag{5.6}$$

where $D_t^{L_{rv}}$ is a dummy variable that takes the value one when vol_t is low and zero otherwise. $D_t^{L_{rv}}$ is the equivalent for high mean quadratic variation market-wide. We should note that the squared market return is a measure of market variance that does not account for the uncertainty the investors in the market face within a day, as it is computed on closing prices daily. By incorporating the extreme uncertainty and stability dummy variables, we can capture the effect that the level of uncertainty within a day has on market-wide herding and the consensus of returns.
After presenting the main methodology, employed in this essay, we now proceed to the description of the data used to apply it. For the purposes of this essay, numerous data sources, for various frequencies are used. We further look into the data below.

5.3 Data

In this essay, we include two types of data frequencies of analysis. The difference in frequency assists us to verify the robustness of our results. What is more, data frequency is affiliated with different types of investors, liquidity and market structure. As different types of investors trade on different frequencies and use different patterns, if the effect of volatility exists in both frequencies, that we use, then the relationship is better established. Below we analyse how we compute our daily and monthly variables, using intraday, daily and monthly data about the Dow Jones Industrial Average 30 and the Standard and Poor's 500 indices.

5.3.1 Intraday Data on a daily frequency

The data we employ to investigate herding daily, come from intraday per minute prices of the thirty components, at each specific time, of the Down Jones Industrial Average 30 (DJIA) between 01/12/2005 and 19/06/2015. We utilise data for 40 companies in total. In order to compute the market mean return, we use daily historical prices for the DJIA index available online at Bloomberg, alongside the unweighted mean of the stock returns of all stocks in the market for comparison's shake. The results are robust to the choice of market return as they stay identical when we use the unweighted average of all stock returns in the portfolio as the

market return. The results using the unweighted mean return of stocks included in the market portfolio can be found in the Appendix. We use these intraday data to compute the daily return, the mean intraday volatility - as the cross sectional mean of the quadratic variation of stocks included in the market portfolio - and the daily cross-sectional standard deviation of assets.

5.3.2 Daily Data on a monthly frequency

We applied our methodology on daily prices of the monthly constituents of the S&P 500, ranging from January 1995 to April 2019. Then, we followed the same principles and we computed the monthly CSSD and the monthly mean of the daily quadratic variations of stocks in the market portfolio.
The choice of the S&P 500 will cover a large part of the U.S. market, in terms of capitalization and trading volume. This choice helps us, not only investigate the effect of a different frequency, but also to look at a bigger part of the market.
We now look into the basic measures and graphs to better comprehend our data. We focus on the intraday data for this task, as they are the main source of information for this essay.

5.3.3 Preliminary Data Analysis: Descriptive Statistics and Graphical presentation

Below we present some important features regarding the variables employed. Among the most important variables are the cross-sectional mean of the quadratic variation, the CSSD and the market return. All results are presented for the intraday data for DJIA 30.
We begin by the relationship between the market return quantiles and the other variables we use. Below we investigate briefly how the quantiles of the market return affect other important variables in our sample. We divided the sample in 20 quantiles by 5%, with respect to the mean return of the DJIA index. In Table 5.1 we present the mean cross-sectional quadratic variation, the mean market return - as the return of the index DJIA 30 - and the CSSD. In Table 5.1 and Figure 5.1 the relationship between the market return and mean volatility - in the form of quadratic variation is displayed. Mean volatility is extremely high on low returns and lesser so on extremely high returns. The form of the curve is of the traditional U shape, as expected (e.g. Hamao et al., 1990).
We also present the time series evolution of variables central to our analysis. The market return of the DJIA index and the mean return of all stocks have a very similar time series evolution as shown in Figure 5.2. We observe high variability of the return around the period of the 2008 crisis and more periodic variability from then on. The distribution of the return is as expected leptokurtic, centred around 0.0002073 -which is very close to zero- with a standard deviation of 0.01202.
In Figure 5.4 we observe the time series evolution of the cross sectional standard deviation and the mean volatility in our sample. Both measures are by construction positive and follow a quite similar pattern. Both the $CSSD_t$ and vol_t are high during the market crisis of 2008. After the crisis, more variation is present in the $CSSD$ than in vol_t. Through the graphical presentation of the variables of interest, it becomes evident that the dispersion of returns is correlated to the cross

Quantile	Mean Volatility	Mean Return	CSSD	CSSD (dji)
0 - 0.05	0.0022482	-0.0331786	0.0256717	0.0264843
0.05 - 0.10	0.0007285	-0.0178251	0.0123738	0.0124509
0.10 - 0.15	0.0006779	-0.0098796	0.0077123	0.0077259
0.15- 0.20	0.0006744	-0.0098823	0.0069854	0.0071193
0.20 - 0.25	0.0008159	-0.0044178	0.0152296	0.0152298
0.25 - 0.30	0.0007840	-0.0066527	0.0121056	0.0123661
0;30 - 0.35	0.0008811	-0.0060646	0.0095025	0.0101970
0.35 - 0.40	0.0005979	-0.0001272	0.0096259	0.0097100
0.40 -0.45	0.0006544	-0.0009849	0.0088260	0.0088492
0.45 - 0.50	0.0005629	-0.0003068	0.0081884	0.0082242
0.50 - 0.55	0.0006724	0.0013001	0.0070340	0.0070359
0.55 - 0.60	0.0005919	0.0001297	0.0134514	0.0135091
0.60 -0.65	0.0008255	0.0009979	0.0194143	0.0194715
0.65 - 0.70	0.0006239	0.0033889	0.0115365	0.0115608
0.70 - 0.75	0.0004148	0.0055195	0.0045287	0.0045400
0.75 -0.80	0.0006967	0.0073554	0.0083916	0.0085328
0.80 - 0.85	0.0006004	0.0080824	0.0133741	0.0134198
0.85 - 0.90	0.0006967	0.0083869	0.0076470	0.0077179
0.90 - 0.95	0.0012212	0.0157652	0.0141792	0.0141984
0.95 - 1.00	0.0011524	0.0155778	0.0178391	0.0180045

Table 5.1: Mean volatility and cross sectional standard deviation with respect to the the quantiles of the market return quantile.

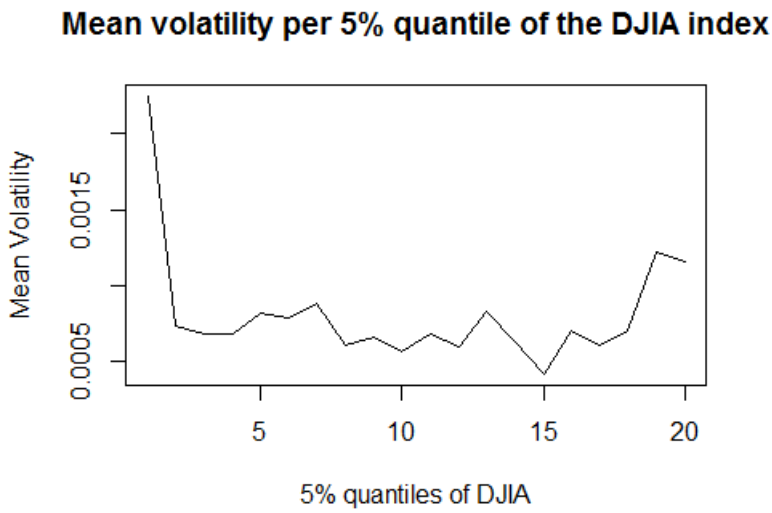


Figure 5.1: Cross sectional mean of quadratic variation and the quantiles of the market return

sectional mean of the quadratic variation. Variability in returns is linked with a higher deviation of returns from the market consensus. The correlation between the two variables is very high - 0.7356 - and significant from zero. The cross sectional standard deviation of returns on a daily frequency seems to be related to trading

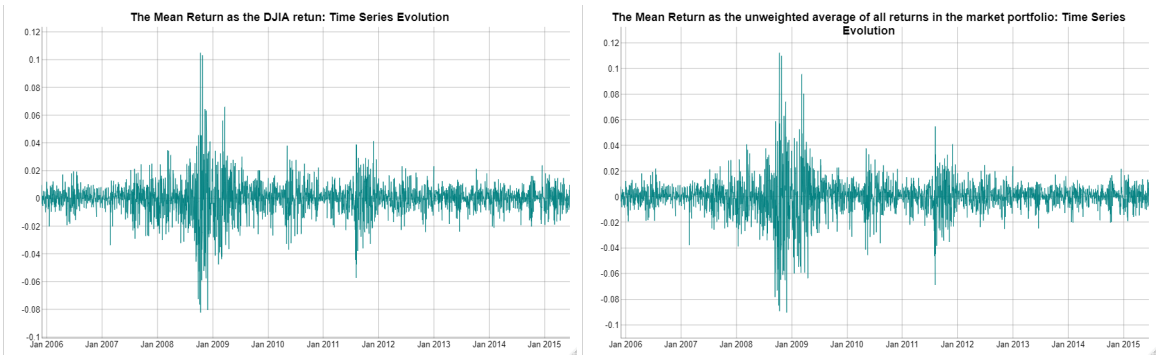


Figure 5.2: Market Return as the DJIA 30 daily return and the unweighted average of the DJIA 30 constituents' returns: Time series evolution.

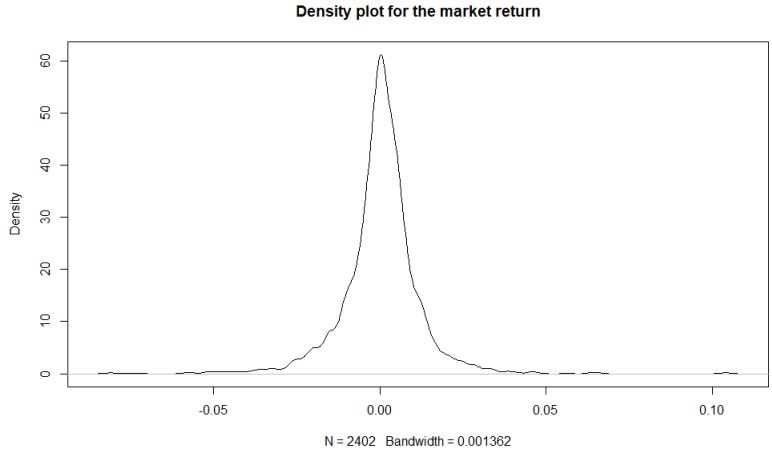


Figure 5.3: Density plot for the DJIA 30 return.

uncertainty and variability of stock returns within the trading day.

In the following section the principal results, in addition to more specifications,

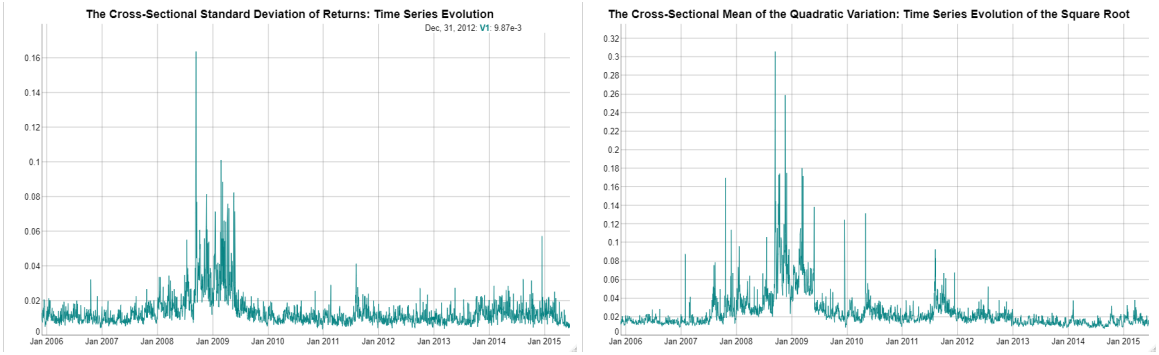


Figure 5.4: The cross sectional standard deviation of returns $CSSD_t$ and the cross-sectional mean of the quadratic variation vol_t: Time series evolution.

required for testing the robustness of our results are developed.

5.4 Empirical Analysis

We divide our empirical analysis in three parts. In subsection 5.4.1 we will investigate the effect of intraday volatility on the CH measure, while in subsection 5.4.2 we present a variety of tests which, alongside with the estimation of equations 5.1 and 5.3 for a lower frequency in subsection 5.4.2, help support the initial empirical findings. In subsection 5.4.3 we apply the methodology developed in equation 5.5 and 5.6 to examine the effect of high uncertainty and high stability on herding when non-linear structures are accounted for. We shall initially focus on the CH method.

5.4.1 The CH method and the cross sectional mean quadratic variation

Below we present the results of the estimation for equation 5.1 and 5.3 in two separate Tables, Table 5.2 for the original CH method and Table 5.3 for the method described by equation 5.3.The Tables are divided into three panels to present all different *extreme* criteria: 1%, 2.5% and 5%. By criteria we refer to the χ % of the market return distribution, used in order to mark the level below and above which we consider a return extreme. Via this specification of pseudo-variables, market stress - as defined by Christie and Huang (1995) - in the form of extreme price movements is accounted for.

In Table 5.2 we observe that the results indicate that no herding occurs during ex-

		Estimate	Std. Error	t value	Pr(>|t|)
Panel A	(Intercept)	0.0133	0.0002	71.44	0.0000
Eq.5.1	D_t^L	0.0264	0.0046	5.71	0.0000
1%	D_t^U	0.0166	0.0037	4.42	0.0000
Panel B	(Intercept)	0.0130	0.0002	72.03	0.0000
Eq.5.1	D_t^L	0.0164	0.0025	6.47	0.0000
2.5%	D_t^U	0.0133	0.0021	6.21	0.0000
Panel C	(Intercept)	0.0128	0.0002	70.53	0.0000
Eq.5.1	D_t^L	0.0112	0.0016	6.95	0.0000
2.5%	D_t^U	0.0092	0.0014	6.77	0.0000

Table 5.2: The CH method for market wide herding. Results for equation 5.1 presented in three Panels: for the 1% criterion (Panel A), for the 2.5% criterion (Panel B) and for the 5% criterion (Panel C).

treme price movements, when the CH methodology is applied without modifications. For all criteria the coefficients β_1 and β_2 are positive and statistically significant. During market extreme movements there is higher dispersion in returns. According to the traditional interpretation of the CH methodology, the result are in line with traditional asset pricing assumptions and models.

When the results are considered in the framework presented in this essay, various questions arise. Do the results of the CH method really indicate no herding in the market? Is herding absent completely or the methodology employed does not capture it? How does the relation between intraday variability, uncertainty and aggregate herding, implied graphically and numerically above, relate to these results? It is important to account for intraday volatility, both as a variable that affects

methodologically the CH model and as a concept that influences the decisions of investors in the market, by defining the market itself. Now we proceed to the estimation of equation 5.3 to test whether the cross sectional mean of the quadratic variation affects the CSSD during extreme price movements and how the β coefficients behave when this effect is accounted for.

In Table 5.3 we observe that when we account for intraday volatility coefficients

		Estimate	Std. Error	t value	Pr(>|t|)
Panel A	(Intercept)	0.0133	0.0002	71.44	0.0000
Eq.5.1	D_t^L	-0.0019	0.0065	-0.29	0.7721
1%	D_t^U	-0.0236	0.0071	-3.31	0.0009
	$vol_t \times D_t^L$	0.2663	0.0659	4.04	0.0001
	$vol_t \times D_t^U$	0.5978	0.1218	4.91	0.0000
Panel B	(Intercept)	0.0130	0.0002	72.03	0.0000
Eq.5.1	D_t^L	-0.0048	0.0030	-1.61	0.1080
2.5%	D_t^U	0.0133	0.0021	6.21	0.0000
	$vol_t \times D_t^L$	0.2932	0.0445	6.58	0.0000
	$vol_t \times D_t^U$	0.5328	0.0750	7.11	0.0000
Panel C	(Intercept)	0.0128	0.0002	70.53	0.0000
Eq.5.1	D_t^L	-0.0066	0.0018	-3.64	0.0003
5%	D_t^U	-0.0103	0.0019	-5.38	0.0000
	$vol_t \times D_t^L$	0.3108	0.0356	8.74	0.0000
	$vol_t \times D_t^U$	0.4683	0.0591	7.92	0.0000

Table 5.3: The CH method and cross sectional mean of the quadratic variation for market wide herding. Results for equation 5.3 presented in three Panels: for the 1% criterion (Panel A), for the 2.5% criterion (Panel B) and for the 5% criterion (Panel C).

β_1 and β_2 change both in terms of sign and in terms of significance. The cross-sectional mean of the quadratic variation is positively related to the CSSD during extreme price movements. The results indicate that trading uncertainty intraday during extreme market movements affects the CH methodology. We observe also that coefficients of herding are negative and significant in the 5% criterion.
We now proceed to several tests and applications of this methodology in order to validate its robustness.

5.4.2 Robustness tests for the CH method and intraday volatility modification

Firstly, we perform various bootstrapping tests in order to examine whether our estimation suffers from bias. Given the nature of the data and the analysis, such tests assist us in assessing the validity of the results. All in all, the results indicate that any existing bias is minor and thus shall not affect our results. All relevant tests are presented in the Appendix of this chapter.
We now begin our analysis by incorporating a measure of fear and sentiment in the market - the return of the VIX, as a measure of investor sentiment and a possible cause of panic.

The introduction of the VIX

The Chicago Board Options Exchange (CBOE) volatility index, generally known as the VIX index represents the market's expectations, regarding the thirty days forward looking volatility affiliated with the S&P 500 options. The VIX is related to market risk and investor sentiment. It could be useful to see how our model behaves when the daily VIX is included as it represents the expectations of the market over the monthly horizon and it is widely used by investors (e.g. Smales, 2017).
We incorporate the VIX into our model, to test whether the effect of intraday variability persists during extreme market returns, when other measures of uncertainty, fear and risk are also accounted for market-wide. The model used is the following:

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \beta_3 vol_t \chi D_t^L + \beta_4 vol_t \chi D_t^U + VIX_t + \epsilon_t \quad (5.7)$$

Equation 5.7 is identical to equation 5.3, with the sole addition of the daily VIX value. What is more, since the return of the VIX index examined here can take negative returns, it might capture asymmetry in the market. The results are presented for the 1%, 2.5% and 5% criteria regarding extreme price movements, defined equally to previous sections, in three panels in Table 5.4.

As we can see in Table 5.4, introducing the VIX index does not affect the signif-

		Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0133	0.0002	70.78	0.0000
A	D_t^L	-0.0014	0.0036	-0.40	0.6915
1%	D_t^U	-0.0239	0.0057	-4.22	0.0000
Eq.5.7	VIX_t	0.0077	0.0026	2.93	0.0034
	vol_t * D_t^L	0.2654	0.0284	9.35	0.0000
	vol_t * D_t^U	0.6007	0.0794	7.56	0.0000
Panel	(Intercept)	0.0130	0.0002	70.67	0.0000
B	D_t^L	-0.0047	0.0019	-2.45	0.0144
2.5%	D_t^U	-0.0139	0.0027	-5.12	0.0000
Eq.5.7	VIX_t	0.0066	0.0025	2.63	0.0087
	vol_t * D_t^L	0.2939	0.0212	13.84	0.0000
	vol_t * D_t^U	0.5302	0.0480	11.05	0.0000
Panel	(Intercept)	0.0127	0.0002	69.41	0.0000
C	D_t^L	-0.0065	0.0013	-4.95	0.0000
5%	D_t^U	-0.0102	0.0016	-6.46	0.0000
Eq.5.7	VIX_t	0.0058	0.0025	2.36	0.0183
	vol_t * D_t^L	0.3110	0.0178	17.45	0.0000
	vol_t * D_t^U	0.4653	0.0327	14.21	0.0000

Table 5.4: The CH method , intraday volatility and sentiment in the market. Results for Equation 5.7 presented in three panels: for the 1% (Panel A), for the 2.5% (Panel B) and for the 5% (Panel C) criteria.

icance of the cross sectional mean of the quadratic variation in market extremes. The results indicate that when investor sentiment is included, the effect of the lower extreme dummy is not significant for the 1% criterion but is significant for 2.5% and 5 % criteria. The coefficients of D_t^L and D_t^U are negative, which is in line with the presence of herding in the market. The coefficient related to the VIX is significant

and positive, indicating that uncertainty and fear are related to a more intense dispersion of assets. This can be an outcome of investors ignoring the market signal during fear and high expected volatility, as they may consider it unreliable.

The CH method and the cross sectional mean quadratic variation: The importance of frequencyy

Following the same logic and principles as above we will now estimate equations 5.1 and 5.3, using 292 monthly observations of the stocks included in the S&P 500 index [7] to compute the CSSD and monthly market return. The cross sectional monthly mean of the daily quadratic variation was computed using daily closing prices.
We begin by demonstrating the results for the classic CH method and then we present our modification. For the 1% criterion the total number of observations that are considered extreme is very low but we demonstrate these results as well, for comparison's sake.

		Estimate	Std. Error	t value	Pr(>|t|)
Panel A	(Intercept)	0.0045	0.0001	37.66	0.0000
1%	D_t^L	0.0067	0.0012	5.75	0.0000
Eq.5.1	D_t^U	0.0031	0.0012	2.66	0.0081
Panel B	(Intercept)	0.0044	0.0001	36.56	0.0000
2.5%	D_t^L	0.0043	0.0007	5.98	0.0000
Eq.5.1	D_t^U	0.0020	0.0007	2.75	0.0063
Panel C	(Intercept)	0.0043	0.0001	37.05	0.0000
5%	D_t^L	0.0046	0.0005	9.23	0.0000
Eq.5.1	D_t^U	0.0020	0.0005	4.04	0.0001

Table 5.5: The CH method, the cross sectional monthly mean of the quadratic variation and market-wide herding on a lower frequency. Results for Equation 5.1 presented in three panels: for the 1% (Panel A), for the 2.5% (Panel B) and for the 5% (Panel C) criteria.

As we can observe in Table 5.5 the results are similar for daily prices on a monthly frequency, for the estimation of equation 5.1. Given the smaller number of observations the statistical significance of the D_t^L and D_t^U parameters is lower, as we observe higher P-values. Nonetheless, D_t^L and D_t^U are positive at all market extreme criteria (1%, 2.5% and 5%) and significant at the 5% level. The traditional CH methodology does not indicate herding in the market.
Below in Table 5.6 we present the results for the estimation of equation 5.3 again in three panels. The same methodology, as for intraday prices, is applied for this case of lower frequency.
The results in Table 5.6, imply similar behaviour of returns in daily prices on a monthly frequency, as on the daily one. In Table 5.6 we can see that the variables D_t^L and D_t^U are not statistically significant for all criteria examined. For the case of 2.5% and 5% criteria, a weak significance at 10% level is encountered, while both variables have a negative effect on the CSSD. Statistically, the higher P-value could be a result of a smaller sample. This effect could also be an outcome of economic

[7] The stocks included in the S&P 500 vary from 501 to 506 between 1994 and 2019

		Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0045	0.0001	38.18	0.0000
A	D_t^L	-0.0006	0.0033	-0.19	0.8492
1%	D_t^U	-0.0039	0.0036	-1.11	0.2687
Eq. 5.3	vol_t * D_t^L	0.0411	0.0174	2.36	0.0189
	vol_t * D_t^U	0.0395	0.0188	2.10	0.0368
Panel	(Intercept)	0.0044	0.0001	38.10	0.0000
B	D_t^L	-0.0034	0.0019	-1.77	0.0784
2.5%	D_t^U	-0.0033	0.0020	-1.69	0.0927
Eq. 5.3	vol_t * D_t^L	0.0488	0.0113	4.31	0.0000
	vol_t * D_t^U	0.0345	0.0120	2.89	0.0042
Panel	(Intercept)	0.0043	0.0001	40.55	0.0000
C	D_t^L	-0.0020	0.0011	-1.86	0.0635
5%	D_t^U	-0.0026	0.0013	-1.95	0.0523
Eq. 5.3	vol_t * D_t^L	0.0395	0.0058	6.77	0.0000
	vol_t * D_t^U	0.0328	0.0090	3.65	0.0003

Table 5.6: The CH method, the cross sectional monthly mean of the quadratic variation and market-wide herding on a lower frequency. Results for Equation 5.1 presented in three panels: for the 1% (Panel A), for the 2.5% (Panel B) and for the 5% (Panel C) criteria.

determinants. In a monthly frequency, returns tend to represent investors who trade on a longer horizon while noise is filtered out. Although the power of the results is lower, it is evident that the CH methodology is affected by the cross sectional mean of the quadratic variation on the monthly frequency as well.
The results suggest that herding does exist on the market consensus and its intensity is declining during market extremes and high volatility. The traditional methods are not able to capture this behaviour. To that effect, we now examine the effect of high and low intraday volatility using the CCK method - as described in our methodology.

5.4.3 The CCK method and intraday volatility: An approach of uncertainty

We now try to examine the effect of low and high quadratic variation for the stocks of the DJIA 30, regarding herding in returns using the CCK method. The CCK method examines the relationship between the dispersion of assets and the squared market return to account for the possible non-linear structure, indicated by the Capital Asset Pricing Model. Although the squared market return is a measure of market variance, it is unable to capture trading uncertainty extensively, as the quadratic variation is (Bollerslev et al., 2017), by construction. We proceed to the estimation of equations 5.5 and 5.6, using the 5%, 10% and 20% criterion for the dummy variables that access the states of uncertainty and variability in the market, based on the cross sectional mean of the quadratic variation, as described above in the methodology section. The results are presented in a common Table, separated in panels.
The results presented in Table 5.7 support the assumption that market uncertainty

		Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0069	0.0002	35.03	0.0000
A	$\|r_{m,t}\|$	0.3352	0.0417	8.05	0.0000
Eq.5.5	$r^2_{m,t}$	0.7847	0.9793	0.80	0.4230
Panel	(Intercept)	0.0066	0.0002	34.73	0.0000
B	$\|r_{m,t}\|$	0.4979	0.0472	10.56	0.0000
5%	$r^2_{m,t}$	-10.8979	1.8936	-5.76	0.0000
Eq.5.6	$D_t^{L_{rv}} r^2_{m,t}$	-22.2096	6.7258	-3.30	0.0010
	$D_t^{U_{rv}} r^2_{m,t}$	9.7809	1.2603	7.76	0.0000
Panel	(Intercept)	0.0068	0.0002	38.07	0.0000
C	$\|r_{m,t}\|$	0.4781	0.0442	10.81	0.0000
10%	$r^2_{m,t}$	-14.2500	2.1249	-6.71	0.0000
Eq.5.6	$D_t^{L_{rv}} r^2_{m,t}$	-11.3586	5.8484	-1.94	0.0522
	$D_t^{U_{rv}} r^2_{m,t}$	13.2488	1.5199	8.72	0.0000
Panel	(Intercept)	0.0069	0.0002	38.80	0.0000
D	$\|r_{m,t}\|$	0.4385	0.0431	10.18	0.0000
20%	$r^2_{m,t}$	-13.2538	2.2581	-5.87	0.0000
Eq.5.6	$D_t^{L_{rv}} r^2_{m,t}$	-15.8696	4.6829	-3.39	0.0007
	$D_t^{U_{rv}} r^2_{m,t}$	12.7144	1.6987	7.48	0.0000

Table 5.7: The CCK measure and uncertainty. Results presented in four Panels: for equation 5.5 (Panel A), for equation 5.6 for the 5% (Panel B), for the 10%(Panel C) and for the 20%(Panel D) criteria based on the cross sectional mean of the quadratic variation.

is negatively related to herding and leads to higher dispersion in returns. When no alteration of the CCK method is applied, no herding is encountered, using this method as well.

When we account for different states of uncertainty, through different levels of the cross sectional mean of the quadratic variation, the results change. The coefficient of the squared term γ_2 is negative and significant when extreme intraday volatility - low or high - is taken into consideration. Low levels of uncertainty are related to herding but their significance is weak - especially in the case of the 5% criterion for the mean quadratic variation- possibly due to the small numbers of observations for which the dummy variables take the value one. The number of observations for which $D_t^{L_{rv}}$ and $D_t^{U_{rv}}$ take the value one when we use the 5% criterion on each side of the mean quadratic variation distribution is small and this could affect the empirical results. What is more, high levels of quadratic variation seem to relate to lower levels of aggregate herding, as γ_4 is positive and significant. We observe that the cross-sectional quadratic variation affects the CCK measure as well. Thus, not accounting for realised volatility renders unreliable results. As seen in Table 5.7, for equation 5.5 the β_2 parameter is not significant, while the incorporation of states of high and low variability within a trading day impact the empirical findings.

All in all, high levels of intraday variability in returns is related to higher dispersion of returns and a weaker consensus. When the intraday variability is low, a slightly stronger consensus is observed, indicating that the fluctuations of individual stock returns within a trading day, affect also the dispersion of returns.

5.5 Conclusion: Results and Limitations

In this essay, we attempt to examine the measures of herding to the market consensus and their ability to capture mimetic behaviour market-wide, when the realised volatility is also considered. Realised volatility is related to measures of herding structurally (Yu and Sharaiha, 2007) and to collective behaviour conceptually. In most cases, empirical models do not encounter herding to the market consensus and thus we try to investigate whether this outcome stems from the uncertainty in the market or not.
We employ the cross sectional mean of the quadratic variation for two essential reasons. The cross sectional mean of the quadratic variation, as a measure of intraday volatility, is directly related to the dispersion of assets, in the form of the CSSD. The second reason lies in the capacity of the intraday volatility to proxy trading uncertainty and its influence on investors' behaviour. Daily variability of stock returns may affect the informational structure in the market, leading to less information being available to investors and possibly loss of efficiency in the market overall (e.g. Brown et al., 1988; Danthine and Moresi, 1993; Bhattacharya et al, 2000; Savor, 2012). What is more, higher levels of realised volatility are, by construction, affiliated to higher dispersion (Yu and Sharaiha, 2007), which affects the results regarding both the CH and the CCK methods. This fact is also highlighted by the strong correlation and time series patterns between the dispersion of assets and the cross sectional mean of the quadratic variation, regarding our data.
Thus, we modify the CH model to examine whether intraday volatility affects the estimation of aggregate herding and in which form. Additionally we examine the effect of high and low variability and uncertainty for the CCK method. Given that realised volatility affects the results, both methodologically and as a variable that influences investor behaviour, it is essential to account for it, when market-wide herding is considered.
All in all, our results indicate that intraday volatility is a vital variable concerning aggregate herding. As it affects uncertainty, it also influences the dispersion of asset returns. When estimating herding, daily variability shall be included in the models in order to obtain robust results, as it is significant as a corrective term. Lastly, our findings imply that herding, in terms of returns, has a negative relation to uncertainty and return variability of individual stocks in the cross section, within a trading day. Uncertainty and fear, either market wide - via the VIX - or within the same market - via the mean quadratic variation - seem to cause investors to deviate more from the consensus. Although, sentiment might affect returns and volatility, it is empirically shown that it is returns and variability that affect sentiment and not the opposite (Wang et al., 2006).
This methodological proposal, described in this essay, shall be implemented to different markets and distinct environments, to investigate whether the outcome is the same in those settings. The choice of the DJIA 30, as the primary focus, may affect the results, due to the composition of the index. It is for this reason, that a broader market is chosen in the case of the lower frequency above. Nonetheless, implementing this methodology on other markets, that contain a broader variety of stocks, on a high frequency, may be beneficial in order to validate and expand or contradict the findings of this essay. What is more, more variables and other measures of uncertainty, both in financial markets and in the economic and political scene, could

be variables of interest, especially regarding aggregate collective behaviour.
Apart from the limitations it faces and the necessity for further examination of its results, this essay contributes to the literature of aggregate herding, by emphasizing on the relationship between the dispersion of returns and realised volatility and uncertainty. The corrective proposition, which accounts for the mean quadratic variation, assists in the explanation of market-wide herding and its peculiar form. The results also relate to concepts of good and bad volatility (Bollerslev et al., 2020), and the notion that some forms of variability may act as a protection against mispricing while other forms of variability may impede the efficiency of the distribution of information. The relation between return variability and market-wide herding is explored, using both the CH and the CCK, and treating variability as a factor that affects both the dispersion and the sentiment and information structure of the market (e.g. Blair et al., 2001; Bollerslev et al., 2017). This essays thus, although limited, contributes, both conceptually and methodologically to the literature regarding the empirical estimation Of herding.

Chapter 6

Conclusion

The objectives of this thesis

This thesis purses to contribute to the literature of mimetic behaviour in financial markets. Herding, as the general manifestation of mimesis, is an essential phenomenon in the markets. As evidence preceding this thesis indicates, herding is both a part of the conventional finance universe and a phenomenon explained by behavioural concepts. This thesis attempts to contribute to both behavioural and rational herding. The dual nature of the human decision making process, that leads to the dual nature of herding, is implied throughout the existing literature.
By examining in depth both the theoretical and the empirical existing contributions, some major issues both conceptually and methodologically, regarding herding, are identified. The main objective of this thesis is to further investigate the reasons why empirical models do not always succeed in adequately representing herding. This thesis is organised in three parts- two of which are empirical- that attempt to contribute to herding both conceptually and methodologically, using empirical tools.
Below the major objectives and findings of these parts are examined. Their place in existing financial literature and the contribution they carry are also discussed.

The main results and their importance

The first part of this thesis represents the literature review, developed critically, to examine herding as a concept, as a theoretical issue and as an empirical problem. As many phenomena in economics and finance, herding is a concept originating from sociology and psychology. The formation of groups, especially during stressful situations - for example riots, wars and uprisings- and the contagion of such groups have been major concepts both in sociology and psychology. In financial markets, the concept of herding was introduced as the formation of investor groups and mimetic behaviour between investors.
Empirically, though, herding has been identified either in the decision of - initially institutional and later on also individual - investors to persistently buy or sell certain stocks or as the aggregate effect of individually taken investor decisions, revealed to the market by price formation and returns. In the case of micro-level herding in flows, the methodology is shown to either overestimate herding- regarding spurious herding and correlated trading also as herding- or underestimating herding - due to the structure of the metric used. Herding nonetheless, is identified on the micro-level

of investors consistently for most markets and is robust to the method of estimation used. On the other hand, herding on the macro-level, thus the consensus of returns, is not identified in most markets, with the notable exception of concentrated, poorly organised and emerging markets. What is more, the methodologies used to identify aggregate herding employ the dispersion of assets, via measures of cross sectional deviation. These methods do not account for variability, are often based on arbitrary choices regarding price movements as an indicator of stress, do not consider the sensitivity of returns to other factors and have an often linear structure that may misrepresent reality.

The critical review of the literature - Part I - assists in observing the evolution of herding as both a concept and a financial phenomenon. By regarding herding, both as a psychological and sociological notion and as a revealed choice, we are able to understand both the nature of the phenomenon and its way of manifestation in the market. Especially, by the examination of the empirical means to investigate herding, this Part manages to encounter several issues and gaps that are worth studying. Such a gap, is explored in Part II through two separate essays. As already mentioned above there exist two major methodologies investigating herding, that are conceptually different and, in lack of a better term, disagree on whether herding exists in the market or not. In Chapter 3, this disagreement is explored. Evidence that it is possible for herding to exist in the micro-level and not manifest on the aggregate level are discovered. This evidence then leads to further investigation of the mechanism of transmission that allows for this to happen.

The initial analysis indicates that micro-level herding, does relate to the consensus, but mostly when it is very low or high. Given, the overwhelming research on the importance of the type of investor, its sophistication and the asymmetrical distribution of information between different investor groups, we suspect that the type of investor may affect the mechanism of transmission of herding, from the level of trading to the level of returns. Indeed, using the mean volume per trade market-wide as an indicator of the market composition in term of investors, we come across findings that imply that the type of investor, or investor group does affect the mechanism of transmission of herding. The findings indicate that on days when trading is dominated by smaller investors, with less sophistication that may face barriers to information, herding in flows transmits to the consensus of returns. On the contrary, when the mean volume per trade is high, indicating a stronger presence of large institutional investors, micro-level herding leads to higher variability, thus implying that institutional investors trade against individual investors to mitigate the effect of herding.

This leads to the natural question of whether the direction of trading and herding reveals information about this equilibrium. The direction of trading and herding are examined in Chapter 4 of the same part. By incorporating measures of the direction and extent of trading - mostly via trading imbalances - we observe that trading direction and magnitude on its own does not affect herding to the consensus. On the other hand, directional herding, when sells and buys are examined separately, does influence the consensus of returns mostly when we account for the trading concentration in terms of investors. When the effect of buy and sell herding and their extreme values are studied jointly, the importance of the balance between sell and buy herding simultaneously is highlighted. Sell herding performed by retail investors relates highly to market-wide herding, indicating higher contagion of

sell herding when the market is dominated by unsophisticated and smaller investors. Moreover, institutional buy herding, examined jointly with institutional sell herding, is able to contribute in explaining a bigger part of market wide herding, implying the importance of institutional buys as informational signals at the same time. The distinct nature of sells and buys and the different variables that affect different investor groups are essential to that fact.

The empirical findings of Part II relate to both conventional and traditional finance. The idea that the market equilibrium is determined by the balance between noise traders and arbitrageurs, is a concept used by traditional financial models. The limits to arbitrage that may lead to inefficiency, due to extensive noise trading, can affect herding as well. If micro-level herding mostly leads to aggregate herding, when performed by retail, inexperienced investors and it is then mitigated via the more sophisticated trades of institutional investors, then the limits that apply to arbitrage theory, also apply to the mechanism of transmission of herding. What is more, the type of investor may also affect both the conventional and the behavioural perspective. Individual investors and small institutions do not have the same access to information, as a large institution does. Furthermore, the cost of effectively accessing, processing and analysing information is not the same for all agents in the market. Additionally, the differences in sentiment and investment style are also related to the results of this specific Part and the overall thesis. Given that retail investors are affected differently by information and that institutional investors have mechanisms in place to avoid this behavioural pitfall, it is only logical for retail investor sentiment to affect herding in the direction that it does.

Even more so, when we consider the direction of trading, the extent of micro-level herding and their relation with the consensus of returns, the difference between the type of investor becomes more essential. It has been both theoretically predicted and empirically demonstrated by existing literature, that the decision to sell is different from the decision to buy. This notion is supported by both conventional and behavioural theories and models and is based on both liquidity constraints and barriers to information, faced by different investor groups, and on the different cognitive process that buys entail compared to sells -and vice versa. Limited liquidity of individual investors, greater analysis tools used by large institutions, attention bias and conservatism are only some of the concepts that affect differently buys and sells and consecutively buy and sell herding. The evidence indicates that individual sell herding and institutional buy herding transmit to the market consensus, when employed simultaneously. Again the information included in volume per trade is related to the mechanism of transmission, implying that both the type and sophistication of investors in the market and their information set, influence the balance between retail investors that herd and institutional investors that counter trade sentiment.

These findings are essential for modelling and analysing herding. Empirically, the intent of herding is not sufficiently examined, at least in the case of market-wide herding. The results of this thesis reveal information about the type of herding that may distort the market, indicating that the smaller, less sophisticated and less informed investors are more prone to herd in a distortive manner. This fact may, at least partially explain why market-wide herding is mostly encountered in emerging markets and in stocks with a challenging valuation process - as in the dot-com crisis. It is essential for academics to account for the source of herding, in order to assess whether or not herding may negatively impact market efficiency. Furthermore, it

is important for market organisers and policy makers to acknowledge the fact that who trades and how is important. The more education and information available to investors, the less market distortion herding may cause. It would be beneficial for the methodological tools, used both by market policy makers and market agents and by academics, to improve in order to account for the dynamics of the mechanism of transmission of herding from flows to returns.
But is the mechanism of transmission of herding the only methodological improvement that shall be made in order to better estimate herding to the consensus? The use of the dispersion of assets, via the cross sectional, or the cross sectional absolute, deviation of returns has been identified by researchers to bear several limitations. Such a limitation is the relation between the dispersion of assets and volatility, both analytically and conceptually. Moreover, the intraday variability that does not necessarily affect closing prices and thus returns, may act as a signal in the market and may affect investor choice within a trading session.
These methodological questions are the main focus of Part III. In Chapter 5 a relation between the cross sectional mean of the quadratic variation during extreme price movements and the dispersion of assets is identified. By modifying the simplest model for herding during extreme price movements, which makes use of the dispersion of assets as a dependent variable, the relation between extreme price fluctuations, realised volatility and the dispersion of assets is explored. The findings suggest that herding is affected by realised variability and that both models currently used are not capable of capturing this effect. By employing the cross sectional mean of the quadratic variation, both during extreme price movements and as a state of the market that may, in its own right, affect herding, evidence of the influence of realised volatility on aggregate herding are highlighted. Realised volatility during extreme price movements is accommodated into the model and the empirical outcome is affected by it, implying that the results of the model are affected by the intraday variability of stock prices. Additionally, market-wide herding is lower, the higher the intraday variability as indeed expected. Given that herding is affected by informational signals, the latter result, relates to theoretical models of informational herding and cascades, that predict that when informational signal are not easily identified, thus during contraindicative signals or uncertainty, herding due to informational cascades does not arise. The methodological link between volatility - precisely realised volatility - and herding is essential for understanding why more often than not, herding is not identified to the consensus of returns but its distortive effects may be present in the market.
The empirical findings, again, lead to the conclusion that empirical models of aggregate herding, neither fully represent the theoretical models of herding nor sufficiently explain the mechanism of the formation of the market consensus. Intraday variability and its significance for the market, both during normal markets and around special events -such as extreme price movements or macroeconomic announcements- is not accounted for when herding is concerned. Existing literature has shown a relation between the arrival of information, stock prices, liquidity and realised volatility. This relation is essential when we consider why herding is not captured by existing models. As choices represent signals and as the interpretation of such signals is influenced by the aforementioned variables, the individually taken decision of an agent to herd and the aggregate effect of these decisions are also affected by variability. High frequency variability may not be observed in returns, but affect the market

participants and thus it shall be accounted for when studying herding. The analytical connection between the volatility and the cross sectional standard deviation is also a key determinant of the essentiality of the consideration of realised volatility empirically.
These results could be essential for both market agents and academic researchers. Although the importance of volatility, in some forms, has been identified by researchers, the link between herding and such variability has not been identified before. The simple linear relation between the dispersion of assets and the market return or the squared market return, employed to identify herding to the consensus, is not always adequate to identify its presence in the market. This is important, both when identifying herding in research and for market agents who decide based on informational signals. Lastly, the concepts of bad and good volatility, albeit volatility that enhances market efficiency in comparison to volatility that poses a barrier to informational symmetry, strongly relate to our results, as the nature of the volatility may also affect herding.
All in all, empirical models of herding reveal restricted images of the market reality and could be improved. These improvements, regarding the mechanism of transmission, the analytical form of the models and the consideration of volatility as a factor could highly benefit both market agents and policy makers. Nonetheless, the empirical findings of this thesis are not without limitations. In the following part, limitations of these results and further research that could benefit the literature of herding are discussed.

Limitations and future research

As any empirical study, this thesis deals with certain limitations, that are relevant both to the concepts explored and to the data used. Many of the limitations of this thesis could be explored by future research in order to validate or confront the empirical findings.
To begin with, herding is a relevant concept, that entails details of human behaviour, including but not limited to the individual's mental health, the cognitive state of the individual, the specific environment of the decision making process, the peer pressure of the individual's group and the place of the individual in this group and many more characteristics. All these variables apply to individual cases and are unique to every singular choice of each individual, either manager or retail investor. It is impossible to aggregate or approximate all these variables in an empirical model, whose purpose is to examine the consensus of returns. Nonetheless, as in the case of the market's composition in terms of investors, certain variables can be approximated for the market mean, especially if we consider their distinct effect on herding. For example the environmental effect and the cognitive stress could be approximated by variables relevant to crises, such as sanitary crises and epidemics -i.e. the Covid-19 pandemic-, economic turmoil and political stress, such as election periods and scandals.
Empirical models and the data used to apply such models are bound to have limitations that will affect both the interpretation of the results and their transferability. To begin with, the empirical models chosen here are modifications of the existing models of herding and thus deal with many of the limitations the latter face. The simple structure, that allows for these models to be easily applicable, limits both

the nature of the relative relations, that we wish to study, and the variables, that we could include.
The data used, for the greatest part of this thesis, are intraday data, inferred from trading. As the inference is based on an algorithm, the results of this thesis bare a relative bias, that stems from errors in the identifications process. Furthermore, in order to identify the market composition in terms of investors, the mean volume per trade was employed. Although, as we have seen, the use of this variable as a proxy for investor type and investor sophistication is supported both by theoretical papers and empirical research, this variable remains an approximation of what this thesis wishes to examine, and as such mean volume per trade may not always adequately represent the market composition in terms of investors. For example, if investors, who probably hold superior information sets, decide to split their order in a time spam that exceeds the trading day, then it is possible for a large institutional investor to perform sequential smaller trades, albeit order splitting. The use of mean volume per trade, may then lead to investor misidentification. Although the DJIA 30 market is less prone to such practices, due to its composition and the type of investor who prefers its stocks, it remains a possibility that order splitting may affect our results, concerning the market composition in terms of investors. Similarly, often the choice of variable or concept may cause stampedes regarding the interpretation and robustness of our results. For the case of the realised volatility measure, that was also examined monthly, the choice of the quadratic variation intraday may limit the results. Other forms of volatility, and other concepts of it, may render different results. Based on data availability, other measures and notions of volatility could also be studied, by future research, in relation to market wide herding. The same could be said for the structure of the modified models used throughout this thesis
As mentioned above, the DJIA 30 is a market with a small composition that includes stocks with certain characteristics and attracts more a certain type of investor. The choice of such a market, although it ensures the necessary trading activity and liquidity, that is a prerequisite for the desired empirical analysis, limits the interpretation of our results. The DJIA 30 consists of large stocks that are, at least in theory, leaders in their respective industries. These type of stocks are by nature less attractive for speculators and noise traders. It would be highly informative to test the assumptions of this thesis in larger markets or in other types of stocks, in order to examine whether the results are similar or not. Apart from that, the DJIA 30 market is part of the larger U.S. market. Interaction between other U.S. stocks and the U.S. market as a whole may also influence the results. Again, future research could address this issue, for example by choosing a larger market. Similarly, this study could be applied to different markets, in order to test the effect of the market's organisation and the influence of the institutional framework in which agents operate.
These are some of the methodological limitations and future research propositions that are related to this thesis. This thesis attempts to examine empirically several concepts of herding and thus several of the results presented can be biased both due to the data selection and due to methodological choices. Apart from that, this thesis contributes both conceptually and empirically, to the literature of empirical herding estimation. Several variables and notions are examined in relation to aggregate herding and aggregate herding is revisited as a concept and a phenomenon.

Appendices

Appendix for Part 2

Appendix for Chapter 3

Microlevel herding in individual stocks: Arbitrary cases

It is important to look at the herding ratios, both based on trades and on value for an individual stock and its evolution in time. Here, we will briefly present for individual stocks the herding measures presented below and their time series evolution. Below, in Figures 1 and 2 we present the simple proportion of buys and the D-ratio for only three stocks in our dataset to examine how these measures evolve for individual stocks. The stocks are chosen arbitrarily with the criterion of existing in the dataset for a different range of time [1]

- American International Group Inc (AIG): From 03/01/2007 to 19/10/2008
- Alcoa (AA): From 0"/01/2007 to 20/09/2013
- American Express (AXP): From 03/01/2007 to 06/12/2019

In Figures 1 and 2 we observe that the D-ratio for the three stocks follow the pattern of the market while the proportion of trades (without extracting the market mean of proportion of trades) presents higher variation especially after 2010.

[1] As the composition of DJIA changes, different stocks exist in the DJIA for different time frames.

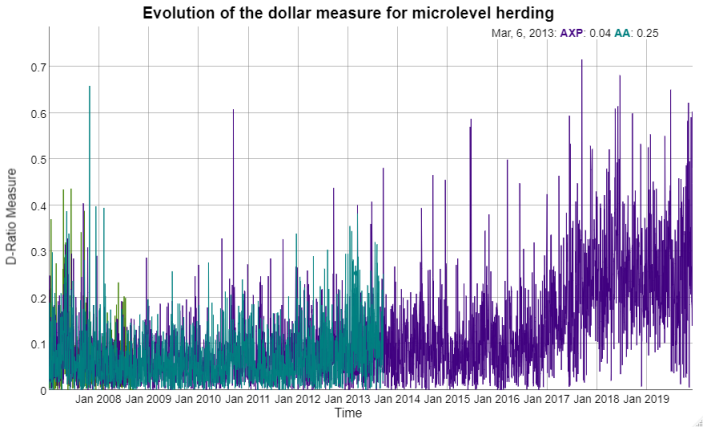


Figure 1: Figure showing the evolution on D-Ratio for AIG, AA and AXP daily

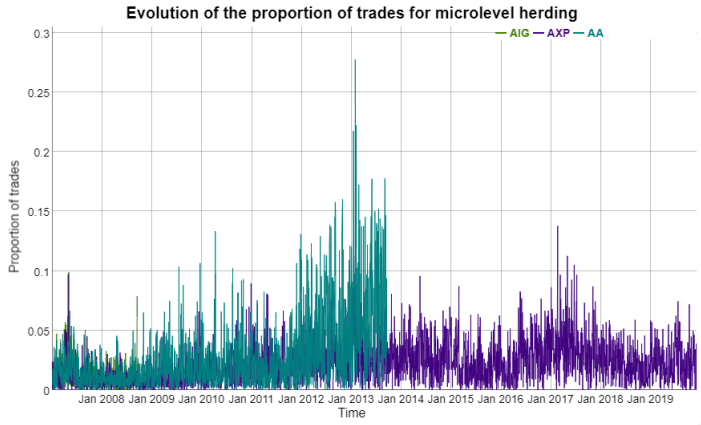


Figure 2: Figure showing the evolution on the proportion of buys for AIG, AA and AXP. We account for the expected proportion of buys for every stock in the market

The CH methodology for market wide herding

As a robustness test to the original CCK methodology by Chang et al. (2000), we present the CH methodology by Christie and Huang (1995), shown below:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{n}(r_{i,t} - r_{m,t})^2}{N-1}} \tag{1}$$

where CSSD is the cross sectional standard deviation computed for the whole sample. Then in order to test for herding we shall run the regression:

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t \tag{2}$$

Where $r_{i,t}$ is the return of asset i, N is the number of assets in the dataset, $\overline{r}$ is the cross sectional average of N returns in the market, D_t^L and D_t^U are dummy variables determining extreme market conditions as discussed in previous sections. According to traditional asset pricing models the estimated coefficients of the regression 5.1 should be positive -or non-significant- as in market stress more deviation , ie. volatility is expected. If herding is present in the market, the estimates of β_1 and β_2 shall be negative, indicating small CSSD in market stress.The results using three criteria, 1%, 2.5% and 5% at each sude of the market return distribution as presented in three separate panels in Table 1 As shown in Table 1, following the CH methodology based on the CSSD, no herding is identified in the market during market extremes.he coefficients of D_L and D_U are positive and statistically significant, so they are in line with the traditional theory as Christie and Huang(1995) also state. Christie and Huang(1995) also use - as a robustness- the CSAD in the place of the dependent variable in the regression presented in equation 2. As shown in the appendix of this chapter the results do not change when we use the CSAD and still no herding is found.
The CH method has been criticized for not accounting for a non- linear structure between the dispersion of returns and the return.

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0112	0.0001	93.5140	0.0000
A	D_L	0.0345	0.0055	6.1830	0.0000
1%	D_U	0.0309	0.0037	8.2490	0.0000
Panel	(Intercept)	0.0109	0.0001	94.0680	0.0000
B	D_L	0.0196	0.0027	7.1160	0.0000
2.5%	D_U	0.0184	0.0020	8.8390	0.0000
Panel	(Intercept)	0.0106	0.0001	94.3570	0.0000
C	D_L	0.0140	0.0015	8.9150	0.0000
5%	D_U	0.0118	0.0012	9.2350	0.0000

Table 1: Herding to the market consensus: The CH method. Results for equation 2 presented in three panels for the 1% (Panel A), for the 2.5% (Panel B)and for the 5% (Panel C) criterion

Using the CSAD as a robustness test for herding in the CH method

In the CH method we use the CSAD as a dependent variable to check the robustness of the results as follows:

$$CSAD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t \tag{3}$$

where the $CSAD_t$ is the cross sectional absolute deviation as computed in Chang et al.(2000).
In Table 2the results for equation 3 for the 1%, 2.5% and 5% criterion are presented in three separate panels. No herding is found. The results are identical to the

Variable		Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0080	0.0001	98.17	0.0000
A	D_L	0.0212	0.0008	26.42	0.0000
1% D_U	0.0213	0.0008	26.57	0.0000	
Panel	(Intercept)	0.0077	0.0001	91.96	0.0000
B	D_L	0.0128	0.0005	24.43	0.0000
2.5% D_U	0.0131	0.0005	25.10	0.0000	
Panel	(Intercept)	0.0075	0.0001	85.28	0.0000
C	D_L	0.0095	0.0004	24.75	0.0000
5%	D_U	0.0086	0.0004	22.39	0.0000

Table 2: Herding to the market consensus: Results for equation 3 using the $CSAD_t$ for the 5% criterion

original model presented in chapter 2.

Modifications to the CH methodology to account for microlevel herding

We use the mean measures of institutional and individual herding in the estimation of the market wide herding using the CH method as follows:

$$CSSD_t = a + \beta_1 D_t^L + \beta_2 D_t^U + \beta 3\overline{H_t} + \beta_4 D_t^L \overline{H_t} + \beta_5 D_t^U \overline{H_t} + \epsilon_t \quad (4)$$

and

$$CSSD_t = a + \beta_1 D_t^L + \beta_2 D_t^U + \beta 3\overline{DR_t} + \beta_4 D_t^L \overline{DR_t} + \beta_5 D_t^U \overline{DR_t} + \epsilon_t \quad (5)$$

The results for equation 4 are presented in Table 3 in three separate panels based on

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0177	0.0004	47.75	0.0000
A	D_L	0.0298	0.0038	7.93	0.0000
1%	D_U	0.0233	0.0036	6.53	0.0000
	$\overline{H_t}$	-0.2489	0.0134	-18.55	0.0000
	$D_L * \overline{H_t}$	0.1086	0.2937	0.37	0.7117
	$D_U * \overline{H_t}$	0.3371	0.2471	1.36	0.1726
Panel	(Intercept)	0.0168	0.0004	42.75	0.0000
B	D_U	0.0254	0.0024	10.74	0.0000
2.5%	D_U	0.0270	0.0021	13.08	0.0000
	$\overline{H_t}$	-0.2254	0.0142	-15.92	0.0000
	$D_L * \overline{H_t}$	-0.6207	0.1580	-3.93	0.0001
	$D_U * \overline{H_t}$	-0.6202	0.1086	-5.71	0.0000
Panel	(Intercept)	0.0158	0.0004	37.67	0.0000
C	D_L	0.0210	0.0018	11.93	0.0000
5%	D_U	0.0214	0.0016	13.15	0.0000
	$\overline{H_t}$	-0.1971	0.0149	-13.21	0.0000
	$D_L * \overline{H_t}$	-0.6411	0.1106	-5.80	0.0000
	$D_U * \overline{H_t}$	-0.5866	0.0779	-7.53	0.0000

Table 3: The effect of microlevel herding to the consensus: Results for equation 4. Results presented in three panels: for the 1% (Panel A), for the 2.5% (Panel B) and for the 5% (Panel C) criterion

the criteria used to determine D_t^L and D_t^U. Similarly, the results for equation 5 are displayed in Table 4. For the 1% criterion the results are not significant. This could be an indication of trading being based on investors having private information in the 1% extreme. The small number of observations for which the market return falls into the 1% upper and lower tail of its distribution could also contribute to these results. For the 2.5% and the 5% we observe that both $\overline{DR_t}$ and $\overline{H_t}$ have a negative effect on the cross sectional standard deviation both on each whole spectrum and in market extremes. This indicates that microlevel herding does correlate to market wide herding. The nature of the results is similar to the modifications performed in the CCK methodology.

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0139	0.0003	49.95	0.0000
A	D_L	0.0422	0.0037	11.28	0.0000
1%	D_U	0.0322	0.0034	9.48	0.0000
	$\overline{DR_t}$	-0.0209	0.0019	-10.81	0.0000
	$D_L * \overline{DR_t}$	-0.1143	0.0457	-2.50	0.0125
	$D_U * \overline{DR_t}$	-0.0209	0.0335	-0.63	0.5318
Panel	(Intercept)	0.0133	0.0003	45.61	0.0000
A	D_L	0.0264	0.0018	14.32	0.0000
2.5%	D_U	0.0234	0.0020	11.62	0.0000
	$\overline{DR_t}$	-0.0186	0.0020	-9.24	0.0000
	$D_L * H_t$	-0.0871	0.0186	-4.69	0.0000
	$D_U * H_t$	-0.0566	0.0185	-3.06	0.0022
Panel	(Intercept)	0.0126	0.0003	41.33	0.0000
C	D_L	0.0206	0.0013	15.87	0.0000
5%	D_U	0.0179	0.0015	12.21	0.0000
	$\overline{DR_t}$	-0.0154	0.0021	-7.41	0.0000
	$D_L * \overline{DR_t}$	-0.0783	0.0122	-6.44	0.0000
	$D_U * \overline{DR_t}$	-0.0636	0.0128	-4.98	0.0000

Table 4: The effect of microlevel herding to the consensus: Results for equation 5. Results presented in three panels: for the 1% (Panel A), for the 2.5% (Panel B) and for the 5% (Panel C) criterion

Accounting for microlevel herding in extremes

We will account for the level of microlevel herding in extremes- and not just the state of microlevel herding being extremely low or high- in a set of equations as follows:

$$CSAD_t = \alpha + \gamma_1 |r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 100\% * DH_t^L * \overline{H_t} r_{m,t}^2 + \gamma_4 100\% * DH_t^U * \overline{H_t} r_{m,t}^2 + \epsilon_t \quad (6)$$

and

$$CSAD_t = \alpha + \gamma_1 |r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 100\% * DDR_t^L * \overline{DR_t} r_{m,t}^2 + \gamma_4 100\% * DDR_t^U * \overline{DR_t} r_{m,t}^2 + \epsilon_t \quad (7)$$

Measures DH_t^L and DH_t^U are dummy variables that take the value one if the $\overline{H_t}$ falls below and above a certain percentage of the distribution respectfully. The same principles applies to the dummy variables DDR_t^L and DDR_t^L regarding the $\overline{DR_t}$ measure. $\overline{H_t}$ and $\overline{DR_t}$ are the market mean microlevel herding at t. The results are presented below in Table 5 The results are similar to those presented in Chapter 3 and are not dependent on the level - extent but the state.

Equations 3.8 and 3.9 for the criterion of 20% on each side of the $\overline{H_t}$ and $\overline{DR_t}$ distributions

For micro-level herding defined either as $\overline{H_t}$ or as $\overline{DR_t}$ we run regressions 3.8 and 3.9 choosing the 20% as a criterion for the determination of the dummy variables.

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0061	0.0002	37.6939	0.0000
A	$\|r_m\|$	0.2692	0.0364	7.3909	0.0000
Eq. 6	r_m^2	1.3547	0.8472	1.5989	0.1099
	$100\% * DH_t^L * \overline{H_t} r_m^2$	0.9156	0.9369	0.9773	0.3285
	$100\% * DH_t^U * \overline{H_t} r_m^2$	-2.4035	0.5722	-4.2009	0.0000
Panel	(Intercept)	0.0061	0.0002	39.8870	0.0000
B	$\|r_m\|$	0.2634	0.0349	7.5534	0.0000
Eq. 7	r_m^2	1.8084	0.9485	1.9067	0.0566
	$100\% * DDR_t^L * \overline{DR_t} r_{m,t}^2$	0.2991	0.1535	1.9489	0.0514
	$100\% * DDR_t^U * \overline{DR_t} r_{m,t}^2$	-0.2313	0.0285	-8.1206	0.0000

Table 5: Herding to the consensus and micro-level herding at extremes: joint effect. Results for the 12.5% criterion presented in two Panels: for equation 6 (Panel A) and for equation 7 (Panel B)

The results are qualitatively similar as the ones presented in chapter 3 concerning only the state of micro-level herding.

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0061	0.0001	55.87	0.0000
A	$\|r_m\|$	0.2668	0.0150	17.82	0.0000
Eq.3.8	r_m^2	2.2386	0.4079	5.49	0.0000
	$r_m^2 * DH_t^L$	-0.4105	0.3224	-1.27	0.2030
	$r_m^2 * DH_t^U$	-10.9385	1.8487	-5.92	0.0000
Panel	(Intercept)	0.0061	0.0001	56.40	0.0000
B	$\|r_m\|$	0.2522	0.0150	16.87	0.0000
3.9	r_m^2	1.7591	0.2356	7.47	0.0000
	$r_m^2 * DDR_t^L$	2.1217	0.3086	6.87	0.0000
	$r_m^2 * DDR_t^U$	-5.4446	1.0093	-5.39	0.0000

Table 6: Herding to the consensus and microlevel herding at extremes. Results for the 20% criterion presented in two Panels: for equation 3.8 (Panel A) and for equation 3.9 (Panel B)

Trading Imbalances as a measure of herding. Estimations for individual stocks and information on equation 3.10

Equation 3.10 implies that the relation between tha market trading imbalance and the trading imbalance of individual stocks is linear. If we suppose that this is true- that is not necessarily the case - then the expected trading imbalance of each stock is affected by the market trading imbalance linearly as follows:

$$E_t[T_i] = \kappa_0 + \kappa_i E_t[T_m - \kappa_0] \tag{8}$$

Where T_i is the trading imbalance for stock i at t while T_m the weighted mean of all trading imbalances for all stocks in a market [2] The above equation is highly inspired by the capital asset pricing model for returns. Here the parameter κ_i shows the impact of the market trading imbalance on each individual stock.
The cross sectional mean of the the absolute residuals of equation 3.10 represents the average absolute trading deviation from the market cross-sectionally. We use then as such to define low or high dispersion of trading imbalances.

[2] Or a portfolio

Ticker	Estimate,	Std Error	t value	Pr
AA	1.3464	0.0430	31.3164	0.0000
AIG	1.3627	0.1845	7.3863	0.0000
AXP	0.3256	0.0135	24.1200	0.0000
BA	0.1583	0.0102	15.5431	0.0000
C	3.2846	0.2174	15.1087	0.0000
CAT	0.1914	0.0114	16.7803	0.0000
DD	0.2336	0.0128	18.2915	0.0000
DIS	0.6622	0.0227	29.1799	0.0000
GE	3.3655	0.0873	38.5516	0.0000
GM	0.9655	0.1271	7.5977	0.0000
HD	0.3787	0.0159	23.8030	0.0000
HON	0.5717	0.0597	9.5770	0.0000
HPQ	0.8042	0.0445	18.0685	0.0000
IBM	0.1763	0.0105	16.7887	0.0000
INTC	2.6122	0.0474	55.0676	0.0000
JNJ	0.5595	0.0170	32.8262	0.0000
JPM	1.0439	0.0275	37.9281	0.0000
KO	1.1360	0.0347	32.6957	0.0000
MCD	0.2603	0.0123	21.0826	0.0000
MMM	0.1082	0.0077	14.1385	0.0000
MO	1.1611	0.0826	14.0519	0.0000
MRK	0.9175	0.0240	38.2058	0.0000
MSFT	3.0186	0.0518	58.2592	0.0000
PFE	2.4037	0.0541	44.4374	0.0000
PG	0.6212	0.0260	23.9099	0.0000
T	1.5630	0.0488	31.9959	0.0000
UTX	0.2132	0.0098	21.8047	0.0000
VZ	1.3448	0.0376	35.7846	0.0000
WMT	0.5480	0.0239	22.9079	0.0000
XOM	0.7676	0.0242	31.6721	0.0000
BAC	5.4553	0.1403	38.8959	0.0000
CVX	0.2953	0.0154	19.1509	0.0000
KFT	0.5928	0.0422	14.0583	0.0000
CSCO	2.5815	0.0813	31.7673	0.0000
TRV	0.1468	0.0113	12.9542	0.0000
UNH	0.2474	0.0195	12.6556	0.0000
GS	0.1922	0.0206	9.3348	0.0000
NKE	0.8245	0.0418	19.7257	0.0000
V	0.9188	0.0388	23.7049	0.0000
AAPL	1.6290	0.1423	11.4476	0.0000
DWDP	0.6208	0.0740	8.3859	0.0000
WBA	1.0280	0.1554	6.6133	0.0000
DOW	0.6549	0.1240	5.2814	0.0000

Table 7: Results for the Estimation of the coefficient κ_i regarding Equation 3.10 across t

Market-wide herding and the type of investor: Equation 3.13 without the natural logarithm

If we use the variable volume per trade without scaling it via a logarithm we have:

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 VpT_t r_{m,t}^2 + \epsilon_t \tag{9}$$

In Table 8 we present the results for this estimation. The nature of the results is not affected by this modification.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0061	0.0001	48.954	0.0000
$\|r_{m,t}\|$	0.2668	0.0271	9.8630	0.0000
$r_{m,t}^2$	-2.8999	1.3620	-2.1290	0.0034
$VpT_t r_{m,t}^2$	0.0058	0.0017	3.3510	0.0008

Table 8: Results for equation 9: The effect of volume per trade as a proxy for market composition

Estimations without accounting for heteroskedasticity

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0060	0.0001	55.33	0.0000
A	$\|r_m\|$	0.2671	0.0153	17.45	0.0000
Eq. 3.6	r_m^2	2.1701	0.3299	6.58	0.0000
	$\overline{H_t} * r_m^2$	-25.1193	26.1968	-0.96	0.3377
Panel	(Intercept)	0.0061	0.0001	56.52	0.0000
A	$\|r_m\|$	0.2678	0.0141	18.96	0.0000
Eq. 3.7	r_m^2	4.9553	0.4112	12.05	0.0000
	$\overline{DR_t} * r_m^2$	-35.0004	3.9397	-8.88	0.0000

Table 9: The aggregate effect of microlevel herding to the consensus. Results presented in two Panels: for equation 3.6 (Panel A) and for 3.7 (Panel B)

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0061	0.0001	55.84	0.0000
A	$\|r_m\|$	0.2679	0.0144	18.58	0.0000
Eq. 3.8	r_m^2	1.7436	0.2912	5.99	0.0000
	$r_m^2 * DH_t^L$	0.1984	0.2398	0.83	0.4081
	$r_m^2 * DH_t^U$	-10.8418	3.0472	-3.56	0.0004
Panel	(Intercept)	0.0061	0.0001	55.83	0.0000
B	$\|r_m\|$	0.2635	0.0146	17.99	0.0000
Eq. 3.9	r_m^2	1.8093	0.2362	7.66	0.0000
	$r_m^2 * DDR_t^L$	1.4965	0.3726	4.02	0.0001
	$r_m^2 * DDR_t^U$s	-5.7124	1.1248	-5.08	0.0000

Table 10: Herding to the consensus and microlevel herding at extremes. Results for the 12.5% criterion presented in two Panels: for equation 3.8 (Panel A) and for equation 3.9 (Panel B)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0061	0.0001	56.48	0.0000
$\|r_{m,t}\|$	0.2976	0.0150	19.88	0.0000
$r_{m,t}^2$	1.8389	0.2350	7.82	0.0000
$DRES_t^L r_{m,t}^2$	-0.0863	0.0117	-7.37	0.0000

Table 11: Results for equation 3.11: Market wide herding and the dispersion of trading imbalances.

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0061	0.0001	59.05	0.0000
$\|r_{m,t}\|$	0.2768	0.0135	20.46	0.0000
$r_{m,t}^2$	-38.6328	2.0873	-18.51	0.0000
$VpT_t r_{m,t}^2$	6.0797	0.3109	19.55	0.0000

Table 12: Herding to the market consensus and the type of investor in the market: Results for equation 3.13

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0061	0.0001	57.75	0.0000
A	$\|r_{m,t}\|$	0.2624	0.0140	18.68	0.0000
10%	$r_{m,t}^2$	1.2576	0.2335	5.39	0.0000
	$DVol_t^L \overline{H_t} r_{m,t}^2$	-2.7282	0.4789	-5.70	0.0000
	$DVol_t^U \overline{H_t} r_{m,t}^2$	2.2503	0.0017	13.37	0.0000
Panel	(Intercept)	0.0061	0.0001	59.02	0.0000
B	$\|r_{m,t}\|$	0.2589	0.0141	18.35	0.0000
20%	$r_{m,t}^2$	0.9669	0.2300	4.20	0.0000
	$DVol_t^L \overline{H_t} r_{m,t}^2$	-2.7920	0.3656	-7.64	0.0000
	$DVol_t^U \overline{H_t} r_{m,t}^2$	2.5048	0.1544	16.22	0.0000
Panel	(Intercept)	0.0061	0.0001	58.71	0.0000
C	$\|r_{m,t}\|$	0.2665	0.0144	18.48	0.0000
30%	$r_{m,t}^2$	0.7058	0.2344	3.01	0.0026
	$DVol_t^L \overline{H_t} r_{m,t}^2$	-3.0003	0.3489	-8.60	0.0000
	$DVol_t^U \overline{H_t} r_{m,t}^2$	2.2099	0.1533	14.42	0.0000

Table 13: Herding to the market consensus, the effect of microlevel herding and the type of trader.Results for equation3.15 regarding the $\overline{H_t}$ presented in three panels: for the 10% (Panel A), for the 20% (Panel B) and for the 30% (Panel C) criterion

Appendix for Chapter 4

Stocks with a positive trading imbalance and market-wide herding

Another variable, that may reveal a lot about trading, is the proportion of stocks during a day with positive or negative trading imbalance using different measures. The extent of imbalance is of course important, but given that different stock returns are weighted equally in order to measure the market return, we should look into what proportion of stocks in a day have a positive trading imbalance based on different types of measure. What is more, a measure which investigates the relative relationship between stocks bought and sold reveals information about market sentiment (in the spirit of Lee and Kumar (2006) for retail investors). In Figure 3 this proportion is graphically displayed - both jointly and separately using the number of trades and value as the determinant for the imbalance. The proportion of stocks with positive trading imbalance is computed as follow:

$$PR^G = \frac{N_1^G}{N_1^G + N_2^G} \tag{10}$$

where G is the indicator of the determinant- albeit number of trades or value- $N1$ is the number of stocks with a positive trading imbalance based on G and $N2$ is the number of stocks with a negative trading imbalance based on G. As we can see in Figure3, the number of stocks with a positive trading imbalance on trades in a day is more stable, while the one on value fluctuates more during and after the crisis. This is an indicator that the stress from the crisis affected more the value based measure.
In order to account for the direction of trading we employ the proportion of stocks with positive trading imbalance daily both measured on trades, on volume and on value. We use the following specification:

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r_{m,t}^2 + \gamma_3 PR_t^G r_{m,t}^2 + \epsilon_t \tag{11}$$

where PR_t^G for $G = tr, vol, \$$ is the proportion of stocks having a positive trading imbalance on counts of trades, volume or value a presented earlier in equation 10. The results for both cases are presented in three separate panels in Table 14.

By incorporating the ratio of stocks with a positive imbalance in the CKK measure, we can observe if the direction of trading in the market as a whole affects market wide herding. There does not seem to exist a relation between the proportion of stocks with a positive trading imbalance and market wide herding for all measures. The direction of trading as captured by the proportion of stocks with a

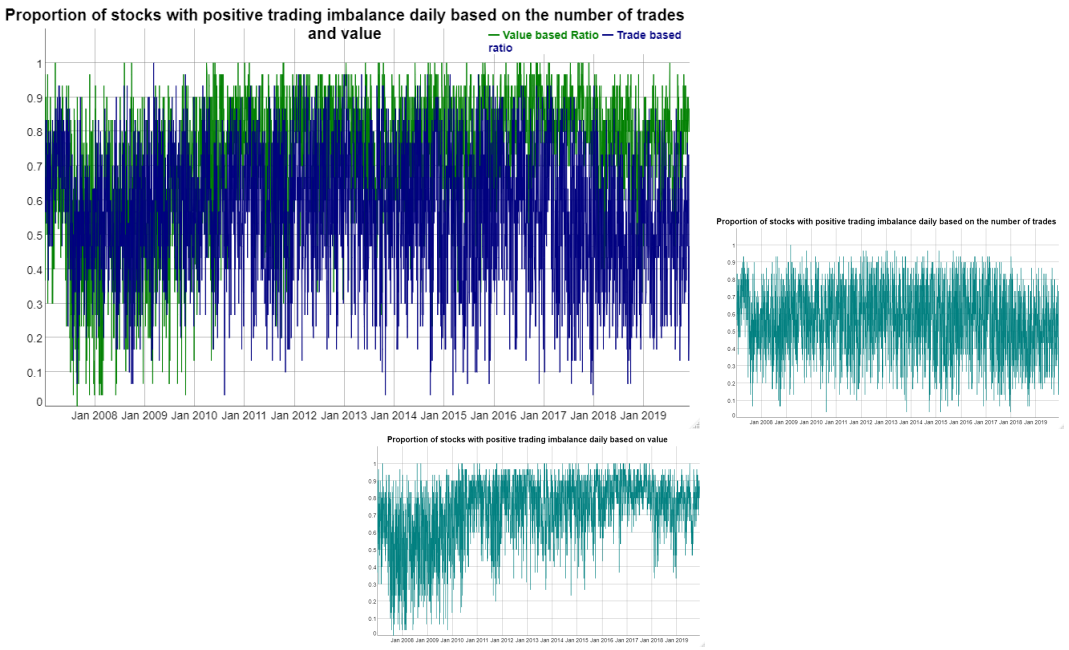


Figure 3: Proportion of stocks with positive trading imbalance daily based on the number of trades and value for the DJIA- joint presentation

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0061	0.0001	43.8100	0.0000
A	$\|r_{m,t}\|$	0.2533	0.0319	7.9450	0.0000
$G = tr$	$r^2_{m,t}$	3.4021	1.1609	2.931	0.0034
	$PR^{tr}_t r^2_{m,t}$	-2.2881	1.4642	-1.5630	0.1182
Panel	(Intercept)	0.0060	0.0001	36.6980	0.0000
B	$\|r_{m,t}\|$	0.2613	0.0388	6.7400	0.0000
$G = vol$	$r^2_{m,t}$	1.8768	1.1569	1.6220	0.1050
	$PR^{vol}_t r^2_{m,t}$	0.1713	1.6567	0.1030	0.9180
Panel	(Intercept)	0.0060	0.0001	36.7530	0.0000
C	$\|r_{m,t}\|$	0.2614	0.0387	6.7550	0.0000
$G = val$	$r^2_{m,t}$	1.8857	1.1686	1.6140	0.1070
	$PR^{val}_t r^2_{m,t}$	-0.1494	1.2200	-1.8754	0.0.9290

Table 14: Herding to the market consensus and the proportion of stocks with positive imbalance: Results for equation 11 presented in three Panels: Panel A($G = tr$), Panel B ($G = vol$) and Panel C($G = \$$)

positive trading imbalance does not affect market wide herding.
We will also employ this measure in its extremes, to look into the effect of extreme the proportion of buys and sells to the market consensus as follows:

$$CSAD_t = \alpha + \gamma_1|r_{m,t}| + \gamma_2 r^2_{m,t} + \gamma_3 D^{PR^G}_L PR^G_t r^2_{m,t} + +\gamma_3 D^{PR^G}_U PR^G_t r^2_{m,t} + \epsilon_t \quad (12)$$

where PR^G_t is defined as above and the two dummy variables $D^{PR^G}_L$ and $D^{PR^G}_U$ define two states of relatively low and high proportion of stocks with a positive trading imbalance, given a certain criterion x%. The results for the 12.5% criterion for $G = tr, vol, \$$. As shown in table 15, no effect of the proportion of stocks with a positive trading imbalance is found on herding to the market consensus.

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0061	0.0002	38.65	0.0000
A	$\|r_{m,t}\|$	0.2474	0.0377	6.56	0.0000
$G = tr$	$r^2_{m,t}$	2.0735	1.4616	1.42	0.1561
	$D_L^{PR^{tr}} PR_t^{tr} r^2_{m,t}$	2.8793	3.9194	0.73	0.4626
	$D_U^{PR^{tr}} PR_t^{tr} r^2_{m,t}$	-1.7222	1.2138	-1.42	0.1561
Panel	(Intercept)	0.0060	0.0002	36.24	0.0000
B	$\|r_{m,t}\|$	0.2623	0.0393	6.68	0.0000
$G = vol$	$r^2_{m,t}$	1.9037	1.3221	1.44	0.1500
	$D_L^{PR^{vol}} PR_t^{vol} r^2_{m,t}$	0.1085	2.7638	0.04	0.9687
	$D_U^{PR^{vol}} PR_t^{vol} r^2_{m,t}$	0.3722	1.1741	0.32	0.7513
Panel	(Intercept)	0.0060	0.0002	36.26	0.0000
C	$\|r_{m,t}\|$	0.2623	0.0392	6.69	0.0000
$G = val$	$r^2_{m,t}$	1.8986	1.3367	1.42	0.1556
	$D_L^{PR^{val}} PR_t^{val} r^2_{m,t}$	0.0757	2.8130	0.03	0.9785
	$D_U^{PR^{val}} PR_t^{val} r^2_{m,t}$	0.5550	1.0990	0.51	0.6136

Table 15: Herding to the market consensus and the extreme proportion of stocks with positive imbalance: Results for the 12.5% criterion for equation 12 presented in three Panels: Panel A($G = tr$), Panel B ($G = vol$) and Panel C($G = \$$)

Estimations without accounting for heteroskedasticity

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.01	0.00	29.02	0.0000
A	$\|r_{m,t}\|$	0.2533	0.0579	4.3755	0.0000
$G = tr$	$r^2_{m,t}$	3.4022	1.5182	2.2409	0.0251
	$PR_t^{tr} r^2_{m,t}$	-2.2881	1.2200	-1.8754	0.0608
Panel	(Intercept)	0.0060	0.0002	26.9007	0.0000
B	$\|r_{m,t}\|$	0.2613	0.0634	4.1184	0.0000
$G = vol$	$r^2_{m,t}$	1.8768	1.3578	1.3822	0.1670
	$PR_t^{vol} r^2_{m,t}$	0.1713	1.4868	0.1152	0.9083
Panel	(Intercept)	0.0060	0.0001	55.67	0.0000
C	$\|r_{m,t}\|$	0.2614	0.0143	18.23	0.0000
$G = \$$	$r^2_{m,t}$	1.8857	0.3072	6.14	0.0000
	$PR_t^{\$} r^2_{m,t}$	0.1494	0.4582	0.33	0.7445

Table 16: Herding to the market consensus and the proportion of stocks with positive imbalance: Results for equation 11 presented in three Panels: Panel A($G = tr$), Panel B ($G = vol$) and Panel C($G = \$$)

	Variable	Estimate	Std. Error	t value	Pr(>|t|)
Panel	(Intercept)	0.0061	0.0001	56.84	0.0000
A	$\|r_{m,t}\|$	0.2832	0.0141	20.07	0.0000
$G = tr$	$r^2_{m,t}$	3.5016	0.2665	13.14	0.0000
	$\|RTI^{tr}_t\| * D^{tr}_B r^2_{m,t}$	-0.7417	0.0673	-11.02	0.0000
	$\|RTI^{tr}_t\| * D^{tr}_S r^2_{m,t}$	-1.5169	0.1708	-8.88	0.0000
Panel	(Intercept)	0.0061	0.0001	55.93	0.0000
B	$\|r_{m,t}\|$	0.2593	0.0143	18.16	0.0000
$G = vol$	$r^2_{m,t}$	2.6038	0.2845	9.15	0.0000
	$\|RTI^{vol}_t\| * D^{vol}_B r^2_{m,t}$	-0.0689	0.0362	-1.90	0.0571
	$\|RTI^{vol}_t\| * D^{vol}_S r^2_{m,t}$	-0.1837	0.0394	-4.66	0.0000
Panel	(Intercept)	0.0061	0.0001	55.92	0.0000
C	$\|r_{m,t}\|$	0.2557	0.0144	17.77	0.0000
$G = \$$	$r^2_{m,t}$	2.6623	0.3016	8.83	0.0000
	$\|RTI^{val}_t\| * D_B S^{val} r^2_{m,t}$	-0.0794	0.0417	-1.90	0.0570
	$\|RTI^{val}_t\| * D^{val}_S r^2_{m,t}$	-0.1660	0.0416	-3.99	0.0001

Table 17: Herding to the market consensus and the direction of relative trading imbalance: Results for equation 4.3 presented in three Panels: Panel A($G = tr$), Panel B ($G = vol$) and Panel C($G = \$$)

Panels		Estimate	Std. Error	t value	Pr(>|t|)
Panel A	(Intercept)	0.0059	0.0001	61.71	0.0000
All	$r_{m,t}$	0.1503	0.0199	7.56	0.0000
Sample	$r^2_{m,t}$	2.8234	0.4298	6.57	0.0000
	$BH_t * r^2_{m,t}$	-110.8225	26.5196	-4.18	0.0000
Panel B	(Intercept)	0.0061	0.0001	58.71	0.0000
15%	$\|r_{m,t}\|$	0.2609	0.0140	18.58	0.0000
Criterion	$r^2_{m,t}$	1.0438	0.2310	4.52	0.0000
	$\overline{BH_t} * D^L_{origins} * r^2_{m,t}$	-234.6450	35.4451	-6.62	0.0000
	$\overline{BH_t} * D^U_{origins} * r^2_{m,t}$	229.1953	14.3230	16.00	0.0000
Panel C	(Intercept)	0.0061	0.0001	58.60	0.0000
20%	$\|r_{m,t}\|$	0.2591	0.0141	18.33	0.0000
Criterion	$r^2_{m,t}$	1.0238	0.2299	4.45	0.0000
	$\overline{BH_t} * D^L_{origins} * r^2_{m,t}$	-247.8931	32.3528	-7.66	0.0000
	$\overline{BH_t} * D^U_{origins} * r^2_{m,t}$	224.2980	13.9911	16.03	0.0000
Panel D	(Intercept)	0.0060	0.0001	56.12	0.0000
50%	$\|r_{m,t}\|$	0.3213	0.0150	21.40	0.0000
Criterion	$r^2_{m,t}$	1.1556	0.3038	3.80	0.0001
	$\overline{BH_t} * D^L_{origins} * r^2_{m,t}$	-306.6978	27.4365	-11.18	0.0000
	$\overline{BH_t} * D^U_{origins} * r^2_{m,t}$	21.4922	18.8494	1.14	0.2543

Table 18: Unscaled results without heteroskedasticity correction: Buy Herding, market herding and different percentages of volume to trade. Results are presented in Panels for equations 4.9 (Panel A) and equation 4.11 for the 15% (Panel B),for 20% (Panel C) and 50% (Panel D)

Appendix for Part 3

Appendix for Chapter 5

Using the mean return of stocks as a market return

Below we present the empirical results for Equations 5.1 and 5.3, regarding the intraday data of the DJIA constituents, when we use the mean return of the the 30 assets included in DJIA as the market return. As we can clearly observe the qualitive meaning of the results does not change. The results for intraday data are:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0164	0.0004	45.42	0.0000
D_t^L	0.0368	0.0036	10.23	0.0000
D_t^U	0.0214	0.0037	5.82	0.0000

Table 19: Equation 5.1: Results for 1% intraday using the mean return of stocks as market return

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0160	0.0004	43.67	0.0000
D_t^L	0.0225	0.0023	9.84	0.0000
D_t^U	0.0162	0.0023	7.11	0.0000

Table 20: Equation 5.1: Results for 2.5% intraday using the mean return of stocks as market return

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0156	0.0004	41.53	0.0000
D_t^L	0.0165	0.0017	9.84	0.0000
D_t^U	0.0114	0.0017	6.87	0.0000

Table 21: Equation 5.1: Results for 5% intraday using the mean return of stocks as market return

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0164	0.0004	45.96	0.0000
D_t^L	0.0017	0.0067	0.25	0.8034
D_t^U	-0.0253	0.0108	-2.35	0.0188
vol_t * D_t^L	0.3313	0.0539	6.14	0.0000
vol_t * D_t^U	0.6947	0.1508	4.61	0.0000

Table 22: Equation 5.3: Results for 1% intraday using the mean return of stocks as market return

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0160	0.0004	45.02	0.0000
D_t^L	-0.0068	0.0037	-1.84	0.0656
D_t^U	-0.0194	0.0052	-3.69	0.0002
vol_t * D_t^U	0.4067	0.0411	9.90	0.0000
vol_t * D_t^U	0.6932	0.0928	7.47	0.0000

Table 23: Equation 5.3: Results for 2.5% intraday using the mean return of stocks as market return

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0156	0.0004	44.00	0.0000
D_t^L	-0.0101	0.0025	-4.01	0.0001
D_t^U	-0.0168	0.0031	-5.47	0.0000
vol_t * D_t^L	0.4656	0.0345	13.50	0.0000
vol_t * D_t^U	0.6763	0.0633	10.68	0.0000

Table 24: Equation 5.3: Results for 5% intraday using the mean return of stocks as market return

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0037	0.0001	47.87	0.0000
D_t^L	-0.0022	0.0011	-2.12	0.0349
D_t^U	0.0053	0.0007	7.13	0.0000

Table 25: Equation 5.1 : Results for 1% daily using the mean return of stocks as market return

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0036	0.0001	48.41	0.0000
D_t^L	0.0017	0.0004	3.93	0.0001
D_t^U	0.0042	0.0004	9.57	0.0000

Table 26: Equation 5.1: Results for 2.5% daily using the mean return of stocks as market return

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0035	0.0001	45.27	0.0000
D_t^L	0.0014	0.0003	4.23	0.0000
D_t^U	0.0028	0.0003	8.43	0.0000

Table 27: Equation 5.1: Results for 5% daily using the mean return of stocks as market return

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0037	0.0001	47.79	0.0000
D_t^L	0.0046	0.0074	0.63	0.5316
D_t^U	0.0037	0.0027	1.37	0.1711
vol_t * D_t^L	-0.0284	0.0311	-0.91	0.3620
vol_t * D_t^U	0.0055	0.0089	0.61	0.5408

Table 28: Equation 5.3: Results for 1% daily using the mean return of stocks as market return

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0036	0.0001	49.40	0.0000
D_t^L	-0.0021	0.0014	-1.53	0.1277
D_t^U	0.0012	0.0014	0.89	0.3716
vol_t * D_t^L	0.0224	0.0077	2.91	0.0039
vol_t * D_t^U	0.0128	0.0055	2.35	0.0196

Table 29: Equation 5.3: Results for 2.5% daily using the mean return of stocks as market return

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0035	0.0001	49.01	0.0000
D_t^L	-0.0021	0.0010	-2.24	0.0258
D_t^U	-0.0014	0.0008	-1.83	0.0683
vol_t * D_t^L	0.0232	0.0059	3.94	0.0001
vol_t * D_t^U	0.0224	0.0037	6.02	0.0000

Table 30: Equation 5.3: Results for 5% daily using the mean return of stocks as market return

Bootstraping Results for Equation 5.1 and 5.3

Firstly, we will perform random sampling with replacement in order to verify that the estimation via ordinary least squares of equation 5.3 is robust.

	original	bootBias	bootSE	bootMed	bootSkew	bootKurt
(Intercept)	0.01	-0.00	0.00	0.01	-0.01	-0.14
D_t^L	0.03	-0.00	0.00	0.03	0.42	0.13
D_t^U	0.02	-0.00	0.00	0.02	0.45	0.76

Table 31: Bootstrapping of R=1000 in 1%: Equation 5.1

	original	bootBias	bootSE	bootMed	bootSkew	bootKurt
(Intercept)	0.01	0.00	0.00	0.01	0.17	0.19
D_t^L	0.02	-0.00	0.00	0.02	0.34	0.13
D_t^U	0.01	-0.00	0.00	0.01	0.16	-0.18

Table 32: Bootstrapping of R=1000 in 2.5%: Equation 5.1

	original	bootBias	bootSE	bootMed	bootSkew	bootKurt
(Intercept)	0.01	0.00	0.00	0.01	0.20	0.04
D_t^L	0.01	-0.00	0.00	0.01	0.20	-0.10
D_t^U	0.01	0.00	0.00	0.01	0.21	-0.08

Table 33: Bootstrapping of R=1000 in 5%: Equation 5.1

	original	bootBias	bootSE	bootMed	bootSkew	bootKurt
(Intercept)	0.01	-0.00	0.00	0.01	-0.01	-0.14
D_t^L	-0.00	0.00	0.01	-0.00	0.13	-0.22
D_t^U	-0.02	0.00	0.01	-0.02	0.00	0.39
vol_t * D_t^L	0.27	-0.02	0.07	0.26	-0.30	-0.55
vol_t * D_t^U	0.60	-0.02	0.14	0.59	-0.32	-0.05

Table 34: Bootstrapping of R=1000 in 1%: Equation 5.3

	original	bootBias	bootSE	bootMed	bootSkew	bootKurt
(Intercept)	0.01	-0.00	0.00	0.01	-0.06	0.16
D_t^L	-0.00	0.00	0.00	-0.00	0.21	-0.27
D_t^U	-0.01	0.00	0.00	-0.01	0.15	-0.02
vol_t * D_t^L	0.29	-0.00	0.05	0.29	-0.09	-0.58
vol_t * D_t^U	0.53	-0.00	0.08	0.53	-0.03	0.12

Table 35: Bootstrapping of R=1000 in 2.5%: Equation 5.3

As we can see above the bootstrapping bias and standard error are quite small. The original errors are bigger in the estimation of equation 5.3 as we can see in tables

	original	bootBias	bootSE	bootMed	bootSkew	bootKurt
(Intercept)	0.01	-0.00	0.00	0.01	0.07	-0.19
D_t^L	-0.01	0.00	0.00	-0.01	0.20	-0.31
D_t^U	-0.01	-0.00	0.00	-0.01	-0.07	-0.04
vol_t * D_t^L	0.31	-0.00	0.04	0.31	-0.01	-0.38
vol_t * D_t^U	0.47	0.00	0.06	0.47	-0.03	0.07

Table 36: Bootstrapping of R=1000 in 5%: Equation 5.3

34, 35 and 36 in comparison with tables 31, 32 and 33 that represent equation 5.1. This happens due to the introduction of more variables to the regression that create a dimensionality problem. By all means, the estimation of equation 5.3 is feasible and the variables are statistically significant but the possibility of errors augments with the number of variables. The results overall indicate that the model is robust.

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DOCTORAT BRETAGNE LOIRE ECONOMIE ET GESTION

UNIVERSITÉ DE NANTES

Titre : **Biais Comportementaux sur les Marchés Financiers : Le Cas Insaisissable de Herding**

Mots clés : Comportement mimétique, Herding, Finance comportementale, Dispersion des actifs

Résumé : Suite à la mise en évidence de certains aspects cognitifs dans les prise de décision économique, plusieurs comportements collectifs en économie et en finance ont été identifiés. Le mimétisme sur les marchés boursiers est l'une de ces manifestations, défini comme la tendance des agents économiques à suivre leurs pairs, en ignorant parfois une information dont ils disposent.
En examinant la littérature, cette thèse identifie une incohérence entre la conception théorique de mimétisme et son identification empirique. Les modèles empiriques sont divisés en deux catégories : ceux s'intéressant aux investisseurs (flux) et ceux examinant les rendements. Les modèles empiriques existants pour le mimétisme sur les rendements ne considèrent pas le mimétisme au niveau micro et certains facteurs importants, comme la variabilité des prix, qui affectent la robustesse de la méthodologie d'identification du mimétisme au niveau macro, basée sur les mesures de dispersion en coupe des rendements.
En utilisant une combinaison de données relatives aux transactions boursières et aux rendements des actions boursières, cette thèse examine dans un premier temps le manque de cohérence des résultats empiriques sur le mimétisme au niveau micro par rapport à celui portant sur le consensus des rendements. Il est montré quele miméstime au niveau micro, sa direction (vente ou achat) et la composition du marché (types d'investisseurs) affectent le mécanisme de transmission du mimétisme vers le consensus sur les rendements. En outre, un examen méthodologique des mesures de dispersion en coupe des rendements des actions révèle la faiblesse des résultats empiriques existants en raison de l'existence d'une relation entre la volatilité réalisée et ces mêmes mesures de dispersion.

Title: **Behavioural Biases in Financial Markets: The Elusive Case of Herding**

Keywords : Mimetic Behaviour, Herding, Behavioural Finance, Dispersion of Assets

Abstract : The introduction of cognitive limitations and psychological barriers to human decision making lies behind the identification of collective behaviour in economics and finance. Herding, is such a manifestation of mimetic behaviour and is defined as the tendency of financial agents to follow their peers, even disregarding their personal information set.
Through examination of the existing literature, this thesis identifies a discontinuity between the theoretical conception of herding and its empirical identification. Empirical models of herding are divided into herding in the level of investors and herding to the consensus of returns. Existing empirical models of herding to the consensus of returns, neither consider herding in micro-level nor account for important factors, such as price variability, that affect both the methodology developed to identify macro-level herding, based on the measures of cross–sectional dispersion of returns, and the decision making process of financial agents.
Using a combination of trading and stock related data, this thesis, initially examines the disagreement of empirical results of herding in the micro level compared to that of consensus of returns. Evidence that micro-level herding, the composition of the market in terms of investors and the direction of herding affect the mechanism of transmission of herding to the consensus of returns arise. Moreover, further methodological examination of the measures of dispersion of assets, reveals a relation between realised volatility and macro-level herding.
This thesis encounters evidence that the existing methodologies for the identificaction of herding, do not consider the mechanism of transmission of herding from flows to returns and the methodological and conseptual importance of price variability.