UNIVERSITÉ DE STRASBOURG

ÉCOLE DOCTORALE AUGUSTINE COURNOT (ED 221)

THÈSE présentée par :

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soutenue le : **01 JUIN 2016**

pour obtenir le grade de : **Docteur de l'université de Strasbourg**

Discipline/ Spécialité : Sciences Economiques

Essays on Monetary Analysis in Russia

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Acknowledgements

I am grateful to my supervisor, Laurent Weill, for his guidance to the completion of this thesis.

My deepest thanks go to Iikka Korhonen, Laura Solanko, Zuzana Fungáčová and others at the Bank of Finland Institute for Economies in Transition (BOFIT) for their encouragement and assistance in conducting and publishing my research projects.

I am indebted toward Björn Fischer, Julian von Landesberger, Michele Lenza, Franziska Schobert and others at the European Central Bank and the Deutsche Bundesbank for fruitful collaboration on monetary analysis.

Finally, I gratefully acknowledge that the research projects that constitute this thesis were completed as part of my work in the Monetary analysis unit of the Bank of Russia headed by Elena Vasilieva. I thank her as well as my other co-authors from the Bank of Russia for their invaluable support.

Brief Contents

Introduction

Les études des dernières décennies dans le domaine de l'analyse monétaire ont aidé les banques centrales à s'orienter dans la prise de décisions. Les modèles relativement simples basés sur les théories « monétaristes » de Milton Friedman sont de plus en plus adoptés en tant qu' instrument fondamental de l'analyse de la politique monétaire depuis les années 1970[1]. Ces modèles suggèrent que le PIB nominal peut être prédit d'une façon assez précise sur la base des taux d'accroissement précédents des indices de la masse monétaire. En fait, la croissance de la masse monétaire entraîne l'inflation et les anticipations d'inflation, alors que Friedman attendait que la croissance réelle reviendrait vite à la tendance qui était auparavant une influence de choc.

Malheureusement, ceux qui avaient accepté cette logique « monétariste », y compris les banques centrales qui avaient adopté le ciblage monétaire, ont été rapidement déçus. L'obtention de la fonction de demande de monnai stable sur laquelle se fondait tout le schéma monétaire s'est révélé une tâche irréalisable. Les objectifs de croissance de la masse monétaire sont devenus par la suite beaucoup moins à la mode, bien que les indicateurs monétaires restent un repère important dans la politique de certaines banques centrales, en particulier de la Banque centrale européenne. De plus, pendant la crise financière subséquente de 2008 l'importance des aspects de l'analyse monétaire précédemment méconnus a été reconnue.

Les banques centrales modernes et le rôle de l'analyse monétaire

L'analyse monétaire est utilisé, en premier lieu, pour identifier les risques pour la stabilité des prix, en particulier sur le long terme. La pertinence de considérations pareilles pour une banque centrale dont le mandat est de maintenir la stabilité des prix à moyen terme ne nécessite pas de preuve. Une ligne importante de cette étude est d'essayer d'identifier avec plus de précision les développements continus dans le domaine de questions monétaires liés à l'évolution du niveau des prix. A cet égard, l'amélioration de l'analyse monétaire lors de ces dernières années combine des éléments importants de continuité et une attention constante de cette analyse aux tendances monétaires et de prix sous-jacentes. L'approfondissement de cette approche traditionnelle à travers le développement de nouveaux outils destinés à étudier la relation entre les tendances monétaires

[1] Voir la revue de White (2013).

et les dynamiques sous-jacentes du niveau des prix est devenu central dans l'ordre du jour des chercheurs contemporains (pour plus de détails voir la recherche de Papademos et Stark (2010)).

La crise financière a aussi prédestiné une autre direction importante de l'analyse monétaire. Les paradigmes dominants avant-crise avaient considéré le secteur financier dans une large mesure en tant qu'un diaporama de fluctuations macroéconomiques. La crise a montré que cette hypothèse était dangereusement erronée. Contrairement à ce qui était souvent affirmé dans la littérature spécialisée, les taux d'intérêt ne peuvent pas exprimer l'essence de toutes les interactions entre le côté financier et le côté réel de l'économie. Les chercheurs sont maintenant à la recherche d'un moyen de corriger cette déficience : en documentant empiriquement le comportement des relations entre l'argent, les crédits, les prix des actifs et l'activité économique réelle ; en élaborant les indicateurs clés de l'effondrement financier ; et en étudiant les propriétés prédicatrices des différents indicateurs financiers, en plus des taux d'intérêt, pour l'activité économique.

Après tout, le mécanisme de création de monnaie est devenu l'un des principaux sujets d'étude de l'analyse monétaire. Ce thème est la pierre angulaire de la compréhension du mécanisme de transmission de la politique monétaire dans un environnement institutionnel donné. La création de monnaie endogène est présente dans un certain nombre de modèles économiques théoriques universels (et dans une certaine mesure hétérogènes) (Godley et Lavoie (2007), Jakab et Kumhof (2015), Brunnenmeier et Sannikov (2015)) et est largement acceptée dans la mise en œuvre pratique de l'analyse monétaire d'aujourd'hui (ECB (2011), McLeay et al. (2014)). Une autre indication du fait que la monnaie est un produit dérivé de crédit, est, cependant, en même temps une proposition de détourner l'attention des passifs bancaire et de la diriger sur les actifs bancaire (c'est-a-dire, de la monnaie au crédit), pour analyser la politique monétaire (Friedman (2012), Turner (2013)). D'après cette conception, l'octroi de crédits crée un nouveau pouvoir d'achat et, par conséquent, est essentiel pour l'analyse économique. La création ultérieure de diverses combinaisons d'instruments des passifs bancaire n'a pas d'importance particulière.

Pourtant, il existe une couche de littérature spécialisée qui attache une importance particulière aux indices de la masse monétaire et notamment à la divergence entre les dépôts et les crédits. L'une des raisons de cette approche est le lien entre ces études et les fluctuations des indicateurs importants de la stabilité financière, tels que l'indicateur de liquidité à long terme et le ratio de financement stable net. En particulier, Hahm et al. (2013) notent que la croissance disproportionnée des passifs bancaires secondaires ('non-core') est un outil essentiel de prévision des crises monétaire et des crédits. En plus, Kim et al. (2013) et Chyung et al. (2015) contestent dans ses ouvrages la disposition sur le fait que certains composants des agrégats monétaires peuvent représenter la part secondaire (c'est-à-dire, instable) des obligations d'une banque. En particulier, Chyung et ses coauteurs (2015) notent que le volume de la masse monétaire peut croître rapidement en raison soit des opérations transfrontalières des sociétés non financières, soit par emprunt direct à l'étranger, ainsi que par des filiales étrangères.

Le rôle du secteur bancaire en Russie

L'utilisation active des intermédiaires financiers dans le secteur bancaire russe est un phénomène relativement nouveau. Avant la crise financière de 1998, les banques russes étaient impliquées surtout dans la spéculation sur le marché des changes et sur le marché de la dette d'Etat ou fonctionnaient comme un trésor pour leurs sociétés mères. La canalisation des ressources dans le secteur réel avait une valeur relativement faible. Dans les années 2000, les banques en Russie ont fortement évolué vers des activités traditionnelles de détail, en particulier, l'octroi de crédits. Bien que le secteur bancaire russe reste faible en termes de rapport entre les actifs nets au PIB par comparaison avec le secteur bancaire à d'autres économies émergentes (Fungáčová et Solanko (2009a)), les flux de crédit vers le secteur réel au cours des dernières années ont augmenté rapidement et sont devenus un facteur important déterminant les flux monétaires dans l'économie. L'ampleur de ces flux était moindre que dans les pays baltes et est comparable à celle des économies asiatiques (Tableau I).

Tableau I. Croissnace nominale des dépôts et crédits bancaires en 2001-2007 (% du PIB total)

	Dépôts bancaires	*Crédits des banques nationales au secteur privé*
Pays industriels	5.4	5.5
Asie	14.8	11.3
Amérique latine	5.1	4.6
Pays baltes	7.1	16.4
Russie	**9.3**	**10.9**

Sources: Mohanty and Turner (2010); Banque centrale de la Russie

Il est à noter que jusqu'en 2009 les opérations extérieures ont également joué un rôle important dans la création monétaire. L'excédent comptable des comptes courants, qui n'a pas été entièrement contrebalancé par la fuite des capitaux, a largement contribué à l'accumulation de fonds dans le secteur non bancaire. En fait, en 2007-2008 l'afflux de capitaux s'est effectué également par des canaux commerciaux et financiers. En revanche, à la fin de l'an 2008 et au début de l'an 2009 les opérations extérieures ont abouti à la réduction de la masse monétaire. Cette sutiation est devenue possible à cause du régime de taux de change ajustable maintenu par la Banque centrale de la Russie dans cette période. Avant la crise de 2008 les réserves de change ont été achetées pour empêcher la réévaluation du rouble, et à la fin de 2008, lors du chaos financier, elles ont été vendues. Après 2009 il y a eu une transition progressive vers le régime de taux de change flexible (bien qu'en 2014 les réserves aient été également dépensées), ce qui a abouti à la balance des transactions financières et non financières dans le secteur non-bancaire et a prédéterminé la diminution du rôle du secteur extérieur dans la création de monnaie.

Une autre source caractéristique russe de fuite de dépôts a été le fonds d'investissement d'Etat. Son accumulation a produit un effet restrictif considérable sur l'expansion monétaire en 2005-2008. Plus tard ses fonds ont été utilisés pour financer le déficit budgétaire en 2009 et 2015. En conséquence, la politique financière anticyclique a aidé à créer des moyens de paiement lors de la phase de confinement du cycle de crédit. On peut affirmer que le fonds d'investissement d'Etat s'est avéré un complément utile à la fois aux outils monétaires et fiscaux.

Les processus monétaires ont effectué un impact rapide sur l'économie réelle en Russie. La croissance rapide des agrégats de crédit en 2006−2008 a conduit à un boom du crédit qui a contribué à une forte croissance économique. Par conséquent, la crise financière en 2008-2009 a provoqué une réduction dramatique mais de court terme du secteur réel de l'économie russe. La chute du PIB de près de 8% en 2009 a été la baisse annuelle la plus forte depuis 1996.

Ce qui est intéressant, c'est que jusqu'en 2008 l'état du secteur financier relativement sous-développé en Russie n'a pas été considéré comme un facteur décisif de la croissance du secteur réel. Le facteur dominant dans l'explication des processus dans le secteur réel russe seront les fluctuations des prix du pétrole. En fait, les flux monétaires générés par l'exportation de pétrole et de gaz sont extrêmement importants pour l'économie russe. Ainsi, une chute brutale des prix du pétrole en 2008-2009 a significativement influencé la demande globale, bien que l'OCDE (2009) note que la baisse normale des prix du pétrole serait logique avec un ralentissement peu fort, plutôt qu'avec une grave récession. Les prix du pétrole sont revenus peu après à nouveau à leur niveau précédent, tandis que la croissance du PIB n'a pas atteint de valeurs d'avant la crise. A titre de comparaison, l'économie russe a diminué de moins de 4% en 2015, tout en découvrant une longue période de baisse des prix du pétrole. Fungáčová et Solanko (2009b) dans leur étude soulèvent la question de ce qu'avec un taux d'imposition marginal des exportations de pétrole élevé, les fluctuations des prix du pétrole n'auraient pas dû avoir une influence décisive sur les revenus des entreprises. On peut disputer que jusqu'à présent le passage dans le secteur privé à cause du choc des prix du pétrole est encore possible, car la hausse des revenus des ventes du pétrole a rendu possible l'implémentation de la politique visant à stimuler la croissance économique. Cependant, cet argument ne peut pas aider à expliquer la récession, parce que, même après avoir perdu des sommes importantes de recettes budgétaires, le gouvernement russe, qui n'a pas réduit les dépenses, a proposé, en plus, un paquet supplémentaire de relance budgétaire (voir, par exemple, l'ouvrage de Ponomarenko et Vlasov 2010). La nécessité d'aller au-delà des chocs des prix du pétrole pour expliquer les processus dans le secteur réel est devenu donc évidente.

Contenu de la these

Dans la présente thèse on voit présenter les résultats de différends aspects de l'analyse monétaire de l'économie russe. En général, c'est une recherche principalement neuve, car autrefois cette méthode n'a pas été appliquée à l'égard de la Russie. Dans certains cas notre apport dans les recherches dans ce domaine consiste non seulement en analyse notamment pour la Russie, mais aussi en application de nos instruments pour un groupe plus étendu de pays avec l'économie de transition.

Dans le premier chapitre[2] nous examinons les facteurs qui entrainent la croissance de la masse monétaire en Russie. La mise en évidence des chocs de la masse monétaire et de leurs conséquences macroéconomiques représente la tâche pratique importante d'analyse de la politique monétaire actuelle. Il existe des modèles élaborés pour interpréter les changements dans le domaine monétaire, mais il est peu probable qu'une simple reproduction des ces instruments soit raisonnable, car le milieu économique et financier en Russie se diffère dans une certaine mesure de la zone euro. Ainsi, par exemple, les marchés financiers en Russie sont plus profonds et moins liquides en comparaison avec la zone euro, et pour la plupart de la population l'argent peut présenter le moyen le plus important de conserver l'épargne. Les périodes d'inflation élevée et d'hyperinflation ne sont pas tellement éloignées dans le mémoire collectif comme dans la zone euro, et les devises étrangères a souvent servi d'abri fiable. La substitution des devises ou, selon la

[2] Ce chapitre se rapporte au Document de travail de la Banque européenne centrale № 1471/2012. Ses auteurs sont conjointement Elena Vasilieva et Franziska Schobert.

définition plus large, la «dollarisation» possède d'une certaine inertie, et les agrégats monétaires qui comprennent les composants exprimés en devises étrangères, se comportent autrement en comparaison avec les agrégats monétaires qui ne contiennent pas ces composants. Enfin, le dernier moment par ordre, mais pas par importance: la Russie est l'exportateur du pétrole, et les fonds du bien-être national aident à alléger l'influence des fluctuations des prix des matières premières et à conserver les ressources financières pour les générations à venir pendant les périodes stables. De même, pendant les périodes des fluctuations des prix ils peuvent jouer le rôle des instruments de crise en accordant le financement supplémentaire. Leur comportement peut considérablement influencer la création de la masse monétaire, c'est pourquoi on peut les examiner en tant que facteurs exogènes ou en tant que facteurs d'offre qui influencent les changements dans le domaine monétaire en complément des facteurs habituels d'offre.

Nous décrivons l'expérience de la Banque de la Russie dans l'utilisation de certains instruments traditionnels d'analyse monétaire, et en premier lieu des fonctions de la demande de monnaie. La fonction de la demande de monnaie représente le rapport fondamental qui reflète l'interaction entre les moyens monétaires et d'autres variables économiques importantes, telles que le revenu et la richesse. De cette manière, le lien stable entre les agrégats monétaires et d'autres variables macroéconomiques peut aider à expliquer et interpréter les événements dans le domaine monétaire. Du point de vue des normes, les modèles de la demande de monnaie présentent le point de départ dans la formation des critères d'estimation du niveau de croissance de la masse monétaire.

Il faut admettre que l'estimation de la fonction de la demande de monnaie stable est la tâche non triviale. Dans les conditions de déclin économique rapide, de substitution des devises et de fluctuations macroéconomiques importantes il est nécessaire de perfectionner les paramètres du modèle et de chercher les variables explicatives supplémentaires. Le travail avec les séries de temps relativement courtes signifie que le choix d'un modèle le plus convenable qui se base sur les propriétés empiriques, peut être impossible au cours d'estimation des modèles (leur instabilité ne peut se manifester que sur le stade plus tardif). En fait, de même que plusieurs modèles économétriques, l'utilisation des séries de temps courtes peut mener à ce fait que les paramètres fonctionnels du modèle soient très sensibles à la comptabilisation de novelles données observées, même dans les cas quand cette comptabilisation ne conduira pas finalement à la rupture des rapports établis. Ainsi, la révision de la demande monétaire est le phénomène répandu. Cela signifie que, pour des raisons pratiques, il est indésirable de faire fond sur un seul modèle qui peut devenir instable avec le temps. Au lieu de cela nous présenterons dans cette thèse l'ensemble de modèles de la demande monétaire qui peuvent être utilisées simultanément pour élever la stabilité des résultats.

Nous en venons à la conclusion que l'analyse monétaire fournit les données de base précieuses pour l'analyse de la Banque de la Russie. Cependant, l'analyse monétaire est le processus qui est en train de développement, c'est pourquoi, dans la limite d'une économie comme dans plusieurs économies de différents pays, les changements des conditions économiques et financières influencent l'analyse et les conclusions se rapportant à la politique économique qui peuvent être faites à sa base. La situation avec la Russie souligne de façon supplémentaire qu'il ne faut pas ramener l'analyse monétaire aux actions purement techniques, et que la connaissance institutionnelle du secteur financier est nécessaire pour lui, de même qu'il est stimulée par cet analyse.

Dans le deuxième chapitre[3] nous estimons, par rapport à la Russie, les indices de l'inflation de base ce que aidera à mettre en évidence les chocs inflationnistes principaux des prix à la consommation qui sont importants pour la politique monétaire, et à présenter l'information sur l'évolution de l'inflation des prix à la consommation à venir ou sur les anticipations inflationnistes actuelles à moyen terme.

Il existe plusieurs méthodes de calcul de l'inflation de base et plusieurs critères (qui ne sont pas contradictoires, mais qui ne sont pas obligatoirement liés entre eux) qui peuvent être utilisés pour l'estimation indirecte des propriétés des indices reçus. Nous avons calculé 20 indices de l'inflation de base en utilisant quatre approches alternatives. Notre approche principale consiste en estimation de la tendance observée qui se base sur les modèles dynamiques factoriels. Le modèle standard est appliqué par Cristadoro et d'autres (2005) qui utilise l'information inclue dans l'ensemble étendu d'indices, pour décomposer l'inflation en deux composants stationnaires orthogonaux non observés – celui habituel et celui idiosyncratique. Le composant habituel peut ensuite être décomposé en constituants à long et à court terme par voie d'identification des fluctuations de basse fréquence avec la périodicité au-dessus du seuil établi. Nous avons aussi réalisé le test de plusieurs combinaisons alternatives dans les modèles dynamiques factoriels. Selon la conception d'inflation «pure» (Rice et Watson, 2010), dans laquelle on voit l'application de cette approche, l'augmentation des prix se décompose en trois composants – l'inflation «pure» qui reflète l'augmentation des prix sous l'action des facteurs monétaires, qui est présente dans l'évolution des prix sur tous les produits et services et qui est, en même temps, à proportion égale,

[3] Ce chapitre se rapporte au Document pour la discussion 24/2015 de l'Institut des problèmes des économies de transition de la Banque de Finlande. Ses auteurs sont conjointement Elena Deryugina, Andrey Sinyakov et Konstantin Sorokin.

les changements des prix relatifs et les fluctuations idiosyncratiques. De même nous utilisons l'approche monétaire à la mesure de l'inflation de base en qualité d'encore un modèle alternatif (pour l'information plus détaillée voir Deryugina et Ponomarenko (2013)). Dans ce cas nous essayons d'estimer le contenu d'information de l'argent en ce qui concerne les changements de l'inflation en utilisant l'approche qui se base sur le modèle dynamique factoriel, à la série de variables qui forment de grands agrégats monétaires (aussi bien que leurs composants), et à la série d'indices différents des prix. Le but de notre approche statistique est d'identifier le processus monétaire de base qui est étroitement lié à l'inflation, par voie de pesage des agrégats monétaires conformément à leur rapport «signal/bruit», notamment à la baisse de l'importance de ceux qui possèdent de grandes fluctuations idiosyncratiques. Probablement, notre approche doit diminuer l'importance des instruments monétaires exposés à l'influence des changements de portefeuille. En même temps, prenant en compte que nous faisons fond sur toute une série d'indices des prix pour exprimer les changements de l'inflation, nous attendons la filtration du composant de volatilité de la croissance d'indice des prix d'usage qui pourrait, dans le cas contraire, déformer le lien avec la croissance de la masse monétaire.

Nous en venons à la conclusion que les indices de l'inflation de base, calculés à l'application des modèles dynamiques factoriels, présentent les meilleurs résultats au titre d'épreuves formelles. Notamment, ces indices ont resté stables pendant les périodes de chocs des prix en 2010 et 2012, mais ils ont exprimé la pression inflationniste plus forte en 2007-2008 et sa baisse en 2009. En tant que résultat, ces indices ont resté informatifs pendant toutes les périodes en ce qui concerne la future dynamique de l'inflation à moyen terme, ils ont été étroitement liés aux fluctuations de la demande cumulée.

Dans le troisième chapitre[4] nous apprécions la croissance durable en Russie.

Ces derniers temps l'appréciation de la croissance potentielle de production sur les marchés des pays avec l'économie de transition a été la tâche difficile. Habituellement, les estimations reçues à l'utilisation des filtres unidimensionnels statistiques traditionnels (par exemple, du filtre de Hodrick–Prescott (HP)), n'ont pas révélé aucuns déséquilibres avant le début de la crise à la fin de l'année 2008. En outre, ces filtres n'ont pas été toujours utiles en cas de décomposition de la baisse après-crise des rythmes de croissance de production en composant cyclique et celui de tendance. Dans ces circonstances il est rationnel de s'appuyer sur les indices macroéconomiques supplémentaires pour réaliser le diagnostic de l'état du cycle de business. Habituellement, on

[4] Ce chapitre se rapporte à l'article publié dans les «Comparative economic studies» № 57, mars 2015. Ses auteurs sont conjointement Elena Deryugina et Anna Krupkina.

estime que la pression inflationniste devient de plus en plus forte dans les cas quand le niveau de production est plus élevé que le potentiel, et elle baisse quand le niveau de production descend au-dessous du potentiel. Donc l'inflation est notamment examinée en tant qu'un des symptômes-clef d'instabilité. C'est aussi exact pour une autre théorie traditionnelle qui relie les fluctuations du taux de chômage avec la rupture entre la production réelle et celle potentielle (la loi d'Okun).

Mais le consensus atteint dans la macroéconomie à ce sujet, a été mis à l'épreuve sévère par la crise financière globale. Il devient de plus en plus clair que certaines activités cycliques ne peuvent pas être englobées par cette approche – par exemple, les changements insoutenable dans le secteur financier. Ainsi, par exemple, les bulles des prix d'actifs peuvent engendrer de vastes cycles de business sans création de l'inflation dont on voit la réflexion dans le panier moyen de biens du ménage qui, à son tour, crée la représentation universellement admise de l'inflation. C'est pourquoi les indices financiers sont très importants pour l'appréciation équilibrée de la croissance de production, et le but de ce travail consiste à incorporer l'information contenue dans ces indices, dans l'appréciation de la croissance durable de production dans les économies de transition.

Nous suivons Alberola et autres (2013), Borio et autres (2013, 2014) et Bernyofer et autres (2014) et formulons le modèle de l'espace des états qui présent le filtre HP multidimensionnel reliant la fluctuation cyclique de PIB avec plusieurs indices des déséquilibres macroéconomiques. Les variables financières, aussi bien que les indices traditionnels de l'inflation à la base de l'indice des prix à la consommation et du taux de chômage font partie de ces indices. Nous recevons les paramètres du modèle en l'estimant au total par rapport à l'ensemble d'économies de transition.

Les résultats montrent que les indices des déséquilibres financièrs sont statistiquement significativs pour expliquer les fluctuations de la rupture entre la production réelle et celle potentielle, surtout pour les pays européens – cela signifie qu'ils contiennent l'information supplémentaire en dehors de celle contenue dans les variables qui présentent le taux d'inflation et de chômage. Il apparaît que l'indice des prix sur le marché boursier présente le meilleur résultat. Prenant en compte que ce modèle n'a pas d'interprétation structurelle, cela ne signifie pas que seuls les changements sur le marché boursier ont été le facteur principal qui a engendré ces fluctuations de la rupture entre la production réelle et celle potentielle, mais cependant, il est possible d'affirmer que la croissance des prix du marché boursier est le symptôme important susceptible d'aider à distinguer l'accélération cyclique et celle de tendance de la croissance de production.

Les écart de production reçus à l'utilisation du modèle estimé, considérablement diffèrent de ceux qui ont été calculés à l'utilisation de la version unidimensionnelle du filtre HP. Il est surtout à noter que les indices de la croissance potentielle de production sont plus stables et, donc, correspondent de manière plus considérable à la notion de production durable. La diminution cumulative de la production après la récession de l'année 2008, estimée à la base du filtre multidimensionnel, peut être comparée (à l'opposé des appréciations reçues à l'utilisation de la version unidimensionnelle) aux cas typiques qui sont décrits en littérature. Ainsi, l'utilisation du filtre multidimensionnel peut aider à agrandir la stabilité du modèle en temps réel, bien que notre approche reste toujours très sensible aux problèmes du point d'arrêt lié à la transformation des variables qui reflètent les déséquilibres financièrs.

Dans le quatrième chapitre[5] nous présentons le système d'indicateurs d'alerte précoce des cycles de boums et de krachs des prix des actifs en Russie.

La récente crise financière a souligné l'importance croissante des fluctuations des prix des actifs pour les évolutions macroéconomiques. Il semble, comme dans le cas des pays développés, qu'une série des économies de transition (surtout en Europe Central et Oriental), est considérablement influencée par ces chocs, parce qu'on suppose que la vite croissance et la baisse suivante des prix des actifs ont beaucoup favorisé à la surchauffe après-crise de ces économies et à la baisse suivante des affaires. C'est pourquoi le système d'indicateurs d'alerte précoce des déséquilibres survenants c'est un instrument dont ceux qui forment la politique ont vraiment besoin.

La conception de ce système à l'utilisation de l'approche qui prend en compte les particularités d'un pays concret, est souvent impossible à cause des données existantes limitées. C'est pourquoi l'approche standard consiste en constitution des estimations pour l'ensemble de pays (dont le pays analysé ne doit pas obligatoirement faire partie) et en application du modèle reçu par rapport à l'économie dont il s'agit. Cette méthode a été utilisée dans plusieurs recherches récentes décrivant les modèles qui peuvent être utilisés pour prévoir la croissance importante et la baisse des prix des actifs. Ici le problème est que la plupart de ces modèles sont adaptés à l'explication des fluctuations des prix dans des pays industriels. Ce n'est pas clair si ces modèles soient utiles par rapport aux marchés des pays avec l'économie de transition, car le caractère des fluctuations de plusieurs variables macroéconomiques utilisées en qualité d'indicateurs d'alerte précoce, diffère de façon importante sur les marchés des pays développés et des pays avec l'économie de transition. Par exemple, cela pourra être difficile de distinguer la croissance excessive du crédit entraînant le gonflage de la bulle des prix des actifs, et la convergence du secteur bancaire insuffisamment développé jusqu'au niveau comparable avec les pays développés. L'identification de la "surchauffe" à la base des variables reflétant les taux de croissance dans le secteur réel qui

[5] Ce chapitre se rapporte à l'article publié dans la «Emerging markets review», volume 15, juin 2013.

subissent les fluctuations importantes à mesure qu'on voit se passer les transformations importantes dans l'économie, peut aussi être difficile pour les économies de transition. En effet, il est connu que les prix des actifs comme tels sont présentés sur les marchés des pays avec l'économie de transition en tant que ceux de volatilité, c'est pourquoi il est tellement difficile des les interpréter. Pour ces motifs, l'approche basée à l'application des indicateurs de prévention précoce, doit être soigneusement étudiée avant son application pour prévoir les cycles des prix des actifs sur les marchés des pays avec l'économie de transition. La principale contribution de cette thèse consiste en application de l'analyse de boums et de krachs des prix des actifs à l'égard de l'ensemble de 29 marchés des pays avec l'économie de transition (avant tout à l'égard de la Russie et d'autres pays d'ex-URSS).

En général, nos résultats ne donnent pas la réponse finale à la question laquelle des approches de la prévision de boums et de krachs des prix des actifs présente les meilleurs résultats. Mais nous affirmons que la conception basée au monitorage de l'ensemble combiné des prix des actifs, de l'activité réelle et des indices financiers, est largement appliquée aux marchés des pays avec l'économie de transition, et son efficacité est confirmée par de différentes combinaisons dans les cadres du modèle. D'après nos appréciations, la croissance du crédit et les investissements (exprimés en taux de croissance comme en part de PIB) deviennent les indicateurs les plus fiables pour prévoir le cycle des prix des actifs. Nous aussi considérons qu'en addition à cet ensemble de variables, le système de prévention précoce pour les pays avec l'économie de transition peut être complété avec les indices de mouvement du capital.

Dans le cinquième chapitre[6] nous modelons les interactions entre les variables qui présentent le secteur monétaire et celui réel, par voie de grand modèle vectoriel autorégressif bayésien.

En Russie la modélisation économique empirique est la tache difficile. Une des limitations les plus importantes est liée aux séries de temps insuffisamment longues ce que rend l'estimation du modèle économétrique global presque impossible. C'est pourquoi les explorateurs sont obligés s'appuyer dans leur travail sur les modèles simples. Les modèles macroéconométriques traditionnels qui se composent d'un grand nombre d'équations simples définies d'avance, présentent un des exemples. En ce qui concerne une approche plus souple qui se base sur l'autorégression vectorielle (VAR), le modèle typique pour la Russie comprendrait pour chaque cas concret la sélection séparée de variables (assez souvent ce ne sont que cinq indices) qui

[6] Ce chapitre se rapporte à l'article publié dans les «Emerging markets finance and trade», volume 51, édition 6, 2015. Un de ses coauteur est Elena Deryugina.

présentent une relation théorique macroéconomique à long terme, ou sont suffisantes pour l'identification des types des chocs économiques établis d'avance, ou qui tout simplement comprennent les indices qui sont les déterminants les plus importants du processus en train de modélisation.

Dans ces conditions, l'approche économétrique développée spécialement pour résoudre le problème de "malédiction de la dimensionnalité", peut être vraiment convenable pour la Russie. Notamment, il est connu que toute une classe de modèles conçus il n'y a pas longtemps et basés sur la grande autorégression vectorielle bayésien (Banbura et autres (2010), Giannone et autres (2012), Banbura et autres (2014)), donne des résultats adéquats même dans les circonstances quand le modèle comprend en même temps un grand nombre de variables. Il est à la mode d'affirmer que le modèle VAR bayésien relativement grand estimé par rapport à l'économie russe à l'utilisation de cette méthode, peut être examiné en tant qu'instrument neuf et précieux de prévision et d'analyse hypothétique. Le but de cette thèse est la réalisation de cette approche en pratique.

En utilisant cette méthode, nous apprécions le modèle vectoriel d'autorégression bayésien comprenant 16 indices principaux qui présentent le secteur intérieur réel, les indices macroéconomiques de prix et ceux monétaires, aussi bien que les variables qui reflètent le secteur extérieur. Nous avons réalisé plusieurs types de tests pour valider notre modèle, notamment l'analyse des fonctions de réponse et la prévision récursive. Nos résultats montrent que la méthode appliquée convient en général à la modélisation économique de l'économie russe.

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Chapter 1: Feedback to the ECB's monetary analysis: The Bank of Russia's experience with some key tools[7]

Abstract

The paper investigates to what extent some basic tools of the ECBs monetary analysis can be useful for other central banks given their specific institutional, economic and financial environment. We take the case of the Bank of Russia in order to show how to adjust methods and techniques of monetary analysis for an economy that differs from the euro area as regards, for instance, the role of the exchange rate, the impact of dollarization and the functioning of sovereign wealth funds. A special focus of the analysis is the estimation of money demand functions for different monetary aggregates. The results suggest that there are stable relationships with respect to income and wealth and to a lesser extent to uncertainty variables and opportunity costs.

Keywords: Monetary aggregates, money demand, cointegration, Russia

JEL classification: E41, E52, E58.

[7] This chapter refers to ECB Working Paper No 1471/2012. This paper has been co-written Elena Vasilieva and Franziska Schobert.

1.1 Introduction

Monetary analysis at central banks has different meanings across the world and over time. Some parts of the world may still focus on quantitative targets for (base) money and thereby blur the meaning of operational and intermediate targets and indicators or reference values. In contrast, in its two-pillar strategy, the ECB makes it clear that it uses the monetary pillar to collect information on medium- to long-term risks to price stability by focusing on the analysis of money and credit aggregates. It thus ensures a "full information approach" that may otherwise be dominated by the analysis of cyclical movements of the economy and the information on short-term risks[8]. Monetary analysis at the ECB has been an evolutionary process during which tools and techniques have developed as described in Papademos and Stark (2010). This process has been monitored by other central banks which set up new strategies for an autonomous monetary policy that focuses on internal price stability rather than on stable exchange rates.

We describe the Bank of Russia's experience in this respect and to what extent some key tools of monetary analysis as practiced by the ECB can be useful for it. On the one hand, the Bank of Russia may benefit from tools that are already regularly used in the ECB's monetary assessment. The composition of drivers behind money-stock growth indicates that the Russian economy is evidently prone to exogenous money-supply shocks. Identifying these shocks and their macroeconomic consequences is an important practical task for day-to-day monetary policy analysis. The models developed to interpret monetary developments which constitute an essential part of the ECB's monetary analysis seem particularly suitable for this task. On the other hand, simply copying the tools would not be advisable as the economic and financial environment in Russia differs to some extent from the euro area. In both, their financial sectors have in common the fact that they are rather bank-based than capital-market-based. Financial markets in Russia, however, are less deep and less liquid compared to the euro area and money might be the most important financial store of value for a large proportion of the population. Furthermore, high inflationary and hyperinflationary periods are closer in the collective memory than in the euro area and foreign currency has often served as a safe haven. Currency substitution, or, in its broader definition, "dollarization" has inertia and monetary aggregates that include foreign denominated components should behave differently to those that do not. External nominal anchors have dominated monetary policy in the past and exchange-rate developments have triggered rapid

[8] Notably, after the Global Financial Crisis the role of monetary analysis is also emphasized in connection with financial stability objective and macroprudential policy. The analysis of this issue however remain beyond the scope of this paper.

reactions of money holders. Last but not least, Russia is an oil-exporting economy and sovereign wealth funds help to buffer the impact of commodity-price fluctuations and to save financial resources for future generations during normal times. During turbulent times they can also function as crisis tools and provide additional funding. Their behavior can significantly influence money creation and thereby, may be understood as exogenous factors or supply-side factors which influence monetary developments beyond the usual money demand factors.

We acknowledge these differences in our study and focus on some key tools of ECB monetary analysis as described in chapters 3 and 4 of Papademos and Stark (2010) which we apply to the Russian case. We start with a brief review of the role of money in the Bank of Russia's monetary policy since the early 1990s and a description of monetary developments, given in Sections 1.2 and 1.3. Section 1.4 forms the core of the paper, as it presents money demand estimations for different monetary aggregates. In Section 1.5 we conclude.

1.2 The role of money in the Bank of Russia's monetary policy – a review

The main stages of evolution of the conduct of monetary analysis and its role in the Bank of Russia's (CBR) monetary policy framework may be provisionally described by considering five different periods. They highlight the role of money in an economic environment which suffered from periods of price and financial instability and shifted from a fixed to a managed exchange rate regime.

The early 1990s. The CBR paid serious attention to monetary analysis and the developments of monetary aggregates as soon as the first steps to liberalize the economy were taken in the early 1990s. The transition from a planned to a market economy caused drastic structural shifts in both the real and the financial sector in Russia. In these circumstances the CBR's monetary policy was conducted against the background of the hyperinflation that followed the lifting of price regulation, deep recession of the real sector, depreciation of the national currency and high macroeconomic uncertainty. The CBR had to find a balance between restraining inflation and supportive measures aimed at preventing the collapse of the real economy and the domestic financial system.

According to the "Guidelines for the Single State Monetary Policy" in early the 1990s, averting hyperinflation by limiting extraordinarily high money growth (see Table 1) had become one of the priority objectives of the CBR's monetary policy together with other tasks such as stabilizing the financial system and the exchange rate. In the Federal Law "On the Central Bank of the Russian Federation (Bank of Russia)", which was passed in 1990, setting targets for money supply growth was indicated as one of the principal tools and methods of the Bank of Russia's monetary policy[9].

During this period the efforts to achieve macroeconomic stability were generally framed in the context of IMF-supported programs. These programs had several components (the exchange rate regime, monetary and exchange rate policies, fiscal policy and structural reforms) and implied setting intermediate targets for a number of macroeconomic (including monetary) variables regarded as nominal anchors. An underlying relationship between money growth and inflation projected in the program was a key assumption, although in practice a much more eclectic set of macroeconomic theories and modeling techniques were used to provide analytical support for the policy design (see Ghosh et al. (2005)). The CBR also studied closely the strategies of other central banks, including the monetary targeting strategy of the Deutsche Bundesbank.

The CBR's monetary policy was conducted by setting limits for the growth of the narrow monetary base[10] and other positions of the central bank's aggregated balance sheet in the Monetary Program. This included strict limits on direct loans by the CBR to the government and the commercial banks. Setting limits for money supply growth was formulated in terms of the monetary aggregate M2 (national definition) that "includes all cash and non-cash funds of resident non-financial and financial institutions (except for credit institutions), and private individuals in rubles."[11] Quarterly targets for CBR's balance-sheet indicators were set and mostly fulfilled. According to these plans, money growth was to be stabilized and subsequently slowed down. Although the CBR changed its interest rates and the reserve requirements during this period its most important tool had undoubtedly been the volume of loans provided to commercial banks and the government.

Obviously setting an adequate quantitative target for money growth was extremely complicated during the period of transition. High uncertainty and volatility of the main macroeconomic indicators caused rapid fluctuations of the demand for money. The situation was hampered even further by the lack of statistical data. Nevertheless, using elements of monetary

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[9] This clause is still present in the Federal Law "On the Central Bank of the Russian Federation (Bank of Russia)", article 35.

[10] The monetary base (narrow definition) consists of the currency issued by the CBR (including cash in the vaults of credit institutions) and required reserves balances on ruble deposits with the CBR.

[11] Money supply (national definition) "is defined as the sum of funds in the Russian Federation currency, intended for use as payment for goods, work and services and for the accumulation of savings by resident non-financial and financial organizations (except for credit ones) and individuals".
Bulletin of Banking Statistics No 5 (216), 2011, pp. 233-234.

targeting in the CBR's monetary policy helped to cope with hyperinflation, stabilized the situation in the financial sector and prevented a systemic banking crisis.

The period 1995-1998. Starting from 1995 the CBR's monetary policy framework changed considerably. Direct CBR loans to the government were discontinued. The exchange rate was used as the nominal anchor and an exchange rate band was introduced and defended by the CBR till the crisis of 1998. Domestic price stability was also mentioned as a monetary policy objective and the prevalent role of monetary expansion in determining inflation rates over the medium-term was acknowledged[12] .

The Monetary Program still included reference growth rates for the narrow monetary base, CBR's net foreign assets and net credit to the government and commercial banks, although its parameters were no longer viewed as strict targets. Under this framework, combined with the exchange rate policy, the CBR managed to bring inflation rates down to an annual 11% and money growth to 30% in 1997, although the state of the financial sector was still far from healthy, as problems with illiquidity and nonpayment of enterprises persisted, leading to widespread use of barter and monetary surrogates.

The CBR's analytical work in the area of monetary analysis in the 1990s was mainly focused on analyzing money demand, money velocity and money multiplier dynamics. Different components of money stock (including foreign-currency-denominated ones) as well as the sources of money growth were monitored. When foreign-currency-denominated deposits were legalized, in 1995 the CBR started to compile and report the dynamics of a broader monetary aggregate - broad money (or M2X)[13].

The crisis of 1998, which was due to unsustainable public finances in Russia and capital outflows from emerging countries, hit the Russian economy hard and determined the need to change the CBR's monetary policy. On the one hand, the CBR had to keep the monetary stance to prevent depreciation of the national currency and combat rising inflation. On the other hand, the dire problems in the financial sector and dysfunctions of the payment system called for liquidity-providing measures. In September 1998, the CBR abandoned the fixed-exchange-rate

[12] CBR, Guidelines for the Single State Monetary Policy in 1997, p. 23.

[13] Broad money comprises cash issued by the Bank of Russia (excluding cash in vaults of the Bank of Russia and credit institutions), funds held by residents (individuals and organizations other than credit institutions) in settlement, current and deposit bank accounts denominated in rubles and foreign currencies, precious metals and all interest accrued on deposit operations.

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peg, allowed the ruble to depreciate sharply, and declared the transition to a managed floating exchange rate regime.

The period 1999-2008. In 1999 the objective of CBR's monetary policy was formulated as achieving stable economic growth in a low-inflation environment. Yet, as the capital inflows (mainly originating from the rise of oil and gas prices) increased, the CBR's commitment shifted towards exchange-rate management. Since 2003 a target for real exchange-rate appreciation was declared together with an inflation target. In 2005 the CBR introduced a bi-currency basket consisting of USD and euro (with current weights of 0.55 and 0.45 accordingly) as its operational target. In order to prevent the ruble's excessive appreciation, the CBR had to conduct substantial foreign exchange interventions which became an important liquidity-providing factor. In an environment of strong capital inflows and relatively high oil prices, the Russian economy grew strongly. From 2000 until mid-2008, the annual growth rates of M2 were above 30%.

Although the relationship between money and inflation in a relatively low inflationary environment was now less evident and the CBR no longer attempted to target money growth, the monetary aggregates retained their role as inflation risk indicators and were monitored closely. Every year the CBR published the references for M2 growth as well as the parameters of the Monetary Program in the "Guidelines for the Single State Monetary Policy". These estimates conform to the scenarios of macroeconomic development produced by the Ministry of Economy. Yet, in practice, the actual outcomes might deviate from these projections significantly. The analysis of causes and consequences of these deviations provides valuable information and is part of the analytical work in the area of monetary analysis. At this stage, the aspects of monetary analysis related to extracting information from monetary developments in order to assess the current monetary stance (as opposed to making the projections of monetary indicators contained in the Monetary Program) started to gain importance. Naturally the relevant tools employed by the ECB for this purpose formed the basis of the analytical framework.

Money growth projections are traditionally formulated in terms of the M2 aggregate (national definition) as well as the general discussion about the monetary developments in Russia. Therefore the money demand studies conducted at the CBR originally concentrated on modeling this indicator. But as the role of monetary analysis expanded beyond the production of such projections, the need to explore the properties of other monetary aggregates and their linkages with other macroeconomic variables became apparent. In fact, the dynamics of broader aggregates that include foreign currency denominated assets are less prone to fluctuations arising from changing currency preferences and are therefore easier to interpret. Foreign currency deposits, as well as cash in foreign currency, serve as a store of value and as a safe haven during turbulent times.

The period after 2008. In recent years the CBR has adjusted the priority of its monetary policy objectives. This was partially a result of the crisis of 2008 which highlighted the impact of financial-sector imbalances on the real sector.

In 2008 the CBR declared in the "Guidelines for the Single State Monetary Policy" that lowering and subsequently maintaining low inflation is the main monetary policy objective[14]. Starting from 2009, the monetary policy horizon was extended to 3 years. The CBR also announced the gradual transition to a flexible exchange rate regime[15]. In 2010 the CBR declared that it would pay special attention to the broad analysis of money and credit developments for the purposes of financial stability and underscored the important role of credit and asset-price developments in identifying financial imbalances. In the "Guidelines for the Single State Monetary Policy in 2011 and for 2012 and 2013" it is noted that "… the Bank of Russia will pursue monetary policy by considering the situation on the financial markets and the risks arising from growth in monetary aggregates, credits and asset prices. It will pay special attention to a more comprehensive analysis of trends in monetary and credit indicators, to ensure that its timely actions in monetary policy and banking regulation and supervision help prevent imbalances in the financial sector of the economy, and thereby not only bring down inflation, but also maintain financial stability and a state of overall macroeconomic equilibrium."[16]

In the "Guidelines for the Single State Monetary Policy in 2012 and for 2013 and 2014" there is a declared intention to complete the transition to an inflation-targeting regime within a 3 year period[17]. At the same time, monetary analysis will retain its prominent role in identifying inflation risks in the medium and long-run. The CBR will also pay close attention to money, credit and asset prices developments for the purpose of maintaining financial stability[18]. As outlined by the CBR's First Deputy Chairman, Alexey V. Ulyukaev: "If you have rapid money growth you will most likely get high inflation or you could get a growth of asset prices, for example of housing or equities, that is not reflected in inflation measures …. We should cross-check inflation targeting with a monetary analysis approach. Methodologically that is what our colleagues in the ECB call two-pillars" (Ulyukaev, 2011).

[14] CBR, Guidelines for the Single State Monetary Policy in 2008, I. Medium-term monetary policy principles, p. 3
[15] CBR, Guidelines for the Single State Monetary Policy in 2009 and for 2010 and 2011, I. Medium-term monetary policy principles, p.4
[16] CBR, Guidelines for the Single State Monetary Policy in 2011 and for 2012 and 2013, I. Medium-term monetary policy principles, pp. 3-4.
[17] CBR, Guidelines for the Single State Monetary Policy in 2012 and for 2013 and 2014, I. Medium-term monetary policy principles, p. 3.
[18] CBR, Guidelines for the Single State Monetary Policy in 2012 and for 2013 and 2014, I. Medium-term monetary policy principles, p. 4

Monetary analysis at the CBR therefore looks not only at price but also at financial stability, since financial imbalances have been more closely connected to high inflationary periods in Russia than in developed economies during the recent past.

Empirical analyses suggest that there should be a long-run link and that the link is closer for high-inflation regimes as discussed in Papademos and Stark (2010), chapter 1.[19] We therefore assess their co-movement for a very long time-sample and by applying filtering techniques in order to capture the trend movements and to eliminate the cyclical fluctuations. For this purpose we compile a historical dataset that although somewhat eclectic (see Annex 1B for data sources description) in our opinion provides an insight on inflation and money growth developments in Russia during the time span 1861-2010. This period however includes two episodes of hyperinflation: the first associated with the First World War and the Russian Revolution of 1917 and the second with the dissolution of the Soviet Union. As we do not consider these developments relevant for the objective of analyzing long-run trends in money and inflation, we deliberately remove these outliers from the data by means of the TRAMO-SEATS pre-adjustment procedure making use of a manually set sequence of deterministic variables over the periods of 1914-1923 and 1991-1993 and then apply the asymmetric Christiano-Fitzgerald filter to extract long-run trends from the data. As in Benati, 2009 we extracted the components with a frequency of oscillation over 30 years.

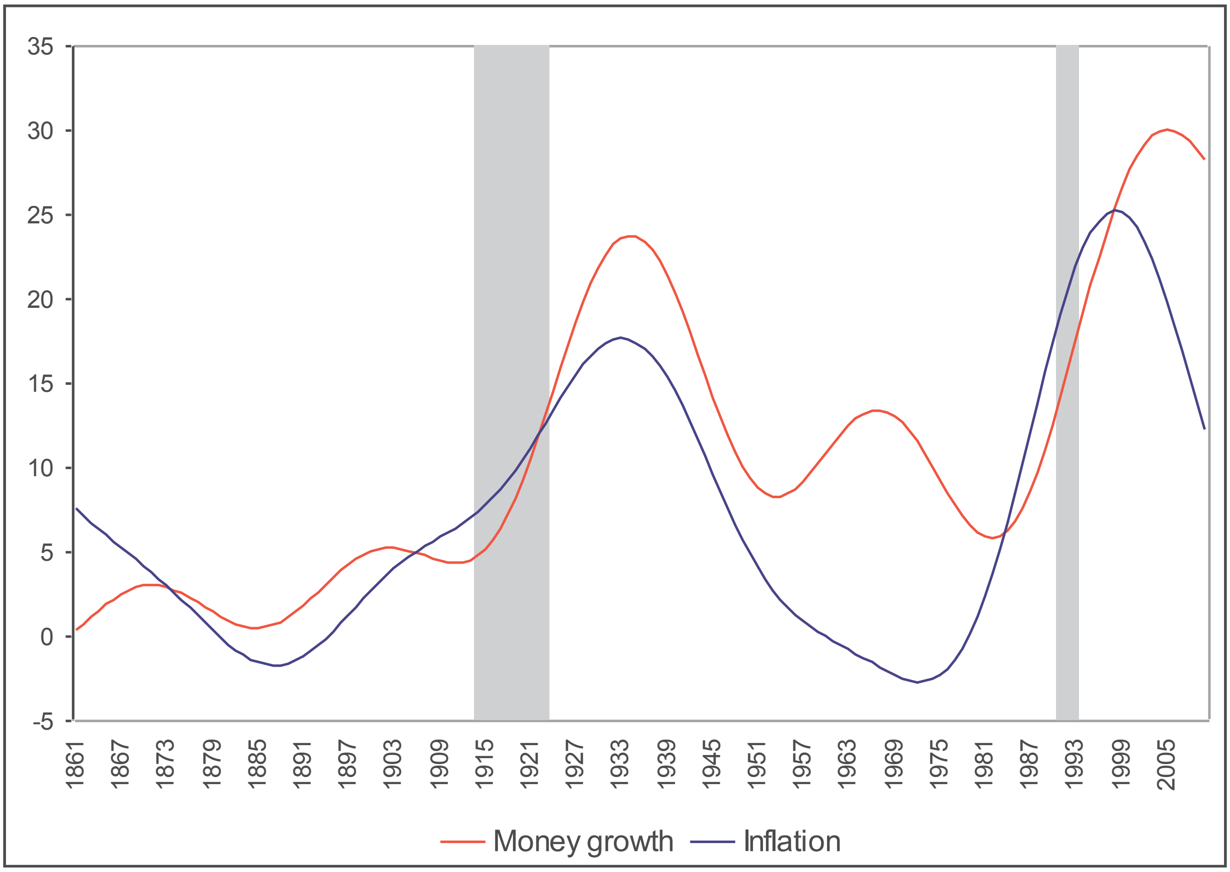
In Figure 1.1 we demonstrate the close co-movement of the two series, at the same time, the charts also suggest, however, that the strength of the correlation may be influenced by the monetary regime and the hyperinflationary regimes which – though filtered – still remain to have a strong influence. During the pre-soviet period the money growth and inflation rates seem to move closely. During the Soviet period of regulated prices, however, a substantial gap between money growth and inflation persisted in the 1960s and 1970s[20]. The post-Soviet period of the Russian economy was characterized by relatively high growth rates of both money and prices.

[19] See, for example, Rolnick and Weber (1997) De Grauwe and Polan (2005) or Benati, 2009

[20] Interestingly, some researchers point out that the monetary overhang accumulated by the late 1980s was one of the reasons that triggered a hyperinflation spiral once prices were liberalized (see e.g. Kim, 1999).

Figure 1.1

Long-run components of money growth and inflation, % (data over shaded periods were cleaned of outliers)



1.3 Monetary developments in Russia

1.3.1 Types of monetary aggregates in Russia and their measurement

Definitions of monetary aggregates spread from narrow, i.e. more liquid aggregates to broader aggregates that also include less liquid components which serve the store-of-value rather than the transactional purposes of money. Moreover, definitions are influenced by the financial environment and the behavior of money holders, for example, financial institutions apart from credit institutions may also serve monetary purposes and some financial products have become so money-near that they should be included in the definition of money. While this has driven considerations for defining monetary aggregates in the euro area, broader Russian monetary aggregates reflect rather the importance of foreign-currency-denominated components.[21] M2 (national definition) is the major aggregate for the analysis and policy formulation at the CBR.

[21] Since 2011 the CBR has published the data on deposits in national and foreign currency, set out by different sectors (financial institution (except credit organizations), public non-financial organizations, other non-financial organizations and households) in the Banking System Survey. This information provides a basis for further enhancing monetary analysis by using the data on sectoral money holdings.
See also "Sectoral structure of money holdings" (CBR, "Quarterly Inflation Review" 2011, Q1, pp. 24-26).

Broad money (M2X), however, includes foreign-currency-denominated components (FC). This aggregate differs substantially in size and development from the aggregates that include only components denominated in national currency (NC). Over the last decades, the Russian economy has been subject to significant fluctuations in the demand for foreign currency. The flows between ruble- and foreign-currency-denominated assets were particularly drastic during the periods of instability which impacted significantly on monetary aggregates. The recent crisis of 2008-2009 is one of the most evident illustrations and shows the need to analyze broader aggregates that partly consist of foreign currency denominated assets.

The data on the monetary aggregates M2 in national currency have been published by the CBR since 1997. The statistical sources are selected liabilities of the monthly consolidated balance sheets of Russian credit institutions and the Bank of Russia.

Two components are singled out as part of the monetary aggregate M2 (national definition)[22]:

The monetary aggregate M0 (cash in circulation) includes banknotes and coins in circulation less currency holdings (cash vaults) of the Bank of Russia and credit institutions.

Non-cash funds in national currency comprise the balances of funds kept by non-financial and financial institutions (except credit institutions) and private individuals in settlement, current, deposit and other demand accounts, including plastic-card accounts, and time-deposits opened with banks in the Russian Federation currency and accrued interest on them. Non-cash funds that are accounted for in similar accounts in credit institutions whose license has been recalled are not included in the composition of the non-cash funds.

The M1 aggregate can also be calculated from the liabilities of the consolidated balance sheet of the banking system. In our study we construct the **M1 aggregate**, which includes cash in circulation outside the banking system and transferable deposits which include current and other demand accounts (including bank card payment accounts) opened by Russian Federation residents (organizations and individuals) with the Bank of Russia and operating credit institutions in national currency[23].

Analyzing national currency monetary aggregates may be not sufficient, since financial dollarization is an important feature of the Russian economy (see Ponomarenko et al. (2013) for review). The hyperinflation that occurred in the early 1990s and the major depreciation events

[22] Bulletin of Banking Statistics No 5 (216), 2011, pp. 233-234
[23] Data source: CBR, Banking System Survey.

(most importantly, the currency crisis of 1998) increased the demand for reserve currency. Money holders however may use money for different purposes. Cash in foreign currency (mostly the USD), for example, served routinely for both transactional and store-of-value functions in the 1990s. Following macroeconomic stabilization and the increase of confidence in the banking system, the role of foreign cash has declined substantially but bank deposits denominated in foreign currency are still popular as a store of value. The shifts of currency preferences are a common reaction to exchange-rate fluctuations and increasing economic uncertainty.

The measure of money stock used by the CBR which includes foreign-currency-denominated deposits is the **broad money (M2X) aggregate.** The statistical data for this indicator was published in the Monetary Survey from 1995 to 2000 and in the Banking System Survey thereafter. Broad money comprises all the components of M2 and foreign-currency-denominated deposits.

In this study we also construct the monetary aggregate M2Y which includes foreign cash holdings in the non-financial sector. The M2Y aggregate is not published by the CBR and, as it includes cash denominated in foreign currency, the accuracy of its measurement is limited. In this study we use the indirectly measured foreign-cash holdings reported in the International Investment Position of the Russian Federation and Balance of Payments of the Russian Federation.[24] In Table 2 we summarize the components of the different monetary aggregates used in this study.

Table 1.1

Components of monetary aggregates

Liabilities	**M0**	**M1**	**M2**	**M2X**	**M2Y***
Currency in circulation	X	X	X	X	X
Demand deposits in NC		X	X	X	X
Time and saving deposits in NC			X	X	X
Deposits in FC				X	X
Cash in FC					X

*-authors' definition

[24] We use the item "Cash foreign currency/Other sectors" from the International Investment Position of the Russian Federation and the Balance of Payments of the Russian Federation.

In our study we also use M2X and M2Y which we adjust for valuation effects of foreign-currency-denominated components (M2X_ADJ and M2Y_ADJ). It may be sensible to do this for the purposes of monetary analysis since the fluctuations caused by the changes in the exchange rate are not linked to any real transactions and could therefore be misleading.[25] On the other hand, the wealth effect caused by these re-evaluations could still have some macroeconomic impact. We therefore analyze both types of aggregates. These were estimated as follows:

First the growth rates were adjusted:

$$\Delta adj = w * \Delta r + (1-w) * \Delta f / e \qquad (1.1)$$

where w is the share of ruble-denominated components at the end of previous period, Δr – growth rate of ruble-denominated components, Δf – growth of foreign-currency-denominated components and e – ruble's depreciation against the bi-currency basket. The base index is then constructed using adjusted growth rates.

1.3.2 Evolution of different monetary aggregates and counterparts

Figures 1.2 and 1.3 show the evolution of different monetary aggregates in Russia since 1998. In Russia, distinguishing between monetary aggregates that include and those that exclude money denominated in foreign currency is particularly useful. As previously mentioned, attributing the store-of-value function mainly to deposits in foreign currency and the transactional function to foreign cash would simplify the microeconomic behavior of different money holders.

[25] Russian monetary statistics so far cannot disentangle changes from transactions as it is the case for monetary data in the Eurosystem.

Figure 1.2

Monetary aggregates (y-o-y growth,%)

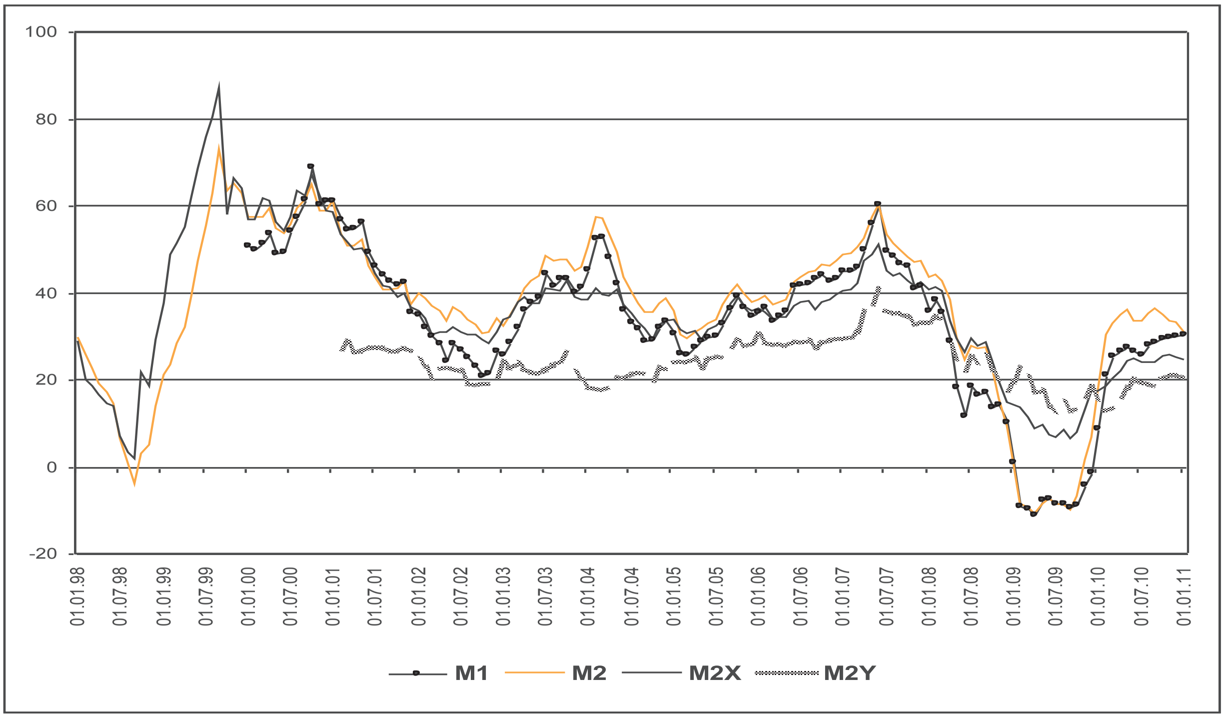


Figure 1.3

Headline and adjusted monetary aggregates (y-o-y growth, %)

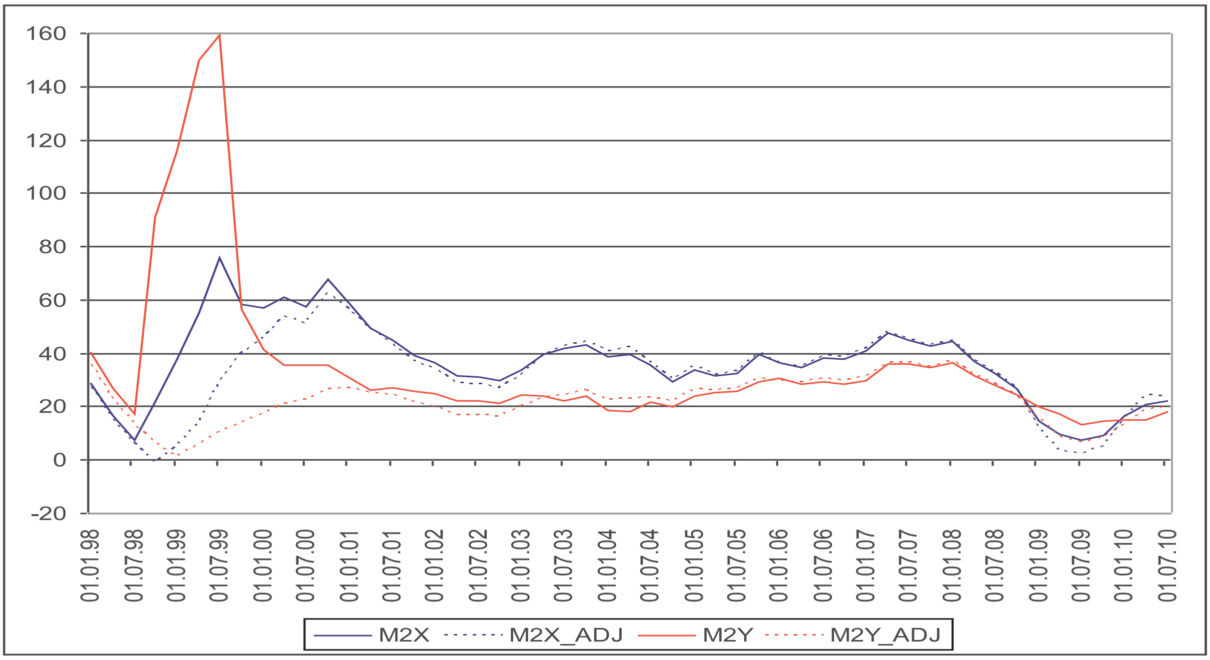
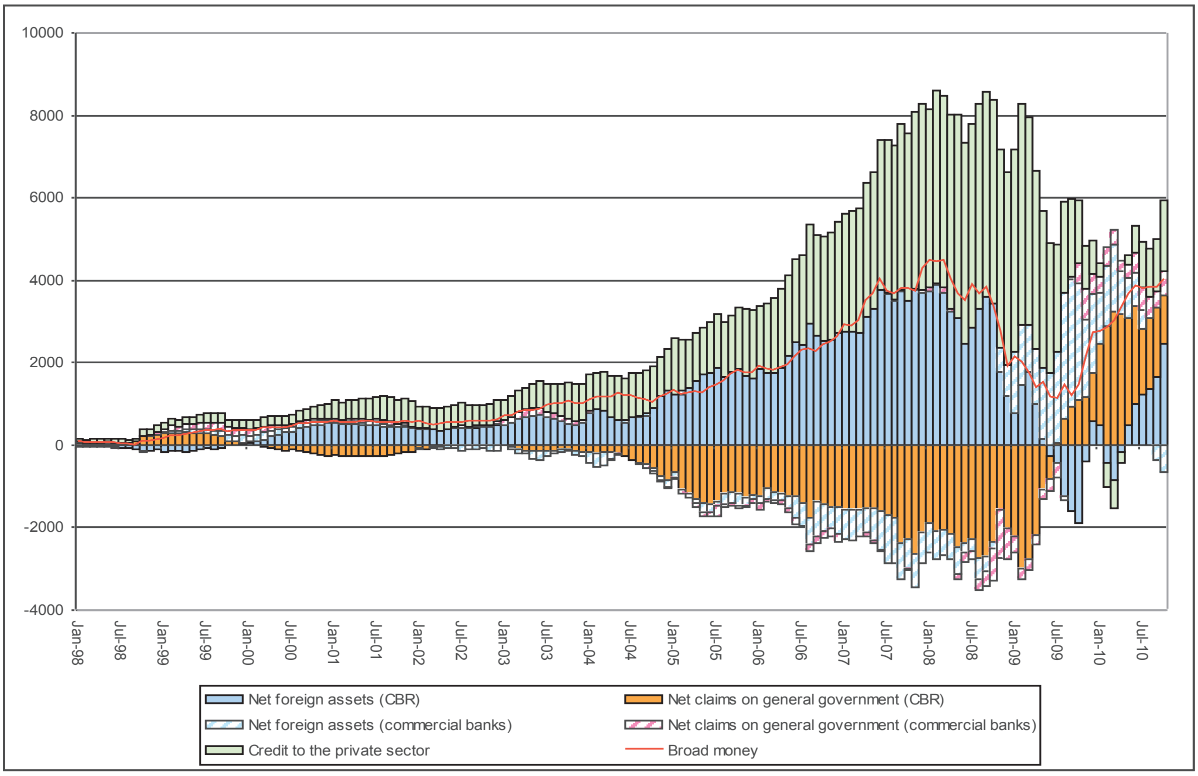


Figure 1.4

Money and its counterparts (annual changes, bln. rubles)



Looking at the evolution of the counterparts of Russian broad money (M2X) in Figure 1.4 reveals the domestic and external driving forces of monetary developments. The most important counterparts of money growth have been the CBR's foreign assets, the CBR's net claims on the government (reflecting the transactions of real domestic sector with the foreign sector) and banks' credit to the non-financial sector. Changes in the CBR's net foreign assets are generally the key driving force of changes in M2X. Changes of net claims to the general government (CBR) reflect the workings of the sovereign wealth funds, since international inflows of foreign currency are partly deposited in a sovereign wealth fund held on the CBR's balance sheet. The presence of significant exogenous growth sources means that the link between money and credit growth may not be very close – we will discuss the drivers behind different episodes of money growth later in this paper. It also means that nominal money stock may be driven by factors totally unrelated to money demand fundamentals. This does not mean however that the money-demand relationship is non-existent (as money growth may trigger the adjustment of other macroeconomic variables towards new equilibrium) or that it is of no practical use. The composition of drivers behind money-stock growth indicates that the Russian economy is evidently prone to exogenous money-supply shocks (as opposed to endogenously-driven money-demand shocks). Identifying these shocks and their macroeconomic consequences is a crucial task for monetary analysis. Using money demand models to assess the degree of correspondence between realized money growth and macroeconomic fundamentals could be regarded as one of the methods of such identification.

In the early 1990s, the transformation from the planned economy in Russia was followed by galloping inflation, a deep recession, a depreciation of the national currency and large permanent government budget deficits. Money growth rates were extremely high. The new Russian banking sector at that time was just emerging and could not provide efficient financial intermediation. In these circumstances the CBR's credit to the government, to commercial banks as well as to selected non-financial enterprises was practically the only source to satisfy money demand. The direct monetization of the government budget deficit played an important role in money growth.

As the direct CBR's credit provision to the government was discontinued in 1995 the growth rates of monetary aggregates in 1996-1997 as well as inflation rates were much lower as compared to earlier 1990s.

During the 2000s, the Russian banking sector underwent a significant transformation. Although it remained small in terms of net assets to GDP, when compared to other emerging economies (Fungáčová and Solanko, 2009a), credit flows to the real sector have increased rapidly in recent years and become an important determinant of cash flows in the economy. The rapid growth of deposits (resulting in part from the cross-border cash inflows in conditions of a heavily-managed exchange-rate regime) have provided banks with a rich resource for lending. Similar conditions have been seen in Asian economies with similar monetary-policy regimes (Mohanty and Turner, 2010).

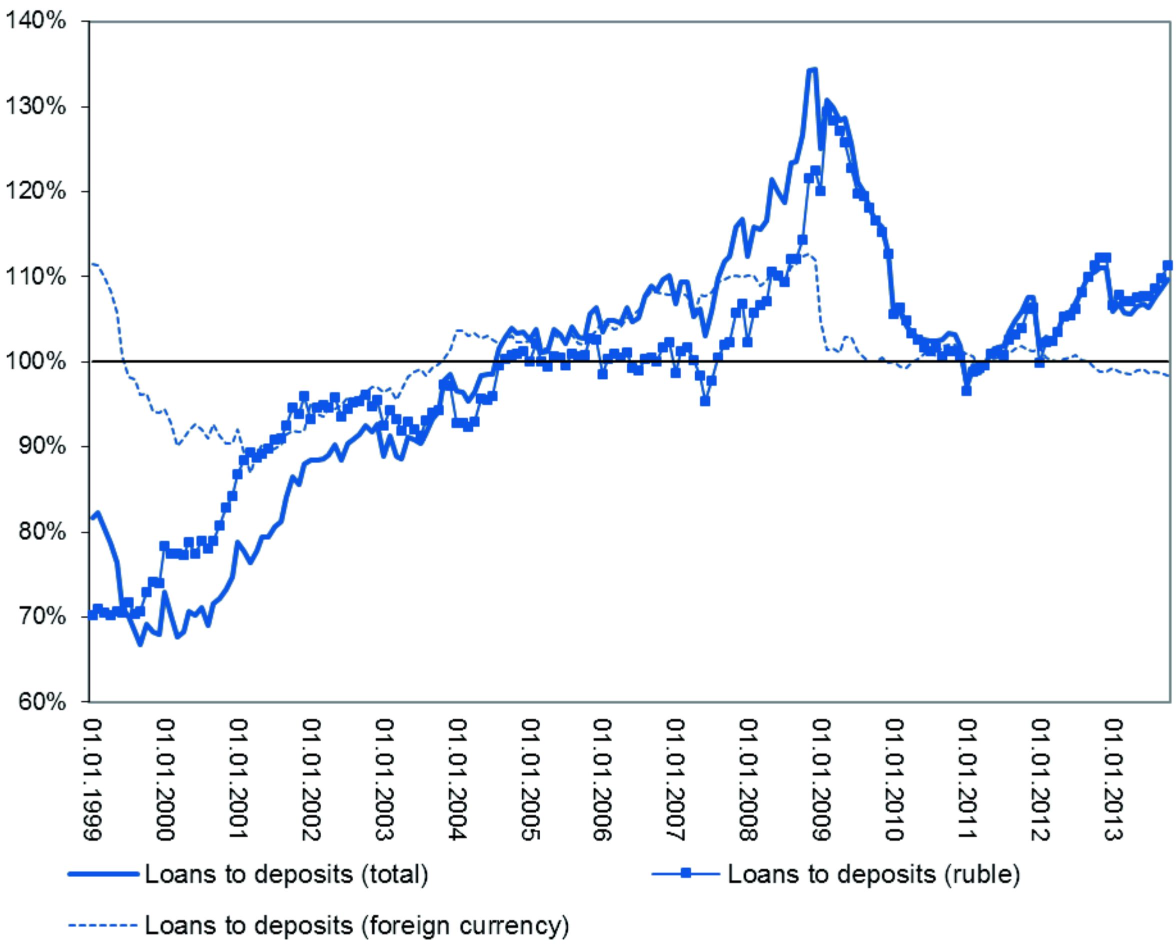
Russia turned to the fiscal mechanism of the sovereign wealth fund to absorb foreign currency from central bank interventions. In 2004 the sovereign wealth fund (the so-called Stabilization Fund which was reorganized into Reserve Fund and National Welfare Fund in 2008) was created within the Russian public finance framework. This institution proved to be very important for monetary developments and has affected the dynamics of the money stock ever since. The main source of the sovereign wealth fund's formation is taxes on oil and gas extraction and custom duties on oil exports. These funds are placed in special accounts of the Federal treasury in the CBR and are managed by the CBR. From 2005 till late 2008 the budget had a large surplus, mainly due to high oil and gas prices, which determined the accumulation of reserves on the sovereign wealth fund's accounts effectively containing money growth[26]. Changes in net foreign

[26] Although the CBR also used liquidity absorbing tools (such as bond issuance) the absorption through fiscal mechanisms had clearly the most important impact on the monetary stance.

assets held at the CBR and net claims on the general government held at the CBR have been the driving counterparts of M2X since 1998. They reflect the functions of the sovereign wealth fund in an oil-rich economy. Its stabilizing effects, for example, are reflected in increasing positive contributions of CBR's net claims on general government after the crisis in 2008 that largely determined the recommencement of M2X growth. This reflects the buffering function of the sovereign wealth funds.

An important distinction between Russian and Asian banks was that the size of the lending booming exceeded deposit growth in 2006−2008, causing funding gaps to emerge. Russian banks relied on external borrowing to finance this gap; interbank lending in particular became dominated by transactions with foreign counterparties (Fungáčová and Solanko, 2009b).

Figure 1.5 Loans to deposits ratio



1.4. Money demand models

An important aspect of the empirical properties of monetary aggregates is the existence of a stable money-demand function. The money-demand function is a fundamental relationship that captures the interactions between money and other important economic variables such as income and wealth. The role of opportunity costs is influenced *inter alia* by the depth and breadth of financial markets and the degree of substitution between domestic and foreign currencies. Thus a robust relationship between monetary aggregates and other macroeconomic variables can help to explain and interpret monetary developments. From a normative perspective, money-demand models are a starting point for developing benchmarks of the level or growth of money. In this study we are able to analyze money demand for different monetary aggregates as described in Section 1.3.

Previous studies on money demand functions in Russia (e.g. Oomes and Ohnsorge (2005); Korhonen and Mehrotra (2010); Mehrotra and Ponomarenko (2010)) report stable money-demand relationships over the pre-crisis period. In our study we will examine if there is still a robust relationship when 2009-2010 observations are added to the sample and we will check that for different monetary aggregates. Interestingly, Oomes and Ohnsorge (2005) also conducted their estimates for several monetary aggregates and found, based on the confidence-intervals width and the recursive estimates of cointegrating vectors' coefficients that the M2Y money demand function was the most stable, while narrower ruble aggregates did not produce stable relationships. We compare these findings with more recent results.

1.4.1 Model specification and data issues

Our specification of the long-run real money demand in the log linear form is:

$$(m\text{-}p)_t = \beta_0 + \beta_1 y_t + \beta_2 w_t + \beta_3 OC_t + \beta_4\, unc_t + \xi_t, \tag{1.2}$$

where *m-p, y* and *OC* are the monetary aggregate deflated by the price level, the scale variable and the vector of opportunity costs accordingly. Modern money-demand studies (e.g. Greiber and Setzer (2007); Beyer (2009)) also control for the wealth effect (which as discussed in Mehrotra and Ponomarenko (2010) may be important for Russia) by adding a real-wealth variable into the money-demand function. Another addition to the traditional specification could be an uncertainty variable as in e.g. Greiber and Lemke (2005), which could also be relevant for emerging economies (see Özdemir and Saygili (2010)) particularly when attempting to model crisis developments. Recent studies by de Bondt (2009) and Seitz and von Landesberger (2010) include both wealth and uncertainty indicators into the money demand function. Therefore we add real wealth (*w*) and uncertainty (*unc*) variables into our model. We estimate four different models with real M1, M2, M2Y and M2Y^{adj} as money stock variables. We do not report the results for real M2X and M2X^{adj} as we fail to find any meaningful money demand relationship for these aggregates. This result is somewhat puzzling. One possible explanation is that the developments of the M2X aggregate are affected by changes of preferences between foreign-cash holdings and foreign-currency-denominated bank deposits. These changes may be difficult to model formally (at least when based only on money-demand fundamentals).

We follow Mehrotra and Ponomarenko (2010) and use a real-asset price index as a proxy for real wealth. The index is the weighted[27] average of housing and equity price indices. Housing wealth may be viewed as constituting a significant part of households' wealth. The 2002 national census found only about 3% of households rent a house or an apartment and that about 20% of households owned a secondary dwelling (mainly for seasonal use). Equities are not a significant component of household financial wealth, but their price can be viewed as a proxy for corporate wealth. As discussed in Mehrotra and Ponomarenko (2010) the rapid growth of asset prices in Russia in 2005-2007 could have positively affected transactions demand for money as transactions in asset markets increased. The increase in wealth due to the growth of asset prices may also be associated with increased demand for other liquid assets (including money) that are part of the wealth portfolio.

We have tested various indicators of uncertainty (e.g. the unemployment rate, oil-price volatility, government budget balance). Based on the models' performance and following Greiber and Lemke (2005) who propose stock-market volatility as one possible indicator of uncertainty we selected the variance of RTS index returns over rolling periods of 180 days as the metric for uncertainty. Interestingly, the interplay between this variable and various monetary aggregates may be different. Increasing uncertainty is generally associated with growing precautionary demand for money, but in case of Russia it may also result in additional demand for foreign-currency-denominated assets at the expense of ruble money stock. Therefore the positive effect on the demand for money may be more pronounced in case of broad monetary aggregates.

[27] Similarly to Gerdesmeier et al. (2010) the weights are inversely proportional to the variables' volatility, i.e. $\Delta\ Asset\ prices = \sigma_{sp}/(\sigma_{sp} + \sigma_{hp})\ \Delta Housing\ prices + \sigma_{hp}/(\sigma_{sp} + \sigma_{hp})\ \Delta Equity\ prices$, where σ is the standard deviation of the respective variable. The resulting weights equaled 0.86 for housing and 0.14 for equity prices and seem economically meaningful and consistent with weights used in Mehrotra and Ponomarenko (2010).

The choice of the opportunity-cost indicator is quite complicated in the case of Russia. The relative underdevelopment of the financial market precludes the use of money market interest rates for this purpose. On the other hand, the exchange-rate fluctuations were identified as important money-demand determinants in Russia by all previous studies as well as in other emerging market economies (see e.g. Dreger et al. (2007)). Interestingly national currency depreciation can be considered as opportunity cost only for holding ruble aggregates, since interflows between ruble and foreign-currency-denominated deposits would not affect broad money measures. In fact national currency depreciation would increase the implied ruble yield of foreign currency-denominated components of broad aggregates. Another opportunity-cost indicator that may be considered (as in e.g. Korhonen and Mehrotra (2010)) is the inflation rate. This leaves us with a range of variables that could be potentially used to proxy for opportunity costs/own yield. Including all these simultaneously into the estimated relationship is hardly appropriate due to length limitations in time series. Instead we choose more parsimonious approach and construct aggregate opportunity costs/own yield measures.

The own yield of ruble components is measured by the interest rate on households' long-term ruble time deposits. The own yield of foreign currency components is the weighted average of interest rates on euro and USD deposits (with time-varying weights equal to those in the CBR's bi-currency basket[28]) plus the ruble's depreciation against the bi-currency basket over the two last quarters, which presumably proxies the exchange rate expectations. The aggregate yield of return is the weighted average (with weights proportional to the shares of ruble and foreign currency deposits in the total amount of deposits) of ruble and foreign-currency components' yields. All opportunity-cost variables are in quarterly terms.

For the money demand functions with M1 we use the aggregate yield of return as the *OC* variable and expect the β_3 coefficient to be negative, since M1 does not include appreciably remunerated components. For money-demand functions with M2 we use the exchange-rate depreciation against the bi-currency basket over the two last quarters as a proxy of the spread between ruble and foreign-currency components' yields and also expect the β_3 coefficient to be negative[29]. For money-demand functions with M2Y we use the spread between the aggregate yield

[28] While the structure of foreign-currency deposits in Russia is unavailable, other subsidiary indicators justify the use of bi-currency basket's weights for this purpose. The bi-currency basket is the operational target of the CBR and consists of the combination of USD and euro with time-varying weights.

[29] While the most obvious choice for M2 model would be to use the spread between ruble and foreign-currency components' yields this approach did not produce meaningful results (the β_3 coefficient had the "wrong" sign). The reason for that could lie with the extremely high ruble interest rates in 1999-2000 (which determined the highly positive values of the spread). Taking into account the state of financial markets and the lack of confidence in the domestic banking system at that time, these interest rates might be not fully representative as an attractive alternative to foreign currency assets. We therefore decided to disregard these interest rates. In other periods the spread was

of return and the realized two quarters CPI inflation rate and expect the β_3 coefficient to be positive. The overall dynamics of the resulting aggregate indicators over tranquil periods are mostly determined by changes of interest and inflation rates, but largest variations are due to exchange rate fluctuations (most notably in 1999 and 2008-2009).

We use GDP as a scale variable and the GDP deflator to calculate money and wealth variables in real terms. All variables except *OC*s and *unc* are in logs. The time sample under review is 1999Q1-2010Q2 which gives us 46 quarterly observations. The order of integration of the variables is determined based on the results of Phillips-Perron, KPSS and ADF-type test which controls for possible structural break over the crisis period (Lanne et al. (2002)) unit root tests (Table A1 in Annex 1A). Despite some indication from the Phillips-Perron test that $M2Y$, $M2Y^{adj}$ and y could be trend-stationary we assume that with the possible exception of *OC*s and *unc* all variables are I(1) and we therefore proceed with the cointegration analysis. This decision was supported by the test for the stationarity of the variables within cointegrated VAR conducted at later stages (Table A2 in Annex 1A).

1.4.2 Cointegration analysis

As a starting point of our analysis we refer to the most commonly applied method in testing for cointegration proposed by Johansen, 1996. The procedure efficiently includes the short-run dynamics in the estimation of the long-run model structure in the system of equations framework. We use the conventional VEC model of the form:

$$\Delta x_t = \Pi x_{t-1} + \Gamma_1 \Delta x_{t-1} + \ldots + \Gamma_p \Delta x_{t-p} + CD_t + \varepsilon_t , \qquad (1.3)$$

where x_t is a (K x 1) vector of endogenous variables and the Γ_p are fixed (K x K) coefficient matrices. We further assume that ε_t follows a white-noise process with $E(\varepsilon_t)=0$. When some or all of the K endogenous variables are cointegrated, the matrix Π has reduced rank r. D_t contains the deterministic terms outside the cointegrating vector, and C is the coefficient matrix associated with

mostly determined by the exchange-rate fluctuations, as the interest rates remained stable, so there were no big differences between the two indicators.

the deterministic terms. In our set-up, the model includes unrestricted constant and seasonal dummy variables. The lag length was set to 4[30].

Table 1.3

Cointegration test results: Bartlett corrected trace statistic (p-value)

Model	Rank			
	0	1	2	3
M1	88.45 (0.00)	48.44 (0.04)	22.69 (0.26)	9.94 (0.29)
M2	70.81 (0.04)	43.67 (0.12)	24.67 (0.17)	6.23 (0.67)
M2Y	89.93 (0.00)	40.52 (0.20)	31.28 (0.03)	13.96 (0.08)
$M2Y^{adj}$	85.47 (0.00)	40.62 (0.20)	26.33 (0.12)	13.50 (0.10)

The tests as shown in Table 1.3 confirm the possibility of cointegration in all models since the rank of zero is rejected. Although there is some indication that the matrix Π may have rank 2 in the M1 model for the sake of economic interpretability we proceed by assuming 1 cointegrating relationship in all the models. The recursively-estimated eigenvalues and Hansen and Johansen (1999) fluctuations tests confirm the stability of cointegrating relationships[31] (Figures A2-A3 in Annex 1A). Admittedly there is considerable uncertainty regarding this specification choice that could potentially bias the model's performance as well as the results of characteristics tests. An alternative way to proceed (assuming a cointegration rank of 2) would be to identify the second cointegrating vector (such as long-run wealth growth relationship in Beyer, 2009) in addition to the money-demand relationship and examine its relevance in the comprehensive system of the simultaneous equations framework. This kind of analysis however was not undertaken in this study.

[30] Most of the traditional information criteria would indicate that a longer lag-length is preferable. But for the reasons of parsimony given the short time sample and given the quarterly data used we limit the lag length to four. Later we examine to what extent the lag-length choice influences the cointegrating vectors.

[31] At this stage we concentrate on the analysis of long-run relationship and therefore excluded the short-run part from the stability tests. The performance of short-run money demand models are discussed elsewhere in this paper.

Table 1.4

Tests for weak exogeneity of variables: F-statistic (p-value)

Variable	*Model*			
	M1	M2	M2Y	$M2Y^{adj}$
M	11.50 (0.00)	4.09 (0.04)	0.15 (0.70)	0.05 (0.82)
Y	30.15 (0.00)	1.85 (0.17)	5.12 (0.02)	6.37 (0.01)
W	0.10 (0.76)	15.04 (0.00)	8.16 (0.00)	9.72 (0.00)
OC	0.09 (0.77)	0.73 (0.39)	63.15 (0.00)	53.43 (0.00)
UNC	0.40 (0.53)	3.16 (0.08)	0.06 (0.81)	0.37 (0.54)

Null hypothesis: variable is weakly exogenous

Although the analysis of the dynamic relationship between money and other macroeconomic variables is beyond the scope this paper we do examine the weak exogeneity tests based on the VEC model reviewed and show the test results in Table 1.4. There are notable differences in the results for different models: while the weak exogeneity of narrower ruble aggregates is rejected, the developments in the broader aggregates seem to be unaffected by the adjustment resulting from the cointegration relationship. This result may contradict the conventional theory associated with the money-multiplier concept which would presume narrow aggregates to be exogenous and broader ones to be endogenous. Yet these findings may be in line with the peculiarities of money-supply factors in Russia. We will further discuss the performance of the models in explaining money-stock developments later in this paper.

Instead of affecting money, the adjustment occurs through other variables such as GDP or real wealth. The results for OC variables are mixed – they seem to be weakly exogenous in the M1 and M2 models and endogenous in M2Y and $M2Y^{adj}$ models.

The cointegration vectors are estimated by the simple two-step estimator (S2S). As Brüggemann and Lütkepohl (2005) show, this estimator produces relatively robust estimates in short samples. The lag length is set to 4. Most of the cointegrating vectors estimated using different lag lengths were relatively robust.

We cross-check the results obtained with S2S method by estimating the cointegration vectors using Fully Modified-OLS (Philips and Hansen (1990)) in a parsimonious single equation set-up. We use pre-whitening with the lag length determined by Schwarz criteria and Barlett kernel with the cut-off determined by the automatic Andrews (1991) procedure.

The cointegration vectors are estimated in the presence of unrestricted constant and seasonal dummy variables. The results are shown in Table 1.5.

Table 1.5

Cointegration vectors (t-statistics)

Variable	*Estimation Method*	*Model*			
		M1	M2	M2Y	$M2Y^{adj}$
M	S2S	1	1	1	1
	FM-OLS	1	1	1	1
Y	S2S	-1.65 (-37.3)	-2.38 (-20.2)	-0.38 (-4.09)	-0.63 (-12.3)
	FM-OLS	-1.76 (-12.6)	-2.6 (-13.1)	-0.61 (-1.68)	-1.05 (-4.85)
W	S2S	-0.47 (-13.8)	-0.34 (-3.49)	-0.88 (-11.2)	-0.67 (-15.5)
	FM-OLS	-0.48 (-4.45)	-0.29 (-1.68)	-0.54 (-1.81)	-0.23 (-1.31)
OC	S2S	2.07 (13.1)	3.73 (9.15)	-3.47 (-5.34)	-1.62 (-4.89)
	FM-OLS	0.93 (3.17)	0.84 (1.25)	2.18 (2.13)	-0.4 (-0.72)
UNC	S2S	-118 (-8.25)	-45.1 (-1.81)	-67.4 (-2.13)	-128.5 (-7.61)
	FM-OLS	-8.4 (0.48)	-44.7 (-1.21)	-152 (-3.16)	-109.8 (-3.86)

The parameters estimated with S2S method are statistically highly significant and economically meaningful. The growth of GDP and real wealth increases money demand. Interestingly, there are striking differences in income elasticities between the models. The M1 and M2 models retain the feature of high income elasticity, which was also reported in all the previous money demand studies for Russia. This peculiarity is usually associated with ongoing institutional changes such as financial deepening and the return of confidence in the national currency. In the cases of M2Y and $M2Y^{adj}$ however the income elasticities are lower, while the parameters for wealth are somewhat higher. The sum of the income and wealth parameters is only slightly higher than unity[32]. In fact these results are consistent with the parameters reported in Greiber and Setzer (2007) for the euro area and the US and in Seitz and von Landesberger (2010) for the euro area. These results seem to be thought-provoking as they show how differently monetary developments in Russia could be interpreted when different money stock measures are used. The opportunity-cost variables all have the expected signs. The increase of uncertainty has a positive effect on money demand. As could be expected it seems to be less evident in case of ruble aggregates.

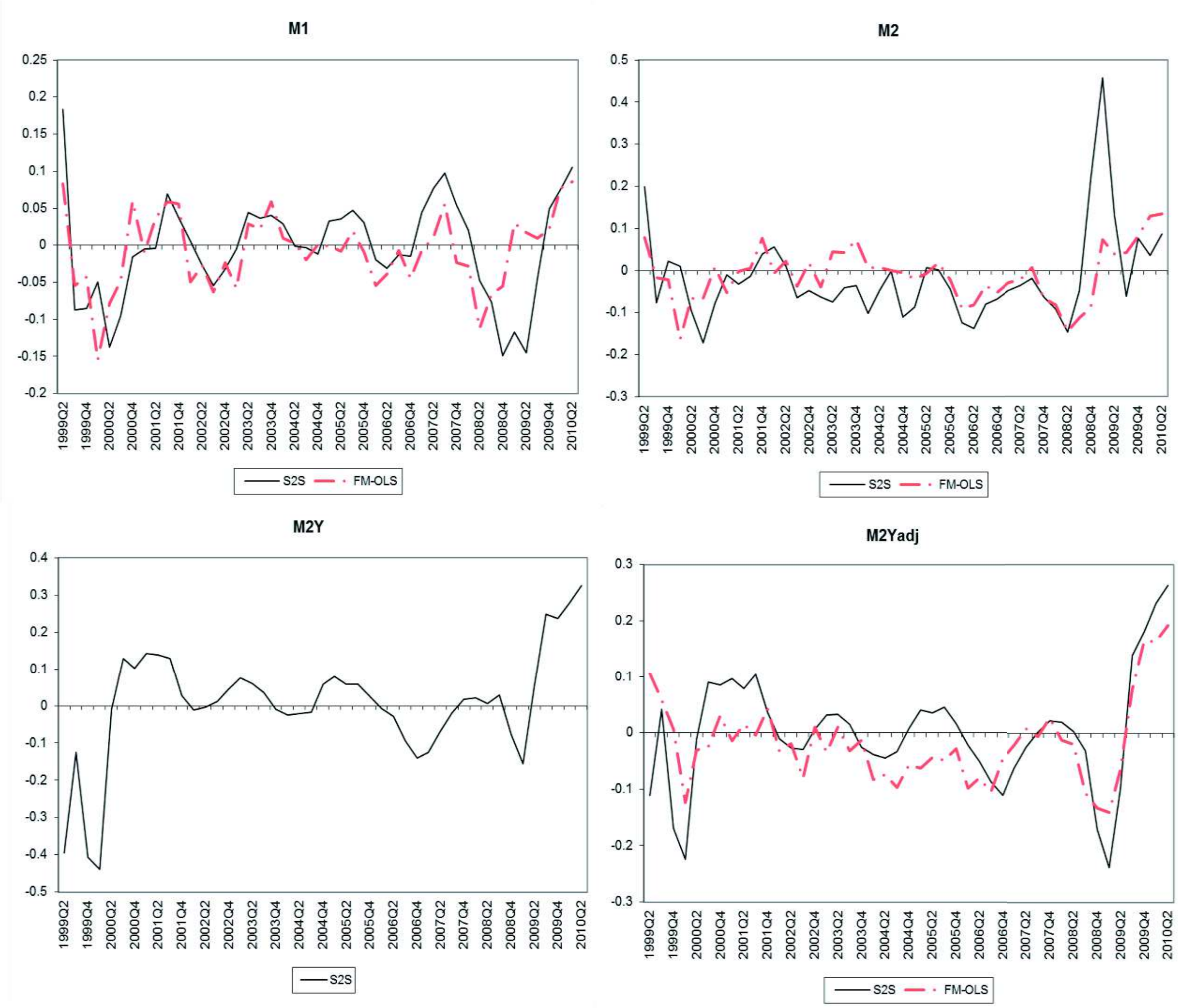
These findings are generally confirmed by FM-OLS estimates for M1, M2 and $M2Y^{adj}$ models, although the uncertainty variable in the M1 model and OC variables in M2 and $M2Y^{adj}$ models are statistically insignificant. Nevertheless we proceed with further analysis of this cointegration vectors as they are economically meaningful. We exclude the FM-OLS cointegration vector for the M2Y model that displays the "wrong-signed" OC variable coefficient.

In order to test the robustness of the results we estimate the cointegration vectors recursively to check if the point estimates remain stable as the post-crisis observations are added into the sample (Figures A3-A6 in Annex 1A). The recursive estimates of income and wealth elasticities are relatively stable in all models irrespectively of the estimation method (with the exception of income elasticity in S2S M2Y model which was insignificant if estimated using only pre-crisis sample). The OC and uncertainty recursive coefficients displayed considerable fluctuations but still seemed meaningful in the models for ruble M1 and M2 aggregates. The recursive estimates of OC variable coefficient in M2Y and $M2Y^{adj}$ models reveal, however, that the OC variables only started to enter the cointegration relationship with the "right" sign after the large number of post-crisis observations had been added to the estimation sample. This result may indicate that the relationship between broader monetary aggregates and OCs is more complex than implied by this money demand relationship or that the financial returns indicators do not fully represent the OCs in the Russian economy. On the other hand, given the limited variation of OCs before the crisis and relatively short time sample we cannot rule out the possibility that adding the observations characterizing the opposite phase of the economic cycle was just necessary to disentangle the true effect of OCs on money demand.

[32] The sum of coefficients equals 1.26 and 1.3. Interestingly, Oomes and Ohnsorge (2005) report an income elasticity of 1.2 for M2Y money demand function without wealth.

Figure 1.6

Monetary overhangs[33]



We may examine monetary overhangs derived from the cointegrating relationships as the measures of excess liquidity and as shown in Figure 1.6. The choice of cointegration vector's estimation method does not seriously change the outcome here. With the exception of fluctuations in the beginning of the sample and the hikes of S2S M2 overhang in early 1999 and 2009 (determined by the sharp exchange rate depreciation episodes) the dynamics of the overhangs seem meaningful. They fluctuate evenly around zero, pick up in 2006 before plummeting to some very low levels in 2008-2009. Then, as money growth picked up while money demand fundamentals' (particularly real asset prices) remained weak, the monetary overhangs climbed to unprecedentedly high levels, in particular for M2Y and adjusted M2Y.

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[33] The monetary overhangs were computed (using seasonally adjusted data) as demeaned error correction terms from the estimated cointegration relationships.

1.4.3 Error correction models

The short-run money-demand models are formulated as conventional ECMs of the form:

$$\Delta(m-p)_t = \alpha_0+\alpha_1 ec_{t-1}+\sum_{j=1}^{2}\alpha_{2j}\Delta(m-p)_{t-j}+\sum_{j=1}^{2}\alpha_{3j}\Delta y_{t-j}+\sum_{j=1}^{2}\alpha_{4j}\Delta w_{t-j}+ \sum_{j=1}^{2}\alpha_{5j}\Delta OC_{t-j}+\sum_{j=1}^{2}\alpha_{6j}\Delta unc_{t-j}+\sum_{i=1}^{3}\sigma_i\ D_{it}+\varepsilon_t \quad ,$$

where *ec* is the error correction term and D_i are the seasonal dummy variables. The equations include two lags of real money growth. The short-run part of the equations also contains up to two lags of first differences of other explanatory variables (these are eliminated if the respective t-statistics are smaller than 1.67). Conventional tests do not find serial correlation or ARCH effect in the equations' residuals. The α_1 coefficients as given in Table 1.6 are of most interest as they show that real money growth adjusts in accordance with the cointegrating relationship.

Table 1.6

ECMs' α_1 loading coefficients (t-statistics)

Estimation period	*Cointegration vector*	*Model*			
		M1	M2	M2Y	$M2Y^{adj}$
1999Q1-2008Q2	S2S	-0.39 (-3.84)	-0.05 (-0.88)	0.05 (1.59)	-0.03 (-0.44)
	FM-OLS	-0.47 (-3.61)	-0.23 (-2.11)	-	-0.4 (-4.00)
1999Q1-2010Q2	S2S	-0.24 (-2.82)	0.01 (0.11)	0.07 (2.25)	-0.02 (-0.56)
	FM-OLS	-0.28 (-2.37)	-0.03 (-0.35)	-	-0.24 (-3.17)
1999Q1-2010Q2 (with dummy variables)	S2S	-0.31 (-3.70)	-0.05 (-0.98)	0.06 (1.93)	-0.01 (-0.16)
	FM-OLS	-0.41 (-3.44)	-0.19 (-2.19)	-	-0.2 (-2.65)

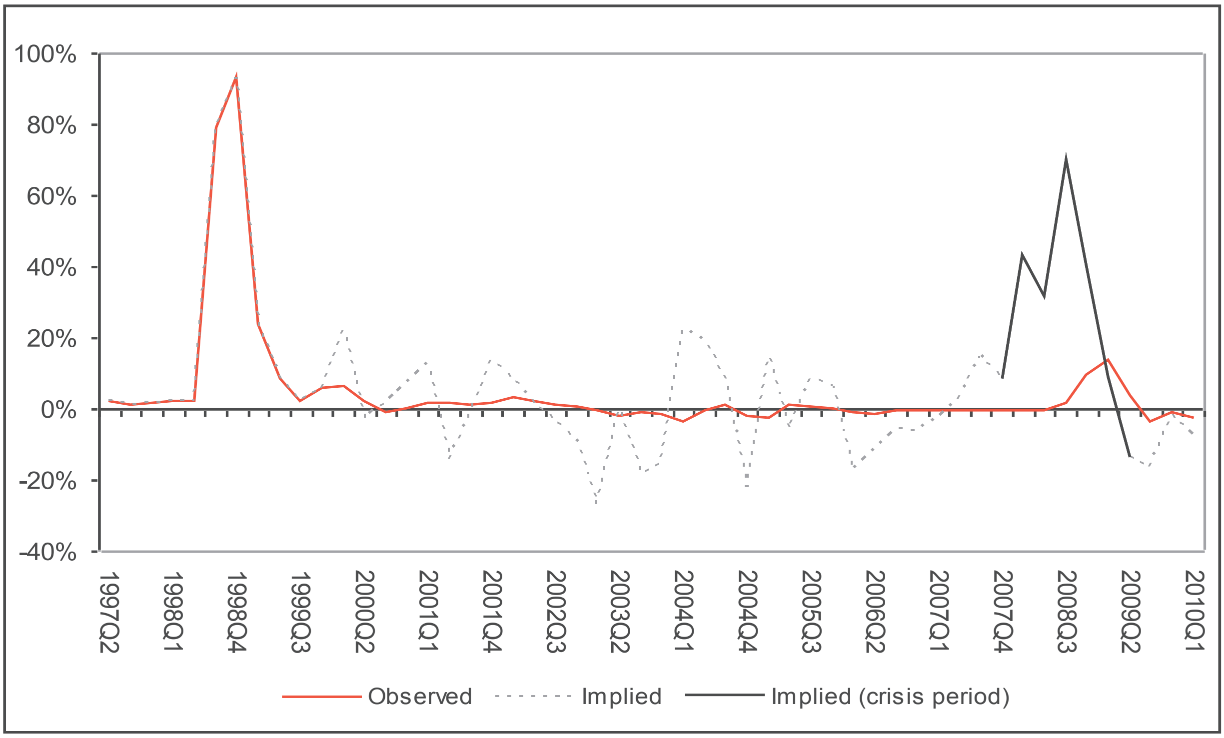
At first we estimate the ECMs on the pre-crisis period prior to 2008Q3. The loading coefficient in the M1 and M2 models is large and statistically highly significant (although the FM-OLS cointegrating vector is clearly more relevant for short-run M2 developments than S2S estimates). Quandt-Andrews breakpoint tests indicate that the models are stable over this sample. When the post-crisis observations are added to the time sample, the loading coefficients deteriorate notably (although in case of M1 it is still significant). The recursive estimates of loading coefficients show that their instability coincided with crisis developments (Figure A7 in Annex 1A). We therefore also examine the ECMs' estimates with the period of 2008Q3-2009Q1 covered with dummy variables. Under this set-up the estimates of the loading coefficient do not change significantly in comparison with the pre-crisis sample estimates.

This result could be expected, given the drastic and unpredictable fluctuations of money stock during the most severe phase of the crisis. The rapid return of dollarization, for example, could not be captured by the exchange rate variable since ruble's depreciation expectations were much stronger than implied by the gradual CBR-controlled depreciation rates. If we assume that the model's error during the crisis was due to the error in measuring exchange-rate expectations we may illustrate this by solving the model for M2[34] back and finding the exchange-rate variable value that implied no error in the model's estimate of money stock. Over most of the sample this estimate would have no economic meaning. Yet, during the depreciation episode this estimated exchange rate variable's value could be used to assess these unobserved expectations.

[34] We used the FM-OLS model for M2 estimated over the 1999Q1 – 2008Q2 time sample.

Figure 1.7

Exchange rate expectations: observed proxy (the average quarterly ruble's depreciation over the last two quarters) and the estimate implied by the model



The results of this exercise, as shown in Figure 1.7, indicate that the expected ruble's depreciation which would be consistent with the intensity of dollarization was higher than the one actually realized. In fact the market participants seemed to expect a depreciation similar to the one that took place during the previous crisis of 1998.

The results of ECMs' estimation for broader aggregates are more ambiguous. In contrast to ruble aggregates the broader M2Y and $M2Y^{adj}$ seem to be unaffected by the cointegrating relationship (at least by those estimated with the S2S method). The α_1 estimates are statistically insignificant under any set-up and in the case of M2Y the loading coefficient is positive which is clearly implausible. We believe that this difference arises from the fact that the nominal volumes of ruble aggregates are quite sensitive to changes of transactional needs and opportunity-cost fluctuations (as households are eager to switch between currencies or between cash and bank deposits). There are however fewer means for nominal volumes of broad aggregates to adjust as their dynamics is only partially determined by demand-driven processes (i.e. financial intermediation) and there are virtually no assets outside M2Y aggregate that are widely used for savings purposes. There still is the chance that the real money stock would adjust due to the increase of the price level, but given the relatively short period under review and the scope of the nominal money-supply shocks which took place during this period, it is unsurprising that such adjustment could go unnoticed by the econometric model. Yet, we cannot rule out the possibility that broad aggregates may be driven by money demand completely as the ECM based on FM-OLS cointegration vector estimate for $M2Y^{adj}$ performs satisfactorily and is not drastically affected by the crisis.

We can summarize our findings as follows. The long-run money demand relationship may be established for M1, M2, M2Y and $M2Y^{adj}$ aggregates. The parameterization of these relationships is notably different, although it is impossible to discriminate between them from a theoretical viewpoint since all sets of parameters might be plausible under certain assumptions. Contrarily to Oomes and Ohnsorge (2005), the narrowest M1 aggregate performs at least as good as the broader aggregates. In fact the recursive estimates of the cointegration vector of M1 money-demand relationship seems to be more stable than those estimated for broader monetary aggregates, in which cases the robustness is questionable. The short-run model of the demand for M1 is obviously the best performing, while M2Y developments seem to be ambiguously affected by the money-demand relationship. Although given the exogenous nature of the sources of nominal money growth in Russia and the underdevelopment of the alternative financial assets that could be used for savings purposes beyond those included into M2Y, this last finding seems plausible.

1.5. Conclusions

Tools and techniques of the ECB's monetary analysis can give valuable input to the conduct of monetary policy at other central banks, if institutional, economic and financial differences are taken into account. We take the case of the Bank of Russia and analyze the changing role of money in its monetary policy.

In the core part of our paper we derive stable money demand functions that are related to income and wealth and to a lesser extent to opportunity costs and uncertainty. Estimations of narrower aggregates that only include components denominated in national currency seem to be more stable than broader aggregates. It signals that monetary developments are influenced by factors that go beyond the usual money-demand factors, such as the buffering function of the sovereign wealth fund in case of Russia. This makes the interpretation of monetary overhangs and the policy implications that can be drawn from them more complex since the impact of the sovereign wealth fund on monetary development is already a policy reaction. Eventually, it should be kept in mind that the concept of monetary overhangs are a starting point for an analysis that also focuses on changes in the stocks rather than analyses that solely focus on changes in the flows. Additionally, we show how money demand functions can be used to derive implied exchange-rate depreciation expectations as compared to actual exchange-rate depreciation.

We conclude that the ECB style monetary analysis gives valuable input to the analysis at the CBR. Monetary analysis, however, is an evolutionary process, so within an economy over time as well as across economies changes of the economic and financial environment have an impact on the analysis and on the policy conclusions that can be drawn from it. The case of Russia furthermore highlights that monetary analysis should not be minimized to a purely technical exercise, but that it needs and enforces institutional knowledge of the financial sector.

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Appendix 1A

Figure A1
Variables used in the model

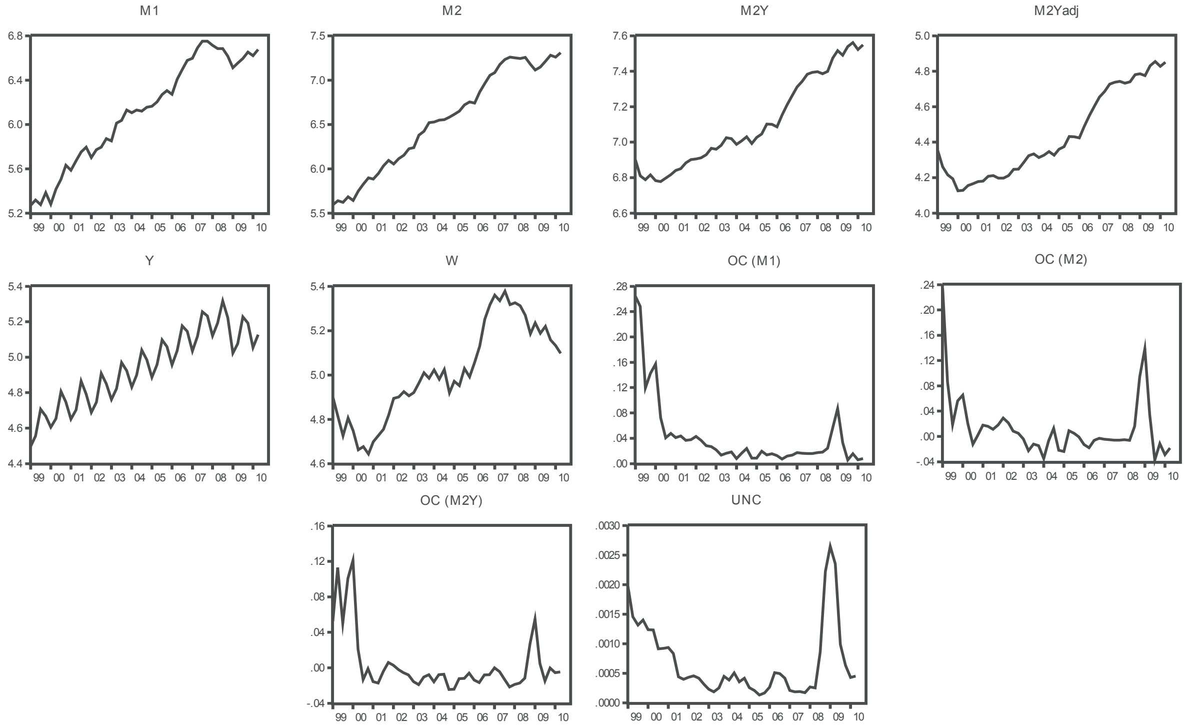


Table A1
Results of the unit root tests
(for PP and KPSS tests the bandwidth is determined by automatic Andrews, 1991 procedure; the unit root test with structural break is conducted in the presence of seasonal time dummy variables and the shift type dummy variable in 2008Q4 (the impulse type dummy variable when the variables are in differences) with lag length set to 4)

Variable	*Test specification*	*PP test statistic (p-value)* Null hypothesis: variable has unit root	*KPSS test statistic* Null hypothesis: variable is stationary	*ADF type unit root test with structural break (Lanne et al. (2002)) test statistic* Null hypothesis: variable has unit root
M1	Levels (constant)	-0.68 (0.84)	0.45*	-1.78
	Levels (constant and trend)	-1.80 (0.69)	0.16**	-2.73
	1st differences (constant)	-7.47 (0.00)	0.14	-3.64**
M2	Levels (constant)	-0.49 (0.88)	0.66**	-1.4
	Levels (constant and trend)	-1.78 (0.70)	0.17**	-2.15
	1st differences (constant)	-5.88 (0.00)	0.14	-3.06**

M2Y	Levels (constant)	1.00 (0.99)	0.67**	-0.22
	Levels (constant and trend)	-3.95 (0.02)	0.15**	-0.77
	1st differences (constant)	-5.16 (0.00)	0.49**	-2.9**
$M2Y^{adj}$	Levels (constant)	-0.00 (0.95)	0.58**	-0.13
	Levels (constant and trend)	-6.78 (0.00)	0.14*	-0.29
	1st differences (constant)	-5.30 (0.00)	0.48**	-3.42**
Y	Levels (constant)	-2.00 (0.29)	0.44*	-1.26
	Levels (constant and trend)	-4.82 (0.00)	0.18**	-2.9*
	1st differences (constant)	-6.63 (0.00)	0.04	-3.24**
W	Levels (constant)	-0.99 (0.75)	0.42*	-2.2
	Levels (constant and trend)	-1.41 (0.85)	0.14*	-2.29*
	1st differences (constant)	-6.84 (0.00)	0.18	-3.14**
OC^{M1}	Levels (constant)	-7.06 (0.00)	0.41*	-3.56**
	Levels (constant and trend)	-5.49 (0.00)	0.16**	-0.2
	1st differences (constant)	-6.56 (0.00)	0.42*	-4.13**
OC^{M2}	Levels (constant)	-21.3 (0.00)	0.31	-1.65**
	Levels (constant and trend)	-20.0 (0.00)	0.16**	-0.81
	1st differences (constant)	-6.82 (0.00)	0.37	-4.75**
OC^{M2Y}	Levels (constant)	-2.83 (0.06)	0.31	-3.94**
	Levels (constant and trend)	-2.97 (0.15)	0.16**	-0.36
	1st differences (constant)	-8.15 (0.00)	0.06	-5.28**
UNC	Levels (constant)	-2.67 (0.09)	0.15	-3.09**
	Levels (constant and trend)	-2.56 (0.30)	0.15*	-1.29
	1st differences (constant)	-4.35 (0.00)	0.13	-2.58

** – rejection of the null at 5%-level

* – rejection of the null at 10%-level

Figure A2

Recursively estimated eigenvalues with 95% confidence bands (for fixed short run dynamics)

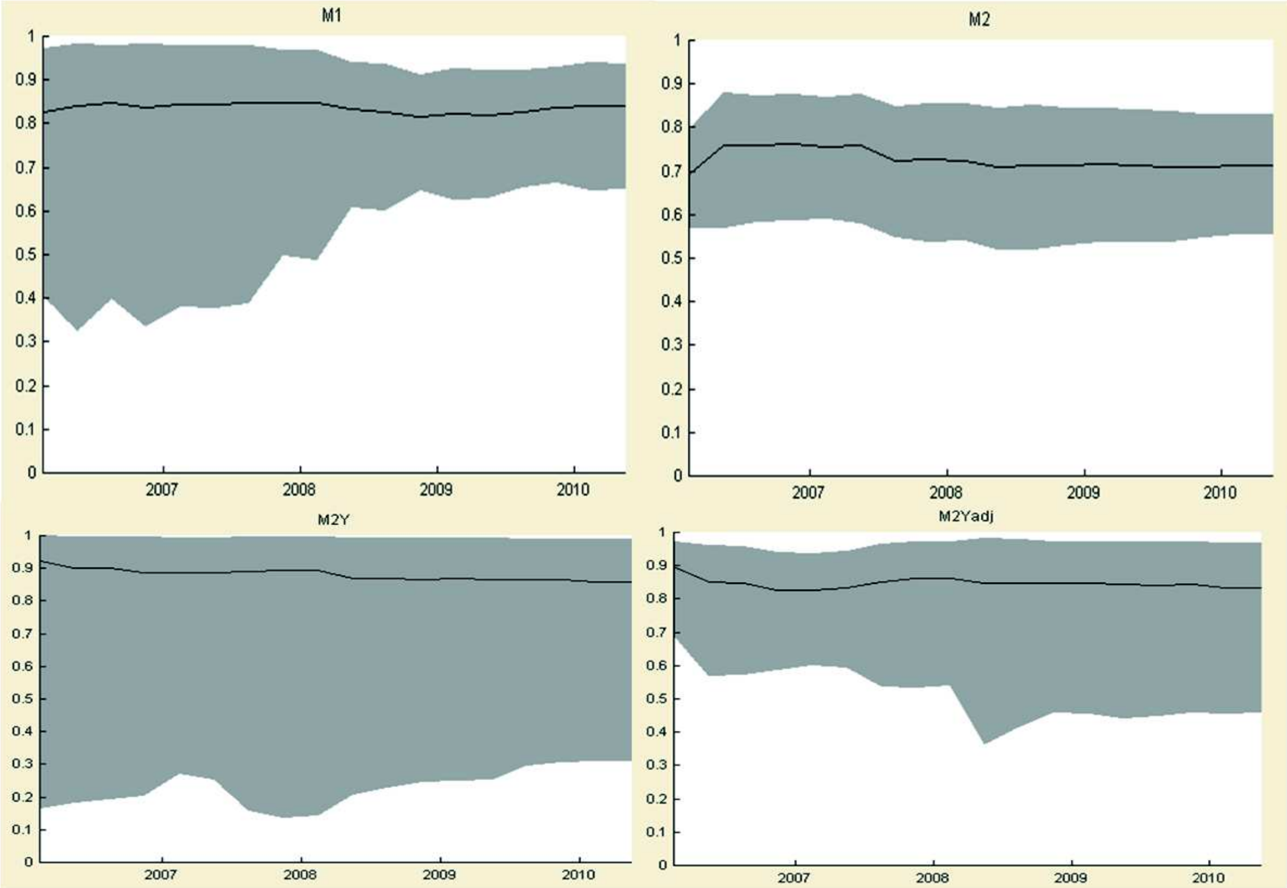


Figure A3

Recursively estimated statistic of Hansen and Johansen (1999) fluctuations test and 95% critical value (for fixed short run dynamics)

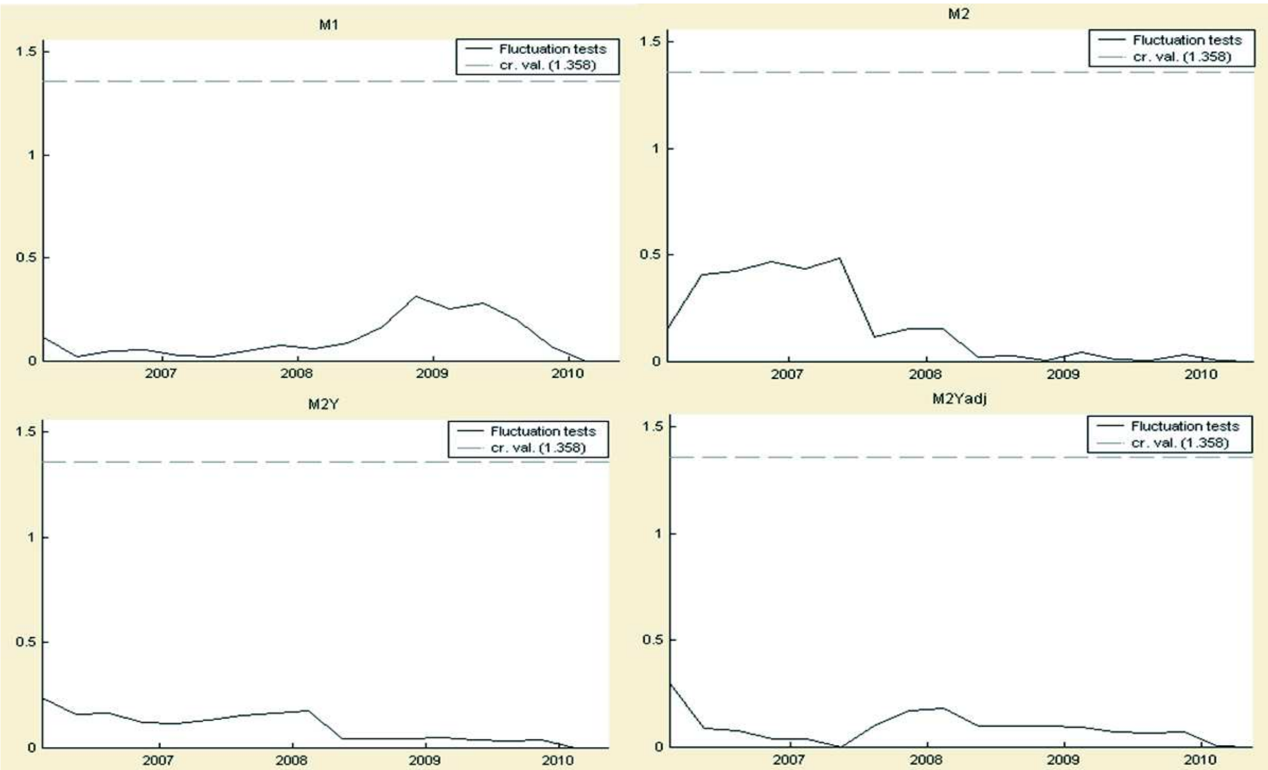


Table A2
Test for stationarity of variables: F-statistics (p-value)

Variable	*Model*			
	M1	M2	M2Y	M2Y^{adj}
M	70.65 (0.00)	46.74 (0.00)	71.53 (0.00)	59.06 (0.00)
Y	71.25 (0.00)	46.55 (0.00)	70.06 (0.00)	60.13 (0.00)
W	67.71 (0.00)	44.33 (0.00)	69.03 (0.00)	53.54 (0.00)
OC	50.06 (0.00)	42.58 (0.00)	31.13 (0.00)	36.57 (0.00)
UNC	33.50 (0.00)	29.00 (0.00)	51.31 (0.00)	51.09 (0.00)

Figure A3
Recursive estimates of M1 money demand model's cointegration vector (±2 S.E.)

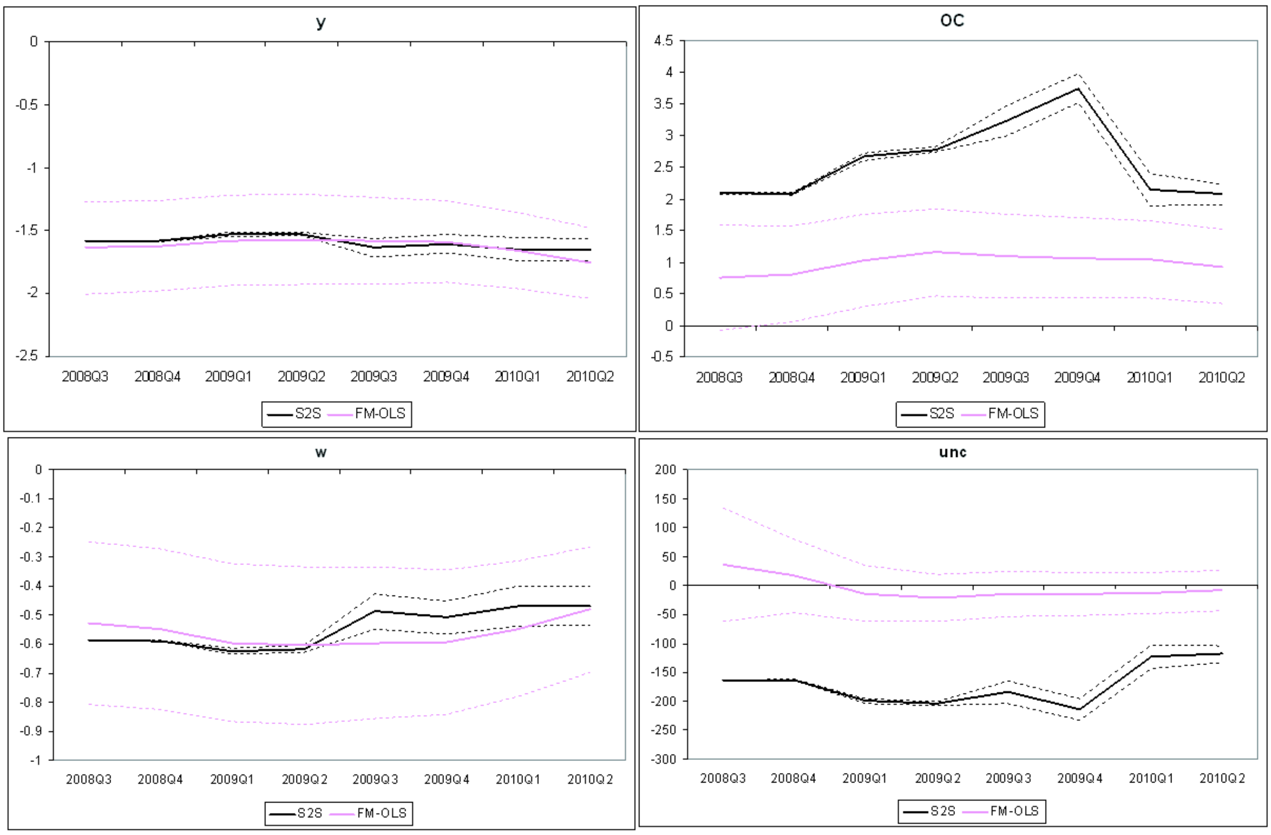


Figure A4
Recursive estimates of M2 money demand model's cointegration vector (±2 S.E.)

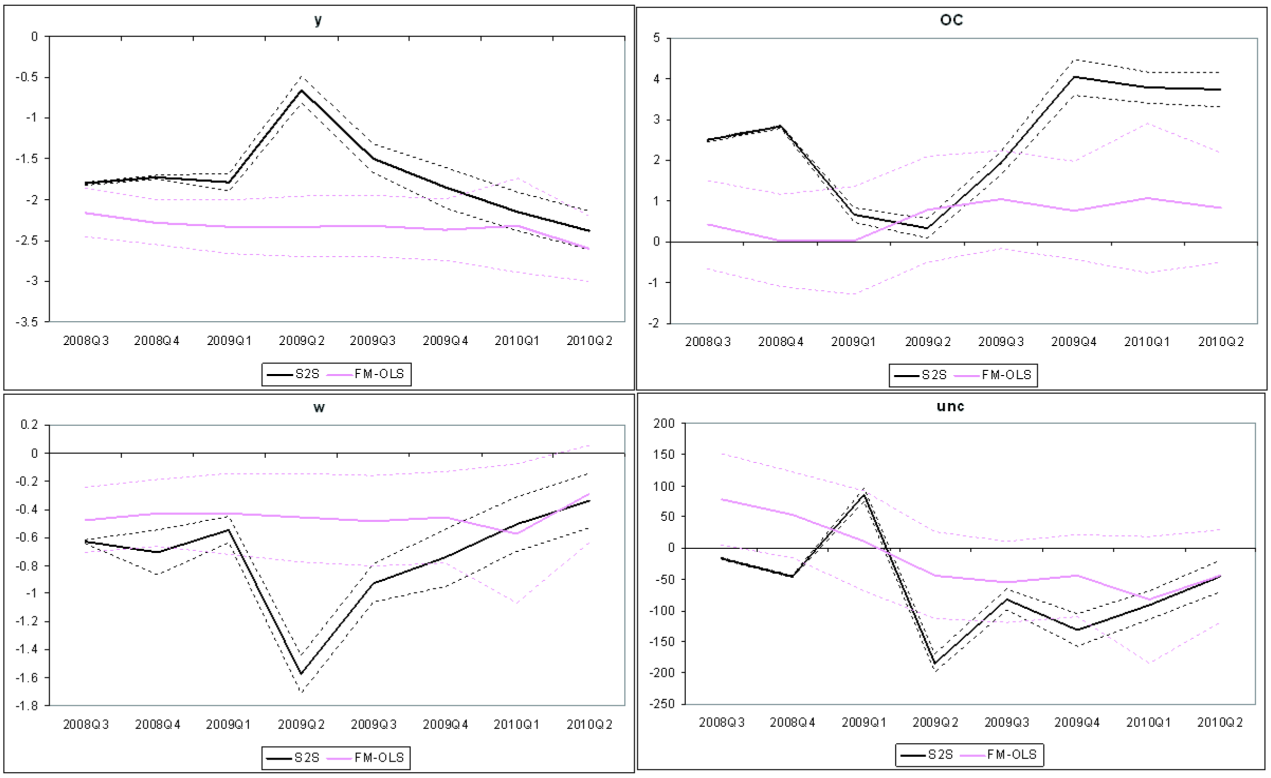


Figure A5
Recursive estimates of M2Y money demand model's cointegration vector (±2 S.E.)

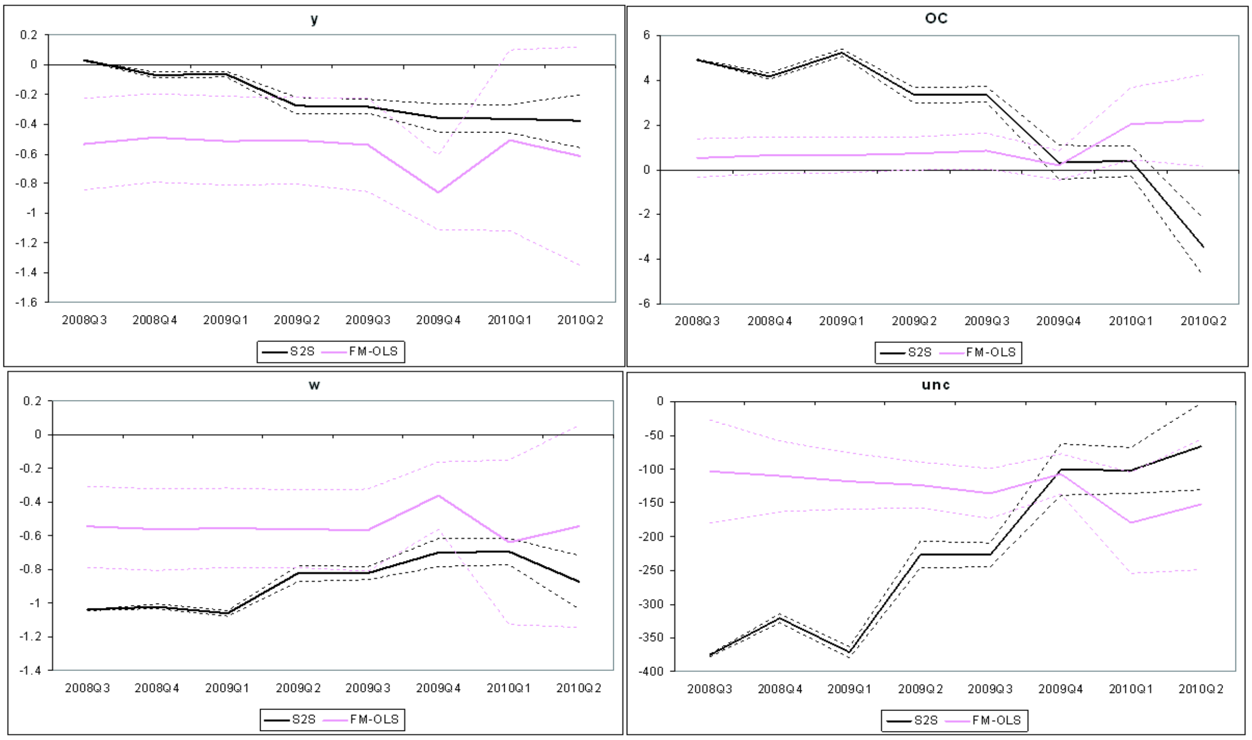


Figure A6
Recursive estimates of M2Y^{adj} money demand model's cointegration vector (±2 S.E.)

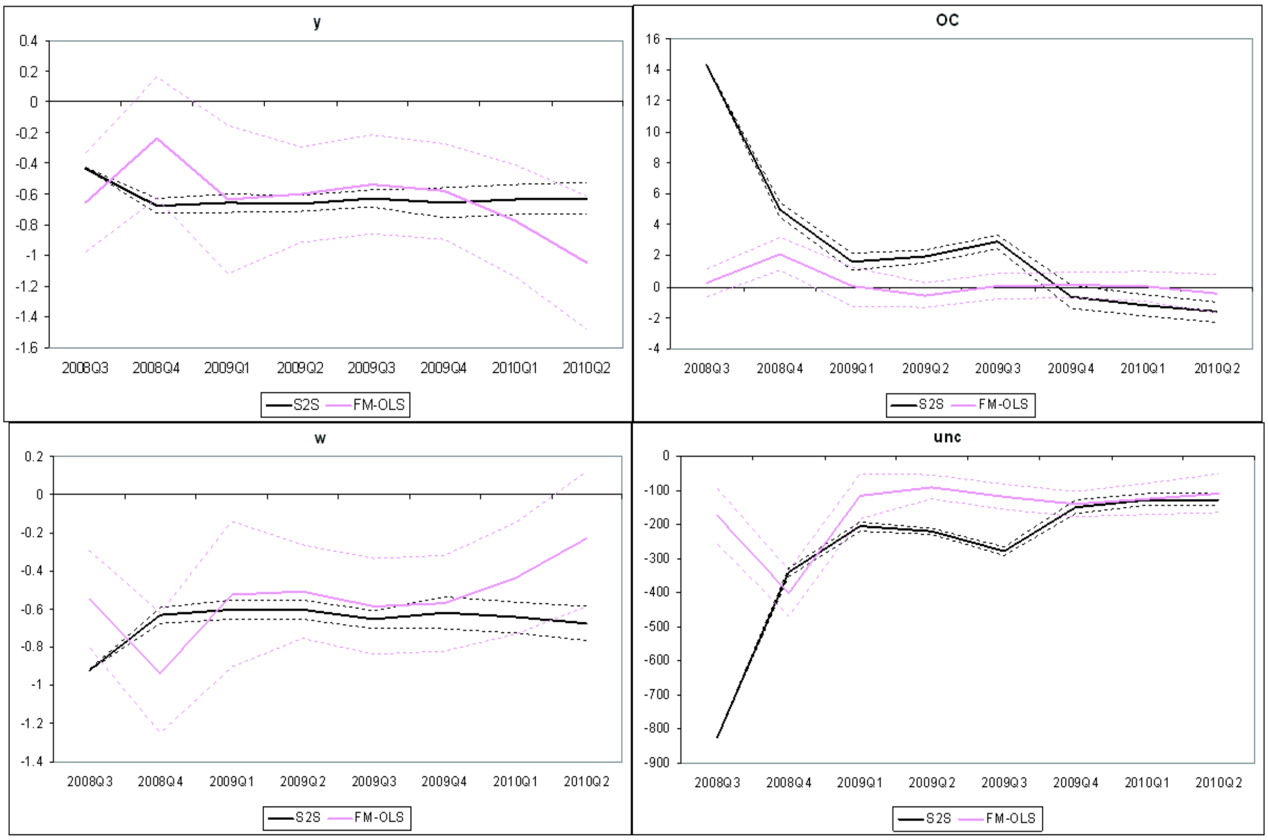
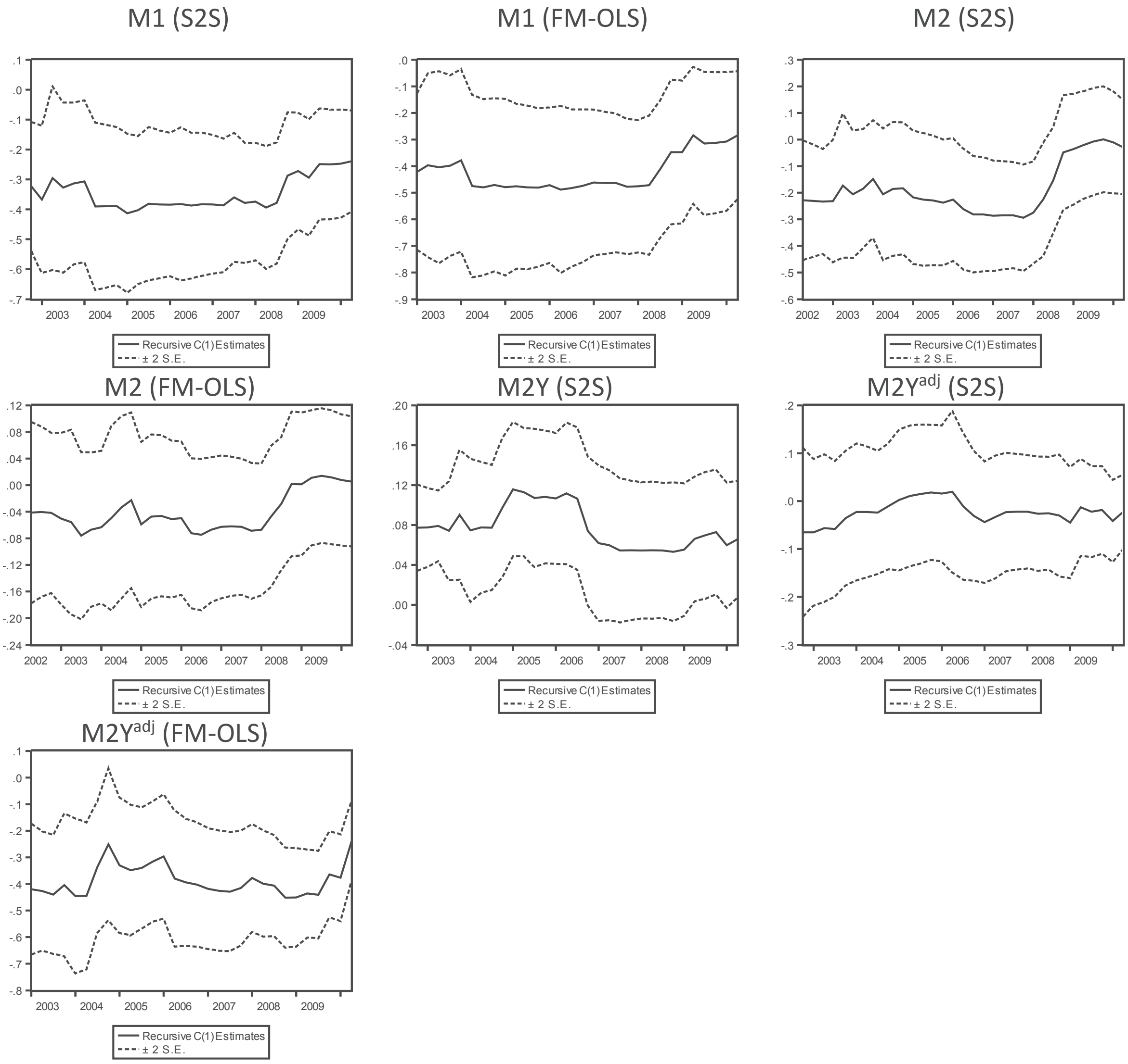


Figure A7
Recursive estimates of ECMs' loading coefficients



Appendix 1B

Historical data

	Money growth (%)	Prices growth (%)
1861	0.1	13.3
1862	-3.2	-5.7
1863	-7.9	-6.9
1864	4.3	4.7
1865	-0.4	5.3
1866	5.4	5.9
1867	-3.2	8.9
1868	4.1	13.2
1869	-1.2	-13.2
1870	0.0	-15.8
1871	8.3	5.5
1872	-0.5	25.2
1873	3.4	2.1
1874	-1.3	-10.9
1875	-1.6	-15.3
1876	2.0	14.4
1877	32.3	29.2
1878	13.6	-10.4
1879	-2.0	28.6
1880	-4.0	16.8
1881	-5.2	-21.0
1882	-5.3	-16.2
1883	-1.4	-10.9
1884	-6.2	1.2
1885	0.8	-5.9
1886	3.8	-3.1
1887	3.2	1.4
1888	0.2	1.8
1889	-4.6	-3.4
1890	-2.3	-3.3
1891	16.2	21.6
1892	1.8	3.0
1893	-0.2	-10.7
1894	-2.3	-15.7
1895	0.7	-6.2
1896	7.4	-0.2
1897	-0.5	16.1
1898	9.5	9.7
1899	3.5	-1.1
1900	8.2	-2.9
1901	-0.4	2.5
1902	3.3	1.4
1903	4.5	-1.5
1904	11.7	3.0
1905	31.2	5.6
1906	-10.2	7.6

1907	-3.0	12.9
1908	-7.3	0.6
1909	6.2	-4.5
1910	3.3	-4.3
1911	7.1	0.2
1912	9.5	7.3
1913	-0.4	-1.5
1914	58.2	13.0
1915	74.3	64.0
1916	55.8	107.0
1917	185.3	500.0
1918	122.1	579.0
1919	267.0	1470.0
1920	419.4	910.0
1921	1400.9	880.0
1922	11271.5	9720.0
1923	182.4	26000.0
1924	124.4	13.9
1925	42.7	10.2
1926	12.5	4.0
1927	17.3	-0.4
1928	20.0	16.7
1929	36.4	8.9
1930	52.2	8.8
1931	30.3	11.1
1932	48.3	12.2
1933	-18.4	42.0
1934	12.7	33.5
1935	25.6	13.3
1936	15.9	46.2
1937	20.7	22.2
1938	26.8	6.8
1939	29.0	10.4
1940	-0.5	15.3
1941	57.1	5.5
1942	32.0	3.9
1943	25.2	3.1
1944	12.5	3.1
1945	14.5	21.5
1946	-10.9	21.5
1947	-79.6	21.5
1948	77.2	21.5
1949	14.1	5.7
1950	22.0	-11.2
1951	2.7	-3.4
1952	7.2	-3.2
1953	5.0	-3.8
1954	19.6	-0.5
1955	2.7	-2.3
1956	16.0	0.1
1957	3.6	-0.1
1958	9.5	2.2

1959	8.5	-0.3
1960	-12.3	-1.3
1961	33.9	-0.6
1962	20.3	0.8
1963	9.0	-3.0
1964	12.3	-0.8
1965	15.4	0.2
1966	17.8	1.5
1967	15.9	-1.0
1968	15.4	-0.8
1969	11.5	3.1
1970	0.3	2.3
1971	9.9	-0.5
1972	10.7	0.3
1973	9.1	-2.0
1974	11.4	-1.8
1975	11.8	0.0
1976	10.6	-1.3
1977	8.4	0.1
1978	6.2	0.7
1979	2.7	0.1
1980	6.7	0.9
1981	1.9	1.3
1982	6.5	4.0
1983	9.2	0.3
1984	6.6	1.0
1985	6.1	0.2
1986	5.5	-1.2
1987	7.8	1.0
1988	14.5	3.4
1989	19.8	4.1
1990	25.6	12.2
1991	18.9	160.0
1992	1690.0	2508.8
1993	790.0	839.9
1994	174.4	215.0
1995	121.1	131.0
1996	28.5	22.0
1997	25.5	11.0
1998	44.1	84.4
1999	41.8	36.5
2000	57.4	20.2
2001	39.4	18.6
2002	30.7	15.1
2003	50.3	12.0
2004	33.8	11.7
2005	30.9	10.9
2006	38.6	9.0
2007	32.9	11.9
2008	2.5	13.3
2009	6.4	8.8
2010	25.4	8.8

Historical data sources

Money series.

1861-1916. Credit notes, gold and silver in circulation as reported in the *Gosudarstvennyi bank (kratkyi ocherk deyatel'nosti za 1860-1910 gody*) (reprint by the CBR*)*.

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1921-1990. Cash in circulation as reported in *Kashin Y. (eds.), Denezhnoe obrashenie v Rossii. Materialy arhivnyh fondov. Vol.3. Moscow, INTERKRIM-PRESS, 2010.*

1991-2010. M0 reported by the *CBR*.

Prices series.

1861-1883. Wheat bread prices as reported in *Rykachev A., Tseny na hleb i trud v S.-Peterburge za 58 let. Vestnik finansov №31, 1911.*

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Chapter 2: Evaluating underlying inflation measures for Russia[35]

Abstract

We apply several tests to the underlying inflation measures used in practice by central banks and/or proposed in the academic literature, in an attempt to find the best-performing indicators. We find that although there is no single best measure of underlying inflation, indicators calculated on the basis of dynamic factor models are generally among the best performers. These best performers not only outdid the simpler traditional underlying indicators (trimmed and exclusion-based measures) but also proved to be economically meaningful and interpretable.

Keywords: Underlying inflation, core inflation, monetary inflation, dynamic factor model, Russia

JEL classification: E31, E32, E52, C32

[35] This chapter refers to BOFIT Discussion Paper No 24/2015. This paper has been co-written with Elena Deryugina, Andrey Sinyakov and Constantine Sorokin.

2.1 Introduction

Headline inflation rates can be volatile. Such volatility in a key price index can make it difficult for policymakers to accurately judge the underlying state of, and prospects for, inflation. In Russia this volatility is often connected with changes in relative prices arising from exchange rate fluctuations and one-off changes in regulated prices. Therefore, it is crucial for the central bank to separate the inflation dynamics from those changes in relative prices and inflation that do not provide information useful for understanding future inflation. The importance of separating relative prices and inflation is noted, for example, in Reis and Watson (2010) and Fisher (1981). Theoretically, one-off changes in relative prices do not affect inflation in the medium term and thus do not require any response from monetary authorities (see Nessen and Soderstrom (2001)). Therefore, a measure of underlying inflation that is useful for monetary policy decisions should help to identify the headline inflation shocks that are relevant for monetary policy and should be designed to inform policymakers of the dynamics of future headline inflation or current medium-term inflation expectations.

Different approaches are described in the literature for constructing measures of underlying inflation, not only and not so much as a statistical measure but as an analytical instrument (Amstad et al. (2014); Meyer et al. (2014); Bilke and Stracca (2008); Wynne (2008, 1999); Lafleche and Armour (2006); Aucremanne and Wouters (1999)). Dementiev and Bessonov (2012) and Tsyplakov (2004) estimate underlying inflation measures for Russia. Considering that underlying inflation is not observable and that there are many approaches to measuring it, a task that emerges is to test which of the underlying inflation measures is best in terms of the definition of underlying inflation. These tests are given in Amstad et al. (2014), Mankikar and Paisley (2004) and Silver (2006). In practice, it may turn out that some underlying inflation measures perform well according to some of the criteria and badly according to others. That is why, for practical purposes, the above studies recommend the use of a set of underlying inflation indicators. With this approach, the probability of a monetary policy error is only reduced, and confidence in the central bank's decisions increases when the range of underlying inflation numbers is narrow, whereas if the range is wide enough, monetary policymakers get the opportunity to analyse the causes of the mixed signals of indicators.

In Section 2.2, we provide a description of the underlying inflation measures, with a focus on dynamic factor models that ultimately have turned out to be the best performers. In Section 2.3, we describe the formal evaluation tests and their results. We also demonstrate the practical application of the best performing underlying inflation indicators as exemplified by our inflation dynamics analysis of the past decade in Russia. Section 2.4 concludes.

2.2 Underlying inflation measures

2.2.1 Data

We use monthly statistics compiled by Rosstat or the Bank of Russia from January 2002 to September 2014. We use Rosstat's consumer price inflation (CPI) and the core inflation index as price indicators, as well as 43 CPI components of the highest aggregation level. Because there are no pre-2006 data on CPI components of the lower aggregation level, we chose to work only with the most aggregated CPI categories. Accordingly, we combined the aggregated categories 'other foodstuffs', 'other non-food products' and 'other services' into a single CPI category, despite their heterogeneous nature. Seasonal smoothing is done with TRAMO/SEATS.

All our calculations are conducted in pseudo-real time. Calculating our underlying inflation measures in pseudo-real time means that the underlying inflation number for any month is based solely on real-time information available to the researcher during that month. The pseudo-real time format aims to obtain a measure of underlying inflation that a central bank could have calculated in the past. Precisely that level of underlying inflation (with parameterisation of models based on information available as of that time) is information that is crucial for the central bank to take monetary policy decisions.

Below, we describe the 20 indicators of underlying inflation that we tested.[36] These include eight exclusion-based indicators, one based on the re-weighing method, four trimmed measures and seven indicators based on dynamic factor models and models with unobserved trend. We also added to this selection Rosstat's core CPI calculated by the exclusion method.

2.2.2 Underlying inflation measures based on dynamic factor models

2.2.2.1 Standard model

Dynamic factor models use information contained in a wide set of indicators and are designed to decompose inflation into two stationary, orthogonal unobservable components – the common χ_{jt} and the idiosyncratic ε_{jt}:

[36] In our work we considered 40 indicators of underlying inflation but later limited those presented here to 20 owing to their similarity. The dynamics of all calculated underlying inflation indicators (recursive and final evaluations) are available on request.

$\pi_{jt} = \chi_{jt} + \varepsilon_{jt}$,

where the common component is driven by a small number of common factors (shocks).

The common component can be decomposed into long-term (x_{jt}^{L}) and short-term (x_{jt}^{S}) constituents by identifying low-frequency fluctuations with periodicity above the designated threshold h (Cristadoro et al. (2005)):

$\pi_{jt} = x_{jt}^{L} + x_{jt}^{S} + \varepsilon_{jt}$

The smoothed (long-term) common component can be obtained by summing up the waves with periodicity $[-\pi/h, \pi/h]$ using spectral decomposition. This long-term component will measure underlying inflation. This measure will not contain idiosyncratic shocks that are not common to all CPI components, or short-term fluctuations, which are not relevant for monetary policy. We do calculations for two alternative threshold periods, h=12 and h=24, and calculate the indicator based on a dynamic factor model without using band-pass filters.

The basic model can be written as

$\pi_{jt} = b_j(L)f_t + \varepsilon_{jt}$,

where: $f_t = (f_{1t}, \ldots, f_{qt})'$ is a vector of q dynamic factors and $b_j(L)$ is a lag operator of order s. If $F_t = (f'_t, f'_{t-1}, \ldots, f'_{t-s})'$. Thus the static representation of the model is

$$\pi_{jt} = \lambda_j F_t + \varepsilon_{jt},$$

where: $b_j(L)f_t = \lambda_j F_t$.

We select the number of dynamic factors so as to ensure that each subsequent factor increases the share of variance explained by the common component by no less than 10% (Forni et al. (2000)). As a result, we use q=3 and assume[37] s=12.

Our data set consists of the seasonally adjusted monthly increases in 44 price indicators (CPI and its components).[38] The econometric estimation procedure was replicated in accordance with Cristadoro et al. (2005).

[37] We found that using a smaller number of lags would worsen the properties of the obtained results.
[38] We used here only price indices, such as Giannone and Matheson (2007), Khan et al. (2013). The use of a wider range of macroeconomic indices as in Cristadoro et al. (2005) and Amstadt et al. (2014) does not lead to improved results.

As a result, we obtained three alternative measures of underlying inflation, depending on the threshold frequency. We also tested simple indicators of underlying inflation, calculated solely on the basis of band-pass filters.

2.2.2.2 Pure inflation model

The 'pure' inflation concept (Reis and Watson (2010)) is an alternative approach to the specification of a dynamic factor model. It is assumed under this approach that the price growth is decomposed into three components:

$$\pi_t = v_t + \rho_t + \varepsilon_t$$

Pure inflation (v), reflecting price growth under the impact of monetary factors should be both present in the dynamics of all goods and services, and equiproportional. This growth should be separated from changes in relative prices (ρ_t) and idiosyncratic fluctuations (ε_t).

We used the same set of data, which we applied to standard dynamic factor models. The econometric procedure was replicated in accordance with Reis and Watson (2010). The model included three common factors and two[39] lags in autoregressive models.

2.2.2.3 Monetary inflation model

We use the monetary approach to underlying inflation measurement as another alternative model (for details, see Deryugina and Ponomarenko (2013)). Here, we attempt to evaluate the information content of money with regard to inflation developments in the spirit of Nobili (2009), i.e. by applying the dynamic factor model approach to a cross-section of variables comprising the broad monetary aggregates (as well as their components) and the collection of different price indices. Our statistical approach aims at extracting the underlying monetary process that is most relevant for inflation by weighting the monetary aggregates according to their signal-to-noise ratio, namely, down-weighting those with large idiosyncratic variances. It is presumed that our approach will downplay those monetary instruments whose behavour is affected by financial innovation as well as portfolio considerations. This parsimonious approach is similar to that of Bruggeman et al. (2005), who identify underlying money growth as a component of money that feeds into inflation movements with certain periodicity. And, given that we rely on a range of price indicators to reflect

[39] Including more lags destabilizes real-time estimates obtained from models presented in Sections 2.2.2.2 and 2.2.2.3

inflation developments, we expect to filter out the volatile component of CPI growth that might otherwise distort the relationship with money growth.

We formulate the dynamic factor model in a state-space representation (for details, see Stock and Watson (2011)):

$$X_{it} = a_i F_t + v_{it}$$

$$F_t = \mu + \sum_{j=1}^{L} D_j F_{t-j} + e_t$$

$e_t = R\, u_t$

The 'measurement' equations represent the dependence of the set of price and monetary variables (X_{it}) on static unobservable factors (F_t) (for details, see Appendix 2.1). The explained part ($a_i F_t$) represents the common component, while the unexplained part (v_{it}) is the idiosyncratic component. The 'transition' equations represent a VAR model of static factors. Structural shocks (u_t) can be subsequently derived from the residuals of the VAR model (e_t). Therefore, as with structural VAR models, we can calculate impulse response functions related to these shocks, and historical decompositions for static factors (and, correspondingly, for observable indicators). We estimate the model using Bayesian methods as proposed in Blake and Mumtaz (2012). The numbers of static factors and their lags are selected on the same criterion as was applied for standard models. As a result, the number of static factors (F_t) was 2 as was the number of lags, L=2.

The structural interpretation of dynamic factor models is rare but hardly unprecedented (Forni et al. (2009); Forni and Gambetti (2010)). We believe that analysis of the macroeconomic properties of structural shocks can be useful for identifying the part of inflation that we can consider as underlying inflation. For this purpose, we decompose the residuals e_t into independent shocks u_t with the help of the principal components approach[40] (Forni et al. (2009)). The function of impulse responses to one of the two identified shocks (see Appendix 2.1) is considered economically substantive. A monetary shock leads to the instant acceleration of the monetary indicators' growth, which persists during the next five quarters. The accelerated growth of price indicators begins later and reaches its peak in six to eight quarters (four quarters for real estate prices) and ends in ten to twelve quarters. These dynamics are in line with the theoretical lag structure of the relationship between rates of growth of money supply and inflation (see, for

[40] The use of the Cholesky decomposition for this purpose does not lead to any considerable change in the results.

example, Nicoletti-Altimari (2001)). At the same time, impulse responses to the second structural shock do not possess such properties.

On these grounds, we exclude both the idiosyncratic part (v_t) and fluctuations caused by 'non-monetary' structural shocks from the underlying inflation measure.

2.2.3 Other underlying inflation measures

2.2.3.1 Exclusion method

In order to calculate the CPI by the exclusion method, certain components which fail to comply with the underlying inflation definition by some criteria are excluded from the consumer goods basket. The weights of the CPI components remaining in the basket are adjusted to represent a total of 100% of a new basket, and the weighted average value calculated from the components' indices will represent the underlying inflation index.[41]

The underlying inflation calculation usually excludes CPI components characterized by high historical volatility (such as energy or fuel prices), the expressly seasonal nature (such as vegetable and fruit prices) or administered nature (such as alcohol prices or the prices of certain social services). The volatility (seasonal or administered) of these prices indicates that a change occurs precisely in relative prices.[42]

We calculated the following underlying inflation measures:

1. Three standard and widely used measures of underlying inflation: a) CPI net of vegetables and fruits, energy and administered prices (namely, housing and utility charges), representing 84% of the CPI in Russia; b) 'Non-food goods excluding energy and fuel' representing 33% of the CPI; c) Rosstat's core CPI, representing 80.5% of the CPI (December 2014) was also included in this group.

2. The CPI net of the eight most volatile components (Lafleche and Armour (2006)), where volatility is measured by the standard deviation of the monthly inflation of certain CPI components

[41] For calculations using the exclusion method on the basis of Russian data; see e.g. Dementiev and Bessonov (2012).

[42] This approach to the exclusion of relative prices is criticized, for example, in Bullard (2011). In particular, it is noted that energy price inflation changed permanently in the 2000s due to the growing demand in Asian countries and, therefore, the exclusion of fuel prices from underlying inflation systematically understates the trend inflation, as inflation retains components that were subjected to downward pressure from demand due to growth in the share of expenditures on fuel in the budget of US households. That is why the exclusion of energy prices from the US underlying CPI is not justified.

in the moving 24-month window. Appendix 2.2 presents CPI components (the most volatile ones) that are most frequently excluded from the underlying inflation index for Russia, using the methodology of the Bank of Canada.

3. We calculated underlying inflation excluding certain specified components, as well as 50% and 75% of the most volatile components, using their weights in the consumer goods basket. As before, our volatility metric was the standard deviation of monthly inflation in the moving 24-month window.

4. The inflation indicators representing 50% of the CPI basket were characterized by the lowest sensitivity concurrently (on the average) to three types of shocks that are frequently sources of change in relative prices: world oil price shocks, world food price shocks and exchange rate shocks. The sensitivity of certain CPI components to the above shocks was determined via the structural VAR model (see Davis (2012); Fukac (2011); Bicchal (2010); for criticism, see Lenza (2011)). An alternative approach was realized using the Local Projection Method; see Jordà (2005)[43]. A detailed description of the calculation algorithm and the results, namely, the most frequently excluded CPI components, is given in Appendix 2.3.

5. Selection of components representing 50% of the CPI based on their ability to forecast future inflation (12 months ahead). A similar index is reported in Bilke and Stracca (2008). This approach boils down to the following: considering that a change in relative prices should not be reflected in future inflation, the components exposed to frequent changes in relative prices (whose inflation reflects a change in relative prices) should be characterized by poor forecasting ability for future headline inflation.

2.2.3.2 Re-weighing CPI components

The approach to an underlying inflation index on the basis of re-weighing of CPI components is similar to the exclusion method (see, for example, Macklem (2001)). This approach uses weights inversely proportional to the historical volatility of the monthly inflation of certain CPI components, where volatility is calculated in the moving 24-month window.

[43] A detailed description of the calculation algorithm and its results are available upon request.

2.2.3.3 Underlying inflation measures based on the trimming method

The trimming method selects only a part of the empirical distribution of the monthly inflation of certain CPI components for the underlying inflation index (normally, the tails of the distributions are cut off) (see, for example, Meyer and Venkatu (2012)). The trimmed distribution, like the exclusion method, aims at eliminating those price changes in the CPI which may be related to changes in relative prices (see, for example, the theoretical model in Bryan and Cecchetti (1993)).

We calculated four underlying inflation indicators using this approach.

Following Meyer and Venkatu (2012), we calculated optimal thresholds for Russian data. Trimming thresholds were selected to minimize the deviation of the current underlying inflation level from either the realized 24-month centred moving averages of monthly inflation or the realized future (over the next 24 months) monthly inflation. We have also constructed the real-time trimmed measure of underlying inflation (using future inflation over the next 24 months as a criterion) based on monthly re-optimisation based solely on data available in pseudo-real time, which is a more accurate measure available to the policymaker. We allowed for asymmetrical lower and higher thresholds. We found that threshold percentiles from 20^{th} to 25^{th} (depending on the sample and optimization criteria) were optimal.

Along with optimal trimmed measures, we calculated the standard underlying inflation indicator as a weighted median (instead of the average as represented by the CPI).

2.3. Evaluating the properties of underlying inflation measures

There is a set of criteria that can be used to assess the relevance of alternative underlying inflation measures. In principle, these tests can be divided into three broad categories (see, for example, Wynne (1999)).

2.3.1 Technical properties

The first category of criteria helps to assess the technical properties of underlying inflation measures:

- **Volatility**: We measure volatility as the average absolute deviation of the annual inflation growth rate from the average value over the moving 25-month period.
- **Bias:** We measure the cumulative deviation of underlying inflation from actual inflation for the period 2003–2014.

- **Stability of real-time estimates**. We measure the deviation of ex-post estimates of annual underlying inflation rates from real-time recursive estimates.

These results, which were not determinative for assessing the quality of underlying inflation measures, are presented for reference in Appendix 2.4.

2.3.2 Forward-looking properties

The most widespread criterion for assessing the quality of underlying inflation measures is their ability to forecast actual inflation. We use the standard model (see, for example, Lafleche and Armour (2006)) for assessing this property for the 12-month horizon (a temporary horizon relevant for monetary policy):

$$(\pi_{t+12} - \pi_t) = \alpha + \beta\,(\pi^U_t - \pi_t) + u_{t+12} \tag{2.1}$$

where π_t is annual CPI growth rates and the π^U_t are annual underlying inflation growth rates.

We use recursive estimates of underlying inflation rates to take into account the model's possible instability. The model is estimated using the sample from July 2006 to September 2014. We use R2 as an indicator of the model's fit. We also conduct the Wald test for α=0 and β=1. If this test is passed, we can say that the current level of underlying inflation is a good benchmark for expected actual inflation.[44]

We also conduct a test for exogeneity of the future value of underlying inflation relative to current actual inflation. If this test is not passed, it may be presumed that the model's latest estimations are unstable, or it may be that fluctuations relevant for further dynamics of other inflation components have been erroneously excluded from the underlying indicator. For this purpose, we estimate[45] an equation of the following type:

$$(\pi^U_{t+12} - \pi^U_t) = \delta + \gamma\,(\pi^U_t - \pi_t) + \varepsilon_{t+12} \tag{2.2}$$

The test for exogeneity is deemed passed if γ is not a statistically significant positive coefficient.

[44] This type of test is conventionally used as the main criterion for forward-looking properties. We found, however, that in the case of Russia this test is easily passed by most models, including those with very low goodness of fit. We therefore augment our analysis by examining R^2.

[45] The significance of the coefficients in equations (1) and (2) was estimated with Newey-West adjustment.

The test results are presented in Table 2.1. In terms of R^2 for equation (2.1), three underlying inflation indicators based on DFM were top ranked in five of seven cases and also passed the Wald and exogeneity tests (with the exception of 'pure' inflation).

Table 2.1. Results of assessing forward-looking properties of underlying inflation measures

Measure	***R^2 of equation (2.1)***	Measures that passed Wald test (α=0 and β=1 in equation (2.1)) at 5% level of significance	Measures that passed exogeneity test (t-statistics < 1.96 for γ in equation (2.2))
DFM (monetary inflation)	0.44	*	*
Band-pass filter (h=12)	0.41		*
DFM (h=12)	0.33	*	*
DFM (h= 24)	0.32	*	*
DFM (all frequencies)	0.22	*	*
CPI ex. 75% of the most volatile components	0.22	*	
DFM (pure inflation)	0.14	*	
CPI ex. 50% of most volatile components	0.14	*	
Band-pass filter (h=24)	0.11	*	*
Non-food products CPI ex. gasoline	0.08		
CPI ex. 50% of the worst forecasters of future inflation	0.05	*	*
Optimal trimmed CPI, optimality criterion: future inflation	0.05	*	*
Optimal trimmed-mean CPI, optimality criterion: moving average inflation	0.04	*	*
CPI ex. vegetables and fruits, gasoline, utilities	0.04	*	*
Volatility-weighted CPI	0.03	*	
CPI ex. 50% of the most sensitive components to shocks in SVAR	0.03	*	*
Core CPI (Rosstat)	0.03	*	

CPI ex.the eight most volatile components	0.02	*	
CPI ex. 50% of the most sensitive components to shocks in LPM	0.01	*	*
Weighted median	0.01	*	
Optimal trimmed inflation (real-time optimization)	0.01	*	*

2.3.3 Economic relevance of underlying inflation measures

Correlation with fundamental inflation indicators is presumably another property that a measure of underlying inflation should possess. This primarily relates to factors that reflect aggregate demand. Specifically, Bryan and Cecchetti (1993) test the relationship of underlying inflation measures with money supply, while Andrle et al. (2013) and Khan et al. (2013) test it with business cycle indicators.

In order to test this property, we estimate the standard equation (Filardo et al. (2014)):

$$\pi_t = \mu + \sum_{j=1}^{L} \Theta_j X_{t-j} + e_t \, , \tag{2.3}$$

where π is the annual underlying inflation growth rate, X is the vector of explanatory variables (annual broad money supply growth rates and output gap[46]).

The estimation was conducted using quarterly data for the period 2002–2014. The number of lags equals L=4. We used R^2 as an indicator of correlation.

Apart from aggregate demand indicators, the relationship of underlying inflation measures with secondary effects (i.e. changes in inflation expectations, wage indexing) that follow price-level increases can characterize their macroeconomic content. Thus, we assume that irrelevant inflation fluctuations will not be reflected in the growth of nominal variables. Correspondingly, inflation measures net of such fluctuations will possess better characteristics as an explanatory factor for wage dynamics. In order to test this property, we estimate the standard equation (Zhang and Law (2010)):

$$w_t = \mu + \lambda \pi_{t-1} + \sum_{j=1}^{L} \Theta_j X_{t-j} + \sum_{j=1}^{L} \Omega_j w_{t-j} + e_t \tag{2.4}$$

[46] Based on the HP-filter

where w represents the quarterly rate of growth in the average nominal wage, π is the annual underlying inflation growth rate, X is the vector of other explanatory variables (unemployment and quarterly productivity growth[47]).

The estimation was accomplished using quarterly data for the period 2002–2014. The number of lags is L=4. The informative nature of the inflation indicator for wage dynamics is characterized by the significance of the (positive) coefficient λ.

The test results are given in Table 2.2. Most underlying inflation measures exceed the CPI in terms of R2 in equation (3), while the three best measures are indicators based on dynamic factor models. Two of these proved to be statistically significant as explanatory indicators for nominal wage dynamics.

Table 2.2. Results of assessing economic relevance of underlying inflation measures

Measure	***R^2 of equation (2.3)***
DFM (h=24)*	0.80
DFM (monetary inflation)*	0.79
DFM (h=12)	0.77
CPI ex. 75% of most volatile components*	0.76
Optimal trimmed CPI, optimality criterion: future inflation	0.76
Optimal trimmed CPI, optimality criterion: moving average inflation	0.75
CPI ex. 50% of the most shock-sensitive components in SVAR	0.74
Rosstat's Core CPI	0.73
Weighted median	0.72
Optimal trimmed CPI (real-time optimization)	0.7
CPI ex. vegetables and fruits, gasoline, utilities	0.68
DFM (all frequencies)	0.68
CPI ex. 50% of the most volatile components	0.67
Volatility-weighted CPI	0.67
CPI ex. the eight most volatile components	0.64
CPI (for reference)	0.61
Band-pass filter (h=24)	0.60

[47] The ratio of real GDP to the number of employed

Band-pass filter (h=12)	0.60
Non-food products CPI ex. gasoline	0.58
CPI ex. 50% of the most shock-sensitive components in LPM	0.56
DFM (pure inflation)	0.48
CPI ex. 50% of the worst forecasters of future inflation	0.34

* - indicators, for which t-statistics > 1.96 for λ in equation (2.4)

2.3.4 Overall assessment

The test results allow us to conclude that underlying inflation measures calculated on the basis of dynamic factor models (except for the 'pure' inflation indicator and indicator calculated with the help of the standard model without application of band-pass filter) possess the necessary properties as regards the requirements of underlying inflation measures. None of the other indicators (including Rosstat's core CPI) possess the balance of properties required for obtaining satisfactory results in many-sided assessment. In this regard, we deem it expedient to use this methodology for the purposes of monetary policy. We therefore combine three measures of underlying inflation (Figure 2.1): indicators based on the standard dynamic factor model (with frequency thresholds of 12 and 24 months), and on 'monetary' inflation. Real-time estimates of this range and its median values are presented in Figure 2.2.[48]

We would assert that fluctuations of the magnitude we have obtained are economically interpretable and represent the main macroeconomic developments in the Russian economy in the past decade. In particular, we can see in the 2008-2009 period preceding the crisis of a clearly defined disinflation phase in 2003–2006 that gave way to the accelerated price growth in 2007–2008, which is consistent with the idea of the economy's overheating in the pre-crisis period. We also note that, for this period, underlying inflation measures would have served as more useful benchmarks for monetary policy than observed CPI and core CPI (their growth continued to slow down rapidly until the second half of 2007, which precluded the need for monetary tightening). In the post-crisis period, the dynamics of underlying inflation measures could also be considered as informative for monetary policy. Specifically, underlying inflation was observed to slow down along with the actual CPI in the period after the 2009 recession, reflecting the impact of aggregate demand fundamentals, whereas in the period 2010–2012, underlying inflation growth rates were sufficiently stable, despite sharp changes in CPI growth. Considering that these fluctuations were

[48] We present the latest data available (up to June 2015) although, as mentioned above, we conduct our assessment using the time sample from January 2002 to September 2014.

related to one-off short-term factors (the drought in 2010 and the changed procedure for indexing administered prices in 2012), the underlying inflation indices net of these factors were more useful for the purposes of monetary policy during this period as well. The presented indicators point to an increase in inflation rates in 2010–2011, which coincides with the period of recovery in economic activity, and the subsequent inflation slowdown in 2012–2013. Observing the sharp deviation of headline inflation from underlying inflation in 2015, one may conclude that it reflects the impact of temporary drivers of inflation related to adjustment of prices for imported goods due to the rouble's depreciation. The uncertainty surrounding the latest estimate has increased as the divergence among models has become larger.

Figure 2.1. Range of underlying inflation measures based on dynamic factor models (annual growth rates, %)

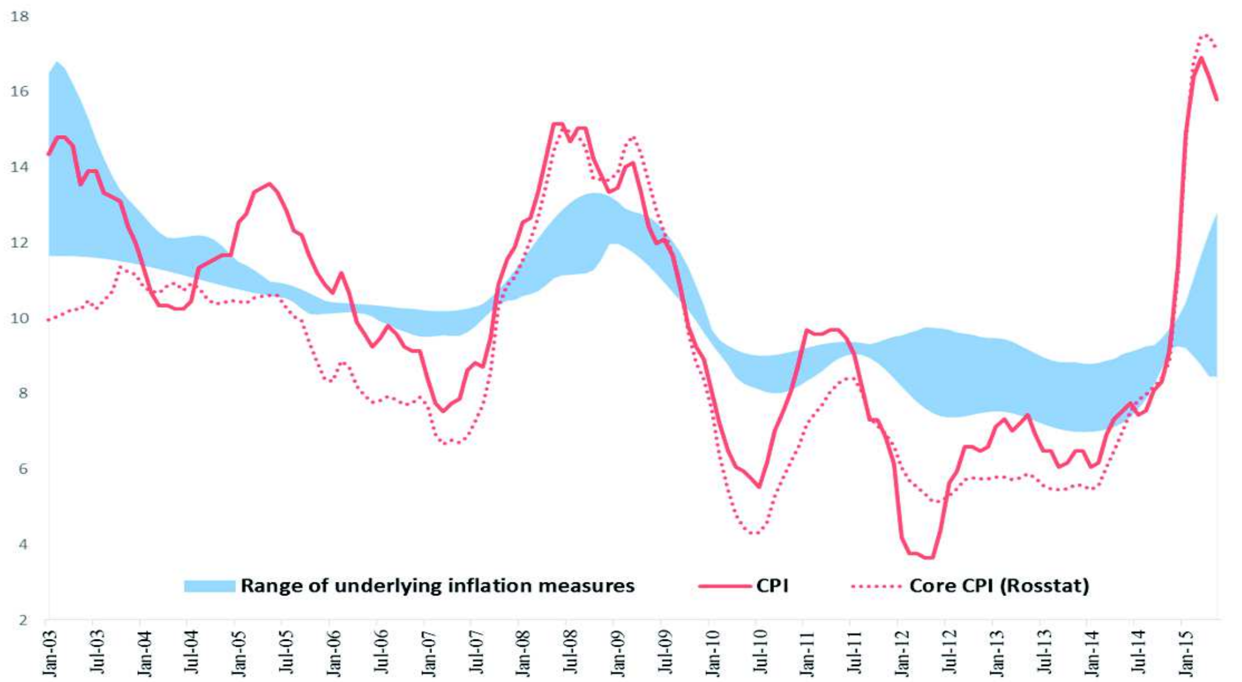
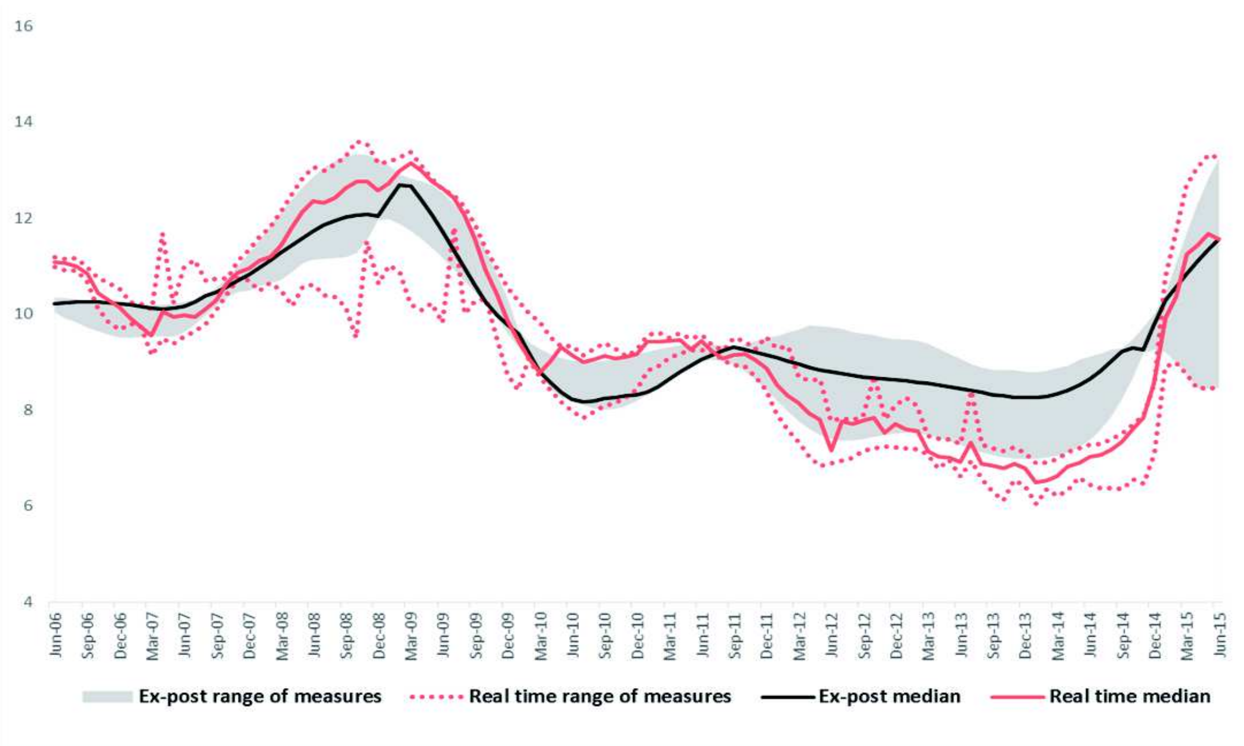


Figure 2.2 Range and medians of underlying inflation measures based on dynamic factor models (annual growth rates, %): final estimate and calculation in pseudo-real time



2.4 Conclusions

An underlying inflation measure, i.e. an inflation indicator that nets out shocks irrelevant for monetary policy, is a key indicator for a central bank whose main task is to maintain price stability. On the one hand, the use of such an indicator can help reveal inflation risks and, on the other hand, render monetary policy more balanced by preventing mechanistic responses to realized price changes irrespective of their nature. At the same time, there is no generally accepted method of determining which shocks are irrelevant for monetary policy. Instead, there are several methodologies for calculating underlying inflation and some criteria (which are not mutually exclusive but are not necessarily interrelated) that can be used to make an implicit estimation of the properties of the indicators obtained. Such methodologies were examined in this paper.

We calculated 20 underlying inflation measures, using four alternative approaches: exclusion, re-weighing, trimming, and estimation of an unobservable trend on the basis of dynamic factor models. We assessed the obtained indices with tests characterizing three aspects of their properties: technical properties, usefulness for forecasting future inflation, and economic interpretability. We concluded that underlying inflation measures calculated using the dynamic factor models are the best performers according to formal tests. In particular, these indicators remained stable in the period of price shocks in 2010 and 2012 but reflected greater inflationary pressure in 2007–2008 and its decrease in 2009. As a result, these indicators remained informative in all the periods with regard to future inflation dynamics in the medium term and were closely related to aggregate demand fluctuations.

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Appendix 2.1

Variables used in monetary dynamic factor model

Monetary indicators	*Price indicators*
M1, households (HH)	CPI
M1, non-financial corporations (NFC)	Core CPI
Term deposits in roubles, HH	Non-food prices
Term deposits in roubles, NFC	Food prices
Divisia M2	Services prices
M2Y	Fixed capital investment deflator
	Housing prices (primary market)
	Housing prices (secondary market)

Figure 2.1A. Impulse response functions for the first (monetary) structural shock

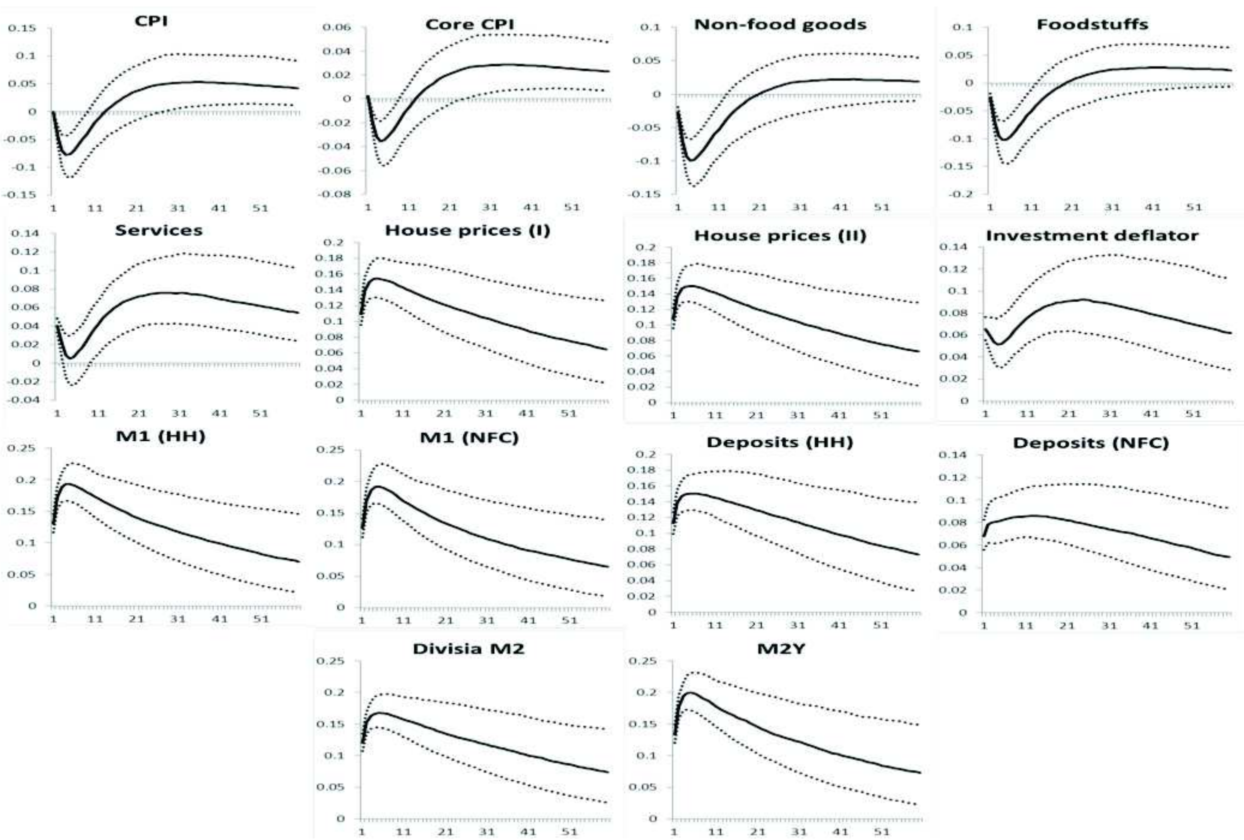
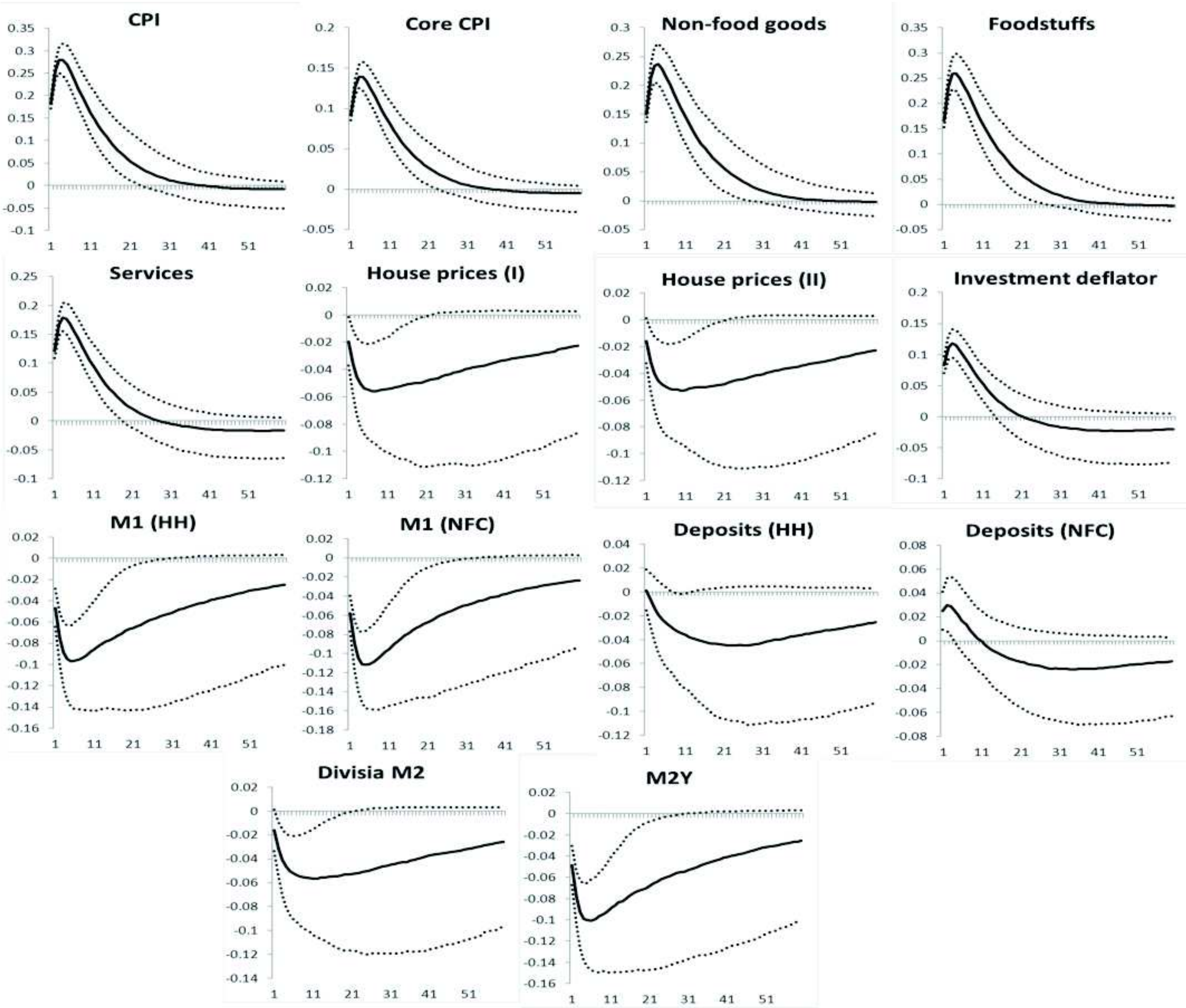


Figure 2.2A Impulse response functions for the second structural shock



Appendix 2.2

CPI components most frequently excluded from underlying CPI based on Lafleche and Armour's (2006) method in moving 24-month window. Percentage of all 132 samples.

Eggs	100
Sugar	100
Vegetables and fruits	100
Gasoline	99
Cheese	87
Pasta products	61
Communication services	54
Butter	46
Other services	45
Milk and dairy products	27
Passenger transport services	19
Other food products	19
Medicine	11
Bread and bakery products	10
Meat and Poultry	7
Alcoholic beverages	4
Phones	3
Tea and coffee	3
TV and radio sets	3
Fish and edible sea products	1
Personal computers	1
Housing and public utilities services	1
remaining components...	0

Appendix 2.3

Most frequently excluded CPI components, % of all pseudo-real time samples, i.e. the share of all parameterisations of the VAR model for determining sensitivity to shocks (overall, 120 observations from January 2005).

Meat and Poultry	100
Fish and edible sea products	100
Butter	100
Sugar	100
Tea and coffee	100
Bread and bakery products	100
Pasta products	100
Vegetables and fruits	100
Tobacco products	100
Electrical appliances	100
TV and radio sets	100
Personal computers	100
Phones	100
Gasoline	100
Medicine	100
Housing and public utilities services	100
Other food products	100
Other services	100
Confectionery	89
Furniture	73
Perfumery	43
Milk and dairy products	0
all remaining products and services...	0

Appendix 2.4

Table 2.1A. Average absolute deviation of annual inflation growth rate from average level in moving 25-month period (p.p.)

Indicator	*Volatility*
DFM (h=24)	0.2
DFM (‘monetary’ inflation)	0.3
DFM (h=12)	0.4
DFM (‘pure’ inflation)	0.4
Inflation excluding 75% of the most volatile components	0.5
Non-food goods excluding energy and fuel	0.6
Shock-insensitive 50% CPI in LPM	0.6
Shock-insensitive 50% CPI in SVAR	0.6
Volatility-weighted inflation	0.7
Weighted median	0.8
Optimal trimmed CPI, criterion: future inflation	0.8
Inflation excluding 50% of the most volatile components	0.8
Exclusion of the eight most volatile components	0.8
Optimal trimmed CPI, criterion: moving average	0.8
DFM (all frequencies)	0.9
Optimal trimmed CPI (real time optimization)	0.9
CPI excluding vegetables and fruits, energy and housing, and utility services	1.0
Band-pass filter (h=24)	1.0
Band-pass filter (h=12)	1.3
50% CPI of the best future inflation predictors	1.3

Table 2.2A Cumulative deviation of underlying inflation from actual inflation 2003–2014 (%)

Indicator	*Deviation*
Inflation excluding 50% of the most volatile components	5.9
DFM (h=24)	2.1
DFM (h=12)	1.8
Exclusion of the eight most volatile components	0.9
Band-pass filter (h=24)	0.8
DFM (all frequencies)	0.4
Band-pass filter (h=12)	0.2
DFM (‘pure’ inflation)	-0.2
Optimal trimmed CPI (real time optimization)	-0.5
Volatility-weighted inflation	-1.6
Inflation excluding 75% of the most volatile components	-2.3
DFM (monetary inflation)	-3.0
Optimal trimmed CPI, criterion: moving average	-4.8
CPI excluding vegetables and fruits, energy and housing, and utility services	-5.2
Optimal trimmed CPI, criterion: future inflation	-9.1
Shock-insensitive 50% CPI in SVAR	-9.4
Shock-insensitive 50% CPI in LPM	-11.4
Weighted median	-11.8
50% CPI of the best future inflation predictors	-20.5
Non-food goods excluding energy and fuel	-29.1

Table 2.3A. Deviation of final estimates of annual underlying inflation growth rates from real-time recursive estimates (p.p.)

Indicator	*Deviation*
Optimal trimmed CPI, criterion: moving average	0.0
Optimal trimmed CPI, criterion: future inflation	0.0
Weighted median	0.0
Optimal trimmed CPI(real time optimization)	0.0
Non-food goods excluding energy and fuel	0.0
CPI excluding vegetables and fruits, energy and housing, and utility services	0.0
Band-pass filter (h=12)	0.2
DFM (h=12)	0.4
DFM (h=24)	0.5
Band-pass filter (h=24)	0.5
Shock-insensitive 50% CPI in SVAR	0.9
Exclusion of the eight most volatile components	0.9
DFM (‘monetary’ inflation)	0.9
Volatility-weighted inflation	0.9
Shock-insensitive 50% CPI in LPM	1.2
DFM (all frequencies)	1.2
Inflation excluding 50% of the most volatile components	1.3
50% CPI of the best future inflation predictors	1.5
DFM (pure inflation)	1.6
Inflation excluding 75% of the most volatile components	1.7

Chapter 3: Estimating sustainable output growth in emerging market economies[49]

Abstract

We present a model that incorporates the information contained in diverse variables when estimating sustainable output growth. For this purpose, we specify a state-space model representing a multivariate HP filter that links cyclical fluctuation in GDP with several indicators of macroeconomic imbalances. We obtain the parameterization of the model by estimating it over a cross-section of emerging market economies. We show that the trend output growth rates estimated by using this model are more stable than those obtained with a univariate version of the filter and thus are more consistent with the notion of sustainable output.

Keywords: output gap, financial cycle, macroeconomic imbalances, emerging markets

JEL classification: E32, E44, C33

[49] This chapter refers to the article published in *Comparative Economic Studies* 57, March 2015. This paper has been co-written with Elena Deryugina and Anna Krupkina.

3.1 Introduction

The concepts of potential growth and the output gap play a key role in the formulation and implementation of macroeconomic policies. Monetary, fiscal and macroprudential policies take into account these estimates in order to adapt the policy stance to reduce possible macroeconomic imbalances and dampen aggregate fluctuations. The relevance and usefulness of these concepts depend on how accurately the potential growth estimate reflects the sustainable path of economic development and the output gap and serves to summarize the imbalances of the economy.

In this regard, the estimation of potential output growth in emerging markets has recently been a challenging task. Estimates obtained by using conventional univariate statistical filters (e.g. the Hodrick–Prescott (HP) filter) generally failed to detect imbalances prior to the onset of the crisis in late 2008. Moreover, these filters were not always helpful in decomposing the post-crisis slowdown in output growth into its cyclical and trend components. For example, Borio et al. (2013, 2014) analyse the real-time performance of the HP filter and show that in the US, the UK and Spain univariate filter estimates had large upward bias before the recent crisis, which was revealed only after the crisis. Traditional approaches also overestimated potential output growth in the euro area before the crisis (ECB (2011); Marcellino and Musso (2011)). This effect is even more pronounced in Central and Eastern European countries (Bernhofer et al. (2014)).

In these circumstances, it seems to be appropriate to rely on additional macroeconomic indicators to diagnose the state of the business cycle. It is generally accepted that inflationary pressure builds when output is above potential and subsides when output falls below potential. As such, inflation in particular is viewed as a key symptom of unsustainability. The same applies to another conventional theory that links fluctuations in unemployment with the output gap (Okun's Law).

As discussed in Bernhofer et al. (2014), this consensus in macroeconomics was severely challenged by the global financial crisis. It is becoming increasingly clear that certain cyclical activities are not captured by this approach, such as unsustainable developments in the financial sector. For example, asset price bubbles can generate huge business cycles without creating any inflation as reflected by the average household consumer basket which is the common notion of inflation. The global financial crisis is a case in point. Hume and Sentance (2009) propose two explanations for the decoupling of asset and output inflation. First, the financial upturn of the 2000s had a relatively limited impact on effective demand. Second, in cases where the demand effect was larger, inflation pressure was dampened by a deterioration of external balances instead of reaching domestic capacity constraints. Borio et al. (2013) discuss four additional reasons why output inflation could remain low and stable against the backdrop of soaring asset price inflation, namely (i) financial booms that coincide with positive supply shocks, (ii) increases in potential output in prolonged economic upturns (as measured by conventional approaches), (iii) capital inflows leading to currency appreciation and (iv) the existence of sectoral misallocation rather than "aggregate" capacity constraints. Financial indicators are therefore essential for the balanced assessment of output growth, and the aim of this paper is to incorporate the information contained in them into the estimation of sustainable output growth in emerging market economies.

Our work is related to the recent literature on the link between business cycles and financial cycles (Alessi and Detken (2011); Claessens et al. (2012); Schularick and Taylor (2012)). We concentrate here on developments in emerging markets, which means that data limitations will effectively restrict our analysis to the latest boom/bust episode. This closely links our work with the literature on the main factors explaining output fluctuations during the crisis of 2008 (Frankel and Saravelos (2010); Lane and Milesi-Ferretti (2011); Cecchetti et al. (2011); Feldkircher (2014)). Our main contribution to these strands of research is that we follow Alberola et al. (2013), Borio et al. (2013, 2014) and Bernhofer et al. (2014) in employing an empirical model that enables us to decompose output fluctuations into cycle and trend components based on the empirical relationships with various measures of imbalances. The resulting indicators may be interpreted, in an economic sense, as metrics of sustainable (i.e. not associated with the build-up of imbalances) output and the output gap.

The remainder of this paper is structured as follows. Section 3.2 discusses the set-up of the model. Section 3.3 presents the dataset, and Section 3.4 reports the empirical results. Section 3.5 discusses the output gap estimates for the cross-section of emerging markets in general and provides more detailed results for Russia. Section 3.6 concludes.

3.2 Model set-up

We follow Borio et al. (2013, 2014) and employ a multivariate HP (MVHP) filter in a state-space form[50]:

$$\Delta y^*_{it} = \Delta y^*_{it-1} + \varepsilon_{it} \tag{1}$$

$$y_{it} - y^*_{it} = \gamma' x_{it-s} + \zeta_{it} \tag{2}$$

$$\varepsilon_{it} \sim N(0, \sigma^2_1) \tag{3}$$

$$\zeta_{it} \sim N(0, \sigma^2_2) \tag{4}$$

$$\sigma^2_2 / \sigma^2_1 = 1600 \tag{5}$$

where y_{it} is the log of real GDP and y^*_{it} is its unobserved trend component. The residuals of state equation (1) and signal equation (2) are assumed to be a normally and independently distributed error with mean zero and variance σ^2_1 and σ^2_2. The so-called signal-to-noise ratio (σ^2_2 / σ^2_1) determines the relative variability of the estimated potential output series. We set this ratio at 1600, which corresponds to the smoothing parameter λ=1600 in a conventional univariate HP filter. x_{it} represents the imbalances indicators with lag order[51] s.

Our analysis lies at the nexus of traditional potential output modelling, which is usually[52] country-specific, and research on financial imbalances, which is conducted almost exclusively based on panel data. We choose the latter approach. We believe that this may be appropriate given that owing to data limitations our time series in most cases start in the 2000s. This means that in each individual case we are effectively limited to the analysis of just one episode of large output fluctuations (i.e. before and after 2008), which is obviously not enough for the empirical validation

[50] Unlike Borio et al. (2013, 2014), we do not use a dynamic version of the HP filter, which involves the addition of a lagged output gap term on the right-hand side of (2). The unrestricted estimation of this term's coefficient yields a value close to unity, which is economically implausible. Arguably, this may be due to insufficient variability in the output gap for the relatively short time sample in emerging markets. In addition, as shown in Borio et al. (2014), when using the dynamic HP filter, the smoothing parameter λ should be recalibrated for each specific case in order to make the results comparable with the static version. That would seriously complicate our analysis, which is based on pooled estimation.

[51] We tested s from 0 to 4 and found that in most cases s=1 yields the best results.

[52] Although not necessarily. See e.g. Senhadji (1999) and Duffy and Papageorgiou (2000) for panel estimates of the production function.

of the model[53]. It may therefore be appropriate to pool the information about the boom/bust episodes in other countries, albeit observed in one wave.

Instead of relying on country-specific analysis, we conduct a pooled estimation for the cross-section of emerging market economies. Technically, this means that we specify a state-space model consisting of blocks comprising equations (1) and (2) attributed to individual countries in the cross-section. We thus allow for country-specific trend GDP (y^*_{it}) but assume common coefficients that link its developments with the imbalances indicators (γ). We use a Kalman filter to obtain the maximum likelihood estimates of these parameters and the unobserved trend GDP.

3.3 Data

The aim of our methodology is to obtain estimates of sustainable growth rates. The sustainable growth rate is defined as the output growth that does not generate or widen macroeconomic imbalances, which are identified through a wide set of indicators. Conveniently, in recent years there have been a significant number of contributions to the literature on such imbalances indicators. In fact, several international organizations have developed various frameworks for the evaluation and early detection of macroeconomic imbalances (see Alberola et al. (2013) for a review). We follow these studies (most notably, Alessi and Detken (2011) and Frankel and Saravelos (2010)) in our choice of imbalances indicators, using those that have produced robust results under a variety of specifications of the model[54]. We use the credit/GDP (C_t) and broad money/GDP (M_t) ratios, as well as stock market capitalization (S_t) (all in logs), as proxies for financial imbalances. We also use the share of gross fixed capital formation in GDP (INV_t). These are combined with traditional imbalances indicators: annual CPI growth (π_t) and the unemployment rate (U_t). All the data are standardized and seasonally adjusted and de-trended by means of the HP filter (λ=100000)[55].

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[53] In particular, we found it extremely challenging to obtain satisfactory results with country-specific models that included more than one or two explanatory variables, as the filter tended to favour only few indicators with the highest correlation with output growth. In the pooled estimates, we obtained more balanced results, as the performance of the explanatory variables was averaged across countries. Admittedly, this approach may be misleading if one expects to find substantial systematic differences in the relationship between the imbalances indicators and output in different countries. The reported results should therefore be regarded as evidence of the general relevance of the imbalances indicators for output gap diagnostics rather than the optimal parameterization of the model.

[54] We tested a broad range of indicators before making this selection. Most notably, indicators of external imbalances (trade balance, external debt, real effective exchange rate), although not included in the final model, worked well in other specifications. In addition, admittedly, the availability of financial indicators for emerging markets is severely limited, making their compilation for the whole cross-section quite difficult. We therefore were unable to test some indicators that could be useful (e.g. housing prices).

[55] This transformation is different from that of Borio et al. (2014), who use de-meaned growth rates. Such a transformation seems less applicable to emerging markets for which sample means are rarely associated with

Our main data source is the IMF IFS database, except for gross capital formation shares and stock market capitalization data, which are from the World Bank WDI database (see Appendix 3). We use quarterly data, and where only annual data are available, we interpolate by using cubic splines.

Based on these data sources, we were able to compile the cross-section of 28 emerging market economies (Table 3.1). The model was estimated over an (unbalanced[56]) time sample from 2000Q1 to 2012Q4. All available data were used for the preliminary de-trending of the imbalances indicators.

Table 3.1. Countries in the cross-section

Argentina	Czech Republic	Korea	Poland
Armenia	Ecuador	Latvia	Romania
Brazil	Estonia	Lithuania	Russia
Bulgaria	Georgia	Macedonia	Slovakia
Chile	Hungary	Malaysia	Slovenia
China	Indonesia	Mexico	Thailand
Croatia	Kazakhstan	Peru	Ukraine

3.4 Empirical results

We begin by estimating the bivariate versions of the model, which include the imbalances indicators individually, and then proceed by including all the indicators jointly (Table 3.2). With the exception[57] of the broad money/GDP variable, all variables have the expected signs and high statistical significance when included in the model together with inflation and unemployment. These results generally confirm the idea that developments in financial variables are associated with cyclical fluctuations in output and importantly can provide information about the state of the business cycle beyond that contained in conventional indicators (i.e. inflation and unemployment).

equilibrium values (e.g. CPI mean growth in the case of gradual disinflation). Admittedly, de-trending the data exacerbates the end-point problem and thus worsens the real-time performance of the model. We experimented with de-trending the imbalances variables jointly with GDP; however, while the model became computationally heavier, the results were not significantly different.

[56] Conducting the estimates on the shorter balanced time sample did not change the results dramatically.

[57] For the models presented in Tables 2–4, we removed those variables with the "wrong" signs.

Table 3.2. Estimates of parameter γ (z-statistics in parentheses)

π_t	U_{t-1}	INV_{t-1}	S_{t-1}	C_{t-1}	M_{t-1}
0.08 (20.5)	-	-	-	-	-
-	-0.19 (-41.6)	-	-	-	-
-	-	0.14 (41.4)	-	-	-
-	-	-	0.16 (51.3)	-	-
-	-	-	-	0.08 (4.9)	-
-	-	-	-	-	0.01 (2.5)
0.03 (5.1)	-0.11 (-11.2)	0.08 (7.7)	0.16 (26.4)	0.05 (3.2)	-

We consider the resulting parameterization to provide a benchmark model, even though arguably one may reasonably use a homogeneous cross-section that includes only relevantly similar economies (e.g. from one region). The caveat here is that it is also desirable to have a dataset that is balanced as regards the presence of boom/bust occurrences. For example, if our dataset only included European countries most of which experienced dramatic output fluctuations, we would be unable to test the performance of the model in a more tranquil environment. Nevertheless, in order to check the robustness of the results, we also report the estimates obtained for the subsamples. First, we split our cross-section into regional groups: Asia, Central and Eastern Europe (CEE), the former Soviet Union (FSU) and Latin America. As might be expected, the estimates (Table 3.3) were most ambiguous (only the inflation and stock prices variables had significant coefficients with the correct signs) for the Asian subgroup, where the boom/bust episode was less pronounced than in the other regions. On the contrary, all parameters were significant for European countries and, most notably, the credit variable's coefficient was much larger than that in the benchmark model. The results obtained for the Latin American region were similar to those for the benchmark model, albeit the credit and inflation variables had low statistical significance.

Table 3.3. Estimates of parameter γ for the regional subsamples (z-statistics in parentheses)

Subsample	π_t	U_{t-1}	INV_{t-1}	S_{t-1}	C_{t-1}
Asia	0.02 (2.6)	-0.01 (-1.0)	-	0.07 (10.8)	-
CEE	0.04 (2.9)	-0.06 (-1.9)	0.08 (3.4)	0.2 (13.3)	0.19 (4.2)
FSU	0.04 (3.1)	-0.26 (-10.2)	0.07 (2.9)	0.17 (8.0)	0.13 (2.6)
Latin America	0.01 (0.3)	-0.09 (-3.9)	0.06 (2.8)	0.16 (11.3)	0.03 (1.4)

Asia: China, Indonesia, Korea, Malaysia, Thailand. **CEE**: Bulgaria, Croatia, Czech Republic, Hungary, Macedonia, Slovakia, Slovenia, Poland, Romania. **FSU:** Armenia, Estonia, Kazakhstan, Georgia, Latvia, Lithuania, Russia, Ukraine. **Latin America:** Argentina, Brazil, Chile, Ecuador, Mexico, Peru.

As pointed out by Bernhofer et al. (2014), the relationship between financial imbalances and output growth might be quite heterogeneous among emerging markets, as these economies have been on a convergence path during the past decade and are at highly different stages of economic development. In other words, the relevance of the financial variables may vary depending on the size of the financial sector. We proxy financial depth by using the credit/GDP ratio (averaged over 2000Q1–2012Q4) and divide our cross-section into quartiles: the first group containing the countries with the lowest credit/GDP ratios and the last group those with the highest. We find no distinct pattern in the results (Table 3.4). For example, the credit variable performs best in the first and last quartiles, while the stock prices variable is highly significant for all subsamples. We conclude that the relevance of the financial indicators for the cyclical output fluctuations variables is not conditioned by the size of the financial sector (at least as measured by using the credit/GDP ratio).

Table 3.4. Estimates of parameter γ for the subsamples by financial sector size (z-statistics in parentheses)

Subsample	π_t	U_{t-1}	INV_{t-1}	S_{t-1}	C_{t-1}
1st quartile	-	-0.14 (-6.7)	0.09 (2.9)	0.14 (3.5)	0.06 (2.1)
2nd quartile	0.05 (3.2)	-0.12 (-3.5)	0.06 (2.4)	0.18 (9.2)	-
3rd quartile	0.04 (2.9)	-0.1 (-3.7)	0.11 (4.3)	0.22 (11.4)	0.04 (1.2)
4th quartile	0.04 (3.3)	-0.09 (-3.7)	0.07 (3.0)	0.12 (11.1)	0.04 (1.6)

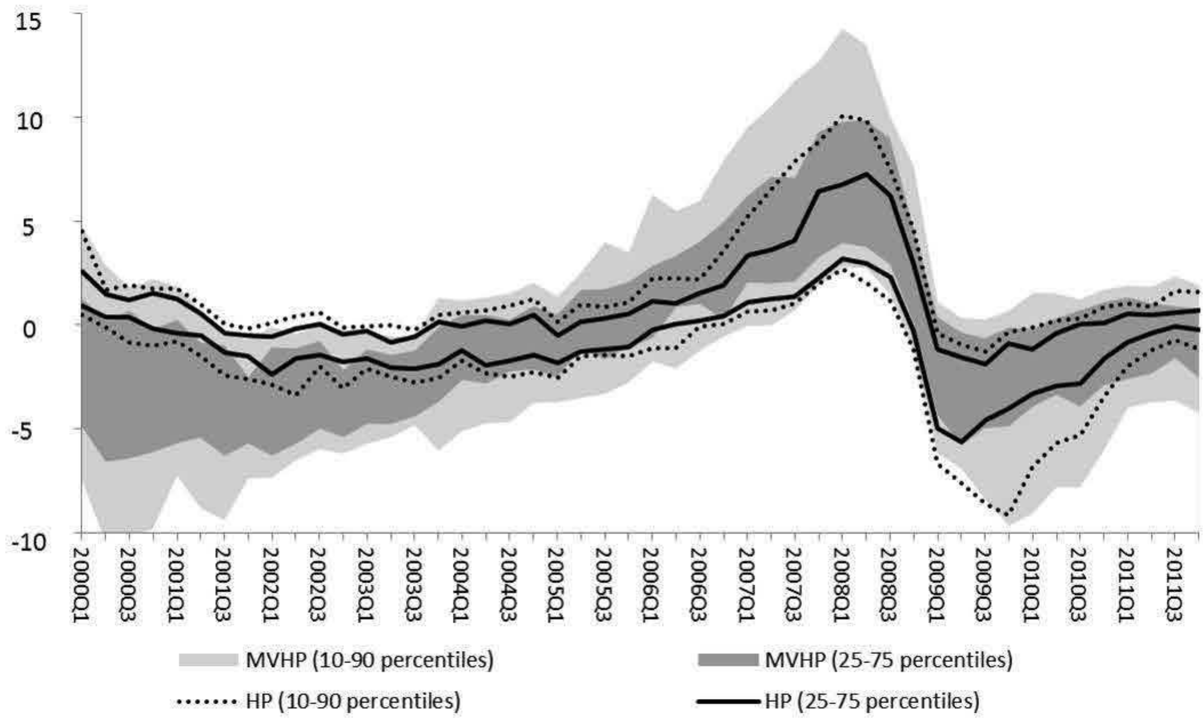
1st quartile: Argentina, Armenia, Ecuador, Georgia, Mexico, Peru, Romania. **2nd quartile**: Indonesia, Kazakhstan, Macedonia, Poland, Russia, Slovenia, Ukraine. **3rd quartile:** Brazil, Bulgaria, Croatia, Czech Republic, Hungary, Lithuania. **4th quartile:** China, Estonia, Korea, Latvia, Malaysia, Slovakia, Thailand.

3.5 Output gap estimates

3.5.1 General results

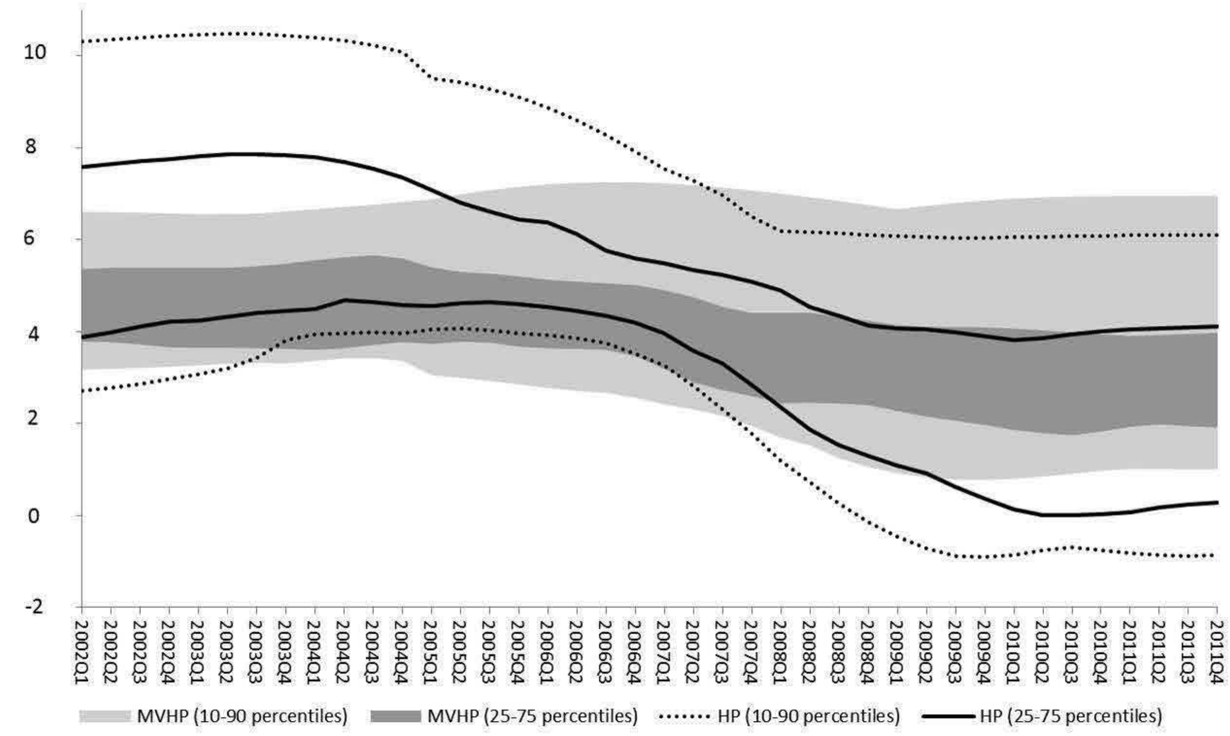
By using the benchmark parameterization reported in Table 3.2, we compute the trend and cycle components of GDP for all the countries in our cross-section. We can then compare the ranges of the output gap estimates obtained with the univariate and multivariate versions of the HP filter (Figure 3.1). Several distinct differences can be identified between the two ranges. Prior to 2006, the standard versions of the output gap were fluctuating close to zero, while the MVHP versions were mostly negative. At their peak in late 2007, the MVHP versions of output gaps were higher and after the crisis lower than those of the standard HP versions. The variability and magnitude of fluctuations in the MVHP versions were also generally larger.

Figure 3.1. Ranges of the output gap estimates (%)



The underlying reason for the difference between these two sets of estimates can be illustrated by plotting the growth rates of trend GDP (Figure 3.2). The growth rate estimates based on the univariate HP filter display notable variability, decreasing by about 4 p.p. in the second part of the time sample compared with the pre-crisis level. This may, of course, be a true reflection of the severe damage caused by the crisis to potential economic growth. However, more likely, given the relatively short time sample and magnitude of output fluctuation during the crisis, the univariate filter "overfits" the data by introducing excessive variability into the trend and weakens its interpretation as the sustainable level of output. As regards the MVHP version, some of the actual GDP fluctuations are explained by the imbalances indicators, ensuring more stable trend GDP growth.

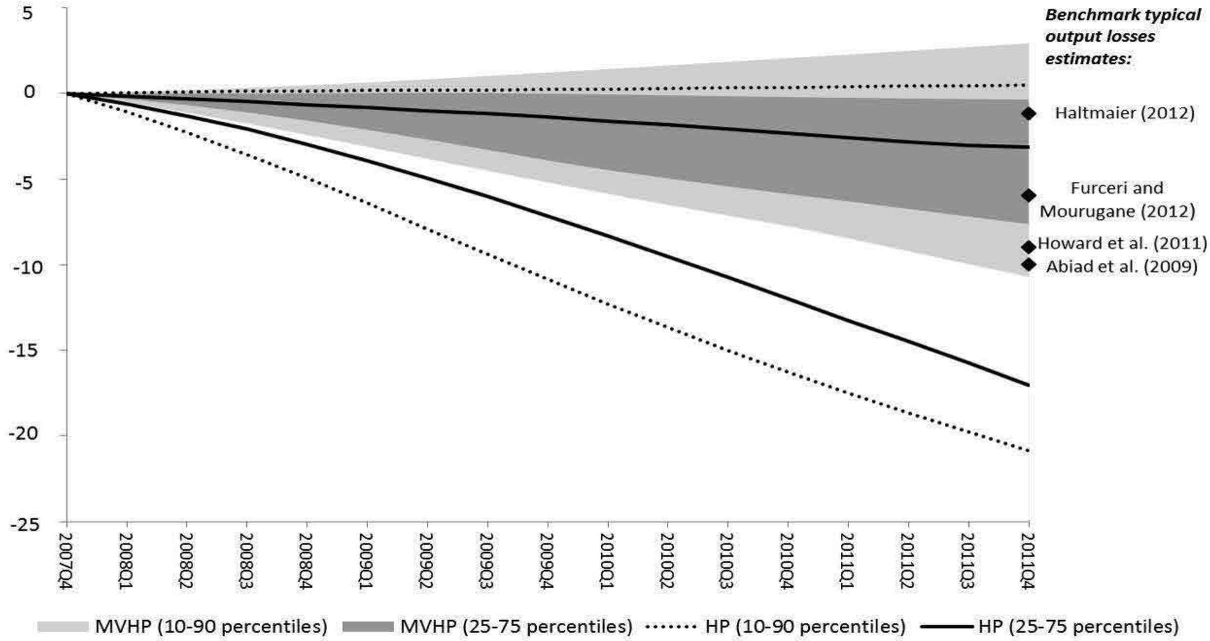
Figure 3.2. Ranges of the trend GDP growth (y-o-y, %)



We also apply the concept of cumulated potential GDP losses to illustrate the difference between the two versions of the filter. To this end, for the period starting from 2008, we estimate the difference between actual trend GDP and the extrapolated[58] trend values. Interestingly, we can compare our results with the estimates of typical output losses over previous recessions reported by existing studies[59] such as Abiad et al. (2009), Furceri and Mourougane (2012), Haltmaier (2012) and Howard et al. (2011). The results obtained with the MVHP filters are generally in line with these estimates, while those derived from the standard HP filters indicate that the output losses after the recent crisis were notably larger than on average in the historical cases.

[58] For extrapolation, we used the average growth rate of trend GDP in 2005–2007.
[59] We report the resultant output evolution values after the banking crises estimated in Abiad et al. (2009) and output as a percentage of the pre-crisis trend after deep and long recessions in emerging economies reported in Howard et al. (2011), the estimated impact of severe financial crisis reported in Furceri and Mourougane (2012) and the average cumulative level change in potential output in emerging markets after stand-alone recessions reported in Haltmaier (2012).

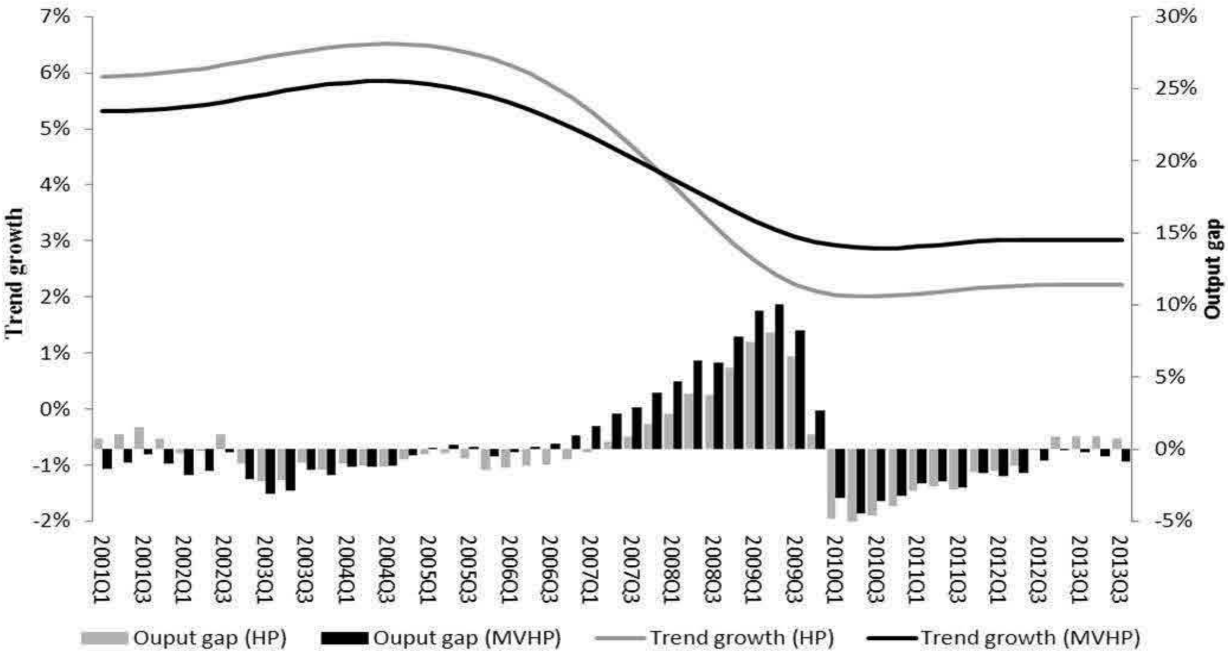
Figure 3.3. Ranges of the cumulative output losses estimates (% of pre-crisis trend)



3.5.2 Country-specific results: the case of Russia

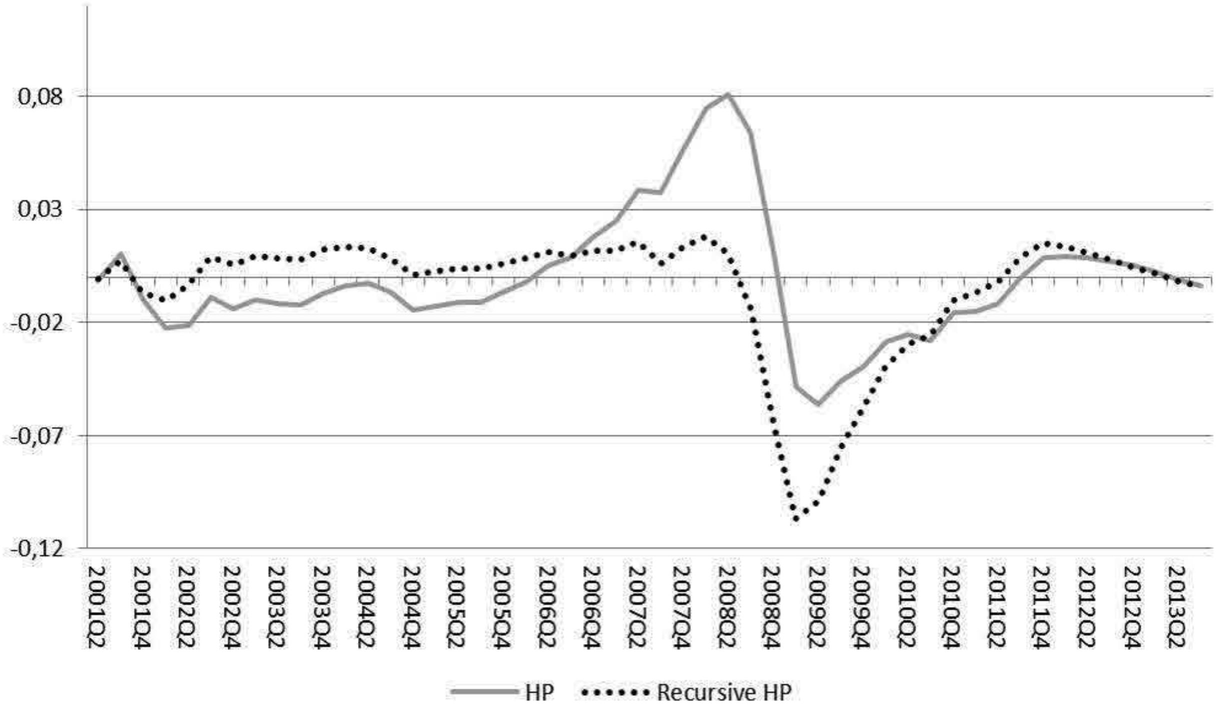
We expand on our findings by providing more detailed results from our model's application to GDP fluctuations in Russia. Similar to the general results for the whole cross-section, the MVHP output gap estimate is wider at its peak and narrower after the crisis compared with the HP version. This finding implies that the annual growth trend decreased from about 5% to 3% after the crisis (from 6% to 2 % in the case of univariate filtering) (Figure 3.4).

Figure 3.4. Actual and trend GDP growth and output gap estimates for Russia (y-o-y, %)



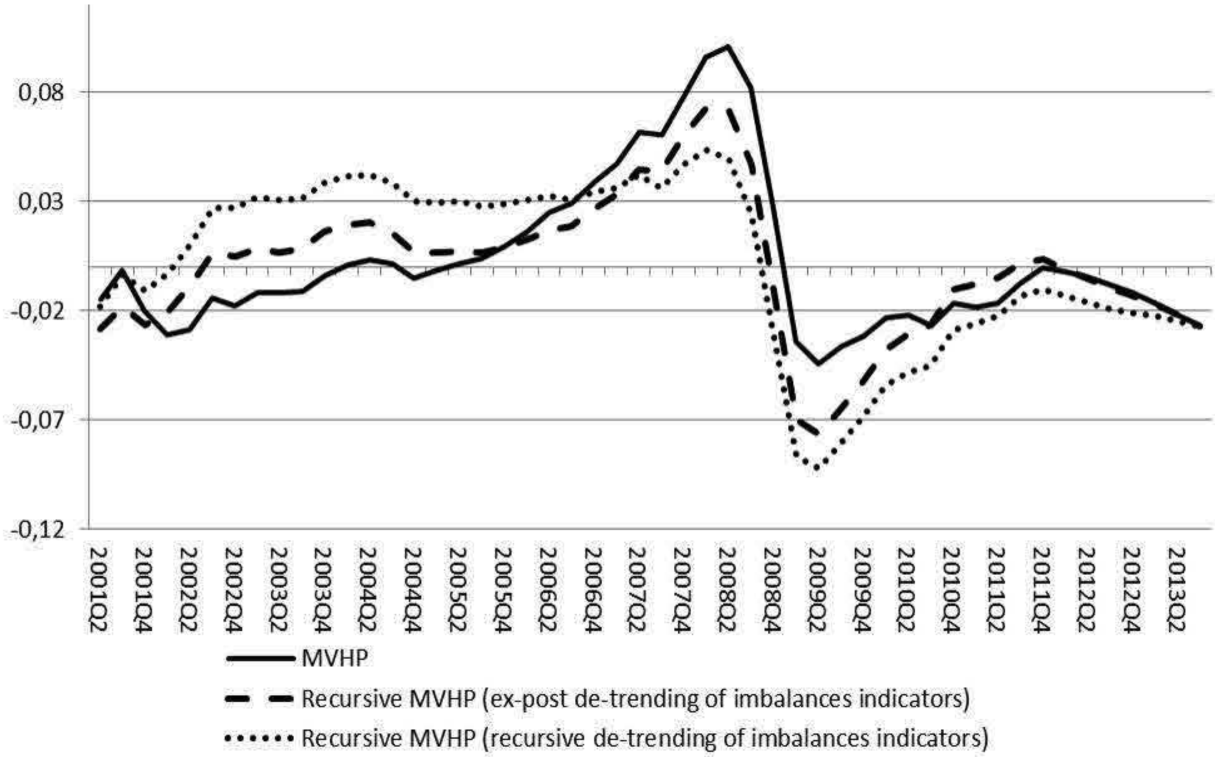
The recursive estimates (Figure 3.5) show that the application of the univariate HP filter to Russian GDP was not sufficiently informative. Multivariate filters may improve the real-time performance of the analysis. We conduct quasi[60] recursive estimates by using the MVHP version of the filter (Figure 3.6). These estimates are much more stable over time. The caveat is that this is no longer the case when the imbalances indicators are also de-trended recursively. Apparently, the model is quite sensitive to the end-point problem that arises in the preliminary step.

Figure 3.5. Recursive HP filter output gap estimates for Russia (%)



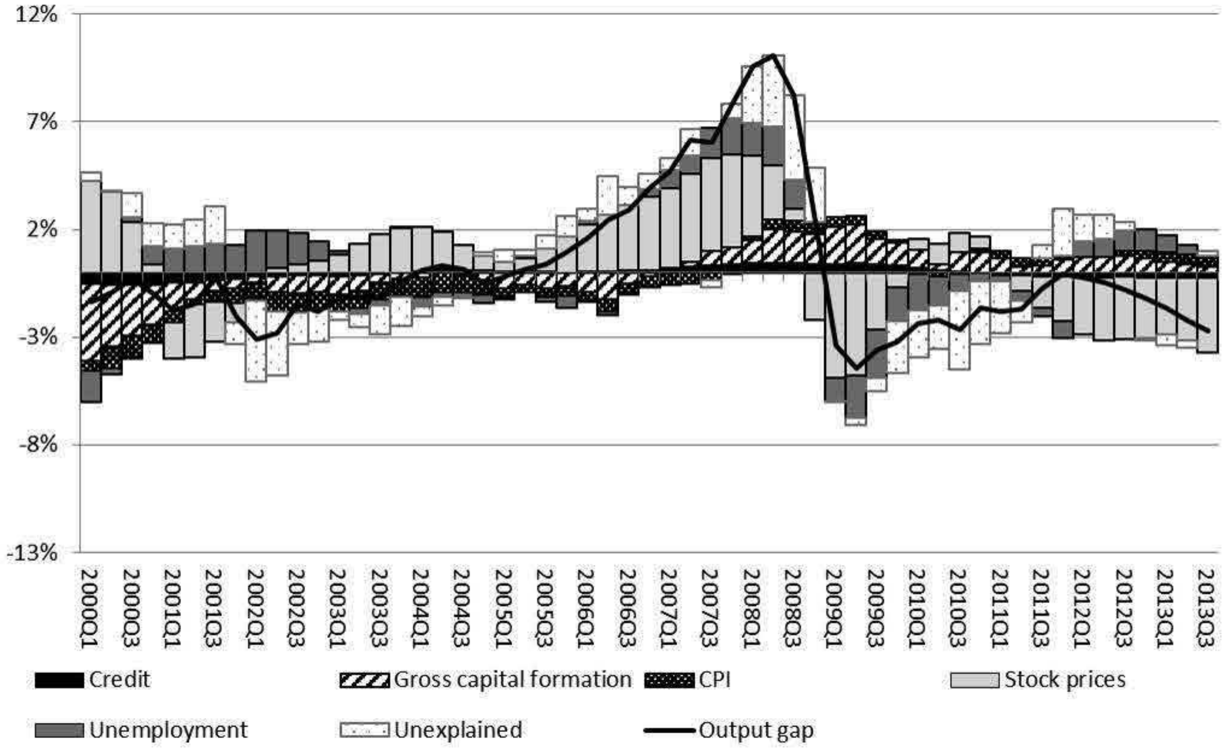
[60] We assume that parameterization γ is known and that it does not conduct recursive estimates for the pooled dataset. We are not able to fully replicate the real-time analysis because in our sample most of the information on boom/bust occurrence comes in one batch.

Figure 3.6. Recursive MVHP filter output gap estimates for Russia (%)



Finally, we examine the contributions of different indicators to the explained part of the output gap (i.e. $\gamma' x_{it-s}$) (Figure 3.7). The results show that prior to the crisis, all the imbalance variables unanimously indicated that GDP was above the sustainable level. For the post-crisis period, the results are ambiguous. Stock price developments are the most important indicator for explaining output gap fluctuations, followed by gross capital formation and unemployment. Credit developments and CPI inflation do not play an important role (at least under this parameterization). Admittedly, our model is purely empirical and does not provide a structural interpretation. It is therefore impossible, based on our results, to say that stock market developments as such were the underlying factor behind the output gap formation in Russia. Instead, we may argue that stock prices could be regarded as a good summary indicator for financial conditions in the economy (perhaps serving as a proxy indicator for e.g. asset price developments, capital inflows, risk perception) and that, based on the observed asset price boom on the Russian stock market, one can analyse the deviation in output growth from the sustainable path.

Figure 3.7. Contributions of individual imbalances indicators to explaining the output gap in Russia (%)



3.6. Conclusions

During the recent financial crisis, doubts were expressed as to the relevance and usefulness of conventional approaches to estimating the output gap. Thinking of potential output only as non-inflationary output or output not associated with a reduced unemployment rate had proven to be too restrictive. Recent history has demonstrated that other imbalances, notably in the financial sector and in asset markets, can emerge as inflation and unemployment remain stable. In our paper, we present a model that helps incorporate the information contained in financial indicators into the estimation of sustainable output growth in emerging market economies.

We specify a state-space model representing a multivariate HP filter that links cyclical fluctuation in GDP with several indicators of macroeconomic imbalances. The latter include financial variables as well as conventional CPI inflation and the unemployment rate. We obtain the parameterization of the model by estimating it jointly for a cross-section of emerging market economies. The results indicate that the imbalances indicators are statistically significant in explaining output gap fluctuations, particularly in the case of European countries, meaning that they contain information beyond that contained in the inflation and unemployment variables. A stock price indicator seems to perform especially well. As the model has no structural interpretation, this does not mean that stock market developments as such were the main factor behind these output gap fluctuations. Nevertheless, one might well claim that a rise in stock prices is an important symptom that could help distinguish between trend and cyclical output growth acceleration.

The output gaps obtained based on the estimated model differ substantially from those calculated with the univariate version of the HP filter. Most notably, trend output growth rates are more stable and therefore more consistent with the notion of sustainable output. Cumulative output losses after the recession in 2008, estimated on the basis of a multivariate filter, are (unlike those estimated by using the univariate version) comparable with typical episodes reported in the literature. Employing the multivariate filter may thus help improve the real-time robustness of the model, although our approach is still quite sensitive to the end-point problem associated with the transformation of the imbalance variables.

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Appendix 3

Table 3.5. Data sources

Variables	Description	Data source
y	Real GDP Index (2005=100)	IMF eLibrary
π	Quarterly CPI growth rate	IMF eLibrary
U	Quarterly unemployment rate	World Bank WDI
INV	Gross fixed capital formation to GDP ratio	World Bank WDI
S	Stock market capitalization to GDP ratio	World Bank WDI
C	Claims on private sector to GDP ratio	IMF eLibrary
M	Broad money to GDP ratio	IMF eLibrary

Chapter 4: Early warning indicators of asset price boom/bust cycles in emerging markets[61]

Abstract

We apply recently developed early warning indicators systems to a cross-section of emerging markets. We find that, with little or no modification, models designed to predict asset price booms/busts in advanced countries may be useful for emerging markets. The concept of monitoring a set of asset prices, real activity and financial indicators is generally found to be efficacious. We also find that, in addition to this set of variables, early warning indicator systems for emerging countries may be augmented with capital flows indicators.

Keywords: Early warning indicators, asset prices, emerging markets

JEL classification: E37, E44, E51.

[61] This chapter refers to the article published in *Emerging Markets Review*, Volume 15, June 2013.

4.1 Introduction

The recent financial crisis has underscored the growing importance of asset price fluctuations for macroeconomic performance. As is the case for developed countries, a number of emerging market economies (particularly in Central and Eastern Europe[62]) seem to be quite prone to such shocks, as the rapid rise and subsequent decline of asset prices have presumably contributed significantly to the pre-crisis overheating of these economies as well as to the following contraction. Therefore, a system of early warning indicators that would help with early identification of emerging imbalances in asset markets is a much sought-after tool for policy-makers.

Development of such a system via the country-specific approach is often impossible because of data limitations. Therefore the standard approach is to make estimations for a group of countries (that may or may not include the analyzed country) and apply the resulting model to the economy in question[63]. A number of recent studies use this method and report on models that can be used to predict asset price booms and busts. These may be valuable to the policy-maker. The caveat here is that most of these models have been fitted to explain asset prices fluctuations in industrialized countries. It is not clear how useful these models are for emerging markets, as movements in many of the macroeconomic variables used as early warning indicators are remarkably different in the developed and emerging markets. For example, one may find it difficult to distinguish between excessive credit growth that leads to an asset price bubble and the convergence of an underdeveloped banking sector to a level commensurate with the industrialized countries. For transition economies, it may also be challenging to identify “overheating” based on growth rates of real sector variables that fluctuate dramatically as the economy undergoes substantial transformation. In fact, asset prices as such are known to be volatile in emerging markets and therefore difficult to interpret. For these reasons the early warning indicators approach needs to be thoroughly studied before it finds use in predicting asset price cycles in emerging markets. Indeed, as emphasized in Reinhart and Rogoff (2009), data coverage is crucial for financial crisis analysis. The main contribution of this paper is the application of asset price boom/bust analysis to the new dataset on emerging markets (most notably former Soviet Union countries).

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[62] See Gardó and Martin (2010) and Égert and Martin (2008) for general review, Brixiova et al. (2010) for the specific case of Estonia, Kuodis and Ramanauskas (2009) for the case of Lithuania and Mumtaz et al. (2012) for the case of Russia.

[63] See Gómez and Rozo (2008) for the example of country specific analysis, Tenjo and López (2010) for the cross-section analysis and Chapter III in BIS (2012) for out-of sample application of existing models.

The rest of the paper is structured as follows. Section 4.2 provides a review of recent contributions in the development of asset price cycle early warning indicator models. Section 4.3 describes the dataset, comprising a cross-section of emerging markets economies, on which we conduct the empirical analysis. Section 4.4 outlines and implements methods to identify boom and bust events that occurred in emerging markets. Section 4.5 presents an evaluation of the efficacy of existing models for predicting asset price developments in emerging markets and reports on the models fitted here to predict asset price booms/busts in the purely emerging markets dataset. Section 4.6 concludes.

4.2 Literature review and modeling strategy

Although a number of recent studies address the issue of asset price fluctuations and designing early warning indicators for emerging markets none of these, to our knowledge, addresses specifically the problem of predicting asset price booms and busts. Herrera and Perry (2003) assess the relative importance of domestic and external factors for determining the probability of an asset price bubble for a cross-section of Latin American countries. Lo Duca and Peltonen (2011) is a comprehensive study that develops a model for predicting systemic financial stress episodes for a sample of countries that includes emerging markets. They find that (in particular, global) measures of asset price misalignments and credit booms are generally useful as leading indicators. Tenjo and López (2010) construct an early warning indicator system for banking crises in a group of Latin American countries, in which asset price indicators play a crucial role. Bunda and Ca'Zorzi (2010) study whether asset price and credit booms can be used as an early warning indicator of financial (banking or currency) crisis, on the basis of a mixed sample of advanced and developing countries. They identify a number of macroeconomic variables that help to distinguish between benign and costly episodes. Olaberría (2012) conducts an empirical analysis of the relationship between capital inflows and booms in stock prices and finds that there is a close association (in particular for debt related inflows). Égert and Mihaljek (2007), Stepanyan et al. (2010), Posedel and Vizek (2011) and Ciarlone (2012) examine house price developments in selected emerging economies and find a strong link between house-price fluctuations and macroeconomic fundamentals. Posedel and Vizek (2011) also find that house price persistence coupled with a slow and asymmetric house price adjustment to fundamentals process might have facilitated the house price boom in some transition countries.

In contrast, there is a vast literature on asset price booms and busts in developed countries. We selected three studies dedicated to early prediction of asset price cycle developments and utilized different methods of identifying asset price boom/busts and a different modeling strategy.

As outlined in chapter 6 of Papademos and Stark (2010) these models are used in a complementary manner as part of the suite of models employed by the ECB for early detection of asset price misalignments by means of monetary analysis. The approaches these models are based on (i.e. signalling and discrete-choice) are also widely used in early warning indicators models for prediction of e.g. banking and currency crises. We therefore consider these models as appropriate example of existing state-of-the-art approaches to asset price booms/busts prediction.

Table 4.1. Selected approaches to asset prices boom/bust cycle prediction

Approach	*Asset prices indicator*	*Event predicted*	*Model*
Alessi and Detken (2011)	Real aggregate asset price index (deviations of levels from trend)	Boom	Stand-alone indicators
Gerdesmeier et al. (2010)	Nominal aggregate asset price index (q-o-q growth rates)	Bust	Discrete choice model
Agnello and Schuknecht (2011)	Real house prices (deviations of levels from trend)	Boom (bust) phases	Discrete choice model

There are some notable differences between the different approaches.

The first such difference is in the measurement of asset prices. Theoretically, the aggregate asset price index should be calculated using carefully constructed weights and should include prices for the selection of assets constituting a sizeable proportion of national wealth (see Borio et al. (1994) for a review). In practice, this approach is usually approximated by averaging between housing and equity prices, as there is an evident lack of data on national wealth in emerging economies. The caveat is that the drivers behind bubble formation in housing and in equity markets might be different, so that these types of assets should be considered separately for the purpose of constructing a system of early warning indicators. It is also questionable how representative the equity prices fluctuations are, given the relatively underdeveloped capital markets and presumably small share of equities in the national wealth of emerging economies. This may justify concentrating on housing prices when examining asset price fluctuations in emerging markets.

Another key choice is the method of boom/bust identification (see e.g. Stążka-Gawrysiak (2011) for discussion). The asset price indicator is usually examined in terms of growth rates or deviations from trend. The latter method may seem preferable, as it enables one to distinguish between changes in trend and cycle components; but it may also be sensitive to the de-trending method whereas the former method is more consistent and easily applicable. Both methods may be sensitive to outliers. Another method suggests analyzing asset prices developments in terms of phases of cyclical fluctuation, the severity of which is characterized by both amplitude and duration. This method is less sensitive to short-run fluctuations but may be more difficult as regards interpretation (e.g. one may argue that a prolonged period of steady asset price rise does not necessarily represent a boom).

The values of the constructed indicators, i.e. the deviations from trend, growth rate or phase severity, above (below) certain thresholds may then be labeled as booms (busts) [64]. The thresholds are usually defined in terms of percentiles or proportion of standard deviation. These may be country-specific (in which case we look for events that are exceptional for a given country) or computed for the whole cross-section (thus discriminating between the normal cyclical fluctuations that may be observed in most of the economies and outstanding boom/bust events).

The same issue is also relevant for explanatory variables that can be expressed in terms of country-specific percentiles. This transformation may seem appropriate for panel data analysis, as it takes into account potential cross-country differences in the scale of regressors. On the other hand this would limit the model's ability to avoid issuing the warning signal since by definition the value of the explanatory variable will be above the chosen threshold in some periods.

There is no clear indication in the literature that some of these methods should be considered superior to others. We thus consider all of the approaches and attempt to apply them to emerging markets data in order to assess the coherence of the results.

Finally, the choice of explanatory variables must be made. The selected studies echo the approach outlined in Borio and Lowe (2002) implying that the combination of asset prices, real sector and financial (e.g. money or credit) variables should be monitored for timely prediction of asset price bubbles. We will adopt a similar strategy.

One notable nuance is that Alessi and Detken (2011) also add global liquidity variables to their models. We do not use explicit measures of global liquidity for the following reasons. As was pointed out in Alessi and Detken (2011), the global private credit gap indicator would have performed exceptionally well in explaining the last wave of boom/bust episodes in 2005-2007.

[64] We do not identify high or low cost asset price booms/busts, which would have been difficult, considering that most booms/busts in the sample occurred prior to the recent global crisis and were followed by a slowing of output growth, irrespective of asset price developments. The question of whether an asset price boom/bust could amplify the output losses is pursued in a different strand of literature.

Due to our limited time sample, we will be dealing almost exclusively with this most recent wave (see Section 4.4). Obviously a global liquidity measure calculated on monetary developments in advanced economies and not being country-specific with regard to the economies in our sample would explain all the boom/bust episodes observed during that period. Although this fact apparently deserves policy-makers' attention it can hardly be considered robust evidence of such an indicator's predictive power, as no other boom/bust episodes are available for examination. Therefore instead of relying on the global liquidity measure we will attempt to capture the spillover[65] from advanced economies using country-specific capital inflow indicators as a proxy for financial exposure[66]. In this we will follow Herrera and Perry (2003), Tenjo and López (2010) and Olaberría (2012) who use capital flow variables in their models.

4.3 Dataset

A significant challenge in constructing the early warning indicators system based on panel data is putting together an appropriate dataset. One may find it logical to use a homogenous cross-section that includes only relevantly similar economies (like Tenjo and López (2010) who use the cross-section consisting of Latin American countries). The caveat here is that it is also desirable to have a dataset that is balanced as regards the presence of boom/bust occurrences. For example, if our dataset only included Central and Eastern European countries (most of which experienced asset price booms/busts) we would be unable to test the performance of the system in a tranquil environment. We, therefore, did not limit our cross-section to any particular group of countries and so included all emerging markets where adequate[67] housing price data were available[68]. Scant availability of these data proved to be the main limitation on the number of countries in the cross-section and in most cases determined the time span of the dataset in our unbalanced panel.

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[65] Admittedly the contagion effect may impact emerging economies not only via the stoppage of capital inflows but also via the deterioration of foreign assets' quality (see Rose and Spiegel (2010) for discussion) since the resulting demand for liquidity and assets sales could also affect conditions in domestic assets markets. However the lack of data on bilateral foreign assets holdings for most of the countries in our sample prevented us from conducting this kind of analysis.

[66] Admittedly these two categories of variables cannot be viewed as complete substitutes, as the interplay between global liquidity and capital inflow variables may not be very distinct. Forbes and Warnock (2011) for example show that global money supply growth is rarely associated with capital inflows episodes. Interestingly, Brana et al. (2012) do not find a definite impact of global liquidity on asset prices, based on panel VAR estimates for a cross-section of emerging markets, while Kim and Yang (2011) find a link between asset prices and capital inflows in emerging Asian economies using a similar modeling framework.

[67] We advisedly do not use construction costs or housing utilities price indicators, as these may not be good proxies for housing prices in emerging markets. For example in many former Soviet Union countries housing utilities prices are largely administered by the government.

[68] Nevertheless we report the models performance indicators separately for two distinct country sub-groups in our cross-section to check the sensitivity of the results (see Table 4.13 in the Appendix).

Accordingly (as reported in Table 4.2) the time sample used in our analysis covers the period from 1993Q1 to 2011Q2, but is highly country-specific (in most cases starting from the early 2000s).

Table 4.2. Emerging markets housing prices data availability

Argentina 1993Q1-2011Q2	Hungary 2001Q4-2011Q2	Poland 2005Q2-2011Q1
Armenia 2002Q1-2009Q1	Indonesia 2002Q1-2011Q2	Russia 1996Q4-2011Q2
Azerbaijan 2001Q1-2009Q3	Israel 2001Q1-2011Q1	Serbia 2003Q1-2010Q4
Bulgaria 1993Q1-2011Q2	Kazakhstan 2001Q1-2009Q3	Singapore 2004Q4-2011Q2
China 1997Q4-2011Q2	Korea 1993Q1-2011Q2	Slovakia 2005Q1-2011Q2
Colombia 1997Q1-2011Q2	Latvia 2005Q1-2009Q3	Slovenia 2003Q1-2011Q1
Croatia 2000Q4-2010Q4	Lithuania 1998Q4-2011Q1	South Africa 1993Q1-2011Q2
Estonia 1997Q1-2009Q3	Malaysia 1999Q1-2010Q4	Thailand 1995Q1-2011Q2
Georgia 2003Q1-2009Q3	Mexico 2005Q1-2011Q1	Ukraine 2000Q2-2009Q3
Hong Kong 1993Q1-2011Q2	Philippines 2004Q4-2011Q1	

We used equity prices as another indicator of asset prices. For real sector variables, we used SNA indicators (GDP, fixed capital investment and private sector consumption). We used broad money (or if unavailable the broadest aggregate reported) for the monetary indicator and credit to private sector for the credit indicator. We used gross indicators of capital inflows. See Tables 10-11 in the Appendix for data description.

We were unable to retrieve the appropriate time series of equity prices for Azerbaijan and Georgia and of capital flows for Azerbaijan, Philippines and Serbia. Therefore these countries are excluded from the analysis wherever the respective indicator was involved. And, for Azerbaijan and Georgia, the housing price index is used instead of the aggregate price index.

All time series are quarterly (seasonally adjusted via X-12, where appropriate). Where variables in real terms were unavailable, GDP deflators were used to deflate, and where quarterly frequency data were unavailable, time series were interpolated via cubic splines.

4.4 Identification of asset price booms and busts

We employ three alternative approaches to identify the stages of asset price cycles.

- *Booms identification*. Following Alessi and Detken (2011) we apply a Hodrick-Prescott filter (λ=100000) to the real aggregate[69] asset price indices. Periods in which the index value exceeds the trend plus 1.5[70] times the standard deviation of the series are defined as booms.
- *Busts identification*. Following Gerdesmeier et al. (2010) we examine the quarterly growth rates of the nominal aggregate asset price index and define as busts those periods in which the nominal aggregate asset price index declined by more than its mean quarterly change minus 1.5 times the standard deviation of the series.
- *Boom (bust) phases identification*. Following Agnello and Schuknecht (2011) we employ "triangular approximation" to distinguish between boom, bust and neutral phases of the asset price cycle. We de-trend the real housing prices indices via a Hodrick-Prescott filter (λ=100000) and then "smooth" the cycle fluctuations by extracting the rapidly adjusting trend with a Hodrick-Precott filter (λ=10). We identify the turning points and compute the persistence of the period from trough to peak (the upswing) and from peak to trough (the downturn) and the magnitude of the price changes over these periods. We consider each housing price phase as a triangle where the height is the magnitude and the base is the persistence/duration, and we use the computed squares of these triangles as severity metrics for the upswings and downturns. We extract the whole distribution of triangle squares and label the values lower than the first quartile as bust phases and values higher than the third quartile as boom phases (See Figures 4.4-4.5 in the Appendix for illustrations).

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[69] The aggregate asset price index was estimated as the weighted average between housing and equity price growth. Similarly to Gerdesmeier et al. (2010) the weights are inversely proportional to the variables' volatility, i.e. Δ*Asset prices* = $\sigma_{sp}/(\sigma_{sp} + \sigma_{hp})$ Δ*Housing prices* + $\sigma_{hp}/(\sigma_{sp} + \sigma_{hp})$ Δ*Equity prices*, where σ is the standard deviation of the respective variable.

[70] The choice of this threshold is somewhat arbitrary. We follow Gerdesmeier et al. (2010) and set it to 1.5, although Alessi and Detken, (2011) for example use higher threshold of 1.75. Applying the threshold of 1.75 does not dramatically alter the results of our research, but we feel that we may proceed with lower 1.5 value as our benchmark choice, since we will combine this identification approach with booms/busts phases analysis (see below) presumably making our results less sensitive to the presence of outliers.

Because different methods may potentially yield conflicting results, it is important to ensure that the boom/bust identification scheme is robust. In theory the events identified by different methods should be part of the same cycle and thus be synchronized. That is, booms should be followed by busts and busts should be preceded by booms. Both events should also occur during respective phases (given the methods that we employed, it is most likely that a boom occurrence would mark the end of a boom phase and a bust event would happen at the start of a bust phase). The degree of our results' compliance to these assumptions is reported in Table 4.3.

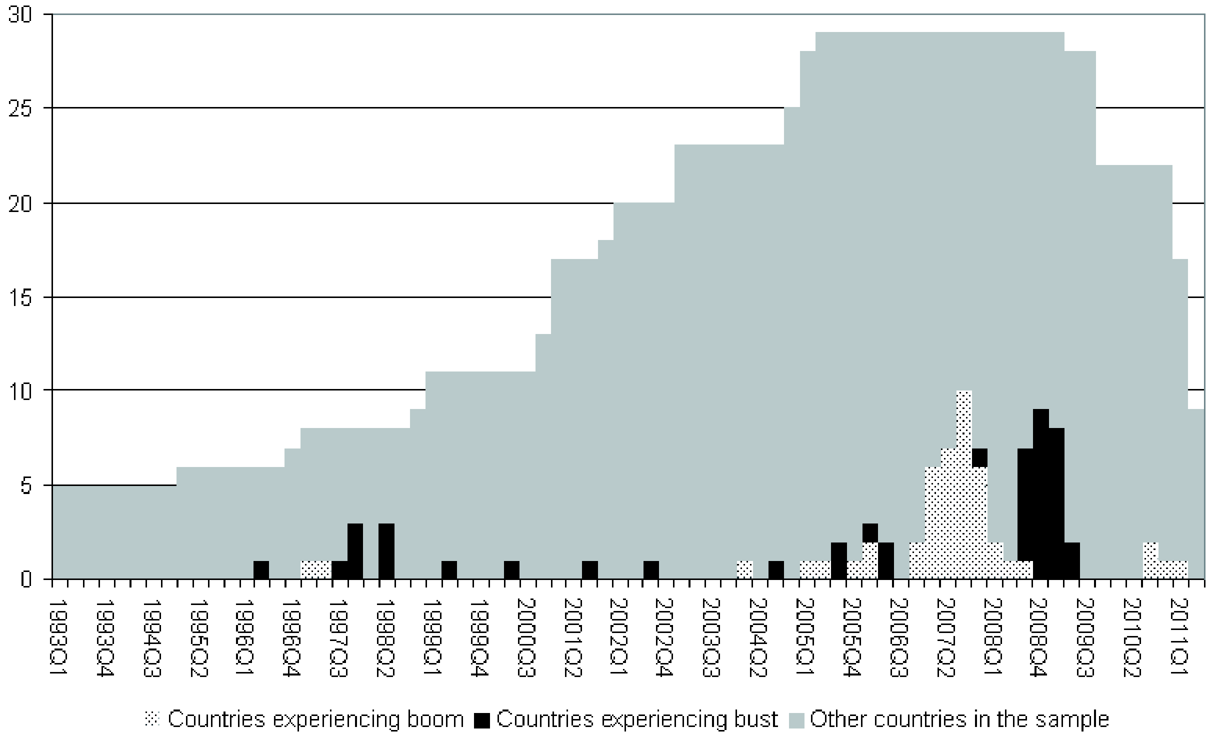
Table 4.3. Methods' synchronization

Event	Number of events identified	% of booms followed by busts within 2 years / % of busts preceded by booms within 2 years	% of booms associated[71] with boom phase / % of busts associated with bust phase
Booms	**68**	**66%**	**69%**
Busts	**64**	**50%**	**69%**

The lack of total synchronization between methods is not surprising (Borgy et al. (2009) for example report that roughly half of booms are followed by busts in developed economies). For further analysis, we decided to count only those observations that were both identified as boom/bust *and* were associated with the respective phases. Presumably this will allow us to disregard both the outliers and the prolonged but tranquil upswings (downturns). By doing so, we expect to increase the robustness of our analysis. Thus we arrive at our final datasets (see Table 4.12 in the Appendix 4 for country specific results).

[71] We counted those boom and bust observations that were within or adjacent respectively to boom or bust phase periods.

Figure 4.1. Number of countries experiencing booms/busts



The overall size of the sample seems sufficient for meaningful empirical results (we identified 45 booms and 32 busts in a total 1263 observations). Yet this new dataset is substantially smaller than the developed countries' datasets (which include about 2700 observations) that were used to estimate the aforementioned models. Another caveat is that in our dataset there is basically only one (most recent) wave of boom/bust episodes available for analysis. This means that modifying the existing models to fit the new dataset might lead to the loss of empirical credibility. This tradeoff should be carefully considered when the models are compared and put into practical use.

4.5 Empirical analysis

We employ the standard approach to assessment of model performance (as in e.g. Kaminsky et al. (1998)). The signal is assumed to be issued when the indicator of interest exceeds a certain threshold. For early-warning purposes, we expect the model to start issuing the signal six quarters before a boom/bust occurrence.

Table 4.4. Model performance

	Boom/bust episode (within 6 quarters)	**No boom/bust episode (within 6 quarters)**
Signal issued	**A**	**B**
No signal issued	**C**	**D**

In this matrix, A is the number of quarters in which the indicator issued a good signal, B is the number of quarters in which the indicator issued a bad signal, C is the number of quarters in which the indicator failed to issue a signal when the boom/bust occurred and D is the number of quarters in which the indicator did not issue a signal when in fact there was no boom/bust. We define the loss function of the policy maker as

$$L = \theta\ (C/(A+C)) + (1- \theta)\ (B/(B+D)) \qquad (4.1)$$

For our analysis we assume equal preferences for issuing false signals and missing boom/bust occurrences by setting θ=0.5. Following Alessi and Detken (2011) we employ the "usefulness" indicator to assess the models:

$$U = \min\ [\theta, 1- \theta] - L \qquad (4.2)$$

One may conclude that the indicator is useful for the policymaker if the loss incurred by ignoring the signal is higher than the loss incurred taking it into consideration (i.e. if the "usefulness" indicator is positive). We rely on this indicator to determine the optimal threshold. As a secondary indicator we use the noise-to-signal ratio:

$$NtS = (B/(B+D))\ /\ (A/(A+C)) \qquad (4.3)$$

We will also report separately the Signal (A/(A+C)) and Noise (B/(B+D)) indicators.

We will not be able to fully replicate the real-time analysis (as in e.g. Lo Duca and Peltonen (2011) who conduct recursive estimation of their models) because in our sample most of the information on boom/busts occurrences comes in one batch. Therefore the models are estimated and thresholds are optimized *ex-post*. We will however do the transformations of the explanatory variables (i.e. de-trending and percentile calculation) recursively.

4.5.1 Signalling approach

Our first approach is to follow Alessi and Detken (2011) and rely on the dynamics of individual macroeconomic variables to predict the boom occurrence. In doing this we apply the signalling approach first developed by Kaminsky et al. (1998), which represented a major contribution to the literature when it appeared and became a benchmark choice for early warning indicators system construction. This approach assumes an extreme non-linear relationship between the indicator and the event to be predicted and transforms the indicators into binary signals: if a given indicator crosses a critical threshold, it is said to send a signal.

We select three macroeconomic variables from three categories (asset prices, real sector and financial variables) to be used as early warning indicators. We choose the variables (as well as their transformations) that were found to be most useful in Alessi and Detken (2011)[72]. We also include capital inflow measures to our set of indicators. As pointed out in Krugman (2000), foreign direct investment inflows help smooth cycles in domestic asset prices and should not be linked to booms. We therefore include an indicator of total capital inflows and one that excludes foreign direct investment.

The signal is assumed to be issued when the indicator's value exceeds a threshold (the same for all countries) defined in terms of the recursively calculated (country-specific) percentile. We make the variable-specific evaluation of indicators' performance under the optimized (in terms of "usefulness" indicator) percentile threshold. We report these optimal percentiles in column 3 and the respective "usefulness" indicator in column 4 of Table 5. We also report noise-to-signal ratios and their sub-components in columns 5-7. As in Andreau et al. (2007), we also calculate the composite index as the weighted average of signals issued by stand alone indicators with weights proportional to "usefulness". The index is normalized to have values between 0 and 1. The assumed threshold value for the composite index is 0.5.

[72] We use the results reported in Table 4 in the Annex of the working paper version of the article (ECB WP No. 1039).

Table 4.5. Stand alone indicators' performance

Category	Variable	Percentile	U	NtS	Signal	Noise
Asset prices	Real agg. asset prices (y-o-y growth)	60	0.17	0.47	0.65	0.31
	Real housing prices (de-trended)	75	0.14	0.54	0.62	0.33
	Real equity prices (de-trended)	90	0.07	0.6	0.36	0.22
Real sector	GDP (de-trended)	75	0.09	0.64	0.51	0.33
	Investment (y-o-y growth)	50	0.11	0.7	0.72	0.51
	Consumption (y-o-y growth)	65	0.13	0.56	0.57	0.32
Financial indicators	Real money (y-o-y growth)	65	0.1	0.63	0.52	0.33
	Real credit (y-o-y growth)	50	0.1	0.72	0.7	0.51
	Long term interest rate (de-trended)	45	0.02	0.95	0.7	0.66
Capital inflows	Total capital inflows	90	0.13	0.5	0.53	0.27
	Non-FDI capital inflows	75	0.13	0.58	0.63	0.36
Composite index			0.18	0.45	0.67	0.3

Asset prices, real sector variables, money and credit are deflated via GDP deflator. Capital inflows are summed over four quarters and are in ratios to GDP. Deviations from trend are calculated via applying recursive Hodrick-Prescott filter (λ=100000) to series in logarithms.

Most of indicators perform reasonably well in terms of performance indicators that are generally comparable with those reported by Alessi and Detken (2011). The values of optimal threshold percentiles are also close to those in the original model. Asset price (in particular aggregate index and housing prices) and capital flow indicators seem to be the best performing categories, followed closely by real sector and financial variables (with the exception of the interest rate indicator). Constructing the composite index by averaging the signal issuance over the whole set of indicators helps to improve the system's performance. In our opinion these results confirm the applicability of the Alessi and Detken (2011) system of early warning indicators to emerging markets.

4.5.2 Discrete choice models: existing models' out-of-sample performance

As a second approach we construct an early warning indicator system in the form of a discrete choice model. This approach makes use of probit regression techniques to evaluate an indicator's contribution to predicting a boom or bust. As pointed out in chapter 6 of Papademos and Stark (2010), this approach has several beneficial features compared to the "signalling" approach. First, the discrete-choice approach allows a test of the usefulness of the threshold concept. Second, this method enables one to take into account correlations between different indicator variables. Finally, the approach allows the statistical significance of individual variables to be evaluated. This methodology consists of running probit regressions on the panel data set and comparing several specifications of the probit models, whereby an assessment of the specifications is made on the basis of probability scores and goodness-of-fit.

We begin by simulating the discrete choice models presented in Table 2 in Gerdesmeier et al. (2010) (GRR(A) and GRR(B)) on our sample and assessing their performance in predicting the bust occurrences in emerging markets.

Similarly to Gerdesmeier et al. (2010), we construct our binary dependent variable, which equals one in the period one to six quarters prior to the bust occurrence (identified as described in Section 4.4) and equals zero in all other periods, implying that we expect our models to start issuing the signal 6 quarters before the bust occurrence.

One may argue that fixed-effects approach may be needed to capture potential differences in equilibrium values and scales of explanatory variables in developed and in emerging market countries (as well as among different emerging market countries) and thus improve the fit of the models. To this effect we use de-meaned variables[73]. Namely we subtract the country-specific means from variables that are not de-trended and re-estimate the common intercept term of the model (while fixing all other coefficients) by running the pooled probit regression over the emerging markets sample. As another test of model robustness, we also report the fully re-estimated models. Interestingly, the coefficients of the re-estimated Specification A model (at least

[73] We do not employ country-specific dummy variables in our analysis because, as noted in Davis and Karim (2008), this approach would lead to information loss for countries that did not experience a boom/bust.

in cases of credit growth and investment/GDP variables) seem to be consistent with the original results, which may be regarded as a confirmation of the model's applicability to emerging markets.

Next we simulate the models and calculate the formal performance indicators. We do this for the optimized probability threshold as well as for the benchmark threshold probability (0.5) as recommended in Roy and Kemme (2012). As in Gerdesmeier et al. (2010) we also report the quadratic probability score (QPS) and log probability score (LPS) to assess the goodness of fit of the models.

Table 4.6. Performance of GRR(A) probit model

Variable/coefficient [p-values in brackets]	**(1) unmodified model**	**(2) de-meaned variables and re-estimated constant**	**(3) de-meaned variables and all re-estimated coefficients**
Nominal credit y-o-y growth	0.016	0.016	0.013 [0.00]
Nominal credit y-o-y growth(-4)	0.024	0.024	0.008 [0.09]
Investment/GDP ratio	0.023	0.023	0.068 [0.00]
Nominal equity prices nominal y-o-y growth(-1)	0.006	0.006	-0.00 [0.18]
Annual changes in long term interest rate	0.126	0.126	0.014 [0.32]
constant	-1.444	-1.33 [0.00]	-1.13 [0.00]
Performance indicators [performance under benchmark threshold probability=0.5 in brackets]			
Optimal threshold probability	*0.75*	*0.2*	*0.25*
U	*0.1 [0.07]*	*0.1 [0.04]*	*0.18 [0.04]*
NtS	*0.42 [0.64]*	*0.48 [0.26]*	*0.2 [0.12]*
Signal	*0.4 [0.59]*	*0.48 [0.13]*	*0.47 [0.09]*
Noise	*0.17 [0.38]*	*0.23 [0.03]*	*0.09 [0.01]*
QPS	*0.21*	*0.1*	*0.09*
LPS	*0.34*	*0.18*	*0.15*
No. of obs	963		

Table 4.7. Performance of GRR(B) probit model

Variable/coefficient [p-values in brackets]	**(1) unmodified model**	**(2) de-meaned variables and re-estimated constant**	**(3) de-meaned variables and all re-estimated coefficients**
Nominal credit y-o-y growth (de-trended)	0.071	0.071	-0.01 [0.5]
Nominal housing prices y-o-y growth (de-trended)	0.029	0.029	0.00 [0.73]
Annual changes in long term interest rate	0.125	0.125	0.02 [0.01]
Investment/GDP ratio	0.02	0.02	0.08 [0.00]
constant	-0.978	-1.08 [0.00]	-1.04 [0.00]
Performance indicators [performance under benchmark threshold probability=0.5 in brackets]			
Optimal threshold probability	*0.6*	*0.25*	*0.2*
U	*0.05 [0.05]*	*0.06 [0.03]*	*0.16 [0.03]*
NtS	*0.37 [0.51]*	*0.56 [0.28]*	*0.37 [0.1]*
Signal	*0.17 [0.27]*	*0.34 [0.1]*	*0.59 [0.08]*
Noise	*0.06 [0.14]*	*0.19 [0.03]*	*0.22 [0.01]*
QPS	*0.15*	*0.13*	*0.11*
LPS	*0.26*	*0.23*	*0.18*
No. of obs	937		

Deviations from trend are calculated via recursive Christiano-Fitzgerald filter.

The results of the models' out-of-sample performance are promising. Both models display acceptable "usefulness" and noise-to-signal indicators even in unmodified form, although Specification A seems to perform better. In fact the NtS indicators are very close to those reported by Gerdesmeier et al. (2010) for the original sample, while the QPS and LPS measures are actually lower (better fits). Using partially modified type (2) models leads to even lower QPS and LPS indicators but not necessarily to better performance in terms of other indicators. The "usefulness" of the models is not huge when assessed under benchmark threshold probability (0.5) due to the small number of signals issued (as pointed out in Roy and Kemme (2012), such an outcome is typical for this approach), although it is still positive. As could be expected, re-estimating all the coefficients substantially improves the models' performance. We will however concentrate on fully re-estimated models for emerging markets in the next section.

4.5.3 Discrete choice models: emerging markets model

As the final step in our empirical analysis we construct a discrete choice model fitted to predict asset price boom/busts on purely a cross-section of emerging market economies. We however try not to deviate from the model setup outlined above.

We design two separate models for predicting boom and bust occurrences. Accordingly, we construct our binary dependent variables to equal one in the period one to six quarters prior to the boom/bust occurrence (identified as described in Section 4.4) and to equal zero in all other periods.

We consider four categories of explanatory variables: asset price indicators (aggregate and housing price indices), real sector indicators (GDP, consumption and investment), financial variables (money and credit) and capital inflows (total and non-FDI). The variables in the first three categories are in real terms (asset price and financial variables are deflated via GDP deflator), in either annual growth rates or deviations from trend[74] (for money and credit, the ratios to GDP were de-trended). Additionally, we consider the investment to GDP ratio. Capital inflows are summed over four quarters and are in ratios to GDP. All variables that are not in deviations from trend are de-meaned.

Our empirical strategy is as follows. We combine the variables (one from each category) and their bivariate interactions in the pooled probit regression framework. The aim is to find a parsimonious model with only statistically significant[75] variables or corresponding interaction terms but with preference given to models that include indicators from all four categories. When several such models were found we selected the one with the best "usefulness" indicator under optimized threshold probability. Thus we arrive at two preferred models for boom and bust prediction. As in the previous section we assess model performance via the standard set of indicators under optimized and benchmark threshold probability.

[74] Deviations from trend are calculated via applying recursive Hodrick-Prescott filter (λ=100000) to series in logarithms.
[75] We assumed the criteria of test statistic>1.5.

Table 4.8. Emerging market booms prediction probit model

Variable	Coefficient	P-value
Real housing prices (y-o-y growth)	0.025	0.00
Real credit (y-o-y growth)	0.014	0.00
Total capital inflows	0.694	0.06
Investment to GDP ratio	-0.591	0.00
Real credit (y-o-y growth) * Investment to GDP ratio	0.002	0.01
constant	-1.312	0.00
Performance indicators [performance under benchmark threshold probability=0.5 in brackets] Number of observations: 853 McFadden R^2: 0.125 QPS: 0.09 LPS: 0.14 Threshold probability:0.15 U:0.19[0.02] NtS:0.37[0.21] Signal:0.68[0.07] Noise:0.25[0.01]		

The boom prediction model includes annual growth of housing prices, total capital inflows and the credit growth variable, which is significant and has the correct sign both as a linear term and in interaction with the investment to GDP ratio[76].

Table 4.9. Emerging market busts prediction probit model

Variable	Coefficient	P-value
Real aggregate asset prices (de-trended)	-2.239	0.00
Real credit (y-o-y growth)	0.014	0.00
Total capital inflows	2.622	0.00
Investment to GDP ratio	0.054	0.00
Real aggregate asset prices (de-trended) * Investment to GDP ratio	0.092	0.13
constant	-1.34	0.00
Performance indicators [performance under benchmark threshold probability=0.5 in brackets] Number of observations: 818 McFadden R^2: 0.17 QPS: 0.08 LPS: 0.13 Threshold probability:0.3 U:0.2[0.08] NtS:0.13[0.06] Signal:0.47[0.16] Noise:0.06[0.01]		

[76] The fact that the linear term of the variable in the interaction (in this case investment to GDP ratio) is negative does not imply that the overall effect of this variable is negative.

The bust prediction model includes similar variables: credit growth, investment to GDP ratio and total capital inflows. In the busts model, the investment to GDP indicator is also included in the form of interaction with the aggregate asset prices indicator. Considering the results presented in Sections 5.1 and 5.2, we conclude that credit and investment are evident candidate variables for boom/bust prediction in emerging markets.

As could be expected, these models have the highest formal performance indicators (U=0.19 and U=0.2) among those assessed in this paper (although the composite index of stand-alone indicators' signals calculated in Section 5.1 is not far behind with U=0.18). There is no clear indication that boom prediction works better than bust prediction (or vice versa), although the busts model is notably less noisy (which is reflected in the low Noise and NtS indicators).

4.5.4 Applying the models to Russia

Most of the models would have offered sensible prediction of asset prices developments in Russia (Figures 4.2 and 4.3). Interestingly it is not clear if emerging market models outperform developed countries models in case of Russia.

Figure 4.2. Predicting booms in Russia

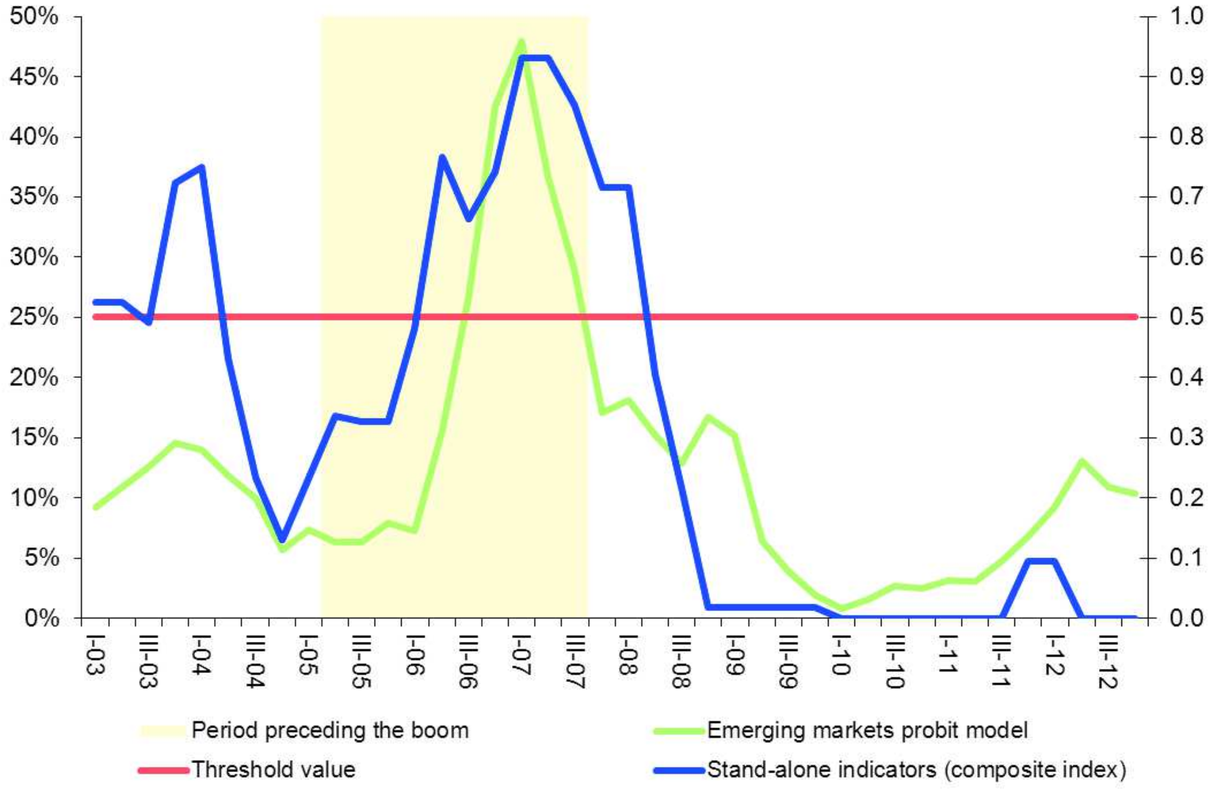
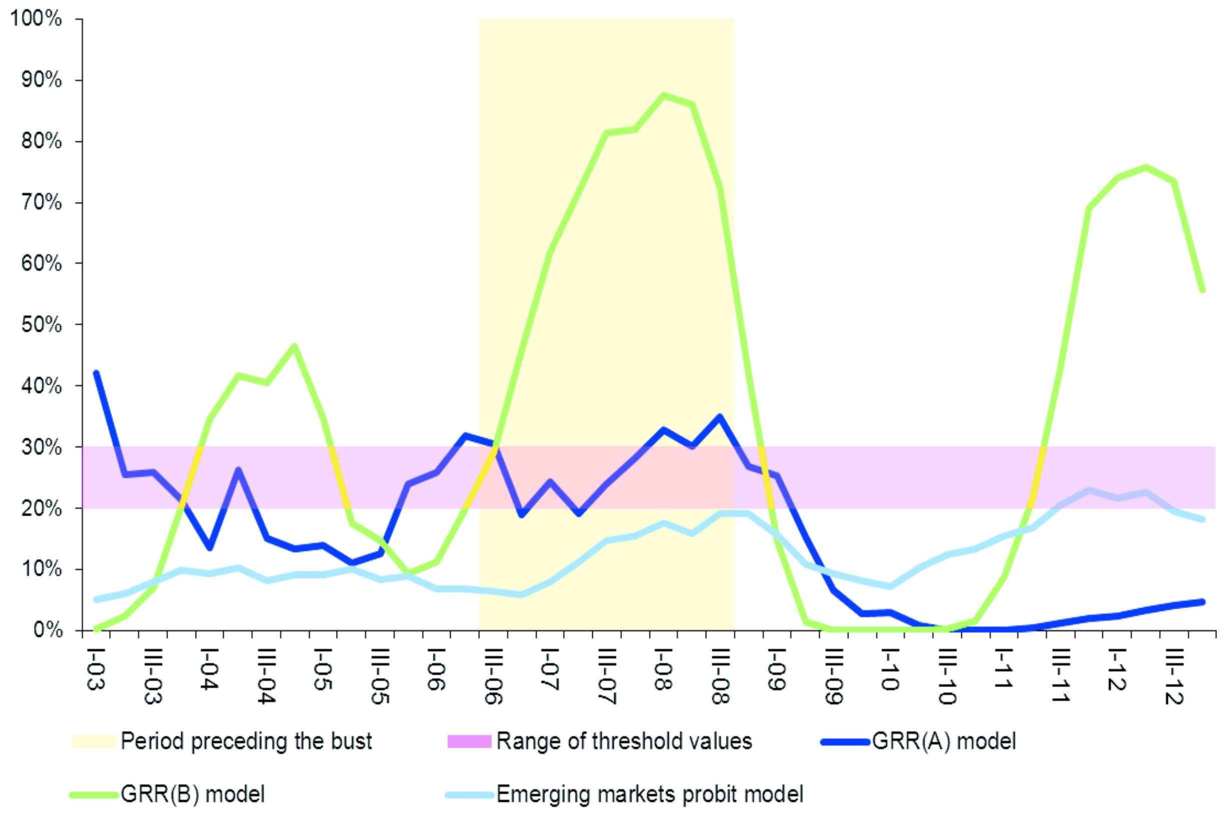


Figure 4.3. Predicting busts in Russia



4.6. Conclusions

This paper contributes to the literature by investigating whether early warning indicator models can be used for predicting asset price boom/bust occurrences in a cross-section of 29 emerging markets. We identify booms/busts using different approaches. The results are not fully synchronized but may still be regarded as cohesive. The sample obtained is large enough for interpretable econometric analysis although its informational content is limited since, for the most part, only one (most recent) wave of booms/busts can be analyzed.

We employ two modeling approaches (stand-alone indicators and discrete choice models) that were previously applied to a cross-section of developed countries. The results seem promising. In fact even the out-of-sample performance of the unmodified developed countries' models is satisfactory on our emerging markets dataset. Naturally further enhancement and re-estimation of these models increases their in-sample predictive performance, although these modifications need not be extensive.

Our results are generally inconclusive as to which approach to predicting asset price boom/bust is superior. But we argue that the concept that relies on monitoring the combined set of asset prices, real activity and financial indicators is widely applicable to emerging markets and its efficiency is confirmed under the different model setups. According to our estimates credit growth and investment (in either growth rates or ratio to GDP) turned out to be particularly reliable indicators for forecasting asset prices cycle. We also find that, in addition to this set of variables, early warning indicator systems for emerging countries may be augmented with capital flows indicators.

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Appendix 4

Table 4.10. Data sources

Indicators	*Sources*
Housing prices	- BIS property price statistics database; - Stepanyan et al. (2010) database; - Global Property Guide (www.globalpropertguide.com); - National statistical agencies
Equity prices	- Stock exchange websites; - Yahoo! Finance
GDP, investment, consumption	- IMF-IFS; - National statistical agencies' websites
Money, credit	- IMF-IFS; - Central banks' websites
Capital flows	- National statistical agencies' websites - Central banks' websites

Table 4.11. Descriptive statistics of variables used in Section 4.5

Variable	*Mean*	*Std Deviation*	*Min*	*Max*
Real aggregate asset prices (y-o-y growth)	7.4	28.9	-100	206
Real aggregate asset prices (de-trended with HP-filter)	-0.02	0.16	-1.07	0.46
Real housing prices (de-trended with HP-filter)	0.02	0.14	-0.81	0.59
Real housing prices (y-o-y growth)	4.35	15.8	-59.4	80.8
Nominal housing prices (y-o-y growth de-trended with CF-filter)	-0.7	7.2	-26.6	41
Real equity prices (de-trended with HP-filter)	0.00	0.34	-1.7	1.44
Nominal equity prices (y-o-y growth)	19.7	49.1	-79.1	670.7
GDP (de-trended with HP-filter)	0.00	0.08	-0.44	0.29
Investment (y-o-y growth)	4.5	18.5	-84.7	228.7
Investment/GDP ratio	24.1	7	9.7	58.6
Consumption (y-o-y growth)	4.5	7.5	-45.4	88.7
Real money (y-o-y growth)	9.2	12.7	-68.1	125.9
Real credit (y-o-y growth)	11.8	22.1	-81.1	162.9
Nominal credit (y-o-y growth)	26.3	42.4	680.9	-61.2
Nominal credit (y-o-y growth de-trended with CF-filter)	-0.4	7.6	-47.4	71.6
Long term interest rate (de-trended with HP-filter)	2	21.1	-248.6	512.4
Annual changes in long term interest rate	-1.5	30.1	-721.6	682.5
Total capital inflows	0.13	0.2	-0.33	1.35
Non-FDI capital inflows	0.08	0.15	-0.5	1.22

Figure 4.4. "Triangular approach" identification of booms/busts: Russian case

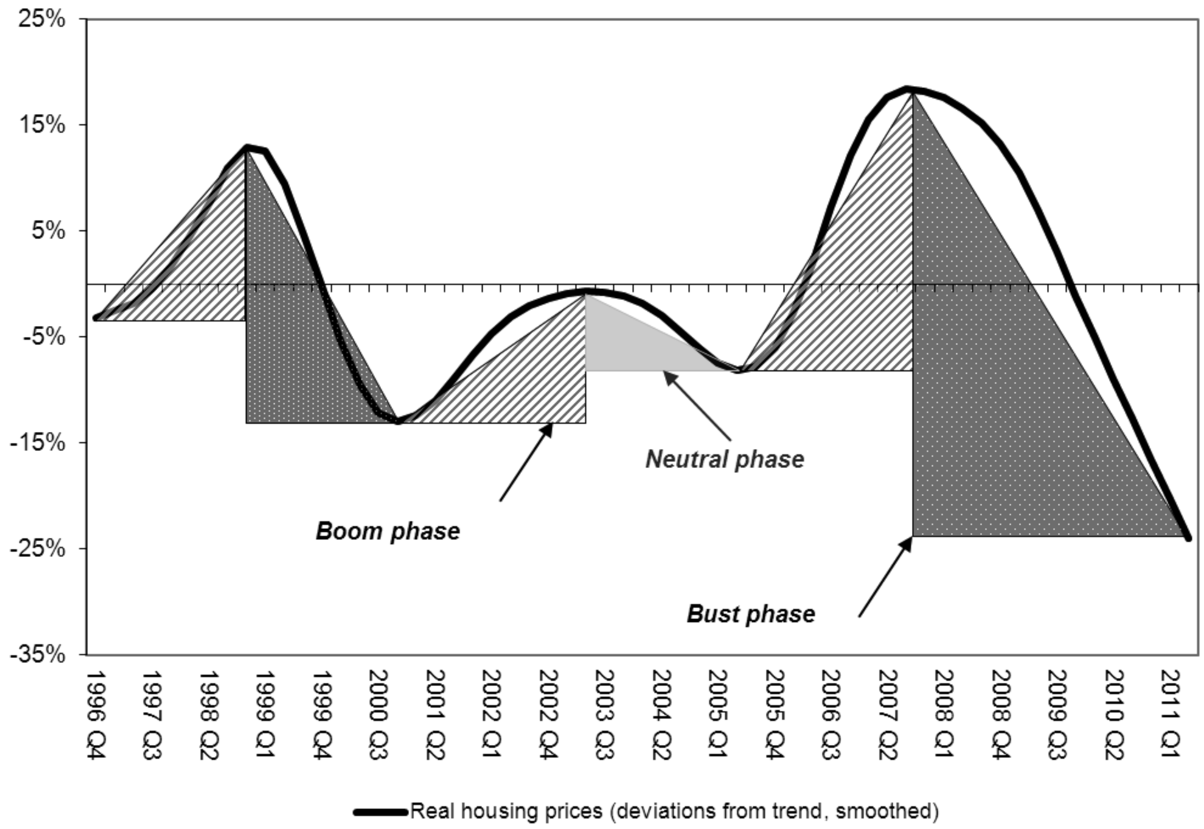


Figure 4.5. Distribution of "severity" measures (triangular squares) of boom/bust phases

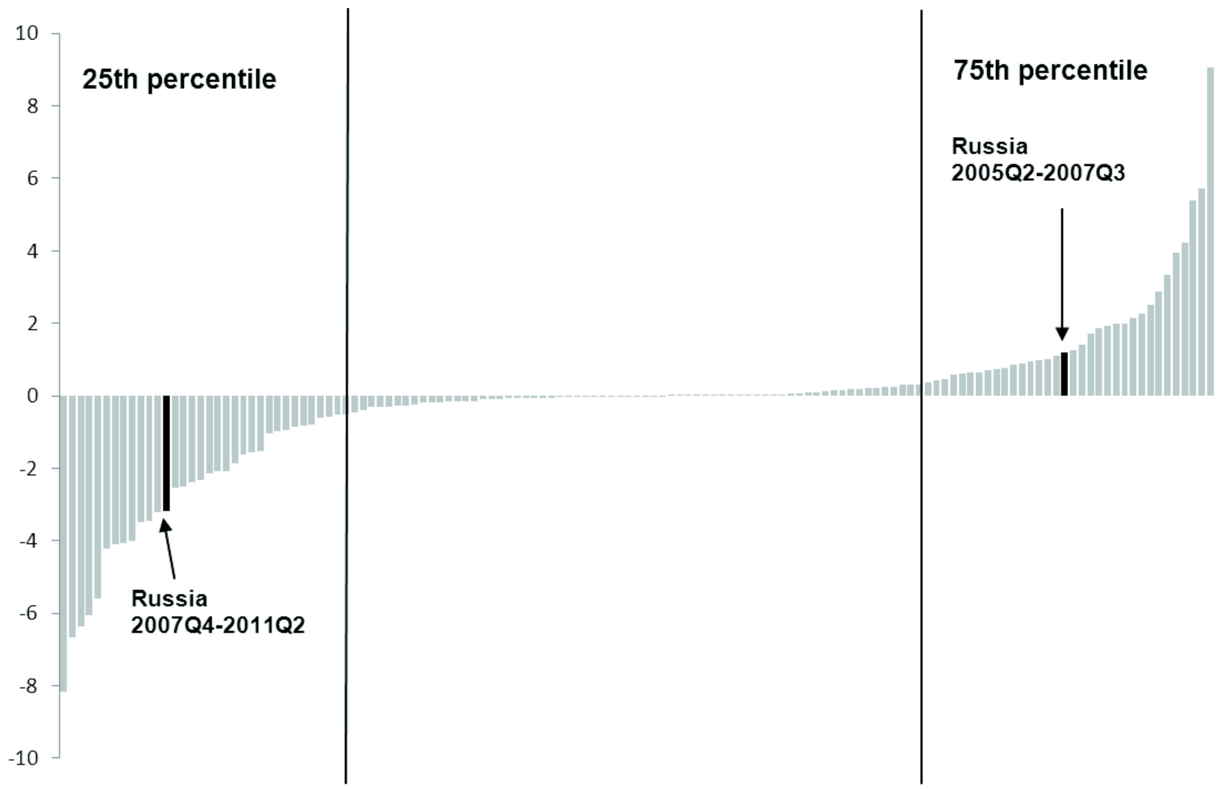


Table 4.12. Identified booms and busts

Country	*Booms*	*Busts*
Argentina	2004Q1	-
Armenia	-	2009Q1
Azerbaijan	-	2005Q3; 2009Q2
Bulgaria	2007Q3-2007Q4	2008Q3-2009Q1
China, P.R.: Hong Kong	1997Q1-1997Q2	1997Q3-1997Q4; 1998Q2; 2001Q3
China, P.R.: Mainland	-	-
Colombia	2007Q3	-
Croatia	2007Q2-2008Q1	-
Estonia	-	2007Q4; 2008Q4
Georgia	2006Q1	2009Q1-2009Q2
Hungary	2005Q1	-
Indonesia	-	2005Q3; 2008Q3
Israel	2010Q3-2011Q1	2002Q3; 2004Q3; 2006Q2
Kazakhstan	2007Q1-2007Q2	2008Q3-2008Q4
Korea	-	1997Q3; 1998Q2
Latvia	-	2008Q4-2009Q1
Lithuania	2005Q4-2006Q1; 2006Q4-2007Q3	2008Q3-2009Q1
Malaysia	2010Q3	-
Mexico	-	-
Philippines	2007Q2-2007Q4	-
Poland	2007Q1-2007Q3	-
Serbia	-	2006Q1-2006Q2
Russia	2006Q4-2007Q4	2000Q2; 2008Q3-2008Q4
Singapore	2007Q3-2007Q4	2008Q3-2009Q1
Slovakia	2007Q4-2008Q3	2008Q4
Slovenia	2007Q1-2007Q4	2008Q4-2009Q1
South Africa	-	1996Q2
Thailand	-	1997Q4; 1998Q2; 1999Q2
Ukraine	2007Q1	2009Q1

Table 4.13. Models performance indicators for country sub-groups

Model	*Central and East Europe and former Soviet Union*			*Southeast Asia*		
	Threshold probability	*U*	*NtS*	*Threshold probability*	*U*	*NtS*
Stand-alone indicators (composite index)	-	0.16	0.52	-	0.3	0.31
Unmodified Gerdesmeier et al. (2010) Specification A	0.75	0.2	0.41	0.4	0.07	0.63
Unmodified Gerdesmeier et al. (2010) Specification B	0.5	0.06	0.51	0.55	0.07	0.23
Emerging markets booms prediction	0.15	0.16	0.43	0.2	0.35	0.14
Emerging markets busts prediction	0.3	0.27	0.18	0.1	0.26	0.27

Models are as reported in Tables 4.5-4.9. Threshold probabilities were re-calibrated for probit models.

Central and East European and former Soviet Union countries sub-group: Armenia, Azerbaijan, Bulgaria, Croatia, Estonia, Georgia, Hungary, Kazakhstan, Latvia, Lithuania, Poland, Russia, Serbia, Slovakia, Slovenia, Ukraine.

Southeast Asia countries sub-group: China, P.R.: Hong Kong, China, P.R.: Mainland, Indonesia, Korea, Malaysia, Philippines, Singapore, Thailand.

Chapter 5: Accounting for post-crisis macroeconomic developments in Russia: A large Bayesian vector autoregression model approach[77]

Abstract

We apply an econometric approach developed specifically to address the 'curse of dimensionality' in Russian data and estimate a Bayesian vector autoregression model comprising 16 major macroeconomic indicators. We conduct several types of exercises to validate our model: impulse response analysis, recursive forecasting and counterfactual simulations. We also show that real sector developments in Russia in 2010–2013 could be accurately forecasted if conditioned on oil price and EU GDP (but not if conditioned on oil price alone). Real growth rates were notably lower than projected in 2014, presumably due to increased economic uncertainty.

Keywords: Bayesian vector autoregression, forecasting, Russia

JEL classification: E32, E44, E47, C32

[77] This chapter refers to the article published in *Emerging Markets Finance and Trade*, Volume 51, Issue 6, 2015. This paper has been co-written with Elena Deryugina.

5.1 Introduction

Empirical economic modelling in Russia is a complicated task. One of the most important limitations comes from the insufficiently long time series that make estimation of a comprehensive econometric model virtually impossible. Researchers therefore have to rely on parsimonious model specifications in their work. One example is traditional macroeconometric models (e.g. Benedictow et al. (2013)) consisting of a large number of pre-specified simultaneous equations. As regards a more flexible vector autoregression (VAR) approach, a typical model for Russia would comprise an ad-hoc selection of variables (often no more than five indicators in total) that either represent a theoretical long-term macroeconomic relationship (Korhonen and Mehrotra (2010), Mehrotra and Ponomarenko (2010)), or are sufficient to identify predetermined types of economic shocks (via a structural identification scheme (Korhonen and Mehrotra (2009)) or sign restrictions on impulse response functions (Granville and Mallick (2010), Mallick and Sousa (2013)), or simply comprise the indicators that are assumed to be the most important determinants of the modelled process (Rautava (2013)).

In this environment, an econometric approach developed specifically to address the 'curse of dimensionality' may be highly relevant for Russia. In particular, the class of recently developed Bayesian VAR models (De Mol et al. (2008), Banbura et al. (2010), Giannone et al. (2012a), Banbura et al. (2014)) is known to produce adequate results even when a large number of variables are included in the model simultaneously. Arguably, a relatively large Bayesian VAR model estimated for the Russian economy using this methodology may be regarded as a novel and valuable tool for forecasting and counterfactual analysis. The aim of this paper is to implement such an approach.

The primary application of the model in this paper, however, is counterfactual simulations (in the spirit of Giannone et al. (2011, 2012b)) that may be helpful in detecting misalignments and irregularities in the developments of observed variables. Based on this exercise we will try to assess whether the post-crisis economic developments in Russia could be explained by conventional factors (such as oil price fluctuations) or whether the economy was behaving differently after the recession in 2009.

The paper is structured as follows. Section 5.2 presents the dataset and the set-up of the model. Section 5.3 reports the empirical results, including the impulse response analysis, recursive forecasting exercise and counterfactual simulations. Section 5.4 concludes.

5.2 Data and model specification

5.2.1 The data

The dataset includes 16 quarterly variables that come from four categories:[78] real, monetary, price and external (Table 5.1). The real variables include GDP, gross capital formation, households' final consumption, real (deflated with CPI) wages and unemployment rate. The price variables category contains the respective GDP and fixed capital formation deflators and the CPI. We have also added asset (housing and stock) prices to our dataset. The monetary category is represented by broad money, broad monetary base and rouble loans to non-financial corporations (NFCs) and households. The external sector is represented by the oil price and EU GDP.

All real and price (except stock price) variables are provided by Rosstat. All monetary variables are provided by the Bank of Russia. Stock prices are represented by the rouble RTS index. EU GDP series are taken from the OECD website and oil prices from Bloomberg.

All series are in logs of levels (except unemployment rate) and seasonally adjusted. The time sample ranges from 2000Q1 to 2014Q4 and is determined by data availability.

[78] We have deliberately excluded monetary policy variables (i.e. exchange rate and interest rate) from the final specification of the model. The results obtained in the presence of these variables (e.g. the impulse response functions) were ambiguous and provided little information about monetary policy effects. One possible explanation is that the monetary policy regime in Russia had undergone substantial transformation from a heavily managed to a more flexible exchange rate. Accordingly, the exchange rate and interest rate determination factors varied substantially over our time sample (see Lainela and Ponomarenko (2012) for a review). Presumably, the macroeconomic effects of changes in the interest rate were also inconstant. In such an environment it may be appropriate to employ additional modelling techniques to capture the time-varying effect or a nontrivial shock identification strategy. This task lies beyond the objectives of this paper. In our specification monetary base may be considered as monetary stance which is not unusual (see e.g. Juurikkala et al. (2011))

Table 5.1. Dataset

Category	***Indicator***
Real	GDP Households' final consumption Fixed capital formation Real wages Unemployment rate
Price	CPI GDP deflator Fixed capital formation deflator House prices Stock prices
Monetary	Broad money Broad monetary base Loans to non-financial corporations Loans to households
External	Oil price EU GDP

5.2.2 The model

Let X_t be the vector including the *n* variables defined in Table 5.1. We estimate a VAR model with p (= 5)[79] lags:

$X_t = A_0 + A_1X_{t-1} + A_2X_{t-2} \ldots + A_pX_{t-p} + \varepsilon_t$
(1).

We address the possible over-fitting issue by shrinking the model's coefficients towards a prior model that is parsimonious but naïve (see De Mol et al. (2008), Banbura et al. (2010)). In practice, we use the 'Minnesota' (random walk), the 'sum-of-coefficients' and 'dummy-initial observation' priors originally proposed by Litterman (1980), Doan et al. (1984) and Sims and Zha (1998). For details on the implementation, see Banbura et al. (2010). As suggested in Giannone et

[79] Choosing five lags for large BVAR models with quarterly variables in levels seems to be a conventional choice (Banbura et al. (2010), Giannone et al. (2012b) choose 13 lags for their monthly models), although our results are robust to the number of lags.

al. (2012a), we select the degree of informativeness of the prior distributions by maximising the marginal likelihood.

More specifically, model (1) can be rewritten as follows:

$y_t = x_t \beta + \varepsilon_t$,
where $y_t = X_t$, $x_t = I_n \otimes [1\ X'_{t-1} \ldots X'_{t-p}]$, $\beta \equiv vec([A_0, A_1, \ldots, A_p]')$, $\varepsilon_t \sim N(0,\Sigma)$.

The baseline prior is a version of the so-called 'Minnesota' prior:

$$E\left[(A_s)_{ij} \mid \Sigma\right] = \begin{cases} 1, & if \quad i = j, \quad s = 1 \\ 0, & otherwise \end{cases}$$

$$\text{cov}\left[(A_s)_{ij}, (A_r)_{hm} \mid \Sigma\right] = \begin{cases} \lambda^2 \dfrac{1}{s^2} \dfrac{\Sigma_{ih}}{\psi_j/(d-n-1)}, & if \quad m = j, \quad r = s \\ 0, \quad otherwise \end{cases}$$

where λ controls overall tightness of the prior, ψ_j equals the residual variance of an AR(1) of j-th variable, Σ_{ih}/ψ_j account for the relative scale of the variables and $d = n+2$ - degrees of freedom of the IW distribution. The prior for the intercept is diffuse.

The 'sum-of-coefficients' prior is implemented via the following dummy observations:

$$y^+ = diag\left(\frac{\bar{y}_0}{\mu}\right)$$

$$x^+ = \left[0, \quad y^+, \quad \ldots, \quad y^+\right],$$

where $\bar{y}_0$ is an $n \times 1$ vector containing the average of the first p observations for each variable, and μ controls the tightness of the prior.

The 'dummy-initial observation' prior can be organised as follows:

$$y^{++} = \frac{\bar{y}'_0}{\delta}$$

$$x^{++} = \left[\frac{1}{\delta}, \quad y^{++}, \quad \ldots, \quad y^{++}\right],$$

where δ controls the tightness of the prior.

We follow Giannone et al. (2012a) using a hierarchical modelling approach to make inferences about the informativeness of the prior distribution. For hyperparameters λ, μ, δ we employ hyperpriors in the form of Gamma distribution with modes equal to 0.2, 1, 1 and standard deviations equal to 0.4, 1, 1 respectively and for $\psi_j/(d-n-1)$ - Inverse-Gamma distribution with scale and shape equal to $(0.02)^2$.

We adopt an empirical Bayesian method in which a prior distribution is estimated from the data. The standard Metropolis algorithm is used to simulate the posterior of the coefficients of the BVAR, including the hyperparameters. This procedure automatically selects the 'appropriate' amount of shrinkage, namely tighter priors when the model involves many unknown coefficients relative to the available data, and looser priors in the opposite case.

For the implementation of conditional forecasting we rewrite our model in the following state space representation (see Banbura et al. (2014) for details):

Measurement equation
$$X_t = \begin{pmatrix} I_n & 0_{n\times np} \end{pmatrix} \begin{pmatrix} X_t \\ \vdots \\ X_{t-p+1} \\ A_0 \end{pmatrix} + v_t ,$$

Transition equation
$$\begin{pmatrix} X_t \\ \vdots \\ X_{t-p+1} \\ A_0 \end{pmatrix} = \begin{pmatrix} A_1 & A_2 & \dots & A_p & I_n \\ I_n & 0_n & \dots & 0_n & 0_n \\ \vdots & \ddots & \dots & \vdots & \vdots \\ 0_n & \dots & I_n & 0_n & 0_n \\ 0_n & \dots & 0_n & 0_n & I_n \end{pmatrix} \begin{pmatrix} X_{t-1} \\ \vdots \\ X_{t-p} \\ A_0 \end{pmatrix} + w_t ,$$

where

$$E[v_t] = 0 \ , \ E[v_t v_{t-s}^{'}] = 0, \forall s$$

$$E[w_t] = 0, \ E[w_t w_{t-s}^{'}] = 0, \forall s \neq 0, \ E[w_t w_t^{'}] = \begin{pmatrix} \Sigma & \dots & 0_n \\ \vdots & \ddots & \vdots \\ 0_n & \dots & 0_n \end{pmatrix}$$

$$E[v_t w_s^{'}] = 0, \forall t, s$$

In order to obtain conditional forecasts, we adopt the solution proposed for forecasting with ragged edge data sets using a Kalman filter methodology. In fact, the variables for which we do not assume the knowledge of a future path can be considered as time series with missing data. This procedure allows us to deal with high dimensional data and long forecast horizons.

5.3 Empirical results

5.3.1 Impulse response analysis

Before presenting our main results we want to make sure that the linkages between the variables established by the model are plausible and statistically significant (which may not be the case if the model is over-fitted or, contrarily, reduced to the random walk process by the tight priors). With this purpose we conduct impulse response analysis. The model is not intended for structural analysis, so instead we assume a simple recursive identification scheme. Although these results may not have a clear economic interpretation they may be used to extract information on the cross correlation and lag-lead relationship of the series of interest implied by the model.

The first shock is the innovation of EU GDP variable which is ordered first (Figure 5.1). We label this external demand shock, although since oil price is also affected we cannot rule out the effect coming through this channel. The second shock is the innovation of monetary base variable which is ordered after external, real and price variables, but before monetary variables and stock prices (Figure 5.2). This ordering approximates monetary shock identification scheme (as in e.g. Giannone et al. (2012b)) assuming monetary base as a monetary stance variable.

The obtained impulse responses are generally consistent with expectations. Expansionary shocks to the aforementioned variables increase real activity, nominal monetary indicators and prices. The main difference is that responses to monetary shock are more sluggish and in most cases become significant only after six quarters, which is also in line with intuition.

Figure 5.1. Impulse responses to an external demand shock (the median and the 16th and 84th quantiles of the distribution)

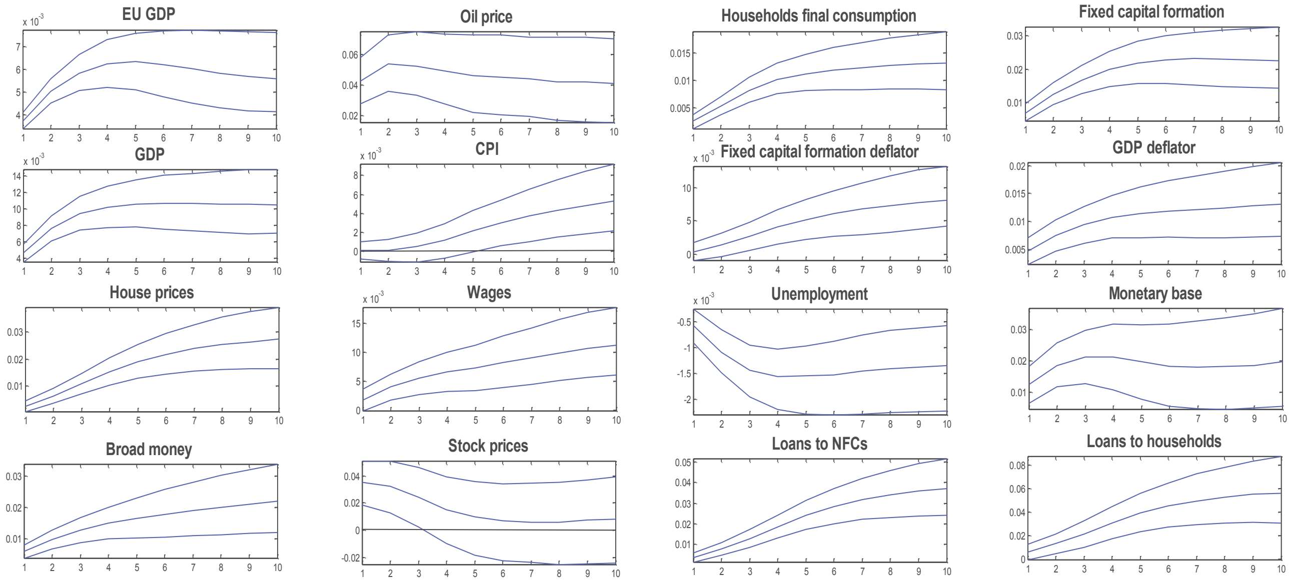
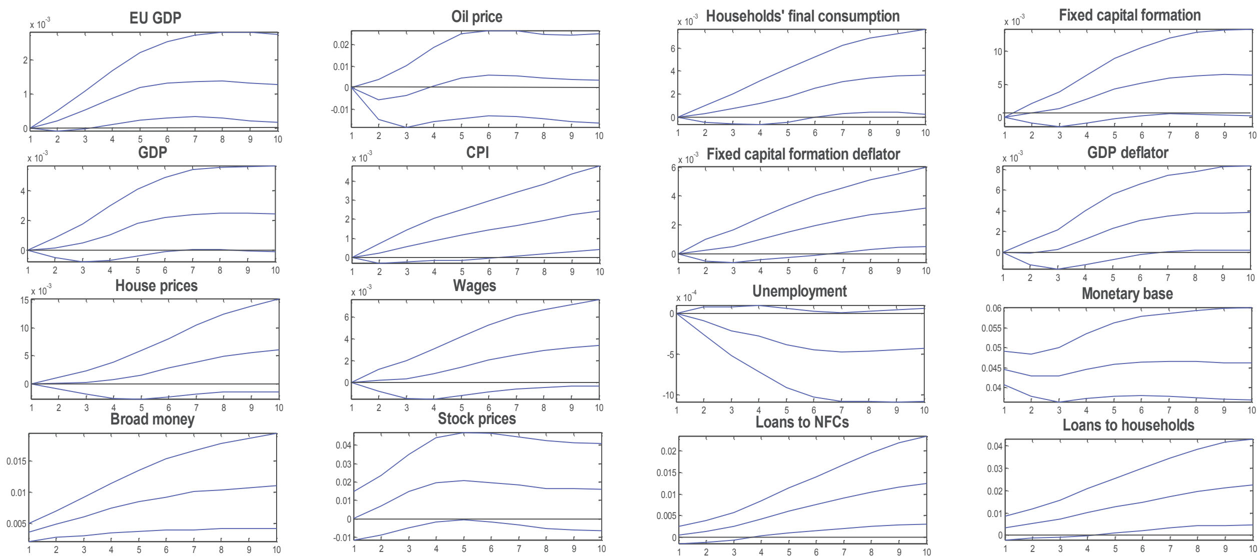


Figure 5.2. Impulse responses to monetary shock (the median and the 16th and 84th quantiles of the distribution)



5.3.2 Forecast evaluation

We further validate our model by running a recursive out-of-sample forecasting evaluation exercise. Since the size of our model is relatively large, we want to make sure that we are not over-fitting the data. In that case, forecasting performance would be poor.

We start by estimating the model from 2000Q1 to 2009Q4,[80] producing a forecast and then iterating the procedure by recursively expanding our estimation sample by one quarter until the end of the sample, 2014Q4. We calculate the forecast in the form of growth rate averaged over h quarters. We consider three horizons: $h = 2$, $h = 4$ and $h = 6$. Point forecasts are evaluated in terms of ratio of the mean squared forecast errors (MSFE). We report the ratio of the MSFE of the competitor models versus the MSFE of our large BVAR model. Numbers smaller than one imply that our model is outperformed by the competitor. We test the equivalence of the obtained MSFEs by means of the Diebold-Mariano test. We also evaluate density forecasts by comparing the frequency with which actual outcomes fall inside 70 percent highest posterior density intervals estimated with the models. Accurate intervals should result in frequencies of about 70 percent. A frequency of more (less) than 70 percent means that, on average over a given sample, the posterior density is too wide (narrow). We test the null of correct coverage by means of chi-squared tests as suggested by Wallis (2001).

The set of competitor models consists of:

- BVAR with 'Minnesota' prior (*MBVAR*). We re-estimate our model using a dogmatic BVAR with a dogmatic 'Minnesota' prior. This approach may be regarded as a representation of the random walk with drift model. We have tested other simpler random walk model specifications and they did not outperform MBVAR.
- Autoregressive model (*AR*). A univariate autoregressive model with two[81] lags for each variable.
- Canonical VAR (*VAR*). We estimate a collection of small canonical VARs each comprising two lags of EU GDP, oil price, broad money, CPI and GDP plus the variable to be forecast.

[80] We report the results for the time sample that excludes the period of sharp real contraction in 2009. Given that the time sample used for the recursive forecasting exercise is rather short and the fluctuations of variables are particularly large during this period, we believe that reporting results for the tranquil period may be more representative. Nevertheless, the inclusion of the recession episode into the time sample would worsen the forecasting performance of our model relative to other models (in particular at longer horizons).

[81] Increasing the number of lags in AR and VAR models does not improve their forecasting performance.

Table 5.2. Forecast MSFEs and coverage rates (forecast horizon $h = 2$)

Variable	*MSFE (as ratio to the MSFE of the large BVAR)*			*Frequencies of actual outcomes falling inside 70% intervals*			
Model	*MBVAR*	*AR*	*VAR*	*BVAR*	*MBVAR*	*AR*	*VAR*
GDP	2.1	3.2*	1.6	0.87	0.4*	0.73	0.67
Households' final consumption	1.3	1.6	1.9	0.53	0.13*	0.73	0.2*
Fixed capital formation	1.7	1.9	1.3	0.67	0.27*	0.67	0.6
Wages	0.9	0.9	1.2	0.4*	0.07*	0.67	0.27*
Unemployment	1.1	6.1*	1.1	0.4*	0.07*	0.73	0.33*
CPI	0.9	0.9	1.0	0.33*	0.27*	0.93*	0.27*
GDP deflator	1.1	1.2	0.8	0.47	0.0*	0.67	0.4*
Fixed capital formation deflator	0.8	1.1	0.9	0.4*	0.33*	0.8	0.4
House prices	1.0	0.4	1.0	0.67	0.47	0.87	0.6
Stock prices	0.9	0.9	0.9	0.67	0.47	0.53	0.67
Broad money	0.7	0.7	0.9	0.47	0.4*	0.73	0.4*
Monetary base	0.7	0.7	1.1	0.67	0.47	0.73	0.6
Loans to NFCs	2.5*	1.2	3.2*	0.8	0.33*	0.87	0.53
Loans to households	1.3	0.8	1.6	0.6	0.13*	0.67	0.2*
Oil price	1.8	2.3	0.8	0.73	0.4*	0.53	0.87
EU GDP	4.0*	2.9*	1.6	0.27*	0.53	0.8	0.6
* - The null of equivalence of large BVAR and competitor model's MSFEs is rejected at 5% level				*- The null of correct coverage is rejected at 5% level			

Table 5.3. Forecast MSFEs and coverage rates (forecast horizon $h = 4$)

Variable	*MSFE (as ratio to the MSFE of the large BVAR)*			*Frequencies of actual outcomes falling inside 70% intervals*			
Model	*MBVAR*	*AR*	*VAR*	*BVAR*	*MBVAR*	*AR*	*VAR*
GDP	2.5	4.5*	1.9	0.73	0.47	0.87	0.8
Households' final consumption	1.6	2.3	2.0	0.73	0.47	0.8	0.47
Fixed capital formation	1.8	1.9	1.1	0.8	0.2*	0.6	0.8
Wages	1.2	1.0	1.5	0.53	0.33*	0.87	0.53
Unemployment	1.0	4.0*	1.3	0.47	0.13*	0.53	0.2*
CPI	0.8	0.7	1.0	0.47	0.33*	1.00*	0.33*
GDP deflator	1.3	1.3	0.9	0.33*	0.07*	0.67	0.33*
Fixed capital formation deflator	0.7*	1.0	0.6	0.27*	0.33*	1.00*	0.67
House prices	0.7	0.5	1.1	0.8	0.47	0.93*	0.8
Stock prices	0.7	0.6*	1.6	0.87	0.53	0.73	0.73
Broad money	0.5*	0.5*	0.5	0.67	0.67	0.93*	0.8
Monetary base	0.5*	0.4*	1.0	0.67	0.67	0.73	0.67
Loans to NFCs	4.0*	2.4	4.5*	0.8	0.53	0.93*	0.4*
Loans to households	1.3	0.9	2.8*	0.67	0.2*	0.6	0.33*
Oil price	1.6	2.3	0.4*	0.64	0.6	0.53	0.87
EU GDP	3.5*	2.4*	1.8	0.47	0.47	0.93*	0.53
* - The null of equivalence of large BVAR and competitor model's MSFEs is rejected at 5% level				*- The null of correct coverage is rejected at 5% level			

Table 5.4. Forecast MSFEs and coverage rates (forecast horizon h = 6)

Variable	*MSFE (as ratio to the MSFE of the large BVAR)*			*Frequencies of actual outcomes falling inside 70% intervals*			
Model	*MBVAR*	*AR*	*VAR*	*BVAR*	*MBVAR*	*AR*	*VAR*
GDP	2.9*	5.8*	1.8	0.93*	0.53	0.93*	0.8
Households' final consumption	2.2	3.1*	1.6	0.73	0.2*	0.8	0.47
Fixed capital formation	1.6	1.7	0.6	0.67	0.2*	0.73	0.8
Wages	0.9	0.8	1.1	0.8	0.4*	0.87	0.8
Unemployment	1.0	3.2*	1.5	0.47	0.0*	0.4*	0.2*
CPI	0.8	0.7	0.9	0.47	0.47	0.93	0.27*
GDP deflator	1.0	0.9	0.6	0.4*	0.13*	0.8	0.8
Fixed capital formation deflator	0.7*	0.8	0.4	0.2*	0.2*	1.0*	0.8
House prices	0.5	0.5	1.3	0.8	0.53	1.0*	0.87
Stock prices	0.4	0.4	3.7*	0.93*	0.87	1.0*	0.6
Broad money	0.3*	0.2*	0.2*	0.47	0.33*	1.0*	1.0*
Monetary base	0.3*	0.2*	0.9	0.67	0.6	1.0*	0.67
Loans to NFCs	3.4*	2.3	4.6*	0.87	0.53	1.0*	0.47
Loans to households	1.6	1.2	4.8*	0.8	0.27*	0.6	0.33*
Oil price	1.1	1.6	0.6*	0.67	0.6	0.67	0.73
EU GDP	3.8*	2.5*	2.6*	0.6	0.47	1.0*	0.47
* - The null of equivalence of large BVAR and competitor model's MSFEs is rejected at 5% level				*- The null of correct coverage is rejected at 5% level			

Our results are presented in Tables 5.2–5.4. We find that the forecasts of our model were most accurate for the real variables (in particular for long horizons). The results are quite opposite in the case of price variables, where our model is unable to outperform the competitor models. These results are consistent with other findings indicating that the random walk forecasts are often the most accurate for this category of variables (D'Agostino et al. (2006), Stock and Watson (2006), Fischer et al. (2009)). The density forecasts produced by the large BVAR for price variables are also inaccurate (too narrow), although in this respect the competitor models do not perform evidently better. The results for monetary variables are mixed. For example, while in the case of loans the forecasting performance of our model was exceptionally good, the forecasts of broad money and monetary base are significantly worse than competitor models. This inconsistency may be explained by the fact that money supply in Russia is not driven solely by credit developments but also by exogenous shocks related to fiscal policy (for example, the substantial fiscal stimulus in 2009–2010 was partially financed from Russian sovereign funds and had a mechanical expansionary effect on the money stock) and transactions with foreign sector (see Ponomarenko et al. (2012) for discussion).

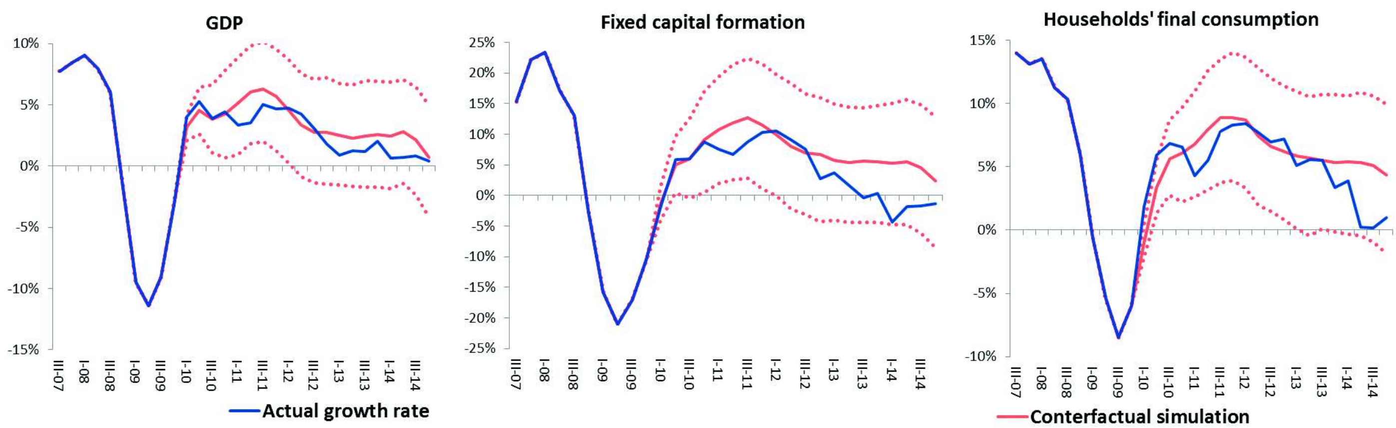
5.3.3 Counterfactual simulations

The exercises conducted in the previous sections are helpful in examining the validity and adequacy of our model, but arguably the model's main purpose is not structural analysis or unconditional forecasting. Rather, this model's capabilities may be most useful in constructing medium-term conditional projections. In this section, we examine the applicability of the model in this respect by testing its stability via counterfactual exercises. On the other hand, the results of this exercise may be used to assess whether the Russian economy behaved in accordance with historical regularities after the crisis or whether some of the developments were atypical.

5.3.3.1 Counterfactual simulations conditional on oil price

For the counterfactual exercise we estimate the model on the pre-crisis time sample 2000Q4–2009Q4 and make the simulation for the remaining period 2010Q1–2014Q4. We begin by conditioning our projections on oil price (i.e. take the realised oil price series as given), which is widely regarded as an important driver of economic growth in Russia. The results for the real sector variables are shown in Figure 5.3. Although the forecasted growth rates are generally correct (particularly in 2010–2012), the confidence bands are relatively wide. The information on oil price was also insufficient to predict the deceleration fixed capital investment growth in 2013.

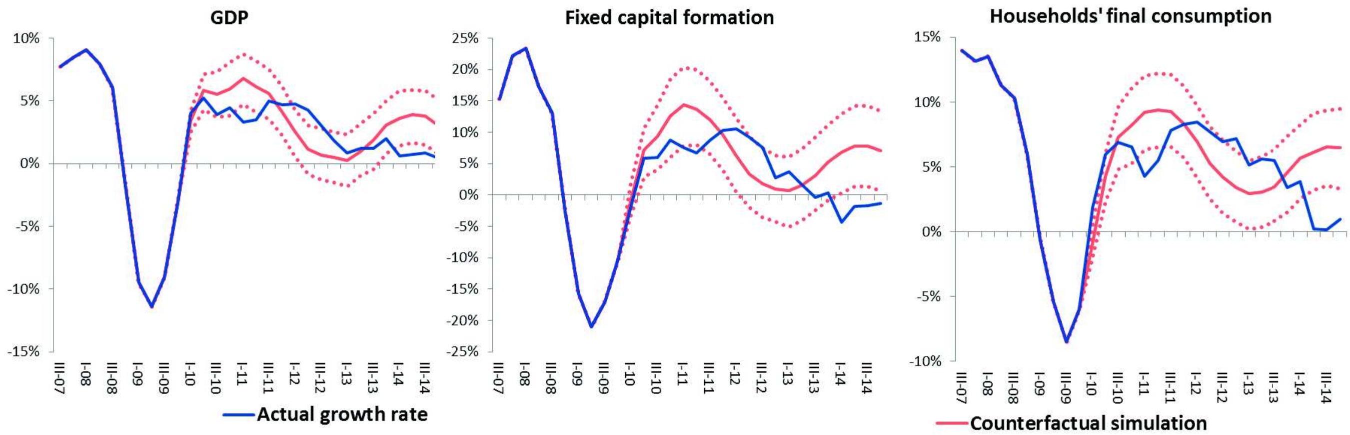
Figure 5.3. Projections of real sector variables' y-o-y growth conditional on oil price (the median and the 16th and 84th quantiles of the distribution)



5.3.3.2 Counterfactual simulations conditional on oil price and EU GDP

Our next step is to make the same simulation conditional on both the actual oil price and actual EU GDP. The results are notably different (Figure 5.4). The information on developments with these two external variables was sufficient to explain most of the variation in domestic real sector variables' growth rate in 2010–2013. The confidence bands are also substantially smaller. The slowdown in 2012–2013 is projected for GDP and fixed capital formation (accordingly the growth rates of consumption are regarded as unexpectedly high in this case). These results provide clear evidence of the vulnerability of the Russian economy to external shocks[82] which is in line with other studies (see e.g. IMF (2014)). Another key finding, however, is that this relationship did not hold in 2014 and GDP growth rate remained at around 0.5% as compared to the 3–3.5% predicted by the model. That does not seem surprising given the increase of macroeconomic uncertainty that happened after the beginning geopolitical tensions between Russia and western countries and the imposition of sanctions. In fact under certain assumptions the difference between the predicted and realised growth rates may be used to measure the effect coming from these shocks.

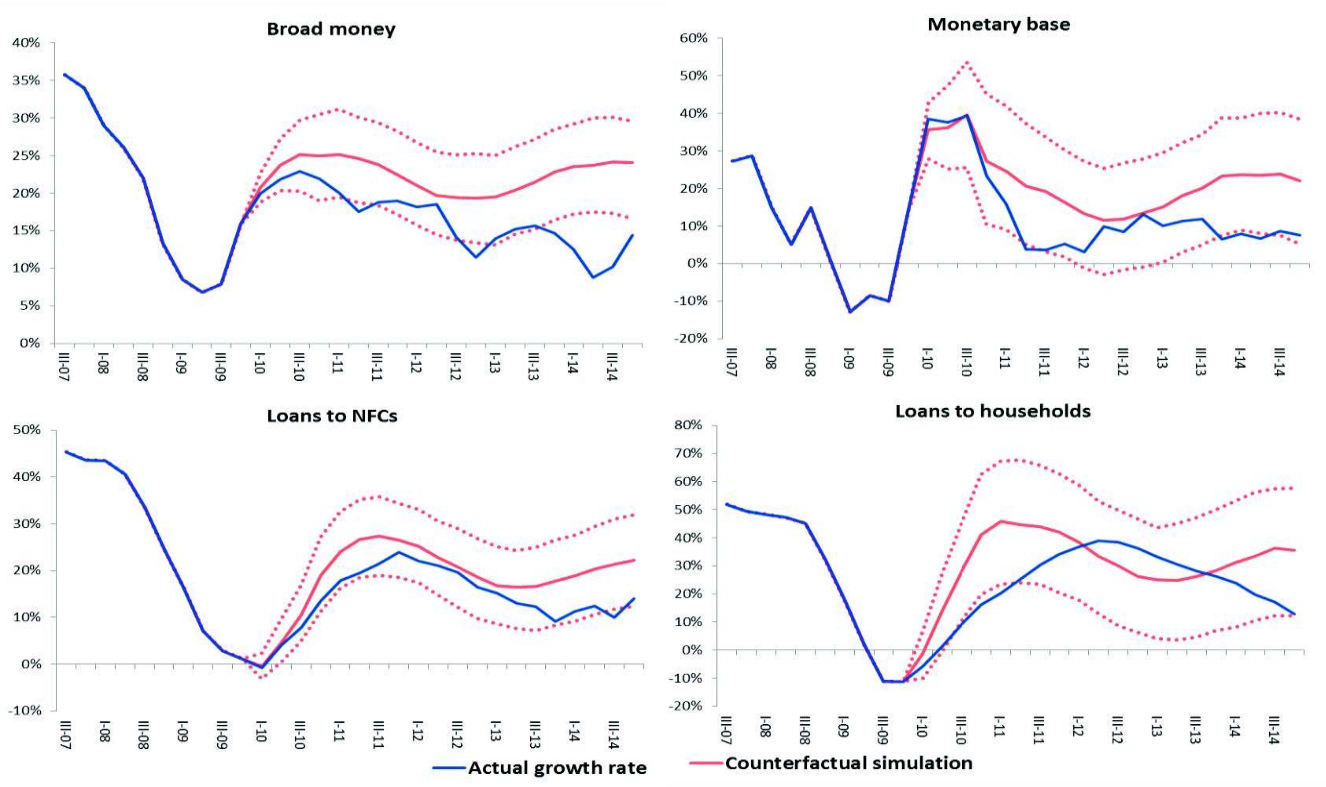
Figure 5.4. Projections of real sector variables' y-o-y growth conditional on oil price and EU GDP (the median and the 16th and 84th quantiles of the distribution)



As regards monetary indicators, the projected growth of broad money and monetary base (and to a lesser extent loans) is continually lower than actual even prior to 2014 (Figure 5.5). This result in itself is not surprising because, as noted earlier, rather than being closely linked to macroeconomic fundamentals, the money supply in Russia is subject to large exogenous shocks. For example, the substantial fiscal stimulus in 2009–2010 was partially financed from Russian sovereign funds and had a mechanical expansionary effect on the money stock.

[82] Admittedly, the exact channels of the transmission of these shocks to the Russian economy may not be fully identified based on this model. We can only state that these shocks are closely correlated with economic activity in the EU. Further research is obviously needed in order to identify these channels and examine how robust this link is (see e.g. Bank of Russia (2014) for an example of adding balance-of-payment variables into the model).

Figure 5.5. Projections of monetary variables' y-o-y growth conditional on oil price and EU GDP (the median and the 16th and 84th quantiles of the distribution)

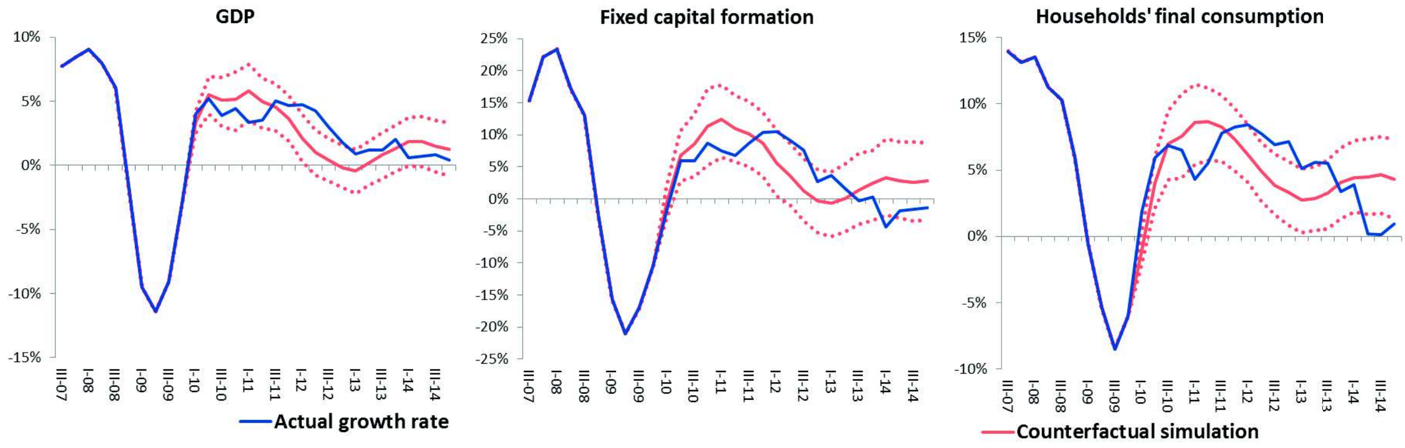


5.3.3.3 Counterfactual simulations conditional on oil price, EU GDP and monetary variables

Accordingly, we condition our next simulation on actual monetary developments as well as the oil price and EU GDP. This helps to improve the average accuracy of the real variable projections with the notable exception of households' consumption (Figure 5.6). Although this does not necessarily mean that uncertainty shocks affected real activity via changes in loan and money supply,[83] these results still indicate that the relationship between monetary and real variables remained intact in 2014.

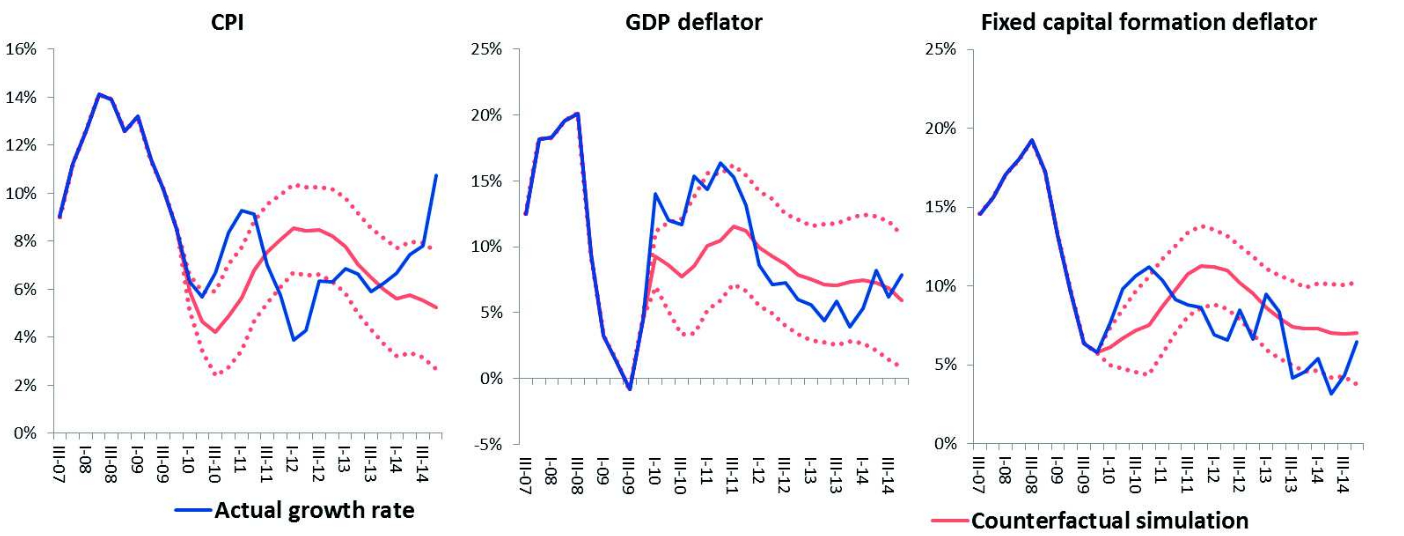
[83] Admittedly this exercise does not allow us to distinguish between demand and supply shocks.

Figure 5.6. Projections of real sector variables' y-o-y growth conditional on oil price, EU GDP and monetary variables (the median and the 16th and 84th quantiles of the distribution)



The projections for prices growth (Figure 5.7) are also on average accurate. For example, even though the short-run fluctuations[84] in the CPI are not reflected in the estimated growth rates, the cumulative error over five years (i.e. difference in price levels) between the actual and projected CPI amounted to just 5%.

Figure 5.7. Projections of price variables' y-o-y growth conditional on oil price, EU GDP and monetary variables (the median and the 16th and 84th quantiles of the distribution)



The accuracy of projections of other variables is also mixed. The median projections for asset price growth (Figure 5.8) are in line with actual data although the confidence band in the case

[84] Essentially, these fluctuations did not seem to be determined by any fundamentals. The increases in the inflation rate in late 2010 was at least partly due to food price shocks caused by drought, while the sharp decrease in early 2012 was associated with the suspension of administered price indexation. See e.g. the Bank of Russia Quarterly Inflation Review (2011 Q1 and 2012 Q1) for a more detailed review of these episodes. Inflation acceleration in 2014 was connected with sharp rouble depreciation.

of the stock prices projection is quite large. The model was not able to establish the link between labour market indicators and other economic variables (Figure 5.9), but as we could see this was not relevant for producing accurate projection of other real variables.

Figure 5.8. Projections of asset price variables y-o-y growth conditional on oil price, EU GDP and monetary variables (the median and the 16th and 84th quantiles of the distribution)

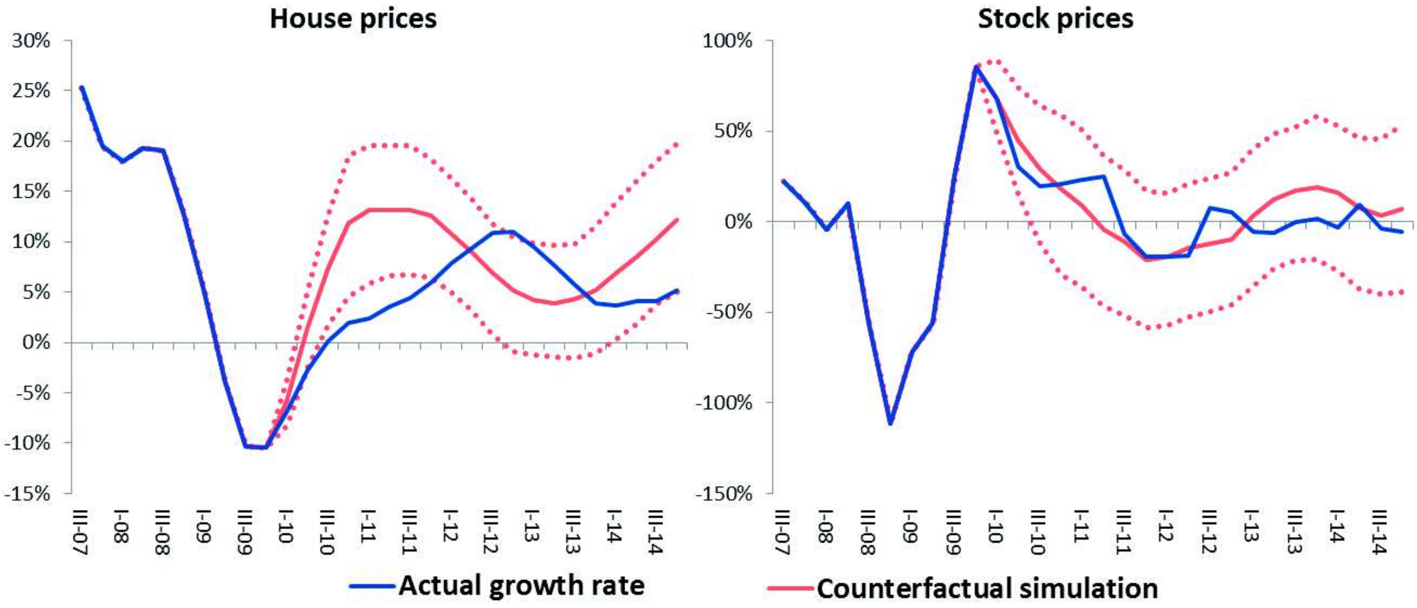
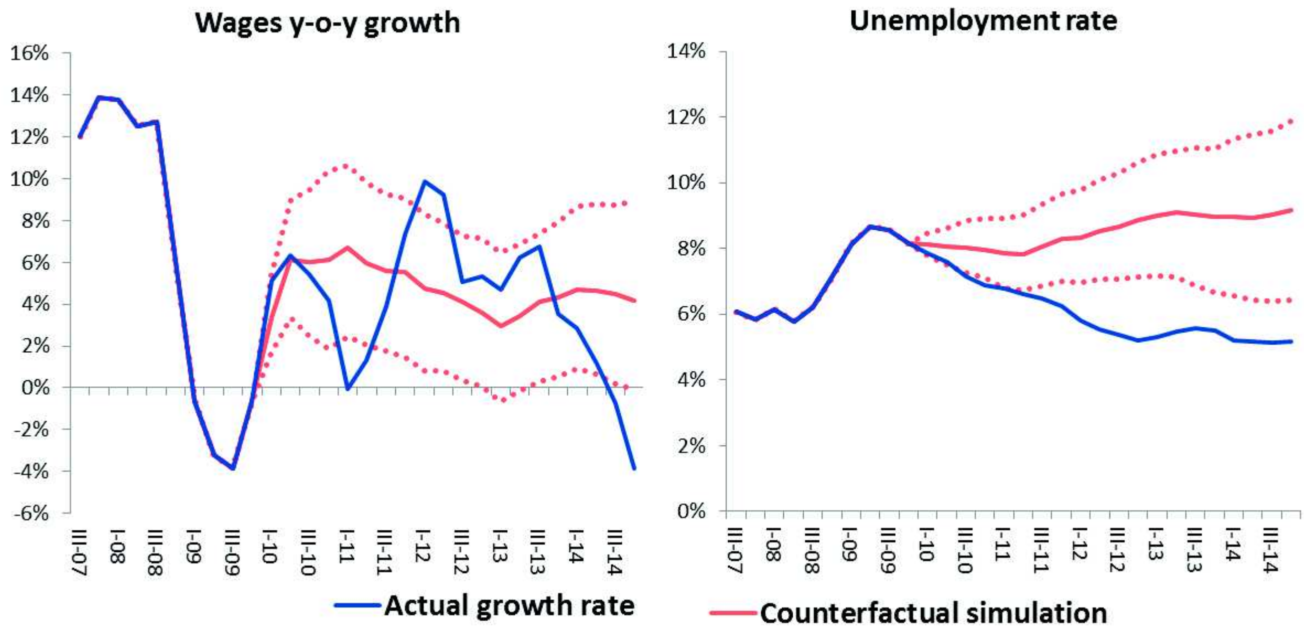


Figure 5.9. Projections of labour market variables conditional on oil price, EU GDP and monetary variables (the median and the 16th and 84th quantiles of the distribution)



5.4. Conclusions

The main objective of this paper was to build a relatively large VAR model while relying on insufficiently long time series for its estimation and to use it for assessment of the economic developments in Russia over the last five years. To this effect we apply the recent econometric approach developed specifically to address the ‘curse of dimensionality’. Using this methodology, we estimate a Bayesian VAR model comprising 16 major domestic real, price and monetary macroeconomic indicators as well as external sector variables.

We conducted several types of exercises to validate our model. These are impulse response analysis and recursive forecasting. Our results demonstrate that the employed methodology is generally appropriate for economic modelling of the Russian economy. The impulse response functions indicate that theoretically plausible linkages between variables in our model may be identified. The results of recursive forecasting show that the model performs satisfactorily and does not suffer from the problem of over-fitting. The forecasting performance is particularly good for real sector variables.

The counterfactual projections indicate that in 2010–2013 real sector developments in Russia were generally in line with the observed external variables. Interestingly, oil price alone did not contain sufficient information to produce an accurate forecast, while conditioning the projections on both oil price and EU GDP growth improves the accuracy significantly. In 2014 the realised GDP growth was about 2.5 p.p. lower than predicted. The difference may be attributed to the effects of economic uncertainty shocks arising from geopolitical tensions and imposed sanctions. The link between real and monetary variables remained stable over the analysed period. The model is not fully able to capture short-run fluctuations in the inflation rate, but makes a good prediction of price levels if conditioned on actual monetary developments.

Admittedly, the presented version of the model is an illustrative example of its applicability rather than its ultimate specification. The composition of the dataset may obviously be further altered depending on the task addressed. Most notably, the link between domestic and foreign sectors may be explored in more detail by adding foreign trade, capital flows and uncertainty variables into the model. Given that (unlike canonical VARs) the number of variables that can be simultaneously included in the model is not severely limited, these possibilities seem particularly promising.

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Conclusion

Les articles présentés sont une contribution théorique, méthodologique et empirique dans la littérature sur les instruments principaux de l'analyse monétaire. En particulier, nous examinons l'applicabilité des méthodes modernes à la Russie (ainsi que, dans certains cas, à d'autres économies de marché émergentes) et faisons des ajustements appropriés. Nos résultats sont pertinents pour des problèmes pratiques de maintien de la stabilité financière et des prix de la part de la Banque centrale.

Dans le premier chapitre nous examinons les facteurs qui entrainent la croissance de la masse monétaire en Russie et décrivons l'expérience de la Banque de la Russie dans l'utilisation de certains instruments traditionnels d'analyse monétaire, et en premier lieu des fonctions de la demande de monnaie.

Nous en venons à la conclusion que l'analyse monétaire fournit les données de base précieuses pour l'analyse de la Banque de la Russie. Cependant, l'analyse monétaire est le processus qui est en train de développement, c'est pourquoi, dans la limite d'une économie comme dans plusieurs économies de différents pays, les changements des conditions économiques et financières influencent l'analyse et les conclusions se rapportant à la politique économique qui peuvent être faites à sa base. La situation avec la Russie souligne de façon supplémentaire qu'il ne faut pas ramener l'analyse monétaire aux actions purement techniques, et que la connaissance institutionnelle du secteur financier est nécessaire pour lui, de même qu'il est stimulée par cet analyse.

Dans le deuxième chapitre nous estimons, par rapport à la Russie, les indices de l'inflation de base ce que aidera à mettre en évidence les chocs inflationnistes principaux des prix à la consommation qui sont importants pour la politique monétaire, et à présenter l'information sur l'évolution de l'inflation des prix à la consommation à venir ou sur les anticipations inflationnistes actuelles à moyen terme.

Nous en venons à la conclusion que les indices de l'inflation de base, calculés à l'application des modèles dynamiques factoriels, présentent les meilleurs résultats au titre d'épreuves formelles. Notamment, ces indices ont resté stables pendant les périodes de chocs des prix en 2010 et 2012, mais ils ont exprimé la pression inflationniste plus forte en 2007-2008 et sa baisse en 2009. En tant que résultat, ces indices ont resté informatifs pendant toutes les périodes en ce qui concerne la future dynamique de l'inflation à moyen terme, ils ont été étroitement liés aux fluctuations de la demande cumulée.

Dans le troisième chapitre nous apprécions la croissance durable en Russie.

Nous suivons Alberola et autres (2013), Borio et autres (2013, 2014) et Bernhofer et autres (2014) et formulons le modèle de l'espace des états qui présent le filtre HP multidimensionnel reliant la fluctuation cyclique de PIB avec plusieurs indices des déséquilibres macroéconomiques. Les variables financières, aussi bien que les indices traditionnels de l'inflation à la base de l'indice des prix à la consommation et du taux de chômage font partie de ces indices. Nous recevons les paramètres du modèle en l'estimant au total par rapport à l'ensemble d'économies de transition.

Les résultats montrent que les indices des déséquilibres financièrs sont statistiquement significativs pour expliquer les fluctuations de la rupture entre la production réelle et celle potentielle, surtout pour les pays européens – cela signifie qu'ils contiennent l'information supplémentaire en dehors de celle contenue dans les variables qui présentent le taux d'inflation et de chômage. Il apparaît que l'indice des prix sur le marché boursier présente le meilleur résultat. Prenant en compte que ce modèle n'a pas d'interprétation structurelle, cela ne signifie pas que seuls les changements sur le marché boursier ont été le facteur principal qui a engendré ces fluctuations de la rupture entre la production réelle et celle potentielle, mais cependant, il est possible d'affirmer que la croissance des prix du marché boursier est le symptôme important susceptible d'aider à distinguer l'accélération cyclique et celle de tendance de la croissance de production.

Les écart de production reçus à l'utilisation du modèle estimé, considérablement diffèrent de ceux qui ont été calculés à l'utilisation de la version unidimensionnelle du filtre HP. Il est surtout à noter que les indices de la croissance potentielle de production sont plus stables et, donc, correspondent de manière plus considérable à la notion de production durable. La diminution cumulative de la production après la récession de l'année 2008, estimée à la base du filtre multidimensionnel, peut être comparée (à l'opposé des appréciations reçues à l'utilisation de la version unidimensionnelle) aux cas typiques qui sont décrits en littérature. Ainsi, l'utilisation du filtre multidimensionnel peut aider à agrandir la stabilité du modèle en temps réel, bien que notre approche reste toujours très sensible aux problèmes du point d'arrêt lié à la transformation des variables qui reflètent les déséquilibres financièrs.

Dans le quatrième chapitre nous présentons le système d'indicateurs d'alerte précoce des cycles de boums et de krachs des prix des actifs en Russie. La principale contribution de cet essai consiste en application de l'analyse de boums et de krachs des prix des actifs à l'égard de l'ensemble de 29 marchés des pays avec l'économie de transition (avant tout à l'égard de la Russie et d'autres pays d'ex-URSS).

En général, nos résultats ne donnent pas la réponse finale à la question laquelle des approches de la prévision de boums et de krachs des prix des actifs présente les meilleurs résultats. Mais nous affirmons que la conception basée au monitorage de l'ensemble combiné des prix des actifs, de l'activité réelle et des indices financiers, est largement appliquée aux marchés des pays avec l'économie de transition, et son efficacité est confirmée par de différentes combinaisons dans les cadres du modèle. D'après nos appréciations, la croissance du crédit et les investissements (exprimés en taux de croissance comme en part de PIB) deviennent les indicateurs les plus fiables pour prévoir le cycle des prix des actifs. Nous aussi considérons qu'en addition à cet ensemble de variables, le système de prévention précoce pour les pays avec l'économie de transition peut être complété avec les indices de mouvement du capital.

Dans le cinquième chapitre nous modelons les interactions entre les variables qui présentent le secteur monétaire et celui réel, par voie de grand modèle vectoriel autorégressif bayésien.

En Russie la modélisation économique empirique est la tache difficile. Une des limitations les plus importantes est liée aux séries de temps insuffisamment longues ce que rend l'estimation du modèle économétrique global presque impossible. Dans ces conditions, l'approche économétrique développée spécialement pour résoudre le problème de "malédiction de la dimensionnalité", peut être vraiment convenable pour la Russie. Notamment, il est connu que toute une classe de modèles conçus il n'y a pas longtemps et basés sur la grande autorégression vectorielle bayésien (Banbura et autres (2010), Giannone et autres (2012), Banbura et autres (2014)), donne des résultats adéquats même dans les circonstances quand le modèle comprend en même temps un grand nombre de variables. Il est à la mode d'affirmer que le modèle VAR bayésien relativement grand estimé par rapport à l'économie russe à l'utilisation de cette méthode, peut être examiné en tant qu'instrument neuf et précieux de prévision et d'analyse hypothétique. Le but de cette thèse est la réalisation de cette approche en pratique.

En utilisant cette méthode, nous apprécions le modèle vectoriel d'autorégression bayésien comprenant 16 indices principaux qui présentent le secteur intérieur réel, les indices macroéconomiques de prix et ceux monétaires, aussi bien que les variables qui reflètent le secteur extérieur. Nous avons réalisé plusieurs types de tests pour valider notre modèle, notamment l'analyse des fonctions de réponse et la prévision récursive. Nos résultats montrent que la méthode appliquée convient en général à la modélisation économique de l'économie russe.

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Essays on Monetary Analysis in Russia

Augustin Cournot
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Dans la présente thèse on voit présenter les résultats de différends aspects de l'analyse monétaire de l'économie russe. En général, c'est une recherche principalement neuve, car autrefois cette méthode n'a pas été appliquée à l'égard de la Russie. Dans certains cas notre apport dans les recherches dans ce domaine consiste non seulement en analyse notamment pour la Russie, mais aussi en application de nos instruments pour un groupe plus étendu de pays avec l'économie de transition.

Mots clés : monnaie, crédit, politique monétaire, Russie

This dissertation presents the results of different aspects of monetary analysis for the Russian economy. This is mostly a novel research that was not applied to Russia previously. In some cases we contribute to the literature not only by conducting Russia-specific analysis but also by applying our tools to the cross-section of emerging market economies.

Keywords : money, credit, monetary policy, Russia