Université Paris Nanterre
200 av. de la République
92001 Nanterre Cedex
www.parisnanterre.fr

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Mathilde Aubouin

Économie du numérique :
Enjeux relatifs à la macroéconomie, les inégalités et l'environnement

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Jury :

Rapporteur :	M. Axel Gautier	Professeur, HEC Management School, Université de Liège
Rapporteur :	M. Thierry Pénard	Professeur, Université de Rennes
Examinatrice :	Mme Maya Bacache-Beauvallet	Membre du collège de l'ARCEP Professeure, Telecom Paris
Examinateur :	M. Éric Darmon	Professeur, Université Paris Nanterre
Examinatrice :	Mme Katheline Schubert	Professeure, Université Paris 1 Panthéon-Sorbonne – PSE
Directeur de thèse :	M. Lionel Ragot	Professeur, Université Paris Nanterre

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Résumé général

Entamée il y a une trentaine d'années, la transition numérique peine à tenir toutes ses promesses. Bien que l'utilisation des technologies du numérique offre de nombreux avantages, les effets escomptés sur la productivité et la croissance économiques ne se sont pas produits. De plus, les technologies du numérique peuvent avoir des retombées négatives, telles que des problèmes de protection de la vie privée, une augmentation des inégalités ou encore une dégradation de l'environnement. Cette thèse vise à étudier certains impacts de la transition numérique. La première partie s'intéresse aux impacts d'un point de vue macro-économique alors que la seconde partie considère l'aspect micro-économique pour mettre en avant l'hétérogénéité entre les individus.

Le premier chapitre offre une revue de la littérature sur le paradoxe de Solow selon lequel les technologies du numérique seraient omniprésentes dans nos sociétés mais n'auraient qu'un impact limité sur la croissance économique. Après avoir défini les principales caractéristiques de la transition numérique, nous étudions ses similitudes et différences avec les deux premières révolutions industrielles. Puis, les différentes barrières entravant l'impact du numérique sur la croissance économique sont présentées. Enfin, l'hypothèse récente selon laquelle l'impact de la transition numérique ne porterait pas sur la croissance économique mais directement sur le bien-être des individus est développée. Les outils de mesure actuels ne seraient plus adaptés, notamment suite à la diffusion de nombreux services en ligne gratuits qui ne sont pas directement pris en compte dans le PIB.

Le second chapitre propose une modélisation du secteur des services numériques gratu-

its dans un modèle de croissance. Pour se financer, les fournisseurs de services numériques collectent les données de leurs utilisateurs afin de vendre un service de publicité personnalisé. Ce modèle nous permet d'étudier les impacts de ce secteur sur les principaux agrégats macroéconomiques et le bien-être. Une attention particulière est accordée à l'importance des données et de l'attention des utilisateurs, à la sensibilité pour la vie privée et à la structure de marché du secteur numérique. Nous mettons en avant que les services numériques gratuits peuvent avoir un impact sur le bien-être et des implications économiques sur le secteur des biens finaux sans impacter la croissance économique.

Le troisième chapitre cherche à identifier les déterminants de la fracture numérique en France. Pour ce faire, nous utilisons les méthodes de pseudo-panel et les enquêtes Technologies de l'Information et de la Communication de l'Insee. Nos résultats montrent des disparités dans l'accès et l'utilisation d'internet qui dépendent principalement de la génération des individus, leur niveau de revenu et de diplôme. Une fois qu'un individu a accès à internet et l'utilise, les disparités dans le type d'utilisation d'internet sont faibles. La lutte contre la fracture numérique doit donc se concentrer sur les individus qui n'ont pas accès à internet. La dernière partie de ce chapitre étudie les raisons derrière le non-accès à internet.

L'objectif du quatrième chapitre est d'étudier l'impact distributif et l'efficacité d'une taxe environnementale sur les forfaits mobiles. Nous estimons un système de demande pour obtenir les élasticités prix de divers biens des ménages français à partir de l'enquête Budget des Familles de l'Insee de 2017. Cela nous permet de connaître et de simuler leur réaction face à une augmentation des prix des forfaits mobiles selon leur décile de revenu. Le calcul de la perte de bien-être suite à une taxe sur les forfaits mobiles montre que cette régulation est régressive et pourrait aggraver la fracture numérique. Dans une seconde partie, nous montrons théoriquement que l'efficacité de cette taxe dépend de la structure de l'offre des télécommunications.

Mots clés : économie du numérique; croissance économique; inégalités; environnement

Abstract

The digital transition began around thirty years ago and has failed to deliver on all its promises. Although digital technology offers many benefits and opportunities, the expected effects on economic growth and productivity have not occurred. In addition, digital technologies can negatively impact households through privacy issues, increased inequality, and environmental degradation. This thesis aims to study and highlight some of the impacts of the digital transition. The first part focuses on impacts from a macro-economic point of view, while the second part considers the micro-economic aspect to highlight heterogeneity between individuals. Empirical and theoretical methodologies are used throughout this thesis.

The first chapter provides a literature review on Solow's paradox, according to which digital technologies are omnipresent in our societies but have a limited impact on economic growth. After defining the main characteristics of the digital transition, we examine its similarities and differences with the first two industrial revolutions. The various barriers hindering the impact of digital technology on economic growth are then presented. Finally, the recent hypothesis that the impact of the digital transition is not on economic growth but directly on individual well-being is developed. The current measurement tools would no longer be appropriate, especially with the spread of numerous free digital services that are not directly taken into account in GDP.

The second chapter proposes a growth model, including the free digital services sector. Digital service providers collect users' data to generate revenue to sell a personalized advertising service. This model enables us to study the impact of this sector on the primary

macroeconomic aggregates and well-being. Particular emphasis is devoted to the importance of users' data and attention, sensitivity to privacy, and the market structure of the digital sector. We highlight that free digital services can have an impact on well-being and several economic implications for the final goods sector without impacting economic growth.

The third chapter investigates the determinants of the digital divide in France. We use pseudo-panel methods and the Insee's Information and Communication Technology surveys between 2007 and 2019. Our results highlight a heterogeneity in internet access and use that depends mainly on individuals' generation, income, and degree levels. Once an individual has access to and uses the internet, the disparities in the type of internet use are weak. The fight against the digital divide must, therefore, focus on individuals who do not have access to the internet. To this end, the final part of this chapter examines the reasons behind non-access to the internet and concludes that the two main barriers to access are lack of skills and cost.

The production and use of digital technology cause environmental degradation that needs to be regulated. However, as highlighted in the third chapter, internet access and use are still unevenly distributed. The fourth chapter aims to study the distributive impact and effectiveness of an environmental tax on mobile data. First, we estimate a demand system (the censored Quadratic Almost Ideal Demand System) to obtain the price elasticities of various French household goods from the 2017 Insee Family Budget survey. This enables us to determine and simulate households' reaction to an increase in mobile internet prices according to their income decile. Calculating the welfare loss following a tax on mobile subscriptions shows that this regulation is regressive and could exacerbate the digital divide. In the second part, we show theoretically that the tax's effectiveness depends on the supply structure of telecommunications.

Keywords : digital economy; economic growth; inequality; environment

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Introduction générale

Cadre général de la thèse

La transition numérique représente la diffusion des technologies du numérique dans l'économie et la société, que ce soit en termes d'accès ou d'utilisation. Développées à partir des années 1950, ces dernières permettent la représentation de l'information en chiffres binaires, rendant possible la dématérialisation de l'information. Parmi ces technologies, la transition numérique a été principalement marquée par l'utilisation des Technologies de l'Information et de la Communication (TIC), représentant l'ensemble des technologies du numérique existantes pour aider les individus, les entreprises et les gouvernements à accéder, produire ou transmettre des informations ainsi qu'à communiquer. Aujourd'hui, les TIC, telles que les smartphones, les ordinateurs et l'internet, sont utilisées massivement par les entreprises et les ménages. Mais ce n'est que depuis les années 1990, lorsque internet est devenu facilement accessible à tous, que l'adoption des TIC a réellement progressé (Cardon, 2019). Plus récemment, l'intelligence artificielle (IA), portée par l'accumulation de données massives, s'impose comme une nouvelle innovation numérique majeure. L'IA représente les technologies numériques capables de simuler l'intelligence humaine. Les progrès dans ce domaine sont rapides et les champs d'application se multiplient : les voitures autonomes se développent, les particuliers utilisent des assistants virtuels tels que Siri et des médecins font de plus en plus appel à l'IA pour trouver le traitement le plus approprié pour leurs patients. La transition numérique touche donc tous les domaines de l'économie.

Si les technologies du numérique génèrent de l'engouement grâce aux nouvelles opportunités qu'elles offrent, leur utilisation n'a pas forcément les effets escomptés. Par exemple, l'impact sur la croissance économique et la productivité est moindre par rapport aux anciennes innovations. Leur utilisation peut aussi engendrer des impacts négatifs pour certains agents économiques tels que des problèmes de vie privée, une amplification des inégalités ou encore une dégradation de la qualité environnementale. Pour que la transition numérique soit efficace, les gouvernements doivent prendre en compte les divers enjeux liés au développement du numérique afin de proposer des politiques publiques adaptées à cette, maintenant bien ancrée, "nouvelle" économie.

Cette thèse s'inscrit principalement dans le champ de l'économie du numérique. Plus précisément, elle s'intéresse aux impacts économiques de la transition numérique sous divers angles. Le manuscrit est composé de quatre chapitres indépendants dont l'objectif est de comprendre et d'identifier les impacts du numérique, qu'ils soient directs *via* l'utilisation des technologies du numérique ou indirects *via* la régulation de leur utilisation. Nous distinguons deux parties principales au sein de ce travail. La première s'intéresse à la mesure du numérique et à son impact sur les agrégats macro-économiques. Une attention particulière est accordée aux services numériques gratuits dont le modèle économique est basé sur la collecte de données et la publicité personnalisée. Puis, une approche micro-économique est adoptée dans une deuxième partie afin d'étudier les impacts hétérogènes du numérique sur les ménages. Nous nous concentrons sur la France et regardons les inégalités numériques en termes d'adoption et d'utilisation, mais aussi celles engendrées par la régulation du numérique. Plus précisément, nous nous intéressons à la régulation environnementale du numérique. De plus, cette thèse bénéficie d'une pluralité méthodologique, alliant les méthodes empiriques et théoriques pour l'étude des divers enjeux du numérique.

La suite de cette introduction générale est structurée comme suit. Les différents enjeux de la transition numérique étudiés dans cette thèse sont présentés pour fournir des éléments de contexte. Puis, nous résumons dans une deuxième partie les différents chapitres de cette thèse, leurs objectifs et contributions.

Éléments de contexte

La mesure de l'économie du numérique

Le premier enjeu de la transition numérique abordé dans cette thèse est : comment mesurer la création de richesse qui résulte des technologies du numérique ? Cette question découle de l'observation faite par Solow (1987) selon laquelle *"vous pouvez voir l'ère de l'informatique partout, sauf dans les statistiques de la productivité"*. En effet, de par leur qualification en technologies multi-usages et du rythme rapide de leurs innovations, les technologies du numérique ont rapidement été vus comme une potentielle source de croissance économique. Néanmoins, les résultats empiriques s'accordent : les technologies du numérique n'ont eu que très peu d'impact sur la croissance économique et la productivité dans les pays développés. Certains pays, principalement les États-Unis, ont connu une hausse de la productivité dans les années 1980 et 1990 grâce à la diffusion et l'utilisation des TIC, mais cet impact a été transitoire (Bergeaud *et al.*, 2016). Une large littérature a alors essayé de répondre à ce paradoxe. Parmi ces explications, une hypothèse ressort : les outils statistiques actuels ne seraient pas adaptés pour mesurer les biens et services issus du numérique (Coyle, 2014).

Les caractéristiques des biens et services numériques (économie d'échelle, effets de réseaux, non-rivalité) permettent la réduction des coûts de recherche (Goldfarb & Tucker, 2019). Cela a permis l'amplification de l'économie collaborative, où des pairs peuvent facilement échanger des biens et services entre eux, ou encore la diffusion de nombreux services numériques gratuits, tels que Google et Facebook pour ne citer que les plus connus (Ahmad & Schreyer, 2016). Or, ces produits ne sont pas considérés comme de la production marchande car, dans le premier cas, les échanges ont lieu entre particuliers, et dans le second, le prix est nul. Leur prise en compte dans les outils statistiques usuels, tels que le Produit Intérieur Brut (PIB), va donc être faible. Dans le cas des services gratuits financés par la publicité, ces derniers sont seulement pris en compte dans la comptabilité nationale à travers les revenus issus de la publicité. Or, cette dernière est considérée comme de la consommation intermédiaire

des firmes et non de la consommation finale ou de l'investissement. Son impact sur le PIB est donc faible. De plus, l'utilité que procurent ces services gratuits est souvent supérieure à une simple estimation des revenus de la publicité (Brynjolfsson *et al.*, 2019). Au-delà de la question des erreurs de mesure, les technologies du numérique semblent également accroître la décorrélation entre les indicateurs de création de richesse et ceux de bien-être. En effet, comme empiriquement mis en évidence par Jones & Klenow (2016), la croissance du bien-être est significativement supérieure à celle du revenu depuis les années 1980 dans les pays développés. L'émergence de nouveaux modèles économiques suite au développement du numérique conforte la recommandation du rapport Stiglitz *et al.* (2009) de regarder *au-delà* du PIB.

L'économie des données et de l'attention

Un avantage des technologies du numérique est de faciliter la collecte, le stockage et le traitement des données personnelles des utilisateurs (Goldfarb, 2014). Ces informations permettent aux firmes de proposer des prix personnalisés, de faire de la publicité ciblée, ou encore d'améliorer leurs produits. Leur caractère non-rival, c'est-à-dire le fait que l'utilisation d'un bien par un individu ne diminue pas sa quantité, rend l'utilisation des données d'autant plus efficaces (Jones & Tonetti, 2020). Leur utilisation a permis l'émergence de services numériques gratuits dont les données sont au cœur du modèle économique. Les fournisseurs de ces services collectent un certain nombre d'informations sur leurs utilisateurs. Elles peuvent être collectées directement (par exemple, lorsque les consommateurs s'inscrivent sur un site et dévoilent des informations telles que leur âge ou leur genre) ou indirectement (les plateformes, *via* des cookies, collectent des informations sur les activités en ligne passées ou présentes). Puis, ces données sont utilisées comme facteurs de production dans le but de produire ou d'améliorer leur bien final. Ce dernier n'est, en général, pas le service en ligne gratuit, mais un service de publicité ciblé vendu aux annonceurs (Zuboff, 2020).

Le développement de cette économie a plusieurs conséquences. Du côté de l'offre, les

caractéristiques des technologies du numérique renforcent les positions dominantes. En effet, le coût marginal de ces services est proche de zéro générant d'importantes économies d'échelle (Shapiro & Varian, 1998). Les firmes numériques bénéficient aussi de forts effets de réseaux. Par exemple, il est souvent plus profitable pour un consommateur d'être sur le même réseau social que son entourage. Il existe aussi des effets de réseau croisés : les annonceurs sont attirés par les services numériques ayant un nombre important d'utilisateurs. Ainsi, deux firmes dominent le marché de la publicité en ligne : Google, avec 30% de parts de marché, et Meta, avec 22% (Bourreau & Perrot, 2020). Les revenus issus de la publicité leur permettent de rivaliser avec les firmes les plus rentables au monde. Par exemple, le chiffre d'affaire de Google était de 279,8 milliards de dollars en 2022.

Du côté des consommateurs, l'utilisation massive des données permet de diminuer les coûts de recherche ce qui permet d'améliorer l'appariement. Ils peuvent aussi bénéficier de produits personnalisés. Par exemple, grâce aux informations collectées, des plateformes, telles que Facebook, offrent un service personnalisé à chacun de ses utilisateurs. Cependant, le partage des données peut aussi avoir des impacts négatifs tels que de la discrimination par les prix ou tout simplement des problèmes de vie privée[3]. Dès lors, les consommateurs doivent arbitrer entre protéger et partager leurs données (Acquisti *et al.*, 2016). Cependant, cet arbitrage n'est pas forcément possible car les consommateurs ignorent souvent la quantité d'informations personnelles partagées, ni leurs utilisations. De plus, des externalités négatives existent : des informations sur une personne peuvent dévoiler des informations sur son entourage. Les enjeux de vie privée sont de plus en plus considérés et discutés et ont mené à plusieurs régulations concernant les consommateurs[4]. Les deux plus importantes sont le Règlement général sur la protection des données (RGPD) mis en place par l'Union Européenne en 2018 et

[3]Dans une revue de littérature sur l'économie de la vie privée, Acquisti *et al.* (2016) retiennent trois définitions de la vie privée : (i) la protection de l'espace personnel d'une personne et son droit d'être laissée seule (Warren & Brandeis, 1890), (ii) le contrôle et la sauvegarde des informations personnelles (Westin, 1967) et (iii) un aspect de la dignité, de l'autonomie et finalement de la liberté humaine (Schoeman, 1984).

[4]Les régulations dont l'objectif est la protection des données peuvent aussi concerner les entreprises. Par exemple, dans le *Digital Markets Act* mis en place en 2023 par l'Union Européenne, un des objectifs est d'interdire aux grandes plateformes numériques telles que Amazon d'utiliser les données que leurs concurrents laissent sur le site mais qui ne sont pas publiques. Dans cette thèse, nous abordons seulement la protection des données des consommateurs.

le California Consumer Privacy Act (CCPA) par l'état de Californie aux États-Unis en 2020. Leur objectif principal est d'assurer une meilleure protection de la vie privée en encadrant la collecte et le traitement de données. Par exemple, les utilisateurs doivent donner de manière explicite leur consentement au traitement de leurs données et ont le droit d'accéder et d'effacer leurs données personnelles.

Inégalités numériques

La diffusion et les bénéfices d'une technologie se font rarement d'une manière homogène. C'est le cas des technologies du numérique. Ces disparités dans l'accès et l'utilisation sont présentes entre et au sein des pays. Dans le cadre de cette thèse, nous nous intéressons seulement aux inégalités au sein d'un pays. Ces inégalités numériques peuvent prendre plusieurs formes et avoir divers impacts sur l'économie et les ménages.

D'un point de vue macro-économique, l'inégale adoption des technologies du numérique peut retarder ses impacts sur la productivité et la croissance économique. En effet, comme mis en avant par Eichengreen (2015), l'impact d'une technologie dépend fortement de son application et de son taux d'utilisation par les différents agents économiques. Par ailleurs, le numérique augmente les inégalités en créant des biais technologiques en faveur des travailleurs qualifiés et des détenteurs des capitaux. Cela a pour conséquence d'augmenter leur rémunération aux détriments des travailleurs peu qualifiés. Or, il est démontré que les inégalités de revenu sont un frein à la croissance économique (Summers, 2014).

D'un point de vue micro-économique, les inégalités numériques entre les ménages, également appelées fracture numérique, peuvent prendre plusieurs formes. La littérature met en avant plusieurs niveaux de la fracture numérique tels que l'accès, l'utilisation, la variété d'utilisation ou encore les bénéfices liés à l'utilisation du numérique entre les individus. Les enjeux de la fracture numérique sont aussi des enjeux de bien-être. Par exemple, les services publics dématérialisent de plus en plus leurs services ce qui nécessite des compé-

tences numériques pour y avoir accès. Par conséquent, le non-accès ou la non-utilisation du numérique peut être excluant et créer des difficultés à l'accès de certains services essentiels comme cela a été le cas lors des confinements mis en place pendant la crise de la Covid-19. De plus, les exclus du numérique ont tendance à se situer dans les populations déjà défavorisées (revenus les plus faibles, niveau de diplômes plus faible...), aggravant les inégalités déjà existantes. Il est donc important d'identifier les individus les plus touchés par cette fracture numérique afin de mettre en place des politiques publiques adaptées.

Environnement et changement climatique

Un dernier enjeu à prendre en compte est la manière de concilier la transition numérique avec la transition écologique actuelle. L'impact environnemental du numérique a longtemps été mis de côté dû à son caractère faussement immatériel. Or, les technologies du numérique, principalement composées des terminaux utilisateurs (ordinateurs, objets connectés), des infrastructures réseaux et des centres de données, génèrent différents types de pollution sur l'ensemble de leur cycle de vie (fabrication, utilisation et fin de vie). Ces pollutions et impacts sont divers et variés et peuvent se présenter sous la forme d'émissions de CO2 ou de particules fines, de consommation énergétiques, d'épuisement des ressources naturelles et abiotiques ou encore de pollution des eaux et des sols (Lange *et al.*, 2020; Li *et al.*, 2021; Lees Perasso *et al.*, 2022). Au total, le numérique représente 4,2% de la consommation mondiale d'énergie primaire et 3,1% des émissions de gaz à effet de serre (Bordage, 2019). La production et l'utilisation des équipements informatiques sont responsables de la majorité des impacts (59% à 84% selon l'indicateur environnemental observé). Vient ensuite l'utilisation des réseaux et des centres de données, notamment à travers la consommation gourmande en électricité. L'augmentation des utilisateurs et de l'utilisation du numérique mais aussi l'accroissement du nombre de terminaux par ménage (objets connectés, taille des écrans) aura pour conséquence d'accroître de manière conséquente l'empreinte environnementale du numérique. Il est donc essentiel de réguler les technologies du numérique sur toutes les phases

de leur cycle de vie.

Le numérique est rarement considéré dans les politiques publiques en faveur de l'environnement. Or, si rien n'est fait, il pourrait représenter 7% des émissions de gaz à effet de serre mondiale dès 2025 (Ferreboeuf *et al.*, 2021). En France, la loi *Réduire l'Empreinte Environnementale du Numérique* (REEN) promulguée le 15 novembre 2021 est la première à proposer des mesures visant à réduire l'empreinte carbone du numérique. Si cette loi est une avancée, elle est finalement moins ambitieuse et contraignante que la proposition sénatoriale initiale. Cette dernière proposait, par exemple, d'allonger la durée de garantie légale des appareils numériques pour lutter contre l'obsolescence programmée ou encore d'interdire les forfaits internet mobiles illimités, plus polluant que les forfaits fixes (Chevrollier & Houllegatte, 2020). Mais ces propositions ont connu un fort rejet de la part des entreprises.

En plus des barrières causées par les firmes, la mise en place de politiques publiques en faveur de l'environnement peut être entravée par un rejet d'une partie de la population. Ce rejet peut être illustré par le mouvement des Gilets Jaunes apparu en 2018 en France contre l'augmentation des prix de l'énergie provenant de la hausse de la taxe carbone. À l'aide d'enquêtes représentatives des ménages français, Douenne & Fabre (2022) montrent que le fait de percevoir une politique comme progressive et efficace sont des déterminants importants de l'acceptabilité des politiques publiques. Il est donc important d'étudier l'effet distributif d'une régulation et de vérifier que cette dernière n'est pas régressive, c'est-à-dire que le poids de la politique n'est pas plus porté par les ménages les moins aisés. L'efficacité d'une mesure doit aussi être étudiée. Pour cela, il faut prendre en compte les réactions des ménages ou entreprises ciblés par la régulation mais aussi la structure du marché impacté.

Présentation de la thèse

Cette thèse étudie les différents enjeux présentés précédemment. Certains de ces enjeux sont traités ensemble dans un même chapitre afin de voir les effets croisés. D'autres sont abordés séparément.

Chapitre 1 : Transition numérique et impacts macro-économiques

Le chapitre 1 intitulé *"Digital Transition and macroeconomic impacts"* offre une revue de la littérature sur les impacts macro-économiques de la transition numérique. Son objectif est double. Une première partie est consacrée à la description de l'économie du numérique et des caractéristiques de ses technologies. Les divers impacts sur l'économie sont présentés afin de fournir un état des lieux de cette "nouvelle" économie et des changements sur l'économie. Puis, un parallèle est effectué entre la transition numérique et les deux premières révolutions industrielles. Cela nous permet de conclure que la transition numérique ne présente pas, pour le moment, les caractéristiques d'une révolution industrielle. Elle ne s'accompagne pas de la découverte d'une nouvelle source d'énergie et n'a pas d'impact significatif sur l'industrie. Cependant, ce constat ne signifie pas que le numérique n'a pas d'impact sur nos économies.

Dans une seconde partie, nous explorons les différentes explications au paradoxe de Solow proposées dans la littérature. Parmi elles, nous développons l'hypothèse de la stagnation, de la phase de transition, des biais technologiques et d'inflation. Puis, nous présentons une hypothèse récemment discutée dans la littérature : les technologies du numérique modifieraient directement les modes de consommation, contrairement à celles des révolutions industrielles qui ont profondément modifié les méthodes de production. Autrement dit, l'impact serait au-delà du PIB, directement sur le bien-être. Cela serait en partie dû à la diffusion de nombreux services numériques gratuits et à l'amplification de l'économie collaborative, non pris en compte par nos outils statistiques actuels. Le numérique accentuerait la décorrélation entre les indicateurs de création de richesse et de bien-être.

Chapitre 2 : Macroéconomie des services numériques gratuits

Le second chapitre intitulé *"Macroeconomy of the Free Digital Services"*, co-écrit avec Lionel Ragot, s'intéresse aux services numériques gratuits et à leurs impacts sur les agrégats macroéconomiques et le bien-être. Pour cela, nous développons un modèle de croissance endogène incluant le secteur des services numériques gratuits et ses interactions avec le secteur traditionnel et les ménages. Le secteur numérique est composé de quelques grands fournisseurs de services numériques et d'un continuum de petits fournisseurs. Ces derniers produisent un service de publicité en utilisant l'attention et les données personnelles de leurs utilisateurs. Les grands fournisseurs ont un avantage dans la production de leur service. Cela leur permet de fournir un service numérique avec une qualité significativement supérieure à celle des services des petits fournisseurs. Les ménages passent donc plus de temps sur les services des grands fournisseurs. Le secteur traditionnel est lui composé de firmes en concurrence monopolistique vendant chacune une variété de biens différenciés. Pour stimuler sa demande, les firmes peuvent améliorer la qualité perçue de leur bien. Pour cela, elles peuvent investir dans l'effort de Recherche & Développement (R&D) et acheter des impressions personnalisées au secteur numérique. Les ménages maximisent leur utilité en consommant des biens différenciés et en passant du temps sur les services numériques. Ils doivent alors aussi déterminer le montant d'information qu'ils acceptent de dévoiler aux firmes numériques. Cet arbitrage se fait entre l'effet positif de la collecte de données (le service est personnalisé avec les données) et l'effet négatif (la collecte de données engendre des problèmes de vie privée).

Cela nous permet de mettre en avant les mécanismes par lesquels ce nouveau secteur interagit avec le secteur des biens traditionnels, mais aussi son impact sur les agrégats macroéconomiques et le bien-être. Nous montrons comment ces services peuvent impacter le bien-être et l'économie sans impacter la croissance économique. A l'aide d'un exercice de statique comparative, nous mettons en avant les conséquences économiques de plusieurs caractéristiques du secteur des services numériques gratuits. Nous montrons que la structure de la compétition fait que les grands fournisseurs de service peuvent avoir un impact positif sur

l'économie et le bien-être. L'amélioration de leur production ou l'entrée d'un nouveau grand fournisseur a pour effet d'augmenter la richesse individuelle, ce qui stimule la demande de biens finaux. Au final, de nouvelles variétés de biens apparaissent dans l'économie. Les petits fournisseurs ont un impact limité. Cela est dû aux fortes préférences des ménages. Nous montrons aussi que le poids accordé aux données et à l'attention dans le processus de production d'impressions peut engendrer des impacts inverses, notamment sur les petits fournisseurs. Lorsque le temps passé en ligne est un facteur de production important dans la production d'impressions, les petits fournisseurs sont lésés par la forte concurrence avec les grands. Au contraire, l'utilisation des données permet aux petits fournisseurs de compenser le fait que les ménages préfèrent passer plus de temps sur les services des grands fournisseurs. Nous finissons par mettre en avant les implications de la sensibilité pour la vie privée.

Chapitre 3 : Déterminants de la fracture numérique: le cas de la France

Le troisième chapitre *"Determinants of the Digital Divide: Evidence from France"* propose une approche micro-économique afin d'étudier l'hétérogénéité entre individus, non prise en compte dans les deux premiers chapitres. Il s'intéresse à l'inégale adoption et utilisation des technologies du numérique par les français. Pour cela, plusieurs niveaux de la fracture numérique sont étudiés : l'accès, l'utilisation et le type d'usage d'internet, ainsi que les raisons du non-accès à une connexion internet. Afin d'identifier les déterminants de ces inégalités, nous utilisons les enquêtes sur les technologies de l'information et de la communication produites par l'Insee entre 2007 et 2019. Ces enquêtes étant des coupes transversales répétées et non un véritable panel, nous mobilisons les techniques de pseudo panel (Deaton, 1985). Cela nous permet de prendre en compte les caractéristiques des français mais aussi l'évolution temporelle de la transition numérique, qui est toujours en cours, sur treize années.

Nos résultats montrent que la génération (année de naissance), le niveau d'éducation et de revenu sont les principaux déterminants des inégalités d'accès et d'utilisation d'internet.

Ces inégalités ne sont plus aussi marquées lorsque l'on étudie les disparités dans la diversité d'usage en ligne (démarche administrative, service bancaire, recherche d'emploi, achat en ligne, achat ou vente en ligne ou autres loisirs). Seule la génération ressort comme un important déterminant des activités en ligne. La réduction de la fracture numérique passe donc par favoriser l'accès à une connexion internet. Nous montrons aussi que les barrières à l'accès diffèrent selon les caractéristiques des individus. Les deux principales barrières sont le manque de compétences informatiques et le coût financier. La première concerne majoritairement les générations plus âgées alors que la seconde concerne les plus jeunes. La recommandation finale de ce chapitre est donc d'investir dans une éducation numérique, accessible à tout âge, mais aussi de mettre en place une aide financière à l'accès aux équipements informatiques.

Chapitre 4 : Effets distributionnels et efficacité d'une taxe environnementale sur les données mobiles

Le quatrième et dernier chapitre intitulé *"Distributional effets and efficiency of environmental tax on mobile data"*, co-écrit avec Paolo Melindi-Ghidi et Jean-Philippe Nicolaï, s'intéresse à l'impact de la régulation environnementale des forfaits internet mobiles en France. Plus précisément, nous étudions l'impact distributif et l'efficacité d'une taxe sur les forfaits internet mobiles. Pour cela, nous examinons empiriquement et théoriquement le comportement des ménages français vis-à-vis de leurs dépenses en internet fixe et mobile. Pour simuler le comportement des ménages et l'impact distributif de la taxe, nous utilisons l'enquête Budget des Familles produite par l'Insee en 2017. Cette dernière nous permet d'estimer des systèmes de demande afin d'obtenir les élasticités prix simples et croisées de la demande de plusieurs biens non-durables, dont les forfaits internet fixe et mobile. Une fois le comportement des ménages estimés, nous simulons leur réaction à court terme suite à une augmentation des prix des forfaits internet mobiles. Puis, nous calculons la perte moyenne en termes de bien-être par décile de revenu résultant de cette hausse des prix. Cela nous permet de constater si l'impact en terme de revenu de la taxe est équitablement réparti entre décile de revenu

ou non. Dans une seconde partie, nous proposons un modèle théorique modélisant les décisions de dépenses en internet fixe et mobile des consommateurs. L'objectif principal est de comprendre comment certains de nos résultats empiriques et l'efficacité de la taxe dépendent de la structure des offres proposées par le marché des télécommunications. Pour cela, nous considérons plusieurs cas : (i) les données fixes et mobiles sont vendues au prix unitaire, (ii) l'existence de forfaits internet fixes illimités, (iii) les forfaits internet fixe sont illimités et vendus avec des services additionnels et (iv) l'existence de forfaits internet mobiles permettant la consommation d'un certain nombre de données mobiles sans frais supplémentaires.

Plusieurs résultats ressortent de ces deux exercices. Nous trouvons des élasticités prix-croisées négatives entre les dépenses en internet fixe et mobile. Cela suggère que ces deux dépenses sont complémentaires. Les résultats de nos simulations indiquent que la mise en place d'une taxe forfaitaire sur les forfaits internet mobiles serait régressive. Un moyen de rendre cette taxe moins régressive serait de taxer seulement les forfaits les plus chers, correspondant aux forfaits ayant une allocation de données mobiles plus élevées. Nous montrons aussi que la structure de l'offre des télécommunications en France peut atténuer l'efficacité de la taxe sur les données mobiles. En effet, les ménages sont plus sensibles à la taxe lorsque les données mobiles sont vendues au prix unitaire ou s'il existe une offre à la fois diversifiée et proche pour permettre au consommateur de changer facilement d'abonnement. Si l'offre n'est pas variée et que les consommateurs ne consomment pas l'intégralité des données disponible dans leur forfait, la taxe peut résulter en une baisse des dépenses sans impacter la consommation, rendant la taxe inefficace d'un point de vue environnemental.

Finalement, ce travail de recherche cherche à contribuer à la littérature sur l'économie du numérique. Le numérique étant aujourd'hui présent dans la plupart des aspects de nos économies, cette recherche mobilise donc d'autres littératures, telles que la macroéconomie dynamique, l'économie des inégalités ou encore l'économie de l'environnement. Pour répondre à ces diverses questions, nous employons différentes méthodologies utilisées en sciences économiques telles que les modèles théoriques de croissance endogène (chapitre 2) et de décisions des consommateurs (chapitre 4) et la micro-économétrie appliquée aux données de panel (chapitre 3) et en coupe transversale (chapitre 4).

Chapter 1

Digital Transition and macroeconomic impacts [1]

[1] A version of this chapter has been published as Aubouin, M. (2022). Transition Numérique et impacts macroéconomiques, **Revue Française d'Economie**, XXXVII, 131-171.

1.1 Introduction

Most governments are currently investing in the digital transition, i.e., in the diffusion of digital technology in the economy and society, both in terms of access and use. Considered as general-purpose technologies, in the same way as the steam engine during the first industrial revolution and electricity during the second one (Aghion & Howitt, 2010), digital technology is presented as an essential tool for households but also necessary for the development of firms. The digital transition is often referred to as the *"Digital Revolution"* or the *"Third industrial revolution."* However, since their development, digital technology has had a limited impact on productivity and economic growth. Indeed, Cette *et al.* (2020) highlight that between 1960 and 2019, Information and Communication Technology (ICT) has had a small contribution to Gross Domestic Product (GDP) and that robotization has significantly impacted productivity only in specific periods and countries. This observation leads to a paradox underlined by Solow (1987) at the end of the 1980s: *"you can see the computer age everywhere, except in productivity statistics."*

This situation coincides with the slowdown and then the stagnation at a low level of economic growth rates experienced by developed countries since the first oil shock in the 1970s. As a result, the secular stagnation hypothesis has come back into the economic debate. The latter, previously highlighted by Hansen (1939) during the Great Depression in the United States, is defined as a long-term situation in which technological progress and demographic growth would no longer be sufficient to stimulate economic growth. Gordon (2012) argues that stagnation is due to insufficient innovation. Indeed, economic growth theory postulates that, in the long run, technical progress is the main driver of productivity and economic growth (Solow, 1957). Despite the rapid pace of innovation characterizing the digital transition and its comparison with the industrial revolutions, digital technology alone does not seem capable of lifting developed countries out of stagnation.

Additional hypotheses to explain stagnation are explored in the literature. According to Summers (2014), it would be due to a demand-side problem. Developed countries would be

characterized by excess savings over investment caused by demographic aging and increasing wealth inequality. It would increase the propensity of households to save. At the same time, the share of non-risky assets in central bank reserves is rising, making the investment in more productive assets less attractive. The real interest rate should be adjusted to reduce the imbalance between savings and investment and stimulate economic growth. However, current nominal interest rates are close to zero, and inflation rates are also low, making it challenging to lower real interest rates. Several economists have explored the demand-side stagnation hypothesis, including studying the impacts of demographic aging (Acemoglu & Restrepo, 2017; Eggertsson *et al.*, 2019), wealth inequality (Ostry *et al.*, 2014), the scarcity of non-risky assets (Caballero *et al.*, 2016), and the zero interest rate bound (Eggertsson *et al.*, 2016) on macroeconomic aggregates.

This chapter focuses on the supply side and studies the impact of the digital transition and the nature of that impact on the economy. The first part defines the main characteristics of the digital transition and examines its similarities and differences with the industrial revolutions. We conclude that the digital transition does not present, at least for the moment, the characteristics of an industrial revolution (discovery of a new energy source, significant impact on industry). Therefore, there is no reason for the impact of the digital transition to be similar to that of industrial revolutions, i.e., a profound change in production methods. In the second part, we develop the different arguments that explain why digital technology has not yet had the expected effect on economic growth (stagnation hypothesis, transition phase, technology biases, and inflation bias). None of these explanations alone resolves Solow's paradox. Finally, a more recent idea is explored: the impact of the digital transition would not be on economic growth but directly on the well-being of individuals. It would be partly due to the creation of numerous digital platforms offering free services and the increase in peer-to-peer exchanges not considered by national accounting. Therefore, the digital transition would impact consumption modes, unlike industrial revolutions, which mainly changed production methods.

The rest of this chapter is structured as follows. Section 1.2 presents the main charac-

teristics of the digital transition and draws a parallel between the digital transition and the first two industrial revolutions. Section 1.3 presents the different explanations for Solow's paradox and highlights the measurement problem inherent in the digital transition. Section 1.4 concludes.

1.2 The digital transition

1.2.1 An overview of the digital transition

Digital technology

Digital technologies are considered multi-purpose technologies, i.e., technologies used in most sectors of the economy and with a high capacity for innovation (Bresnahan & Trajtenbergb, 1995; Aghion & Howitt, 2010). They, therefore, have the potential to affect production and innovation in many areas of the economy. The OECD (2018b) highlights four main characteristics that benefit these technologies: (i) strong network effects, (ii) economies of scale, (iii) transfer costs and lock-in effects, and (iv) a complementarity effect. According to the first, the utility of digital goods and services increases with the number of users. The second is mainly because the marginal cost of digital goods and services is very low or even zero. In general, only a fixed cost is incurred to produce a digital good, as they are often non-rival due to their immaterial nature. The third characteristic encourages consumers to stay with one operating system to avoid incurring monetary or psychological costs such as losing personal data or contacts. This enables a few digital firms to dominate their markets and generate substantial sales, such as GAFAM (Google (Alphabet), Apple, Facebook (Meta), Amazon, and Microsoft). Finally, the complementarity between digital goods and services increases consumer utility (the utility derived from a smartphone increases with the number of compatible applications).

These technologies have led to the creation of numerous platforms, which are now

widespread. They are new intermediaries between agents and act as a two-sided market (Rochet & Tirole, 2003; Armstrong, 2006). Weyl (2010) identifies three specific characteristics of these markets: (i) the platform offers distinct services to both sides of the market, (ii) there are cross-network effects, i.e., the utility derived from participation depends on the extent of user participation on the other side of the market, and (iii) the platform sets prices on both sides of the market. Through these specific features, digital platforms facilitate matching and increase trading efficiency by reducing search costs (Goldfarb & Tucker, 2019).

Some of these digital platforms have a business model that can be described as traditional: the firm finances itself through sales. However, many platforms can also be used free of charge by consumers. The latter are mainly financed by advertising or the direct sale of users' personal data (Lambrecht *et al.*, 2014). This is the case, for example, with Google and Facebook. Nevertheless, even if the data is not sold directly, it is, in general, widely used in the production process of the platforms, whether to offer a targeted advertising service or establish a typical profile of these consumers (Varian, 2019; Jones & Tonetti, 2020). Finally, some platforms have been built on an "open collaboration" model, such as Wikipedia.

The characteristics of digital technologies enable digital firms to sell cheaper goods and services (Brynjolfsson & Hitt, 2000; Brown & Goolsbee, 2002) and thus compete with traditional firms selling an equivalent or similar good or service. Digital firms can then negatively impact traditional firms' revenues or even replace them. Postal delivery services have thus been negatively impacted by new digital modes of communication (Hong & Wolak, 2008), the online press is increasingly read at the expense of paper newspapers (Gentzkow, 2007), and streaming music is gradually replacing CD sales (Aguiar & Waldfogel, 2018). This competition is not confined to the goods and services markets. It also occurs in the financial markets, where new players compete with traditional banks by offering cheaper online financial services (Rochet & Verdier, 2021).

The emergence of digital technology has also impacted the labor market. Berger & Frey (2016) show that the spread of digital technology has changed the skills demand. Neverthe-

less, the direct impact on employment is weak; digital technology seems to transform work rather than create it. Frey & Osborne (2013) estimate that digital technologies can automate 47% of jobs in the USA. Indeed, these technologies can replace manual tasks, but also cognitive ones, when they can be performed according to explicit rules (Autor *et al.*, 2003). Today, for instance, the trader profession is largely carried out by high-frequency trading algorithms, which enable financial operations to be carried out at speeds unattainable by humans (Goupil, 2013). Non-standard jobs have also emerged thanks to platforms that connect professionals in various fields with customers (e.g., Uber, Deliveroo). While these jobs were initially presented as bringing greater flexibility and autonomy to professionals, the OECD (2020b) highlights a deterioration in these jobs. These platforms have also enabled the amplification of the collaborative economy, where individuals exchange goods and services with strangers for payment or free of charge. A specific feature of the collaborative economy is that it changes the role of the consumer: the passive consumer can become a creator, producer, collaborator, or supplier.

Digital technologies' characteristics have changed how households consume, and they also benefit firms and public authorities. However, the digital transition remains slow and marked by many disparities in digital use between countries, firms, and individuals.

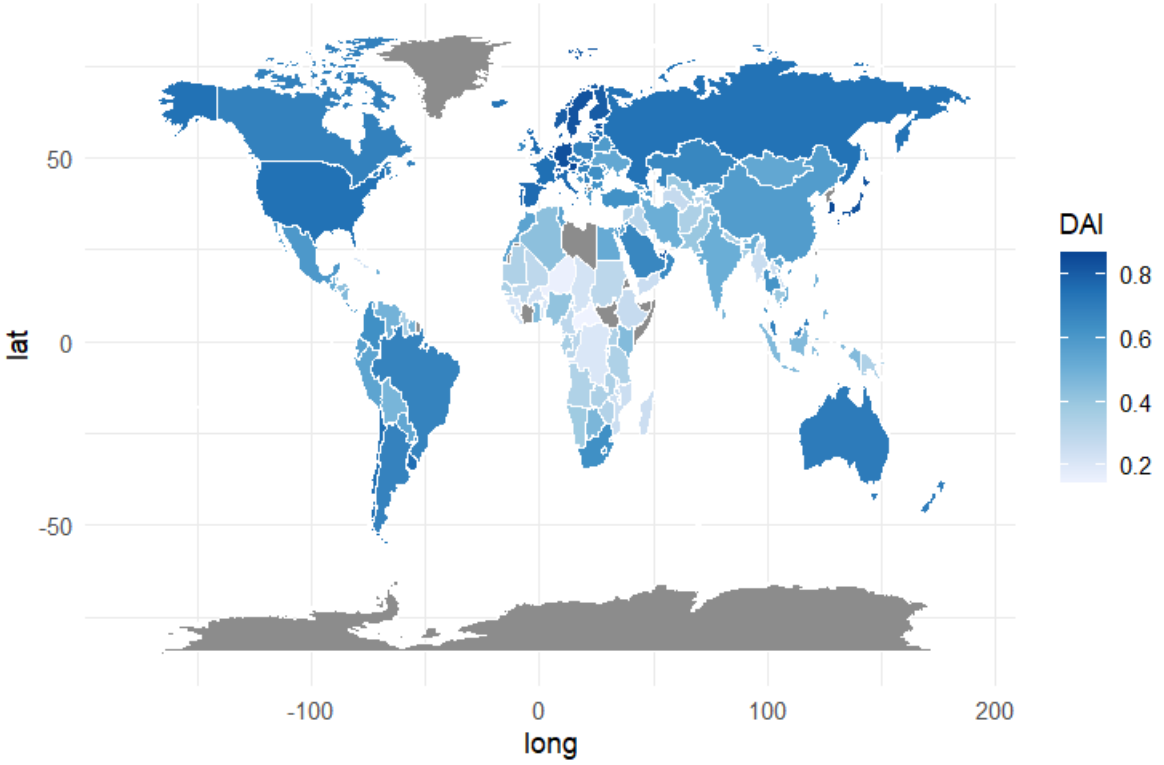
A slow and unequal transition

The digital transition is still underway, but some countries are further ahead than others. According to the Digital Adoption Index (DAI)[2] in 2016, the countries most advanced in their digital transition were the developed countries, in particular Northern Europe, Germany, Austria, Japan, and South Korea (see Figure 1.1). Some emerging countries, such as Brazil, Chile, and Russia, had a digital adoption index comparable to developed countries like the USA, the UK, and France. On the other hand, African countries were lagging in the diffusion

[2]The Digital Adoption Index, created by the World Bank, measures the diffusion of digital technologies for most of the world's countries. It takes into account the adoption of digital technologies by firms, households, and governments.

of digital technologies, mainly due to the low use of digital technologies by firms (World Bank Group, 2016).

Figure 1.1: Digital Adoption Index in 2016.



Source: Digital Adoption Index, World Bank.

The I-DESI (International Digital Economy and Society Index) considers a country's access to digital technologies and how these technologies are used.[3] As a result, some countries that rank highly in terms of digital access no longer perform well when the use of these technologies is also taken into account (see Figure 1.2). For example, according to the DAI, in 2016, Austria was one of the most advanced countries in digital adoption. However, it was

[3]The DESI for countries in the 28-member European Union and the I-DESI (International-DESI) for 17 non-EU countries (Australia, Brazil, Canada, Chile, China, Iceland, Israel, Japan, Mexico, New Zealand, Norway, Russia, Serbia, South Korea, Switzerland, Turkey and the USA) were developed by the European Commission (European Commission, 2018) to obtain international comparisons of countries' digital economy performance. They consider five dimensions: connectivity, human capital, use by citizens, integration of technologies in firms and public services.

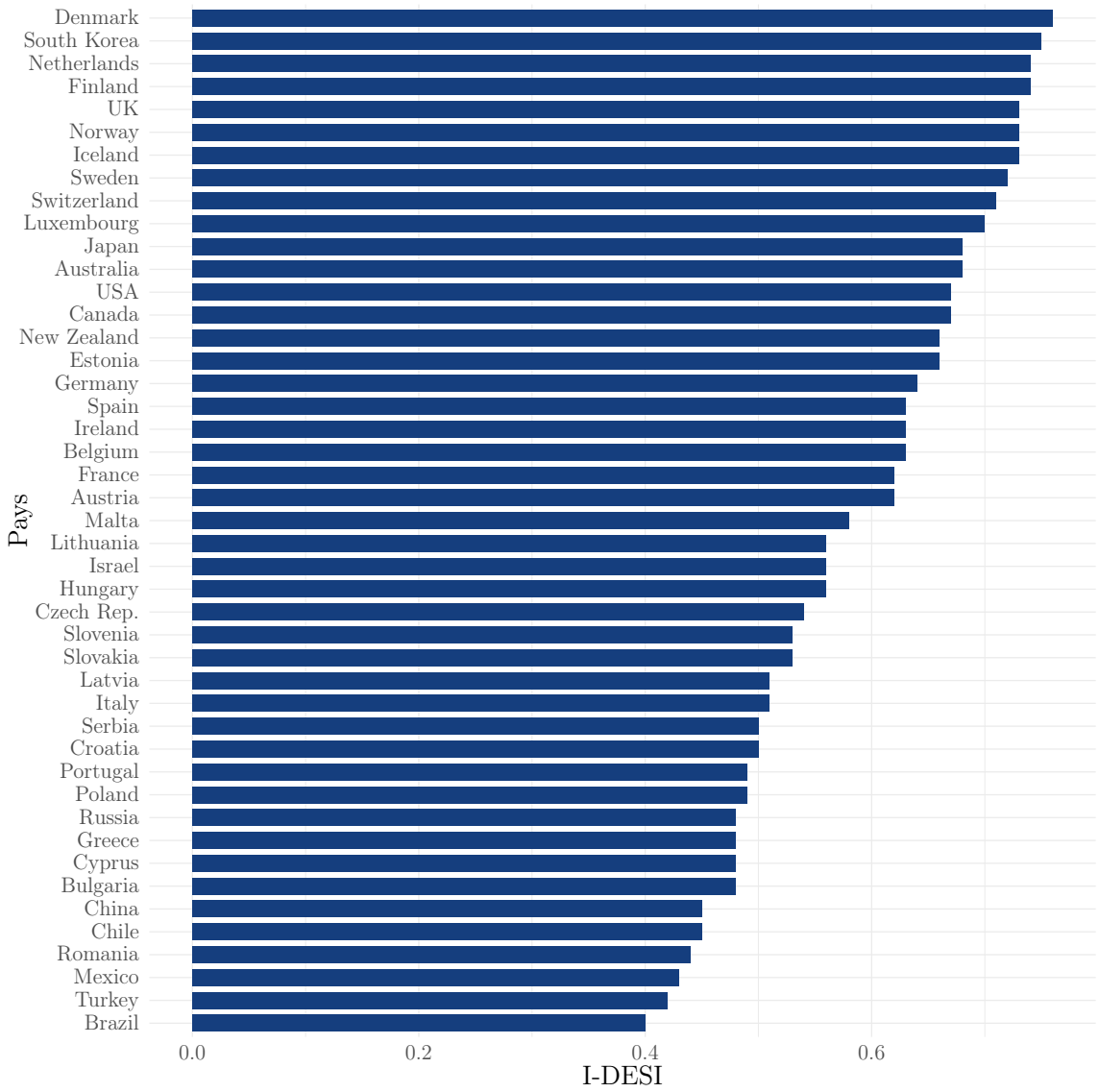
just average among developed and emerging countries regarding digital economy performance according to the I-DESI. In addition, some emerging countries, such as Chile and Russia, had better digital access than several European countries, but their usage was lower. Developed countries are generally the most advanced in the digital economy and therefore use these technologies better. However, regardless of their progress in the digital transition, the OECD (2020b) underlines that performance in the digital economy is hampered by a significant number of disparities in the use of digital technologies within countries.

First of all, there are disparities at the sector level. Calvino *et al.* (2018) point out that some sectors, such as Information Technology (IT) and telecoms services, financial, marketing, and legal, are advanced in their digital transition.[4] While others, such as agriculture, real estate, and mining, make very little use of digital tools. Moreover, even in the sectors with the highest use of digital technologies, firms are experiencing disparities in their usage. In 2019, 93% of OECD firms had access to broadband coverage and used basic digital technologies such as computers. However, few firms were using enterprise resource planning, cloud computing, or big data due to a lack of ICT skills or financial pressures. Finally, there are significant inter-individual disparities: digital users are under-represented among the elderly and low-income individuals (Lythreatis *et al.*, 2022).

The digital transition is still ongoing, but as the latest OECD (2020b) report on the digital economy points out, countries' digital performance tends to improve over time, whether this concerns households, firms, and governments. The development of the digital economy is partly due to the willingness of governments to invest in the digital transition. Most OECD countries are implementing digital strategies at the national level, through the creation of dedicated ministries, or at the international level. For example, the majority of European Union countries have signed up to the *"Digital Agenda for Europe"* (European Commission, 2010), whose main objectives are to improve digital administration and develop telecommunications infrastructures and skills for digital transformation. The OECD (2020b) highlights

[4] Calvino *et al.* (2018) propose a measure of the digital intensity of different economic sectors based on ICT investment, the purchase of ICT intermediaries, the use of robots, ICT human capital, and online sales.

Figure 1.2: The International Digital Economy and Society Index in 2016



Source: European Commission (2018).

that the COVID-19 crisis has amplified all aspects of the digital transition.

Given the prominence of digital technology, the development of the digital transition suggests that it could significantly impact the economy. However, the nature of this impact does not appear evident today. Digital technology has changed consumption patterns in many areas, but their impact on production is debated. Can we refer to it as the *third*

industrial revolution?

1.2.2 Toward a third industrial revolution?

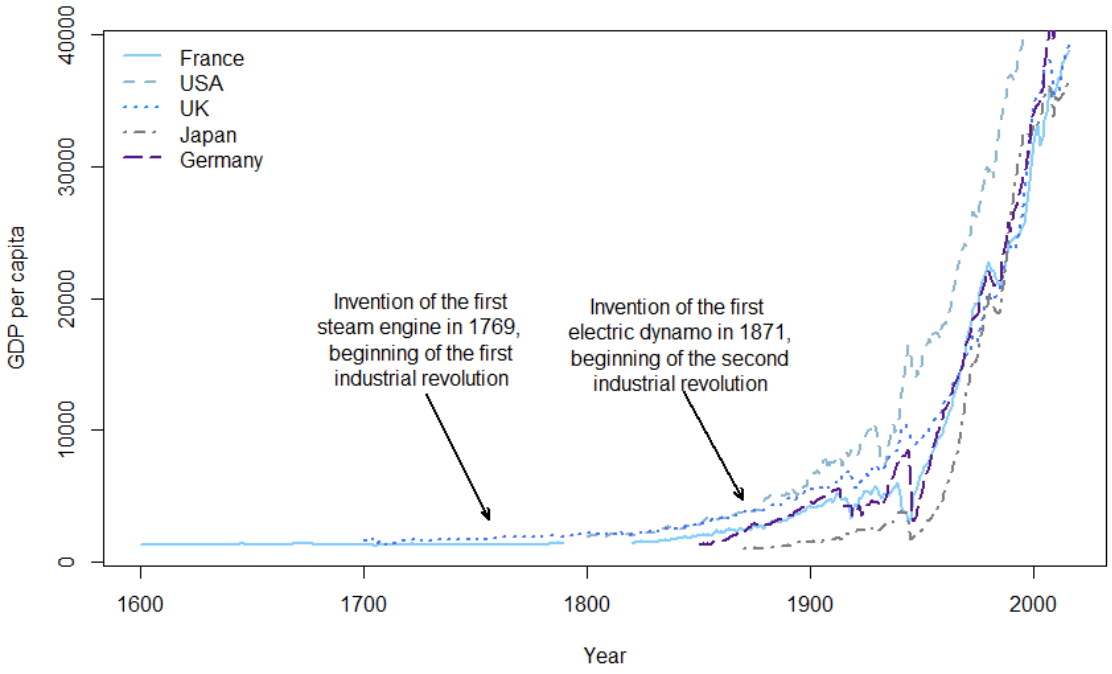
A brief history of the industrial revolutions

The first industrial revolution and the subsequent launch of economic growth would not have taken place without major innovations in the agricultural sector (Rostow, 1959; Gollin *et al.*, 2002). Before these agricultural developments, countries were all caught in the Malthusian trap, i.e., in a situation where population and production were close to a steady state. According to Malthus (1826), the population grew exponentially while resources were only increasing arithmetically. An increase in population was then confronted with a scarcity of food resources, leading to a decline in the standard of living and famines. At the beginning of the 18th century, new cultivation methods and machines, such as the seed drill, the tile drainage, and the quadrennial rotation, spread in the United Kingdom (UK). Agricultural yields increased considerably, invalidating the Malthusian process. It had two consequences: a significant increase in population due to the reduction of famines and the reallocation of part of the agricultural workforce to the emerging industry (Mokyr, 1990). Indeed, the increase in technological progress led to a rise in income and, consequently, a shift in demand for manufactured goods (Laitner, 2000). Europe gradually shifted from an agricultural to an industrial economy.

The first industrial revolution is often dated to 1769 in Great Britain with the invention of the steam engine by James Watt. The increasing use of steam energy due to coal exploitation was one of the driving forces behind this revolution. Water power was also widely used. The many innovations of the first industrial revolution, combined with new energy sources and population growth, have increased worker productivity, wages, and total output. They ended the Malthusian trap, allowing economic growth to begin (see Figure 1.3). Like the first industrial revolution, the second was marked by taming a new energy source: electricity

through oil exploitation. Essential innovations were then developed. The impressive impact on GDP growth, observed in Figure 1.3, is mainly because electricity benefited all economic actors, from firms to households, unlike the steam engine, whose use was limited to the textile industry and railroads during the first industrial revolution (Eichengreen, 2015). From then on, several industrial sectors experienced significant developments. Mokyr (1990) also highlights the importance of technological systems and networks, such as railroads, electrical systems, telegraph, telephone, and water supply systems. These networks significantly improved the standard of living of all economic agents.

Figure 1.3: GDP per capita in France, USA, UK, Japan, and Germany since 1600



Source: Maddison Project Database, 2018 version.

Mokyr (1990) describes the industrial revolutions as *"an age of energy technology."* Indeed, industrial revolutions are characterized by the taming of new energy sources and the creation and diffusion of numerous general-purpose technologies, marking the transition from agrarian to industrial society. Today, the expression *"third industrial revolution"* is some-

times used to designate the digital transition. However, does it have the same characteristics as the industrial revolutions that fundamentally changed our production?

The digital transition is not (yet) an industrial revolution

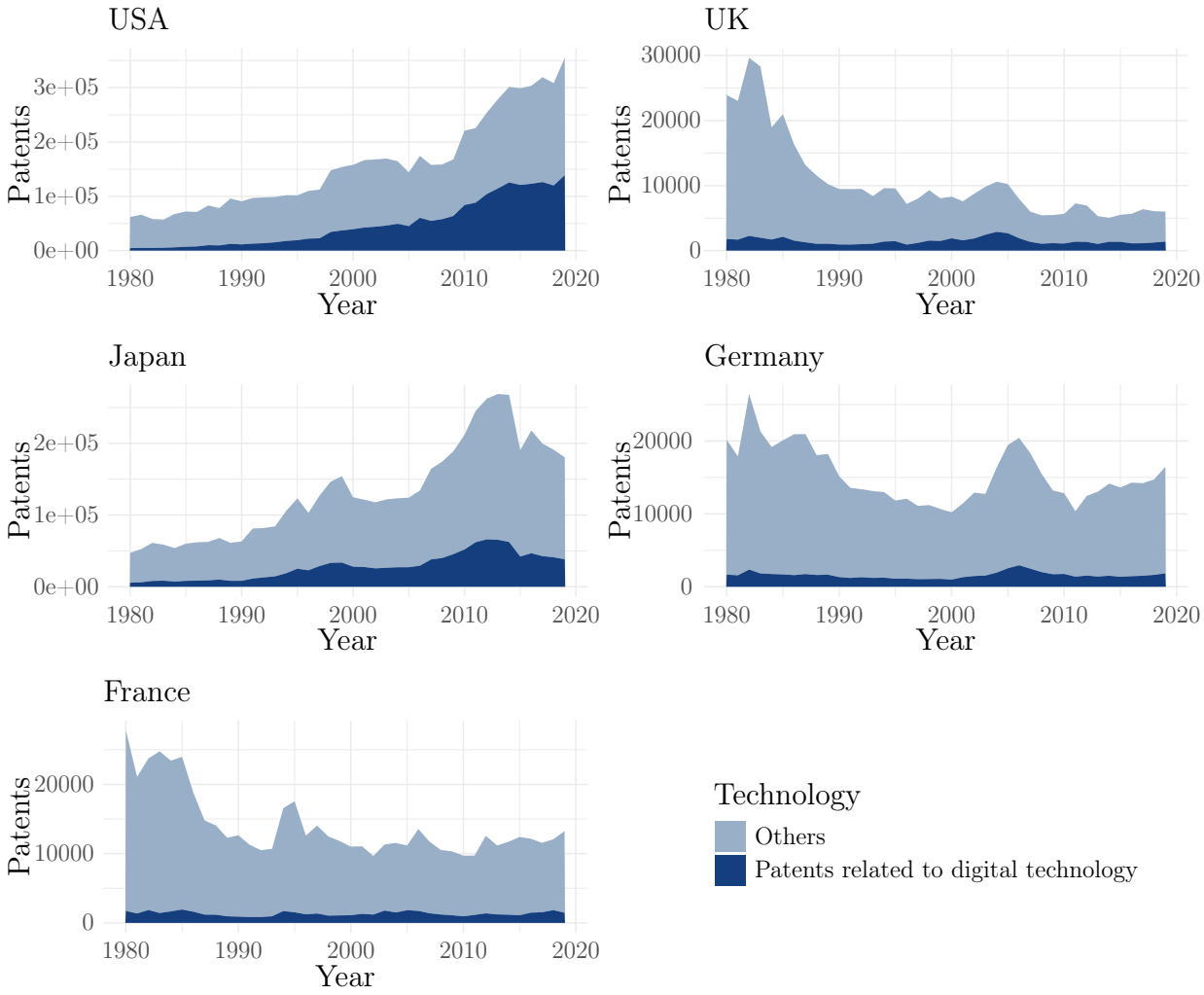
The two reasons that suggest that the digital transition is an industrial revolution are the characterization of these technologies as general-purpose and the rapid pace of these innovations. It can be partly illustrated by the number of patents granted for digital technologies in developed countries.[5] Digital technologies represent a large and growing share of total patent grants in the United States and Japan, the most innovative countries (see Figure 1.4). In countries where the number of patents granted has declined since the 1980s, patents relating to digital innovations are increasing. The developed economies are thus well characterized by a sustained pace of innovation, notably through digital technologies.

One of the characteristics identified by the industrial revolutions was the significant impact of their innovations on the industry. Today, however, the economies of developed countries are turning into service economies (see Table 1.1). The share of the service sector in GDP is increasing over time, particularly in the United States, where it reached 81% of GDP in 2019. The increase is also impressive in France, where the share of services in production rose from 60% in 1970 to 79% in 2019. Even in countries where production is heavily dependent on industry, such as Germany and Japan, the share of services in GDP increases at the expense of industry. Finally, although agriculture's production share has already reached a low level, it continues to decline.

These structural changes in the allocation of production and labor between the three main

[5]The World Intellectual Property Organization (WIPO) defines a patent as *"an exclusive right granted over an invention."* The number of patents granted in a country is often used to measure a country's innovation. However, it should be noted that this measure is not "perfect"; various phenomena can over or underestimate the number of patents. For example, there are many patent trolls whose main activity is the accumulation of patents without any productive activity to generate profits through licensing and patent litigation. Conversely, some highly innovative firms will prefer tacit protection of their intellectual property to the use of patents.

Figure 1.4: Total patent grants in USA, UK, Japan, Germany, and France between 1980 and 2019



Source: World Intellectual Property Organization statistics database. Last updated: January 2021.

sectors are first explained by Fourastié (1949).[6] He explains that a developing country moves from an agricultural economy to a tertiary economy in the long run. Between these two states, the industry is developing (industrial revolutions). However, due to the saturation of the demand for manufactured and agricultural goods and the important productivity gains of the industry relative to the tertiary sector, a country's labor force is gradually reallocated to the service sector. Baumol (1967) takes up Fourastié's thesis in a theoretical model and shows

[6]See Alcouffe & Le Bris (2020) for a review of the literature on Jean Fourastié's theory.

Table 1.1: Share of agriculture, industry, and services in the GDP of France, Germany, Japan, the UK, and the US between 1970 and 2019.

Sector (% of GDP)	**1970**	**1980**	**1990**	**2000**	**2010**	**2019**
France						
Agriculture	8%	4%	4%	2%	2%	2%
Industry	33%	31%	27%	24%	20%	19%
Services	60%	65%	69%	74%	78%	79%
Germany						
Agriculture	3%	2%	1%	1%	1%	1%
Industry	48%	41%	38%	31%	30%	30%
Services	49%	57%	61%	68%	69%	70%
Japan						
Agriculture	6%	3%	2%	2%	1%	1%
Industry	45%	40%	39%	33%	29%	29%
Services	49%	57%	58%	66%	70%	70%
United-Kingdom						
Agriculture	2%	2%	1%	1%	1%	1%
Industry	39%	37%	31%	26%	21%	20%
Services	59%	61%	68%	73%	78%	79%
USA						
Agriculture	2%	2%	2%	1%	1%	1%
Industry	32%	31%	26%	23%	20%	18%
Services	66%	67%	73%	76%	79%	81%

Source: National Accounts Estimates of Major Aggregates, United Nations Statistics Division.

that sectors characterized by rapid productivity growth experienced a long-term decline in their share of GDP. In contrast, those with slow productivity growth increased. Herrendorf *et al.* (2015) find that differences in technological progress between sectors, and not differences in sectoral technologies, are at the origin of the reallocation of factors of production between sectors. Boppart (2014) considers the heterogeneity of consumer preferences according to their income levels. He confirms that structural changes are as much due to a supply effect, *via* different technological progress between sectors, as to a demand effect, *via* different income elasticities of demand for goods and services.

Beyond the limited impact on the industry, the digital transition is not accompanied by

the discovery or the taming of a new energy source. This point is, in fact, essential for some economists, such as Mokyr (1990), who consider that industrial revolutions are also energy revolutions. Indeed, and although the causal direction between energy and growth is still debated, many economists consider that energy is a necessary factor for economic growth (Stern, 2000; Apergis & Tang, 2013; Pablo-Romero & Sánchez-Braza, 2015).[7] Rifkin (2011), therefore, argues that the digital transition could stimulate economic growth and constitute a new industrial revolution if it converges with an energy revolution.

Therefore, the current digital transition does not have the characteristics of an industrial revolution as identified. Nevertheless, it would be worth noting that for some, the digital transition would indeed use a new source of *"energy"*: data (Varian, 2019). Digital technology makes it possible to collect and store large amounts of information used in the production process (Goldfarb, 2014). The non-rivalry of data makes it all the more efficient (Jones & Tonetti, 2020). In this case, the digital transition would be a *"tertiary revolution"* where data would replace energy.

1.3 What is the nature of the impact of the digital transition?

This section focuses on the nature of the impact of the digital transition. First, several explanations for Solow's Paradox are presented. Then, the hypothesis according to which the impact of digital technology is beyond GDP is developed.

1.3.1 The Solow Paradox

The digital transition does not, for the moment, have the characteristics of an industrial revolution. It is a first explanation of the Paradox of Solow (1987), according to which *"you*

[7] See Ozturk (2010) for a literature review on the debate on the link between energy and growth.

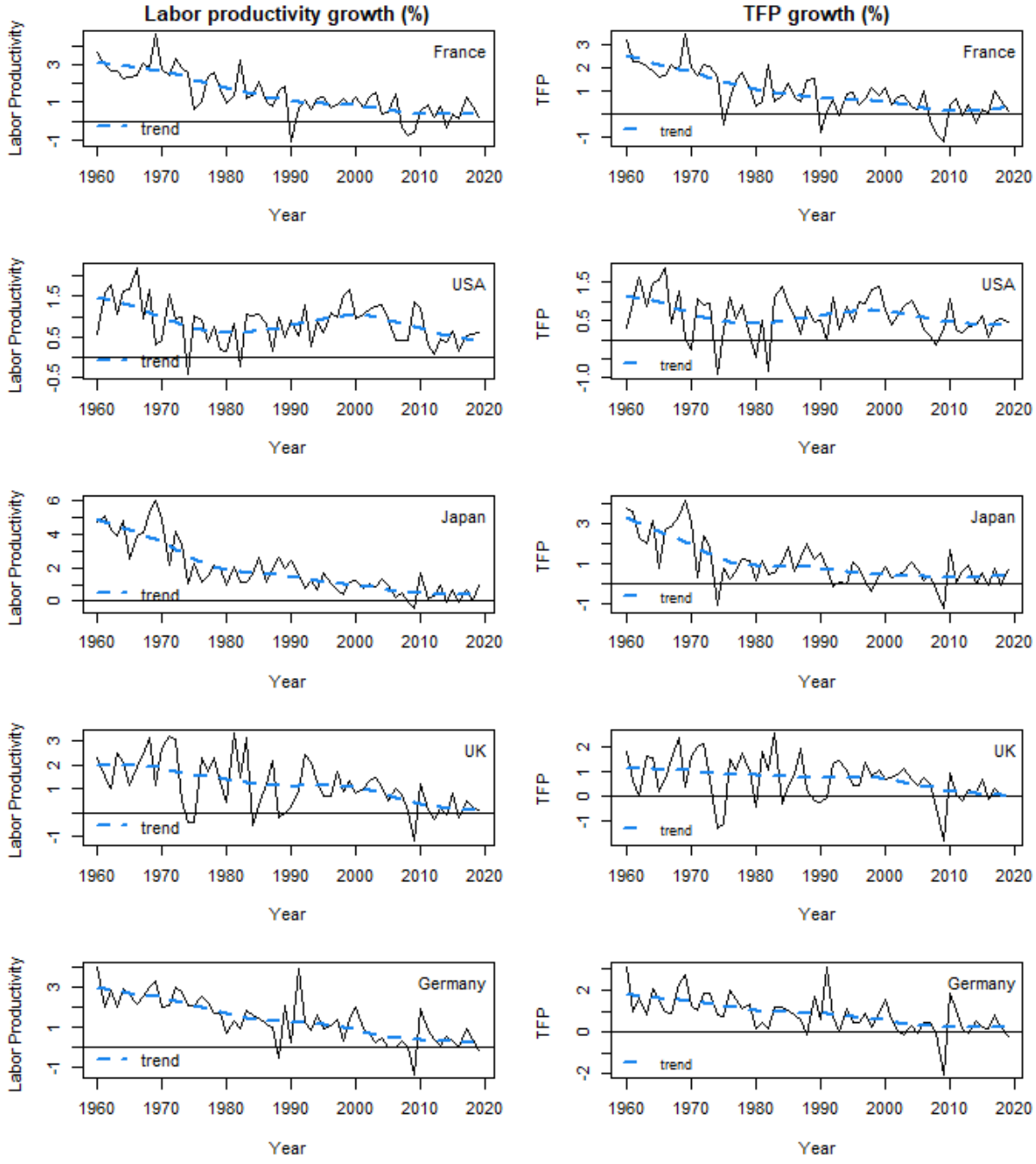
can see the computer age everywhere except in productivity statistics." Indeed, since the first oil shock of the 1970s, the growth of labor productivity and total factor productivity (TFP) in developed countries has been characterized by a downward trend (see Figure 1.5). This decline in productivity was more pronounced in the countries most affected by the Second World War, such as France, Germany, and Japan, which had significantly benefited from the *Trente Glorieuses*. Thanks to this period of full employment and reconstruction, the growth rate of labor productivity in France and Germany reached 3% in 1960 and 5% in Japan. TFP growth in these countries was also higher than in many developed countries. It was about 2% in France and Germany and over 3% in Japan in 1960.

We can also observe in Figure 1.5 that the United States was the only country that benefited from significant productivity gains from ICT in the 1980s and 1990s (Bergeaud *et al.*, 2016). Note that Japan did not benefit from these productivity gains even though it is one of the most advanced countries in its digital transition, both in terms of usage and innovation (see the previous section and Figure 1.4). At the end of the 1990s, hopes of reversing the downward trend resurfaced following the rapid spread of the internet and digital tools among economic actors. However, this hope was quickly undermined by the internet bubble bursting in the early 2000s; productivity growth rates have declined again. Finally, since the economic and financial crisis in 2008, the trend in productivity growth rates has stagnated at a low level. How can we explain Solow's paradox?

The stagnation hypothesis

Several economists attribute the low GDP growth rates to weak innovation rates. Gordon (2012) argues that the productivity improvements brought by digital technology would be insufficient to compensate for the decline in potential growth, especially in developed countries characterized by demographic aging. We would be in a situation of secular stagnation; the strong economic growth experienced by countries after the industrial revolutions was exceptional. Cowen (2011) even considers that we have reached a technological plateau where

Figure 1.5: GDP per capita growth in France, USA, Japan, UK, and Germany between 1960 and 2019.



Source: Data are from Bergeaud *et al.* (2016). Trends are estimated using a Hodrick-Prescott filter with $\lambda = 500$ as in Bergeaud *et al.* (2016).

innovation is increasingly rare. This conclusion seems consistent with Bloom *et al.* (2020) results. They study the idea production function at a micro-level to directly observe what happens to research productivity and, thus, to technical progress. They note that while the research effort, i.e., the number of researchers and investment in R&D, has increased, *"ideas, and the exponential growth they imply, are getting harder to find."*

The work of Fourastié (1949) tackles the stagnation hypothesis from another angle. It is not innovation that is scarce, but rather productivity gains in services that are low relative to those in the industry. Because of productivity differences between sectors and the saturation of demand for agricultural and manufactured goods, the share of the population working in services will increase in the long term. Since lower productivity gains characterize services, this translates into lower productivity gains in the economy and, consequently, the stagnation of economic growth. The dynamic general equilibrium model of Gray *et al.* (2018) offers a theoretical formalization that explains the structural and long-term growth trend change by taking up Fourastié's assumptions.

Nevertheless, not all economists are as categorical about the future impact of digital and have different explanations about the Solow paradox. The digital transition may not be an industrial revolution, but that does not mean that the technologies that result from it cannot impact productivity and economic growth.

The transition phase

A second explanation for Solow's paradox is that we are in a transition phase between the invention of digital technologies and their full effectiveness as innovations, as for the dynamo-electric. Indeed, David (1990) has highlighted a 50 to 60-year gap between the invention of the operational dynamo-electric in 1868 and its fully effective use in the 1920s and 1930s. This transition phase is common to all general-purpose technologies (Bresnahan & Trajtenbergb, 1995). Jovanovic & Rousseau (2005) point out that the deployment of a general-purpose technology is followed by a slowdown in productivity, which corresponds to a period of adap-

tation and learning and a phenomenon of creative destruction in many sectors following the diffusion of innovations. Helpman & Trajtenberg (1998) explain the slowdown in economic growth to the high cost of the factors of production necessary for developing and producing new general-purpose technology. These technologies become profitable when the accumulation of these factors is large enough.

However, although the digital transition is not yet complete, it started more than 70 years ago and is already well-advanced in developed countries, raising doubts about the relevance of this hypothesis. Empirical studies show that the gap between innovations and their impacts on the real economy is shorter with the main technologies of the digital transition. Brynjolfsson & Hitt (2003) estimate that an investment in IT takes 5 to 7 years before generating productivity gains, and Basu & Fernald (2007) point to a lag of 5 to 15 years in the US industry between the growth of ICT capital and the acceleration of TFP. This lag only concerns the United States, the only country whose economic growth has significantly benefited from the digital transition. This phenomenon can also be explained by the fact that the introduction of new technologies into the production process of firms must be accompanied by organizational changes, which take time. This adaptation phase for firms can be facilitated by good people management practices (Bloom *et al.*, 2012). Unlike European firms, American firms would have benefited from better productivity gains from digital technology thanks to better management and organization of their activities.

The technological biases

Well-documented in the economic literature, innovation is one of the main drivers of economic growth (Solow, 1957). However, depending on who benefits from technical progress, it can indirectly harm economic growth. One explanation of Solow's paradox is that digital innovations tend to increase wealth inequality, which would tend to slow down economic growth by increasing the average propensity to save (Summers, 2014).[8] Aghion *et al.* (2019a)

[8]Note that the direction and sign of causality between inequality and growth are still debated in the literature (see Voitchovsky (2009) for a literature review of the debate).

analyze the correlation between patents and income inequality. They conclude that the increase in inequality among the top 1% of incomes is partly due to innovation. Brynjolfsson & McAfee (2014) highlight two technological biases through which digital innovation would impact inequality: a technological bias toward skilled workers and capital.

Firstly, skilled workers use digital technologies more, increasing their productivity and, consequently, their wages. It also tends to increase the demand for skilled workers at the expense of unskilled workers (Goldin & Katz, 1998). The technological bias in favor of skilled workers is thus partly responsible for increased income inequality since the 1980s (Caselli, 1999). Acemoglu (2002) argues that technological change in inequality has been amplified by organizational and institutional changes such as de-unionization and an increase in international trade with less developed countries. These factors have lowered the wages of low-skilled workers, which was not observed in the first two industrial revolutions. On the contrary, as illustrated by the Luddite movement in England or the Canuts revolt in France in the first half of the 19th century, skilled workers feared losing their jobs to unskilled workers using weaving machines.

Secondly, digital technology creates a bias toward capital; some technologies substitute for labor rather than complement it. In this case, workers are simply replaced by machines. This phenomenon is not new; the automation of tasks is standard. However, with digitalization, even skilled workers can be replaced by technology (Autor *et al.*, 2003). While the share of GDP attributed to labor has remained stable for decades, as outlined in the stylized facts of Kaldor (1957), Karabarbounis & Neiman (2014) show that it has tended to decrease since the 1980s. Consequently, the remuneration of capital owners tends to increase at the expense of workers, skilled or not. Nevertheless, the recent work of Gutiérrez & Piton (2020) questions the decline in labor share in favor of capital in production, especially since the arrival of ICT. This phenomenon would only have been temporary.

Thus, the wealth inequalities caused by these two technological biases would hinder the impact of digital technology on economic growth. We can also ask ourselves why the United

States, one of the most unequal countries in wealth among developed countries, was the only one whose growth rate benefited from digital technology.

The inflation bias

A more recent explanation of Solow's paradox is that inflation is mismeasured. Indeed, the rapid pace of digital innovations creates another challenge: distinguishing whether a price change is due to inflation or a change in quality (Boskin *et al.*, 1996). Suppose a price increase is attributed to inflation while it is due to a quality improvement. In that case, this leads to overestimating inflation and, thus, underestimating real GDP.

Matched model methods are generally used to construct inflation measures such as the Consumer Price Index. In these methods, the prices of representative items collected periodically are selected. Then, the prices of items with the same characteristics are compared over time. However, sectors, where innovations are rapid, are characterized by fast improvements in product characteristics and products that quickly become obsolete. In the first case, matching methods do not always capture the change in quality because the improved items are considered to have the same characteristics as the previous ones. The change in quality is, therefore, considered a price increase. In the second case, items that become obsolete are simply removed from the sample. Therefore, the significant price decline in obsolete products is not included in the price indices, creating an upward bias in the inflation measures.

This price overestimation is observed with digital technologies, such as communication equipment, computer software, computers, peripheral equipment, and microprocessors (Byrne & Corrado, 2017; Byrne *et al.*, 2015). In these studies, hedonic pricing methods are used to correct the bias in price measures. This method captures quality change better than matched model methods (Aizcorbe & Pho, 2005), regardless of whether the bias is due to item exit or unmeasured characteristics (Erickson & Pakes, 2011).

By correcting for the bias in digital prices, studies show that inflation is indeed overesti-

mated in the United States (Broda & Weinstein, 2010) and most OECD countries (Ahmad *et al.*, 2017; Reinsdorf & Schreyer, 2019). Nevertheless, according to Byrne *et al.* (2016), this measurement problem is not new and was observed even before the internet bubble of the 2000s and, thus, before the productivity slowdown. Moreover, although the productivity slowdown has been pronounced in IT-producing industries and in those industries that use IT the most (Fernald, 2014), there is no link between the slowing of economic growth and the importance of ICT in a country (Cardarelli & Lusinyan, 2015; Syverson, 2017). Therefore, the productivity slowdown cannot result from underestimating the value of real GDP due to a poor accounting of digital assets. Looking at the economy as a whole, Aghion *et al.* (2019b) find a more significant bias in the inflation measure. According to the authors, there is significant *"missing growth"*. However, this missing growth is concentrated in the hotel, restaurant, and retail sectors and accelerates only modestly after 2005. The inflation bias hypothesis also fails to resolve Solow's Paradox.

Reinsdorf & Schreyer (2019) also point out the difficulty of considering the many free digital services that, in addition to having a zero price, are non-rival and can therefore be consumed by an unlimited number of consumers. This applies not only to inflation but also to wealth creation. A recent hypothesis trying to explain Solow's paradox has emerged from the literature: digital technology would not impact economic growth but beyond because current indicators are not constructed to measure certain developments linked to digital technology.

1.3.2 Digital, an impact beyond GDP?

GDP and well-being

A recurrent criticism of the use of GDP is that it is wrongly used as a proxy for the well-being of a population, while its creator himself stated that *"the welfare of a nation can scarcely be inferred from a measure of national income"* (Kuznets, 1934). Welfare is indeed positively correlated with GDP. However, as the report of Stiglitz *et al.* (2009) points out,

it depends on factors other than production, such as health, inequality, leisure, education, and environmental quality, which are not taken into account in the measurement of national income.

In addition, the calculation of GDP excludes much non-market production, such as home production. It can pose a problem for comparisons between and within countries over time. For example, due to the decline in the number of housewives, households have hired more housekeepers or caretakers, services previously performed free of charge by the wife. As a result, women's entry into the labor market has, in part, *"artificially"* increased GDP, posing a problem of comparison (Folbre & Nelson, 2000). Therefore, Stiglitz *et al.* (2009) recommend looking *"beyond GDP"*, considering domestic and non-market production, focusing on the measurement of consumption rather than production, and improving welfare indicators.

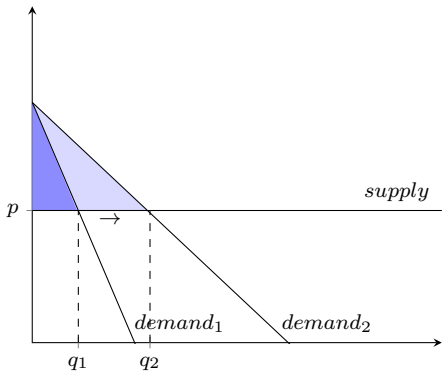
Fleurbaey & Gaulier (2009) and Jones & Klenow (2016) propose measures of well-being alternatives to GDP, including leisure, mortality, and inequality in a country. Fleurbaey & Gaulier (2009) use consumption, as recommended by Stiglitz *et al.* (2009), while Jones & Klenow (2016) consider income. Their main findings are that GDP per capita is correlated with individual welfare but that income inequalities across countries differ from welfare inequalities. For example, Jones & Klenow (2016) conclude that living standards in Western European countries are much closer to those in the United States when their welfare indicator is considered rather than GDP per capita, but also that welfare growth is generally higher than GDP growth in developed countries.

Therefore, using GDP as the only indicator does not provide a good measure of the population's well-being in developed countries. Nevertheless, beyond these problems, GDP, in what it seeks to measure, faces new difficulties in measuring wealth creation with the arrival of digital technology.

Digital technology is changing the production frontier

With the development of the digital transition, the difficulties of measuring wealth creation are increasing. Digital technology has created many free services for consumers, making it difficult to measure their wealth creation. Increasing the consumption of a traditional good increases GDP and consumer surplus (see Figure 1.6). On the other hand, an increase in the consumption of these new digital services has no impact on production because the national accounts do not consider them because they are free. However, it would still increase consumer surplus (see Figure 1.7). Finally, there is sometimes a paid equivalent to the free digital service. If the two services are perfectly substitutable, consumers prefer the free version. This substitutability will hurt GDP, although consumer surplus increases (see Figure 1.8). It can be illustrated by the decline in GDP revenues of the music, road maps, and newspaper sectors, while the consumption of these goods has not decreased or even increased due to music streaming, GPS, and subscription-free online press (Bean, 2016).

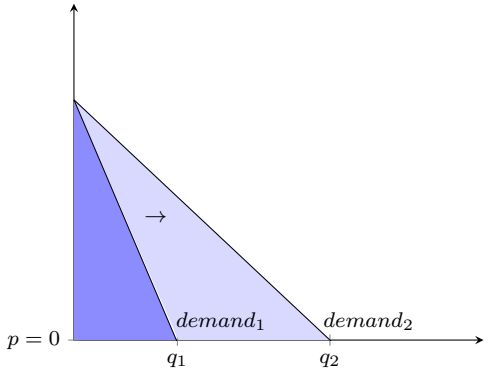
Figure 1.6: Consumer surplus and revenue for classic goods



Source: Brynjolfsson *et al.* (2017). Increasing the demand for "classic goods" will increase the quantity produced, GDP, and consumer surplus.

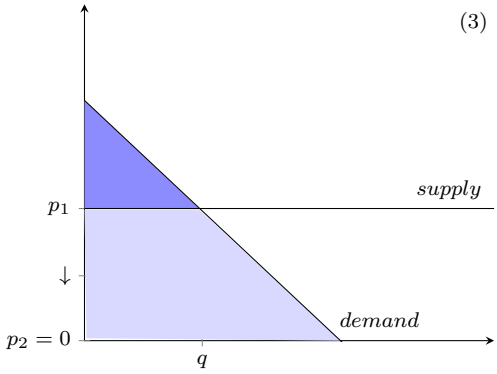
Digital also increases domestic production by eliminating some intermediaries by creating platforms easily accessible to consumers. For example, households can now simply and freely

Figure 1.7: Consumer surplus and revenue for purely digital goods



Source: Brynjolfsson *et al.* (2017). A purely "digital good" is a good resulting from digital technology whose price is zero. Hence, increasing digital goods demand will only increase consumer surplus without impacting GDP.

Figure 1.8: Consumer surplus and revenue for transition goods



Source: Brynjolfsson *et al.* (2017). A "transition good" is a digital good whose price is zero but for which there is a "classical good" equivalent whose price is different from zero (e.g., encyclopedias). The introduction of these goods on the market decreases GDP but increases consumer surplus.

organize a trip online without going through a travel agency. This domestic production is not accounted for in GDP and can even hurt if it replaces market activities. It is the opposite effect of what was observed when women entered the labor market; services previously provided by a firm are now transformed into domestic production.

Moreover, digital has considerably developed the collaborative economy, defined as a temporary or permanent exchange of goods, services, and knowledge between individuals, whether paid or not. These exchanges between individuals are not new but have been amplified by digital platforms connecting people who own a specific underused good with those who need it easily and for little or no cost. However, the sale of second-hand goods is often considered bartering. Therefore, it is not included in GDP under certain conditions (Blanchet *et al.*, 2018).[9] Moreover, as in the case of free digital services, the collaborative economy is likely to undermine the wealth creation of *"traditional"* economy, which can harm GDP. For example, Airbnb's activities reduce the revenues of the hotel market. An estimate in the Austin area values this loss at 8-10% (Zervas *et al.*, 2017). Nevertheless, these peer exchanges positively impact social welfare (Benjaafar *et al.*, 2019). Individuals can benefit from time savings, access to cheaper goods, and additional income. Some even engage in these exchanges for social or environmental benefits.[10]

Therefore, the development of digital technology tends to increase the decorrelation between GDP and well-being; this is one of the possible explanations for Solow's paradox. Based on a theoretical model, Hulten & Nakamura (2017, 2019) show how digital technology increases the difference between GDP and welfare. Based on Lancaster (1966) model, according to which consumer utility depends not only on the product consumed but also on its use and the domestic time allocated to its production and use, the authors include in an Expanded Gross Domestic Product (EGDP) two forms of technical progress: resource-saving

[9]For example, in France, individuals do not have to declare their sales of second-hand items when the revenue generated is less than 3,000 euros per year, or they have made fewer than 20 transactions.

[10]Some see the collaborative economy as an alternative to mass consumption and *"better"* for the environment. Indeed, by exchanging (renting or selling) goods between individuals, production should decrease, limiting the degradation of environmental quality. However, this impact appears to be small or even negligible at present (ADEME *et al.*, 2016).

and output-saving. The first is classical technical progress included in the production function, allowing the production of as many goods with fewer inputs. The second is technological progress included in the utility function, allowing the production of as much welfare with fewer goods and services. By summing up the traditional GDP and the *"compensatory/equivalent change due to the technical change allowing to reduce production"*, the authors obtain the EGDP. An increase in output-saving can thus significantly impact the EGDP but not the GDP.

How to estimate the utility created by digital technology?

Several empirical studies attempt to estimate the utility generated by digital technology. The first approach is based on production costs and uses the non-monetary valuation method on which non-market services are based. Lambrecht *et al.* (2014) distinguish three forms of financing digital goods: (i) users pay a subscription fee, (ii) firms collect and sell consumer data, and (iii) advertising. The first is obviously included in GDP. The following two are considered intermediate consumption and are not directly included in GDP. Nakamura & Soloveichik (2015) consider that the value of free media (e.g., newspaper, television) financed by advertising can be estimated with the cost of advertising as if advertisers paid consumers to use the free media. However, although these estimates increase consumption and real economic activity, the impact on real GDP growth is small (only 0.019% per year in the US). A similar methodology can be used when products are funded via the sale of personal data. Ahmad *et al.* (2017) estimate that online users' maximum value of data left was about 8.1 billion in 2016. They conclude that it can only increase GDP growth by 0.02%

The cost-of-production estimation is limited: only the supply side is considered. Consequently, this estimate is not a measure of welfare but of the cost of provision. This is a frequent criticism of public service measures. Byrne & Corrado (2019) highlight that the use of internet content has drastically increased but not the cost of access. They then estimate these free digital contents by the intensity of the use and quality of computer capital by

households. They find that these innovations contributed to the United States' real GDP growth by 0.5 percentage points between 2007 and 2017 and increased consumer surplus by nearly $1800 per connected user per year between 1987 and 2017.

An alternative approach is quantifying the welfare gains from using the internet and free digital services using data on online time. Indeed, it is more interesting to consider time rather than the cost of production because the quality of consumption of a digital service does not depend on the cost of access. In general, only an internet subscription is required for unlimited access. Goolsbee & Klenow (2006) estimate the median consumer earnings from spending time online in the US in 2005 to be about $3,000. Brynjolfsson & Oh (2012) estimate that free internet services create a consumer surplus of $100 billion per year in the US between 2007 and 2011.

More recently, Brynjolfsson *et al.* (2019) and Coyle & Nguyen (2020) proposed a method to estimate the welfare generated by different types of goods through a series of choice experiments. They estimate consumer surplus by asking thousands of individuals to choose between using a good or not being able to use it for a certain period in exchange for monetary compensation. They show that consumer surplus for traditional goods is generally the same as the income they generate. In contrast, digital goods tend to be more valuable to consumers even though they do not impact national accounts.

The literature on estimating the value of free digital services is growing. Studies on the impact of peer-to-peer exchanges are rare. In general, papers are limited to theoretical microeconomics, such as studying the impact of a peer-to-peer rental market on the consumer decision (Benjaafar *et al.*, 2019), on the producing firm (Jiang & Tian, 2018), and the competitive firm (Einav *et al.*, 2016), or the impact of the peer-to-peer second-hand market (Feng *et al.*, 2019). Some studies also attempt to measure the size of the collaborative economy (Goudin, 2016; Vaughan & Daverio, 2016). All these estimates are limited to monetary transactions. Coyle (2016) points out that while the impact is probably small today, the rapid growth of the collaborative economy makes it a significant issue in the near future.

1.4 Conclusion

Solow's paradox dates back to 1987 but is still relevant today. Indeed, 30 years after the diffusion of digital technologies to the general public, they are still not reflected in productivity data. This chapter focuses on the main characteristics of the digital transition and its effects on the economy. After providing an overview of the digital transition, a first contribution was to situate it in the history and typology of industrial revolutions. We conclude that it does not have, at least for the moment, the fundamental characteristics of an industrial revolution (no energy discovery, no significant impact on industry). We then present the different barriers that can hinder the impact of digital technologies on economic growth (stagnation hypothesis, transition phase, technology, and inflation bias). However, these proposals alone do not resolve Solow's paradox.

The absence of observable effects on macroeconomic aggregates does not mean that digital technology has no economic effect. The final contribution of this chapter is to highlight the impacts of digital technology *beyond* GDP. Indeed, national accounting does not consider some of the activities created by digital technology, such as the many free services and the collaborative economy that tend to replace traditional services. However, these activities benefit households. From a macroeconomic point of view, digital technology's observable effects are weak, but there are many benefits that our current measurement tools do not observe. If industrial revolutions fundamentally changed how we produce, the digital transition changed how we consume.

The following chapter builds on this observation and focuses on free digital services. It proposes a theoretical growth model including the free digital services financed by advertising and its interactions with the traditional sector and households. The aim is to understand the link between the free digital services sector, macroeconomic aggregates, and welfare.

Chapter 2

The Macroeconomy of the Free Digital Services [1]

[1] This chapter is a joint work with Lionel Ragot (EconomiX-CNRS, University of Paris Nanterre and CEPII).

2.1 Introduction

In recent years, many free digital services have emerged and are expanded (see Figures 2.1 and 2.2). Google and Facebook are two examples, along with many other websites and applications. These services are not only growing in number but also in use. For instance, the number of monthly active Facebook users has grown from 100 million in 2008 to 3,030 million in 2023, and the average time spent on social media by internet users has increased from 90 minutes per day in 2012 to 153 minutes in 2023.[2] These services have no monetary cost to the consumer but require time and attention. To be financed, free digital service providers collect users' personal data in exchange for usage and then analyze the collected information to sell targeted advertising services (Zuboff, 2020). This business model enables them to generate significant revenue, particularly for the most popular platforms, as digital has considerably reduced the cost of targeting (Goldfarb, 2014).

Figure 2.1: Number of available apps in Google Play and the Apple App Store from 2008 to 2022

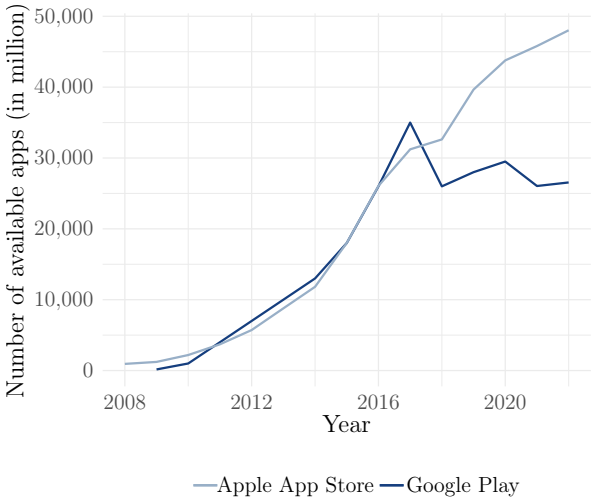
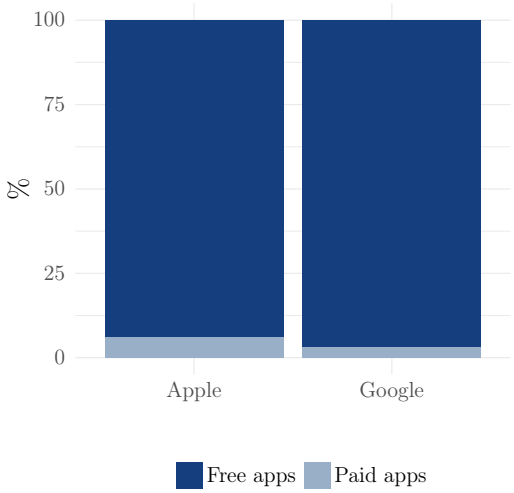


Figure 2.2: Share of free and paid apps in Google Play and Apple App Store in 2022



Source: Statista

The impact of the free digital services sector on macroeconomic aggregates is ambiguous.

[2]Data are from Statista and were downloaded on 20 August 2023 on the following webpages: https://www.statista.com/statistics/264810/number-of-monthly-active-facebook-users-worldwide/ and https://www.statista.com/statistics/433871/daily-social-media-usage-worldwide/.

The consumption of free digital services is not considered as final consumption of households in the national accounting system, as their price is zero. However, they can be a substitute for traditional services and harm the Gross Domestic Product (GDP). Advertising revenue is considered intermediate consumption and, therefore, deducted from a country's value-added calculation. The impact on real GDP will depend on how they are incorporated into the final goods price. Blanchet *et al.* (2018) point out that if the advertising price is finally charged to the consumer, the impact of this new activity on economic growth is limited. Moreover, despite the significant increase in digital advertising spending, advertising represents a constant share of GDP (Greenwood *et al.*, 2021) because digital advertising substitutes for traditional advertising (Goldfarb & Tucker, 2011; Seamans & Zhu, 2014). Nevertheless, Brynjolfsson *et al.* (2018) show evidence that even if free digital services do not contribute substantially to GDP, consumers benefit from them.[3] As a consequence, they can increase welfare without impacting economic growth (Hulten & Nakamura, 2017, 2019).

Building on these facts, this chapter aims to study the long-term impact of free digital services financed by advertising on the macroeconomy and welfare. To this aim, we develop an endogenous growth model without scale effects *à la* Young (1998). It includes the free digital services sector and its interactions with the traditional sector and households. The traditional sector comprises firms in monopolistic competition selling differentiated varieties of goods to households as in Dixit & Stiglitz (1977). Following Grossmann (2008), traditional firms must invest both in research & development (R&D) and advertising to improve the perceived quality of their goods. We stand out by considering that advertising is outsourced and sold by the digital sector. The latter is a mixed market that comprises a fixed number of large digital service providers and a continuum of small providers (Shimomura & Thisse, 2012). They propose differentiated digital services to households in exchange for personal data. Each digital service provider uses the collected information and the attention of its users (the time they spend on the digital service) to supply targeted impressions to the traditional sector. Finally, households derive utility from consuming different varieties of

[3]The reader may refer to the previous chapter to see how the surplus brought by free digital services is measured in the literature.

goods and spending time on digital services. They also face positive and negative impacts from the data collection.[4] As data are non-rivals (Jones & Tonetti, 2020), digital services providers use them to personalize their service for each household. On the other hand, data collection raises privacy issues that harm households' utility. Consequently, users have to choose the quantity of data they accept to disclose to the digital service providers.

The purpose of the model is twofold. First, it contributes to understanding the link between the free digital services sector, macroeconomic aggregates, and welfare. Second, it enables an analysis of the economic implications of free digital services. To this aim, we derive comparative-static to highlight (i) the importance of data and time in impressions production, (ii) the role of the advantage of large digital service providers over small ones, (iii) the impact of the entry of a new large provider, and (iv) the implications of households privacy sensitivity. The model is consistent with some empirical trends experienced in developed countries, such as the increase in digital leisure time (Wallsten, 2013; Aguiar *et al.*, 2020), the decrease in worked hours (Vandenbroucke, 2009; Kopytov *et al.*, 2023), and the slowdown of productivity (Cette *et al.*, 2016). We also capture that welfare growth has been higher than income growth since the 1980s, as highlighted by Jones & Klenow (2016).

Our results highlight that the free digital services sector impacts households' intertemporal utility and has several macroeconomic consequences. Moreover, we emphasize the implications of the imperfect competition in the digital sector, composed of a few large providers of digital services and a continuum of small providers. Large providers have a quality advantage over small ones, leading to strong household preferences for these services. These preferences, which can be due to the true quality of the service as well as lock-in, popularity, or habits effects, imply that large providers positively impact the economy and welfare. We find that improving their production or the entry of new large providers increases individual wealth, stimulating the demand for final goods. However, only the number of varieties of goods increases, not the effort of R&D and, therefore, economic growth. Small providers

[4]Users can also experience security problems, misinformation, addiction, and others from using digital services (OECD, 2019). This chapter only considers privacy issues as the negative impact of digital technology. Digital inequalities and environmental impacts are tackled in the two following chapters.

have a limited impact on the economy and, in some cases, have a negative impact. It is a specificity of the mixed market (Shimomura & Thisse, 2012). We also highlight that the importance of users' data and attention in advertising production has economic implications, particularly for small providers. Indeed, if attention is an important production factor in impression production, small providers are harmed by the high competition with large providers. Data collection provides an opportunity for small providers to compensate for the households' preferences of spending time on the services of large providers.

The remainder of this chapter is structured as follows. Section 2.2 provides a literature review, and Section 2.3 describes the free digital services market. Section 2.4 presents the model. Equilibrium is presented in section 2.5. In section 2.6, we derive comparative statistics to study the impacts of the free digital sector on the main macroeconomic variables. Section 2.7 concludes.

2.2 Related literature

This chapter is related to the theoretical literature on the macroeconomic impacts of digital technology. More specifically, this chapter is part of the recent literature on data economy. The use of data in the production process is not new. However, digital technology has significantly reduced the cost of collecting and storing data, increasing their use (Goldfarb, 2014). In a growth model, Farboodi & Veldkamp (2022) highlight that data and new prediction algorithms improve the quality of goods and increase economic growth. However, in the long run, data accumulation is similar to capital accumulation in the model of Solow (1956) and cannot sustain economic growth. Jones & Tonetti (2020) emphasize the non-rival nature of the data. In their growth model *à la* Romer (1990), data, which are a by-product of consumption, improve the quality of ideas in the production function and can be sold and used by other firms. They study three cases: (i) firms own data, (ii) consumers own their data and can sell them, and (iii) the government outlaws the selling of data. They highlight that

data regulation can have significant economic implications and that enabling consumers to sell their data leads to the optimal situation regarding privacy, output, and consumer welfare. In the same line, Arrieta-Ibarra *et al.* (2018) propose considering data as labor, not capital. They argue that digital firms should pay consumers for their data. Cong *et al.* (2021) enable consumers to sell their data to firms depending on their privacy concerns. As in Jones & Tonetti (2020), the non-rivalry of data is horizontal (they are only used in the R&D sector, not in the final goods sector). They find that data use results in an over-accumulation of data and under-employment, leading to sustainable economic growth with lower welfare. In addition to horizontal non-rivalry, Cong *et al.* (2022) enable data to be used across sectors. They find different results: data are under-used because of privacy concerns. They also highlight that data is more efficient in innovation than in the production sector.

Most articles on the data economy consider privacy sensitivity, which is modeled as a disutility resulting from disclosing personal data. In the present chapter, data is a by-product of the consumption of free digital services. Only digital service providers collect and use data. We consider the horizontal non-rivalry nature of data: digital services and advertising are personalized according to individual data. Households also have a sensitivity for privacy. By making a trade-off between data collection's positive and negative impacts, they must choose how much data they disclose to digital services providers.

This chapter is also related to the theoretical literature on the link between advertising, innovation, and economic growth. The paper of Grossmann (2008), on which we build our approach, is the first to consider the interaction between advertising and R&D in a growth model. He follows Young (1998)'s theoretical framework, which enables qualitative growth and the absence of scale effects in the growth process. In the model, advertising modifies the perceived quality of the selling good and is combative in the sense that *"an increase in marketing expenditure of a single firm creates a negative externality on demand faced by other firms."* In contrast, R&D investment improves the true quality of the goods and provides a positive externality in the research activity. However, the advertising sector is not included. Firms in the final goods sector realize advertising activity. We stand out by

modeling digital service providers and studying their impacts on welfare and their role in advertising activity. Further research extends the literature by focusing on the role of firm size (Cavenaile & Roldan-Blanco, 2021), market concentration and markups (Cavenaile *et al.*, 2022), and informative advertising (Klein & Şener, 2022). These papers find that advertising and innovation are substitutes, which can depress economic growth.

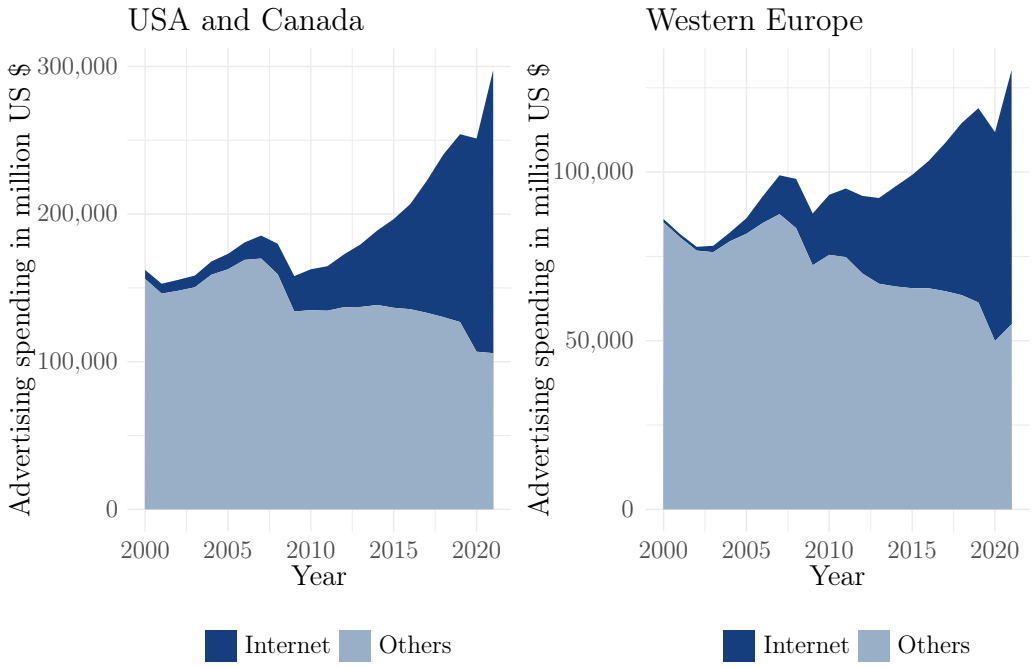
Few papers model digital advertising in a macroeconomic framework. Greenwood *et al.* (2021) model the interaction between traditional and digital advertising. Digital advertising has the advantage of targeting consumers. As in our model, consumers are exposed to advertising by spending time on free media-leisure goods. The authors focus on the impact on welfare and price competition, arguing that GDP is not a good measure of free media goods. Rachel (2021) also models free digital leisure in a growth model. He is interested in the impacts on productivity and seeks to explain the decline in hours worked due to the emergence of the attention economy. In the two papers, consumers do not reveal personal information through free digital services usage. Therefore, there are no privacy and data aspects. We stand out from the literature by considering digital advertising, which depends on users' data and attention, and privacy issues in an endogenous growth model.

2.3 The free digital services market

Firms in the free digital services market, also called the attention market, act like two-sided platforms (Rochet & Tirole, 2003; Armstrong, 2006). On the first side, they offer free digital services to consumers, enabling them to collect various data on their behavior. The users can directly provide this information by filling in a subscription form on the service. It can also be collected indirectly by creating cookies that follow the user's online path inside and outside the website. Digital service providers use this information to build a profile of their users based on their demographic characteristics and online behavior. The non-rivalry nature of the data enables the platforms to improve and personalize the digital service as well as

to produce and sell targeted advertising to the second side: traditional firms. These digital firms benefit from important economies of scale due to their characteristics. Firstly, the marginal cost of digital services is nearly zero as the production cost is mainly fixed (Shapiro & Varian, 1998). Moreover, they benefit from significant network effects on the same side (user's utility increases with the number of users) and between the two sides of the market. The more users and usages a digital platform has, the more personal data it obtains and the more it can improve its advertising service. Increasing usage also increases users' exposure to advertising. Therefore, digital firms are incentivized to attract as many users as possible for as long as possible by investing in the quality of their service. Online advertising is also attractive to traditional firms because the cost of targeting is reduced compared to offline advertising, as digital facilitates the collection and storage of data (Goldfarb, 2014). This is illustrated by the increase in internet advertising spending in the United States, Canada, and Western Europe, to the detriment of traditional advertising (see Figure 2.3).

Figure 2.3: Advertising spending in the United States, Canada, and Western Europe between 2000 and 2021



Source: Statista.

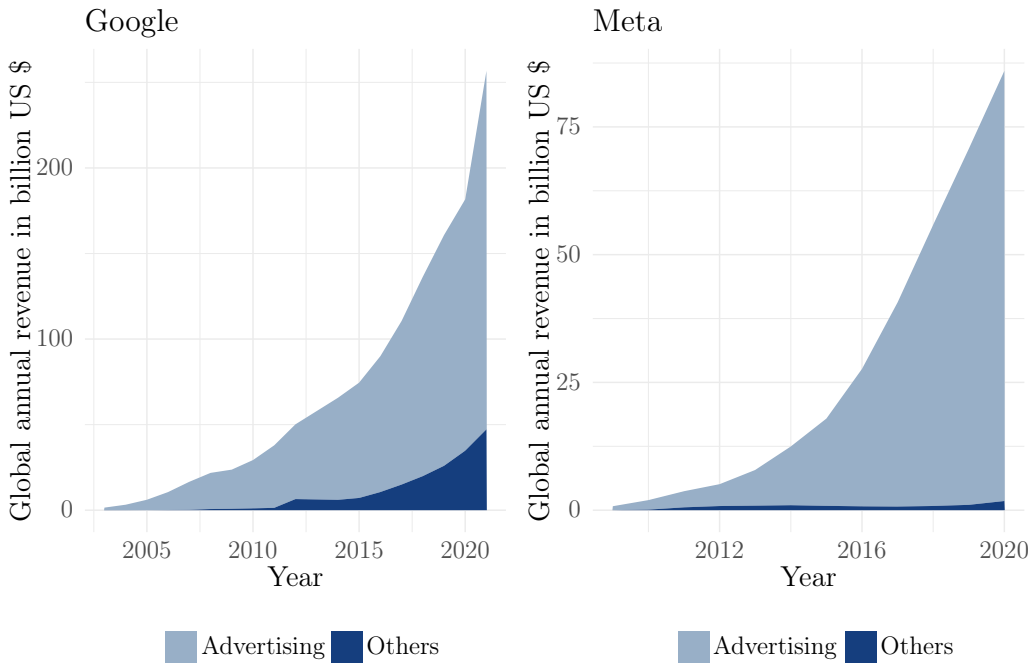
Large returns to scale, which benefited digital firms, foster dominant positions. Consequently, few firms mainly dominated the market. Among the large providers of digital services, the most well-known and meaningful ones are Google and Facebook. The two firms do not offer the same free digital service. Google had a 91% share of the search engine market and Facebook 70% of the social media market in 2020 (Bourreau & Perrot, 2020). However, they shared half of the online advertising market share (30% for Google and 22% for Facebook). Their advertising revenues, which represent their primary revenue source, are growing exponentially and have reached $209.49 billion for Google in 2021 and $84.169 billion for Facebook in 2020 (see Figure 2.4). A continuum of websites and applications shares the rest of the market. Note that Amazon is the third largest online advertising supplier (it represents 9% of the market share) but is not included in the free digital services market as its main activity is e-commerce.[5] In addition to being the most visited platforms, the two firms have acquired several platforms, some very popular today, such as YouTube for Google and Instagram for Facebook. It has enabled them to consolidate their position in various digital sectors and accumulate a significant amount of data and attention, creating barriers to entry. Nevertheless, despite the important revenues earned by some free digital service providers, there has been little research (theoretical and empirical) on the macroeconomy impact of the free digital services sector.[6]

Moreover, the issue of regulating digital platforms is often debated, particularly concerning preventing anti-competitive practices and abuses of dominant positions. Other practices of online platforms are also questioned. For instance, the ability to easily collect personal information creates privacy issues. Users have to make a trade-off between protecting and disclosing personal information (Acquisti *et al.*, 2016). Nevertheless, Acquisti *et al.* (2020) pointed out that if users care about privacy, they face psychological and economic barriers. To address this problem, the European Union adopted in 2016 and implemented in 2018 the General Data Protection Regulation (GDPR), Regulation (EU) 2016/679, to protect users'

[5]This point can be discussed as Amazon is sometimes used as a search engine for goods. However, this paper focuses on pure-player firms, i.e., firms that only sell advertising.

[6]As an example, Google's advertising revenues are equivalent to Iraq's GDP in 2021, according to the World Bank data.

Figure 2.4: Revenue of Google between 2003 and 2021 and Meta (formerly Facebook Inc.) between 2009 and 2020

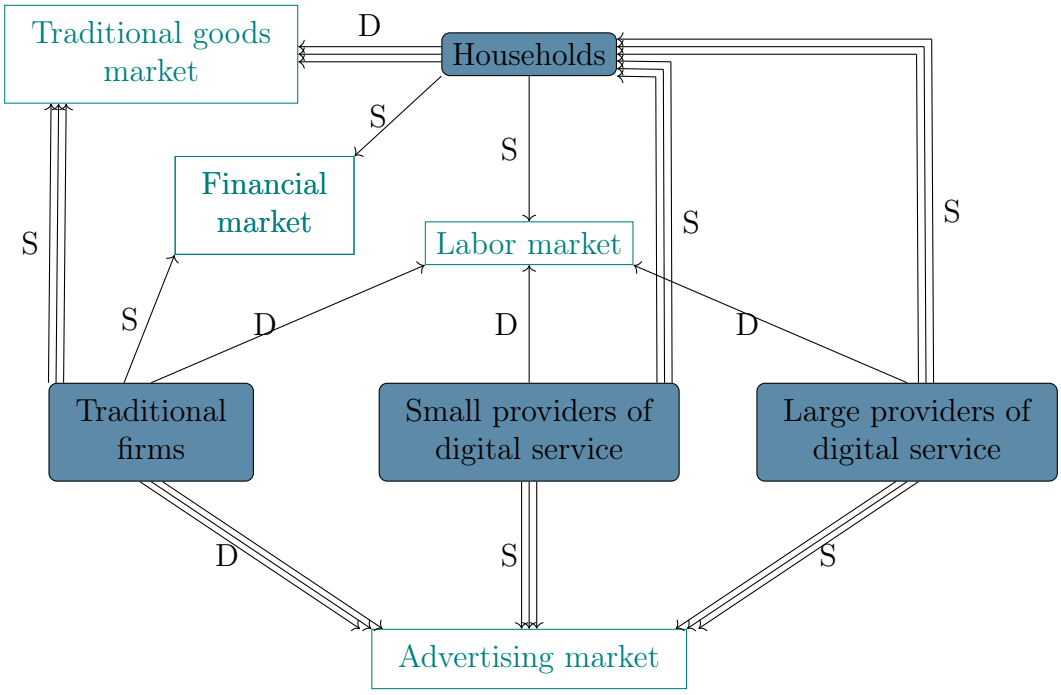


Source: Statista.

privacy. This legislation gives users greater control over the information they leave online. It gives the right to access and delete their data and requires platforms to obtain explicit consent before collecting data. On the other hand, making it more challenging to collect data, the main production factor of free digital service providers, can have economic implications. It is, therefore, important to consider users' behavior concerning their choice to disclose their data.[7]

[7]The first empirical studies highlight a decrease in the traffic of websites (Goldberg *et al.*, 2021). Congiu *et al.* (2022) find this impact stronger for small and large platforms while intermediate ones are less affected. In addition, Aridor *et al.* (2020) highlight a 12.5% decrease in observed consumers, but those who agree to give personal information are observed longer. In the end, user value increased, offsetting the negative impact of the GDPR. Peukert *et al.* (2021) show that platforms have reduced the number of third parties with which they request cookies, favoring large platforms like Google, whose market share has since increased. Consistent with the previous result, Janssen *et al.* (2022) found a decrease in the number of new applications.

Figure 2.5: Main interactions between the model's economic agents



Legend: D is for demand and S for supply.
$\rightarrow$ means that goods/services are homogeneous.
$\rightrightarrows$ means that goods/services are differentiated.

2.4 Model

This section presents the model structure composed of households and two sectors (traditional and digital). The main interactions between the economic agents are summarized in Figure 2.5. Model variables are summarized in Table 2.A.1 in Appendix 2.A to facilitate reading.

2.4.1 Households

The economy comprises H identical households, and the population is constant over time. Each household seeks to maximize its utility by consuming differentiated varieties of goods, spending time on free digital services, and choosing the quantity of data she discloses to the

digital service providers. The intertemporal utility of an individual $h \in \mathcal{H} = \{1, ...H\}$ is given by:

$$U_{h,0} = \sum_{t=0}^{\infty} \rho^t u(C_{h,t}, D_{h,t}) \tag{2.1}$$

with $0 < \rho < 1$ the discount factor, $C_{h,t}$ a goods consumption index, and $D_{h,t}$ a digital services consumption index.

Following Grossmann (2008), we model the utility derived from consumption as in Dixit & Stiglitz (1977) adding a variable for the perceived quality of the different varieties of good. The index of goods consumption for the household h is given by:

$$C_{h,t} = \left(\int_0^{I_t} (\tilde{z}_{h,t}(i) c_{h,t}(i))^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}} \tag{2.2}$$

where $\sigma > 1$ is the elasticity of substitution between the different varieties of good, I_t the number of differentiated varieties of good, $c_{h,t}(i)$ is the quantity of variety $i \in \mathcal{I} = [0, I_t]$ consumed by household h in period t, and $\tilde{z}_{h,t}(i)$ the perceived quality of the variety i by household h in period t (optimally chosen by traditional firms).

Households divide their online time between large and small digital services. Following Shimomura & Thisse (2012), the digital service sector is modeled as a "mixed market" with a fixed number J of large providers, indexed $j \in \mathcal{J} = [1, ..., J]$, and a mass of K_t small providers, indexed $k \in \mathcal{K} = \{0, ..., K_t\}$, offering differentiated digital services. The number of small providers is not fixed, as there is free entry into this sub-category of digital services. The utility derived from digital services depends on the time spent on each digital service, the perceived quality of each digital service, and the quantity of data collected by the digital service providers on the household's behavior. Perceived quality of the digital service by a household h depends on the quality of the service (q), optimally chosen by the digital service provider and which is the same for all households, and on the data collected by the digital service providers on the household (d_h). Indeed, data are used to personalize the digital

service tailored to the user's profile.[8] The more a household discloses its data, the more the perceived quality of the digital services is high for her (perceived quality is individual). However, data collection also harms utility as it raises privacy concerns. Following Wein (2022), the (des)utility of spending time on the digital service j and k takes the form of a Cobb-Douglas such as:

$$(s_{h,j,t}q_{j,t}d_{h,j,t})^{\alpha}(\overline{d}_h - d_{h,j,t})^{1-\alpha} \tag{2.3}$$

$$(s_{h,t}(k)q_t(k)d_{h,t}(k))^{\alpha}(\overline{d}_h - d_{h,t}(k))^{1-\alpha} \tag{2.4}$$

where $s_{h,j,t}$ and $s_{h,t}(k)$ are, respectively, the time spent on the digital service j and k by household h, $q_{j,t}$ and $q_t(k)$ the quality of the digital service j and k, $d_{h,j,t}$ and $d_{h,t}(k)$ the quantity of data the household h agrees to be collected by the digital service providers j and k (or voluntarily discloses to providers), $\overline{d}_h$ the maximum quantity of data that digital service providers can collect and $\alpha \in]0,1[$ a preference parameter for privacy. The higher α is, the more the household discloses its data. We assume that the GDPR gives consumers the choice of how much data they want to give. Today, users no longer have the choice between giving away all their data or only the essential ones, but they can choose which type of data they are willing to provide. Therefore, households choose the optimal quantity of data they will disclose by making a trade-off between data collection's positive and negative impact on utility. As households are homogeneous in the model, this is also a convenient approach to modeling average data collection among all users, rather than modeling heterogeneous households where some give everything and others nothing.

To consider the substitution between the different digital services, the utility derived from online time takes the form of a nested Constant Elasticity of Substitution. Households can substitute digital services belonging to the same category and between the digital services of

[8]Note that data are non-rivals. Therefore, they will also be used in the production of impressions.

the small and large providers. Overall, it is given by:

$$D_{h,t} = \Big[\sum_{j=1}^{J}\Big((s_{h,j,t}q_{j,t}d_{h,j,t})^{\alpha}(\overline{d}_h - d_{h,j,t})^{1-\alpha}\Big)^{\epsilon} + \Big(\int_0^{K_t}\Big((s_{h,t}(k)q_t(k)d_{h,t}(k))^{\alpha}(\overline{d}_h - d_{h,t}(k))^{1-\alpha}\Big)^{\epsilon}dk\Big]^{\frac{1}{\alpha\epsilon}} \tag{2.5}$$

where $\epsilon \in]0,1[$ is a substitution parameter between the digital services. Note that the mixed market as in Shimomura & Thisse (2012) implies that each digital service of large providers has a positive and significant impact on household utility. In contrast, each digital service of small providers has a negligible impact. Digital services of large providers have a higher quality than those of small providers. Therefore, users spend significantly more time. This is due to large providers' higher quality of digital services compared to small ones. Nevertheless, the aggregate impact on the utility of the continuum of digital services of small providers can be comparable to that of digital services of large providers.

To simplify, we assume that the instantaneous utility function of the household h takes the form of an additive function given by:

$$u(C_{h,t}, D_{h,t}) = \ln C_{h,t} + \ln D_{h,t} \tag{2.6}$$

The total time available for each household is equal to l. Consequently, if a household spends a time $S_{h,t} = \sum_{j=1}^{J} s_{h,j,t} + \int_0^{K_t} s_{h,t}(k)dk$ online, its work time is $(l - S_{h,t})$. It allows us to capture the long-term decline in working hours associated with the rise in leisure activities, mainly digital leisure (Rachel, 2021).[9]

As digital services are free, only the consumption of differentiated commodities has a monetary cost. The intertemporal budget constraint of the representative household h is

[9]Empirical research has shown a trend toward declining hours worked and increasing leisure time over the past few decades. Aguiar & Hurst (2007) estimate that leisure time has increased by roughly six to nine hours per week for men and four to eight hours for women between 1965 and 2003 in the US. Vandenbroucke (2009) and Kopytov *et al.* (2023) show evidence that decreased work hours in several countries since 1900 are due to decreased leisure prices. Some studies highlight the importance of digital leisure in the reallocation of time. Wallsten (2013) shows that digital leisure is a substitute for other types of leisure and work. Aguiar *et al.* (2020) show that innovation in digital, more precisely the quality improvement of recreational computing and gaming, is responsible for the decline in worked hours by young men.

given by:

$$b_{h,t+1} = (1 + r_t)b_{h,t} + (l - \sum_{j=1}^{J} s_{h,j,t} - \int_0^{K_t} s_{h,t}(k)dk)w_t + \frac{1}{H}\sum_{j=1}^{J} \pi_{j,t} - \int_0^{I_t} p_t(i)c_{h,t}(i)di \quad (2.7)$$

with $b_{h,t}$ the individual wealth, r_t the interest rate, w_t the wage rate, $\pi_{j,t}$ the profit of the large providers of digital services equally redistributed to households (large providers are the only type of firms to make profits in the model), and $p_t(i)$ is the price of the variety of good i.

The representative household maximizes the intertemporal utility function under the law of wealth evolution given by (2.7). The household program is the following:

$$\begin{aligned} &\max_{c_{h,t}(i), s_{h,j,t}, s_{h,t}(k), d_{h,j,t}, d_{h,t}(k)} U_{h,0} = \sum_{t=0}^{\infty} \rho^t \Big[\ln C_{h,t} + \ln D_{h,t}\Big] \\ &s.t \quad b_{h,t+1} = (1 + r_t)b_{h,t} + (l - \sum_{j=1}^{J} s_{h,j,t} - \int_0^{K_t} s_{h,t}(k)dk)w_t + \frac{1}{H}\sum_{j=1}^{J} \pi_{j,t} - \int_0^{I_t} p_t(i)c_{h,t}(i)di \end{aligned} \quad (2.8)$$

with $b_{h,0}$ is given.

We solve this program in several steps. In the first step, the household decides the optimal quantity of data she discloses to each digital service provider. To this aim, at each period, she chooses the quantity of data $d_{h,j}$ and $d_h(k)$ which maximize the utility function of spending time online given by equation (2.5).[10] The optimal quantity of data disclosed by the household h to each digital service provider j and k is obtained by solving the following First Order Conditions (FOCs):

$$\frac{\partial D_{h,t}}{\partial d_{h,j}} = 0 \quad (2.9)$$

and

$$\frac{\partial D_{h,t}}{\partial d_h(k)} = 0 \quad (2.10)$$

[10]We omit the time index t for all static programs to simplify notation.

It gives us:

$$d_{h,j} = d_h(k) = \alpha \overline{d}_h \tag{2.11}$$

Households disclose the same quantity of personal information to each digital service provider. Indeed, the use of tracking cookies enables digital providers to follow the online activity of each household. A single provider can, therefore, record users' online behavior on all the digital services if the user has accepted cookies. The sensitivity to privacy is identical for all digital services. Data collected by digital services is higher when the sensitivity to privacy is low (high α). Note that if the privacy parameter α equals 1, the household consents to provide all personal data (within the limit of what the digital firm can collect). On the contrary, if α equals 0, households do not provide any data. This situation means that households do not consume digital services, which is irrelevant to this chapter. It could also correspond to the case where a regulation prohibits data collection. In this case, digital service providers should change their business model, for example, by pricing access to the service.[11]

By substitution and using the optimal quantity of data disclosed to each digital services provider given by equation (2.11), we can rewrite the equation (2.5) as:

$$D_h = \alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}} \overline{d}_h^{\frac{1}{\alpha}} \Big[\sum_{j=1}^{J} (s_{h,j} q_j)^{\alpha\epsilon} + \int_0^K (s_h(k) q(k))^{\alpha\epsilon} dk \Big]^{\frac{1}{\alpha\epsilon}} \tag{2.12}$$

We have:

$$(s_{h,0} q_0)^{\alpha} = \Big(\int_0^K (s_h(k) q(k))^{\alpha\epsilon} dk \Big)^{\frac{1}{\epsilon}} \tag{2.13}$$

We can, therefore, rewrite the equation (2.12) as:

$$D_h = \alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}} \overline{d}_h^{\frac{1}{\alpha}} \Big(\sum_{j=0}^{J} (q_j s_{h,j})^{\alpha\epsilon} \Big)^{\frac{1}{\alpha\epsilon}} \tag{2.14}$$

[11] Since April 1, 2021, the French Data Protection Authority (Commission Nationale de l'Informatique et des Libertés - CNIL) requires that users be able to refuse cookies as easily as they accept them. Without clear and explicit consent, websites can not collect personal data. Nudges are forbidden. Some platforms considered that this lack of data could threaten their existence and now propose that consumers accept giving their data or pay for the service.

The household now has to determine (i) the optimal time spent on each digital service of small providers and (ii) the optimal time spent on each digital service (large and total small) by solving the two following programs:

$$\begin{aligned} &\min_{s_h(k)} \int_0^K s_h(k)dk \\ &s.t. \quad q_0 s_{h,0} = \Big(\int_0^K (q(k)s_h(k))^{\alpha\epsilon}\Big)^{\frac{1}{\alpha\epsilon}} dk \end{aligned} \tag{2.15}$$

and

$$\begin{aligned} &\min_{s_{h,j}} \sum_{j=0}^{J} s_{h,j} \\ &s.t. \quad QS_h = \Big(\sum_{j=0}^{J} (q_j s_{h,j})^{\alpha\epsilon}\Big)^{\frac{1}{\alpha\epsilon}} \end{aligned} \tag{2.16}$$

The optimal demand for the digital service of small provider k (or optimal time spent on the digital service k) is given by:[12]

$$s_h(k) = s_{h,0}\Big(\frac{q(k)}{q_0}\Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon}} \tag{2.17}$$

with $s_{h,0} = \int_0^K s_h(k)dk$ the total time spent on all digital services of small providers and $q_0 = (\int_0^K q(k)^{\frac{\alpha\epsilon}{1-\alpha\epsilon}})^{\frac{1-\alpha\epsilon}{\alpha\epsilon}} dk$ an index of the quality of all digital services of small providers.

The optimal time spent on the digital service j is given by:

$$s_{h,j} = S_h\Big(\frac{q_j}{Q}\Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon}} \tag{2.18}$$

with $S_h = \sum_{j=0}^{J} s_{h,j}$ the total time spent on all digital services and $Q = (\sum_{j=0}^{J} q_j^{\frac{\alpha\epsilon}{1-\alpha\epsilon}})^{\frac{1-\alpha\epsilon}{\alpha\epsilon}}$ an index of the quality of all digital services.

According to equation (2.18), we have $s_{h,0} = S_h\Big(\frac{q_0}{Q}\Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon}}$. We can easily deduce that

[12]See proof 1 in appendix 2.B.1.

equation (2.17) can be rewritten as:

$$s_{h,t}(k) = S_h\Big(\frac{q(k)}{Q}\Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon}} \tag{2.19}$$

Time spent on each digital service depends on the total online time, the relative quality of the service, but also on the sensitivity to privacy α (equations (2.17) and (2.18)). Consequently, an increase in the quality of a digital service negatively impacts the demand for other digital services. Moreover, the lower the privacy sensitivity (high α), the higher the household spends time on the digital service. Indeed, the sensitivity to privacy decreases the utility of spending time online through disutility from data collection.

At the last stage, the household determines its optimal consumption $c_h(i)$ of good i at each period by solving the following program:

$$\begin{aligned} \max_{c_h(i)} C_h &= \left(\int_0^I (\tilde{z}_h(i)c_h(i))^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}} \\ s.t. \quad E_h &= \int_0^I p(i)c_h(i)di \end{aligned} \tag{2.20}$$

With this traditional Dixit & Stiglitz (1977) formulation and for a given expenditure level E_h, the optimal demand of household h for the good i is:

$$c_h(i) = \tilde{z}_h(i)^{\sigma-1}\frac{E_h}{P}\left(\frac{p(i)}{P}\right)^{-\sigma} \tag{2.21}$$

with P is an index of all variety's prices given by:

$$P = \left(\int_0^I \left(\frac{p(i)}{\tilde{z}_h(i)}\right)^{1-\sigma} di\right)^{\frac{1}{1-\sigma}} \tag{2.22}$$

and $E_h = PC_h = \int_0^I p(i)c_h(i)di$.

Finally, the household has to choose the optimal level of the consumption index $C_{h,t}$ and

the optimal time spent on digital services $S_{h,t}$ by solving the intertemporal program given by equation (2.8). Note that we can rewrite the budget constraint given by equation (2.7) as:

$$b_{h,t+1} = (1 + r_t)b_{h,t} + (l - S_{h,t})w_t + \frac{1}{H}\sum_{j=1}^{J}\pi_{j,t} - P_{h,t}C_{h,t} \tag{2.23}$$

and the online time utility function given by (2.14) as:

$$D_{h,t} = \alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}}\overline{d}_h^{\frac{1}{\alpha}}(S_{h,t}Q_t) \tag{2.24}$$

Therefore, the intertemporal utility program can be rewritten as:

$$\begin{aligned} &\max_{C_{h,t},S_{h,t}} U_{h,0} = \sum_{t=0}^{\infty}\rho^t\left[\ln C_{h,t} + \ln S_{h,t}Q_t + \ln\alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}}\overline{d}_h^{\frac{1}{\alpha}}\right] \\ &s.t \quad b_{h,t+1} = (1 + r_t)b_{h,t} + (l - S_{h,t})w_t + \frac{1}{H}\sum_{j=1}^{J}\pi_{j,t} - P_tC_{h,t} \end{aligned} \tag{2.25}$$

By solving the following intertemporal Lagrangian with respect to $C_{h,t}$, $S_{h,t}$, and the state variable $b_{h,t+1}$, we obtain the optimal online time which depends on the optimal consumption expenditure level of the representative household and the wage rate:

$$S_{h,t} = \frac{P_tC_{h,t}}{w_t} = \frac{E_{h,t}}{w_t} \tag{2.26}$$

and the optimal dynamics of total consumption expenditure (Keynes-Ramsey equation):

$$E_{h,t+1} = \rho(1 + r_{t+1})E_{h,t} \tag{2.27}$$

The transversality condition is given by:

$$\lim_{t\to\infty}\rho^t\frac{b_{h,t}}{E_t} = 0 \tag{2.28}$$

2.4.2 Traditional firms

The traditional sector is composed of a continuum of I_t firms indexed by i in monopolistic competition, each selling a (horizontally) differentiated variety *à la* Dixit & Stiglitz (1977). The number of firms is endogenously determined for each period as there is free entry of firms into the traditional (or final goods) market. The production function of traditional firms is given by:

$$x_t(i) = L_t^x(i) \tag{2.29}$$

where $x_t(i)$ is the production of the variety of good i in period t and $L_t^x(i)$ is the quantity of labor used in the production of the variety of good i in period t.

Following Grossmann (2008), each firm can improve the perceived quality of its good to stimulate its demand. For this purpose, firms can improve the true quality of the goods and buy advertising in the digital sector. In Grossmann (2008), firms incur advertising expenditures by employing a quantity of marketing labor. In this chapter, we model the specificity of digital advertising. Firms buy a quantity of personalized impressions from digital service providers to display their advertising to users on digital services.[13] Impressions are personalized because digital service providers use personal information collected to target advertising. The more impressions of a good i a household h views, the more she will value the quality of the good i.[14] To improve the true quality $z_t(i)$ of the good i in period t, the firm i have to invest in R&D by employing in period $t-1$ a quantity of labor $L_{t-1}^R(i)$, such

[13]There is a wide range of payment methods in the digital advertising market. In this chapter, we model the Cost Per Impression method, where firms pay for the number of advertising displayed and viewed by a user on the website. Other popular methods include the Cost Per Click, where the firms pay only when a user clicks on the advertising. In general, impressions price is determined by an auction system (Goldfarb, 2014). For the sake of simplicity, we do not model auction systems.

[14]There is a debate about the effect of advertising on consumers. In a literature review on the economics of advertising, Bagwell (2007) identifies three types of advertising views: the persuasive (advertising modifies consumers' tastes and preferences) (Robinson, 1933; Braithwaite, 1928), informative (advertising is supplementary information on the product) (Ozga, 1960; Stigler, 1961), and complementary (advertising is complementary to the advertised good) (Stigler & Becker, 1977). Following Grossmann (2008), we consider that advertising influences the consumption of differentiated goods by changing the perceived quality. Households only notice the perceived quality of each variety, which depends on its true quality and the relative marketing expenditure of the firm.

as:

$$z_t(i) = \overline{z}_{t-1} L_{t-1}^{R}(i)^{\beta} \tag{2.30}$$

with $\beta > 0$ a parameter of the effectiveness of R&D and $\overline{z}_t = \frac{1}{I_t}\int_0^{I_t} z_t(i)di$ the state of technology in $t-1$ representing the average knowledge accumulation acquired by previous R&D activities. Knowledge acquired by each firm is private information for one period. Therefore, $\overline{z}_{t-1}$ provides a positive externality in the research activity of firms in the following period (intertemporal spillover). Improving $\overline{z}_{t-1}$ enables less labor to obtain the same quality of goods. Research activity is, therefore, the growth driver of our model.[15]

As in Grossmann (2008), advertising is combative in the sense that *"an increase in marketing expenditure of a single firm creates a negative externality on demand faced by other firms"*. As a consequence, the perceived quality of the variety i by household h is not influenced by the number of impressions she saw but by the quantity of impressions on good i view by household h relative to the average quantity of impressions view by household h:

$$m_{h,t}(i) = \frac{a_{h,t}(i)}{\overline{a}_{h,t}} \tag{2.31}$$

where $a_{h,t}(i)$ is the quantity of impressions purchased by the firm i in period t displayed to household h and $\overline{a}_{h,t} = \frac{1}{I_t}\int_0^{I_t} a_{h,t}(i)di$ the average quantity of impressions by firms displayed to household h.

Finally, the perceived quality $\tilde{z}_{h,t}(i)$ of good i by household h in period t is given by:

$$\tilde{z}_{h,t}(i) = z_t(i) m_{h,t-1}^{\eta}(i) \tag{2.32}$$

where $\eta \geqslant 0$ measures the effectiveness of advertising on the perceived quality by household

[15]This approach to model endogenous growth was introduced by Young (1998) and extended by Dinopoulos & Thompson (1998), Peretto (1998), and Howitt (1999). It enables to have endogenous growth without scale effects on the growth rate. In these papers, a rise in population proportionally increases the number of varieties in the economy. Therefore, the size of each sector and the effort of R&D in each sector are unaffected by the population increase. Population growth does not impact the economic growth rate but only has scale effects on income per capita. The reader may refer to Jones (1999) for more details.

h of good i.

The profit $\pi_t^x(i)$ of the traditional firm i in period t is given by:

$$\pi_t^x(i) = p_t(i)x_t(i) - L_t^x(i)w_t \tag{2.33}$$

By substitution and using the optimal demand of household h for the variety i given by equation (2.21) and the perceived quality function (2.32), we can rewrite the profit function of the firm i as:

$$\pi_t^x(i) = (p_t(i) - w_t)\sum_{h=1}^{H}\left(\overline{z}_{t-1}{L_{t-1}^R}^{\beta}(i)(\frac{a_{h,t-1}(i)}{\overline{a}_{h,t-1}})^{\eta}\right)^{\sigma-1}\frac{E_{h,t}}{P_t}\left(\frac{p_t(i)}{P_t}\right)^{-\sigma}\Big) \tag{2.34}$$

Each firm also incurs a fixed labor cost $f^x > 0$ at period $t-1$, which can be interpreted as organization costs. Therefore, in period $t-1$, firms face three costs to improve the perceived quality of their goods in t (fixed, R&D, and advertising costs). Firms borrow in the perfect financial market in $t-1$ to be financed and repay their debt with interest in the next period. Indeed, traditional firms are in monopolistic competition, and there is free entry into the market. Therefore, they do not have any assets in $t-1$ since they will only make profits in t, which will cover the repayment of the loan generated in the previous period.

At period $t-1$, the firm i chooses the quantity of labor $L_{t-1}^R(i)$, the number of impressions $a_{h,t-1}(i)$ destined to each household h, and the price $p_t(i)$ that maximize the firm's value:

$$\begin{aligned} V_{t-1}(i) =& \frac{\pi_t^x(i)}{1+r_t} - L_{t-1}^R(i)w_t - p_{t-1}^a\sum_{h=1}^{H}a_{h,t-1}(i) - f^x \\ =& \frac{p_t(i)-w_t}{1+r_t}\sum_{h=1}^{H}\left(\overline{z}_{t-1}{L_{t-1}^R}^{\beta}(i)(\frac{a_{h,t-1}(i)}{\overline{a}_{h,t-1}})^{\eta}\right)^{\sigma-1}\frac{E_{h,t}}{P_t}\left(\frac{p_t(i)}{P_t}\right)^{-\sigma} \\ & - L_{t-1}^R(i)w_{t-1} - p_{t-1}^a\sum_{h=1}^{H}a_{h,t-1}(i) - f^x \end{aligned} \tag{2.35}$$

where p_{t-1}^a is the price of one impression in period $t-1$ and $p_{t-1}^a\sum_{h=1}^{H}a_{h,t-1}(i)$ the total

value of impressions bought by in period $t-1$.

FOCs with respect to $p_t(i)$, $L^R_{t-1}(i)$, and $a_{h,t-1}(i)$ gives us the optimal price of variety i, the optimal quantity of labor employed in the R&D of the variety i, and the optimal quantity of impressions bought by the firm i destined for the household h:

$$p_t(i) = w_t \frac{\sigma}{\sigma - 1} \tag{2.36}$$

$$L^R_{t-1}(i) = (\sigma - 1)\beta \left(\frac{p_t(i) - w_t}{1 + r_t} \right) \frac{\sum_{h=1}^{H} c_{h,t}(i)}{w_{t-1}} \tag{2.37}$$

$$a_{h,t-1}(i) = (\sigma - 1)\eta \left(\frac{p_t(i) - w_t}{1 + r_t} \right) \frac{c_{h,t}(i)}{p^a_{t-1}} \tag{2.38}$$

The demand for labor for R&D activity of good i and impressions of good i displayed to household h positively depends on the price of the variety i, the parameter of efficiency associated, and the demand for the good i and negatively on the wage rate. The demand for impressions also negatively depends on prices.

We deduce that the ratio between the labor allocated to research activity and the quantity of impressions purchased destined to the household h depends on the ratio of their respective effectiveness and the price of the advertising:

$$\frac{L^R_t(i)}{a_{h,t}(i)} = \frac{\beta}{\eta} \frac{p^a_{t-1}}{w_{t-1}} \frac{\sum_{h=1}^{H} c_{h,t}(i)}{c_{h,t}(i)} \tag{2.39}$$

2.4.3 Digital service providers

The digital sector is composed of a constant number of large digital service providers, indexed $j \in \mathcal{J} = [1, ..., J]$ and a competitive fringe with K_t small digital service providers, indexed $k \in \mathcal{K} = \{1, ..., K_t\}$ as in Shimomura & Thisse (2012). Each digital service provider is identical within its category. The difference between the two categories is that large providers have an advantage in digital service quality over small providers. The quality production

functions of the digital service for large and small providers are given by the two following equations:

$$q_{j,t} = \beta^j L^q_{j,t} \tag{2.40}$$

$$q_t(k) = \beta^k L^q_t(k) \tag{2.41}$$

with $\beta^j > \beta^k$ and $L^q_{j,t}$ and $L^q_t(k)$ are, respectively, the quantity of labor employed by the digital service provider j and k which determine the quality of the digital service. Households spend more time on the digital services of large providers as their quality is much higher than small ones. Indeed, these services benefit from significant network effects, making using services used by other users more attractive.

Digital service providers generate revenue by selling advertising to traditional firms. They need households' attention (households must spend time on their digital service) and household data to produce impressions. Time and data are substitutable in the production function. The more time the household spends on the digital service, the more impressions the providers can display to her. Moreover, digital service providers use data to produce personalized impressions for each household h. Data enables digital service providers to match advertising with users interested in the advertised good. Therefore, they supply impressions tailored to each household to traditional firms. The more information the firm has about the household, the more impressions it can display (impressions are displayed only if it is relevant to the household). The production function of impressions destined for the household h for large and small providers is given by:

$$a^s_{h,j,t} = s^\gamma_{h,j,t} d^{1-\gamma}_{h,j,t} \tag{2.42}$$

$$a^s_{h,t}(k) = s_{h,t}(k)^\gamma d_{h,t}(k)^{1-\gamma} \tag{2.43}$$

where $0 < \gamma < 1$ is an indicator of the importance of data collection in the production of impressions. To simplify, we now assume that $\overline{d}_h$, the maximum quantity of data that a provider can collect on the household h, is equal to $S_{h,t}$, the total online time of the household

h. Indeed, by using cookies, digital service providers can track their users' online activity. Therefore, we assume that the more a household spends time online, the more data she can disclose. However, we assume that households do not consider that $\overline{d}_h$ depends on the time spent on digital services and, therefore, they take as given this variable.[16] By substitution and using the optimal quantity of data given by households (equation (2.11)) and the optimal time spent on each digital service (equations (2.17) and (2.18)), the production function of impressions destined for the household h can be rewritten as:

$$a^s_{h,j,t} = \alpha^{1-\gamma} S_{h,t} \Big(\frac{q_{j,t}}{Q_t} \Big)^{\frac{\gamma\alpha\epsilon}{1-\alpha\epsilon}} \tag{2.44}$$

$$a^s_{h,t}(k) = \alpha^{1-\gamma} S_{h,t} \Big(\frac{q_t(k)}{Q_t} \Big)^{\frac{\gamma\alpha\epsilon}{1-\alpha\epsilon}} \tag{2.45}$$

There is free entry into the competitive fringe but not into the digital service of large providers. Large digital service providers have a higher fixed cost than small providers. This creates an entry barrier to joining large digital service providers (the incumbents). The profit functions for large and small digital service providers are given by:[17]

$$\pi_{j,t} = p^a_t \Big(\sum_{h=1}^{H} a^s_{h,j,t} \Big) - L^q_{j,t} - F \tag{2.46}$$

$$\pi_t(k) = p^a_t \Big(\sum_{h=1}^{H} a^s_{h,t}(k) \Big) - L^q_t(k) - f \tag{2.47}$$

with F and f the fixed cost incurred by the large and small providers and $F > f$. By substitution and using the production functions of quality (equations (2.40) and (2.41)) and impressions (equations (2.44) and (2.45)), the profit functions are:

$$\pi_{j,t} = p^a_t \alpha^{1-\gamma} \Big(\frac{q_{j,t}}{Q_t} \Big)^{\frac{\gamma\alpha\epsilon}{1-\alpha\epsilon}} \sum_{h=1}^{H} S_{h,t} - \frac{1}{\beta^j} q_{j,t} - F \tag{2.48}$$

[16] If $\overline{d}_h$ were a household control variable, with the functional form retained in our model, households could increase their welfare by increasing this maximum amount while keeping the volume of data collected unchanged. This does not seem realistic.

[17] To ensure the concavity of the profit functions, we have to impose that $\alpha\epsilon(1+\gamma) < 1$.

$$\pi_t(k) = p_t^a \alpha^{1-\gamma} \Big(\frac{q_t(k)}{Q_t}\Big)^{\frac{\gamma\alpha\epsilon}{1-\alpha\epsilon}} \sum_{h=1}^{H} S_{h,t} - \frac{1}{\beta^k} q_t(k) - f \tag{2.49}$$

All digital service providers are price and quality takers, as large providers have no strategic behaviors.[18] Therefore, each provider seeks to maximize its profit by choosing the optimal digital service quality. FOC's give us the optimal quality of each type of digital service:

$$q_j = \Big(\beta^j p^a \frac{\alpha^{2-\gamma}\gamma\epsilon}{1-\alpha\epsilon} \sum_{h=1}^{H} S_h\Big)^{\frac{\alpha\epsilon-1}{\alpha\epsilon(1+\gamma)-1}} Q^{\frac{\gamma\alpha\epsilon}{\alpha\epsilon(1+\gamma)-1}} \tag{2.50}$$

$$q(k) = \Big(\beta^k p^a \frac{\alpha^{2-\gamma}\gamma\epsilon}{1-\alpha\epsilon} \sum_{h=1}^{H} S_h\Big)^{\frac{\alpha\epsilon-1}{\alpha\epsilon(1+\gamma)-1}} Q^{\frac{\gamma\alpha\epsilon}{\alpha\epsilon(1+\gamma)-1}} \tag{2.51}$$

Using equations (2.50) and (2.51), we obtain the ratio between the quality of the large digital service j and the small one k:

$$\frac{q_j}{q(k)} = \Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon-1}{\alpha\epsilon(1+\gamma)-1}} \tag{2.52}$$

which mainly depends on the difference between the quality efficiency of large and small digital service providers. As $\beta^j > \beta^k$, the quality level of large providers is higher than that of small providers. Households, therefore, consume a higher quantity of digital services from large providers than small ones.

2.5 Equilibrium

We now characterize the macroeconomic equilibrium. We assume that the number of households is significantly higher than the labor fixed costs ($H >> f^x + f + F$) to ensure labor resources necessary to produce traditional goods and digital services. Moreover, we choose labor as the numeraire. The wage rate is normalized to 1. We are at the symmetric equi-

[18] Modeling strategic behavior among large digital service providers does not provide an analytical solution.

librium. All households, traditional firms, large digital service providers, and small ones are identical. Therefore, households consume the same quantity of each variety, such as:

$$c_{h,t}(i) = c_t = \frac{E_t}{pI_t} \tag{2.53}$$

and the time spent on digital services of large and small providers is given by:

$$s_{h,j,t} = s_t^j = \frac{E_t}{J + \left(\frac{\beta^j}{\beta^k}\right)^{\frac{\alpha\epsilon}{\alpha\epsilon(1+\gamma)-1}} K_t} \tag{2.54}$$

$$s_{h,t}(k) = s_t^k = \frac{E_t}{K_t + \left(\frac{\beta^j}{\beta^k}\right)^{\frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}} J} \tag{2.55}$$

The total time spent online by each household is given by:

$$S_{h,t} = S_t = E_t \tag{2.56}$$

The price index of the traditional variety of goods at the symmetrical equilibrium is given by:

$$P_t = \frac{p}{\tilde{z}_t} I_t^{\frac{1}{1-\sigma}} \tag{2.57}$$

and the equilibrium price of each traditional price:

$$p = \frac{\sigma}{\sigma - 1} \tag{2.58}$$

At the symmetric equilibrium, all traditional firms employ the same quantity of labor in the R&D activity and buy the same quantity of impressions destined for each household:

$$L_{t-1}^R(i) = L_{t-1}^R = (\sigma - 1)\beta\Big(\frac{p-1}{1+r_t}\Big)x_t \tag{2.59}$$

$$a_{h,t-1}(i) = a_{t-1} = (\sigma - 1)\eta\Big(\frac{p-1}{1+r_t}\Big)\frac{x_t}{Hp_{t-1}^a} \tag{2.60}$$

with $x_t = Hc_t$ is the total supply of goods of a traditional firm. Note that the total quantity of impressions bought by a firm is given by:

$$Ha_{t-1} = (\sigma - 1)\eta\Big(\frac{p-1}{1+r_t}\Big)\frac{x_t}{p^a_{t-1}} \tag{2.61}$$

Advertising is combative in this model. Therefore, at the symmetric equilibrium, the perceived quality given by equation (2.32) is equal to the true quality as the quantity of impressions bought by a firm relative to the average impressions is equal to 1 (equation (2.31)).

There is a free entry of the firms into the traditional sector. Consequently, the firm value is equal to zero. Using this condition and the optimal demand of good given by the equation (2.53), we obtain:

$$\frac{p-1}{1+r_t}\frac{HE_t}{I_t} = L^R_{t-1} + p^a_{t-1}Ha_{t-1} + f^x \tag{2.62}$$

The quality of each digital services providers j and k is given by:

$$q_{j,t} = q^j_t = \Big(\beta^j p^a_t \frac{\alpha^{2-\gamma}\gamma\epsilon}{1-\alpha\epsilon}HS_t\Big)^{\frac{\alpha\epsilon-1}{\alpha\epsilon(1+\gamma)-1}} Q_t^{\frac{\gamma\alpha\epsilon}{\alpha\epsilon(1+\gamma)-1}} \tag{2.63}$$

$$q_t(k) = q^k_t = \Big(\beta^k p^a_t \frac{\alpha^{2-\gamma}\gamma\epsilon}{1-\alpha\epsilon}HS_t\Big)^{\frac{\alpha\epsilon-1}{\alpha\epsilon(1+\gamma)-1}} Q_t^{\frac{\gamma\alpha\epsilon}{\alpha\epsilon(1+\gamma)-1}} \tag{2.64}$$

and the total impressions sold by digital service providers j and k by:

$$Ha^j_{h,t} = a^j_t = H\alpha^{1-\gamma}S_t\Big(\frac{q^j_t}{Q_t}\Big)^{\frac{\gamma\alpha\epsilon}{1-\alpha\epsilon}} \tag{2.65}$$

$$Ha^k_{h,t} = a^k_t = H\alpha^{1-\gamma}S_t\Big(\frac{q^k_t}{Q_t}\Big)^{\frac{\gamma\alpha\epsilon}{1-\alpha\epsilon}} \tag{2.66}$$

where

$$Q_t = q^j\Big(J + \Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon}{\alpha\epsilon(1+\gamma)-1}}K_t\Big)^{\frac{1-\alpha\epsilon}{\alpha\epsilon}} = q^k\Big(K_t + \Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}}J\Big)^{\frac{1-\alpha\epsilon}{\alpha\epsilon}} \tag{2.67}$$

Using the quality index of digital services given by equation (2.67), the total impressions equations of digital service providers j and k (equations (2.65) and (2.66)) can be rewritten

as:

$$a_t^j = H\alpha^{1-\gamma} S_t \Big(\Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon}{\alpha\epsilon(1+\gamma)-1}} K_t + J \Big)^{-\gamma} \tag{2.68}$$

$$a_t^k = H\alpha^{1-\gamma} S_t \Big(\Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}} J + K_t \Big)^{-\gamma} \tag{2.69}$$

and the quality of each digital service (equations (2.63) and (2.64)) as:

$$q_t^j = (\beta^j p^a \frac{\alpha^{2-\gamma}\gamma\epsilon}{1-\alpha\epsilon} H S_t) \Big(\Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon}{\alpha\epsilon(1+\gamma)-1}} K_t + J \Big)^{-\gamma} \tag{2.70}$$

$$q_t^k = (\beta^k p^a \frac{\alpha^{2-\gamma}\gamma\epsilon}{1-\alpha\epsilon} H S_t) \Big(\Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}} J + K_t \Big)^{-\gamma} \tag{2.71}$$

Following an increase in impression price, digital service providers will improve the quality of their services to incentivize households to spend more time on their services. It will enable them to collect more data and attention and increase the quantity of impressions supplied.

Using the profit function of small digital service providers (equation (2.49)), the production function quality (equation (2.41)), and the supply of impressions by small digital service providers (equation (2.64)), the free entry among small digital service providers imposes:

$$p_t^a \alpha^{1-\gamma} \Big(\frac{q^k}{Q_t} \Big)^{\frac{\gamma\alpha\epsilon}{1-\alpha\epsilon}} H S_t = \frac{1}{\beta^k} q^k - f \tag{2.72}$$

Finally, the macroeconomic equilibrium must satisfy the different markets' equilibrium conditions. Advertising, traditional goods, and labor market clearing conditions are given by:[19]

$$I_{t+1} H a_t = K_t a_t^k + J a_t^j \tag{2.73}$$

$$H c_t = x_t = L_t^x \tag{2.74}$$

$$H(L - s_t) = I_{t+1}(L_t^R + f^x) + I_t L_t^x + K_t(L_t^k + f) + J(L_t^j + F) \tag{2.75}$$

[19] According to Walras' law, the financial market is in equilibrium if the labor, advertising, and traditional goods markets are in equilibrium.

At the steady state, we find a unique equilibrium, for which E is (see proof 2 in appendix 2.B.2):

$$E^* = \Big(\frac{\sigma}{\rho - 1 + 2\sigma}\Big)\Big[L + \frac{1}{H}J\Big(\Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}} f - F\Big)\Big] \tag{2.76}$$

At steady state and symmetric equilibrium, the optimal expenditure for each household positively depends on the worked hours and the profit of the large digital service providers and negatively on the discount rate and the substitution parameter σ (an increase in substitution between traditional goods will decrease the price of traditional goods p). Note that to ensure that their profits are positive, we have $\left(\frac{\beta^j}{\beta^k}\right)^{\frac{\alpha\epsilon}{2\epsilon(1+\gamma)-1}} f > F > f$. The gap between the fixed cost of large and small digital service providers cannot be too high.

Equilibrium values of the number of firms in the traditional sector, the demand for labor in the R&D activity by each firm, and the quantity of impressions bought by each firm are given by (see the proof 2 in appendix 2.B.2):

$$I^* = \frac{1}{\sigma}\frac{EH}{f}(1 - (\sigma - 1)(\beta + \eta)) \tag{2.77}$$

$$L^{R*} = \frac{(\sigma - 1)\beta f^x}{1 - (\sigma - 1)(\beta + \eta)} \tag{2.78}$$

$$a^* = \eta\frac{\sigma - 1}{\sigma}\rho\frac{E}{Ip^a} \tag{2.79}$$

At equilibrium, most of the traditional sector's endogenous variables are unaffected by the digital sector. This disconnect between the final goods and digital sectors comes from the linearity of household preferences. In our model, the main connections between the two sectors come from labor and advertising.

In the digital sector, the equilibrium values of the number of small providers, the quality of digital services provided by small and large providers, and the price of advertising are given by (see proof 2 in appendix 2.B.2):

$$K^* = \eta\rho E\frac{\sigma - 1}{\sigma}f^{-1}H\frac{1 - \alpha\epsilon(1+\gamma)}{1 - \alpha\epsilon} - \Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}} J \tag{2.80}$$

$$q^{k*} = \frac{\alpha\gamma\epsilon}{1-\alpha\epsilon(1+\gamma)}\beta^k f \tag{2.81}$$

$$q^{j*} = \frac{\alpha\gamma\epsilon}{1-\alpha\epsilon(1+\gamma)}\beta^{k\frac{\alpha\epsilon\gamma}{\alpha\epsilon(1+\gamma)-1}}\beta^{j\frac{\alpha\epsilon-1}{\alpha\epsilon(1+\gamma)-1}} f \tag{2.82}$$

$$p^{a*} = \eta\frac{\sigma-1}{\sigma}\rho\alpha^{\gamma-1}\left[K+\left(\frac{\beta^j}{\beta^k}\right)^{\frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}}J\right]^{\gamma}\left[K+\left(\frac{\beta^j}{\beta^k}\right)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}}J\right]^{-1} \tag{2.83}$$

The GDP is given by the sum of final consumptions. At the symmetric equilibrium, it is equal to $H_t I_t c_t$. At the steady state, all of the three variables are constant. Therefore, in our model, there is no GDP growth.[20] GDP does not grow at the equilibrium, but the individual welfare can increase through the increase in the quality of the goods included in the index of consumption C_h.[21] We find that the consumption index is given by (see proof 3 in appendix 2.B.2):

$$C_{h,t} = \frac{\sigma-1}{\sigma}I^{*\frac{1}{\sigma-1}}\overline{z}_0(L^{R*})^{\beta t}E^* \tag{2.84}$$

and the growth rate of the consumption index by:

$$g_C = \beta\ln(L^{R*}) \tag{2.85}$$

The consumption index given by equation (2.84) depends on the number of varieties, the state of technology (and thus the quality of the goods), and the optimal level of expenditure. As a consequence, it can be impacted by the digital sector through a change in optimal expenditure as the latter is related to the online time (equation (2.56)). Nevertheless, at the steady state, the optimal expenditure is constant. Therefore, the only driver of the consumption index growth given by equation (2.85) is R&D. The latter depends solely on parameters specific to the final goods sector and is therefore not impacted by the digital sector (equation (2.78)). The higher the investment in R&D (L^R) or the higher the efficiency of R&D (β), the higher the perceived quality of the goods will be and, therefore, the consumption index growth.

[20] GDP growth is approximately equal to $\ln\left(\frac{H_t I_t c_t}{H_{t-1} I_{t-1} c_{t-1}}\right)$.

[21] Jones & Klenow (2016) empirically highlighted that income and welfare growth are different. Using data from the United Kingdom, India, France, United States, Italy, Indonesia, and Mexico, they find that the average welfare growth was around 3.1% between the 1980s and mid-2000s while income growth was around 2.1%.

Indeed, due to the spillover effects of R&D, the true quality of the differentiated goods is constantly improving. In our model, in contrast to traditional goods, digital services do not benefit from a permanent increase in quality. Indeed, technical progress is significantly lower in services activities than in manufacturing (Herrendorf *et al.*, 2015).

The intertemporal utility is given by (see proof 3 in appendix 2.B.2):

$$U_0 = \frac{\rho}{1-\rho}\left(\frac{1}{\sigma-1}\ln I^* + \frac{1}{1-\rho}g_C + \frac{1}{\rho}\ln E + \frac{1}{\rho}E^{\frac{1+\alpha}{\alpha}}Q^*\right) + X \tag{2.86}$$

where $X = \frac{1}{1-\rho}(\ln\frac{\sigma-1}{\sigma}\overline{z}_0 + \ln(\alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}})) + \frac{1}{\sigma-1}\ln I_0$ and $E = PC = S$. Several components impact the intertemporal utility. First, it depends on the consumption of differentiated goods and the true quality of these goods. Moreover, households benefit from an increase in the number of traditional firms due to the taste for variety (Dixit & Stiglitz, 1977). The intertemporal utility also depends on the digital sector; it positively depends on online time and digital service quality.

2.6 The macroeconomic impacts of free digital services

In this section, we derive comparative statistics to analyze the impact of the free digital services sector on the economy. We explore four cases: (i) an increase in the importance of attention versus data in impression production, (ii) a change in the gap of quality between large and small providers, (iii) the entry of a new large provider of digital service in the market, and (iv) a reduction in sensitivity to privacy. We discuss the impacts on the traditional and digital sectors and households' intertemporal utility. As mentioned above, the digital sector does not impact R&D activity and, thus, the consumption index growth rate. The most important result's proofs of the comparative-static are presented in appendix 2.B.3.

2.6.1 The importance of data and time in impressions production

In our model, providers need users' attention and data to produce impressions. The quality of the service directly determines attention, while the amount of data collected only depends on the total online time.[22] The weight given to data in impression production (γ) compared to attention will determine several results.

Impact on traditional sector

An increase in γ positively impacts the optimal level of expenditure E and thus the number of traditional firms I. All providers collect the same amount of data, as it only depends on the total online time. However, households do not spend the same time on each digital service; it depends on its quality. The digital services quality of large providers is significantly higher than that of small providers. Therefore, users spend more time on their services. Large providers benefit from increased γ because users' attention is now more important in impression production than data. It enables them to produce more impressions compared to small providers. This advantage increases the profits of the large providers. There is no free entry among the large digital service providers; they have, therefore, non-zero profits. As a consequence, the optimal expenditure level increases through this increase in wealth (in our model, all profits are redistributed to households). This rise in household expenditure increases the value of traditional firms. New firms enter the final goods market as we assume free entry.

[22]Large digital service providers, such as Google and Meta, have an advantage in the number of data collected. However, most small providers do not have the financial capacity to produce their advertising services. They, therefore, use Google AdSense to monetize their service. Using their user databases, Google displays advertisers' impressions on small providers' spaces. In this case, the users' attention (or users' clicks on the impression) makes the difference between digital services.

Impact on digital sector

An increase in γ increases the quality of all digital services. Indeed, digital service providers are incentivized to invest in the quality of their services to attract users for a longer time, as attention is now a more important production factor. The rise in the quality of digital services increases online time, which can benefit large and small providers. Secondly, more data is collected as households have higher (or longer) online activities. They disclose more information about them online. Large providers' profits rise through the increase in the two production factors of impressions.

However, two opposite effects can occur on small providers. Firstly, quality improvement leads to an increase in the time spent on their services. Combined with the rise of data collected, small providers produce more impressions and, therefore, increase their potential profits. Due to free entry, new small providers enter the market. However, if γ is already high, this effect is offset by the additional increase in γ, which widens the gap in the advantage between large and small providers.[23] Impression production is significantly more efficient among larger providers than smaller ones because they capture users' attention more effectively. In this case, some small providers exit the market.

Households intertemporal utility

An increase in γ can impact the intertemporal utility in various ways. Households benefit from increased consumption and time spent online but also from the wider variety of available goods due to their taste for diversity. However, they can be negatively impacted by the decrease in the quality index of digital services when the choice of digital services is reduced.

[23]We find that an increase in γ decreases K when $\gamma > \frac{1-\alpha\epsilon}{\alpha\epsilon}\left(\frac{\eta(\sigma-1)-(\rho+2\sigma-1)}{\eta(\sigma-1)}\right) = \overline{\overline{\gamma}}$. However, we are uncertain under what conditions and whether the number of small providers can be reduced following an increase in γ. See proof 4 in appendix 2.B.3 for more details.

2.6.2 The quality advantage of large providers over small ones

The gap between β^j and β^k is one of the main determinants of the advantage of large providers over small ones. This section investigates the impact of a change on this gap.

Impact on traditional sector

We find that an increase in the gap between β^j and β^k, through an increase in β^j or a decrease in β^k, has a positive impact on the optimal expenditure (E). It is achieved through two channels. Firstly, increasing the efficiency parameter in digital quality production of large digital providers compared to small ones enables them to engage in less work. There is a reallocation of work to the production of the final goods, which increases the production. Secondly, the increase in efficiency in production quality increases the profit of large providers, which increases individual wealth. The optimal expenditure level of households increases. The two effects increase the production of final goods, the firms' value, and, thus, the number of traditional firms due to the free entry assumption. Moreover, when γ is high, an increase in the quality advantage of large providers reduces the advertising price by significantly increasing advertising supply (see proof 5 in appendix 2.B.3 for more details). Production costs are decreasing in the traditional sector, which increases potential firms' profits and allows new firms to enter the market.

Conversely, a decrease in the quality advantage of large providers over small ones, through a decrease in β^j or an increase in β^k, harms the traditional economy. It also increases the production of final goods through a reallocation of work. However, it decreases the profit of large providers by reducing the quality advantage of large providers over small ones. Due to the free entry assumption, an increase in small providers' production does not increase individual wealth as their profits are zero. This effect dominates, resulting in a decrease in optimal spending through a reduction in household resources. The number of traditional firms decreases. Moreover, when γ is high, this effect is exacerbated by the increase in

advertising price (see proof 5 in appendix 2.B.3 for the proof).

Impact on digital sector

The first and direct impact of an increase in β^j and β^k is to improve large and small providers' digital service quality respectively. An increase in the gap between β^j and β^k have two opposite effects on the number of small providers. First, large providers become more attractive, and households spend more time on these services. It also increases the online time and enables all providers to collect more data. The increase in data increases small providers' potential profits as they are both production factors of impression. Due to free entry, the number of small providers increases. However, an increase in β^j also widens the gap in quality between the large and the small providers. As households value more digital services of large providers than small ones, the demand for digital services of small providers decreases. Small providers' profits decrease, and, therefore, some of them exit the market. The prevailing effect depends on the value of γ, the importance of attention compared to data in impression production. If γ is low, the first effect prevails.[24] As data is an important production factor, increasing it significantly increases impression production. On the contrary, if γ is high, large providers are more efficient at producing advertising, as the time spent on their services is much higher than the time spent on digital services of small providers. The additional advantage for large providers is detrimental to small providers. In addition, when the value of γ is high, the significant increase in impression supply of large providers decreases the advertising price, contributing to the decline in profits for small providers. A decrease in the quality advantage of large providers over small ones has the opposite effect.

Interestingly, a change in β^k decreases the digital service quality of large providers, while a change in β^j does not modify those of small providers. Indeed, the decline in households' online time, combined with the declining attractiveness of large providers' services compared to small providers, results in a decline in time spent on large providers' services. Their profits

[24] A low γ means that $\gamma < \frac{1-\alpha\epsilon}{\alpha\epsilon}\left(\frac{\eta(\sigma-1)-(\rho+2\sigma-1)}{\eta(\sigma-1)}\right) = \overline{\overline{\gamma}}$. See proof 4 in appendix 2.B.3.

decrease, and they can invest less in their service quality. If γ is high, this effect is exacerbated by the rise in the number of small providers and the decrease in advertising price (see proofs 4 and 5 in appendix 2.B.3). No symmetrical effect exists when β^j changes. Indeed, an increase in β^j increases the total time spent online, which can increase the potential profits of small providers through an increase in data. However, this effect is offset by the increase in the gap between β^j and β^k, decreasing the demand for digital services of small providers.

Households intertemporal utility

An increase in the gap between β^j and β^k improves the intertemporal utility by increasing final goods consumption and online time. In the case of low γ, households also benefited from a wider choice of goods and digital services. However, when γ is high, only the number of varieties increases, while small providers' digital services decrease.

On the contrary, a decrease in the quality advantage of large providers negatively impacts the intertemporal utility through decreased consumption, variety of goods, and online time. When γ is high, households can still benefit from the increased choice of digital services. Households have strong preferences for the services of large providers (habits, lock-in effect...). Therefore, these services are significantly more valuable to households than services of small providers. The increase in the quality of services from small providers does not compensate for the drop in the quality of services of large providers.

2.6.3 Entry of a new large digital service provider

In this section, we explore another impact of the market structure of the digital sector by looking at how our economy evolves when a new large provider enters the market for free digital services, which increases the number of large providers of digital services J.

Impact on traditional sector

An increase in J positively impacts the optimal level of expenditure E and the number of traditional firms I. The more large providers are, the higher their total profits are. This result comes from the industry structure. Indeed, Shimomura & Thisse (2012) demonstrate that in a mixed market composed of large firms and a continuum of small firms, the entry of a new incumbent raises the profit of each large firm. They explained it by the decrease in small firms' potential profit. In our model, and as demonstrated hereafter, small providers are not necessarily negatively affected by this increase in competition. The increase in large providers' profits is, therefore, also due to the strong preference of the households for digital services of large providers. Households significantly increase their online time following the entry of a new large provider. A rise in large providers' profits increases the individual wealth and, thus, households' optimal level of expenditure. Through the mechanisms explained above, the number of traditional firms increases.

Impact on digital sector

The number of large providers does not impact the quality of digital services of large and small providers (q^j and q^k). However, it can impact small providers' potential profits. On the one hand, the entry of a new large digital service provider increases the total online time. It can positively impact small providers' profits through increased attention and data. On the other hand, introducing a new large provider enhances competition, reducing impression price (see proof 5 in appendix 2.B.3). In the case of a high γ, the first effect is offset by the second. The increase in production factors does not compensate for the increase in competition and the decrease in impression price. The profits of small providers decrease and, therefore, their number. In the other case, the advantage in the impression of large providers is not too high. Small providers benefit from the increase in production factor, especially data, which plays a significant role in production when γ is low. It increases their production of impressions. New small providers enter the market.

Households intertemporal utility

As households have strong preferences for the services of large providers, an increase in their number will positively impact their utility. The increased consumption, the number of goods varieties, and time spent online will also positively impact the intertemporal utility. Furthermore, if γ is low (high), the intertemporal utility will be positively (negatively) impacted by the increase (decrease) in the choice of digital services. Note that in Shimomura & Thisse (2012), the entry of a new incumbent increases the welfare despite the decrease in the variety of digital services of small providers. In this kind of market, households benefit from the presence of large firms.

2.6.4 Sensitivity for privacy

We end this exercise of static-comparative by exploring the impact of the privacy sensitivity, measured by the parameter α. The higher α, the lower the household is sensitive to privacy issues. Note that α is also a substitution parameter between digital services (see equation (2.14)), which can be interpreted as the taste for the digital services diversity. We, therefore, have to remain cautious in interpreting these results. Nevertheless, the link between privacy and taste for diversity is not unrealistic, as we can assume that users with low privacy concerns will be more likely to use many different digital services.

Impact on traditional sector

An increase in α positively impacts the optimal level of expenditure E and thus the number of traditional firms I. If households are less sensitive to privacy, they will value the positive effect of data collection more than the negative one. Therefore, they spend more time online, increasing the production of impressions. Large providers' profits increase, increasing households' optimal expenditure level and consumption of final goods, leading to an increase in the number of traditional firms. The optimal level of expenditure also increases through

another channel. Indeed, less sensitivity to privacy results in more prolonged use of digital services for the same level of quality. Labor is thus reallocated from the digital sector to the traditional sector, increasing the production of final goods, their profits, and, therefore, the number of firms.

Impact on digital sector

The increase in α has a similar impact to the increase in γ, i.e., an increase in the quality of digital services and a drop in the number of small providers according to the level of γ. However, these impacts are achieved through another channel. A lower sensitivity for privacy increases the time spent on each digital service, and the number of data households accept to disclose. It enables digital service providers to increase their production of impressions. However, if γ is too high, the advantage of large providers prevails and outweighs the increase in production factors of small providers. Their profits are declining, resulting in a reduction in the number of small providers.

Households intertemporal utility

Results are similar to an increase in γ presented in section 2.6.1. In addition, an increase in α also directly affects the intertemporal utility. Indeed, the less a household is sensitive to privacy, the less data collection generates disutility.

2.7 Conclusion

The emergence of free digital services has changed household consumption as well as the allocation of their time. It has also resulted in the creation of large digital service providers, often called Big Tech, which dominated their market. It is the case of Google and Meta. These providers of free digital services generate revenues similar to those of the largest traditional

firms. However, their business model differs from traditional firms as the service is free. The novelty is that the digital service is used to collect data about its users, which is then used in the production of targeted advertising. However, advertising is not directly considered in the GDP measure. Consequently, firms with significant revenues can have no direct impact on economic growth, while it can impact the other sectors of the economy and the households.

This chapter proposes an endogenous growth model without scale effect, including the free digital services sector, to understand the link between the main macroeconomic aggregates and welfare. It models the interaction between digital and traditional sectors and households. The traditional sector comprises a continuum of monopolistic firms that sell differentiated goods. To improve their good's perceived quality, they can increase the effort in the R&D activity and buy targeting impressions to the digital sector. The latter comprises a fixed number of large digital service providers and a continuum of small providers. To produce targeted impressions, they need users' attention and data. To this aim, they improve the quality of their service to attract for as long as possible. Finally, households optimally choose their level of consumption of traditional goods and the time spent online. They suffer from a disutility of data collection due to their sensitivity to privacy, but also an advantage, as the data is used to personalize the service. Households, therefore, must choose how much data they disclose to maximize their utility.

Our results highlight that the free digital services sector can have macroeconomic implications without impacting economic growth. We also emphasize that the market structure of the digital sector, users' data, and attention, as well as sensitivity to privacy, are important characteristics that determine several results. Firstly, we find that using data in impression production enables small providers of digital services to compete with large providers. It enables them to counter the advantage in quality of large providers and, therefore, the households' preferences in favor of digital services of large providers. In line with Shimomura & Thisse (2012), we find that an increase in competition, through an increase in the advantage in quality of large providers over small ones or the entry of a new large provider, has a positive impact on large providers. The increase in their profits positively impacts the

economy and households' welfare by increasing the optimal expenditure and the number of traditional firms. Therefore, the economy and households benefit more from large providers than small ones due to the market structure of the digital sector.

We finish the conclusion by discussing two points. Firstly, we model advertising as combative. Traditional firms must buy impressions if they want their product to be seen. At the equilibrium, all firms buy the same amount of impressions, which lead to a waste of resource. An increase in advertising spending of the firms can decrease the investment in R&D because labor is allocated to sectors linked directly or not with advertising production. It can depress the economic growth. We do not capture this mechanism with our model. However, this simplification is not an issue as advertising spending represents a constant share of the GDP, even since the development of digital advertising (Greenwood *et al.*, 2021).

Finally, we find that privacy sensitivity harms the economy through the difficulty of collecting data. Without data regulation, firms are incentivized to collect as much information as possible to improve their profits. Data can also be used in the R&D sector to improve economic growth and welfare in various domains, including medical research (Jones & Tonetti, 2020). However, although firms mainly collect data for commercial purposes, data regulation such as GDPR is important. Besides protecting privacy, the aim is to increase the responsibility of firms to avoid data sharing, which can result in user manipulation, as we have seen in the Facebook-Cambridge Analytica data scandal in the 2010s. The sharing of personal information can also lead to security or addiction issues. These negative impacts and scandals increase household concerns about digital risks (OECD, 2020b). Data protection regulation is a way to reduce privacy fear and, therefore, offset its negative impact on the economy.

2.A Variables description

Table 2.A.1: Variables description

Variable	Description
$s_{h,j}$	Time spent on the digital service of the large provider j by the household h
$s_h(k)$	Time spent on the digital service of the small provider k by the household h
$s_{h,0}$	Total time spent on all digital services of small providers by the household h
S_h	Total time spent online by the household h
q_j	Quality of the digital service of the large provider j
$q(k)$	Quality of the digital service of the small provider k
q_0	Index of the quality of digital services of small providers
Q	Index of the quality of all digital services
$c_h(i)$	Consumption of the variety of good i by the household h
$p(i)$	Price of the variety of good i
C_h	Consumption index of differentiated goods of the household h
P	Price index of differentiated goods
b_h	Individual wealth of the household h
r	Interest rate
E_h	Consumption expenditure level of the household h
$\tilde{z}(i)$	Perceived quality of the variety of good i by the household h
$z(i)$	True quality of the variety of good i
$\overline{z}$	State of technology (average investment in R&D)
$x(i)$	Production of the variety of good i by firm i
$a_h(i)$	Quantity of impressions bought by the firm i to be displayed to household h
$\overline{a}$	Average quantity of impressions displayed to household h
$m_h(i)$	Quantity of impressions bought by firm i to be displayed to household h relative to average impressions displayed to this household
$a^s_{h,j}$	Production of impressions by the large digital service provider j for display to household h
$a^s_h(k)$	Production of impressions by the small digital service provider k for display to household h
p^a	Price of one unit of impression
$d_{h,j}$	Data collected by the large digital service provider j on household h

$d_h(k)$	Data collected by the small digital service provider k on household h
$\overline{d_h}$	Maximum quantity of data on household h that can be collected by digital service providers
L	Individual work time
$L^x(i)$	Labor used in the production of the variety of good i
$L^R(i)$	Labor used in the activity of R&D of firm i
L_j^q	Labor used to improve the quality of the digital service of the large provider j
$L^q(k)$	Labor used to improve the quality of the digital service of the small provider k
f^x	Fixed labor cost incurred by firm i
F	Fixed labor cost incurred by large digital service provider j
f	Fixed labor cost incurred by small digital service provider k
$\pi^x(i)$	Profit of the firm i
π_j	Profit of the large digital service provider j
π_k	Profit of the small digital service provider k
H	Population's size
I	Number of traditional firms
J	Number of large digital service providers
K	Number of small digital service providers
ρ	Time preference rate
σ	Substitution parameter between varieties of consumption goods
ϵ	Substitution parameter between digital services
α	Preference parameter for privacy
η	Effectiveness parameter of advertising
β	Effectiveness parameter of R&D
β^j	Effectiveness parameter of the digital service quality of large providers
β^k	Effectiveness parameter of the digital service quality of small providers
γ	Indicator of the importance of data collection in the production of impressions

2.B Proofs

2.B.1 Optimum results

PROOF 1: the optimum values of $s_h(k)$ and $s_{h,j}$

The Lagrangian associated with the minimization program given by (2.15) is:

$$\mathcal{L} = \int_0^K s_h(k)dk + \lambda(s_{h,0}q_0 - \Big(\int_0^K \Big((s_h(k)q(k))^{\alpha\epsilon}\Big)^{\frac{1}{\alpha\epsilon}}dk\Big)) \tag{2.B.1.1}$$

FOC's with respect to $s_h(k)$ gives us:

$$1 = \lambda\Big(\int_0^K \Big((s_h(k)q(k))^{\alpha\epsilon}\Big)^{\frac{1}{\alpha\epsilon}-1}dk\Big)q(k)^{\alpha\epsilon}s_h(k)^{\alpha\epsilon-1} \tag{2.B.1.2}$$

We can write the ratio between the FOCs with respect to $s_h(k)$ and $s_h(k')$ as:

$$s_h(k) = s_h(k')\Big(\frac{q(k)}{q(k')}\Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon}} \tag{2.B.1.3}$$

Multiplying by $q(k)$ and integrating with respect to k, we obtain:

$$\Big(\int_0^K \Big((s_h(k)q(k))^{\alpha\epsilon}\Big)^{\frac{1}{\alpha\epsilon}}dk\Big) = s_h(k')q(k')^{\frac{\alpha\epsilon}{\alpha\epsilon-1}}\Big(\int_0^K \Big(q(k)^{\frac{\alpha\epsilon}{1-\alpha\epsilon}}\Big)^{\frac{1}{\alpha\epsilon}}dk\Big) \tag{2.B.1.4}$$

By setting $s_{h,0} = \int_0^K s_h(k)dk$ the total time spent on digital services of small providers and $q_0 = (\int_0^K q(k)^{\frac{\alpha\epsilon}{1-\alpha\epsilon}})^{\frac{1-\alpha\epsilon}{\alpha\epsilon}}dk$ a quality index of the digital services of small providers, the optimal time spent on the digital service k is given by:

$$s_h(k) = s_{h,0}\Big(\frac{q(k)}{q_0}\Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon}} \tag{2.B.1.5}$$

The same methodology is used to solve the minimization program given by (2.16). The

Lagrangian associated is:

$$\mathcal{L} = \sum_{j=0}^{J} s_{h,j} + \lambda\Big(QS_h - \Big(\sum_{j=0}^{J}(q_j s_{h,j})^{\alpha\epsilon}\Big)^{\frac{1}{\alpha\epsilon}}\Big) \tag{2.B.1.6}$$

By setting $S_h = \sum_{j=0}^{J} s_{h,j}$ the total time spent on all digital services and $Q = (\sum_{j=0}^{J} q_j^{\frac{\alpha\epsilon}{1-\alpha\epsilon}})^{\frac{1-\alpha\epsilon}{\alpha\epsilon}}$ an index of the quality of all digital services, we obtain the optimal time spent on each digital services of large provider:

$$s_{h,j} = S_h\Big(\frac{q_j}{Q}\Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon}} \tag{2.B.1.7}$$

2.B.2 Equilibrium results

Proof 2: macroeconomic equilibrium values of E^*, K^*, q^{j*}, q^{k*}, I^*, L^{R*}, and p^{a*}

By substitution and using the Keynes-Ramsey equation (equation (2.27)) and the equilibrium price of traditional goods (equation (2.58)) in the equation of free entry in the traditional market (equation (2.62)), we obtain:

$$\frac{\rho}{\sigma}\frac{H}{I_t}E_{t-1} = L^R_{t-1} + p^a_{t-1}Ha_{t-1} + f^x \tag{B.2.1}$$

By adding the total supply of goods given by equations (2.53) and (2.74) in the previous equation and combining with the labor market equilibrium (equation (2.75)), we have:

$$\frac{\rho+\sigma-1}{\sigma}E_tH = H(L-S_t) - K_t(L^k - f) - J(L^j - F) + I_{t+1}a_t p^a_t H \tag{B.2.2}$$

Finally, using the free entry condition on the small digital service market (equation (2.72)) and the equilibrium in the advertising market (equation (2.73)), the previous equation can be rewritten as:

$$\frac{\rho+\sigma-1}{\sigma}E_tH = H(L-S_t) - J(L^j - F) + J(a^j_t p^a_t) \tag{B.2.3}$$

Using the advertising market equilibrium (equation (2.73) and the two previous equations, we obtain:

$$K_t a_t^k + J a_t^j = H\alpha^{1-\gamma} S_t \Big(K_t + \Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}} J\Big)^{-\gamma} \Big((K_t + \Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon}{\alpha\epsilon(1+\gamma)-1}} J\Big) \tag{B.2.4}$$

At the steady state, the Keynes-Ramsey rule implies $r = \frac{1-\rho}{\rho}$. Using it in demand for impressions by household (equation (2.60)), we obtain:

$$I p^a a = \eta\rho E \frac{\sigma - 1}{\sigma} \tag{B.2.5}$$

By substitution and using equations (B.2.4) and (B.2.5), we can rewrite the advertising market equilibrium as:

$$\eta\rho\Big(\frac{\sigma - 1}{\sigma}\Big) E = p^a \alpha^{1-\gamma} S \Big(K_t + \Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}} J\Big)^{-\gamma} \Big((K + \Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon}{\alpha\epsilon(1+\gamma)-1}} J\Big) \tag{B.2.6}$$

By substitution and using equation (2.69) in the free entry in the small digital service market condition, we obtain:

$$\Big(K + \Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}} J\Big)^{-\gamma} = f(p^a H S)^{-1} \Big(\frac{\alpha^{1-\gamma}(1 - \alpha\epsilon(1-\gamma))}{1 - \alpha\epsilon}\Big)^{-1} \tag{B.2.7}$$

By combining equations (B.2.6) and (B.2.7), we obtain the equilibrium value of the number of small digital service providers at the steady state:

$$K^* = \eta\rho E \frac{\sigma - 1}{\sigma} f^{-1} H \frac{1 - \alpha\epsilon(1+\gamma)}{1 - \alpha\epsilon} - \Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}} \tag{B.2.8}$$

Using equation (2.68), we obtain that:

$$p^a a^j - \frac{1}{\beta^j} q^j = \Big(J + \Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon}{\alpha\epsilon(1+\gamma)-1}} K\Big)^{-\gamma} p^a H S \frac{\alpha^{1-\gamma}(1 - \alpha\epsilon(1-\gamma))}{1 - \alpha\epsilon} \tag{B.2.9}$$

By substituting equation (B.2.7), we have:

$$p^a a^j - \frac{1}{\beta^j} q^j = f\Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon}{\alpha\epsilon(1+\gamma)-1}} \tag{B.2.10}$$

By including this previous equation in equation (B.2.3) and using the optimal online time (equation (2.56)), we find the value of optimal expenditure at the equilibrium:

$$E^* = \Big(\frac{\sigma}{\rho - 1 + 2\sigma}\Big)\Big[L + \frac{1}{H} J\Big(\Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon\gamma}{\alpha\epsilon(1+\gamma)-1}} f - F\Big)\Big] \tag{B.2.11}$$

By substitution and using the free entry condition into the small digital service providers and the equilibrium value of a^{k*} (equation (2.69)) in equation (2.71), we obtain the equilibrium value of q^k:

$$q^{k*} = \beta^k f \frac{\alpha\epsilon\gamma}{1 - \alpha\epsilon(1+\gamma)} \tag{B.2.12}$$

We deduce the equilibrium value of q^{j*} by including the previous equation in the equation (2.70):

$$q^{j*} = \frac{\alpha\epsilon\gamma}{1 - \alpha\epsilon(1+\gamma)} f \beta^{j\frac{\alpha\epsilon-1}{\alpha\epsilon(1+\gamma)-1}} \beta^{k\frac{\alpha\epsilon\gamma}{\alpha\epsilon(1+\gamma)-1}} \tag{B.2.13}$$

Combining equations (B.2.1) and (B.2.5), we obtain:

$$\frac{\rho}{\sigma}\frac{HE}{I} = L^R + H\eta\rho\frac{\sigma-1}{\sigma}\frac{E}{I} + f^x \tag{B.2.14}$$

Moreover, by substitution and using the demand of variety (equation (2.53)), and the equilibrium price of traditional variety (equation 2.58)), we can rewrite the labor demand in the R&D activity (equation (2.59)) as:

$$L^R = \frac{\sigma-1}{\sigma}\beta H\rho\frac{E}{I} \tag{B.2.15}$$

we deduce the number of traditional firms at equilibrium by introducing the previous equation

in equation (B.2.14):

$$I^* = \frac{1}{\sigma}\frac{HE}{f^x}(1-(\beta+\eta)(\sigma-1)) \tag{B.2.16}$$

and the equilibrium value of labor in R&D such as:

$$L^{R*} = \frac{\beta(\sigma-1)f^x}{1-(\beta+\eta)(\sigma-1)} \tag{B.2.17}$$

Finally, by combining the equations (B.2.5) and (2.73), we obtain that:

$$\eta\frac{\sigma-1}{\sigma}\rho\frac{E}{I} = p^a(Ka^k + Ja^J) \tag{B.2.18}$$

By substitution and using the equilibrium values of a^k and a^j given by equations (2.69) and (2.68), we obtain the equilibrium value of advertising price:

$$p^{a*} = \eta\frac{\sigma-1}{\sigma}\rho\alpha^{\gamma-1}\Big[K + \Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}}J\Big]^{\gamma}\Big[K + \Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}}J\Big]^{-1} \tag{B.2.19}$$

PROOF 3: equilibrium values of $C_{h,t}$ and U_0

At the symmetric equilibrium, the consumption index given by equation (2.2) can be rewritten as:

$$C_{h,t} = I_t^{\frac{\sigma}{\sigma-1}}\tilde{z}_t c_t \tag{B.2.20}$$

All traditional firms buy the same number of impressions at the symmetric equilibrium. Therefore, the perceived quality of traditional goods equals the true quality. By substitution and using the optimal demand of each variety by household (equation (2.53)), we have:

$$C_{h,t} = \overline{z}_{t-1}(L^R_{t-1})^{\beta}\frac{E_t}{p}I^{\frac{1}{\sigma-}} \tag{B.2.21}$$

Moreover, the state of technology at the symmetric equilibrium is equal to $\overline{z}_{t-1} = z_{t-1} = \overline{z}_{t-2}(L^{R*}_{t-1})^{\beta} = \overline{z}_0(L^{R*}_{t-1})^{\beta t-1}$. Therefore, using the equilibrium price of good (equation (2.58)),

we have:

$$C^* = \frac{\sigma-1}{\sigma} I^{*\frac{1}{\sigma-1}} \overline{z}_0 (L^{R*})^{\beta t} E^* \tag{B.2.22}$$

Note that at period 0, consumption index is simply equal to $C^*_{h,0} = \frac{\sigma-1}{\sigma} I_0^{*\frac{1}{\sigma-1}} \overline{z}_0 E^*$ as the investment in R&D occurs in t-1. The intertemporal utility can be rewritten as:

$$\begin{aligned} U_0 &= \ln C_{h,0} + \sum_{t=1}^{\infty} \rho^t \ln C_{h,t} + \sum_{t=0}^{\infty} \rho^t \ln D_{h,t} \\ &= \frac{1}{\sigma-1} \ln I_0^* + \ln(\frac{\sigma-1}{\sigma} \overline{z}_0 E^*)(1 + \sum_{t=1}^{\infty} \rho^t) + \sum_{t=1}^{\infty} \rho^t \ln(I^{*\frac{1}{\sigma-1}} (L^{R*})^{\beta t}) + \sum_{t=0}^{\infty} \rho^t \ln D^*_{h,t} \end{aligned} \tag{B.2.23}$$

We have $\sum_{t=0}^{\infty} \rho^t = \frac{1}{1-\rho}$ and $\sum_{t=1}^{\infty} \rho^t = \frac{\rho}{1-\rho}$. Therefore:

$$U_0 = \frac{1}{\sigma-1} \ln I_0^* + \frac{1}{1-\rho} \ln(\frac{\sigma-1}{\sigma} \overline{z}_0 E^*) + \frac{1}{\sigma-1} \frac{\rho}{1-\rho} \ln I^* + \frac{\rho}{(\rho-1)^2} \beta (L^{R*}) + \sum_{t=0}^{\infty} \rho^t \ln D^*_{h,t} \tag{B.2.24}$$

At the symmetric equilibrium and using the fact that $\overline{d}_h$ is equal to S_h and equation (2.56), the digital consumption index given by equation (2.24) can be rewrite as:

$$D_{h,t} = \alpha (1-\alpha)^{\frac{1-\alpha}{\alpha}} E^{*\frac{1+\alpha}{\alpha}} Q^* \tag{B.2.25}$$

We can deduce that

$$\sum_{t=0}^{\infty} \rho^t \ln D^*_{h,t} = \frac{1}{1-\rho} \ln(\alpha (1-\alpha)^{\frac{1-\alpha}{\alpha}} E^{*\frac{1+\alpha}{\alpha}} Q^*) \tag{B.2.26}$$

By substitution and using the previous equation and the consumption index growth rate given by equation (2.85), the intertemporal utility is given by:

$$\begin{aligned} U_0 =& \frac{\rho}{1-\rho} (\frac{1}{\sigma-1} \ln I^* + \frac{1}{1-\rho} g + \frac{1}{\rho} \ln E + \frac{1}{\rho} E^{\frac{1+\alpha}{\alpha}} Q^*) \\ &+ \frac{1}{1-\rho} (\ln \frac{\sigma-1}{\sigma} \overline{z}_0 + \ln(\alpha (1-\alpha)^{\frac{1-\alpha}{\alpha}})) + \frac{1}{\sigma-1} \ln I_0 \end{aligned} \tag{B.2.27}$$

2.B.3 Static-comparative results

PROOF 4: the sign of $\frac{\partial K^*}{\partial \beta^j}$, $\frac{\partial K^*}{\partial \beta^k}$, $\frac{\partial K^*}{\partial \gamma}$ and $\frac{\partial K^*}{\partial J}$:

According to equations (2.76) and (2.80), the number of small providers at the equilibrium is given by:

$$K^* = \frac{\eta\rho(\sigma-1)}{\rho+2\sigma-1}\frac{1-\alpha\epsilon(1+\gamma)}{1-\alpha\epsilon}\frac{H}{f}\Big(L+\frac{J}{H}\Big(\Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}}f-F\Big)\Big)-\Big(\Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}}\Big)J \tag{B.3.1}$$

We have:

$$\frac{\partial K^*}{\partial \beta^j} = \frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}\beta^{j\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}-1}\beta^{k\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}}J\Big[\frac{\rho\eta(\sigma-1)}{\rho+2\sigma-1}\frac{1-\alpha\epsilon(1+\gamma)}{1-\alpha\epsilon}-1\Big] \tag{B.3.2}$$

Therefore, $\frac{\partial K^*}{\partial \beta^j} > 0$ if the term in the brackets is positive, i.e., if:

$$\gamma < \frac{1-\alpha\epsilon}{\alpha\epsilon}\Big(\frac{\eta(\sigma-1)-(\rho+2\sigma-1)}{\eta(\sigma-1)}\Big) = \overline{\overline{\gamma}} \tag{B.3.3}$$

and negative if $\gamma > \overline{\overline{\gamma}}$.

We find the opposite results for $\frac{\partial K^*}{\partial \beta^k}$, i.e., it is positive if:

$$\gamma > \frac{1-\alpha\epsilon}{\alpha\epsilon}\Big(\frac{\eta(\sigma-1)-(\rho+2\sigma-1)}{\eta(\sigma-1)}\Big) = \overline{\overline{\gamma}} \tag{B.3.4}$$

and negative if $\gamma < \overline{\overline{\gamma}}$.

We find that:

$$\begin{aligned}\frac{\partial K^*}{\partial \gamma} =& -\frac{\eta\rho(\sigma-1)}{\rho+2\sigma-1}\frac{\alpha\epsilon}{1-\alpha\epsilon}\frac{H}{f}\Big(L+\frac{J}{H}\Big(\Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}}f-F\Big)\Big)\\ &+\frac{\eta\rho(\sigma-1)}{\rho+2\sigma-1}\frac{1-\alpha\epsilon(1+\gamma)}{1-\alpha\epsilon}J\Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}}\frac{\alpha\epsilon(1-\alpha\epsilon)}{(1-\alpha\epsilon(1+\gamma))^2}\ln\Big(\frac{\beta^j}{\beta^k}\Big)\\ &-J\Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}}\frac{\alpha\epsilon(1-\alpha\epsilon)}{(1-\alpha\epsilon(1+\gamma))^2}\ln\Big(\frac{\beta^j}{\beta^k}\Big) \qquad \text{(B.3.5)}\\ =& -\frac{\eta\rho(\sigma-1)}{\rho+2\sigma-1}\frac{\alpha\epsilon}{1-\alpha\epsilon}\frac{H}{f}\Big(L+\frac{J}{H}\Big(\Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}}f-F\Big)\Big)\\ &+J\Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}}\frac{\alpha\epsilon(1-\alpha\epsilon)}{(1-\alpha\epsilon(1+\gamma))^2}\ln\Big(\frac{\beta^j}{\beta^k}\Big)\Big[\frac{\eta\rho(\sigma-1)}{\rho+2\sigma-1}\frac{1-\alpha\epsilon(1+\gamma)}{1-\alpha\epsilon}-1\Big]\end{aligned}$$

The first term of the equation is always negative. The sign of the second term depends on the sign of the term in the brackets. Therefore, we can conclude that $\frac{\partial K^*}{\partial \gamma} < 0$ if the term in the brackets are negative, i.e., if:

$$\gamma > \frac{1-\alpha\epsilon}{\alpha\epsilon}\Big(\frac{\eta(\sigma-1)-(\rho+2\sigma-1)}{\eta(\sigma-1)}\Big) = \overline{\overline{\gamma}} \qquad \text{(B.3.6)}$$

In the other case, we can not conclude the effect of γ on K^*.

Finally, we find that:

$$\frac{\partial K^*}{\partial J} = \Big(\frac{\beta^j}{\beta^k}\Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}}\Big[\frac{\rho\eta(\sigma-1)}{\rho+2\sigma-1}\frac{1-\alpha\epsilon(1+\gamma)}{1-\alpha\epsilon}-1\Big] \qquad \text{(B.3.7)}$$

Therefore, as for $\frac{\partial K^*}{\partial \beta^j}$, $\frac{\partial K^*}{\partial J}$ is positive if:

$$\gamma < \frac{1-\alpha\epsilon}{\alpha\epsilon}\Big(\frac{\eta(\sigma-1)-(\rho+2\sigma-1)}{\eta(\sigma-1)}\Big) = \overline{\overline{\gamma}} \qquad \text{(B.3.8)}$$

and negative if $\gamma > \overline{\overline{\gamma}}$

PROOF 5 of the sign of $\frac{\partial p^{a*}}{\partial \beta^j}$, $\frac{\partial p^{a*}}{\partial \beta^k}$, and $\frac{\partial p^{a*}}{\partial J}$

The equilibrium price of advertising is given by:

$$p^{a*} = \eta \frac{\sigma - 1}{\sigma} \rho \alpha^{\gamma - 1} \Big[K + \Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}} J \Big]^{\gamma} \Big[K + \Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}} J \Big]^{-1} \tag{B.3.9}$$

where

$$K^* = \frac{\eta\rho(\sigma-1)}{\rho + 2\sigma - 1} \frac{1 - \alpha\epsilon(1+\gamma)}{1 - \alpha\epsilon} \frac{H}{f} \Big(L + \frac{J}{H} \Big(\Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}} f - F \Big) \Big) - \Big(\Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}} \Big) J \tag{B.3.10}$$

We find that:

$$\begin{aligned} \frac{\partial p^{a*}}{\partial \beta^j} =& \eta \frac{\sigma - 1}{\sigma} \rho \alpha^{\gamma - 1} \Big(K + \Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}} J \Big)^{\gamma - 1} \Big(K + \Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}} J \Big)^{-2} \\ & \Big[\gamma \Big(K + \Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}} J \Big) \Big(\frac{\partial K^*}{\partial \beta^j} + \frac{\alpha\epsilon}{1 - \alpha\epsilon(1+\gamma)} \beta^{j \frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)} - 1} \beta^{k - \frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}} J \Big) \\ & - \Big(K + \Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}} J \Big) \Big(\frac{\partial K^*}{\partial \beta^j} + \frac{\alpha\epsilon\gamma}{1 - \alpha\epsilon(1+\gamma)} \beta^{j \frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)} - 1} \beta^{k - \frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}} J \Big) \Big] \end{aligned} \tag{B.3.11}$$

The sign of the above derivative depends on the bracketed term, that we can rewrite as:

$$\begin{aligned} A =& \frac{\partial K^*}{\partial \beta^j} \Big[\gamma \Big(K + \Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}} J \Big) - \Big(K + \Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}} J \Big) \Big] \\ & + \frac{\alpha\epsilon\gamma}{1 - \alpha\epsilon(1+\gamma)} \beta^{j \frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)} - 1} \beta^{k - \frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}} J \Big[\Big(K + \Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}} J \Big) \\ & - \Big(K + \Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}} J \Big) \beta^{j \frac{\alpha\epsilon(\gamma-1)}{1-\alpha\epsilon(1+\gamma)}} \beta^{k \frac{\alpha\epsilon(1-\gamma)}{1-\alpha\epsilon(1+\gamma)}} \Big] \\ =& \frac{\partial K^*}{\partial \beta^j} \Big[\gamma \Big(K + \Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon\gamma}{1-\alpha\epsilon(1+\gamma)}} J \Big) - \Big(K + \Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}} J \Big) \Big] \\ & + \frac{\alpha\epsilon\gamma}{1 - \alpha\epsilon(1+\gamma)} \beta^{j \frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)} - 1} \beta^{k - \frac{\alpha\epsilon}{1-\alpha\epsilon(1+\gamma)}} J \Big[K - \Big(\frac{\beta^j}{\beta^k} \Big)^{\frac{\alpha\epsilon(\gamma-1)}{1-\alpha\epsilon(1+\gamma)}} K \Big] \end{aligned} \tag{B.3.12}$$

The first bracketed term is negative as $0 < \gamma < 1$. Therefore, the first part of the above expression depends on the sign of $\frac{\partial K^*}{\partial \beta^j}$. It is, therefore, positive if $\gamma > \overline{\overline{\gamma}}$ and negative

otherwise (see the proof of the sign of $\frac{\partial K^*}{\partial \beta^j}$ detailed above). The second bracketed term is always positive as $0 < \gamma < 1$. Therefore, we can conclude that $\frac{\partial p^{a*}}{\partial \beta^j} > 0$ if $\gamma > \overline{\overline{\gamma}}$. In the others cases, we can not conclude on the effect of β^j on p^{a*}.

Using the same approach, we find the opposite result, such as $\frac{p^{a*}}{\beta^k} < 0$ if $\gamma > \overline{\overline{\gamma}}$.

Chapter 3

Determinants of the Digital Divide: Evidence from France[1]

[1] A version of this chapter has been accepted for publication in **Annals of Economics and Statistics**.

3.1 Introduction

In 2019, the OECD (2019) highlighted that: *"safe digital technologies improve the lives of those who have the skills to use them."* The correct use of digital technologies can facilitate access to essential services such as health, education, banking, and administrative services. One year later, the COVID-19 crisis and the many resulting lockdowns accelerated the digital transition and reinforced the need to access and use digital tools. The OECD (2020a) points out that digital inequalities have increased during the crisis and should be addressed. For this purpose, it is necessary to identify the individuals most affected by the digital divide and the determinants of these inequalities. This chapter investigates the French digital divide by exploring three different research issues. What are the determinants of the inequalities in internet access and use? Are there digital disparities in the variety and type of internet use? Finally, what are the reasons for not accessing the internet?

The digital divide refers to disparities in access and use of digital technology between individuals. It raises multiple issues. Eichengreen (2015) argues that the macroeconomic impact of technology depends strongly on its range of applications and use by economic actors. Therefore, as mentioned in Chapter 1, digital inequalities can hinder the digital transition and its impact on productivity and economic growth. Reducing digital inequalities is also an issue for the well-being of households. The OECD (2019) emphasizes that digital literacy facilitates social participation in various areas. For instance, public services are increasingly present online, and medical teleconsultations are on the rise and help improve healthcare access. Digital illiteracy is also an obstacle to employment as an increasing number of jobs require basic digital skills (Berger & Frey, 2016). In fact, Eynon *et al.* (2018) point out that digital access and usage contribute to social class mobility. In 2019, 67,5% of French people considered the internet necessary to feel integrated into our society.[2] While digital technology improves the well-being of those who use it (Pénard *et al.*, 2013), it tends to exclude those who do not, whether concerning participation in society or the labor market.

[2] https://www.data.gouv.fr/fr/datasets/barometre-du-numerique/, downloaded in July 2022.

In recent years, France has made progress in reducing the digital divide. In 2019, 85.2% of the French population used the internet at home, compared to only 51.2% in 2007, placing France at the OECD average (OECD, 2020b). This improvement can be attributed to a combination of factors, such as the time required for technology to be adopted and the government's commitment to fighting the digital divide. In line with OECD countries, the first public policies focused on investing in high-speed internet infrastructure throughout the territory. It was the objective of the "law in the fight against the digital divide" in 2009, the national broadband program of 2010, and the "France Très Haut Débit" plan of 2013. Investment has also been made to equip schools with appropriate digital tools to improve students' digital skills and prevent the digital divide among the younger. In 2018, the French government implemented a national strategy for inclusive digital. It proposes, among others, digital passes that allow access to digital courses and digital advisors to help perform administrative tasks online. However, despite important progress, the digital divide still exists in France. It is essential to investigate if the time effect is still at play and if public policies in place are adequate to address the reasons behind non-access to the internet and help the concerned population. The issue is all the more important since the French government aims to digitize all public services, which can reinforce the existing inequalities (Défenseur des droits, 2019).

This chapter contributes to the existing literature by addressing several of its limits. While previous studies have highlighted that the factors contributing to the digital divide vary across countries, there have been only limited contributions on this issue in France. Most research uses cross-sectional data because of the difficulty of interviewing the same individuals each year to create a panel survey. As a result, temporal evolution is ignored while the digital transition is ongoing. This chapter applies pseudo-panel methodology (Deaton, 1985) using French Institute of Statistics (INSEE) household surveys on Information and Communication Technologies (ICT) from 2007 to 2019. This methodology allows for the use of panel methodology with repeated cross-sectional data and, therefore, captures the temporal evolution of digital consumption over thirteen years and the characteristics of the French case.

To this aim, we consider cohorts formed according to their generation instead of individuals.[3] This approach in terms of cohorts allows capturing intra and intergenerational inequalities, highlighting that those born closer to the diffusion of digital technologies are more likely to have access to and use the internet. Furthermore, we study several levels of the digital divide. We provide an in-depth empirical investigation of the determinants of inequality in internet access and use. The diversity of online activities in which individuals engage can create opportunities. Therefore, we also focus on internet users and explore whether disparities exist in the variety and type of internet usage (administrative and banking services, social media, leisure, e-commerce, collaborative economy, and job search). It provides a profile of those most affected by the digital divide regarding access and diversity of internet use. Identifying barriers to digital access is essential to establishing effective public policies to reduce the digital divide. Hence, we also focus on individuals who do not have internet access at home and investigate the reasons behind their lack of access to the internet.

Our results highlight significant inequalities between generations. The younger ones have better access to and use of the internet than the older ones. The access and use of digital technology have been improving over time for all French population. In addition, intra-generational inequalities appear through income and education levels. A gender gap in favor of men emerges, but only for older generations. The household size impacts only the probability of accessing the internet at home, not its usage. Our results also show that population density is not a determinant of the digital divide in France, suggesting that digital infrastructure is not an important barrier to digital access in France, as the internet relatively well covers the French territory. If there is a rural/urban digital divide, it concerns the quality of the internet. Indeed, access to broadband internet, such as fiber, is not uniform throughout the territory. Intra-generational inequalities are no longer apparent when one focuses on internet users to study the diversity and type of internet usage. The probability of individuals engaging in an online activity depends mainly on their generation. Finally, we highlight that not accessing the internet because of a lack of skills and interest mainly concerns the older

[3]A generation is a group of individuals born in the same period. In a second time, we form the cohorts according to gender and generation to investigate a potential gender digital gap.

generations, while the young ones are more likely not to have the internet because the cost of the equipment or the internet connection is too expensive. In light of our results, we discuss public policies implemented in France to reduce the digital divide. While investments are made to improve digital skills and provide access to quality infrastructure, a financial support policy, such as equipment checks to rent or purchase a computer, is missing.

The remainder of this chapter is structured as follows. Section 3.2 provides a literature review of the determinants of the digital divide. Methodology and data are presented in Section 3.3. Section 3.4 presents the empirical results. Section 3.5 discusses the results in the context of French public policies, and Section 3.6 concludes.

3.2 Literature review

The digital divide was first studied as a problem of access to ICT. Goolsbee & Klenow (2002) studied the determinants of computer adoption in the United States of America (USA) in 1997. They found strong local spillover effects in computer diffusion, such as living in an area with a high proportion of computer ownership and having a friend or family member who owns a computer. As computers became more widespread, studies turned to the adoption of more recent technologies. Prieger & Hu (2008) investigated the determinants of broadband access in the USA. They highlighted that the demand for broadband access is higher for individuals with high income and education levels and lower for individuals from ethnic minorities. Reddick *et al.* (2020) obtained similar results. However, studying the case of San Antonio, they point out that digital disparities are often perceived as a rural/urban divide, while there are inequalities within cities. A second level of the digital divide rapidly came to light: the disparities in usage once the individual has access to digital equipment (Hargittai, 2002). Indeed, access is a necessary but not sufficient condition for the effective use of digital technologies. Furthermore, Montagnier & Wirthmann (2011) point out that the main determinants of digital access and use can differ. Considering 18 European countries,

Canada and South Korea, in 2008, they identified income level, children's presence in the home, and living in an urban area as the main determinants of computer and internet access. Internet use, on the other hand, is more influenced by age, economic inactivity, and education. Korupp & Szydlik (2005) find that computer and internet usage in Germany between 1997 and 2003 mainly depend on education, computer use at work, income, having teenagers or young adults in the home, gender, and being born in the *"computer"* generation. Helsper (2010) identifies a digital gender gap in internet use in favor of men that is smaller among young people. Nevertheless, that research also points out that this difference between young and old is not only due to a generational effect but also depends on different life stages (occupation and marital status). Schleife (2010) observes disparities in internet use between German counties. She demonstrates that these disparities are not explained by differences in population density but rather by differences in the composition of individual characteristics of each county. Besides the socio-demographic characteristics, Goldfarb (2006) emphasizes the university's major role in the diffusion of digital technology. Its impact is even more significant as the individual's income is lower.

Once an individual has access to and uses the internet, disparities in the mode of use may exist between individuals. Using a survey conducted in 2001 in the USA, Goldfarb & Prince (2008) showed that while income is a key determinant of digital adoption, lower-income individuals tend to spend more time online when they do have internet access. They explained this result by the differences in the opportunity cost of leisure time. Age negatively impacts internet use and the time spent online. Pantea & Martens (2013), Haight *et al.* (2014), and van Deursen & van Dijk (2014) find similar results for low-income individuals in France, Germany, Italy, Spain, and the United Kingdom (UK), migrants in Canada, and individuals with disabilities in the Netherlands, respectively. Hitt & Tambe (2007) highlight that a high-quality infrastructure, such as broadband access, increases the time spent online. Nevertheless, these disparities in time spent online are not necessarily inequalities. This is especially true as digital overuse, which is more frequent among individuals with a low level of education, harms well-being (Gui & Büchi, 2021). Consequently, studies have turned to the

"quality" of use rather than its quantity. Hence, Pantea & Martens (2013) and van Deursen *et al.* (2015) point out that individuals with a high level of education and the older use the internet for improving their human capital, while those least educated and the younger do so for leisure. In the same line, Elena-Bucea *et al.* (2021) point out that the most educated have greater use of online services (banking, submitting government forms, making medical appointments, and taking online courses). Social network adoption is more influenced by age. Consequently, digital inequalities emerge from the diversity and ways of using the internet, not from the average online time.

Some authors focus on the reasons behind digital exclusion. Eynon & Helsper (2011) point out that the reasons for not using computers depend on the individual's socio-demographic characteristics. Younger people are more likely to suffer from financial constraints, while older people are more likely to have a lack of interest. Using British and Swedish surveys between 2005 and 2013, Helsper & Reisdorf (2017) also observe that the reasons for the digital exclusion among non-users and ex-users differ over time and between countries. The main reason for the non-use of the internet was a lack of interest for the British and Swedish. The lack of skill and internet access were also important determinants. Ex-users in both countries mention a lack of interest. However, many British ex-users no longer use the internet because of the cost, which is different for Swedish ex-users. Finally, the reasons for the non-use of the internet may vary over time. Between 2005 and 2013, the importance of non-access to the internet and lack of skills as barriers to internet use declined in Great Britain but not Sweden. In contrast, a lack of interest is increasingly mentioned in both countries as a reason for not using the internet.

In this chapter, we study the different digital divide levels highlighted above (internet access, use, variety of usage, and reasons for non-access) by focusing on the French case. We investigate whether the determinants highlighted in other countries, such as income, level of education, household size, and population density, are also determinants of the French digital divide. We stand out from the literature by our methodological approach. We use pseudo-panel methods to consider the temporal evolution of digital diffusion between 2007

and 2019. As being born close to the spread of digital is an important factor in internet adoption and use, we study inequalities within and between generations.

While this chapter focuses on the first two levels of the digital divide, there is also a third level that concerns the inequalities in the outcomes of digital use (Scheerder *et al.*, 2017). Online activities, especially leisure, are often provided for free, making it difficult to measure the utility gained. Goolsbee & Klenow (2006) estimate the welfare gains from internet use based on time spent online and a utility model. Pantea & Martens (2016) apply their methodology to France, Germany, Italy, Spain, and the UK, controlling for household characteristics. They find that the utility gain from spending time online for leisure is higher for low-income individuals in all countries. In general, individuals with lower levels of education, men, younger individuals, and individuals living alone benefit more from online leisure. The significance of these variables is country dependent. Using a life satisfaction survey in Luxembourg, Pénard *et al.* (2013) show that internet users are more satisfied with their lives than non-users. However, they highlight disparities among users: the influence of the internet on well-being is more substantial among the youngest and the poorest individuals. Bartikowski *et al.* (2018) find that the perceived effect of digital technology is weaker for ethnic minorities than for other users. Castellacci & Tveito (2018) also indicate that the impact of digital use on well-being depends on individual characteristics such as psychological functioning, capabilities, and framing conditions. Finally, Lythreatis *et al.* (2022) note that further levels of the digital divide may cover algorithmic awareness and data inequality.

3.3 Methodology and Data

3.3.1 Pseudo-Panel methods

The empirical methodology used in this chapter is based on a panel model. This makes it possible to control for individual heterogeneity (Baltagi, 2013). The general model to

estimate is:

$$y_{it} = x_{it}\beta + \alpha_i + \lambda_t + \epsilon_{it} \tag{3.1}$$

$$i = 1, ..., N; t = 1, ..., T$$

where y_{it} is the dependent variable for the individual i at time t, x_{it} a vector of explanatory variables for individual i at date t, β a vector of parameters to be estimated associated with the explanatory variables, α_i the fixed effect of individual i, λ_t the time fixed effect for each period t, and ϵ_{it} the *independent and identically distributed (i.i.d)* error term.

The annual ICT Household survey used in this chapter does not survey the same individuals yearly. Since the samples differ every year, we do not have panel data but 13 individual cross-sections. We use the pseudo-panel method theorized by Deaton (1985) to overcome this problem. This method allows the use of independent cross-sectional data in a panel model and is used to address various issues in economics.[4] For this purpose, individuals are no longer considered, but the focus is on cohorts. These cohorts represent groups of individuals with common fixed characteristics over time. In our case, these characteristics are generations; their common characteristic is to have been born in the same period. In the second step, we form cohorts according to generation and gender.

The principle of pseudo-panel is to replace the individual variables of the panel model with their intra-cohort means. Equation (3.1) is transformed as:

$$y^*_{ct} = x^*_{ct}\beta + \alpha^*_c + \lambda_t + \epsilon^*_{ct} \tag{3.2}$$

$$c = 1, ..., C; t = 1, ..., T$$

where for a variable z, $z^*_{ct} = E(z_{it}|i \in c)$, y^*_{ct} is the expectation of the dependent variable for cohort c at survey date t, x^*_{ct} a vector of the expectations of the explanatory variables for

[4]Pseudo-panel methods are often used to analyze household behavior because the same individuals are rarely interviewed in surveys every year. Gardes *et al.* (2005) use it to compute elasticities of food consumption, Bernard *et al.* (2011) household electricity demand, and Imai *et al.* (2014) to identify determinants of child nutritional status. Pseudo-panel is also used with other data such as real estate transactions (Baltagi *et al.*, 2015).

cohort c at survey date t, β a vector of parameters associated with the explanatory variables, α_c^* the fixed cohort effect, λ_t the time fixed effect for each period t, and ϵ_{ct}^* the $i.i.d$ error term.

The true values of y_{ct}^* and x_{ct}^* are not known. Only the average of the values observed in the sample for the individuals of the same cohort are known and can be used. The model is then:

$$\overline{y}_{ct} = \overline{x}_{ct}\beta + \overline{\alpha}_c + \lambda_t + \overline{\epsilon}_{ct} \tag{3.3}$$

$$c = 1, ..., C; t = 1, ..., T$$

where for a variable z, $\overline{z}_{ct} = \frac{1}{n_{ct}} \sum_{i \in c} z_{it}$ and n_{ct} the number of observations in cohort c at time t.

To avoid measurement errors, Verbeek & Nijman (1992) demonstrate that starting from 100 individuals per cohort, the calculated averages tend towards their true value. They advise that cohorts comprise at least 200 individuals to avoid measurement errors. Estimation biases are then negligible. Nevertheless, increasing the cohort size reduces the number of cohorts in the panel and increases the heterogeneity within each cohort. It may increase the estimator's variance and decrease its efficiency. It is, therefore, necessary to make a trade-off between cohort size and the number of cohorts to avoid any measurement error. Moreover, fixed effects can be considered constant over time if the criteria for selecting our cohorts is stable over time and if each cohort is large enough as specified by Verbeek & Nijman (1992). When the three conditions are respected (large enough cohorts, enough cohorts, and stable selection criterion for cohorts), the model (3.3) may be estimated as a regular panel with fixed effects. We estimate the pseudo-panel model with a Least-Squares Dummy Variable estimator. To highlight the relevance of the pseudo-panel in this chapter, we also estimate the model with pooled data where the observations are the individuals of the survey. It enables us to demonstrate which biases and errors are avoided with the pseudo-panel. Survey data has limitations in that explanatory variables are restricted to the survey questions, which can result in omission bias. Using fixed-effect panel methodologies to estimate the model instead

of cross-sectional methodologies helps reduce the resulting endogeneity bias (Cameron & Trivedi, 2005). Indeed, this bias is captured by the time-invariant fixed cohort α_c effects. Moreover, aggregating the data reduces the correlation between our explanatory variables and the fixed effect (Gardes *et al.*, 2005). We, therefore, assume that our explanatory variables are uncorrelated with the error term.

Our dependent variables are initially qualitative, such as y_i equals 1 when the individual performs the task (e.g., has access to the internet) and 0 if not. The dependent variable is logit transformed in order to obtain a linear logit share equation. The dependent variable is now a logarithm of the share ratio, and the model is linear in parameters, allowing us to estimate the model as a regular panel model. The estimated model is:

$$\ln(\frac{\bar{y}_{ct}}{1-\bar{y}_{ct}}) = X_{ct}\beta + \alpha_c + \lambda_t + \epsilon_{ct} \tag{3.4}$$

with $\ln(\frac{\bar{y}_{ct}}{1-\bar{y}_{ct}})$ the explanatory variable of cohort c at date t, X_{ct} is a vector of average explanatory variables for cohort c at survey date t, α_c the cohort fixed effect, λ_t the time fixed effect, and ϵ_{ct} the $i.i.d$ error term.

3.3.2 Data and descriptive statistics

Cohorts

This chapter uses the annual ICT Household Survey conducted by INSEE for the European survey program between 2007 and 2019. For the first three years, individuals were mainly interviewed by telephone, although a complementary survey was conducted in 2008 and 2010 by mail and online. Since 2011, individuals have been drawn from the data of the Housing Tax and can be interviewed by phone, mail, or online. In order to improve representativeness, INSEE corrected potential coverage bias between 2007 and 2010 using new weights calculated in 2012. INSEE regularly uses the survey to provide an overview of digital consumption by

the French and Eurostat for international comparisons. It collects information on individual and household characteristics, access to ICT, use of computers, use of the internet, ICT skills, and security on the internet. Households living in French Overseas Departments were not surveyed before 2009. As a consequence, we only consider households residing in metropolitan France. Moreover, we only take into account individuals aged from 24 to 82. Indeed, young people are poorly represented in the survey as they are usually interviewed when financially independent. Individuals surveyed after age 82 (the average life expectancy in France) no longer represent their generation, as wealthier individuals tend to live longer. This restriction enables us to have a relatively stable population over time and use pseudo-panel methods. In addition, we consider cohorts present in the 13 years of our sample to work on a balanced panel.

To have non-biased and efficient estimators in a pseudo-panel, we have to make a trade-off between the size and the number of cohorts. Therefore, we must adjust the cohort definition depending on the studied sub-population. First, when studying inequalities in access and use on the whole population, we compose cohorts of two-year generations. In total, we have 23 cohorts per year, corresponding to 299 observations. On average, a cohort is composed of 288 individuals, and only 20 cohorts, representing 6,7% of the sample, are composed of less than 100 individuals (Table 3.B.1), preventing measurement errors (Verbeek & Nijman, 1992). It may be difficult to capture gender specificity in a pseudo panel by including a variable for gender since a dummy variable represents the percentage of individuals in the cohort with a specific characteristic. For gender, this will be approximately 50% of each cohort. Consequently, we estimate a second model where cohorts are distinguished by generation and gender. This increases the number of cohorts and decreases the number of individuals in each cohort. In order to have enough individuals in each cohort, we consider five-year generations, resulting in 36 cohorts per year for 216 observations. Each cohort comprises 346 individuals on average, and 12 cohorts are less than 100 individuals, representing 5% of the sample (Table 3.B.2). In the second part, we restrict the sample to internet users and, in the third, to those without internet access. We use cohorts of five-year generations composed,

on average, of 537 individuals to study the diversity of internet uses among those who use it (Table 3.B.3). To investigate the reasons for non-access to the internet, focusing solely on the population without internet connection at home, we consider ten-year generations composed, on average, of 281 individuals (Table 3.B.4). As a robustness check, we re-estimate all models by changing the cohort composition but always respecting the Verbeek & Nijman (1992)'s conditions.

Dependent variables

To analyze inequalities in digital access and use, we consider two questions from the survey: does the individual have access to an internet connection at home (*Access*), and does he use the internet (*Use*)? Access to the internet can be a fixed and mobile connection. In the second part, we restrict the study to internet users. We aim to analyze whether disparities in use are also present when individuals access and use the internet. We consider seven usages of the internet: (i) accessing online banking services, (ii) filling out or sending administrative forms, (iii) buying goods online, (iv) doing leisure activities (radio, music, television, games), (v) creating a profile or posting messages on social media, (vi) searching for a job, and (vii) selling products online. We have chosen these activities for their diversity and because they are present for most of the survey year. Some are more related to leisure or social interaction, others to commercial activities such as buying and selling goods online. The rest is linked to online organizational services such as job search, administrative, and banking services. In the last part, we restrict the sample to individuals who do not have internet access at home to investigate the reasons behind digital exclusion. The purpose is to understand the different barriers to digital access according to socio-economic characteristics. We consider the four main reasons for not having internet access at home: (i) equipment or access is too expensive, (ii) internet is not needed, (iii) insufficient household skills, and (iv) security or privacy reasons.[5] All dependent variables are described in Table 3.A.1 in the appendix.

[5]Between 2007 and 2019, among individuals who do not have an internet connection at home, only 6% report that it is because of a lack of digital infrastructure. Therefore, we do not take this reason into account.

Explanatory variables: possible determinants of the digital divide

In this section, we present some statistics descriptive of the possible determinants of internet access and use. Table 3.1 shows that the diffusion and adoption of digital technologies is an ongoing process. It also underlines the importance of considering the temporal dimension in our study. Between 2007 and 2019, households with internet access at home drastically increased from 47% to 86%. Internet users have increased similarly as only 51% of French people over the age of 15 used the internet in 2007 compared to 85% in 2019. The difference between access and use is that an individual may have access to the internet at home but not use it because the subscription belongs to another household member. Alternatively, an individual may not have access to the internet at home but uses it outside the home (e.g., at work or in a public library). We can also observe that access has increased more rapidly than use. Before 2011, the share of users was higher than the number of individuals having an internet connection at home. Since 2011, this trend has been reversed.

Table 3.1: Share of French with an internet connection at home (Access) and who have used the internet in the year (Use) between 2007 and 2019 (in %)

	2007	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Access	47.5	55.7	51.6	61.0	75.1	78.8	78.4	83.2	82.9	84.9	84.2	87.1	86.9
Use	51.2	59.1	53.1	62.9	73.7	78.6	77.7	82.5	83.1	83.8	83.8	85.1	85.2

Source: INSEE annual household survey on ICT between 2007 and 2019. Only individuals over 15 years old and living in metropolitan France are considered.

Access to and usage of the internet can also differ from one individual to another. Table 3.2 reveals that the average characteristics of individuals vary depending on whether we study the entire population or only those who have access to and use the internet. For instance, the average age is lower when we only consider individuals who have access to and use the internet. Figure 3.1 displays the share of individuals who have used the internet according to age in 2007 and 2019. We observe that internet use decreases with age but increases over time. We observe a similar trend for different online activities among internet users, even though the utilization rates have not increased similarly for all activities, and the gaps between individuals of different ages are not always as pronounced. Figure 3.2 illustrates the

evolution of internet use by different generations over time. It shows an upward trend for all generations. In other words, digital use increases with time, regardless of age. Several other trends are also observable. First, the younger the generation, the higher the internet use. It reflects the trend that younger generations have grown up with digital tools. Furthermore, younger generations have relatively similar internet use despite their different ages, enhancing the digital lag of the older generations. Therefore, pseudo-panel methods are appropriate for our research questions since generation and time are essential determinants of digital consumption.

As emphasized in the literature review section, other variables can influence internet access and use. There are more internet users among individuals with a high level of education (Table 3.2). Between 2007 and 2019, 95% of those with a degree beyond the second year of university used the internet, compared to only 58% of those with less than a high school diploma. Standard of living and education appear to facilitate access and use of digital technology, which is unsurprising since the two main barriers to home internet access are the lack of skills and cost. Moreover, the average number of people over 15 years old in the household is higher when considering only those with home internet access or use rather than the entire population. The entourage can influence the probability of accessing and using the internet. Even if the lack of infrastructure is not one of the main reasons for the lack of access to the internet at home, we examine the impact of the location of residence. To this aim, we first studied the effects of the living region population density of the individual. Population density may be considered a proxy of the urban area and digital infrastructure. Indeed, *"white spots"*, i.e., territories not covered by any internet operator, are often located in areas with a low population density. Since 2013, the INSEE ICT survey has provided information on the size of the urban unit where the surveyed individual lives. We, therefore, estimate our model with another specification over a shorter period (2013-2019) but with more precise information on the place of residence.

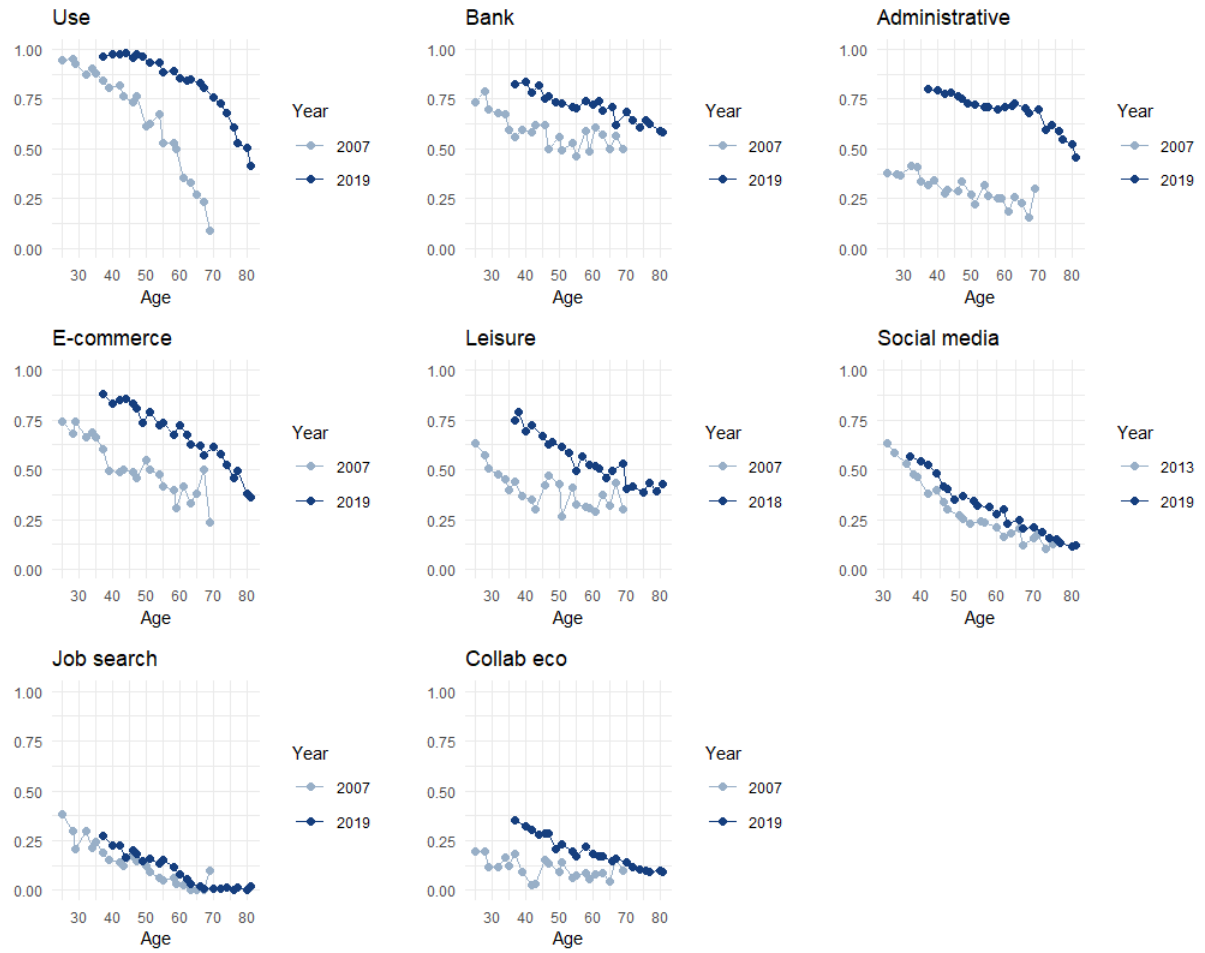
The explanatory variables of our study are chosen according to the trends highlighted in this section, the literature described in section 3.2, and the variables available over the

Table 3.2: Descriptive statistics

Variable	**All**	**Use**	**Access**
Age (mean)	54.3	52.1	52.6
Women (%)	50.2	49.5	49.5
Household size* (mean)	1.92	1.98	2.01
Monthly income			
- less than 1000€(%)	9.29	6.60	6.27
- between 1000 and 1500€(%)	17.1	13.8	13.8
- between 1500 and 3000€(%)	39.5	39.8	40.1
- more than 3000€(%)	34.1	39.8	39.7
Education level			
- Low (%)	52.2	43.3	45.1
- Middle (%)	26.8	31.3	30.4
- High (%)	21.0	25.3	24.5
*Urban unit size***			
- rural area (%)	25.1	24.6	24.7
- 2,000 to 4,999 residents (%)	6.81	6.68	6.71
- 5,000 to 9,999 residents (%)	6.07	5.98	5.98
- 10,000 to 19,999 residents (%)	5.10	4.97	5.00
- 20,000 to 49,999 residents (%)	6.50	6.28	6.30
- 50,000 to 99,999 residents (%)	7.26	7.05	7.07
- 100,000 to 199,999 residents (%)	6.29	6.29	6.24
- 200,000 to 1,999,999 residents (%)	22.8	23.2	23.1
- Paris (%)	12.9	14.8	14.7

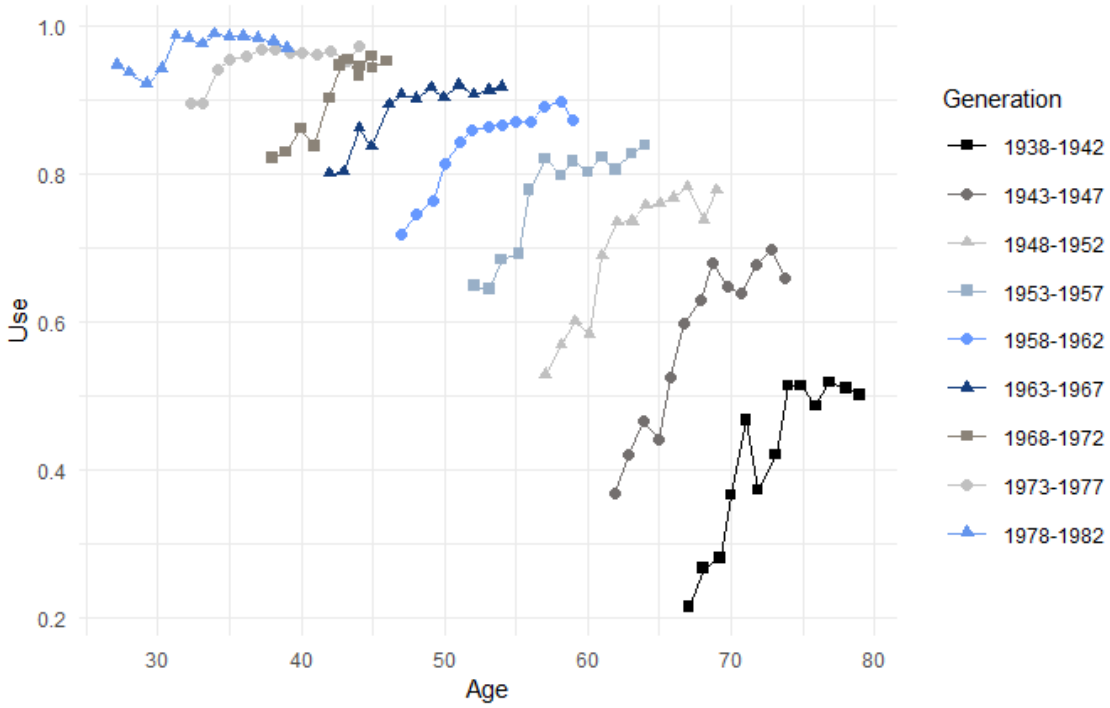
Note: INSEE annual household survey on ICT between 2007 and 2019. All the variables are described in Table 3.A.2 in the appendix A.
*Number of persons over 15 years old in the household.
**Percentage calculated for the 2013-2019 period.

Figure 3.1: Share of individuals who have used the internet (among the whole population) and different online activities (among the population who use the internet) according to the age



Source: INSEE annual household survey on ICT. All the variables are calculated among the internet users, except for the variable Use, where the whole population is considered. Variables are described in Table 3.A.1 in appendix A.

Figure 3.2: Share of individuals who have used the internet in the year according to age from one generation to another



Source: INSEE annual household survey on ICT between 2007 and 2019.

thirteen years of the survey. Therefore, we consider generation, income and education level, gender, household size, the population density of the region, and the size of the urban unit as potential determinants. The description and source of all variables are presented in Table 3.A.2 in the appendix.

3.4 Empirical results

This section presents the estimation results of the determinants of the digital divide in France. As a reminder, we estimate the equation (3.4), and the dependent variables change according to the digital divide level studied. Four models are estimated. Models (1) and (3) consider the variable income level, while in models (2) and (4), we include only the level of education

as income and education levels are highly correlated. Models (3) and (4) are estimated only between 2013 and 2019 and consider the size of the urban unit instead of its density. The first sub-section studies internet access and use inequalities for the whole population. In addition to the pseudo-panel estimation, we also estimate the four models with a pooled logit where observations are individuals, not cohorts. It enables us to show what the pseudo-panel methods bring compared to pooled data regressions in the chapter context. The second subsection focuses on disparities in internet use among internet users. The last sub-section studies individuals who do not have the internet at home. Finally, we also perform robustness checks by changing the cohort definition. Results tables are presented in appendix 3.C.

3.4.1 Inequalities in digital access and use

Results estimations of internet access and use determinants are presented in Table 3.C.1 in appendix C. First, we find significant inter-generational inequalities for all models (Table 3.C.1). Cohort-fixed effects highlight that the younger the generation, the greater their advantage in accessing and using internet (Figures 3.3 and 3.4). These inequalities are more substantial among older generations and are more pronounced in use than in access. Indeed, an individual can access an internet connection at home but not use it. All the time-fixed effects in all the models of Table 3.C.1 are significantly different from zero and increase with time (Figures 3.5 and 3.6). Internet access and use have increased over time regardless of the individual's characteristics. Nevertheless, a plateau seems to be reached for usage: time-fixed effects between 2014 and 2019 are not significantly different. This is not the case for time-fixed effects for access, even if the increase has been slower in the past few years. These results highlight the need for public policies to reduce the digital divide. Note that time-fixed effects can also capture the improvement in the territory's internet coverage or the decrease in the price of hardware and internet connection (Arcep, 2022b).

In line with the literature, we find intra-generational inequalities. The income bracket and the level of education are significant drivers of digital access and use. More specifically,

Figure 3.3: Cohort effects for Access

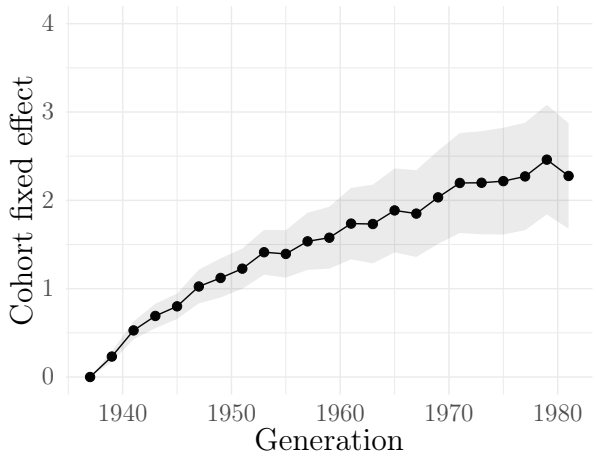
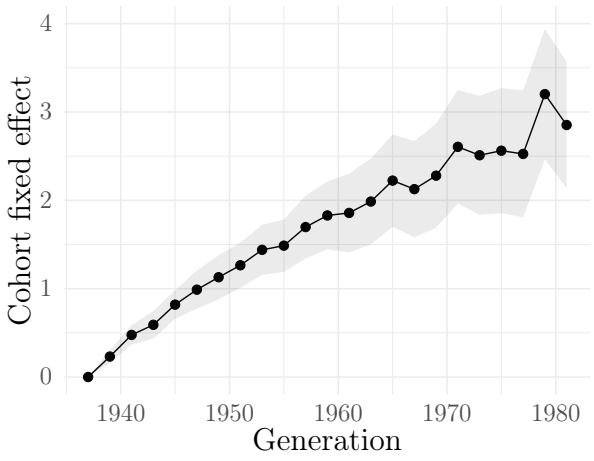


Figure 3.4: Cohort effects for Use



Note: The 1937-1938 generation is the reference cohort. Each fixed effect is to be compared to this cohort. A positive fixed effect significantly different from 0 means that the generation has an advantage in digital access and use over the 1937-1938 generation. The grey area represents the 95% confidence interval of fixed effects for each generation of the models (2) and (2') in Table 3.C.1.

earning more than 1500 euros per month is a significant determinant of digital access and use.[6] The level of education is also a determinant of digital access and use, especially for individuals with a degree higher than a high-school diploma.[7] The comparison of the R-squared suggests that the impact of education appears to be more important for the use than the access. On the contrary, income level is a more significant determinant of access than internet use. Indeed, a lack of financial resources can be a barrier to household internet access. However, once a household has access to the internet, the main obstacle to its use is the lack of digital skills.

The household size is only positively significant in model (1) in internet access estimation (Table 3.C.1). It suggests that many people over 15 in a home can make it easier to access the internet but does not impact the internet's use. Indeed, a household can have an internet

[6]Performing a Wald test, we find that estimated coefficients associated with the variable "monthly income between 1000 and 1500 euros" and "monthly income of less than 1000 euros" are not statistically different.

[7]Estimated coefficients associated with the variable middle level and high level of education are not statistically different for access and use estimations.

Figure 3.5: Time fixed effects for Access

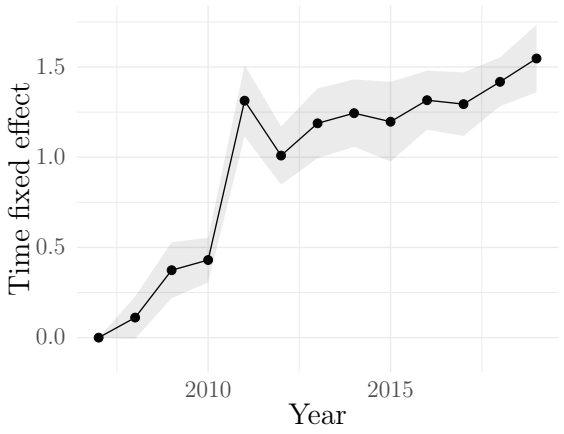
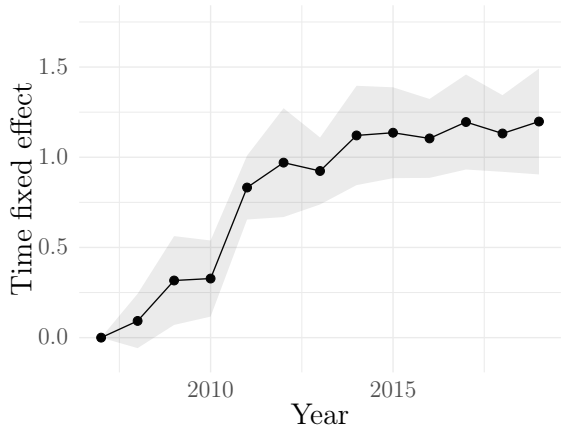


Figure 3.6: Time fixed effects for Use



Note: 2007 is the reference year. Each time fixed effect is to be compared to this year. A positive fixed effect significantly different from 0 means that the year has an advantage in digital access and use over 2007. The grey area represents the 95% confidence interval of the time-fixed effects of the models (2) and (2') in Table 3.C.1.

connection because a member uses it, even if the surveyed individual does not use it themselves. Our result differs from Korupp & Szydlik (2005), who found that having teenagers or young adults at home determined computer and internet access in Germany between 1997 and 2003.

None of our measures of urbanization (density and size of the urban unit) are significant regardless of the estimated model (Table 3.C.1).[8] Our results show no difference between living in Paris and rural areas. The area of residence has no impact on digital access and usage. This result is consistent with Schleife (2010), who demonstrates that internet use among German counties is not explained by differences in population density but rather by differences in the composition of individual characteristics in each county. The digital divide is more prevalent in rural areas because, on average, the population is older and has lower incomes than in urban areas. This is consistent with the fact that among households that

[8]As a robustness check, we tested all the models by changing the urban unit size's reference and the division of the urban units into five urban units instead of nine (rural area, between 2,000 and 19,999 inhabitants, between 20,000 and 199,999 inhabitants, between 200,000 and 1,999,999 inhabitants, and Paris). Results remain unchanged.

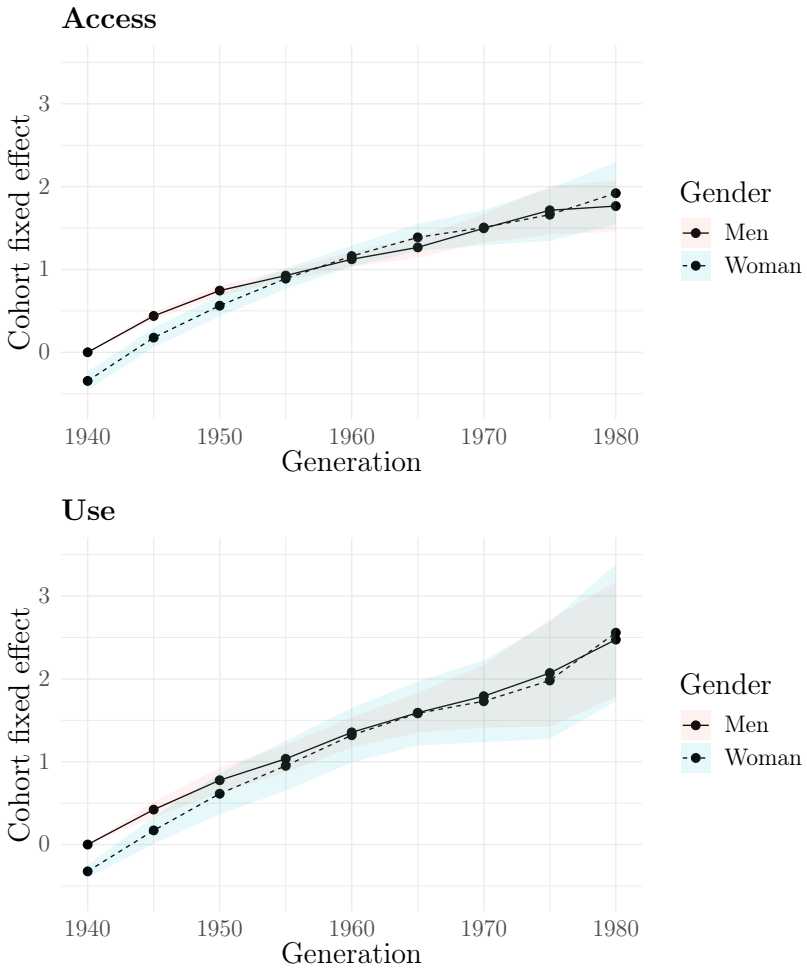
do not have an internet connection at home, only 6% explain it by the absence of broadband infrastructure in their locality. Therefore, the place of residence, often considered an infrastructure proxy, does not appear to be a barrier to digital access and use. This has not always been the case, especially in the early days of internet diffusion when infrastructures were located in the most profitable areas, i.e., in the most densely populated areas. Meanwhile, the internet coverage of France's territory has improved through various laws. For instance, the law on the digital divide in 2009 created a fund for the digital development of territories, whose objective was to assist in implementing the infrastructure required for broadband access in areas where digital communications operators considered that the necessary efforts were beyond their funding capacities.[9] The perception that place of residence is a key determinant of the digital divide is also based on the fact that the quality of internet service varies depending on location. In 2019, the mobile coverage rate was 92,1% in metropolitan France, but only 81,5% of housing and offices enjoyed broadband and 52,9% from very high-speed broadband (Antoine & Simon, 2020). Moreover, Croutte & Muller (2021) point out that, among internet users, people living in rural areas are less satisfied with their internet connection than their urban counterparts. They also highlight that 11% of French internet users consider that an insufficient quality of internet service is a barrier to internet use. Among the internet non-users, only 4% consider the quality of internet service as a barrier. Therefore, there is a digital divide between cities and the countryside, not because of a lack of infrastructure but because of its poor quality.

Gender appears to be a determinant of internet use and not access (Table 3.C.1). Women seem to use the internet more than men. However, results for constant variables such as gender in pseudo-panel models should be treated cautiously. Indeed, the proportion of men and women should be similar between generations; variations over time and within cohorts may be due to measurement errors. Therefore, we perform other regressions where cohorts are separated by generation and gender. This enables us to compare the cohort effect between women and men of the same generation. Results are presented in Table 3.C.2 in the appendix.

[9]French law n°2009-1572 of December 17, 2009, on the fight against the digital divide.

We find that fixed effects of the same generation are statistically different according to the gender of the individuals born between 1938 and 1952, both for access and use (Figure 3.7). The younger cohort's fixed effects value is the same for each generation of a different gender. Consequently, there is a digital gender gap favoring men for the older generations, but this gap does not appear for younger generations.

Figure 3.7: Generation and gender effects



Note: The 1936-1938 men generation is the reference cohort. Each fixed effect is to be compared to this cohort. A positive fixed effect significantly different from 0 means that the cohort has an advantage in digital access and use over men from the 1936-1938 generation. The red (blue) area represents the 95% confidence interval of the men (women) fixed effects for each generation of models (2) and (4) in Table 3.C.2.

As a robustness check, we re-estimate the models by considering one and three-year

generation cohorts for access (Table 3.C.3) and use (Table 3.C.4) and three-year generation separated by gender (Table 3.C.5). Results remain similar.

We also re-estimated the models with a pooled logit. Results are presented in Table 3.C.6, and we compare them with the pseudo-panel results in Table 3.C.1. Both methodologies give similar results for generation and time effects and the education and income level variables. These variables' coefficients are generally slightly higher in the pooled logit (Table 3.C.6) than in the pseudo-panel (Table 3.C.1). Other variables estimation differ between the pooled logit and the pseudo-panel models. The population density and the size of the urban unit are significantly positive in the pooled logit but not in the pseudo-panel model. Regarding household size and gender, coefficients depend on the model. Household size coefficients are always positively significant when studying internet access (Table 3.C.6). However, they are larger in the model with the education level variable (models (2) and (4)) than the income level variable (models (1) and (3)). In the study of internet use (Table 3.C.6), the household size is only significant for models (2') and (4'). The sign of the women variable varies according to the model: positive in models (1') and (3') and negative in models (2') and (4'). These results suggest that the pooled logit coefficients are biased. Since they depend on the inclusion of explanatory variables, we suspect an endogeneity issue due to an omission bias. This endogeneity bias does not appear in the pseudo-panel models as it is reduced by the inclusion of the fixed cohort effects and the aggregation of the variables (Gardes *et al.*, 2005). It reinforces our choice to use pseudo-panel methods for our chapter. With pseudo-panel methodology, only the heterogeneity within cohorts is studied rather than between individuals. This is not a problem as the generation used to form the cohorts is a main determinant of the digital divide, both in the pooled logit and pseudo-panel estimates. Panel methodology also enables us to consider the temporal evolution in the model, which is important to consider since the digital transition is still ongoing. Therefore, in the rest of the chapter, we only consider the estimation results from the pseudo-panel models.

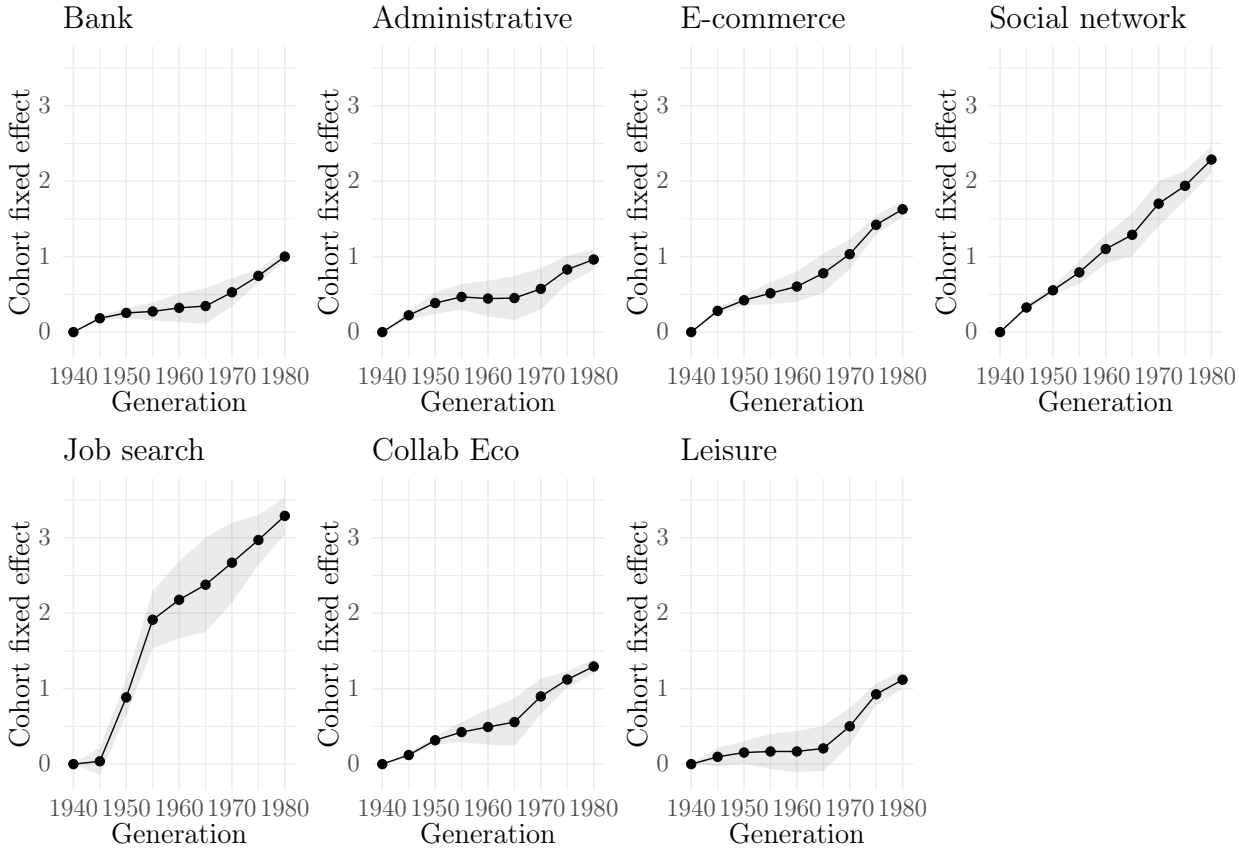
3.4.2 Disparities in the diversity of internet use

In this section, we focus on whether these intra and inter-generational inequalities exist in usage once an individual has access to the internet and uses it. In other words, do an individual's socioeconomic characteristics influence the diversity and the type of internet use? Although other variables influence the probability of doing an online activity, we restrict the analysis to the explanatory variables used in the previous section. Results are presented in Table 3.C.7 in the appendix. We perform a robustness check by changing the definition cohort from five-year to two-year generations (Table 3.C.8).

Inter-generational inequalities still exist for all selected activities, but the scale depends on the activity (Figure 3.8). The probability of shopping online, being on social media, and selling goods online (collaborative economy) increases with the generation's youth. Individuals born after 1968 also have a higher probability of listening to the radio or music, watching television, and playing games (leisure). The generational effect is less pronounced for organizational activities. Young people are more likely to do administrative procedures online, but generational differences are less marked than in other activities. For instance, the 1953-1957 generation does not have a lower probability of doing an administrative procedure over the internet than the 1968-1972 generation. The probability of using online banking is high for younger generations, but there is no significant difference between the 1938-1942 and 1963-1967 generations. Inter-generational differences appear in the probability of doing online job searching, but they primarily represent the generations of age to seek work.

Once an individual uses the internet, the disparities within a generation observed in the previous section are no longer necessarily present. The effects of level of education, gender, and the number of people in the household depend on the activity and are not always significant. The level of qualification is only a determinant of buying goods online (model (6) in Table 3.C.7). Individuals purchasing goods online generally have a degree above the bachelor's level. Low-income individuals are more likely to participate in the collaborative economy due to the potential for additional income by selling second-hand goods (model (13)

Figure 3.8: Cohort effect on the probability of doing an activity online

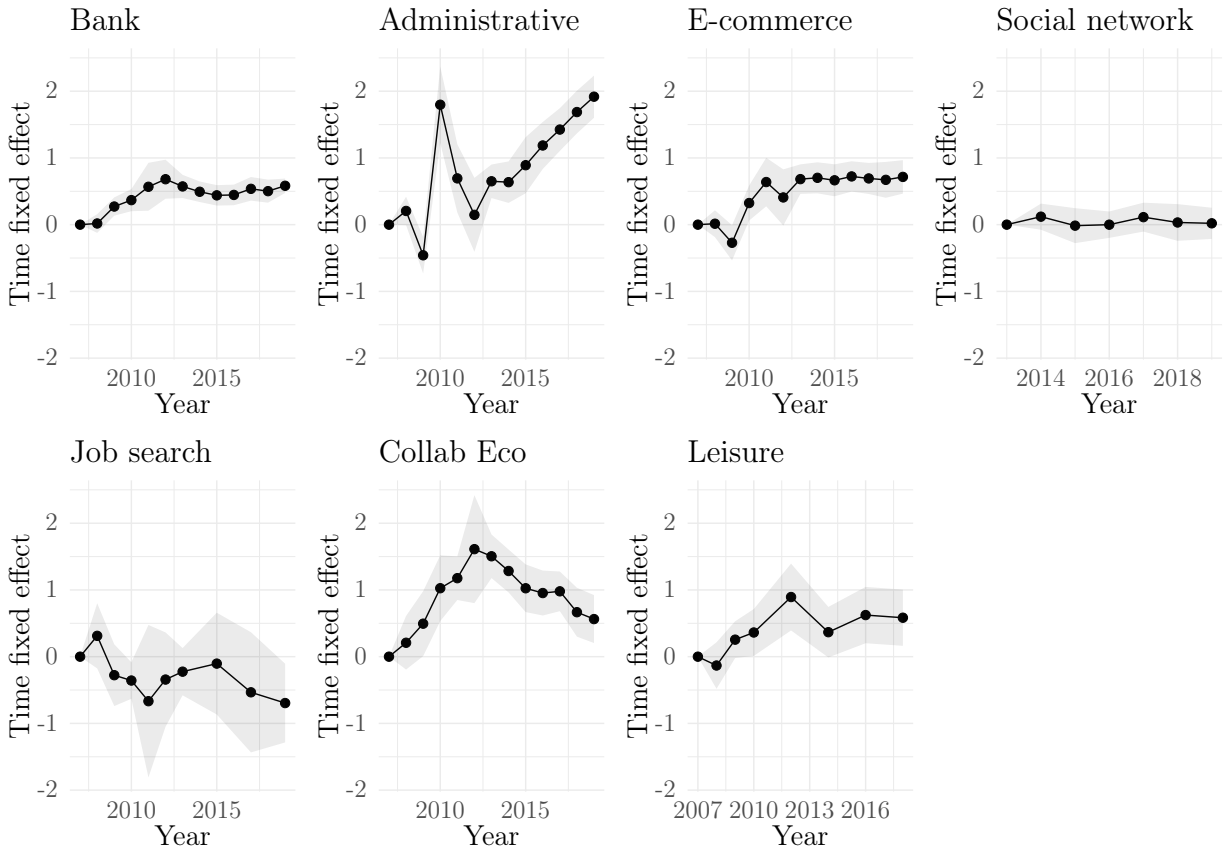


Note: the 1938-1942 generation is the reference cohort. Each fixed effect is to be compared to this cohort. A positive fixed effect significantly different from 0 means that the generation has an advantage in digital access and use over the 1938-1942 generation. The grey area represents the 95% confidence interval of fixed effects for each generation of the models (1), (3), (5), (7), (9), (11), and (13) in Table 3.C.7.

in Table 3.C.7). Women tend to use more internet to search for a job online (model (11) and (12) in Table 3.C.7), while men tend to buy or sell goods (model (6), (13), and (14) in Table 3.C.7). Nevertheless, we remain cautious about these results as they are not significant anymore when we consider two-year generations instead of five as a robustness check (Table 3.C.8). In addition, as mentioned earlier, the specificity of gender can be difficult to capture in a pseudo-panel model.

Time effects depend on the activities studied (Figure 3.9). The probability of being on social media and doing online job searches has not changed over time. Online leisure

Figure 3.9: Time effect on the probability of doing an activity online



Note: 2007 is the reference year. Each time fixed effect is to be compared to this year. A positive fixed effect significantly different from 0 means that the year has an advantage in digital access and use over 2007. The grey area represents the 95% confidence interval of the time-fixed effects of the models (1), (3), (5), (7), (9), (11), and (13) in Table 3.C.7.

has experienced a limited increase since 2007. The likelihood of completing administrative procedures online has increased significantly over time. Two changes can be observed. First, 2010 was marked by an increased individuals doing administrative procedures online. This can be due to the creation of the site *mon.service-public.fr* by the French government in December 2008, enabling citizens to register to vote, to declare a change of address, a death, a loss of identity papers, and to create a company or an association online. In 2010, this site was improved and simplified, mainly by extending access to its services to the entire territory.[10] Previously, only a few pilot municipalities had access to its online services. In 2014, the French

[10] https://www.senat.fr/rap/a09-106-6/a09-106-64.html.

government pursued its project of modernizing the public service by merging its various sites to simplify all administrative procedures. Other laws also increased online administrative procedures, particularly the obligation for households with internet access to declare revenues online in 2016. The French government's investment in digitalizing public services appears to produce results. Online banking and purchasing goods also experienced increased usage over time, but only until 2011. Finally, the online sale of goods increased until 2014 and has since declined. Goudin (2016) explains that the collaborative economy experienced growth following the economic and financial crisis of 2008 because it was perceived as a way to save money or earn additional income.

To conclude, once an individual has access to and uses the internet, intra-generational inequalities in usage are no longer present, but intergenerational inequalities remain prevalent. The inequalities in the usage of online banking and administrative procedures are more concerning due to the dematerialization of these services. The priority is to focus on digital access, marked by more significant inequalities, to overcome the digital divide. To this end, identifying barriers to digital access in France is essential.

3.4.3 Reasons for non-access to internet

Internet access in France increased significantly between 2007 and 2019, but some French people still do not have internet. Our previous results indicate a slowdown in the increase in the number of new households with an internet connection. This section restricts the sample to households who do not have internet access at home to investigate the reasons behind this. Sub-sections 3.4.1 and 3.4.2 provide a profile of the individuals most affected by the digital divide to help determine where public policies should be focused. Understanding and knowing the different barriers to digital access will allow these public policies to be adapted to different populations. Estimation results are presented in Table 3.C.9 in the appendix. We also present in Table 3.C.10 robustness results where we change the definition cohort from ten-year to five-year generations.

Income and education are essential determinants of internet access and use in France. However, they do not explain the differences in the reasons for not accessing the internet. Those who are more skilled tend to consider security and privacy issues less of a barrier to internet access than those less skilled. They are also more likely not to have an internet connection because they are not interested in it. Education and standard of living do not impact the likelihood of not having the internet for financial reasons or lack of skills. Women are more affected by financial barriers than men. Household size decreases the likelihood of not having access to the internet for security or privacy reasons. This may be because one member of the household may acquire an internet connection regardless of the fears of other members.

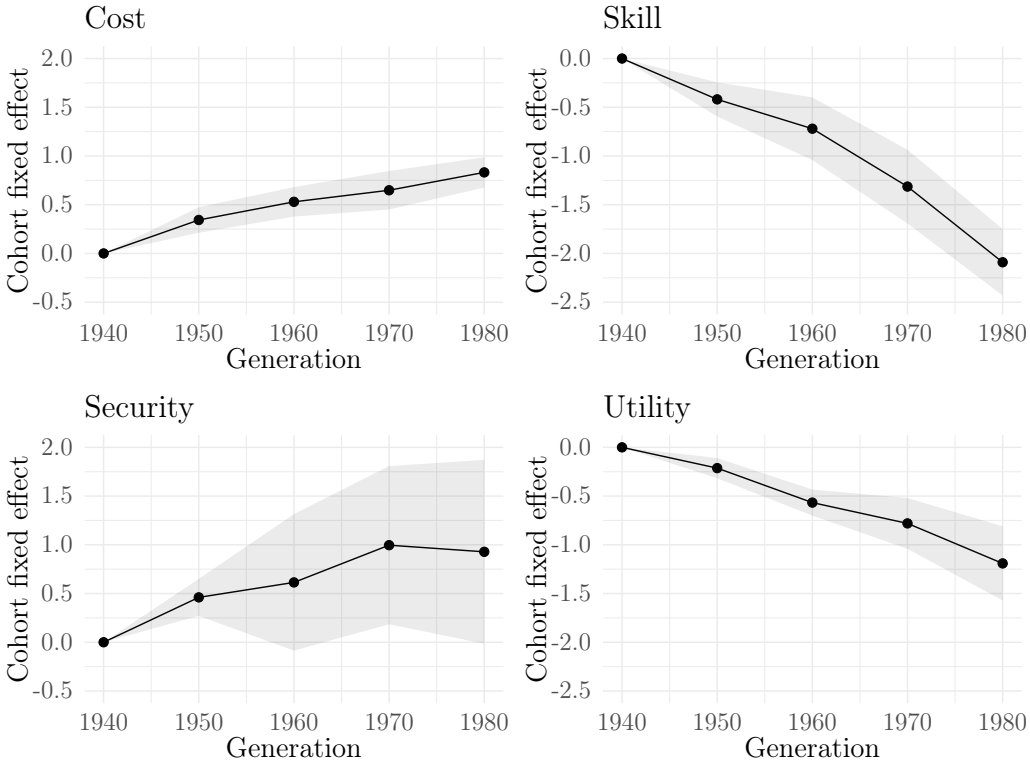
The generation mainly drives the reasons behind the non-access to the internet. The younger generations are more likely to lack internet access due to the cost of equipment or connection (see Figure 3.10). In contrast, older generations are more likely to cite a lack of skill or interest as the reason for not having internet access. Privacy and security concerns are prevalent among all generations. The reasons for not having internet access have remained relatively stable since 2007 (Figure 3.11), except for a decreasing number of individuals who report not finding the internet useful. The cost of access, lack of skills, and eventual security or privacy issues are always important reasons for non-access.

3.5 Discussion

Digital tools are one of the pillars of the French government's recovery plan after the COVID-19 crisis. To reduce the digital divide, 250 million euros are dedicated to digital inclusion. This section compares our results with the public policies implemented in France.

One of the groups most affected by the digital divide is the elderly population. Their main barriers are the lack of skill and interest (Figure 3.10). Providing digital education is, therefore, crucial. This training must be concentrated on the oldest populations but can be

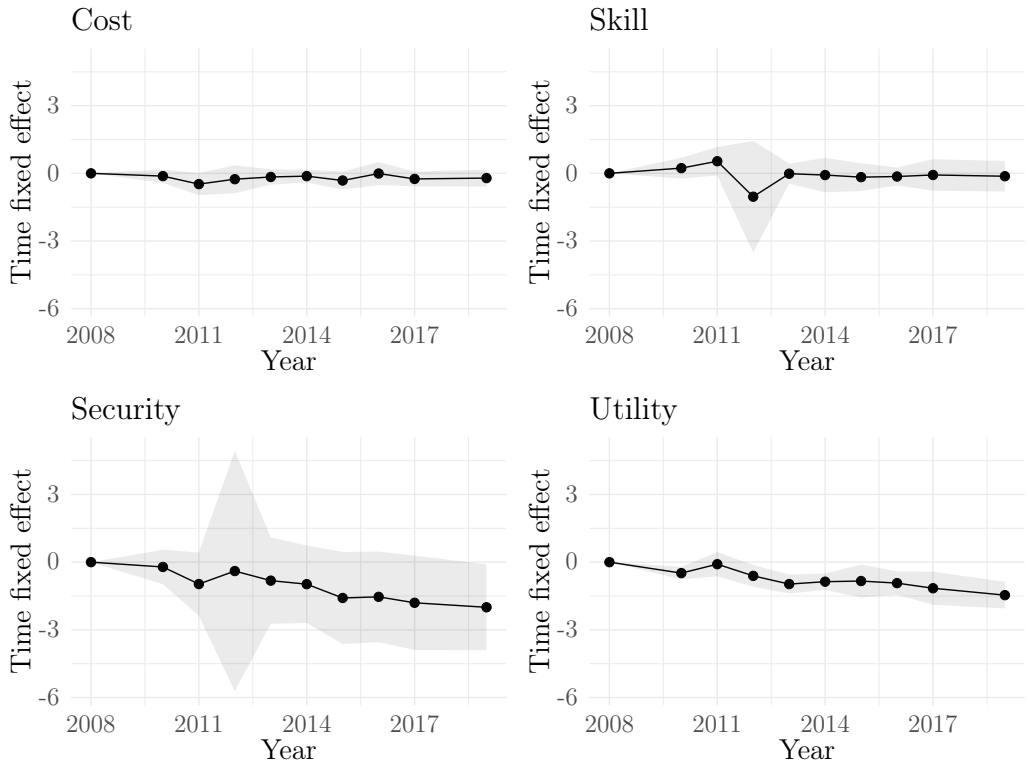
Figure 3.10: Cohort effect on the probability of not having internet for a reason



Lecture: the 1935-1944 generation is the reference cohort. Each fixed effect is to be compared to this cohort. A positive fixed effect significantly different from 0 means that the generation has an advantage in digital access and use over the 1935-1944 generation. The grey area represents the 95% confidence interval of fixed effects for each generation of the models (1), (3), (5), and (7) in Table 3.C.9.

offered to the poorest and the less educated ones. It must also explain the advantages of using the internet and, in particular, introduce the administrative procedures that can be carried out online, such as income tax returns. Indeed, even if the digital exclusion is voluntary, not being online can exclude a person, especially in France, where administrative procedures for public services are done digitally. The lack of interest may be due to a lack of knowledge and skills. Security and privacy issues remain barriers to internet access (Figure 3.11). Digital education is also a way to avoid misuse of the internet, which can result in security or privacy problems. To address this issue, the French government offers "digital passes" that allow individuals with digital difficulties to follow dedicated training. Education that takes the issues mentioned above into account would reduce digital inequalities. Moreover, legislation

Figure 3.11: Time effect on the probability of not having internet for a reason



Note: 2008 is the reference year. Each time fixed effect is to be compared to this year. A positive fixed effect significantly different from 0 means that the year has an advantage in digital access and use over 2008. The grey area represents the 95% confidence interval of the time-fixed effects of the models (1), (3), (5), and (7) in Table 3.C.9.

strengthening online security and requiring digital platforms to protect users' privacy, such as the General Data Protection Regulation, should be pursued.

The cost of equipment and connection is also an important reason for not accessing the internet in France. As skill barriers, financial constraints remain important barriers to internet access (Figure 3.11). Our results highlight that financial barriers mainly concern the younger groups. These populations are less likely to be affected by the digital divide, but when they are, it is rarely because of a lack of interest. These excluded individuals should, therefore, be the target of public policies. However, there is no financial support specific to digital access, as pointed out by Vall (2020), who proposes implementing "equipment checks" for the rental or purchase of digital equipment. Finally, in line with the Défenseur

des droits (2019), we recommend that non-digital and accessible solutions be offered for essential services (e.g., tax returns, requests for help) for fear that part of the population be excluded and inequalities increased.

3.6 Conclusion

Bridging the digital divide is one of the objectives of the United Nations Development Program. The OECD (2018a) emphasizes that digital technologies provide various opportunities, such as *"additional income, additional employment opportunities, and improved access to knowledge and general information."* In addition, inequalities in digital access and skills can drag on productivity and economic growth (Eichengreen, 2015). Therefore, it is essential to reduce digital inequalities.

This chapter studies the determinants of the digital divide in France at different levels. Firstly, we focus on inequalities in internet access and use. Our results demonstrate intra and inter-generational inequalities in internet access and use, which decrease over time. Income and level of education are significant determinants of internet access and use. Household size has a positive impact on access but not on usage. There is a gender digital gap in favor of men among the older generations. Finally, we find no urban/rural digital divide in internet access and use in France. When we examine the variety and types of online uses, we find that inter-generational inequalities in favor of younger people remain strong for several online activities. However, intra-generational inequalities among internet users are low. The French digital divide is mainly a problem of access and use. Finally, we highlight that barriers to internet access differ between individuals. Older people are more affected by a lack of skills and interest, while younger people are affected by financial barriers. Lack of interest, security, and privacy barriers are decreasing over time. The two main barriers to internet access remain the lack of digital skills and financial cost. Therefore, we recommend continuing to invest in digital education and creating a financial aid system to access digital

equipment. We also advise continuing to offer a non-digital, accessible option in addition to the dematerialization of public services to avoid reinforcing the digital divide.

One of the limitations of this chapter is that some aspects of the digital divide are not considered due to the lack of available information in the survey. For instance, the Covid-19 crisis and the resulting lockdowns have shown that access to the internet and a computer is insufficient for large families. Nevertheless, we do not have information on the number of devices in the household. Another limitation of our study is that it considers that digital technology has only positive effects. However, inadequate use of digital technology can cause many security and privacy problems (OECD, 2019). The internet has also allowed the proliferation of *"fake news"* on a large scale and the polarization of opinions. The digital divide must be reduced while learning to use these tools correctly. We also chose to study the differences in basic access and use of the internet. Inter- and intra-generational disparities can appear if we examine the intensity of use, as some individuals use the internet more intensively than others. It will also be helpful to study the inequalities in access to high-quality internet, as broadband does not cover the entire territory for now, and the overseas territories. Finally, this chapter takes a dichotomous view of the digital divide and considers only the first two levels of the digital divide. However, as Bléhaut *et al.* (2023) point out, the digital divide can also be measured in terms of capabilities, i.e., considering inequalities in the ability to turn the opportunities offered by digital technologies into benefits. They also recommend moving away from the binary vision of the digital divide and representing digital inequalities as a halo.

3.A Variables description

Table 3.A.1: Description of the dependent variables

Variable	**Description**	**Available years**
Inequalities in internet access and use		
Access	The individual has an access to the internet at home	2007-2019
Use	The individual uses the internet	2007-2019
Inequalities in the variety of usage		
Administrative	The individual has used the internet to fill out or send administrative forms	2007-2019
Bank	The individual used the internet to access his bank account	2007-2019
E-commerce	The individual has used the internet to buy a good online	2007-2019
Leisure	The individual has listened to the radio or music, watched television, played or downloaded games, pictures, video, music	2007-2012, 2014, 2016, 2018
Social media	The individual has used the internet to create a profile or post messages on social media	2013-2019
Job search	The individual used the internet to search for a job	2007-2013, 2015, 2017, and 2019
Collaborative Economy	The individual has used the internet to sell products and services on online sites	2007-2019
Reasons for non-access of the internet		
Cost	Household does not have internet at home because equipment or access is too expensive	2007-2017 and 2019
Utility	Household does not have internet at home because internet is not needed	2007-2017 and 2019
Skills	Household does not have internet at home because of insufficient household skills	2008-2017 and 2019
Security	Household does not have internet at home for security or privacy reasons	2008, 2010-2017, and 2019

Source: Households ICT surveys, INSEE

Table 3.A.2: Description of the explanatory variables

Variable	**Description**	**Source**
Generation	Year of birth	ICT Household survey, INSEE
Woman	Be a woman	ICT Household survey, INSEE
Household size	Number of persons over 15 years old in the household	ICT Household survey, INSEE
Density	Population density of the region where the individual lives	INSEE & Eurostat
Urban unit size		
- rural area	Live in a rural area	ICT Household survey, INSEE
- 2,000 to 4,999 residents	Live in an urban unit of 2,000 to 4,999 residents	ICT Household survey, INSEE
- 5,000 to 9,999 residents	Live in an urban unit of 5,000 to 9,999 residents	ICT Household survey, INSEE
- 10,000 to 19,999 residents	Live in an urban unit of 10,000 to 19,999 residents	ICT Household survey, INSEE
- 20,000 to 49,999 residents	Live in an urban unit of 20,000 to 49,999 residents	ICT Household survey, INSEE
- 50,000 to 99,999 residents	Live in an urban unit of 50,000 to 99,999 residents	ICT Household survey, INSEE
- 100,000 to 199,999 residents	Live in an urban unit of 100,000 to 199,999 residents	ICT Household survey, INSEE
- 200,000 to 1,999,999 residents	Live in an urban unit of 200,000 to 1,999,999 residents	ICT Household survey, INSEE
- Paris	Live in Paris	ICT Household survey, INSEE
Monthly income		
- less than 1000€	Earn a monthly income of less than 1000€	ICT Household survey, INSEE
- between 1000 and 1500€	Earn a monthly income between 1000 and 1500€	ICT Household survey, INSEE
- between 1500 and 3000€	Earn a monthly income between 1500 and 3000€	ICT Household survey, INSEE
- more than 3000€	Earn a monthly income of more than 3000€	ICT Household survey, INSEE
Education level		
- Low	Below baccalauréat (high school diploma)	ICT Household survey, INSEE
- Middle	Between the baccalauréat and the second-year university degree	ICT Household survey, INSEE
- High	Higher than two years of higher education	ICT Household survey, INSEE

3.B Cohort's size

Table 3.B.1: Cohort's size: two-year generation

Generation	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
1937-1938	114	180	152	104	106	147	345	147	218	285	243	260	281
1939-1940	140	162	131	121	101	152	314	197	223	261	256	285	323
1941-1942	96	149	102	104	93	179	269	142	237	300	301	278	293
1943-1944	112	149	128	140	127	234	405	225	314	318	298	324	345
1945-1946	111	168	139	133	138	232	466	252	390	395	370	343	379
1947-1948	147	243	171	160	172	351	576	380	468	530	482	533	478
1949-1950	164	227	176	157	184	345	571	402	514	532	488	515	508
1951-1952	155	219	148	138	168	306	540	359	443	543	507	451	528
1953-1954	146	209	154	145	150	320	561	315	449	516	423	517	501
1955-1956	142	189	145	121	158	288	474	322	453	514	496	499	466
1957-1958	127	191	151	103	174	275	463	303	446	518	443	480	479
1959-1960	139	175	123	111	149	287	503	308	477	527	468	475	527
1961-1962	144	188	104	111	145	294	445	299	450	519	461	425	484
1963-1964	119	198	126	86	138	268	492	261	394	494	444	457	476
1965-1966	137	218	120	106	149	282	447	279	454	490	413	426	455
1967-1968	138	194	119	88	122	291	496	243	440	459	443	393	468
1969-1970	146	202	125	110	145	281	415	283	476	471	366	420	442
1971-1972	153	182	114	78	153	341	461	281	424	461	407	426	422
1973-1974	164	192	97	73	144	318	486	303	430	437	390	428	426
1975-1976	112	164	89	66	109	266	440	235	431	415	316	404	376
1977-1978	97	148	67	64	112	270	413	218	394	391	362	376	385
1979-1980	99	146	61	37	94	275	366	273	391	417	313	319	368
1981-1982	76	146	44	37	76	221	362	268	395	433	344	361	375
Total	2978	4239	2786	2393	3107	6223	10310	6295	9311	10226	9034	9395	9785

Table 3.B.2: Cohort's size: five-year generation by gender

Generation	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Woman													
1938-1942	157	207	204	159	138	226	364	201	258	363	382	388	400
1943-1947	159	256	201	199	188	338	472	323	419	480	451	487	494
1948-1952	240	347	231	207	222	395	657	420	513	700	596	648	606
1953-1957	187	273	208	183	210	364	601	374	508	649	616	643	631
1958-1962	170	248	155	146	221	352	558	342	479	652	565	579	603
1963-1967	168	265	159	141	165	377	543	329	462	600	539	534	580
1968-1972	120	131	93	81	120	222	315	205	311	355	284	331	334
1973-1977	172	246	115	89	164	394	565	322	495	546	448	479	509
1978-1982	123	205	75	45	126	372	484	347	480	531	455	463	455
Total	1496	2178	1441	1250	1554	3040	4559	2863	3925	4876	4336	4552	4612
Men													
1938-1942	132	188	113	117	108	185	395	211	310	343	287	325	347
1943-1947	129	168	141	152	170	319	667	352	526	494	467	420	484
1948-1952	161	235	189	170	209	416	762	523	671	644	631	611	654
1953-1957	166	213	174	128	182	401	660	419	622	646	546	611	601
1958-1962	175	218	140	134	163	347	627	412	666	647	564	563	622
1963-1967	153	260	144	101	174	313	634	322	612	615	544	526	606
1968-1972	99	156	94	67	95	210	358	210	379	344	299	305	321
1973-1977	150	188	103	84	137	314	558	324	553	501	442	505	486
1978-1982	103	157	65	59	108	270	460	304	513	515	380	441	480
Total	1268	1783	1163	1012	1346	2775	5121	3077	4852	4749	4160	4307	4601

Table 3.B.3: Cohort's size: five-year generation (internet users)

Generation	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
1938-1942	57	97	84	38	115	153	272	217	293	344	349	367	382
1943-1947	101	171	155	59	188	392	650	460	619	628	630	640	652
1948-1952	203	316	240	97	297	596	965	723	908	1036	971	941	1004
1953-1957	222	302	254	92	305	628	937	652	912	1074	940	1048	1048
1958-1962	239	333	223	94	324	601	964	661	1012	1135	1017	104	1079
1963-1967	246	405	251	88	303	626	1006	602	978	1133	993	980	1102
1968-1972	171	230	160	70	194	411	583	400	663	658	560	602	636
1973-1977	278	379	203	82	289	686	1035	627	1021	1019	876	946	980
1978-1982	207	333	125	52	231	631	878	648	998	1042	834	900	917
Total	1724	2566	1695	672	2246	4724	7290	4990	7404	8069	7170	6528	7800

Table 3.B.4: Cohort's size: ten-year generation (Individuals without internet access)

Generation	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2019**
1935-1944	422	548	442	392	282	464	859	393	586	649	608	522
1945-1954	373	508	340	313	227	413	687	362	524	533	502	471
1955-1964	224	294	190	140	100	234	341	218	330	354	298	270
1965-1974	183	222	99	74	42	112	186	99	184	158	170	119
1975-1984	78	146	39	29	23	76	95	49	98	84	61	51
Total	1280	1718	1110	948	674	1299	2168	1121	1722	1778	1639	1433

3.C Estimation results

Table 3.C.1: Pseudo-panel estimation results for Internet Access and Use (cohorts: two-year generations)

	Access				**Use**			
	(1)	(2)	(3)	(4)	(1')	(2')	(3')	(4')
Woman	0.501	0.252	1.330	0.590	0.615	0.534	1.930**	1.434
	(0.445)	(0.457)	(1.071)	(1.082)	(0.458)	(0.424)	(0.740)	(0.843)
Household size	0.374**	0.274	0.146	0.271	0.055	0.019	0.029	0.084
	(0.149)	(0.170)	(0.296)	(0.262)	(0.171)	(0.221)	(0.415)	(0.359)
Density	0.001	0.002	-	-	0.000	0.000	-	-
	(0.001)	(0.001)	-	-	(0.001)	(0.001)	-	-
Monthly income								
- less than 1000€	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*	-
- between 1000 and 1500€	0.681	-	0.288	-	0.713	-	0.314	-
	(0.781)	-	(1.112)	-	(0.781)	-	(2.331)	-
- between 1500 and 3000€	1.485***	-	2.755***	-	1.717***	-	2.615**	-
	(0.463)	-	(0.931)	-	(0.385)	-	(1.115)	-
- more than 3000€	2.183***	-	3.880***	-	1.825**	-	3.202**	-
	(0.668)	-	(1.021)	-	(0.710)	-	(1.411)	-
Education level								
- Low	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*
- Middle	-	1.692***	-	1.816***	-	2.680***	-	1.493
	-	(0.471)	-	(0.607)	-	(0.665)	-	(1.015)
- High	-	1.102*	-	4.098***	-	2.661***	-	4.446***
	-	(0.585)	-	(1.020)	-	(0.687)	-	(1.403)
Urban unit size								
- rural	-	-	*ref.*	*ref.*	-	-	*ref.*	*ref.*
- 2,000 to 4,999 residents	-	-	-0.136	-0.639	-	-	0.428	0.068
	-	-	(1.430)	(1.541)	-	-	(1.157)	(1.279)
- 5,000 to 9,999 residents	-	-	-0.761	0.036	-	-	1.173	1.855
	-	-	(1.151)	(1.417)	-	-	(1.555)	(1.658)
- 10,000 to 19,999 residents	-	-	1.157	-0.847	-	-	3.198*	1.457
	-	-	(1.705)	(1.708)	-	-	(1.565)	(1.138)
- 20,000 to 49,999 residents	-	-	-1.298	-1.755*	-	-	0.179	-0.075
	-	-	(0.998)	(1.003)	-	-	(1.523)	(1.513)
- 50,000 to 99,999 residents	-	-	-1.069	-0.921	-	-	-0.625	-0.513
	-	-	(0.922)	(1.184)	-	-	(1.299)	(1.253)
- 100,000 to 199,999 residents	-	-	0.712	-0.707	-	-	1.229	-0.396
	-	-	(1.075)	(0.961)	-	-	(1.228)	(1.140)
- 200,000 to 1,999,999 residents	-	-	-0.111	-0.478	-	-	1.256	0.701
	-	-	(0.759)	(0.599)	-	-	(1.086)	(1.129)
- Paris	-	-	0.683	0.279	-	-	2.042	1.386
	-	-	(0.953)	(0.829)	-	-	(1.217)	(1.061)
Generation								
- 1937- 1938	*ref.*	*ref.*	*ref.*	*ref.*	*ref.*	*ref.*	*ref.*	*ref.*
- 1939 - 1940	0.233***	0.232***	0.177***	0.231***	0.318***	0.232***	0.201***	0.221***
	(0.021)	(0.030)	(0.039)	(0.036)	(0.019)	(0.034)	(0.055)	(0.052)
- 1941 - 1942	0.503***	0.527***	0.467***	0.497***	0.569***	0.476***	0.463***	0.462***

	(0.042)	(0.049)	(0.062)	(0.067)	(0.032)	(0.053)	(0.053)	(0.084)
- 1943 - 1944	0.682***	0.691***	0.578***	0.531***	0.756***	0.591***	0.600***	0.503***
	(0.051)	(0.067)	(0.073)	(0.083)	(0.035)	(0.076)	(0.084)	(0.122)
- 1945 - 1946	0.773***	0.800***	0.752***	0.747***	0.976***	0.819***	0.921***	0.870***
	(0.066)	(0.069)	(0.075)	(0.088)	(0.044)	(0.078)	(0.080)	(0.125)
- 1947 - 1948	1.007***	1.025***	0.991***	0.934***	1.220***	0.989***	1.122***	1.013***
	(0.074)	(0.092)	(0.083)	(0.106)	(0.053)	(0.104)	(0.099)	(0.160)
- 1949 - 1950	1.116***	1.121***	1.105***	1.000***	1.402***	1.129***	1.275***	1.124***
	(0.083)	(0.107)	(0.085)	(0.121)	(0.058)	(0.121)	(0.102)	(0.192)
- 1951 - 1952	1.211***	1.227***	1.247***	1.115***	1.534***	1.265***	1.455***	1.284***
	(0.082)	(0.110)	(0.077)	(0.113)	(0.066)	(0.123)	(0.102)	(0.182)
- 1953 - 1954	1.393***	1.413***	1.352***	1.238***	1.730***	1.440***	1.538***	1.377***
	(0.098)	(0.123)	(0.090)	(0.126)	(0.075)	(0.137)	(0.124)	(0.204)
- 1955 - 1956	1.367***	1.393***	1.404***	1.340***	1.770***	1.487***	1.640***	1.548***
	(0.104)	(0.130)	(0.094)	(0.124)	(0.086)	(0.143)	(0.139)	(0.194)
- 1957 - 1958	1.508***	1.536***	1.484***	1.371***	2.027***	1.697***	1.864***	1.712***
	(0.122)	(0.156)	(0.115)	(0.150)	(0.102)	(0.171)	(0.177)	(0.239)
- 1959 - 1960	1.552***	1.577***	1.568***	1.374***	2.190***	1.829***	1.986***	1.760***
	(0.132)	(0.169)	(0.128)	(0.178)	(0.111)	(0.185)	(0.201)	(0.268)
- 1961 - 1962	1.725***	1.737***	1.715***	1.552***	2.270***	1.857***	2.130***	1.928***
	(0.138)	(0.195)	(0.161)	(0.209)	(0.129)	(0.215)	(0.250)	(0.316)
- 1963 - 1964	1.725***	1.732***	1.674***	1.439***	2.438***	1.986***	2.166***	1.906***
	(0.159)	(0.215)	(0.188)	(0.244)	(0.138)	(0.234)	(0.293)	(0.360)
- 1965 - 1966	1.879***	1.886***	1.787***	1.470***	2.699***	2.223***	2.514***	2.181***
	(0.159)	(0.229)	(0.207)	(0.274)	(0.144)	(0.252)	(0.324)	(0.398)
- 1967 - 1968	1.888***	1.850***	1.846***	1.420***	2.693***	2.127***	2.592***	2.161***
	(0.155)	(0.237)	(0.208)	(0.291)	(0.138)	(0.263)	(0.336)	(0.433)
- 1969 - 1970	2.124***	2.034***	2.115***	1.637***	2.980***	2.279***	2.798***	2.271***
	(0.162)	(0.254)	(0.219)	(0.327)	(0.130)	(0.284)	(0.328)	(0.470)
- 1971 - 1972	2.362***	2.197***	2.388***	1.702***	3.468***	2.606***	3.167***	2.420***
	(0.156)	(0.273)	(0.195)	(0.334)	(0.120)	(0.310)	(0.311)	(0.486)
- 1973 - 1974	2.439***	2.199***	2.291***	1.531***	3.489***	2.510***	3.194***	2.374***
	(0.156)	(0.281)	(0.175)	(0.342)	(0.107)	(0.325)	(0.272)	(0.507)
- 1975 - 1976	2.519***	2.217***	2.512***	1.653***	3.635***	2.562***	3.274***	2.344***
	(0.148)	(0.292)	(0.171)	(0.347)	(0.095)	(0.341)	(0.246)	(0.525)
- 1977 - 1978	2.614***	2.270***	2.651***	1.807***	3.660***	2.525***	3.334***	2.409***
	(0.142)	(0.293)	(0.176)	(0.345)	(0.091)	(0.346)	(0.233)	(0.529)
- 1979 - 1980	2.815***	2.461***	2.635***	1.784***	4.355***	3.202***	3.911***	2.975***
	(0.138)	(0.299)	(0.171)	(0.345)	(0.084)	(0.356)	(0.224)	(0.531)
- 1981 - 1982	2.693***	2.276***	2.566***	1.740***	4.022***	2.853***	3.755***	2.871***
	(0.123)	(0.288)	(0.165)	(0.338)	(0.073)	(0.345)	(0.193)	(0.522)
Year								
- 2007	*ref.*	*ref.*	-	-	*ref.*	*ref.*	-	-
- 2008	0.062	0.111*	-	-	0.024	0.093	-	-
	(0.072)	(0.057)	-	-	(0.093)	(0.073)	-	-
- 2009	0.307***	0.374***	-	-	0.313**	0.317**	-	-
	(0.082)	(0.075)	-	-	(0.117)	(0.119)	-	-
- 2010	0.382***	0.430***	-	-	0.377***	0.328***	-	-
	(0.062)	(0.060)	-	-	(0.098)	(0.102)	-	-
- 2011	1.632***	1.314***	-	-	1.146***	0.832***	-	-
	(0.159)	(0.095)	-	-	(0.113)	(0.085)	-	-

- 2012	0.765***	1.009***	-	-	0.870***	0.970***	-	-
	(0.189)	(0.078)	-	-	(0.217)	(0.146)	-	-
- 2013	1.302***	1.188***	*ref.*	*ref.*	1.029***	0.924***	*ref.*	*ref.*
	(0.090)	(0.093)			(0.069)	(0.090)		
- 2014	1.360***	1.244***	0.105	0.083	1.222***	1.121***	0.100	0.093
	(0.086)	(0.090)	(0.085)	(0.087)	(0.096)	(0.133)	(0.124)	(0.133)
- 2015	1.343***	1.197***	0.179*	0.108	1.212***	1.136***	0.183	0.151
	(0.097)	(0.106)	(0.101)	(0.114)	(0.087)	(0.121)	(0.143)	(0.154)
- 2016	1.449***	1.316***	0.243***	0.209**	1.173***	1.104***	0.082	0.078
	(0.078)	(0.079)	(0.086)	(0.095)	(0.068)	(0.105)	(0.110)	(0.143)
- 2017	1.438***	1.295***	0.249**	0.204*	1.275***	1.195***	0.159	0.147
	(0.080)	(0.085)	(0.099)	(0.104)	(0.088)	(0.127)	(0.136)	(0.152)
- 2018	1.549***	1.418***	0.358***	0.312***	1.201***	1.132***	0.111	0.088
	(0.061)	(0.065)	(0.088)	(0.107)	(0.067)	(0.102)	(0.107)	(0.137)
- 2019	1.684***	1.547***	0.494***	0.451***	1.267***	1.198***	0.182*	0.166
	(0.090)	(0.090)	(0.078)	(0.096)	(0.102)	(0.141)	(0.100)	(0.125)
Constant	-3.834***	-2.671***	-3.176**	-1.273	-3.296***	-2.473***	-4.187***	-2.423***
	(0.660)	(0.480)	(1.299)	(1.054)	(0.563)	(0.472)	(1.412)	(0.742)
Observations	299	299	161	161	298	298	161	161
Adjusted R-squared	0.962	0.960	0.975	0.974	0.967	0.969	0.976	0.977

The dependent variable Access specifies whether or not the individual has access to the internet and Use if he uses it in the last three months.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered at the level of each cohort are reported in parentheses.

Table 3.C.2: Pseudo-panel estimation results for Internet Access and Use (cohorts: five-year generations separated by gender).

	Access				**Use**			
	(1)		**(2)**		**(3)**		**(4)**	
Household size	0.352*	(0.177)	0.259*	(0.146)	0.126	(0.215)	0.063	(0.182)
Density	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)
Monthly income								
- less than 1000€	*ref.*		-	-	*ref.*		-	-
- between 1000 and 1500€	1.296*	(0.720)	-	-	0.723	(0.587)	-	-
- between 1500 and 3000€	1.141**	(0.527)	-	-	1.025*	(0.540)	-	-
- more than 3000€	1.605**	(0.615)	-	-	1.348	(0.832)	-	-
Education level								
- Low	-	-	*ref.*		-	-	*ref.*	
- Middle	-	-	1.896***	(0.437)	-	-	2.874**	(1.025)
- High	-	-	1.215***	(0.416)	-	-	2.459***	(0.622)
Generation								
Women								
1938-1942	-0.199*	(0.100)	-0.346***	(0.053)	-0.246**	(0.086)	-0.324***	(0.038)
1943-1947	0.382***	(0.062)	0.177***	(0.056)	0.386***	(0.054)	0.171**	(0.077)
1948-1952	0.834***	(0.045)	0.563***	(0.061)	0.981***	(0.036)	0.614***	(0.117)
1953-1957	1.205***	(0.024)	0.890***	(0.061)	1.403***	(0.025)	0.951***	(0.143)
1958-1962	1.496***	(0.036)	1.162***	(0.060)	1.851***	(0.050)	1.320***	(0.157)
1963-1967	1.764***	(0.072)	1.388***	(0.078)	2.238***	(0.088)	1.584***	(0.184)
1968-1972	1.998***	(0.055)	1.507***	(0.101)	2.596***	(0.071)	1.731***	(0.234)
1973-1977	2.320***	(0.045)	1.662***	(0.150)	3.145***	(0.053)	1.981***	(0.335)
1978-1982	2.697***	(0.039)	1.921***	(0.178)	3.899***	(0.042)	2.558***	(0.393)
Men								
1938-1942	*ref.*		*ref.*		*ref.*		*ref.*	
1943-1947	0.516***	(0.023)	0.439***	(0.022)	0.564***	(0.029)	0.422***	(0.046)
1948-1952	0.864***	(0.040)	0.745***	(0.030)	0.989***	(0.048)	0.777***	(0.071)
1953-1957	1.061***	(0.049)	0.926***	(0.031)	1.265***	(0.060)	1.035***	(0.079)
1958-1962	1.262***	(0.064)	1.123***	(0.043)	1.624***	(0.075)	1.355***	(0.086)
1963-1967	1.454***	(0.071)	1.267***	(0.059)	1.958***	(0.081)	1.592***	(0.114)
1968-1972	1.820***	(0.071)	1.497***	(0.082)	2.409***	(0.078)	1.792***	(0.180)
1973-1977	2.284***	(0.067)	1.715***	(0.139)	3.080***	(0.074)	2.071***	(0.306)
1978-1982	2.389***	(0.061)	1.766***	(0.147)	3.549***	(0.060)	2.475***	(0.327)
Observations	234		234		234		234	
Adjusted R^2	0.965		0.967		0.966		0.969	
Constant	Yes		Yes		Yes		Yes	
Time Fixed-Effect	Yes		Yes		Yes		Yes	

The dependent variable Access specifies whether or not the individual has access to the internet and Use if he uses it in the last three months.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered at the level of each cohort are reported in parentheses.

Table 3.C.3: Pseudo-panel estimation results for Internet Access (cohorts: one and three-year generations)

Dep var: internet access	**One-year generation**				**Three-year generation**			
	(1)	(2)	(3)	(4)	(1')	(2')	(3')	(4')
Woman	0.312	0.163	0.960*	0.394	0.856	0.310	1.416	0.758
	(0.257)	(0.260)	(0.544)	(0.556)	(0.620)	(0.534)	(1.014)	(1.257)
Household size	0.363**	0.331**	0.275	0.382	0.346*	0.147	0.169	0.323
	(0.135)	(0.150)	(0.244)	(0.235)	(0.166)	(0.152)	(0.287)	(0.300)
Density	0.001*	0.001*	-	-	0.001	0.002	-	-
	(0.000)	(0.000)	-	-	(0.001)	(0.002)	-	-
Monthly income								
- less than 1000 €	ref.	-	ref.	-	ref.	-	ref.	-
- between 1000 and 1500€	0.883	-	0.970	-	1.744**	-	0.137	-
	(0.560)	-	(0.873)	-	(0.631)	-	(1.560)	-
- between 1500 and 3000€	1.413***	-	2.448***	-	1.621***	-	2.650**	-
	(0.401)	-	(0.683)	-	(0.367)	-	(1.007)	-
- more than 3000€	2.437***	-	3.681***	-	2.195***	-	3.577***	-
	(0.485)	-	(0.845)	-	(0.701)	-	(1.214)	-
Education level								
- Low	-	ref.	-	ref.	-	ref.	-	ref.
- Middle	-	1.667***	-	1.542**	-	1.858**	-	1.416*
	-	(0.366)	-	(0.657)	-	(0.656)	-	(0.806)
- High	-	1.208***	-	2.850***	-	0.802	-	2.743***
	-	(0.352)	-	(0.738)	-	(0.606)	-	(0.937)
Urban unit size								
- rural	-	-	ref.	ref.	-	-	ref.	ref.
- 2,000 to 4,999 residents	-	-	-1.750**	-1.567*	-	-	-0.542	-0.606
	-	-	(0.801)	(0.882)	-	-	(1.535)	(1.853)
- 5,000 to 9,999 residents	-	-	-0.257	-0.127	-	-	-0.013	0.982
	-	-	(0.974)	(0.960)	-	-	(1.731)	(1.915)
- 10,000 to 19,999 residents	-	-	0.288	-0.258	-	-	-0.016	-1.212
	-	-	(1.383)	(1.411)	-	-	(2.157)	(2.346)
- 20,000 to 49,999 residents	-	-	-1.451	-1.324	-	-	-1.314	-2.645
	-	-	(0.956)	(1.015)	-	-	(1.738)	(1.664)
- 50,000 to 99,999 residents	-	-	-0.785	-0.826	-	-	-1.916	-1.823
	-	-	(0.906)	(1.037)	-	-	(1.844)	(2.046)
- 100,000 to 199,999 residents	-	-	0.254	0.158	-	-	-0.345	-1.729
	-	-	(0.861)	(0.857)	-	-	(0.934)	(1.099)
- 200,000 to 1,999,999 residents	-	-	-0.533	-0.695	-	-	-0.675	0.170
	-	-	(0.760)	(0.759)	-	-	(1.276)	(1.377)
- Paris	-	-	0.118	0.171	-	-	-0.080	0.036
	-	-	(0.550)	(0.521)	-	-	(1.046)	(1.079)
Observations	609	609	329	329	231	231	118	118
Adjusted R-squared	0.935	0.933	0.945	0.943	0.979	0.978	0.985	0.983
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Fixed-Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed-Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable specifies whether or not individuals have access to the internet.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Standard errors clustered at the level of each cohort are reported in parentheses.

Table 3.C.4: Pseudo-panel estimation results for Internet Use (cohorts: one and three year generations)

Dep var: internet access	**One-year generation**				**Three-year generation**			
	(1)	(2)	(3)	(4)	(1')	(2')	(3')	(4')
Woman	0.396	0.223	1.951***	1.463**	0.838	0.667	3.017**	3.007**
	(0.392)	(0.375)	(0.647)	(0.632)	(0.718)	(0.674)	(1.140)	(1.203)
Household size	-0.004	-0.092	0.256	0.269	0.227	0.170	0.243	0.253
	(0.128)	(0.140)	(0.286)	(0.291)	(0.140)	(0.177)	(0.259)	(0.245)
Density	0.000	-0.000	-	-	0.001	0.000	-	-
	(0.001)	(0.001)	-	-	(0.001)	(0.001)	-	-
Monthly income								
- less than 1000 €	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*	-
- between 1000 and 1500€	1.117*	-	1.410	-	1.795***	-	-1.303	-
	(0.647)	-	(1.139)	-	(0.351)	-	(2.033)	-
- between 1500 and 3000€	1.483***	-	2.437***	-	1.607***	-	1.286	-
	(0.435)	-	(0.798)	-	(0.420)	-	(1.442)	-
- more than 3000€	2.247***	-	3.134***	-	2.148***	-	1.164	-
	(0.471)	-	(1.087)	-	(0.455)	-	(1.121)	-
Education level								
- Low	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*
- Middle	-	2.361***	-	1.641**	-	2.795**	-	0.843
	-	(0.570)	-	(0.640)	-	(0.978)	-	(0.905)
- High	-	1.531***	-	2.673***	-	2.614***	-	5.077***
	-	(0.394)	-	(0.925)	-	(0.840)	-	(1.457)
Urban unit size								
- rural	-	-	*ref.*	*ref.*	-	-	*ref.*	*ref.*
- 2,000 to 4,999 residents	-	-	-1.129	-0.867	-	-	-0.809	-0.576
	-	-	(0.844)	(0.860)	-	-	(2.080)	(2.180)
- 5,000 to 9,999 residents	-	-	0.635	0.664	-	-	3.138	3.003*
	-	-	(1.005)	(0.928)	-	-	(2.033)	(1.452)
- 10,000 to 19,999 residents	-	-	0.910	0.419	-	-	2.355	0.661
	-	-	(1.271)	(1.206)	-	-	(2.313)	(1.972)
- 20,000 to 49,999 residents	-	-	-1.205	-1.128	-	-	-2.252	-3.062*
	-	-	(0.988)	(1.031)	-	-	(1.959)	(1.454)
- 50,000 to 99,999 residents	-	-	-0.424	-0.379	-	-	-3.121	-3.617*
	-	-	(0.966)	(1.054)	-	-	(2.451)	(1.767)
- 100,000 to 199,999 residents	-	-	0.594	0.437	-	-	-0.388	-1.627
	-	-	(1.051)	(0.930)	-	-	(2.058)	(1.671)
- 200,000 to 1,999,999 residents	-	-	-0.021	-0.319	-	-	-0.192	-0.831
	-	-	(0.698)	(0.638)	-	-	(1.808)	(1.725)
- Paris	-	-	-0.105	-0.109	-	-	0.333	-0.131
	-	-	(0.735)	(0.736)	-	-	(1.749)	(1.546)
Observations	598	598	326	326	231	231	118	118
Adjusted R-squared	0.938	0.939	0.950	0.950	0.978	0.979	0.984	0.986
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Fixed-Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed-Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable specifies whether or not individuals have used the internet.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the level of each cohort are reported in parentheses

Table 3.C.5: Pseudo-panel estimation results for Internet Access and Use (cohorts: three-year generations separated by gender)

	Access				**Use**			
	(1)		**(2)**		**(3)**		**(4)**	
Household size	0.246	(0.151)	0.195	(0.130)	0.015	(0.117)	0.052	(0.135)
Density	0.000	(0.001)	0.001	(0.001)	-0.000	(0.001)	-0.000	(0.001)
Monthly income								
- less than 1000€	*ref.*		-	-	*ref.*		-	-
- between 1000 and 1500€	1.069**	(0.488)	-	-	1.366*	(0.728)	-	-
- between 1500 and 3000€	1.250**	(0.512)	-	-	1.442*	(0.723)	-	-
- more than 3000€	1.949***	(0.448)	-	-	2.130***	(0.635)	-	-
Education level								
- Low	-	-	*ref.*		-	-	*ref.*	
- Middle	-	-	1.299***	(0.468)	-	-	2.271***	(0.666)
- High	-	-	0.460	(0.365)	-	-	2.162***	(0.592)
Generation								
Women								
- 1936-1938	-0.246**	(0.096)	-0.523***	(0.057)	-0.390***	(0.123)	-0.540***	(0.067)
- 1939-1941	0.222***	(0.073)	-0.013	(0.044)	0.182*	(0.095)	-0.010	(0.051)
- 1942-1944	0.566***	(0.047)	0.356***	(0.045)	0.488***	(0.056)	0.227***	(0.064)
- 1945-1947	0.818***	(0.043)	0.628***	(0.045)	0.861***	(0.046)	0.593***	(0.066)
- 1948-1950	1.114***	(0.043)	0.912***	(0.060)	1.249***	(0.043)	0.869***	(0.096)
- 1951-1953	1.359***	(0.030)	1.156***	(0.068)	1.519***	(0.032)	1.105***	(0.110)
- 1954-1956	1.512***	(0.031)	1.324***	(0.073)	1.718***	(0.038)	1.315***	(0.111)
- 1957-1959	1.722***	(0.041)	1.537***	(0.095)	2.129***	(0.044)	1.659***	(0.137)
- 1960-1962	1.970***	(0.052)	1.778***	(0.113)	2.274***	(0.060)	1.721***	(0.159)
- 1963-1965	2.139***	(0.078)	1.954***	(0.138)	2.537***	(0.082)	1.930***	(0.186)
- 1966-1968	2.164***	(0.075)	1.978***	(0.142)	2.787***	(0.079)	2.139***	(0.197)
- 1969-1971	2.467***	(0.069)	2.221***	(0.163)	3.142***	(0.075)	2.313***	(0.243)
- 1972-1974	2.614***	(0.062)	2.346***	(0.178)	3.479***	(0.069)	2.544***	(0.276)
- 1975-1977	2.596***	(0.066)	2.273***	(0.193)	3.464***	(0.064)	2.416***	(0.307)
- 1978-1980	3.053***	(0.063)	2.688***	(0.201)	4.273***	(0.060)	3.141***	(0.322)
- 1981-1983	3.043***	(0.059)	2.634***	(0.200)	4.085***	(0.045)	2.951***	(0.319)
Men								
- 1936-1938	*ref.*		*ref.*		*ref.*		*ref.*	
- 1939-1941	0.281***	(0.016)	0.303***	(0.020)	0.263***	(0.021)	0.206***	(0.029)
- 1942-1944	0.729***	(0.032)	0.741***	(0.038)	0.714***	(0.039)	0.578***	(0.058)
- 1945-1947	0.899***	(0.041)	0.906***	(0.045)	0.982***	(0.046)	0.802***	(0.071)
- 1948-1950	1.191***	(0.049)	1.189***	(0.058)	1.292***	(0.061)	1.073***	(0.087)
- 1951-1953	1.243***	(0.054)	1.251***	(0.056)	1.411***	(0.064)	1.216***	(0.083)
- 1954-1956	1.391***	(0.061)	1.385***	(0.067)	1.626***	(0.074)	1.390***	(0.094)
- 1957-1959	1.450***	(0.069)	1.448***	(0.076)	1.776***	(0.086)	1.527***	(0.102)
- 1960-1962	1.661***	(0.078)	1.645***	(0.091)	2.073***	(0.093)	1.774***	(0.118)
- 1963-1965	1.750***	(0.085)	1.724***	(0.106)	2.226***	(0.094)	1.884***	(0.135)
- 1966-1968	1.873***	(0.082)	1.833***	(0.112)	2.514***	(0.091)	2.109***	(0.149)
- 1969-1971	2.257***	(0.091)	2.201***	(0.131)	2.862***	(0.100)	2.337***	(0.190)
- 1972-1974	2.432***	(0.090)	2.259***	(0.158)	3.295***	(0.088)	2.528***	(0.246)
- 1975-1977	2.700***	(0.081)	2.461***	(0.172)	3.582***	(0.075)	2.698***	(0.275)
- 1978-1980	2.755***	(0.079)	2.502***	(0.176)	3.928***	(0.071)	3.029***	(0.279)

- 1981-1983	2.713***	(0.063)	2.382***	(0.168)	3.882***	(0.047)	2.943***	(0.268)
Observations	416		416		414		414	
Adjusted R^2	0.952		0.951		0.958		0.960	
Constant	Yes		Yes		Yes		Yes	
Time Fixed-Effect	Yes		Yes		Yes		Yes	

The dependent variable Access specifies whether or not the individual has access to the internet and Use if he uses it in the last three months.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the level of each cohort are reported in parentheses.

Table 3.C.6: Pooled logit estimation results for Internet Access and Use

	Access				**Use**			
	(1)	(2)	(3)	(4)	(1')	(2')	(3')	(4')
Woman	0.213***	0.013	0.277***	0.053	0.133**	-0.086**	0.148**	-0.078
	(0.042)	(0.036)	(0.050)	(0.041)	(0.054)	(0.044)	(0.060)	(0.047)
Household size	0.468***	0.907***	0.466***	0.928***	-0.043	0.314***	0.020	0.370***
	(0.047)	(0.040)	(0.053)	(0.048)	(0.031)	(0.024)	(0.038)	(0.035)
Density	0.000***	0.000***	-	-	0.000***	0.000***	-	-
	(0.000)	(0.000)	-	-	(0.000)	(0.000)	-	-
Monthly income								
- less than 1000euro	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*	-
- between 1000 and 1500euro	0.561***	-	0.606***	-	0.495***	-	0.506***	-
	(0.033)	-	(0.044)	-	(0.042)	-	(0.051)	-
- between 1500 and 3000euro	1.492***	-	1.537***	-	1.481***	-	1.466***	-
	(0.037)	-	(0.042)	-	(0.045)	-	(0.047)	-
- more than 3000euro	2.661***	-	3.043***	-	2.744***	-	2.779***	-
	(0.063)	-	(0.074)	-	(0.050)	-	(0.056)	-
Education level								
- Low	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*
- Middle	-	1.242***	-	1.266***	-	1.664***	-	1.634***
	-	(0.058)	-	(0.056)	-	(0.032)	-	(0.039)
- High	-	1.843***	-	1.955***	-	2.519***	-	2.431***
	-	(0.071)	-	(0.071)	-	(0.068)	-	(0.079)
Urban unit size								
- rural	-	-	*ref.*	*ref.*	-	-	*ref.*	*ref.*
- 2,000 to 4,999 residents	-	-	0.064	0.099*	-	-	0.039	0.076
	-	-	(0.062)	(0.060)	-	-	(0.059)	(0.061)
- 5,000 to 9,999 residents	-	-	0.089	0.098**	-	-	0.082	0.086
	-	-	(0.055)	(0.047)	-	-	(0.069)	(0.067)
- 10,000 to 19,999 residents	-	-	0.065	0.072	-	-	0.029	0.028
	-	-	(0.052)	(0.046)	-	-	(0.054)	(0.048)
- 20,000 to 49,999 residents	-	-	0.120***	0.118***	-	-	0.098**	0.089*
	-	-	(0.034)	(0.042)	-	-	(0.047)	(0.050)
- 50,000 to 99,999 residents	-	-	0.137***	0.084	-	-	0.087*	0.024
	-	-	(0.045)	(0.057)	-	-	(0.047)	(0.057)
- 100,000 to 199,999 residents	-	-	0.184***	0.144***	-	-	0.190***	0.118**
	-	-	(0.061)	(0.052)	-	-	(0.051)	(0.050)
- 200,000 to 1,999,999 residents	-	-	0.280***	0.196***	-	-	0.259***	0.143***
	-	-	(0.038)	(0.038)	-	-	(0.038)	(0.039)
- Paris	-	-	0.350***	0.313***	-	-	0.335***	0.218***
	-	-	(0.037)	(0.045)	-	-	(0.038)	(0.045)
Generation								
- 1937- 1938	*ref.*	*ref.*	*ref.*	*ref.*	*ref.*	*ref.*	*ref.*	*ref.*
- 1939 - 1940	0.271***	0.260***	0.290***	0.322***	0.295***	0.284***	0.290***	0.335***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
- 1941 - 1942	0.591***	0.575***	0.634***	0.641***	0.551***	0.539***	0.545***	0.572***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
- 1943 - 1944	0.806***	0.761***	0.846***	0.812***	0.793***	0.745***	0.812***	0.781***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
- 1945 - 1946	0.948***	0.923***	1.062***	1.020***	1.052***	1.034***	1.103***	1.082***

	(0.002)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)
- 1947 - 1948	1.227***	1.156***	1.337***	1.256***	1.300***	1.235***	1.317***	1.260***
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)
- 1949 - 1950	1.373***	1.281***	1.512***	1.381***	1.514***	1.423***	1.539***	1.428***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
- 1951 - 1952	1.487***	1.376***	1.641***	1.485***	1.670***	1.572***	1.692***	1.565***
	(0.003)	(0.003)	(0.006)	(0.004)	(0.004)	(0.003)	(0.005)	(0.003)
- 1953 - 1954	1.682***	1.571***	1.803***	1.637***	1.846***	1.746***	1.829***	1.695***
	(0.004)	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)
- 1955 - 1956	1.706***	1.571***	1.900***	1.700***	1.952***	1.829***	2.004***	1.834***
	(0.005)	(0.002)	(0.008)	(0.004)	(0.008)	(0.004)	(0.008)	(0.004)
- 1957 - 1958	1.834***	1.669***	1.966***	1.751***	2.197***	2.038***	2.210***	2.018***
	(0.006)	(0.003)	(0.008)	(0.004)	(0.009)	(0.005)	(0.008)	(0.004)
- 1959 - 1960	1.895***	1.712***	2.035***	1.784***	2.343***	2.151***	2.338***	2.096***
	(0.006)	(0.003)	(0.008)	(0.003)	(0.011)	(0.005)	(0.011)	(0.005)
- 1961 - 1962	2.136***	1.889***	2.273***	1.983***	2.508***	2.262***	2.558***	2.292***
	(0.008)	(0.004)	(0.009)	(0.003)	(0.013)	(0.007)	(0.012)	(0.007)
- 1963 - 1964	2.122***	1.851***	2.225***	1.896***	2.604***	2.319***	2.590***	2.271***
	(0.009)	(0.004)	(0.010)	(0.002)	(0.015)	(0.008)	(0.015)	(0.009)
- 1965 - 1966	2.272***	1.966***	2.312***	1.920***	2.950***	2.624***	2.950***	2.553***
	(0.011)	(0.006)	(0.012)	(0.004)	(0.017)	(0.010)	(0.018)	(0.010)
- 1967 - 1968	2.294***	1.953***	2.396***	1.953***	2.951***	2.578***	3.009***	2.556***
	(0.009)	(0.007)	(0.012)	(0.005)	(0.016)	(0.009)	(0.018)	(0.010)
- 1969 - 1970	2.534***	2.155***	2.720***	2.249***	3.191***	2.773***	3.279***	2.792***
	(0.009)	(0.010)	(0.011)	(0.005)	(0.016)	(0.009)	(0.020)	(0.011)
- 1971 - 1972	2.776***	2.290***	2.977***	2.407***	3.647***	3.114***	3.629***	3.034***
	(0.008)	(0.013)	(0.011)	(0.011)	(0.013)	(0.009)	(0.016)	(0.009)
- 1973 - 1974	2.807***	2.305***	2.945***	2.339***	3.722***	3.156***	3.725***	3.083***
	(0.008)	(0.015)	(0.010)	(0.013)	(0.012)	(0.008)	(0.013)	(0.009)
- 1975 - 1976	2.922***	2.344***	3.154***	2.509***	3.779***	3.132***	3.793***	3.102***
	(0.008)	(0.018)	(0.010)	(0.016)	(0.010)	(0.007)	(0.011)	(0.009)
- 1977 - 1978	3.056***	2.454***	3.360***	2.720***	3.852***	3.167***	3.854***	3.162***
	(0.007)	(0.019)	(0.009)	(0.016)	(0.009)	(0.007)	(0.010)	(0.009)
- 1979 - 1980	3.159***	2.559***	3.313***	2.699***	4.488***	3.808***	4.377***	3.708***
	(0.007)	(0.018)	(0.009)	(0.016)	(0.009)	(0.007)	(0.009)	(0.007)
- 1981 - 1982	3.131***	2.492***	3.298***	2.660***	4.341***	3.625***	4.361***	3.678***
	(0.007)	(0.019)	(0.011)	(0.017)	(0.009)	(0.004)	(0.010)	(0.005)
Year								
- 2007	*ref.*	*ref.*	-	-	*ref.*	*ref.*	-	-
- 2008	0.118**	0.160***	-	-	0.057	0.092	-	-
	(0.054)	(0.050)	-	-	(0.065)	(0.070)	-	-
- 2009	0.367***	0.430***	-	-	0.253***	0.326***	-	-
	(0.085)	(0.078)	-	-	(0.087)	(0.088)	-	-
- 2010	0.448***	0.492***	-	-	0.304***	0.340***	-	-
	(0.054)	(0.046)	-	-	(0.075)	(0.078)	-	-
- 2011	1.823***	1.372***	-	-	1.278***	0.848***	-	-
	(0.063)	(0.063)	-	-	(0.076)	(0.083)	-	-
- 2012	0.718***	1.315***	-	-	0.420***	1.052***	-	-
	(0.077)	(0.052)	-	-	(0.077)	(0.060)	-	-
- 2013	1.445***	1.407***	*ref.*	*ref.*	1.068***	1.055***	*ref.*	*ref.*
	(0.062)	(0.053)			(0.061)	(0.059)		

- 2014	1.603***	1.569***	0.149***	0.157***	1.220***	1.214***	0.147***	0.157***
	(0.062)	(0.052)	(0.045)	(0.040)	(0.064)	(0.069)	(0.043)	(0.042)
- 2015	1.596***	1.553***	0.139***	0.141***	1.245***	1.236***	0.168***	0.180***
	(0.064)	(0.055)	(0.038)	(0.039)	(0.062)	(0.069)	(0.042)	(0.043)
- 2016	1.721***	1.674***	0.270***	0.263***	1.263***	1.253***	0.187***	0.196***
	(0.061)	(0.045)	(0.042)	(0.045)	(0.052)	(0.051)	(0.032)	(0.032)
- 2017	1.752***	1.683***	0.304***	0.272***	1.386***	1.342***	0.309***	0.285***
	(0.047)	(0.043)	(0.039)	(0.039)	(0.069)	(0.074)	(0.030)	(0.037)
- 2018	1.893***	1.834***	0.448***	0.425***	1.362***	1.337***	0.287***	0.281***
	(0.050)	(0.045)	(0.050)	(0.047)	(0.059)	(0.073)	(0.053)	(0.052)
- 2019	1.925***	1.871***	0.487***	0.467***	1.382***	1.364***	0.312***	0.309***
	(0.069)	(0.054)	(0.047)	(0.036)	(0.068)	(0.070)	(0.044)	(0.041)
Constant	-3.975***	-3.590***	-2.822***	-2.381***	-3.024***	-2.612***	-2.149***	-1.681***
	(0.099)	(0.072)	(0.111)	(0.079)	(0.091)	(0.071)	(0.107)	(0.072)
Observations	86645	86645	64908	64908	86645	86645	64908	64908
Adjusted R-squared	0.260	0.243	0.253	0.219	0.274	0.281	0.256	0.251

The dependent variable Access specifies whether or not the individual has access to the internet and Use if he uses it in the last three months.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered at the level of each cohort are reported in parentheses.

Table 3.C.7: Pseudo-panel estimation results for the online population (cohorts: five-year generations)

	Bank		**Administrative**		**E-commerce**		**Leisure**		**Social media**		**Job search**		**Collab eco**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Woman	-0.162	-0.033	-0.415	-0.360	-0.679	-0.843**	0.059	-0.001	0.304	0.552	3.945**	3.678*	-1.524***	-1.573**
	(0.361)	(0.433)	(1.091)	(1.208)	(0.545)	(0.326)	(0.965)	(1.074)	(0.670)	(0.800)	(1.540)	(1.765)	(0.370)	(0.473)
Household size	0.092	0.008	0.411*	-0.008	0.223	0.063	0.537**	0.399	-0.198	-0.276*	0.726	0.791	0.156	0.204
	(0.178)	(0.209)	(0.207)	(0.201)	(0.173)	(0.128)	(0.196)	(0.290)	(0.155)	(0.143)	(0.525)	(0.513)	(0.251)	(0.213)
Density	0.000	0.000	0.002*	0.002*	0.001	0.001	-0.001	-0.001	-0.002	-0.002	-0.000	-0.000	-0.002*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Monthly income														
- less than 1000€	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*		*ref.*	-	*ref.*	-
- between 1000 and 1500€	-2.322	-	2.292	-	-4.562	-	0.345	-	-1.163	-	-0.748	-	-4.899**	-
	(2.223)	-	(2.979)	-	(2.849)	-	(2.785)	-	(2.110)	-	(6.169)	-	(2.041)	-
- between 1500 and 3000€	-0.325	-	3.478	-	-2.254	-	0.431	-	-2.272	-	-4.502	-	-2.748*	-
	(1.494)	-	(2.218)	-	(1.908)	-	(1.151)	-	(1.575)	-	(3.828)	-	(1.456)	-
- more than 3000€	-1.318	-	2.707	-	-2.146	-	-0.995	-	-2.653	-	-2.771	-	-3.677*	-
	(1.305)	-	(2.670)	-	(2.243)	-	(1.652)	-	(2.085)	-	(3.862)	-	(1.816)	-
Education level														
- Low	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*
- Middle	-	1.038	-	1.928**	-	2.589***	-	0.354	-	0.588	-	1.041	-	0.799
	-	(0.577)	-	(0.783)	-	(0.543)	-	(0.279)	-	(0.645)	-	(1.418)	-	(0.556)
- High	-	1.078*	-	0.127	-	1.508***	-	-0.442	-	0.362	-	0.955	-	0.736
	-	(0.559)	-	(1.997)	-	(0.403)	-	(0.987)	-	(1.693)	-	(0.883)	-	(1.021)
Observations	117	117	117	117	117	117	72	72	63	63	86	86	117	117
Adjusted R^2	0.868	0.869	0.928	0.935	0.945	0.960	0.870	0.862	0.978	0.975	0.933	0.930	0.920	0.914
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Fixed-Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed-Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Definition of the dependent variables:

- Bank: the individual uses the internet to access his bank account
- Administrative: the individual uses the internet to fill out or send administrative forms
- E-commerce: the individual uses the internet to buy a good online
- Leisure: the individual has listened to the radio or music, watched television, played or downloaded games, pictures, video, music
- Social media: the individual uses the internet to create a profile or post messages on social media
- Job search: the individual uses the internet to search for a job
- Collab Eco: the individual uses the internet to sell products and services on online sites

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the level of each cohort are reported in parentheses.

Table 3.C.8: Pseudo-panel estimation results for the online population (cohorts: two-year generations)

	Bank		**Administrative**		**E-commerce**		**Leisure**		**Social media**		**Job search**		**Collab eco**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Woman	-0.009	-0.000	-0.190	-0.170	-0.711	-0.889	-0.056	-0.049	0.044	0.193	1.298	0.977	-0.733	-0.728
	(0.314)	(0.306)	(0.707)	(0.636)	(0.406)	(0.440)	(0.350)	(0.381)	(0.371)	(0.306)	(1.086)	(0.959)	(0.454)	(0.500)
Household size	-0.069	-0.069	0.114	-0.102	0.129	0.105	0.224	0.097	-0.056	-0.226	0.639*	0.409	0.072	0.092
	(0.114)	(0.093)	(0.183)	(0.206)	(0.120)	(0.128)	(0.173)	(0.156)	(0.190)	(0.183)	(0.255)	(0.247)	(0.252)	(0.243)
Density	-0.000	-0.000	0.001	0.001	0.001	0.001	0.000	0.001	-0.001	-0.001	-0.000	-0.001	0.000	0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Monthly income														
- less than 1000€	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*	-
- between 1000 and 1500€	-0.022	-	-0.252	-	-2.352*	-	-0.547	-	1.505	-	-1.895	-	-3.518*	-
	(0.645)	-	(1.664)	-	(0.975)	-	(2.299)-	-	(1.129)	-	(2.555)	-	(1.555)	-
- between 1500 and 3000€	0.400	-	0.603	-	-0.583	-	0.136	-	-0.218	-	-4.481*	-	-3.241*	-
	(0.661)	-	(1.705)	-	(0.747)	-	(1.080)	-	(0.717)	-	(1.926)	-	(1.387)	-
- more than 3000€	0.643	-	0.279	-	0.233	-	-0.650	-	-0.483	-	-3.591	-	-3.144*	-
	(0.649)	-	(1.668)	-	(0.548)	-	(1.200)	-	(0.705)	-	(1.807)	-	(1.273)	-
Education level														
- Low	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*
- Middle	-	0.596*	-	1.683**	-	1.679**	-	0.417	-	-0.203	-	2.230*	-	0.582
	-	(0.239)	-	(0.374)	-	(0.458)	-	(0.527)	-	(0.609)	-	(1.028)	-	(0.547)
- High	-	0.632	-	0.391	-	1.021**	-	-0.162	-	-0.343	-	0.462	-	0.501
	-	(0.402)	-	(0.814)	-	(0.356)	-	(0.550)	-	(0.751)	-	(1.175)	-	(0.584)
Observations	299	299	299	299	299	299	184	184	161	161	201	201	299	299
Adjusted R^2	0.751	0.754	0.880	0.891	0.889	0.888	0.826	0.825	0.953	0.950	0.874	0.874	0.844	0.837
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Fixed-Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed-Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Definition of the dependent variables:

- Bank: the individual uses the internet to access his bank account
- Administrative: the individual uses the internet to fill out or send administrative forms
- E-commerce: the individual uses the internet to buy a good online
- Leisure: the individual has listened to the radio or music, watched television, played or downloaded games, pictures, video, music
- Social media: the individual uses the internet to create a profile or post messages on social media
- Job search: the individual uses the internet to search for a job
- Collab Eco: the individual uses the internet to sell products and services on online sites

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the level of each cohort are reported in parentheses.

Table 3.C.9: Pseudo panel estimation results for reasons of non-access of Internet (cohorts: ten-year generations)

	Too expensive		**Lack of skills**		**Security**		**Not useful**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Woman	-1.247	-1.250*	0.489	1.226	-1.945	-1.949	-0.622	-0.711
	(0.768)	(0.546)	(1.152)	(1.322)	(2.423)	(1.588)	(0.773)	(0.826)
Household size	0.152	0.197	0.106	0.681*	-1.791	-2.223*	-0.876	-1.008
	(0.147)	(0.261)	(0.133)	(0.297)	(1.249)	(0.802)	(0.528)	(0.496)
Density	0.000	0.000	0.001	0.001	0.000	0.005	0.000	-0.002**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)	(0.001)	(0.001)
Monthly income								
- less than 1000€	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*	-
- between 1000 and 1500€	0.471	-	2.912**	-	-4.445	-	1.211	-
	(0.833)	-	(0.908)	-	(2.670)	-	(0.847)	-
- between 1500 and 3000€	0.168	-	0.882	-	-5.472*	-	1.532**	-
	(0.905)	-	(0.643)	-	(1.975)	-	(0.518)	-
- more than 3000€	0.375	-	3.056	-	-4.340*	-	0.209	-
	(0.520)	-	(1.669)	-	(1.766)	-	(0.405)	-
Education level								
- Low	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*
- Middle	-	-0.330	-	-0.000	-	4.191*	-	0.230
	-	(0.632)	-	(1.170)	-	(1.816)	-	(1.246)
- High	-	0.248	-	-0.663	-	-5.928**	-	2.325*
	-	(0.566)	-	(0.821)	-	(1.895)	-	(1.042)
Observations	50	50	50	50	50	50	50	50
Adjusted R^2	0.931	0.931	0.956	0.940	0.792	0.829	0.948	0.951
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Dependent variables definition:

- Too expensive: the individual does not have internet at home because of equipment or access is too expensive
- Lack of skills: the individual does not have internet at home because internet is not needed
- Security: the individual does not have internet at home because of insufficient household skills
- Not useful: the individual does not have internet at home for security or privacy reasons

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered at the level of each cohort are reported in parentheses.

Table 3.C.10: Pseudo panel estimation results for reasons of non-access of Internet (cohorts: five-year generations)

	Too expensive		**Lack of skills**		**Security**		**Not useful**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Woman	0.319	0.430	-0.654	-0.457	0.242	0.230	-0.421	-0.607
	(0.480)	(0.585)	(0.692)	(0.754)	(1.543)	(1.439)	(0.574)	(0.787)
Household size	-0.029	-0.066	-0.275	-0.476	-1.017	-1.363*	-0.133	-0.037
	(0.201)	(0.265)	(0.386)	(0.285)	(0.449)	(0.434)	(0.430)	(0.440)
Density	-0.000	-0.000	-0.000	0.000	-0.001	0.001	0.001	0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Monthly income								
- less than 1000€	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*	-
- between 1000 and 1500€	-0.146	-	0.014	-	-2.381	-	0.014	-
	(0.318)	-	(0.561)	-	(1.374)	-	(0.754)	-
- between 1500 and 3000€	-0.552	-	-0.661	-	-2.370	-	-0.715	-
	(0.443)	-	(0.674)	-	(1.523)	-	(0.864)	-
- more than 3000€	0.620	-	-0.237	-	-2.766*	-	-0.002	-
	(0.437)	-	(0.756)	-	(0.828)	-	(0.638)	-
Education level								
- Low	-	*ref.*	-	*ref.*	-	*ref.*	-	*ref.*
- Middle	-	-0.028	-	-2.639*	-	2.257	-	-0.049
	-	(0.287)	-	(0.976)	-	(1.915)	-	(1.136)
- High	-	-0.594	-	-3.099**	-	-4.430**	-	1.310
	-	(0.601)	-	(0.686)	-	(0.932)	-	(0.708)
Observations	90	90	89	89	90	90	90	90
R^2	0.793	0.783	0.869	0.901	0.620	0.666	0.831	0.832
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Dependent variables definition:

- Too expensive: the individual does not have internet at home because of equipment or access is too expensive
- Lack of skills: the individual does not have internet at home because internet is not needed
- Security: the individual does not have internet at home because of insufficient household skills
- Not useful: the individual does not have internet at home for security or privacy reasons

$p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Standard errors clustered at the level of each cohort are reported in parentheses.

Chapter 4

Distributional Effect and Efficiency of Environmental tax on Mobile Data[1]

[1]This chapter is a joint work with Paolo Melindi-Ghidi (EconomiX-CNRS, University of Paris Nanterre & AMSE, Aix-Marseille University) and Jean-Philippe Nicolaï (CNRS, INRAE, Grenoble INP, GAEL University of Grenoble Alpes, and Chair Energy & Prosperity).

4.1 Introduction

In 2020, the environmental impact of digital technology represented 3,2% of French greenhouse gas (GHG) emissions (Bordage *et al.*, 2021) and is expected to increase by 45% by 2030 due to the rapid increase in digital consumption and production (ADEME & ARCEP, 2023). Digital technology does not only impact climate change but is also responsible for various pollution and the depletion of natural resources. The environmental impact of digital is multifaceted, encompassing all stages of the lifecycle, including production, usage, and end-of-life, of the equipment and infrastructures required for digital functioning (end-user devices, data centers, and network infrastructures). However, digital is often ignored in environmental public policies. To achieve carbon neutrality and meet the Paris Agreement objectives, it is imperative to regulate these new sources of pollution through a complete approach based on several levers.

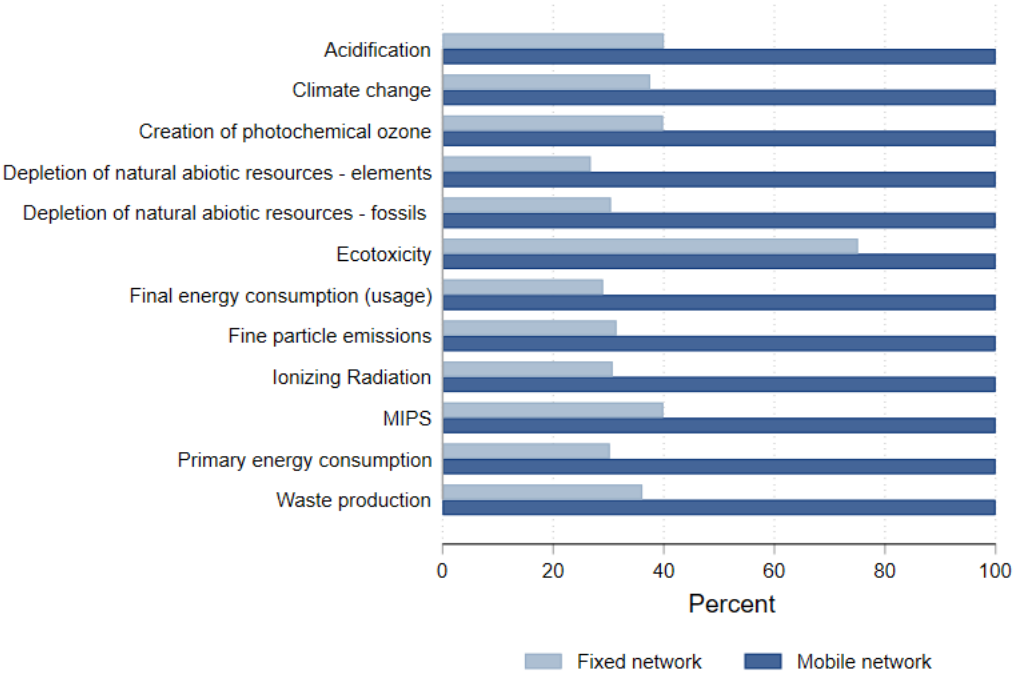
This chapter focuses on network infrastructure regulation. More specifically, we study the regulation of mobile internet, which is demonstrated to be less efficient from an environmental point of view than fixed internet (Lees Perasso *et al.*, 2022).[2] Indeed, the environmental impact per gigabyte is much higher for the mobile network than the fixed, regardless of the indicator considered (Figure 4.1). On average, using a gigabyte of internet on mobile networks pollutes three times more than on fixed networks. This discrepancy arises primarily due to the high energy intensity of mobile network usage.[3] Moreover, the amount of data consumed in total and per user has drastically increased over the last few years (Figure 4.2 in appendix). This trend is expected to remain with the new digital usages, such as the Internet of Things and high-quality video. The implementation of 5G infrastructure could also increase traffic.

In 2020, the French senate proposed to *"ban as a preventive measure mobile packages*

[2]Fixed internet includes all FTTx and xDLS technologies, and mobile internet includes 2G, 3G, 4G, and 5G technologies.

[3]New generations of mobile internet are more energy-efficient but experience a rebound effect. Moreover, they do not appear to be a substitute for older; their deployment does not result in the suppression of an older one. Ferreboeuf *et al.* (2021) highlight that both effects prevent a reduction in energy consumption.

Figure 4.1: Comparison of impacts by GB between fixed and mobile networks in France in 2020

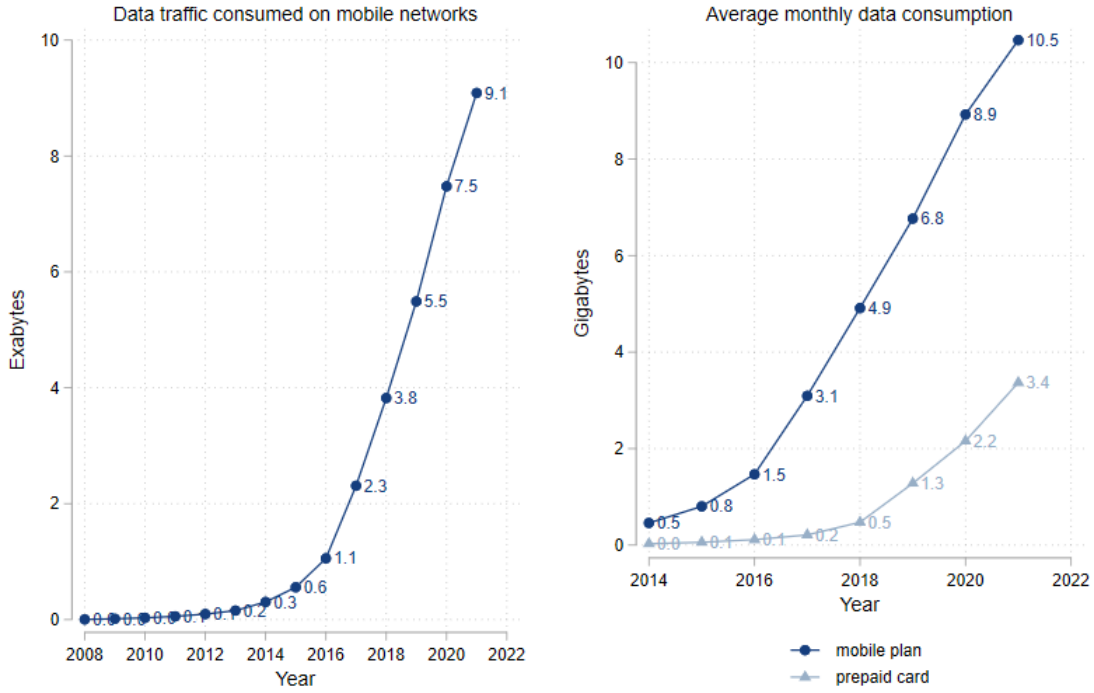


Source: Data are from Lees Perasso *et al.* (2022). The impacts of mobile networks are scaled down to 100%. Environmental impacts are assessed using a Life Cycle Assessment methodology.

with unlimited access to data and made compulsory a proportional pricing to the amount of data of the package" (Chevrollier & Houllegatte, 2020). This proposition faced substantial opposition from telecom operators and was not adopted in the "Réduire l'Empreinte Environnementale du Numérique" (Reducing the Environmental Footprint of Digital) law adopted on November 15, 2021. However, the question of the limitation remains and is relaunched by the recent debates on sobriety.[4] The aim of such a regulation is twofold. Firstly, it encourages sobriety by decreasing users' mobile internet consumption. Secondly, the objective is also to

[4]Measure 7 of the roadmap on digital and environment of the Conseil national du numérique (2021) proposes to "encourage subscription with limited internet data allowance, including on the fixed network, in order to avoid an indirect subsidy of high traffic users by all users (knowing that once the threshold is exceeded, the idea is to switch to lower speeds)." Note that the senate proposition law indicates that the fixed offers will not be concerned because they are less energy intensive. Moreover, the French government's sobriety plan recommends "encourage employees to use Wi-Fi when it is available in the firm" (Gouvernement français, 2022).

Figure 4.2: Data traffic on French mobile networks



Source: ARCEP, Observatoire des communications électroniques, https://www.data.gouv.fr/fr/datasets/r/f30bc772-7dff-49d6-940e-42865f32a9da

incentivize using fixed internet instead of a mobile. Several measures can be implemented as an alternative to the ban, such as raising awareness of the environmental footprint of mobile data or taxing mobile offers.

In this chapter, we are interested in studying the main economic effects of taxing mobile subscriptions. Tax is not very popular in France, but its acceptability can increase if households perceive it as progressive and efficient (Douenne & Fabre, 2022). Therefore, this chapter aims to investigate the distributive effect and efficiency of an environmental tax on mobile internet in France.

We highlighted in the previous chapter that there is still a digital divide. Low-income households are less equipped with digital equipment and type of connection than high-income

households. Moreover, they are more likely to have only one type of equipment (computer or smartphone) and one type of internet access (fixed or mobile). Moreover, the share of expenditures allocated to the internet is higher for low-income than high-income households. The revenue effect of a tax on mobile prices should be higher for the first income deciles. As a consequence, the regulation of mobile data could be regressive. The substitutability or complementarity between fixed and mobile internet, still discussed in the literature, can also play a role. The impact of a tax may lead to either a substitution of mobile internet usage with fixed internet or simply a reduction in consumption, depending on how households respond to a price increase. Increasing mobile prices can, therefore, reinforce the existing digital divide. Furthermore, the market structure can alter tax efficiency. The French telecommunications industry is very competitive and offers among the cheapest internet subscriptions in the developed countries (OECD, 2021). Telecom operators offer many mobile internet subscriptions at low prices and large data allowances, including unlimited data. However, the availability of subscriptions with intermediate data allowances is limited in France. The lack of diversification supplied can mitigate the price signal of the tax because it is difficult to reduce the "quantity" of mobile data.

We investigate the distributive effect and efficiency of the tax in two parts. Firstly, we analyze the consumption behavior of French households by estimating the (cross) price elasticities of several non-durable goods, including fixed and mobile internet connections. To this aim, we use a censored Quadratic Almost Ideal Demand system (Banks *et al.*, 1997; Shonkwiler & Yen, 1999) and the Budget des Familles survey (Household budget survey) produced by the French Institute of Statistics (INSEE) in 2017. It enables us to simulate the short-term behavioral responses of a hypothetical mobile price increase and to compute and compare the average welfare loss across different income deciles. In addition, the computation of cross-price elasticities allows us to conclude on the substitutability or complementarity between fixed and mobile internet in the case of the French market. In the second part of the chapter, we propose a simple theoretical model that explains the purchasing decisions for fixed and mobile internet. It enables us to understand how tax efficiency depends on

the market structure and that non-substitutability between fixed and mobile subscriptions arises from the tariff offers present in the market. To this aim, we model a consumer who chooses her expenditure on mobile data, fixed data, services associated with fixed data, and a composite good. Several cases representing different market structures are considered: unit prices of fixed and mobile data, subscriptions for unlimited use of fixed data, bundles including unlimited use of fixed data and services, and subscriptions allowing consumption of a certain volume of mobile data without additional charges.

Our results highlight that, on average, French households react to a change in fixed and mobile internet prices. The uncompensated price elasticities for fixed and mobile internet are around -0,774 and -0,832, and the compensated are around -0,687 and -0,766. Moreover, the price sensitivity decreases with the income decile for fixed and mobile internet. We find small but significant negative cross-price elasticities between fixed and mobile internet, indicating that these two types of spending are complementary. Finally, our simulations demonstrate that a tax on mobile internet subscriptions is regressive. The welfare loss following the tax is higher for low-income households than high-income households, considering only mobile internet users and all populations. A less regressive measure is to tax only the most expensive subscriptions, often those with mobile data-intensive allowances.

We then show that tax on mobile data is more efficient (i.e., tax will decrease mobile internet consumption) when data is sold at the unit price or the offers are numerous and close to allow consumers to change subscriptions easily. In other cases, some households do not modify their mobile data consumption. Moreover, consumption and expenditure differ when mobile data are not sold at the unit price. Tax efficiency can be mitigated if households do not consume all the data allowances of their subscriptions. Tax can lead to a decrease in mobile expenditure without a decrease in consumption. We also highlight that the efficiency of mobile data tax also depends on fixed subscription offers. The higher the price of a fixed internet subscription, the less households will react to a change in mobile price.

The remainder of this chapter is structured as follows. We present the related literature in

Section 4.2 and a description of the French telecommunication market in Section 4.3. Section 4.4 presents the data, methodology, and results of the distributional impact of a mobile tax. Section 4.5 highlights how tax efficiency depends on the market structure in a theoretical framework. Section 4.6 concludes.

4.2 Literature review

This chapter is related and contributes to several strands of the literature. First, it contributes to the literature on consumer behavior regarding fixed and mobile internet. Cardona *et al.* (2009), Srinuan *et al.* (2012), Grzybowski *et al.* (2014), and Nakamura (2015) find that fixed and mobile internet are substitutable for Austria in 2006, Sweden in 2009, Slovakia in 2011, and Japan in 2010. These researches were conducted at the beginning of mobile internet diffusion, and all used discrete choice models where consumers can only choose between fixed and mobile connection. Grzybowski & Liang (2015), Liang & Petulowa (2018), Vélez-Velásquez (2019), and Ros (2023) use models that let consumers choose a fixed-mobile bundle with data on French, Colombian, and Mexican households. They show evidence that fixed and mobile internet services are complementary in these countries. Madden *et al.* (2015) estimate internet adoption with a nested logit where consumers can also choose a fixed-mobile bundle. They find that fixed and mobile subscriptions are substitutes in Thailand. Lee *et al.* (2011) estimate a logistic model of broadband diffusion with aggregated data for thirty OECD countries between 2003 and 2008. They find that mobile is complementary to fixed internet services in many countries. Finally, Kongaut & Bohlin (2016) and Quaglione *et al.* (2020) were interested in activities carried out online. They highlight that fixed and mobile are complementary for some activities, particularly data-intensive activities such as gaming, video streaming, and cloud services. These activities can be used outside with a mobile connection and then at home with a fixed connection, providing unlimited data allowances. The different conclusions in the literature suggest that consumer behaviors regarding fixed and mobile internet strongly depend on the country and, therefore, on the telecommunications

market.

This chapter is also related to the large literature on the distributive effects of the carbon tax. Wang *et al.* (2016) and Ohlendorf *et al.* (2021) provide, respectively, a literature review and a meta-analysis on this topic.[5] Main conclusions are that the carbon tax is regressive, i.e., the welfare loss decreases with household income. It has been studied on direct energy goods, such as electricity, car fuels or gas (Bureau, 2011; Rosas-Flores *et al.*, 2017), and on indirect energy goods, such as food (Caillavet *et al.*, 2019) in several countries. There is further literature pointing out that the unequal distributive effects of the carbon tax are also horizontal, such as between rural and urban households (Beck *et al.*, 2016), states or regions (Williams *et al.*, 2014), or according to the household composition (Eisner *et al.*, 2021). Finally, several papers show evidence that a carbon tax can be progressive if recycled through a lump-sum rebate (Williams *et al.*, 2015; Fremstad & Paul, 2019; Douenne, 2020).

Finally, this chapter contributes to the recent literature on how to regulate the environmental impact of digital. The regulation can concern all the different economic actors. For instance, Nicolaï & Peragin (2022) focus on digital players, such as internet service providers, digital service providers, or data centers. They discuss the possibility of implementing digital sobriety certificates based on the model of the white certificates, whose objective would be to impose obligations to invest in digital sobriety. Devaux & Nicolaï (2022) propose imposing a duty of digital care on firms. The environmental degradation caused by their digital activities would have to be considered; otherwise, the legislator would have to intervene. Poudou & Sand-Zantman (2023) are interested, within a theoretical framework, in how to encourage content providers to reduce their environmental footprint. They show that the negative environmental impact can be lowered when a regulator charges content providers for the congestion they create on the network. In this chapter, we focus on the environmental regulation impacts on the demand side.

[5]For a comprehensive literature review on the carbon tax and its issues in general, the reader may refer to Timilsina (2022).

4.3 The French telecommunications market

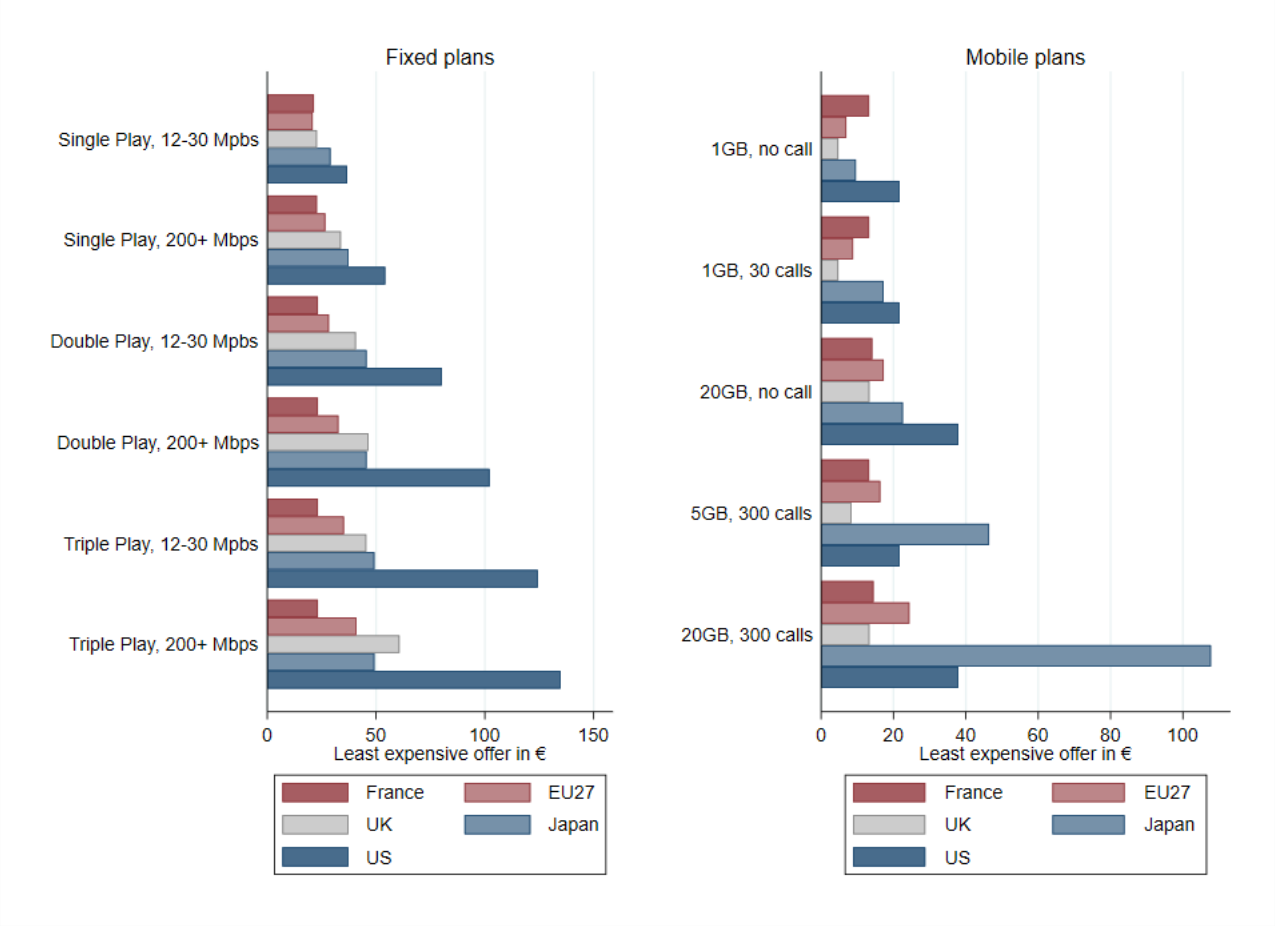
Today, the French telecommunications market (fixed and mobile) comprises four leading operators: Orange, SFR, Bouygues Telecom, and Free. This has not always been the case. Following the opening of the French fixed internet market to competition, Free joined Orange (formerly France Telecom, the former state monopoly) in 1999. Then, in 2008, Bouygues Telecom and SFR became fixed internet providers. Orange, SFR, and Bouygues Telecom have long been the three leading operators in the mobile industry. Two main events impacted the mobile industry in the early 2010s. The first was the introduction of Free Mobile as a Mobile Network Operator (MNO) in 2012.[6] The latter proposes low-cost offers to consumers, such as tariffs with no commitment and no handset subsidy.[7] It forced existing operators to launch low-cost brands (Soch for Orange, B&You for Bouygues Telecom, and RED for SFR). Bourreau *et al.* (2021) highlight that this increase in the variety of mobile plans has benefited consumers. Furthermore, between 2012 and 2014, 4G technology offers were launched. Consequently, the price of mobile telecommunication decreased in France through increased competition due to the new technology and the entry of a fourth operator with low-cost offers decrease (Nicolle *et al.*, 2018).

In addition to France, several other OECD countries have witnessed the introduction of a fourth operator in their mobile communication markets. For instance, Slovenia in 2008, Iceland in 2010, the Netherlands in 2012, Chile in 2015, and Italy in 2016. Four-to-three mergers were also frequent, such as in Austria in 2013, Denmark and Germany in 2014, Norway in 2015, Australia in 2018, and the United States in 2019. These mergers are motivated by the need to invest in broadband access in a context where operator revenues decline because of competition with internet players. However, Genakos *et al.* (2018) find that mergers in

[6]There are also several Mobile Virtual Network Operators (MVNOs), i.e., operators that offer mobile telecommunication services without owning the network infrastructure. They must reach agreements to obtain access to the mobile network of one of the MNOs, i.e., Orange, SFR, Bouygues Telecom, and Free Mobile. Their market share is low compared to the four leading operators (the 25 MVNOs represented 9.2% of the market in 2018 (OECD, 2021)).

[7]Offers with handset subsidies and commitment periods represented almost all the offers in 2010, but only 19% of them in 2021 (Arcep, 2022a).

Figure 4.3: International comparison of the least expensive offer in 2021



Source : European Commission (2022)
Double Play offers include fixed internet connection and fixed telephony. Triple play includes, in addition, the television. EU27 is the average price of the least expensive offers in 27 European Union countries.

the mobile telecommunication sector from 2006 to 2014 increased prices and investment per individual operator without contributing to a rise in total industry investment. Moreover, OECD (2021) points out that countries with four MNOs, due to the blocking of a merger or the entry of a new operator, have more attractive mobile offers than countries where a four-to-three merger has taken place.

The OECD (2021) considers that *"France has one of the most dynamic mobile markets in the OECD area"*. In 2021, French telecommunication operators proposed some of the cheapest mobile subscriptions among developed countries (Figure 4.3). Unlike in other countries,

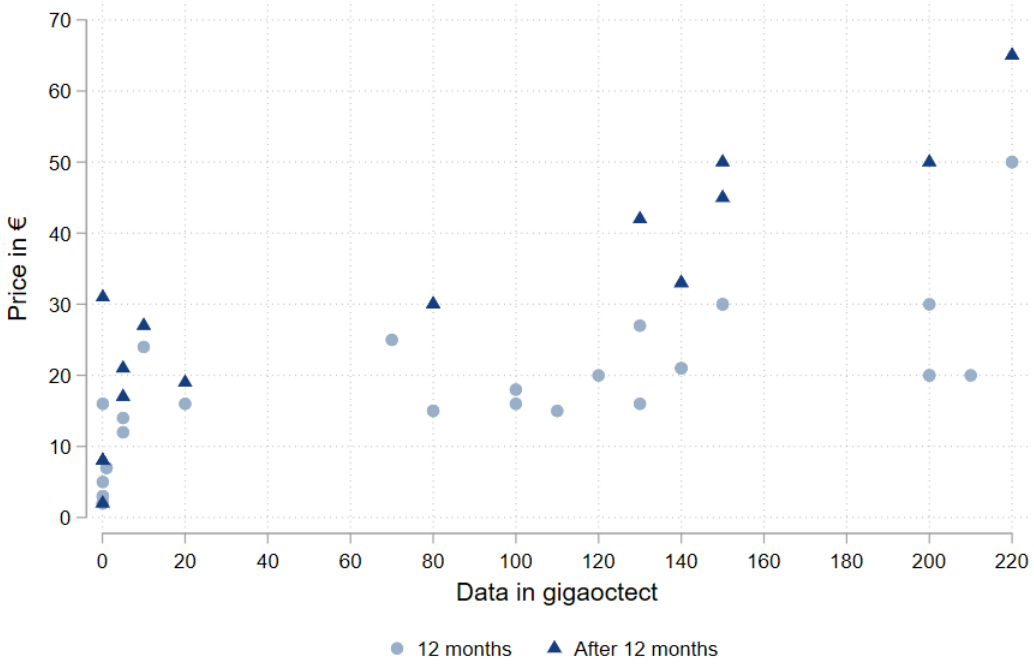
the price of the cheapest offers according to different baskets, defined by the European Commission (2022), does not significantly change. French telecommunication operators propose low-cost and complete offers. For instance, fixed internet plans are often offered with fixed telephony and television services (known as triple play). When considering a basket with low calls and data, the cheapest offer in France is more expensive than the European average, the United Kingdom (UK), and Japan. (Figure 4.3). On the other hand, France offers competitive prices for mobile subscriptions with more calls and data allowances. Even if there are mobile offers with a minimal amount of data (between 50 and 100 mega-octet (Mo)) and limited calls, most mobile plans propose unlimited calls and at least five giga-octet (Go) of data. Intermediate data allowances are scarce. For instance, Free Mobile proposes an offer with 50 Mo data allowances. Its second least expensive mobile plan proposes 110 Go. Free even proposes unlimited mobile data access. Figure 4.4 highlights that the price increases with the data allowance, but less than proportionally. The price difference for offers with the same amount of mobile data is mainly due to the options proposed by the different operators (unlimited calls, free calls abroad, 5G access, dual sim). Convergent offers, which include fixed and mobile services from the same operator, also exist and enable a discount on the price of the service. Moreover, operators often propose promotional deals.

4.4 The distributional impact of a mobile tax

4.4.1 Data

We use the *Budget des Familles* survey of Insee in 2017, which is the only representative survey about all the expenditures and revenues of French households. It is divided into two parts: an interview and a diary survey. The interview takes two visits and collects information on household characteristics, the rate of equipment in durable goods, and expenditures that can not be obtained with the diaries. The diaries collect all the household spending for one week. The survey was conducted over six waves at two-month intervals between September

Figure 4.4: Overview of the mobile offers in France in 2023



Source: Mobile offers prices have been collected on the websites of the four leading French operators and their low-cost brands (Orange, Free Mobile, Bouygues Telecom, SFR, Soch, B&You, and Red by SFR) on January 25, 2023. The price of most of the offers increases after twelve months. Users can benefit from a reduction if they subscribe to a fixed offer from the same operator. We only consider offers without this reduction.

2016 and September 2017 to account for the seasonality of some expenditures. We only use the latest Budget des Familles survey in 2017 because mobile internet expenditures were weak in the previous one in 2011.[8]

The Insee survey includes a telephone, internet, and television subscription module. It gives us information on the number and type of internet subscriptions as well as the expenditures and prices paid by each household for each of these subscriptions. Fixed internet expenditures include high and low-speed fixed internet subscriptions. Mobile internet expenditures include all types of mobile subscriptions and prepaid cards. For households without internet expenditure, we replace the missing price with the average subscription price for all households by survey wave and income decile level. In addition to fixed and mobile internet, we consider the expenditures on seven other non-durable goods categories to estimate a complete demand system: food, clothing, water, electricity, fuels, leisure, and restaurants. We describe in Table 4.A.1 in Appendix 4.A the non-durable goods categories included in the demand system. We only consider non-durable goods in the demand system because the survey only reports expenditures over a short period. Since prices for each good are not given in the survey, we use Insee's monthly consumer price indices. For each household, we match the monthly price index of each subcategory of goods to the corresponding subcategory and survey wave. To obtain the final price index of each good category, we construct a Stone-Lewbel price index (Lewbel, 1989) for each household defined as:

$$\ln(p_{ih}) = \sum_{l=1}^{N_i} \frac{w_{lh}}{w_{ih}} \ln(p_{lh}) \tag{4.1}$$

where p_{ih} is the price index of good category i for each household h, p_{lh} is the price index of the subcategory of good l that belongs to good category i, w_{ih} is the share of expenditure of good category i in total expenditure of the household h, and w_{lh} is the share of expenditure of sub-category of good l in total expenditure of good category i. Stone-Lewbel price indices

[8]We do not consider households living in French Overseas Departments because they are over-represented in the Insee survey. They represent almost 30% of the surveyed households but only 2% of the French population. The final sample is composed of 11,920 households.

introduce more variability into the prices to produce more robust estimators than a standard aggregate price index (Hoderlein & Mihaleva, 2008).

Table 4.1 presents descriptive statistics on internet household expenditures. On average, households allocate nearly 4% of their non-durable goods budget to access fixed internet connections and 1.5% for mobile internet. Nevertheless, some households do not incur any internet-related expenditure. The average expenditures share related to a fixed internet connection increases to 5.4% when considering households with a fixed connection and those related to a mobile connection to 4.1% for households with a mobile connection. It represents an average annual expenditure of 486.10 euros for the fixed connection and 420.78 euros for the mobile. Note that it corresponds to spending by households and not individuals. Internet expenditures share differ according to the household's income level. Among low-income households, internet expenditures constitute a more significant share of their total non-durable goods expenditures compared to high-income households (Figures 4.5 and 4.6). As a result, any increase in the price of mobile internet services would likely have a more important impact on low-income households due to the higher share of their expenditure allocated to these expenses.

Table 4.1: Descriptive statistics

	All sample	**Household with fixed internet**	**Household with mobile internet**
Average expenditure share			
Fixed Internet	0.040	0.054	0.034
Mobile Internet	0.014	0.015	0.041
Average annual expenditures (euro)			
Fixed Internet	361.35	486.10	356.41
Mobile Internet	149.63	167.85	420.78
Average monthly price (euro)			
Fixed Internet		38.82	
Mobile Internet			24.06
Number of observations	11,920	8,861	4,239

Source: 2017 Budget des Familles survey, Insee.

Figure 4.5: Average share of fixed internet connection expenditure by income decile

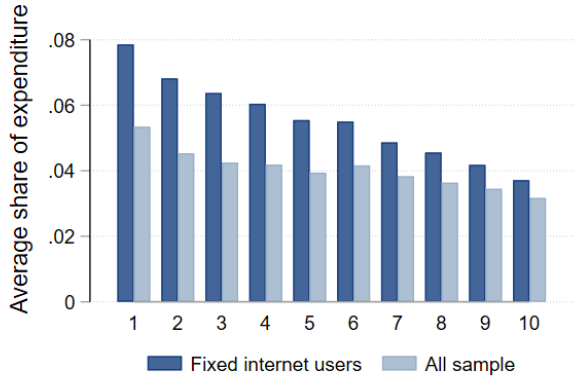
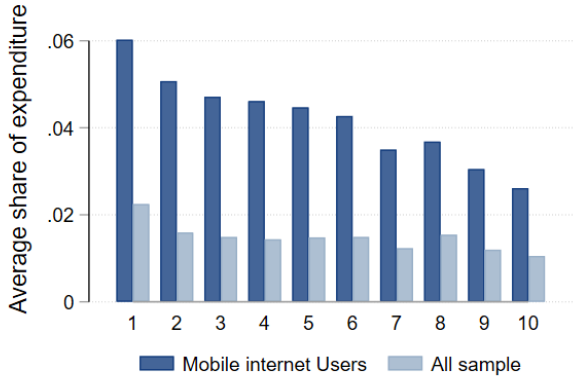


Figure 4.6: Average share of mobile internet connection expenditure by income decile



Source: Family Budget Survey 2017, INSEE.

In addition to the household's expenditure level and the price of the goods, we consider the age, household size, and digital equipment access (computer and mobile phone), which can influence the probability of accessing the internet. Computer and mobile phone access are dummy variables equal to 1 if the household has the equipment and zero if not. We do not include income and education as explanatory variables as they are correlated with the expenditure level.

4.4.2 Methodology

Demand system: the censored QUAIDS

To estimate consumers' response to a change of price, we estimate a *Quadratic Almost Ideal Demand System* (QUAIDS) introduced by Banks *et al.* (1997). This demand system extends the AIDS of Deaton & Muellbauer (1980), allowing for non-linear Engel curves. It assumes that the indirect utility function takes the following form:

$$\ln V = \left[\left(\frac{\ln m - \ln a(p)}{b(p)} \right)^{-1} + \lambda(p) \right]^{-1} \tag{4.2}$$

with m the total spending of the household and $a(p)$, $b(p)$, and $\lambda(p)$ three prices indexes given by:

$$\ln a(p) = \alpha_0 + \sum_{i=1}^{k} \alpha_i \ln p_i + \frac{1}{2} \sum_{j=1}^{k} \sum_{i=1}^{k} \gamma_{ij} \ln p_i \ln p_j \tag{4.3}$$

$$b(p) = \beta_0 \Pi_{i=1}^{k} p_i^{\beta_i} \tag{4.4}$$

$$\lambda(p) = \sum_{i=1}^{k} \lambda_i \ln p_i, \quad \text{with} \quad \sum_{i=1}^{k} \lambda_i = 0 \tag{4.5}$$

where p_i is the price index of the goods category i and k the number of good category.

The expenditures share w_i of the goods category i can be derived by applying Roy's identity to the indirect utility function given by equation (4.2). We obtain:

$$w_i = \alpha_i + \sum_{j=1}^{k} \gamma_{i,j} \ln p_j + \beta_i \ln \left(\frac{m}{a(p)} \right) + \frac{\lambda_i}{b(p)} \left[\ln \left(\frac{m}{a(p)} \right) \right]^2 \tag{4.6}$$

Some conditions must be set on parameters to respect the theory:

$$\sum_{i=1}^{k} \alpha_i = 1, \quad \sum_{i=1}^{k} \beta_i = 0, \quad \sum_{i=1}^{k} \gamma_{ij} = 0, \quad \gamma_{ij} = \gamma_{ji} \tag{4.7}$$

where the first three are additivity constraints ensuring that the sum of the expenditure shares ($\sum_{i=1}^{k} w_i$) is equal to 1. The third is a constraint of homogeneity of degree zero on prices and income (a change in income and prices by the same factor does not modify the demand). Finally, the fourth condition is a symmetry (Slutsky) constraint.

Several households have no internet expenditure (Table 4.1). Therefore, we must consider that the dependent variables (the shares of expenditures) are censored. To this aim, we apply Shonkwiler & Yen (1999)'s methodology, which estimates the QUAIDS in two stages to correct for the censor bias. The first step consists of estimating a probit model to estimate the probability of having a positive expenditure for each good. The probit model is estimated with the same variables as the QUAIDS. It enables us to predict the cumulative distribution (Φ)

and probability density functions (ϕ) associated with each expenditure for each household. They are then used in the second step to modify the budget equation given by equation (4.6), such as:

$$w_i^* = \hat{\Phi}_i w_i + \hat{\phi}_i \tag{4.8}$$

where w_i^* is the new budget share of the good category i corrected for the censored bias.

The censored-QUAIDS is used to estimate households' responses to prices and simulate the introduction of a carbon tax (Moz-Christofoletti & Pereda, 2021; Renner *et al.*, 2018). It is also used to study the distributional effects of other taxes (Walls & Ashenfarb, 2022). We stand out from the literature by considering the tax on mobile data.

In addition to addressing the censoring of our data, this methodology allows us to identify the determinants of accessing a fixed and mobile internet connection with the probit model. We estimate the equation (4.8) for the k categories of goods using an iterated feasible generalized non-linear least-squares estimator (Poi, 2012; Caro *et al.*, 2021). Control variables z can be add in the constant term ($\alpha_i = \alpha_0 + \sum_{j=1}^{k} \delta_{ij} z_j$). In this case, we have to impose a new constraint such as $\sum_{i=1}^{k} \delta_i = 0$ to ensure the additivity constraint.

Using the estimation results of the censored-QUAIDS, we compute the budget elasticities such as:

$$e_i = 1 + \frac{\Phi_i \mu_i}{w_i} \tag{4.9}$$

with

$$\mu_i = \frac{\partial w_i}{\partial \ln m} = \beta_i + \frac{2\lambda_i}{b(p)} \left[\ln \left(\frac{m}{a(p)} \right) \right] \tag{4.10}$$

the uncompensated (Mashallian) price elasticities:

$$e_{ij}^u = \frac{\Phi_i \mu_{ij}}{w_i} - \delta_{ij} \tag{4.11}$$

with

$$\mu_{ij} = \frac{\partial w_i}{\partial \ln p_j} = \gamma_{ij} - \mu_i(\alpha_j + \sum_k \gamma_{jk} \ln p_k) - \frac{\lambda_i \beta_i}{b(p)} \left[\ln \left(\frac{m}{a(p)} \right) \right]^2 \tag{4.12}$$

and compensated (Hicksian) price elasticities:

$$e_{ij}^{c} = e_{ij}^{u} + e_i w_j \tag{4.13}$$

where δ_{ij} is the Kronecker delta which is equal to one if $i = j$, and zero otherwise. As a reminder, uncompensated (cross) price elasticity measures the percentage change in the spending of good i following a price increase of the good i (j), holding other price and budget constant. The compensated (cross) price elasticity ignores the income effect and focuses only on the substitution effect. It measures the percentage change in the spending of good i following a price increase of the good i (j) when purchasing power stays constant.

Simulation and welfare effects

To measure the distributional impact of a tax, we simulate a hypothetical increase in the price of mobile subscriptions. The results of the censored-QUAIDS enable us to compute the welfare loss of each household through the Compensating Variation, i.e., the amount of money the household needs to maintain the same level of utility before the price increase. Compensating Variation is defined as:

$$CV = e(p_1, u_1) - e(p_1, u_0) \tag{4.14}$$

where $e(p, u)$ is an expenditure function of the price p and the utility u. Following Friedman & Levinsohn (2002), we approximate the Compensating Variation relative to the total household expenditures with a second-order Taylor expansion of the minimum expenditure function such as:

$$CV_{per_exp} = \sum_{i=1}^{k} w_i \Delta \ln p_i + \frac{1}{2} \sum_{i=1}^{k} \sum_{j=1}^{k} w_i e_{ij} \Delta \ln p_i \Delta \ln p_j \tag{4.15}$$

Finally, we compute the average Compensating Variation in the total expenditure by income decile level to compare the welfare loss.

4.4.3 Empirical results

Household's behavior

The probit estimations results are in Table 4.B.1 in Appendix. In line with the literature, the level of expenditure, age, and digital equipment access are determinants of fixed and mobile internet adoption. Having a computer is a better determinant of having a fixed internet connection than having a mobile phone. This is the opposite for mobile internet connection; mobile phone owners have a higher probability of having a mobile internet connection than computer owners. Household size does not impact the probability of having an internet connection. As expected, price negatively impacts the probability of adopting an internet connection. Interestingly, the price of fixed (mobile) internet also significantly negatively impacts the probability of adopting mobile (fixed) internet. It suggests that fixed and mobile spending are complementary, consistent with the results of Grzybowski & Liang (2015) and Liang & Petulowa (2018). The prices of the other goods categories have a positive or no impact on internet adoption.

Table 4.2 displays the budget elasticities for the nine goods categories. Fixed and mobile internet are normal goods as their budget elasticities are significantly positive. Mobile internet budget elasticity is higher than that of fixed internet. It is worth noting that internet spending is different from internet consumption. Generally, fixed internet subscriptions include unlimited access to the internet. The difference in subscription prices comes from internet quality (e.g., fiber and ADSL) and the additional services included, such as fixed telephony and television. Therefore, a change in fixed internet spending does not necessarily result in a change in internet consumption. Mobile subscriptions rarely offer unlimited access to mobile internet data but a volume of data that can be used without additional charges. Therefore, a change in mobile internet spending can result in a change in mobile data consumption. Nevertheless, we must keep in mind that mobile subscriptions also include additional services (e.g., mobile telephony). Furthermore, the user does not necessarily consume all the mobile data of its subscription. She can, therefore, switch to a cheaper

subscription with less data or additional services without reducing her internet consumption. We maintain this distinction between consumption and expenditure and discuss it in more detail in the theoretical framework presented in the following section, as it has important implications for tax efficiency.

Table 4.2: Budget elasticities

Fixed internet	**Mobile internet**	**Food**	**Clothing**	**Water**	**Electricity**	**Fuels**	**Leisure**	**Restaurant**
0.844***	0.960***	0.881***	0.851***	2.069***	0.186***	0.636***	1.274***	0.994***
(0.010)	(0.004)	(0.011)	(0.019)	(0.062)	(0.080)	(0.021)	(0.028)	(0.004)

Note: This table presents the budget elasticities calculated at the sample mean and obtained with the results of censored-QUAIDS estimation. Budget elasticity measures the percentage change in the spending of good i in response to an increase in the household's budget.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are reported in parentheses.

Tables 4.3 and 4.4 present the uncompensated and compensated cross-price elasticities between the goods categories. Price elasticities of a good category are given in diagonal of the tables, while cross-price elasticities between goods categories are the terms off-diagonal. We find that French households react to a change in fixed and mobile internet prices, although the price elasticity is less than 1 in absolute value. Mobile internet spending is more price elastic than fixed internet: uncompensated and compensated price elasticities of mobile internet are around -0,832 and -0,766, while those of fixed internet are around -0,774 and -0,687. The (un)compensated price elasticities of the other goods categories show the expected negative sign.

We notice negative cross-price elasticities between fixed and mobile internet. As suspected with the probit estimation results, it indicates that fixed and mobile subscriptions are complementary. There are several factors contributing to this result. While mobile internet can be used outside the home, mobile subscriptions rarely propose unlimited data consumption, contrary to fixed subscriptions (Grzybowski & Liang, 2015). Moreover, an internet subscription is rarely limited to internet access. They are frequently bundled with additional services such as fixed telephony and television for fixed internet subscriptions and mobile telephony for mobile subscriptions. This means it is not necessarily the same product behind the fixed and mobile internet subscriptions. Moreover, Liang & Petulowa (2018) explain that fixed

and mobile subscriptions are complementary because consumers are heterogeneous in price sensitivity and the valuation of fixed internet. Low-income individuals have a higher price sensitivity and value less fixed internet. They are, therefore, more likely to have only a mobile connection than high-income individuals. They also emphasize the importance of the market dynamics. Indeed, the French telecommunications market is very competitive. Bundle offers, which include fixed and mobile internet, television, and fixed and mobile telephony, are widespread. They enable access to multiple services for a discount and encourage consumers to have both internet connection types. Furthermore, one fixed internet subscription is generally enough for a household, while mobile subscriptions are individual.

Nevertheless, it is worth noting that the complementary effect is weak. Considering the uncompensated cross-price elasticities given in Table 4.3, an increase in 1% of mobile internet price would lead to a decrease in fixed internet expenditure of around 0.07%. An equivalent increase in the price of fixed internet would result in a slightly more substantial impact, reducing mobile internet expenditure by approximately 0.13%. The impact is weaker if we consider compensated cross-price elasticities given in Table 4.4.

Table 4.3: Uncompensated cross-price elasticities

	Fixed internet	**Mobile internet**	**Food**	**Clothing**	**Water**	**Electricity**	**Fuels**	**Leisure**	**Restaurant**
Fixed internet	-0.774***	-0.077***	0.007***	0.001***	0.001***	0.001***	-0.001***	-0.003***	-0.005***
	(0.013)	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mobile internet	-0.128***	-0.832***	0.006***	0.001***	0.006***	0.002***	0.001	-0.001***	-0.003***
	(0.006)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Food	0.005	0.022	-1.007	0.003***	0.001***	0.005***	0.003***	0.002***	0.003***
	(0.014)	(0.013)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Clothing	0.012	0.002	0.006***	-1.018***	-0.001	0.008***	0.012***	0.011***	0.022***
	(0.012)	(0.012)	(0.001)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Water	0.04	0.068**	0.031***	0.007***	-1.316***	-0.029***	0.011***	0.022***	0.033***
	(0.029)	(0.029)	(0.002)	(0.001)	(0.019)	(0.001)	(0.001)	(0.001)	(0.001)
Electricity	0.081	0.211*	0.028***	0.006***	0.021**	-0.934***	0.001	-0.001	-0.006***
	(0.101)	(0.112)	(0.002)	(0.001)	(0.009)	(0.015)	(0.001)	(0.001)	(0.001)
Fuels	0.012	-0.039*	-0.007***	-0.004***	0.001	-0.009***	-0.884***	-0.012***	-0.025***
	(0.018)	(0.021)	(0.000)	(0.000)	(0.001)	(0.000)	(0.003)	(0.000)	(0.000)
Leisure	-0.013	0.034**	-0.002***	-0.002***	-0.001***	-0.006***	-0.007***	-1.014***	-0.013***
	(0.018)	(0.017)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.000)
Restaurants	-0.001	-0.001	-0.001***	-0.002***	0.001	-0.004***	-0.005***	-0.005***	-0.985***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)

Note: This table presents the uncompensated cross-price elasticities calculated at the sample mean and obtained with the results of censored-QUAIDS estimation. The element in row i and column j is the uncompensated price elasticity of good i to the price of good j.
Uncompensated (cross) price elasticity measures the percentage change in the spending of good i in response to an increase in the price of the good i (j), holding other price and budget constant.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are reported in parentheses.

Table 4.4: Compensated cross-price elasticities

	Fixed internet	**Mobile internet**	**Food**	**Clothing**	**Water**	**Electricity**	**Fuels**	**Leisure**	**Restaurant**
Fixed internet	-0.687***	-0.019**	0.350***	0.051***	0.013***	0.121***	-0.044***	-0.070***	-0.143***
	(0.013)	(0.010)	(0.004)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)
Mobile internet	-0.029***	-0.766***	0.396***	0.059***	0.020***	0.138***	-0.048***	-0.07***	-0.160***
	(0.006)	(0.007)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Food	0.095***	0.082***	-0.649***	0.056***	0.013***	0.131***	-0.041***	-0.067***	-0.140***
	(0.014)	(0.013)	(0.004)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)
Clothing	0.100***	0.061***	0.352***	-0.967***	0.011***	0.129***	-0.031***	-0.055***	-0.116***
	(0.012)	(0.012)	(0.008)	(0.004)	(0.000)	(0.002)	(0.001)	(0.001)	(0.003)
Water	0.253***	0.211***	0.871***	0.132***	-1.287***	0.265***	-0.094***	-0.140***	-0.304***
	(0.030)	(0.030)	(0.025)	(0.004)	(0.019)	(0.008)	(0.003)	(0.005)	(0.010)
Electricity	0.101	0.224**	0.104***	0.017***	0.024***	-0.908***	-0.008**	-0.015***	-0.037***
	(0.101)	(0.112)	(0.033)	(0.005)	(0.009)	(0.019)	(0.004)	(0.006)	(0.012)
Fuels	0.077***	0.003	0.251***	0.033***	0.009***	0.081***	-0.916***	-0.062***	-0.129***
	(0.018)	(0.021)	(0.008)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)
Leisure	0.117***	0.122***	0.514***	0.073***	0.016***	0.174***	-0.072***	-1.115***	-0.221***
	(0.017)	(0.017)	(0.011)	(0.002)	(0.001)	(0.004)	(0.001)	(0.008)	(0.004)
Restaurants	0.101***	0.066***	0.402***	0.057***	0.014***	0.137***	-0.056***	-0.083***	-1.148***
	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)

Note: This table presents the compensated cross-price elasticities calculated at the sample mean and obtained with the results of censored-QUAIDS estimation. The element in row i and column j is the compensated price elasticity of good i to the price of good j.
Compensated (cross) price elasticity measures the percentage change in the spending of good i in response to an increase in the price of the good i (j), when purchasing power stays constant.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are reported in parentheses.

Table 4.5 provides the uncompensated and compensated price elasticities of fixed and mobile internet across income deciles. We find that the price elasticities in absolute value decrease with the income level. It highlights that low-income individuals are more sensitive to an internet price change. Indeed, as the internet represents a higher share of expenditures among low-income households, any increase in internet prices exerts a more important impact on their budget. They are, therefore, more likely to reduce their internet expenditures. They will switch to cheaper subscriptions or even stop using mobile internet. Moreover, low-income households are also more likely to have only one type of internet connection or even no internet connection. Besides being regressive, implementing the tax can also reinforce the existing digital divide. Implementing a tax on mobile data must ensure that it will not exacerbate existing digital inequalities.

Table 4.5: (Un)compensated price elasticity by income decile

	Uncompensated price elasticity		**Compensated price elasticity**	
	Fixed internet	Mobile internet	Fixed internet	Mobile internet
Income decile : 1	-0.804***	-0.863***	-0.711***	-0.792***
	(0.011)	(0.007)	(0.010)	(0.007)
Income decile : 2	-0.797***	-0.850***	-0.707***	-0.780***
	(0.011)	(0.006)	(0.011)	(0.006)
Income decile : 3	-0.787***	-0.842***	-0.700***	-0.775***
	(0.012)	(0.007)	(0.012)	(0.006)
Income decile : 4	-0.787***	-0.848***	-0.698***	-0.779***
	(0.012)	(0.006)	(0.012)	(0.006)
Income decile : 5	-0.775***	-0.834***	-0.689***	-0.768***
	(0.013)	(0.007)	(0.013)	(0.007)
Income decile : 6	-0.777***	-0.838***	-0.688***	-0.771***
	(0.013)	(0.007)	(0.013)	(0.007)
Income decile : 7	-0.764***	-0.813***	-0.678***	-0.750***
	(0.014)	(0.008)	(0.014)	(0.008)
Income decile : 8	-0.762***	-0.827***	-0.675***	-0.762***
	(0.014)	(0.007)	(0.014)	(0.007)
Income decile : 9	-0.746***	-0.804***	-0.665***	-0.742***
	(0.015)	(0.008)	(0.015)	(0.008)
Income decile : 10	-0.733***	-0.794***	-0.654***	-0.734***
	(0.016)	(0.008)	(0.016)	(0.008)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are reported in parentheses.

Distributional effects of the internet mobile tax

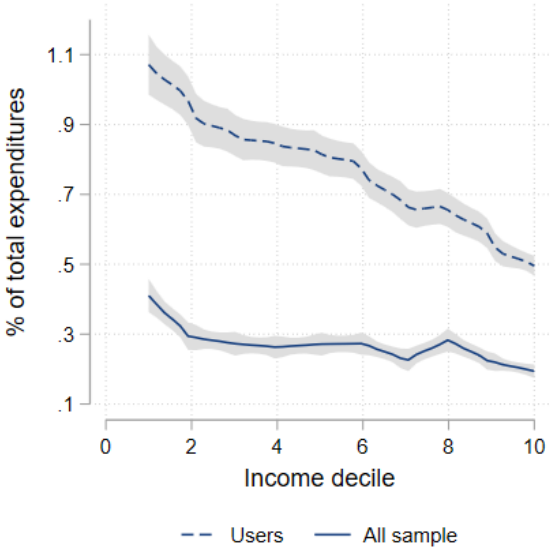
In this section, we investigate the households' welfare loss following a hypothetical increase in mobile internet prices. We assume that this hypothetical increase in price is due to the implementation of a tax on mobile internet offers. Figure 4.7a displays the compensating variation relative to total expenditure by income decile level following a 20% increase in mobile internet prices.[9] It highlights that the short-run distributional effect of mobile internet price increase is regressive: the welfare loss is higher for low-income households than high-income. The tax's regressivity is more pronounced when we compute the average welfare loss only among mobile internet users (dotted line in Figure 4.7a). This is due to many households without mobile internet connection (Table 4.1). It emphasizes the heterogeneity within the income groups and that the tax regressivity can be underestimated without an only-users approach. Indeed, low-income are more likely not to have an internet connection. Note that our data is from 2017; internet adoption has increased since then in France. The gap between users and non-users should be lower with more recent data.

The aim of a tax on mobile data should be to encourage consumers not to exceed a certain amount of mobile data to limit environmental impact. This tax could then be implemented only on data-intensive offers. We do not have any information on the amount of mobile data in the offers. However, we know that French mobile internet subscription prices increase with data allowance, as empirically highlighted by Nicolle *et al.* (2018). Therefore, we simulate a mobile offers price increase, but only above a specific price, assuming that offers with a high price represent data-intensive subscriptions. There are some limits to this approach. Indeed, Nicolle *et al.* (2018) also show evidence that the price of mobile subscriptions depends on several other variables, such as the commitment period, unlimited voice allowances in the country or abroad, and the quality of Internet access (3G, 4G...). French operators also regularly propose promotional deals offering affordable packages with a significant volume of data. Nevertheless, our results provide an intuition of the regressivity of a tax on data-

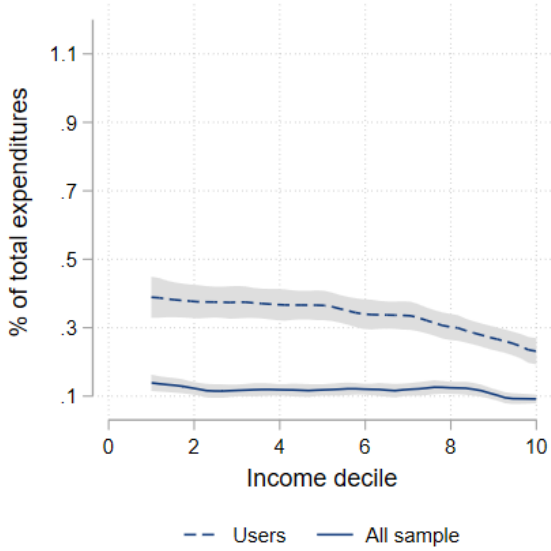
[9]The 20% increase was chosen for illustrative purposes. The results of a higher or lower price increase are similar; only the magnitude is modified.

Figure 4.7: Compensating variation by income decile following a 20% increase in:

(a) all mobile offers prices



(b) mobile offers prices over 30€



The grey area represents the 95% confidence interval. Compensating variation is expressed as a percentage of household expenditures.

intensive mobile offers compared to a tax on all offers.

Figure 4.7b presents the average compensating variation relative to household expenditures following a 20% increase in internet mobile prices only on subscriptions over 30€. It highlights that the tax is less regressive when only the price of mobile subscriptions over 30€ increased, although the tax burden is still higher for the first income deciles when considering only users. We also simulate it for an increase in the price of mobile offers of more than 15, 20, and 25€ (Figures 4.B.1a, 4.B.1b, and 4.B.1c in Appendix). We find that the higher the minimum price taxed, the less regressive the tax. This is because high-income households tend to have more expensive subscriptions with more mobile data allowances (Arcep, 2021). Fewer low-income households are affected by the price increase when the tax is only applied to the more expensive offers.

Discussion

We show evidence that implementing a flat tax on all mobile subscriptions is regressive and can negatively impact households with a low volume of mobile data allowance. Taxing only the most expensive offers, used as a proxy for mobile data-intensive subscriptions, makes the tax less regressive. A redistributive policy is needed to make the tax fair. Moreover, the tax could be in contradiction with the objective of bridging the digital divide. Ensuring the adoption rate does not fall due to increased internet prices is important. To this aim, the tax collected can be used to support access to digital equipment. This could take the form of equipment vouchers or loans and could be used to buy or rent a reconditioned computer. We recommend the computer because it is an important determinant of access to a fixed Internet connection (see probit results in Table 4.B.1 in Appendix), which has a lower environmental impact than mobile internet. Moreover, the complementary nature between fixed and mobile internet means that the tax on mobile offers will not encourage households to access a fixed internet connection instead if they do not already have one. The tax would, therefore, be an incentive to reduce mobile data consumption. Redistribution could enable, in addition to making the tax progressive, to encourage households to use fixed internet connections to not exacerbate the digital divide.

Studying the distributional effects of a tax is important to increase the acceptability of public policies. However, it must be ensured that the tax is efficient. Here, the environmental objective of the tax is to reduce mobile data consumption per user. We study its efficiency in the following section.

4.5 Theoretical analysis of data expenditures

This section proposes a theoretical model to explain fixed and mobile data purchasing decisions. This section has three objectives: (i) To develop a model for decision-making regarding fixed and mobile data expenditures and compare the theoretical outcomes of the model with

the empirical results obtained in the previous section. (ii) To demonstrate that the lack of substitution between mobile data and fixed data expenditures arises from the tariff offers present in the market. (iii) To analyze the effectiveness of introducing a tax on mobile data based on the types of available mobile and fixed data offers in the market.

We consider a representative agent who decides on her data purchases. She potentially has access to mobile data, fixed data, and services associated with fixed data and can also buy another good (the numeraire). We study different cases ranging from various possible tariff offers, unit prices of data, subscriptions for unlimited use of fixed data, bundles including unlimited use of fixed data and services, to subscriptions allowing consumption of a certain volume of mobile data without additional charges.

First, let us introduce the assumptions and study the benchmark case, such as all the goods sold at unit prices.

4.5.1 The assumptions and the benchmark with unit prices

We focus our work on a decision-theoretic framework. We concentrate on consumer decisions rather than internet service providers' strategies. Indeed, consumers' decisions regarding data are notably distinct from decisions regarding other consumer goods. Therefore, environmental policies' effectiveness at reducing data-generated pollution depends on consumers' reactions. We then treat the offers of internet service providers as exogenous. However, we will discuss this hypothesis later. More precisely, we analyze agents' decisions to purchase mobile data, fixed data, and data-related services.

As previously explained, the distinction between purchase and consumption is crucial for these types of goods. Indeed, Internet offers, including unlimited data and services, are available to consumers. However, the latter consumes a limited volume of fixed data. Similarly, mobile internet subscriptions allow a certain volume of data to be consumed without additional charges. Here again, consumers do not necessarily use all the volume of mobile

data available. That is why we are focusing on data purchases. Nevertheless, when the prices of these goods are unit, consumption is equivalent to purchases. That is why this case will serve as our benchmark. Let us note that purchasing decisions are made ex-ante consumption decisions.

To deeply study decisions concerning data, we focus our attention on the following four goods: mobile data, fixed data, services associated with fixed data, and the consumption good, which can be considered as the numeraire. Considering the first two mentioned goods is important because the means of obtaining data are different, sometimes the providers are different, and most importantly, their environmental impact varies. The services associated with fixed data are often included in internet providers' offers and serve to differentiate the packages. For the sake of simplicity, we do not consider services associated with mobile data. However, considering them does not qualitatively change our results. Finally, the consumption good allows us to take into account the wealth effects resulting from an increase or decrease in data prices. Let us denote by x_0 the quantity of consumption good, by x_m the quantity of mobile data, by x_f the quantity of fixed data, and by s_f the quantity of fixed data-related services.

We consider a representative agent who is price-taker. The representative agent is characterized by a utility function $U(x_0, x_m, x_f, s_f)$ and a wealth w. Let us assume that

$$U(x_0, x_m, x_f, s_f) = x_0^{\alpha} x_m^{\beta} x_f^{\gamma} s_f^{1-\alpha-\beta-\gamma}.$$

We have chosen to consider a Cobb-Douglas utility function and, therefore, assume that the four goods under consideration are substitutable. As we explained earlier, one of the purposes of this theoretical work is to show that non-substitution between mobile and fixed data expenditures, empirically highlighted in the previous section, stems from the tariff offers available on the market. It could explain the contradictory results found in the literature. In other words, we want to show that under some conditions regarding existing tariff offers, mobile and fixed data expenditures are not substitutable even with goods that are substi-

tutable between offers. Of course, if the goods were complementary, expenditures would be *de facto* non-substitutable.

Let us denote by p_0, p_m, p_f, and p_s, respectively, the prices of the consumption good, mobile data, fixed data, and services related to fixed data. Moreover, we assume that $p_0 = 1$. The budget constraint is then given by:

$$w \leq p_f x_f + p_m x_m + p_s s_f + x_0 \tag{4.16}$$

The Lagrangian is given by:

$$U - \lambda(w - (x_0 + p_f x_f + p_m x_m + p_s s_f)) \tag{4.17}$$

By differentiating the Lagrangian and rewriting the derivatives, we obtain the following relationships among the quantities of the different goods.

$$\begin{cases} x_0 = \frac{\alpha}{\beta} p_m x_m \\ x_0 = \frac{\alpha}{\gamma} p_f x_f \\ x_m = \frac{\beta}{\gamma} \frac{p_f}{p_m} x_f \\ x_m = \frac{\beta}{1-\alpha-\beta-\gamma} \frac{p_s}{p_m} s_f \\ x_f = \frac{\gamma}{1-\alpha-\beta-\gamma} \frac{p_s}{p_f} s_f \end{cases} \tag{4.18}$$

By substituting these relationships into the budget constraint, we obtain the following

demand functions:

$$\begin{cases} x_0 = \alpha w \\ x_m = \frac{\beta}{p_m} w \\ x_f = \frac{\gamma}{p_f} w \\ s_f = \frac{1-\alpha-\beta-\gamma}{p_s} w \end{cases} \tag{4.19}$$

The above results are standard: the representative agent allocates a portion of their income to each good, which is given by α for the good x_0, β for the good x_m, γ for the good x_f, and $1-\alpha-\beta-\gamma$ for the good s_f. When considering unit prices, we observe that purchases are equivalent to consumption. Changing the price of mobile data alters the consumption of this good. Studying the sensitivity of mobile data consumption (and purchases) to an increase in mobile data prices is particularly important. Indeed, implementing a tax on mobile data to reduce environmental impact will alter the price of data in a similar way. Put differently, we want to examine the efficiency of implementing a data tax.

In the following, we will study how mobile data purchases are sensitive to the types of tariff offers provided by fixed internet and mobile telephony providers.

4.5.2 Subscriptions for unlimited fixed data

Let us now focus on the case where a subscription allowing unlimited internet use via a fixed connection is offered. To do this, we need to make some additional assumptions. We assume that the representative agent can take out a subscription at a price of T, allowing her to consume as much fixed data as she wishes. The prices of the other three goods remain unchanged and are always unit prices. The representative agent can, therefore, either purchase the subscription or not.

Now, we can clearly identify the distinction between consumption and purchase. If the

representative agent buys this subscription, she can consume as much as she likes, but she will consume a limited volume of data. Moreover, decisions are taken before data consumption takes place. Thus, we assume that the representative agent anticipates a fixed level of data consumption. We call $\tilde{x}_f$ the representative agent's ex-ante anticipation of fixed data consumption to know whether to purchase the subscription package. We will come back to this assumption and propose some refinements later on.

We now consider that the representative agent decides whether to purchase the subscription and then decides on consumption for the other three goods. Compared with the previous case, the purchase decisions are no longer simultaneous. The rationale for subscription decisions being taken before other decisions is that these decisions have an impact over a longer period and are taken before day-to-day decisions. Finally, an additional assumption is necessary. We have to assume that if the representative agent does not buy the subscription, she can access the fixed data of the public networks. Of course, we could have considered this in the case of unit prices (previous subsection), but this does not change the qualitative results or the case comparisons. From now on, we denote by $\bar{x}_f$ the level of mobile data the agent uses when she has not purchased a subscription. This level depends on the expectations of the representative agent but also on public spending to promote free public fixed Internet access. We can, therefore, inquire about the impact of introducing an unlimited subscription for fixed data usage on the sensitivity of mobile data demand to a price increase for mobile data.

Due to the timing of purchase decisions and by solving by backward induction, we first determine the consumption of the other three goods according to whether or not the agent has subscribed to the subscription. We then determine the conditions under which the representative agent does or does not take out the subscription.

Let us first consider that the representative agent has not subscribed. Her utility is then $U(x_0, x_m, \bar{x}_f, s_f)$ and her available wealth w. The consumer maximizes her utility by choosing x_0, x_m and s_f. We proceed exactly as in the previous case, and we determine the demand

functions for the three goods, which are given by:

$$\begin{cases} x_0 = \frac{\alpha}{1-\gamma} w \\ x_m = \frac{\beta}{1-\gamma} \frac{w}{p_m} \\ s_f = \frac{1-\alpha-\beta-\gamma}{1-\gamma} \frac{w}{p_s} \end{cases} \tag{4.20}$$

We observe that the demand for these three goods is higher than in the previous case, as the income shares allocated to these goods are larger.

We can now examine the scenario where the agent has purchased the subscription. Her utility is then $U(x_0, x_m, \tilde{x}_f, s_f)$ and her available wealth $w - T$. She determines the quantities purchased for the consumption good, the mobile data, and the services. The demand functions are as follows:

$$\begin{cases} x_0 = \frac{\alpha}{1-\gamma} (w - T) \\ x_m = \frac{\beta}{1-\gamma} \frac{w-T}{p_m} \\ s_f = \frac{1-\alpha-\beta-\gamma}{1-\gamma} \frac{w-T}{p_s} \end{cases} \tag{4.21}$$

Let us note that the available income is lower than in the unit prices case, and the income shares devoted to these three goods are higher. The comparison between the demand functions in this case and the unit price case depends on the price of the subscription T.

The representative agent purchases the subscription if $U(x_0, x_m, \tilde{x}_f, s_f) > U(x_0, x_m, \bar{x}_f, s_f)$. By substituting equations (4.20) and (4.21) in the above inequality, we obtain that the consumer purchases the mobile subscription if and only if

$$T < \left(1 - \left(\frac{\bar{x}_f}{\tilde{x}_f} \right)^{\frac{\gamma}{1-\gamma}} \right) w.$$

The greater the consumption anticipation, the higher the threshold. At the same time, the more developed the public Internet network, the lower the threshold.

We compare the consumer's reaction to a change in mobile data prices following the introduction of a mobile data price change with the case where prices are unitary. If the consumer does not buy a subscription allowing unlimited data consumption, she is more sensitive, as the proportion of income devoted to mobile data is greater. If the consumer buys an unlimited data subscription, it depends on the price of the subscription. Two effects are at work: first, the proportion of income devoted to mobile data is greater, and income is lower because of the subscription. Second, for a high price, the consumer is less sensitive to an increase in the price of mobile data. Put differently, in such a case, the mobile data tax is less effective in reducing the use of mobile data.

4.5.3 Bundle with unlimited fixed data and services

We now assume that Internet service providers differentiate their package offers for unlimited fixed data usage with data-related services. These services can also be seen as quality. We then assume that the representative agent is always faced with unit prices for the consumption good and mobile data and has a choice between two bundles 1 and 2, both offering unlimited use of fixed data and different services. Each bundle has a price T_i and a service level s_i. We assume that $T_1 < T_2$ and $s_1 < s_2$. We make an additional assumption. The anticipation of data use is greater for the representative agent if she takes the bundle 2, because she anticipates more services and better quality, and therefore anticipates greater data use (if you have access to a faster internet, you anticipate consuming more data). We therefore assume $\tilde{x}_f^2 > \tilde{x}_f^1$. Finally, we suppose that if the agent has not purchased a package, as previously, she consumes for free $\bar{x}_f$ on the public network and level of services also provided by the public network $\bar{s}_f$.

We assume that, initially, the agent can choose between not taking out a subscription and choosing the first package or the second. Secondly, she decides on his consumption of the consumer good and mobile data. Resolving backward, we first determine x_0 and x_m according to whether the agent has not purchased a package or purchased the first or the

second.

If the representative agent has not subscribed, her utility is then $U(x_0, x_m, \bar{x}_f, \bar{s}_f)$ and her available wealth w. The consumer maximizes her utility by choosing x_0 and x_m. The demand functions for these two goods are given by:

$$\begin{cases} x_0 = \frac{\alpha}{\alpha+\beta} w \\ x_m = \frac{\beta}{\alpha+\beta} \frac{w}{p_m} \end{cases} \tag{4.22}$$

If the representative agent has purchased the bundle i, her utility is then $U(x_0, x_m, \tilde{x}_f^i, s_i)$ and her available wealth $w - T_i$. The consumer maximizes her utility by choosing x_0 and x_m, and the demand functions are as follows:

$$\begin{cases} x_0 = \frac{\alpha}{\alpha+\beta}(w - T_i) \\ x_m = \frac{\beta}{\alpha+\beta} \frac{w - T_i}{p_m} \end{cases} \tag{4.23}$$

By substituting equations (4.22) and (4.23), we obtain that the consumer purchases the bundle 1 instead of not purchasing if

$$T_1 < \left(1 - \left(\frac{\bar{x}_f}{\tilde{x}_f^1}\right)^{\frac{\gamma}{\alpha+\beta}} \left(\frac{\bar{s}_f}{s_1}\right)^{\frac{1-\alpha-\beta-\gamma}{\alpha+\beta}}\right) w$$

and she purchases the bundle 2 instead of the bundle 1 if

$$T_2 < \left(1 - \left(\frac{\tilde{x}_f^1}{\tilde{x}_f^2}\right)^{\frac{\gamma}{\alpha+\beta}} \left(\frac{s_1}{s_2}\right)^{\frac{1-\alpha-\beta-\gamma}{\alpha+\beta}}\right) w + \left(\frac{\tilde{x}_f^1}{\tilde{x}_f^2}\right)^{\frac{\gamma}{\alpha+\beta}} \left(\frac{s_1}{s_2}\right)^{\frac{1-\alpha-\beta-\gamma}{\alpha+\beta}} T_1.$$

We see that the threshold for the limit value of T_2 depends on that of T_1. Consequently, a change in one of the two prices can alter the choice between the two subscriptions.

We can make several comments. Firstly, the higher the bundle purchased (with more services), the less sensitive the consumer is to changes in mobile data prices, as her disposable

income is lower. Furthermore, an increase in the price of the higher bundle (T_2) can have different effects on mobile data consumption. Mobile data consumption will fall if the price rises but does not lead to a switch to the cheaper bundle. However, suppose the price of the bundle increases and that of the other bundle does not (or not sufficiently). In that case, the consumer buys the cheaper bundle, and his mobile data consumption increases.

4.5.4 Subscriptions for mobile phone data

We now introduce a new tariff offer while maintaining all the assumptions made to date. We are studying the effect of cell phone subscriptions that allow a certain volume of mobile data to be consumed at no extra cost. Here again, subscription decisions for mobile data are taken ahead of current decisions and at the same time as subscription decisions for fixed data. For the same reasons as above, we assume that the agent anticipates the consumption it will make, and we call $\tilde{x}_m$ the quantity of mobile data that the representative agent anticipates consuming. We assume that the representative agent can choose between two offers, 1 and 2. Each offers i is characterized by a price F_i and a maximum quantity $\overline{q}_i$ of mobile data it can use.

In such a case, the only current consumption good is x_0 and the consumer will allocate all available income to this good. Therefore, $x_0 = w - T_i - F_i$, according to which option for accessing data the representative agent chooses. In the first stage, there are several possibilities: the agent buys no subscription at all, buys no mobile data subscription, and takes a fixed data subscription, either the first or the second, buys no fixed data subscription but buys a mobile data subscription, either the first or the second, or buys both a fixed data and a mobile data subscription, thus having four choices.

Of course, this exercise is simply a case comparison where the case with the highest utility is chosen, and we face corner solutions here. We understand that the choice depends mainly on the value of the chosen parameters, and a numerical exercise can illustrate the results.

We focus on the case where the consumer subscribes to both subscriptions and buys the two most expensive ones. We then study the effect of an increase in the subscription price for fixed data and that for mobile data. As in the previous case, an increase in the price of a fixed data subscription has two effects: an increase or a decrease in expenditure due to switching to a cheaper subscription. The difference with the previous case is that increased available income does not necessarily lead to increased mobile data consumption. Indeed, and this is the main point of the case, an increase in disposable income does not necessarily lead to a change in mobile data subscription choices. The greater the number of mobile subscription offers, and the closer these offers are, then an increase in disposable income or a change in the subscription price for mobile data would affect mobile data purchases.

We can now discuss the empirical results of the previous section and the effectiveness of introducing a data tax.

An important empirical result we found is that higher fixed data prices lead to lower spending on fixed data but also to a (small) drop in expenditure on mobile data. Here, we can observe the case where, with an increase in fixed data prices (T_1 and T_2), the consumer can change his subscription from the 2 bundle to the 1 bundle (which leads to a drop in spending), but does not change his expenditure on mobile data and consumes more of the consumption good. We can ask ourselves where the difference comes from (between a slight drop in mobile data expenditures and no change in mobile data expenditures). One explanation may come from internet providers offering bundles, including unlimited fixed data, internet-based services, and mobile data. Choosing such a bundle can reduce both fixed and mobile data expenses. Another explanation could be based on behavioral motives. Rising prices may make consumers realize that they need to change their mobile telephony contract, and at the same time, they might want to take a closer look at the various mobile data offers. In other words, rising fixed (or mobile) data prices make it more salient to change mobile (fixed) data subscription contracts. A final explanation may come from the fact that the goods are slightly complementary, and this effect is added to that coming from the pricing offers in use in this market.

Secondly, we can return to the question of the effectiveness of a data tax. To investigate this, we can study, as in the previous cases, the sensitivity of mobile data spending and consumption to the price of mobile data. Here, sensitivity does not depend on the unit price of mobile data (p_m) as in previous cases but on the price of the mobile data subscription (F_i), the maximum amount of data that the representative agent can consume free of charge ($\overline{q}_i$), or both. Put another way, we assume that telecommunication operators respond to the introduction of a data tax by modifying their offer, which is well characterized by $\overline{q}_i$ and F_i. Indeed, it seems unlikely that the introduction of a data tax will lead to the introduction of a unit cost or even the disappearance of subscriptions. For this reason, we assume that the tariff offer will change, and we study sensitivity as a function of these two characteristics. Changing one or both offers does not necessarily lead to a reduction in mobile data consumption. To reduce mobile data consumption, the maximum authorized amount of mobile data must be lower than the amount anticipated (or consumed) before the modification. This can be achieved by lowering the maximum authorized amount or switching to a subscription with a lower maximum amount. Such a result is possible if the anticipated volume of mobile data consumed is close to the maximum authorized volume or if the offers are close and the change in pricing conditions leads to a change of subscription. Under these conditions, sensitivity is greater than in the unitary case. However, introducing a data tax will only impact a few consumers (those falling within the restrictive conditions explained above). Let us remark that if there were many different offers, the results would be close to the case where consumers are confronted with unit tariffs.

4.5.5 Implications and robustness

We will now discuss the results and their robustness and present directions for further extension. We have seen that the type of tariff offers (unit prices, flat rate for unlimited fixed data use, bundles including unlimited fixed data use and services, and subscriptions allowing free data consumption below a certain volume) affects the effectiveness of a data tax. A priori, it

seems preferable to implement such a tax when prices are unitary and when there are a large number of offers for mobile data. It would be particularly useful to carry out simulations with random draws on the parameters, particularly on income, to study the effectiveness of data taxes on a population of consumers.

We have studied how consumers react to a change in price offers. It would be particularly interesting to use industrial organization models to understand how mobile data providers would pass on the data tax in their tariff offers. To do this, we must consider that providers use offers to discriminate against consumers. It would be just as interesting to introduce equipment (computers, smartphones) into agents' decisions as our empirical results highlight that equipment is a determinant of internet adoption (Table 4.B.1).

The representative agent's choice is based on an anticipation that may be erroneous, but it could also, once subscribed, be re-optimized between decisions concerning the consumption of other goods and the consumption of fixed data. The problem here arises from unlimited usage, which disconnects purchasing decisions from consumption decisions. By consuming more fixed data without paying, the consumer could reduce his mobile data consumption (due to assumed substitutability). We could introduce a readjustment process (for example, re-optimizing fixed data consumption while remaining on the same utility curve). We intend to develop this mechanism in future research.

4.6 Conclusion

The development of the digital transition creates externalities that negatively affect the environmental quality. The regulation of these impacts is, therefore, needed. It can concern the digital players (e.g., internet service providers, digital service providers, and data centers), the firms using digital technologies, as well as households to encourage digital sobriety. In this chapter, we focused on regulating household consumption by implementing a tax on internet mobile data. We study both the distributional effects and the efficiency of the tax. To this

aim, we use two different methodologies. Firstly, using the "Budget des Familles" of Insee, we estimate a censored Quadratic Almost Ideal Demand system. It enables us to estimate fixed and mobile internet expenditures' (cross) price elasticities. We model the short-term response of households to an increase in price and compute the associated welfare loss. The average welfare loss is compared between income decile levels to highlight the distributional effect of the tax. In the second part, we propose a theoretical framework to emphasize that the purchasing decision for fixed and mobile internet and the tax efficiency depend on the offers proposed by the market.

The estimation of the households' behavior shows that fixed and mobile internet subscriptions are complementary expenditures. Indeed, we find small but significant cross-price elasticities between the two expenses. Moreover, we theoretically demonstrate that households are more sensitive to an increase in mobile internet price when data is sold at the unit price or the offers are numerous and close to each other. The French telecommunication market offers attractive mobile subscriptions with a large volume of data bundled with additional services. However, intermediate data allowances are scarce. Therefore, it can be difficult for a household to switch to another subscription, reducing tax efficiency. We also show that the complementary between fixed and mobile internet expenses comes from the lack of diversified offers in the mobile telecommunications market. Finally, our empirical simulations highlight that the tax on mobile data internet is regressive and could enhance the digital divide. Taxing only the offers with high data allowances would make the tax less regressive.

4.A Data description

Table 4.A.1: Description of the non-durable goods categories included in the demand system estimation

COICOP	Good category
Food products and non-alcoholic beverages	
C0111	Bread and cereals, cereal-based products
C0112	Meat
C0113	Fish and seafood
C0114	Milk, cheese and eggs
C0115	Oils and fats
C0116	Fruits
C0117	Vegetables including potatoes and other tubers
C0118	Sugar, jam, honey, chocolate, ice cream and confectionery
C0119	Other food products
C0121	Coffee, tea, cocoa
C0122	Mineral water, soft drinks, syrups, and juices
Clothing and footwear	
C0312	Clothing
C0313	Other articles of clothing, clothing accessories and haberdashery
C0314	Cleaning, repair, and rental of clothing
C0321	Shoes and other footwear
C0322	Shoe repair and rental
Water	
C0443	Water Bills
Electricity, gas, and other fuel	
C0451	Electricity
C0452	Gas and liquefied fuels (town gas, butane...)
C0453	Purchases of liquid fuels: fuel oil, heating oil, petrol
C0454	Purchases of solid fuels: charcoal, coal, coke, wood, other fuel
C0455	Thermal energy
Fuels and lubricants, antifreeze	
C0722	Fuels and lubricants, antifreeze...
Leisure	
C0941	Sports and recreation services
C0942	Cultural services
C0943	Games of chance
Restaurants and hotels	
C1111	Restaurants and cafes
C1112	Cafeteria
C1120	Hosting Services

Note: COICOP is the Classification of Individual Consumption by Purpose implemented by the United Nations Statistics Division.

4.B Empirical results

Table 4.B.1: Estimates of the probit model

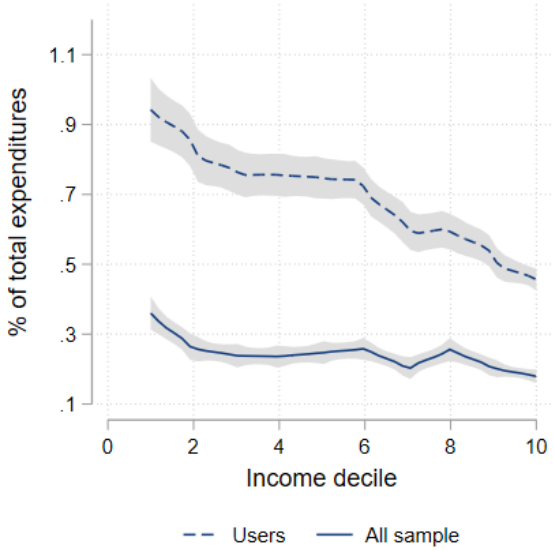
	Dependent variables			
	Fixed internet connection		**Mobile internet connection**	
Log of fixed internet price	-0.420***	(0.041)	-0.452***	(0.029)
Log of mobile internet price	-0.145***	(0.035)	-0.631***	(0.031)
Log of food price	0.006***	(0.001)	0.004***	(0.001)
Log of clothing price	0.001***	(0.001)	0.000	(0.001)
Log of water price	0.002**	(0.001)	0.002*	(0.001)
Log of electricity price	-0.001	(0.001)	-0.000	(0.001)
Log of fuels price	0.003***	(0.001)	0.002***	(0.001)
Log of leisure price	0.002***	(0.001)	-0.001	(0.001)
Log of restaurant price	0.003***	(0.001)	0.002***	(0.001)
Log of expenditure	0.449***	(0.029)	0.413***	(0.027)
Age	-0.007***	(0.001)	-0.014***	(0.001)
Household size	-0.011	(0.014)	-0.006	(0.011)
Computer	1.319***	(0.036)	0.124***	(0.038)
Mobile phone	0.526***	(0.066)	1.582***	(0.159)
Constant	-3.533***	(0.341)	-2.016***	(0.159)
Observation	11,920		11,920	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses

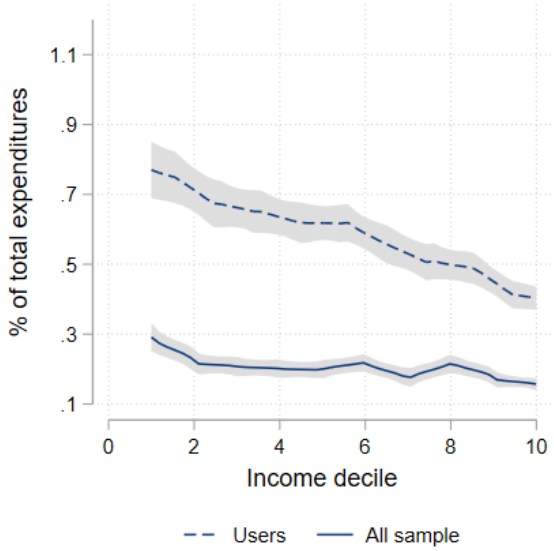
See Table 4.A.1 for more information on goods categories.

Figure 4.B.1: Compensating variation by income decile following a 20% increase in:

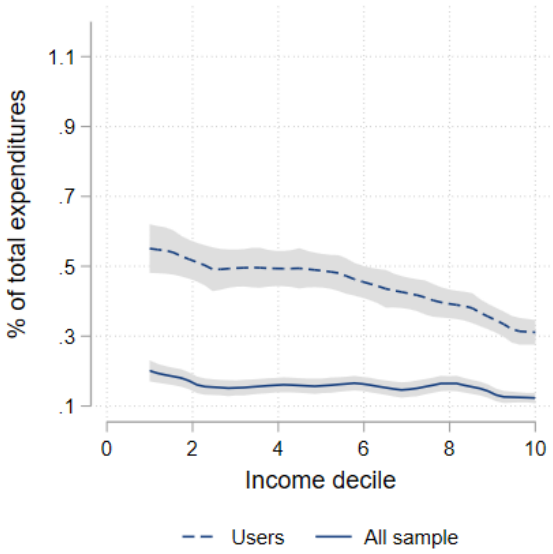
(a) mobile offers prices over 15€



(b) mobile offers prices over 20€



(c) mobile offers prices over 25€



The grey area represents the 95% confidence interval. Compensating variation is expressed as a percent of household expenditures.

Conclusion générale

Cette thèse s'inscrit dans la littérature sur l'économie du numérique et cherche à y contribuer en fournissant des éléments de réponse aux enjeux découlant de la transition numérique. Parmi ces enjeux, un accent particulier est mis sur la mesure de l'économie du numérique, l'économie des données et de l'attention, les inégalités numériques, et l'impact dela régulation environnemental du numérique.

La première contribution de cette thèse a été de fournir un état des lieux des caractéristiques spécifiques aux technologies du numérique et aux impacts économiques qui en découlent. À travers le premier chapitre, nous mettons en avant que les impacts de la transition numérique ne sont pas forcément similaires à ceux connus lors du développement d'autres technologies, notamment celles développées lors des révolutions industrielles. Puis, les différentes explications données dans la littérature au Paradoxe de Solow sont présentées. Parmi elles, une a retenu notre attention : l'impact du numérique ne serait pas sur la croissance économique mais directement sur le bien-être des individus. Le développement de l'économie des données et de l'attention a permis la diffusion de nombreux services numériques gratuits, imparfaitement mesurés par les indicateurs de création de richesse usuels utilisés par la comptabilité nationale.

Ce dernier constat a motivé notre deuxième chapitre qui s'intéresse aux impacts de ce nouveau secteur des services numériques gratuits sur les agrégats macroéconomiques et le bien-être. Pour cela, nous formalisons dans un modèle de croissance endogène les interactions entre les fournisseurs de services numériques gratuits, les firmes traditionnelles et les

ménages. La première contribution de ce chapitre est de montrer théoriquement comment les services numériques gratuits peuvent impacter le bien-être et avoir de nombreuses implications sur l'économie, sans affecter la croissance économique. De plus, nous mettons en avant l'importance de l'utilisation des données et de l'attention des utilisateurs dans le développement du secteur numérique. Nous mettons aussi en évidence les répercussions de la structure de marché du secteur numérique, composé de grands fournisseurs de services numériques, détenant la majorité des parts de marché de la publicité, et de petits fournisseurs. Nous trouvons que dû aux caractéristiques spécifiques des technologies du numérique (effets de réseaux, économies d'échelle) et aux préférences des ménages, les positions dominantes dans le secteur du numérique peuvent être bénéfiques aux ménages et à l'économie en générale.

Les deux derniers chapitres adoptent une approche microéconomique et se concentrent principalement sur la demande et la France. L'objectif principal est de mettre en avant que la diffusion du numérique mais aussi sa régulation peuvent amplifier les inégalités déjà existantes que nous ne considérons pas dans l'analyse macroéconomique de la première partie. Dans le troisième chapitre, nous mettons en avant les déterminants de la fracture numérique en France. Nous montrons que la fracture numérique en France est principalement un problème d'accès à internet. Les principaux déterminants des inégalités d'accès et d'utilisation d'internet identifiés sont la génération, le niveau d'éducation et de revenu. Ces populations, dont la principale raison du non-accès est le manque de compétence, doivent donc être ciblées avec attention. Cependant, nous soulignons que des populations moins touchées par les inégalités numériques, telle que les jeunes générations, doivent aussi être considérées dans les politiques publiques de lutte contre la fracture numérique. En effet, la perte en termes d'utilité est plus importante pour les individus exclus du numérique et appartenant à une catégorie l'utilisant. Des politiques d'aides financières pour accéder au numérique devraient donc être mises en place.

Le quatrième et dernier chapitre s'intéresse à la régulation environnementale du numérique et à ses impacts sur les ménages. Plus précisément, nous cherchons à déterminer l'impact distributif d'une taxe sur les forfaits internet mobiles en France. Puis, nous nous interrogeons

sur l'efficacité d'une telle taxe au regard du marché des télécommunications français. Nos résultats montrent que mettre en place une taxe sur les forfaits mobiles est une mesure régressive qui pourrait aggraver la fracture numérique. Pour limiter sa régressivité, une solution serait de ne taxer que les forfaits les plus chers et ceux avec un volume de données mobiles élevé. Par ailleurs, des mesures de redistribution pourraient être mises en place. Ces dernières peuvent prendre la forme d'un transfert monétaire mais aussi d'aide à l'accès aux forfaits internet fixe ou aux équipements informatiques. Outre la régressivité, nous mettons aussi en avant que l'efficacité de la taxe est réduite par l'offre peu diversifiée des forfaits mobiles en France. De plus, la différence entre consommation et dépense, spécifique aux offres internet, crée une difficulté supplémentaire. En effet, un grand nombre de ménages ne consomment pas l'intégralité de l'allocation de données autorisées. Une taxe pourrait simplement diminuer les dépenses en internet et amplifier les inégalités sans diminuer la consommation de données et donc l'impact environnemental.

Au-delà des contributions à la littérature économique, cette thèse s'efforce d'utiliser diverses méthodologies utilisées en sciences économiques pour répondre aux différentes questions mises en avant précédemment. Dans le premier chapitre, nous offrons une revue de la littérature afin de faire une synthèse des études sur les impacts et enjeux macroéconomiques de la transition numérique. Dans les chapitres 2 et 4, nous mobilisons des méthodologies théoriques. Le chapitre 2 utilise les modèles de la théorie de la croissance économique. Cela nous permet d'analyser la dynamique économique de long terme des services numériques gratuits et leurs impacts sur la macroéconomie. Le chapitre 4 se tourne plutôt vers les modèles microéconomiques cherchant à modéliser le comportement des consommateurs. Nous pouvons, grâce à ces modèles, comprendre comment les ménages vont ajuster leurs décisions d'achat suite à une augmentation des prix mais aussi vis-à-vis de l'offre proposée. Nous appliquons des méthodologies empiriques dans les chapitres 3 et 4. Le chapitre 3 utilise les méthodes de pseudo-panel. Ces dernières permettent d'employer les méthodes de panel et donc de prendre en compte à la fois la dimension temporelle et individuelle, sur des données en coupe transversale. Cette méthodologie est particulièrement utile pour exploiter des

enquêtes annuelles qui n'ont pas les moyens techniques ou financiers d'interroger les mêmes individus d'une année à l'autre. C'est le cas des enquêtes "Technologies de l'Information et de la Communication" produites par l'Insee et utilisées dans ce chapitre. Cela nous a permis de mettre en avant les déterminants de la fracture numérique en France sur treize années, mais aussi d'étudier l'évolution de la diffusion d'internet depuis 2007. Le chapitre 4 mobilise aussi les méthodologies issues la microéconométrie appliquées aux données d'enquêtes mais pour estimer des systèmes complets de demande. A l'aide de la méthodologie *Quadratic Almost Ideal Demand System* et des enquêtes "Budget des Familles" de l'Insee, nous avons pu estimer le comportement des ménages français vis-à-vis de leur consommation en biens non-durables. Une fois les élasticités prix et revenus estimées, nous avons pu simuler leur réaction suite à une augmentation des prix et calculer la perte d'utilité en résultant.

Plusieurs extensions et prolongements de ce travail de recherche sont possibles. Le chapitre 2 étudie le secteur des services numériques gratuits dans un cadre purement théorique. Il serait intéressant de tester empiriquement certaines hypothèses du modèle. Par exemple, l'importance accordée aux données des utilisateurs et à leur temps passé sur chaque service dans la production de publicité détermine plusieurs résultats. Il serait pertinent d'estimer le poids de ces deux facteurs dans la production d'impression publicitaire. L'aspect environnemental du numérique n'est abordé que dans le dernier chapitre. Or, il apparaît essentiel de prendre en compte les impacts de ces services numériques gratuits sur la dégradation de la qualité environnementale et des ressources. En effet, la collecte et le stockage des données nécessitent de nombreuses infrastructures très gourmandes en énergie mais aussi en métaux et en eau. L'augmentation de l'utilisation des services numériques utilisant des équipements numériques de plus en plus sophistiqués participent aussi à la hausse de l'empreinte carbone mondiale. Enfin, nous pouvons aussi remettre en question le modèle basé sur la publicité qui génèrent des pollutions directes *via* sa production mais aussi indirectement en incitant à la consommation de biens traditionnels.

Le chapitre 3 étudie les déterminants de la fracture numérique jusqu'à l'année 2019. Il serait pertinent d'ajouter les deux dernières vagues de l'enquête "Technologies de

l'Information et de la Communication" à notre étude. Cela nous permettrait de voir si, par exemple, la crise de la Covid-19 et ses confinements ont eu un impact sur la diffusion d'internet chez les ménages français. Nos résultats montrent que l'adoption d'internet a ralenti ces dernières années, mais cela a pu changer depuis. De plus, l'étude des autres niveaux de la fracture numérique serait intéressante pour offrir un panorama complet des inégalités numériques en France. Ces dernières peuvent être des inégalités dans les bénéfices liés à l'utilisation du numérique.

Une des limites du dernier chapitre est que seule la réaction de la demande est prise en compte. Nous étudions donc seulement l'impact à très court terme de l'introduction de la taxe. Il serait pertinent d'étudier la réaction de l'offre, c'est-à-dire des opérateurs de télécommunications. Plusieurs réactions sont possibles. Par exemple, la taxe peut avoir comme effet de modifier les offres sur le marché ou encore d'augmenter les prix des forfaits mobiles. Les opérateurs peuvent aussi décider de ne pas augmenter leurs prix et de répercuter la taxe sur d'autres services tels que l'internet fixe, les communications ou d'autres services additionnels. Cela annulerait l'objectif environnemental de la taxe. De plus, les données utilisées présentes des limites dans le cadre de notre étude. Si l'enquête "Budgets des Familles" a l'avantage d'être la seule enquête représentative sur les dépenses et revenus des ménages français, le détail sur la composition des abonnements internet est faible. Il serait intéressant d'approfondir cette recherche en utilisant des données plus précises sur le nombre de données mobiles autorisées par forfaits selon les caractéristiques des ménages français ou, dans le meilleur des cas, des données sur la consommation réelle des données mobiles.

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