conseil d'analyse économique

Focus

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Dynamiques de consommation dans la crise : les enseignements en temps réel des données bancaires

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Résumé non technique

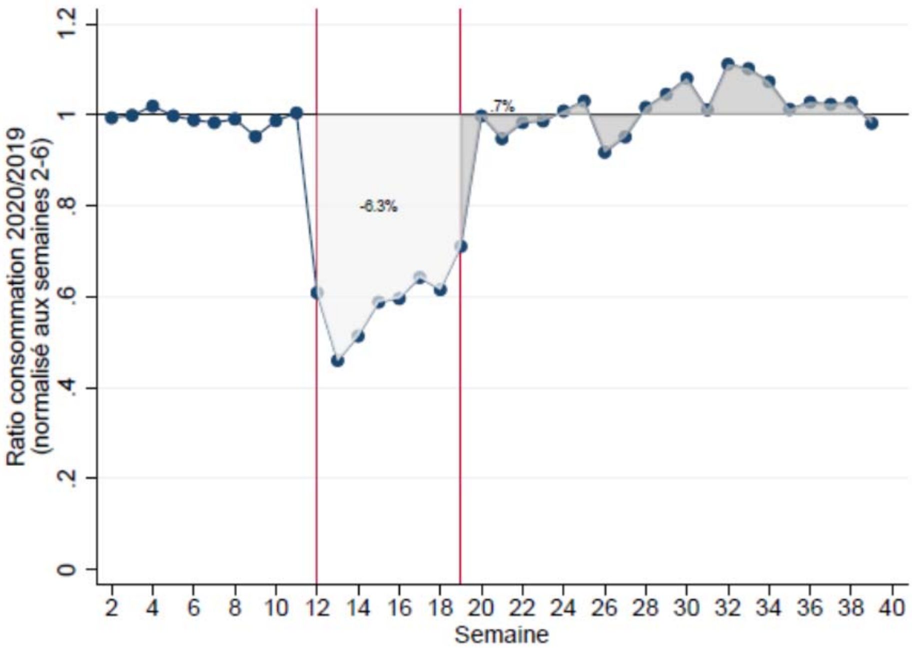
Le contexte inédit de la crise sanitaire a renforcé le besoin de mobiliser des sources de données « en temps réel », c'est-à-dire très rapidement disponibles, suffisamment représentatives et détaillées afin de pouvoir décrire les hétérogénéités des situations durant la crise. À ce titre, les données bancaires sont particulièrement riches. Grâce à des partenariats noués entre le CAE et le Groupement des Cartes Bancaires CB, Télécom Paris (dans le cadre de la Chaire « Finance Digitale » placée sous l'égide de la Fondation du Risque en partenariat avec le Groupement Cartes Bancaires CB, Telecom ParisTech et l'Université Panthéon-Assas), et Crédit Mutuel Alliance Fédérale, que nous remercions tous ,un travail de recherche original a été rendu possible en s'appuyant sur ces données. L'accès à ces données agrégées et strictement anonymisées s'est effectué dans une procédure sécurisée (voir encadré). Les données de transactions par cartes bancaires permettent de construire un baromètre de la consommation des ménages puisqu'elles en couvrent environ 60 % (hors charges fixes). Elles permettent également de produire des analyses sectorielles et géographiques et des hétérogénéités entre les ménages. Les données de comptes bancaires Crédit Mutuel Alliance Fédérale, sur la base d'un échantillon de 300 000 ménages strictement anonymisés, permettent d'aller plus loin dans l'analyse en disposant d'informations sur les dépenses des ménages (achats par cartes bancaires, retraits d'espèces, chèques et prélèvements) et sur les soldes des comptes (compte courant, compte d'épargne, compte titre, assurance vie, crédits). Avec de telles données, il est ainsi possible notamment d'étudier la dynamique de l'épargne globale, et selon différentes catégories de ménages.

(1) Télécom Paris ; (2) Télécom Paris ; (3) IEP Paris et CAE ; (4) McGill ; (5) LSE et CAE ; (6) CAE ; (7) LSE ; (8) CAE.

1. La dynamique de la consommation agrégée

Les données de cartes bancaires permettent de suivre en temps réel l'évolution de la consommation en temps de crise Covid et de mieux comprendre ses déterminants. Après la chute de la consommation pendant le confinement qui a correspondu à une perte annualisée de 6,3 % par rapport à 2019, la consommation, telle que mesurée par les données de cartes bancaires, a rapidement rebondi avec depuis le déconfinement un retour à une consommation à un niveau normal avec même, en terme annualisé à nouveau, une augmentation de 0,7 %. Il n'y a pas eu pour autant de rattrapage de la consommation au niveau agrégé puisque le rebond ne compense pas du tout la perte pendant le confinement (voir graphique 1). C'est un point important qui est la source du risque accru de défaillance et qui suggère que nombre d'entreprises sont exposées à un risque de solvabilité et non pas seulement de liquidité.

Graphique 1. Dynamique globale des dépenses par carte

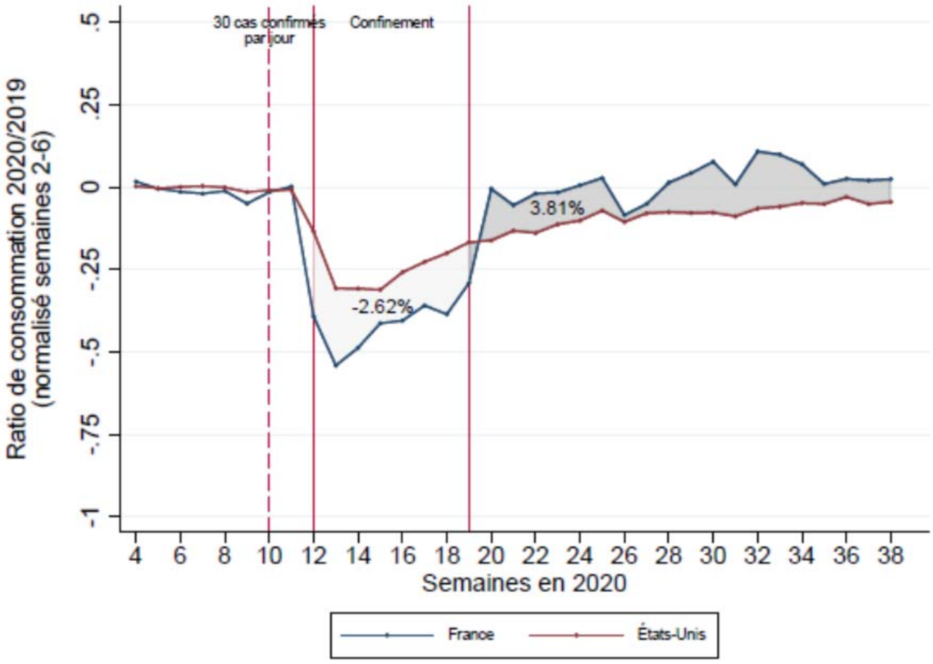


Source : Exploitation des données Groupement Cartes Bancaires CB.

Le rebond de la consommation a été particulièrement fort en juillet et août mais les données les plus récentes en particulier fin septembre montrent un léger essoufflement, en cohérence avec les récentes analyses de l'INSEE et de la Banque de France. Les mauvaises nouvelles sanitaires en sont peut-être la cause même si elles n'ont pas, jusqu'ici, induit un comportement de retrait massif des consommateurs. De ce point de vue, ceux-ci semblent donc s'adapter aux nouvelles conditions sanitaires. Un exemple de cette adaptation est la substitution des cartes bancaires au paiement en espèces.

En comparaison des autres pays où les données de cartes bancaires sont aussi mobilisées, la consommation en France a un profil plus heurté. Elle a davantage chuté pendant le confinement (qui a été plus strict qu'ailleurs) mais s'est plus fortement redressée ensuite. C'est par exemple le cas si l'on compare avec les États-Unis pour lesquels des données équivalentes récentes sont disponibles. Depuis la fin du confinement, la France a retrouvé un niveau de consommation semblable à 2019 (graphique 2) (net de la trajectoire de croissance pré-crise), tandis qu'aux États-Unis, la chute de consommation se maintient.

Graphique 2. Comparaisons internationales : États-Unis *vs* France

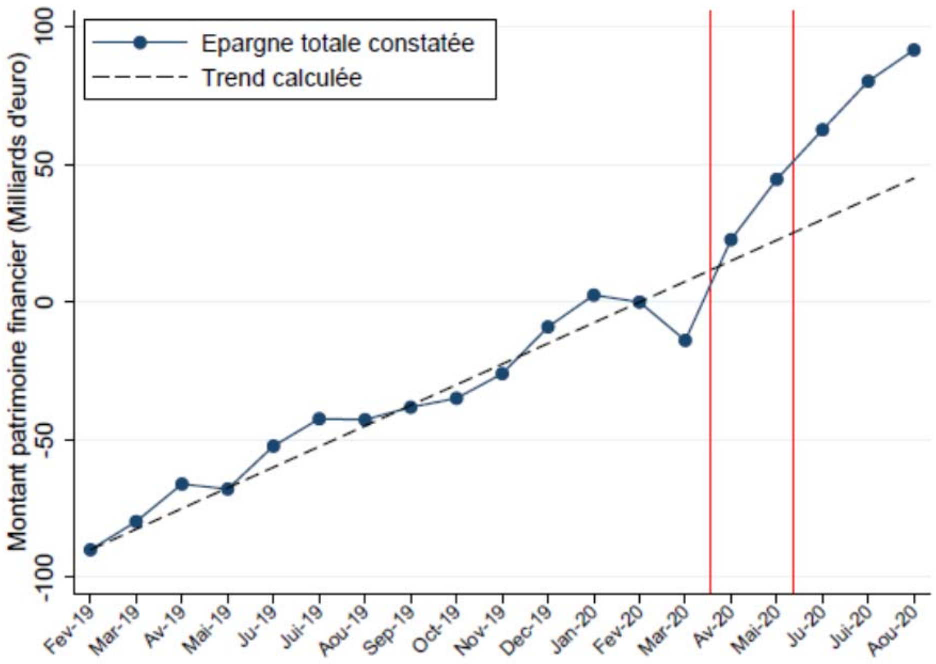


Source : Exploitation des données Groupement Cartes Bancaires CB.

2. La dynamique globale de l'épargne des ménages

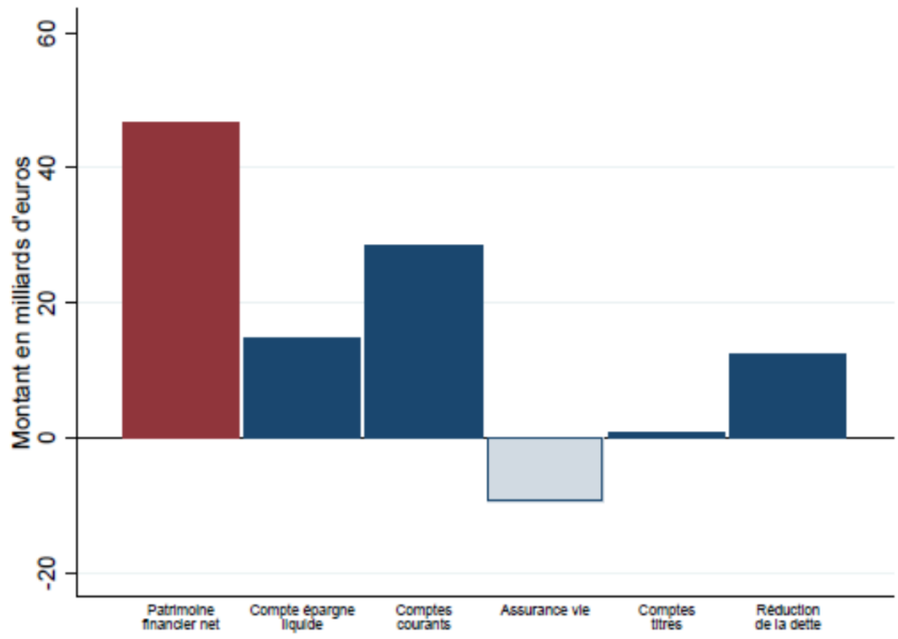
Grâce aux données de comptes bancaires, nous pouvons aussi analyser la dynamique de l'épargne. Nous estimons l'accumulation faite par les ménages depuis le confinement sur leurs comptes courants, comptes d'épargne, comptes d'assurance vie et comptes titres, nette des variations de leur dette. En déviation par rapport à la croissance de la période pré-Covid (soit de fin février 2019 à fin février 2020), le surcroît d'épargne depuis le confinement est très important. Sur la base des données bancaires utilisées, qui ne peuvent qu'être partielles puisque les clients d'une banque peuvent placer une partie leur épargne au sein d'autres établissements bancaires, nous l'évaluons à un peu moins de 50 milliards d'euros fin août 2020 (voir graphique 3). Ce surcroît d'épargne s'est matérialisé surtout par une augmentation des soldes des comptes courants et des comptes d'épargne et par une diminution de la dette, très peu par une augmentation des comptes titres, tandis que l'assurance-vie est en net recul (voir graphique 4).

Graphique 3. Estimation de l'évolution du patrimoine financier net



Source : Exploitation des données Crédit Mutuel Alliance Fédérale.

Graphique 4. Contribution de chaque classe d'actifs à l'évolution du patrimoine financier net

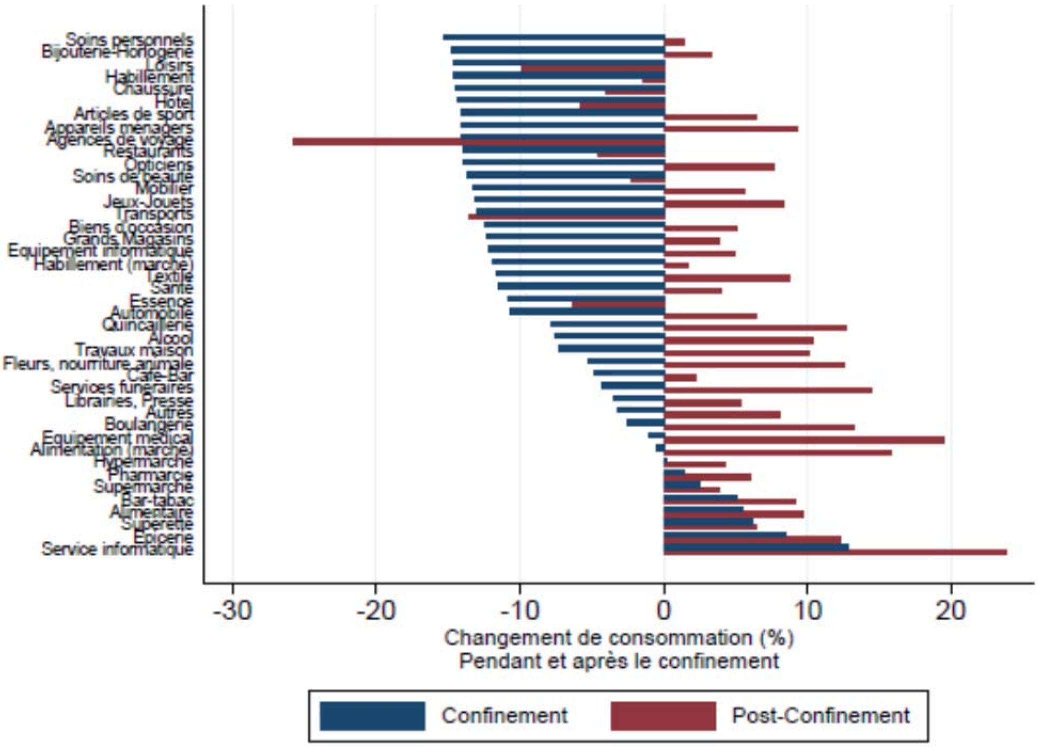


Source : Exploitation des données Crédit Mutuel Alliance Fédérale.

3. L'hétérogénéité sectorielle

Les données permettent aussi une analyse fine de l'hétérogénéité sectorielle de la consommation. Celle-ci est en effet exceptionnellement forte et sans précédent pendant cette crise avec des secteurs très fortement « perdants » et des secteurs « gagnants » (graphique 5). Ainsi, à un extrême le secteur des services à la personne a chuté en terme annualisé de 15 % pendant le confinement (avec un faible rebond post confinement). À l'autre extrême les services informatiques ont vu leur consommation augmenter de 13 et 24 % pendant et après le confinement respectivement. Ces chiffres suggèrent que l'approche sectorielle dans l'aide aux entreprises est indispensable.

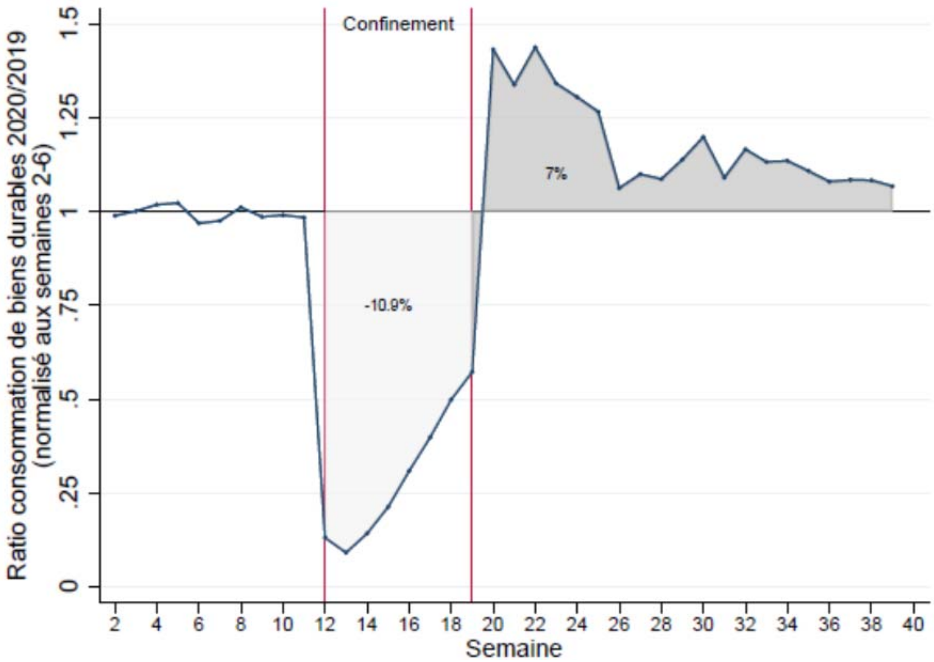
Graphique 5. Hétérogénéité sectorielle de la consommation



Source : Exploitation des données Groupement Cartes Bancaires CB.

Cette hétérogénéité peut aussi se mesurer en se focalisant sur deux types de consommations qui montrent des comportements très différents. D'une part les biens durables (automobile, ameublement, électroménager, ordinateurs…) dont la nature permet une forte substituabilité intertemporelle : leur achat peut facilement être reporté. Ainsi ces biens ont connu une chute extrêmement forte pendant le confinement, 10,9 %, mais également un rebond à partir de mai de 6,7 %, et donc dans une certaine mesure, un rattrapage (graphique 6). La crise devrait moins affecter les entreprises de ces secteurs.

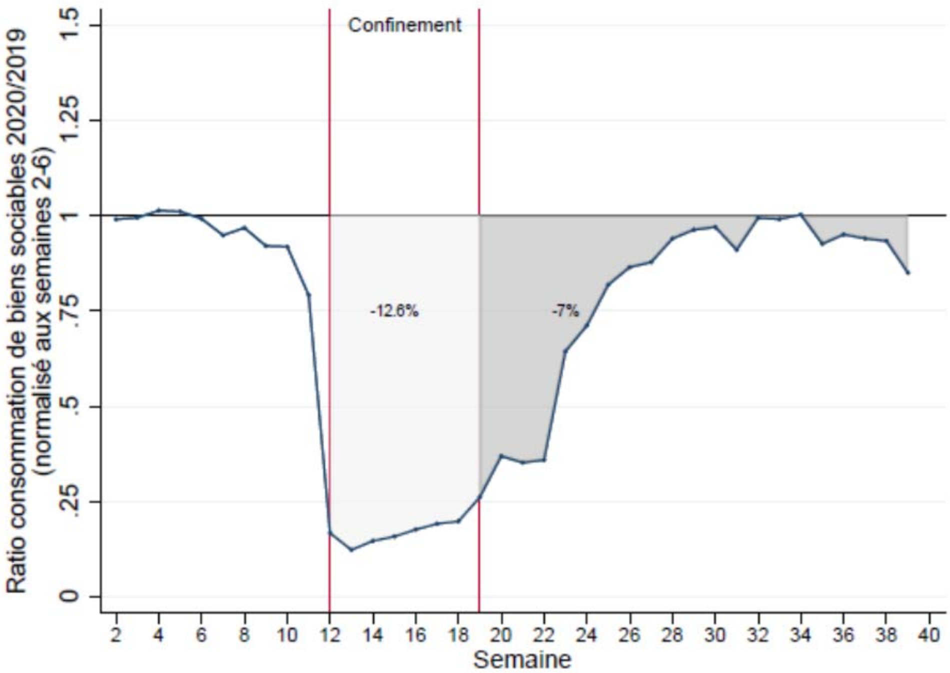
Graphique 6. Consommation de biens durables



Source : Exploitation des données Groupement Cartes Bancaires CB.

En revanche, les secteurs qui requièrent des interactions sociales et pour lesquels la consommation est difficilement substituable entre périodes (restaurants, spectacles, culture, etc.) la chute pendant le confinement n'a pas été compensée après celui-ci.

Graphique 7. Consommation dans les secteurs de la restauration et des loisirs

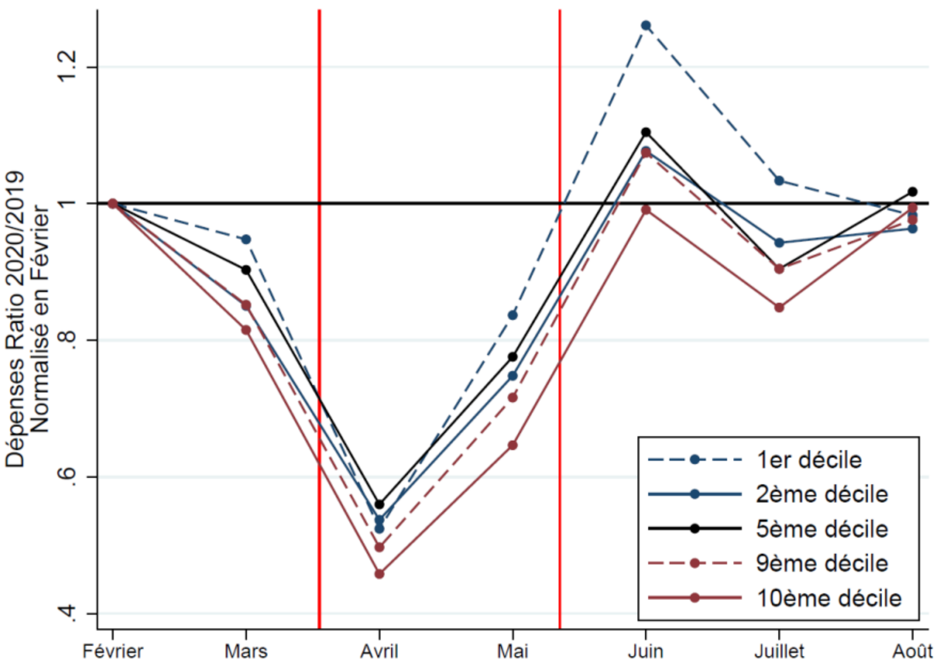


Source : Exploitation des données Groupement Cartes Bancaires CB.

4. L'hétérogénéité entre les ménages

Les données de comptes bancaires permettent d'analyser finement comment la dynamique de consommation diffère selon les groupes. La consommation est mesurée ici par la somme des achats par cartes bancaires, des retraits d'espèces et des paiements par chèque. Elle n'intègre donc que peu voire pas du tout les charges « fixes » des ménages qui sont le plus souvent réglées par virement ou prélèvement (loyers, abonnements électricité, téléphone, etc.). Sur ce périmètre de consommation, nous avons calculé les déciles de consommation par ménage en 2019 : celle du 1er décile est au maximum à 245 euros par mois, tandis que les bornes inférieures des 9e et 10e déciles sont respectivement de 3 252 et 4 826 euros par mois. Utilisant ces déciles comme approximation du revenu(9), le graphique 8 indique que les personnes les plus aisées (10e décile) ont le plus baissé leur consommation pendant le confinement et, même si celle-ci rebondit après, elle reste en retrait par rapport à la consommation observée en 2019 et à la tendance de la période pré-Covid de début 2020. Cette relation s'observe au-delà du dernier décile : plus les personnes sont aisées et plus leur consommation a baissé sur toute la période.

Graphique 8. Dynamique de la consommation par déciles de dépenses pré-Covid



Source : Exploitation des données Crédit Mutuel Alliance Fédérale.

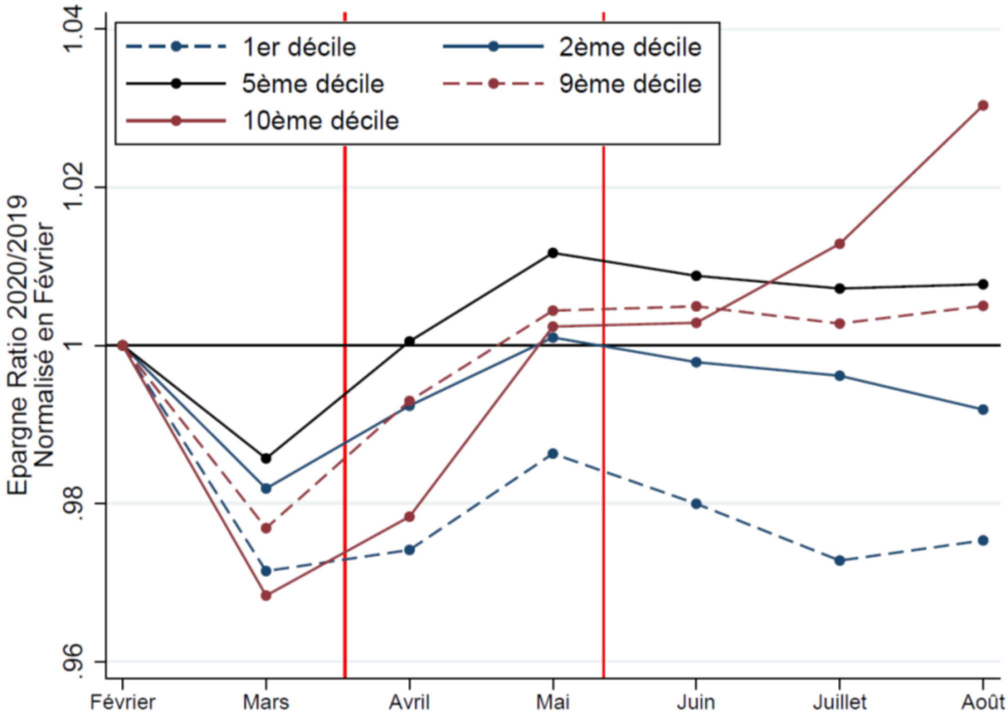
En effet, la consommation habituelle de ces ménages va bien au-delà des biens essentiels. Or c'est précisément ce type de consommation qui était impossible pendant le confinement, ce qui explique une chute de consommation proportionnellement plus forte. À l'inverse, les ménages modestes ont moins baissé leur consommation, puisque celle-ci se concentre plus sur les biens essentiels. Ils ont néanmoins connu un rebond ensuite. Ces différences de dynamique de consommation vont se traduire par des différences de dynamique d'épargne.

Le graphique ci-dessous laisse ressortir une divergence des dynamiques d'épargne entre le premier et dernier décile (déciles de consommation en 2019) : alors que l'épargne est très au-dessus de la normale pour les plus aisés en fin de période, elle est en dessous pour les plus modestes

(9) Au moment de la rédaction de ce document, nous n'avons pas encore accès aux données des revenus. Celles-ci pourraient être disponibles pour des analyses futures.

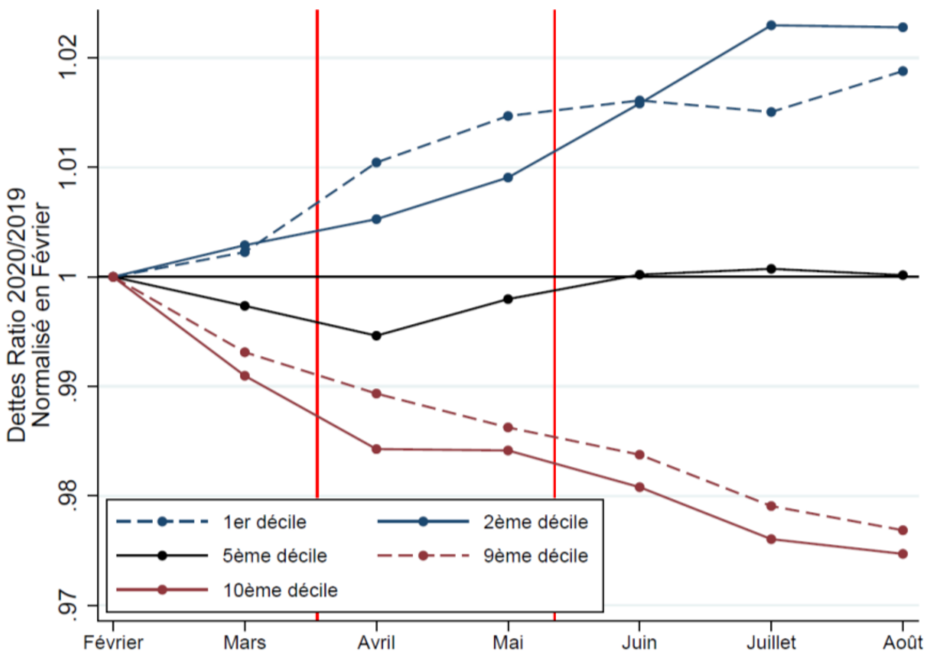
(graphique 9). Cela peut s'expliquer non seulement par la différence de comportement en termes de consommation (expliquée ci-dessus) mais aussi potentiellement par une différence en termes de revenus que (au moment de la rédaction de ce document) nous n'observons pas encore directement. Cela se traduit aussi par une baisse de l'endettement des plus aisés (probablement expliqué par un moindre recours au crédit) contre une augmentation pour les plus modestes (graphique 10).

Graphique 9. Dynamique de l'épargne liquide par déciles de dépenses pré-Covid



Source : Exploitation des données Crédit Mutuel Alliance Fédérale.

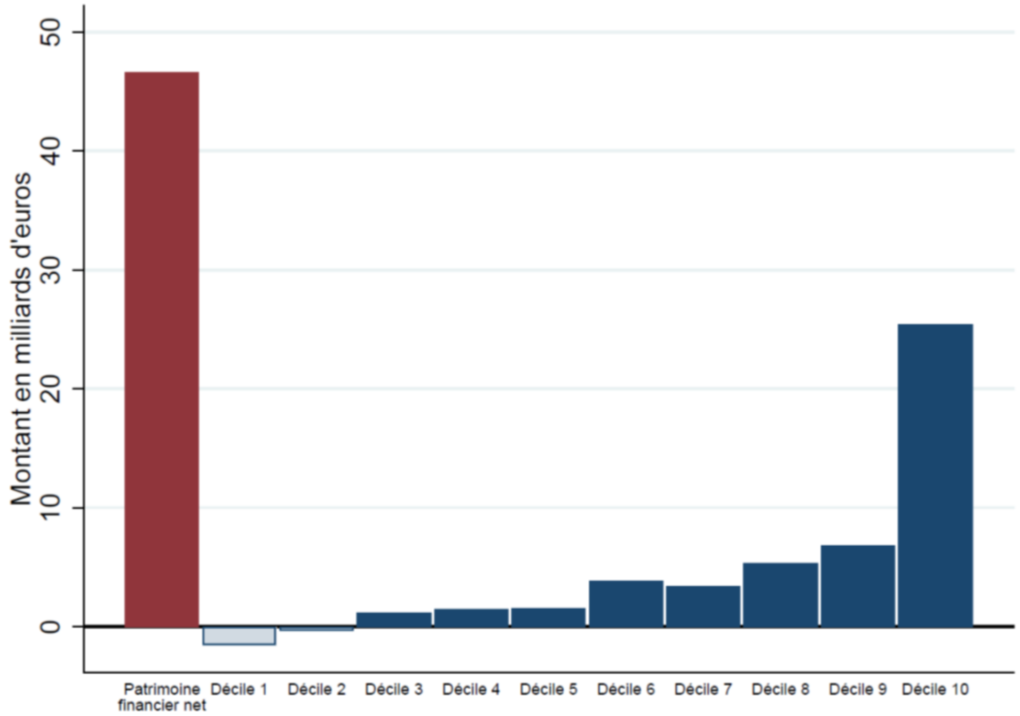
Graphique 10. Dynamique des dettes par déciles de dépenses pré-Covid



Source : Exploitation des données Crédit Mutuel Alliance Fédérale.

L'accumulation d'épargne pendant la période récente a donc été très inégale. Si l'épargne globale des ménages pendant la période a été massive (près de 50 milliards d'euros de plus que ce qu'aurait prédit la continuation de la tendance pré-Covid), elle a été très fortement concentrée sur les deux derniers déciles. Le surcroît d'épargne des deux déciles les plus aisés s'élève en effet à 32 milliards d'euros. Près de 70 % du surcroît de l'épargne ont donc été faits par 20 % des ménages. Les deux premiers déciles ont en revanche beaucoup moins pu épargner sur cette période (voir graphique 11).

Graphique 11. Contribution à la croissance du patrimoine financier net par décile de dépenses pré-Covid



Source : Exploitation des données Crédit Mutuel Alliance Fédérale.

La granularité des données nous permet d'analyser en temps réel l'impact de politiques précises. Ainsi, nous regardons l'impact de la distribution de l'ARS (Allocation de rentrée scolaire) sur les ménages éligibles. Nous calculons une propension marginale à consommer, c'est-à-dire la part du montant reçu qui est dédié à la consommation. Cette analyse confirme la grande sensibilité des ménages à bas revenus et à faible épargne aux variations du revenu. En effet la propension marginale à consommer est par exemple plus élevée chez les ménages disposant de moins d'épargne liquide.

Elle suggère qu'un soutien beaucoup plus franc aux ménages les plus modestes, plus exposés aux conséquences économiques des mesures sanitaires, va très rapidement s'avérer nécessaire.

5. Conclusion

L'utilisation et l'analyse de données bancaires microéconomiques en temps réel, inédit en France, permet un suivi précieux pour la compréhension des effets de la crise sur les ménages français. Cette analyse mérite d'être continuée. Ces données, mises à disposition récemment, recèlent encore un fort potentiel inexploité. Les auteurs souhaitent approfondir les analyses décrites ci-dessus, notamment en termes d'hétérogénéité des réponses face à la crise, encore mal captée par les classifications économiques usuelles (âge, profession et catégories socioprofessionnelles). L'exploitation plus fine des données pourrait également conduire à un calibrage précis des politiques publiques en identifiant les publics prioritaires de populations particulièrement soumises à la crise, notamment en termes de chute du revenu.

Encadré. Crédit Mutuel Alliance Fédérale et Groupement Cartes Bancaires CB

Première banque à adopter le statut d'entreprise à mission, Crédit Mutuel Alliance Fédérale a contribué à cette étude par la fourniture de données de comptes bancaires sur la base d'un échantillon de ménages par tirage aléatoire. Toutes les analyses réalisées dans le cadre de cette étude ont été effectuées sur des données strictement anonymisées sur les seuls systèmes d'information sécurisés du Crédit Mutuel en France. Pour Crédit Mutuel Alliance Fédérale, cette démarche « s'inscrit dans le cadre des missions qu'il s'est fixé :

- contribuer au bien commun en œuvrant pour une société plus juste et plus durable : en participant à l'information économique, Crédit Mutuel Alliance Fédérale réaffirme sa volonté de contribuer au débat démocratique ;
- protéger l'intimité numérique et la vie privée de chacun : Crédit Mutuel Alliance Fédérale veille à la protection absolue des données de ses clients ».

Le Groupement des Cartes Bancaires CB, Groupement d'Intérêt Économique qui définit les modalités de fonctionnement du schéma de paiement par carte CB (physique ou dématérialisée dans le mobile) a également contribué à cette étude par la fourniture de ses données (agrégées) et par la possibilité de solliciter des traitements sur des données individuelles anonymisées dans un espace strictement sécurisé et dans le cadre de son partenariat avec la Chaire Finance Digitale. « Ce partenariat entre CB et le monde académique va permettre de développer de nouvelles filières de compétence. Il reflète aussi la démarche citoyenne et responsable de CB, qui a pour volonté de servir l'intérêt général et favoriser l'inclusion sociale et sociétale », déclare Philippe Laulanie, Directeur général de CB.

Consumption Dynamics in the COVID Crisis: Real Time Insights from French Transaction & Bank Data

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Abstract

We use anonymised transaction and bank data from France to document the evolution of consumption and savings dynamics since the onset of the pandemic. We find that consumption has dropped very severely during the nation-wide lockdown but experienced a strong and steady rebound during the Summer, before faltering in late September. This drop in consumption with met with a significant increase in aggregate households' net financial wealth. This excess savings is extremely heterogenous across the income distribution: 50% of excess wealth accrued to the top decile. Households in the bottom decile of the income distribution experienced a severe decrease in consumption, a decrease in savings and an increase in debt. We estimate marginal propensities to consume and show that their magnitude is large, especially at the bottom of the income and liquidity distributions.

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1 Introduction

The explosive dynamics of the coronavirus shock has created a new historic need for “extreme nowcasting” to monitor the impact of the shock on the economy. This in turn requires access to new data that are quickly available (for reactivity), representative (for robustness) and granular (to allow for rich distributional analysis, as well as quasi-experimental analysis to learn about mechanisms).

Furthermore, the covid shock is unprecedented in both its magnitude and its nature. This poses a series of original issues to policy-makers in their response to the crisis. How is the economic shock distributed in the population? What is the causal role of health risk in explaining behaviors? How much are consumption and savings behavior driven by precautionary savings in response to the significant rise in uncertainty regarding future income and employment dynamics? Etc.

In this work, we offer insights coming from the use of original anonymous and de-identified transaction and bank data in the French context. The data comes from two unique sources. First, from the universe of card transactions from the French consortium of card providers “Groupement Cartes Bancaires CB” (CB thereafter). Second, from a large balanced panel of 300,000 households randomly sampled from the clients of the French Bank Credit Mutuel Alliance Federale (CM thereafter).[1]

We first investigate the dynamics of aggregate transactions. We find that card transaction expenditures experienced a severe decline of about 50% during the nation-wide lockdown period that started in mid-March in France, and lasted until mid-May. Interestingly, we find that after that initial phase, expenditures bounced back almost immediately to their 2019 levels, and remained steady throughout the summer. In that sense, the French recovery in terms of consumption has been much stronger than in other countries such as the US or the UK. There is nevertheless an extreme amount of sectoral heterogeneity in the dynamics of expenditures, which is a unique feature of the covid-induced recession. Furthermore, there are clear signs that consumption expenditures have been faltering in the last weeks of September, as a second epidemic wave was gaining momentum in France.

Using the richness of the CM data, we also explore the dynamics of financial wealth and savings behavior during the crisis. We find that aggregate financial wealth has increased by about €50 billions since the onset of the crisis, compared to the counterfactual of a prolongation of the 2019 trend. Interestingly, most of this excess financial wealth is accounted for by an increase in liquid savings. Moving to distributional

[1] All data is de-identified, and accessed through secure internal IT servers. We provide all details on the data, and on the procedures for data access and for preserving data privacy in the Data section of this paper, as well as in the Appendix.

analysis, we find that more than 50% of this excess "savings" accrued to households in the top decile of the income distribution. At the bottom of the distribution, consumption and savings have both decreased since the start of the pandemic, indicative of severe income shocks experienced by these households, despite the social insurance and welfare transfer policies put in place by the French government since the start of the crisis.

Finally, we also show how this unique source of data can be used to explore the respective role of three potential drivers of consumption dynamics. We investigate the importance of income dynamics and income expectations by estimating marginal propensities to consume, taking advantage of the granularity of the CM data, combined with quasi-experimental variation in welfare transfer payments. We find large but heterogeneous MPCs, with households at the bottom of the liquid savings distribution being particularly sensitive to additional cash-on-hand. We then turn to exploring the role of health risk, vis-a-vis that of lockdown and restriction policies. We find relatively little role of health risk perceptions on consumption dynamics on average, but a strong role for lockdown policies.

The remainder of the paper is organized as follows. Section 2 presents the data, Section 3 analyzes the evolution of aggregate consumption and savings. Section 4 documents sectoral heterogeneity, while section 5 delves into the distributional impact of the crisis. Finally, section 6 explores the mechanisms driving consumption dynamics since the beginning of the covid crisis.

2 Data

2.1 Carte Bancaires

Cartes Bancaires CB is one of the leading consortium of payment service providers, banks and e-money institutions. It was created by the French banks in 1984, and by 2019 had more than 100 members. As of 2019 there were more than 71.1 million CB cards in use in the CB system, and 1.8 million CB-affiliated merchants.

Thanks to a partnership with Cartes Bancaires CB, we are able to observe the universe of CB card transactions at a very granular level. A CB card transaction is characterized by its amount, the precise time and date of the transaction, the geographical location of the merchant, the statistical classification of the type of purchase, and the type of purchasing channel used during the transaction, i.e. off-line or online. By definition, all the other card transactions carried out with payment card schemes such as Visa or

MasterCard are not covered and part of the analysis, as they are not CB card transaction. Similarly, the payments made by checks, direct debits and credit transfers are not transactions covered by the CB card network.

The data set of CB card transactions is exceptional in its coverage, allowing us to capture a significant proportion of all consumer expenditure in France. To appreciate the richness of the Cartes Bancaires CB data, consider a few comparisons with national statistics provided for the full year 2019 by the National Institute of Statistics and Economic Studies (INSEE). GDP in France in 2019 was estimated as €2,427 billion, with €1,254 billion (52 percent of GDP) representing household consumption expenditure. Excluding fixed charges (rents, financial services, insurances) from household consumption expenditure, as these are typically paid by checks, direct debits and credit transfers, the remaining part of consumer expenditure amounts to €828 billion (34 percent of GDP). Comparing these figures with total CB card payments (€494 billion), the value of CB card payments represents 20 percent of French GDP, 39 percent of total household consumption expenditure, and finally 60 percent of total household consumption expenditure excluding fixed charges. CB card transactions thus captures the most cyclical part of household consumption expenditure, which is very useful for economic nowcasting.

The real-time and detailed information on timing and location of the transaction, the nature of the merchant, allows us to provide fine-grained descriptions of consumption fluctuations, and to contrast consumption patterns along the geographical and sectoral dimensions.[2] For more details on the CB data, see Bounie, Camara and Galbraith [2020], who provide a detailed analysis of consumption dynamics in the early months of the crisis.

2.2 Credit Mutuel Alliance Fédérale

Sampling

The data used in this paper comes from a balanced panel of 300,000 randomly selected clients of the French National retail bank CIC, a subsidiary of Crédit Mutuel Alliance Fédérale. As opposed to the Crédit Mutuel which is deeply rooted in the East of France, the CIC is less regionally concentrated and has more than 2,000 agencies spread across the country.

The sampling procedure was the following. We selected customers according to their age and department (French administrative geographical area called "département")

[2] We limit the sample to Metropolitan France, which excludes the overseas territories.

of residency. We defined 6 age groups (18-25, 26-35, 36-45, 46-55, 56-65 and 66+). From each of the 94 departments and age groups we randomly selected a certain number of customers. For the 31 most populated departments in France we selected 1,000 customers per cell (age-groupe - department). For the next 26, we selected 500, for the next 13 300 and finally 100 for the last 24 departments. This sampling procedure ensured a better representativity of the sample but also guaranteed anonymity, by making sure that the fraction of sampled customers in each cell did not exceed a specific threshold.

Furthermore, the customers were chosen out of a sub-sample of all CIC clients. The customers had to be "principal customers", meaning that the CIC is their main bank where they domiciliate their income and main assets and credits. They had to be a physical entity and alive. We do have self-employed individuals in our sample but no firms. All customers in our sample had to be customers at least before January 2019. We excluded residents of Corsica, French overseas territories and customers outside of France. Finally we also excluded employees of Crédit Mutuel Alliance Fédérale and individuals banned from holding a bank account.

The sampling resulted in a little over 300,000 customers defined at the group level (i.e household level) which amounts to approximately 550,000 individuals. In cases where the household composition changed (marriage, divorce ...), we kept in the sample all of the initial members of the groups. The sampling was performed in June 2020.

Reweighting

In order for our sample to better match national data, we reweight each age-group department cell to match French census data from INSEE. Note that for now, we only use age and geography as observables characteristics in our reweighting approach, but more sophisticated approaches can be used, to match other aggregate or distributional statistics in the French population.

Data structure

We use pseudo-anonymized data located on a secure distant server.[3]

We were granted access of three tables containing information on card expenditures, cash withdrawals, check payments, bank balances, savings accounts, equities, life insurances and household debts. Moreover we have some information on wire transfers and for the year 2020 we have information on direct debits and daily information on

[3]See appendix for more detail information on data access and the partnership with Crédit Mutuel Alliance Fédérale.

card expenditures that allows us to know in which sector (MCC classification) the spending was made.

We also have access to some information regarding the account owner and household members : department, age, socio-professional category (PCS)[4], marital status and whether or not the individual is self-employed. Note that the definition of households in the CM data is different from the standard INSEE definition usually retained in French survey data.[5].

Descriptive statistics

Our sampling strategy led to an overrepresentation of young people and an underrepresentation of older people. Appendix Table 1 provides descriptive statistics for our original sample, as well as our reweighted sample, and then compares these statistics to external INSEE data on the universe of the French population. The reweighting procedure allows us to get a more representative sample of the French population. But we still slightly underrepresent retirees.[6]

[4]"Nomenclature des Professions et catégories socio-professionnelles" which can translate to "Nomenclature of Professions and Socioprofessional Categories"

[5]Indeed, whereas INSEE considers that a household is defined by a shared home, and not by kinship, allowing roomates, for example, to form a unique household, this is not the case in the Crédit Mutuel Alliance Fédérale databases. Their definition of a household is much more restricted: only blood or marriage related people are considered to be a unit. Moreover, children turning 18 are by default transferred to a new household unit even though they may still be living with their parents.

[6]Our interpretation of this deviation is that even though the sample has been reweighted and does better at comparing with the actual percentage of older people in the French population (66+ people attainted 21.13% after the weighting procedure against 16.70% before it for a total of 24.61% as reported by the INSEE census in 2018), because the Crédit Mutuel Alliance Fédérale data must be updated by the account owners themselves, few of them actually declare their retirement right away, hence PCS variables are often updated with significant delay at retirement.

3 Aggregate Consumption & Savings Dynamics

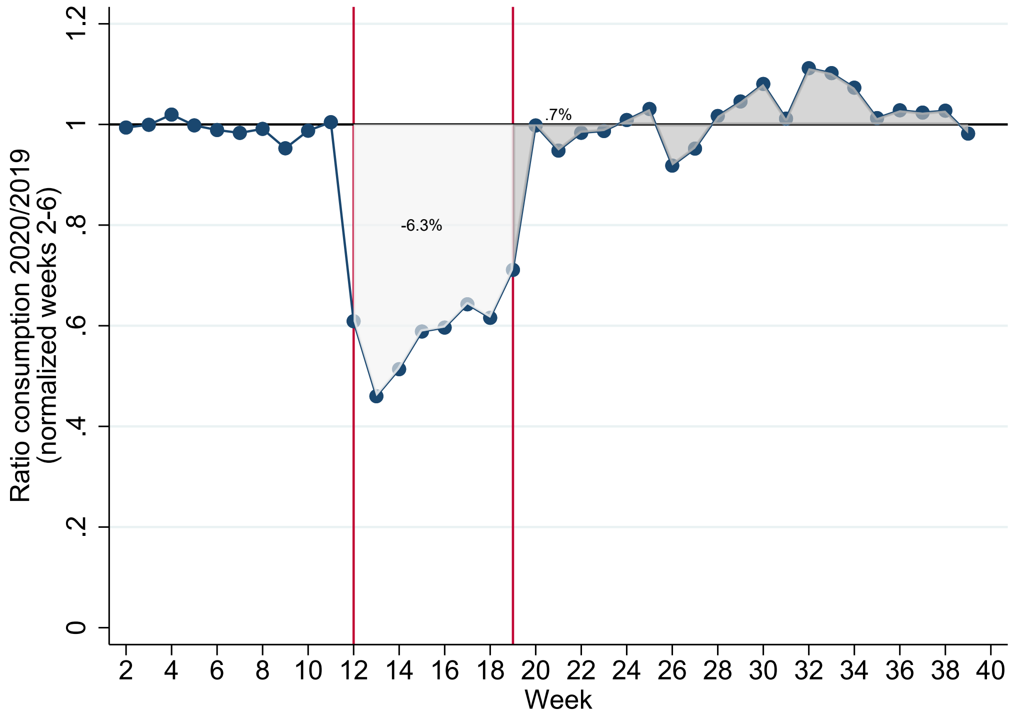
3.1 Consumption

We start by documenting the evolution of aggregate consumption dynamics in France since the beginning of the pandemic. We focus on aggregate credit card expenditures measured in the CB data. We aggregate transactions at the weekly level. To deal with seasonality, we divide aggregate transactions in week t of 2020 by aggregate transactions in the exact same week t in 2019: C_t^{2020}/C_t^{2019}. We further take away the general trend in aggregate consumption between 2019 and 2020. To this effect, we normalize these expenditure ratios by the average ratio between week 2 and week 6 in 2020: $\bar{C}_{t\in[2;6]}^{2020}/\bar{C}_{t\in[2;6]}^{2019}$. In other words, we assume that the overall trend observed in expenditures between the first weeks of 2020 and the first weeks 2019 would have continued absent the COVID crisis. We then report $c_t = \frac{C_t^{2020}/C_t^{2019}}{\bar{C}_{t\in[2;6]}^{2020}/\bar{C}_{t\in[2;6]}^{2019}}$, which measures how consumption deviates from its 2019 level, once accounting for the general trend that would have occured between 2019 and 2020 absent the pandemic.

Sharp Decline & Steep Recovery Figure 1 shows the evolution of credit card transactions from the CB data since the start of 2020. The first red line corresponds to the start of the nation-wide lockdown in France (week 12) and the second red line corresponds to the end of the lockdown in week 19. The figure shows that aggregate transactions did not experience much of a decline before the start of the lockdown. But the lockdown was associated with a brutal and severe decline in transactions, of about 50%. Transactions remained extremely depressed throughout the seven weeks of lockdown despite a small improvement after the initial sharp contraction of week 13. Interestingly, aggregate consumption bounced back immediately to pre-crisis levels as soon as the lockdown ended, and has been stable at this level ever since. There does not seem to be signs of a decrease in expenditures since late August, as a second wave of covid infections has been quickly spreading across the country.

A few important lessons emerge from these patterns of aggregate consumption dynamics. First, the overall contraction in spending during the lockdown has been massive in France. If we cumulate the aggregate amount of spending "lost" from week 12 to week 19 (the light grey area in Figure 1), this corresponds to a 6.3% loss in annual spending. Second, although the recovery in credit card transactions has been quick and steady since the end of the lockdown, transactions have reached their pre-crisis level, but did not overshoot: there is no sign of intertemporal substitution at the aggregate level. In other words, the 6.3% loss in annual spending during the lockdown is a permanent loss. Third, there does not seem to be strong signs of correlation in the time series between credit card expenditures and the dynamics of the epidemic since the end of the lockdown.

Figure 1: Evolution of Aggregate Weekly Credit Card Expenditures in the CB Data



Notes: The Figure reports the evolution of aggregate weekly credit card expenditures observed in the CB data. The graph plots $c_t = (C_t^{2020}/C_t^{2019})/(\bar{C}^{2020}_{t\in[2;6]}/\bar{C}^{2019}_{t\in[2;6]})$, where C_t^{2020} corresponds to aggregate expenditures in week t of 2020 and $\bar{C}^{2020}_{t\in[2;6]}$ corresponds to the average aggregate expenditures in week 2 to 6 of 2020. This normalization procedures deals with both seasonality in expenditures, and the overall trend in expenditures over time. The graph therefore measures how consumption deviates from its 2019 level, once accounting for the general trend that would have occurred between 2019 and 2020 absent the pandemic.

Accounting for Substitution Across Payment Types While the CB data has the advantage of capturing the universe of credit card transactions, it does not account for expenditures that are done using other payments types such as cash, cheques, or wire transfers for instance. We now turn to the CM data to evaluate the dynamics of expenditures for these different payment methods and assess whether the pandemic has caused a substitution across payment types.

Figure 17 shows the evolution of monthly aggregate expenditures for different payment methods, where we use the same normalization methodology as in Figure 1 above. Panel A reports the evolution of aggregate credit card expenditures in the CM data. For comparison, we also plot on the same graph the series from the exhaustive CB data. The two series display similar dynamics, although the CM series is a little more volatile. Panel B focuses on payments by cheque and shows that such payments have decreased more than credit card payments during the lockdown. Furthermore, they are still at a level that is 5 to 10% lower than pre-crisis level. Panel C shows similar patterns for cash withdrawals, which are currently 15% below their pre-crisis levels. This suggests that consumers have significantly moved away from cash payments in response to the pandemic. In panel D, we show the dynamics of total expenditures, that is credit card transactions, cash withdrawals, cheques (XX what about prelevements automatiques etc??). The graph confirms that accounting for all payment methods, the level of consumer expenditures has bounced back vigorously after the sharp contraction of the lockdown. However, the level of total expenditures is, after the lockdown, about 2 to 3% lower than what it would have been absent the pandemic.

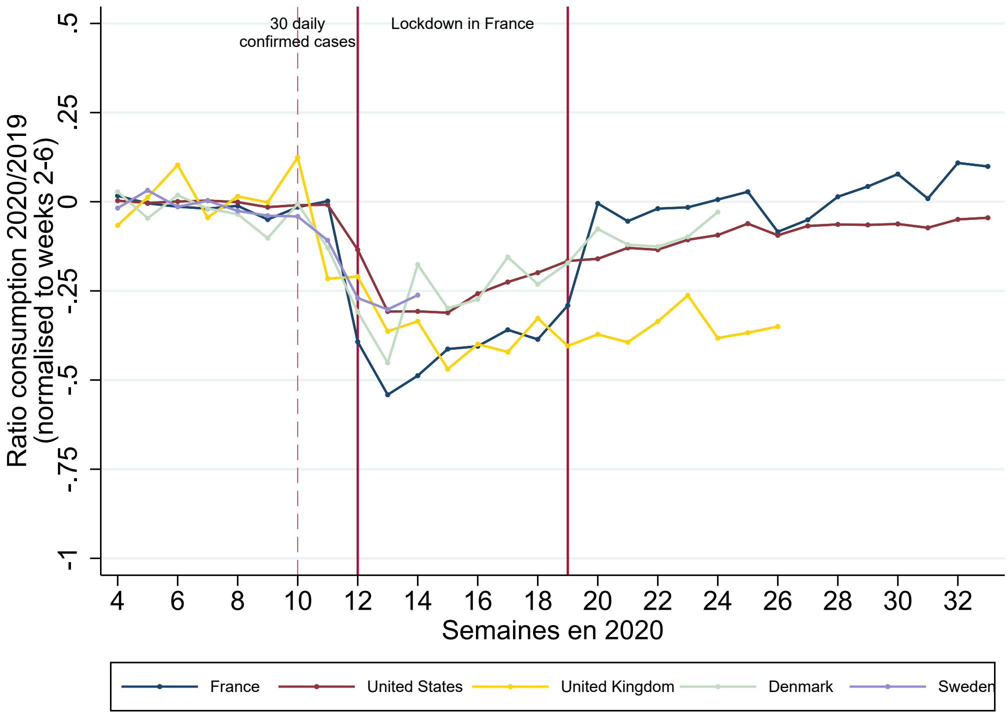
International Comparisons We now compare the evolution of consumption dynamics in France and in a series of countries for which similar data is available. The data for Denmark and Sweden comes from Andersen et al. [2020], the data for the US comes from Chetty et al. [2020] and the data from the UK is from Hacioglu, Känzig and Surico [2020]. For all countries, we use the same normalization as in Figure 1. Note that all five countries experienced a roughly similar timing for their first wave of the covid epidemic.

Several important insights transpire from this comparison. First, in the second half of March 2020, all five countries witnessed a sudden drop in spending, and this drop was of roughly similar magnitude. This happened despite the drastically different levels of severity of the restrictions put in place at that time across these five countries. This evidence prompted the interpretation that this is the epidemic, and not policies, that caused the severe contraction in spending (e.g. XX johanesen paper). Interestingly though, after this initial phase that saw remarkably similar dynamics across countries, consumer transactions have been experiencing drastically different patterns across countries. These differences suggest that the policy paths chosen by the different countries have had a significant impact on the dynamics of aggregate consumption. We see for instance that, countries like France, which entered a strict nation-wide lockdown, had a much more severe decrease in aggregate transactions, than countries that did not mandate nation-wide lockdowns like Sweden or the US. But we also see that after this initial phase of severe decline in consumption, the recovery in credit card transactions has been much more rapid in France than anywhere else. In the UK for instance, overall consumption remained heavily depressed throughout May and June. In panel B, we focus on the comparison between France and the US. Due to its severe lockdown, France experienced until May a decline in expenditures relative to the US equivalent to 2.6% in annual term (i.e. light grey area in panel B). But since the end of the lockdown, the quick recovery has made up for all this loss: French expenditures have recovered 2.6% in annual term relative to the US. As a consequence, so far, the cumulated decline in consumption expenditures over the year 2020 appears equivalent in both countries despite drastically different trajectories.

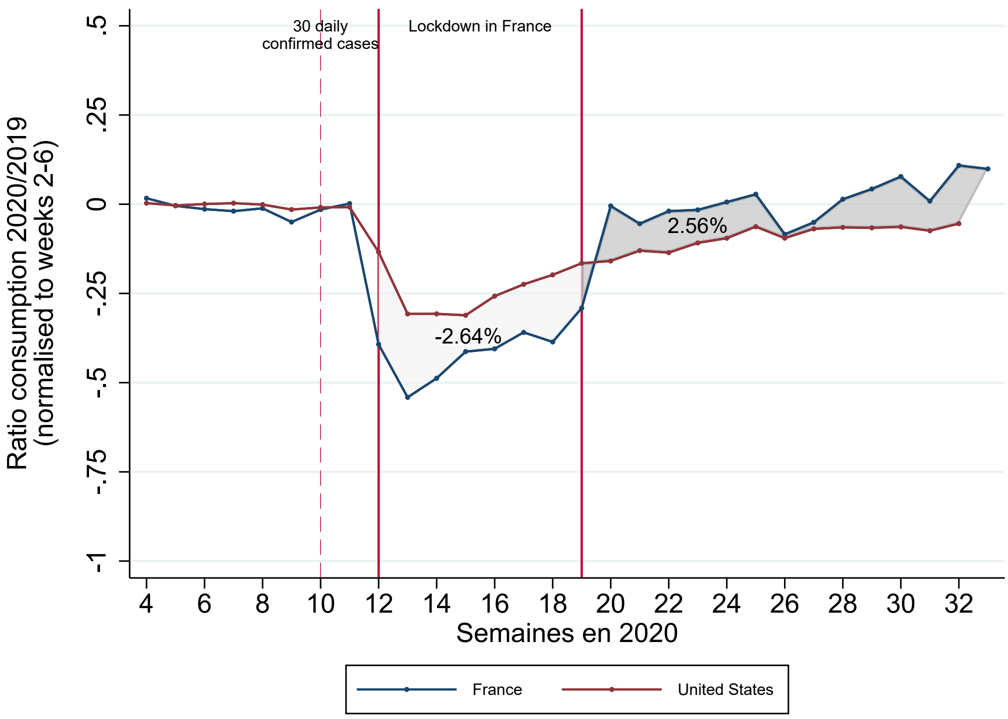
Overall, evidence from Figure 2 confirms that policies do actually matter, and that their impact must be measured by taking into account their full long run dynamic effects.

Figure 2: Evolution of Aggregate Weekly Credit Card Expenditures: International Perspective

A. Consumption Dynamics Across All 5 Countries



B. Comparing France & the US



Notes: The Figure reports the evolution of aggregate weekly credit card expenditures observed in the CB data following the same methodology as in Figure 1 in France and in four other countries. The normalization procedures deals with both seasonality in expenditures, and the overall trend in expenditures over time. The graph therefore measures how consumption deviates from its 2019 level, once accounting for the general trend that would have occurred between 2019 and 2020 absent the pandemic. Data from Denmark & Sweden comes from Andersen et al. [2020]. Data from the US comes from Chetty et al. [2020] and data from the UK comes from Hacioglu, Känzig and Surico [2020].

3.2 Household Balance Sheet & Savings Dynamics

The household balance-sheet data from CM allows us to also investigate the dynamics of household savings during the pandemic. We start by explaining the content of the household balance-sheet data currently available. What we observe in the data are:

- W_{it}^{B}: balances of all bank accounts held with CM in month t
- W_{it}^{S}: balances on all liquid savings accounts held with CM in month t (e.g. "comptes sur livret", PEL, etc)
- W_{it}^{M}: balances of all mutual funds held with CM in month t (e.g. "comptes titres")
- D_{it}: balance of all household debt held with CM in month t (e.g. consumer loans, credit card debt, etc.) also including mortgage

From this information, we create a measure of household financial wealth net of debt

$$W_{it} = W_{it}^{B} + W_{it}^{S} + W_{it}^{M} - D_{it} \tag{1}$$

It is important to acknowledge a couple of important limitations of this measure. First, we do not observe the balance of accounts or assets held outside the bank. Second, there are important components of the household balance sheet that we do not observe. In particular, at this point, we do not observe the value of real estate wealth W_{it}^{R} owned by households.In that sense, our measure is not a comprehensive measure of household wealth, but a measure of net financial wealth.

We start by documenting the evolution of our measure of household financial wealth. But we are also interested in measuring savings, that is, in separating what, in the dynamics of household wealth, is driven by the dynamics of asset prices, and what is due to active savings behaviors of household.

To define households' active savings, it is useful to start from the definition of the household budget constraint:

$$C_{it} = Z_{it} - \underbrace{\sum_{k} p_{kt} \left[A_{ikt} - A_{ikt-1}\right]}_{\text{Savings}}, \tag{2}$$

where Z_{it} captures all sources of income net of taxes and transfers, $\mathbf{A}_{it} = A_{i1t}, .., A_{iKt}$ denotes the portfolio of assets and $\mathbf{p}_{t} = p_{i1t}, .., p_{iKt}$ the corresponding vector of prices at which they are traded. We can re-write the asset component of the identity in (2) as

$$p_{kt} \Delta A_{ikt} = \Delta W_{ikt} - \Delta p_{kt} A_{ikt-1},$$

where we use the difference notation $\Delta X_t = X_t - X_{t-1}$. The above expression highlights that only the active rebalancing of assets participates in the flow of active savings. To measure active savings, we therefore need to substract from the change in the value of the portfolio (ΔW_{it}) the passive gains on assets induced by changes in the price of these assets.

In practice, we do not observe the prices for each individual asset held by each household to offer a household-specific measure of passive capital gains on each asset class. We therefore operationalize our measure of savings in the following way:

$$S_t = \Delta W_{it} - \overbrace{\frac{\Delta p_t}{p_{t-1}} \cdot W^M_{it-1}}^{\text{Passive K gains}} - Y^S_{it} + \underbrace{r_t \cdot D_{it}}_{\text{Interests on debt}}$$

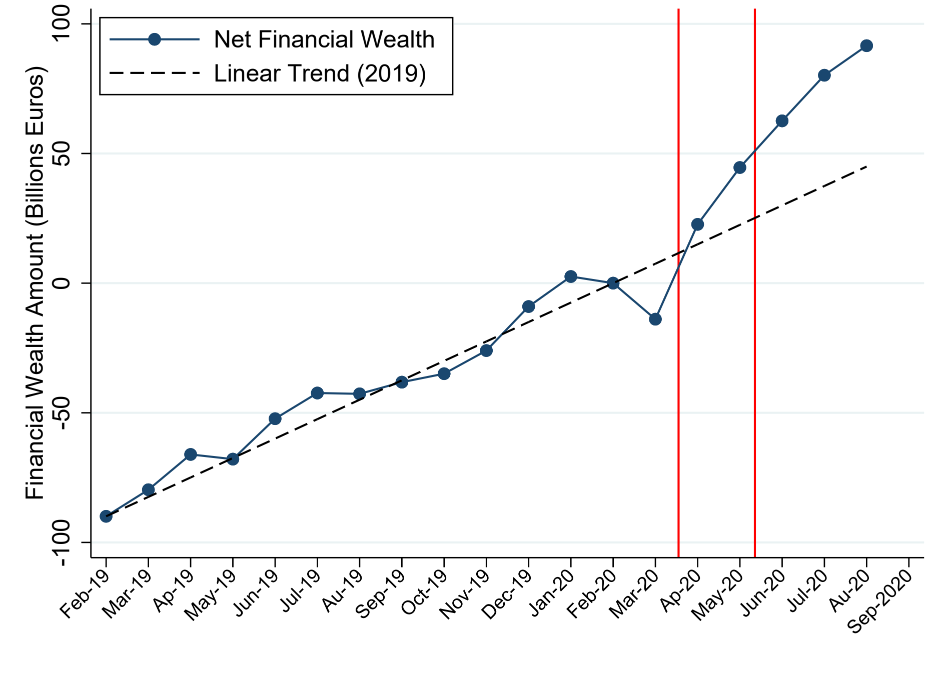
That is, we use the evolution of average prices of stocks to measure passive capital gains on wealth held in mutual funds (W^M_{it}), and the average interest rate on debt to measure the contribution of the change in the price of household debt. Y^S_{it} is the observed interest income on liquid savings accounts.

Kolsrud, Landais and Spinnewijn [2020] and Eika, Mogstad and Vestad [2020] provide a detailed discussion of the measurement error created by using average (rather than individual-specific) price indices to retrieve savings and consumption flows from household balance-sheet data.

Dynamics of Net Financial Wealth W_t. In Figure 3, we present the evolution of total net financial wealth, normalized to zero at the end of January 2020. Note that aggregate wealth is computed using our designed sample weights, so that we interpret this total as representative of total net financial wealth (as defined in (1)) in the population living in the French Metropolitan area. The Figure shows that, after a sharp initial dip in March 2020, W_t rebounded strongly. Overall, W_t has grown by about €90 billions between January 2020 and beginning of September 2020. The Figure also highlights that W_t was already trending strongly upwards in 2019. We report in red on the graph the linear trend in W_t computed over the period January 2019 to January 2020. We measure the effect of the pandemic shock on wealth W_t as the deviation from this trend. We find that total net financial household wealth has increased by €5X billions in the aftermath of the covid crisis, relative to the counterfactual of what would have happened if it had continue to grow according to its 2019 trend.

In Figure 4, we decompose the evolution of net financial wealth W_t into its different components. For each component W^k_t observed in month t, we deal with both seasonality and trend using the same methodology as in Figure 1. That is, we report the ratio

Figure 3: Estimated Evolution of Total Net Financial Wealth W_t



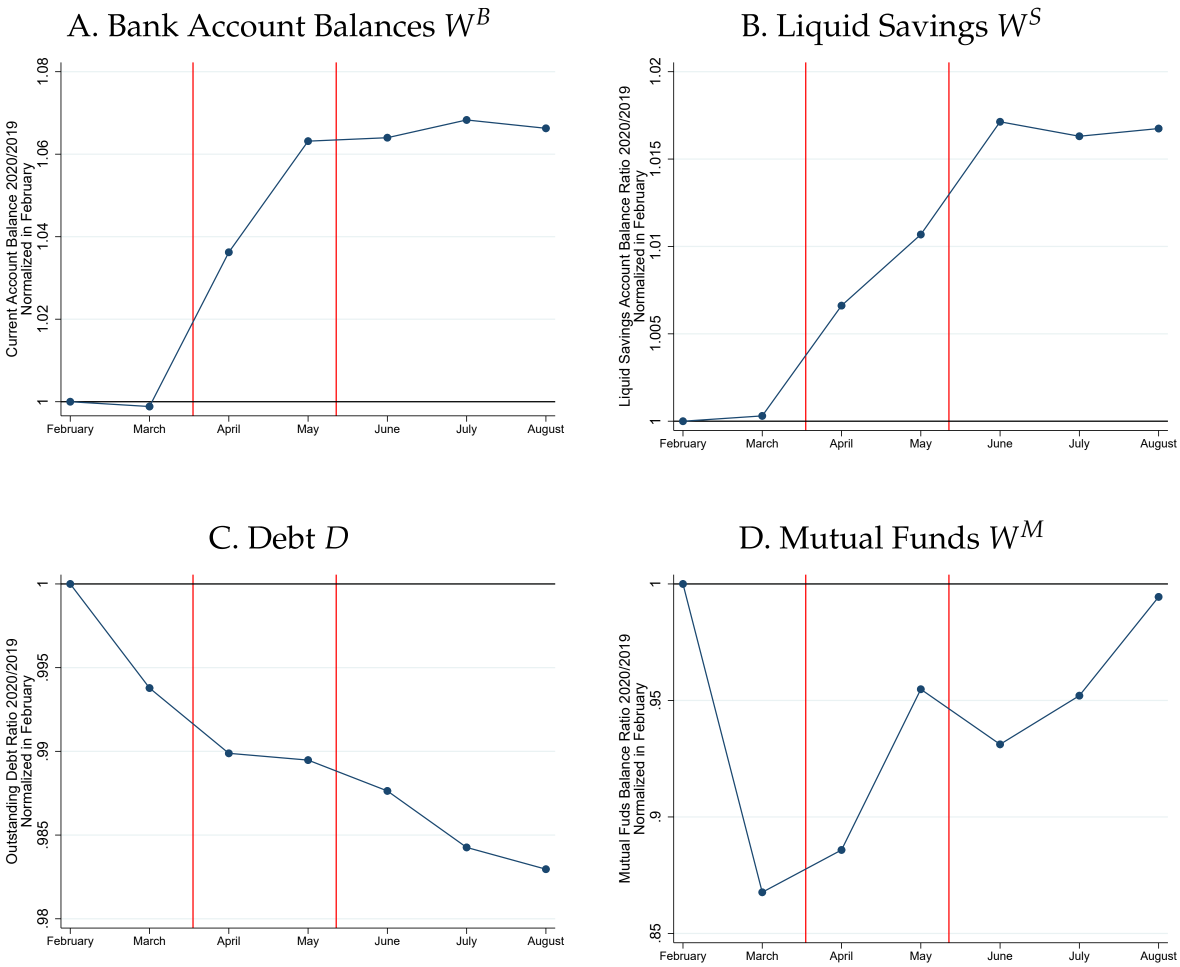
Notes: The Figure reports the evolution of total net financial wealth W_t as defined in equation (1), and normalized to zero at the end of January 2020. The total is weighted by our sample weights to reflect total net financial wealth in the whole population living in the French metropolitan area. Net financial wealth does not include real estate wealth, but includes mortgage debt. See text for more details on our measure of W_t and its potential limitations. The figure also reports in red the overall linear trend in W_t computed over the period January 2019 to January 2020. We measure the effect of the pandemic shock on wealth as the deviation from this trend.

$(W_t^{k,2020}/W_t^{k,2019})/(W_{Jan}^{k,2020}/W_{Jan}^{k,2019})$. Panel A shows the evolution of bank account balances. Bank account balances experienced a sharp increase during the lockdown period, increasing by more than 6% in two months, compared to the counterfactual of what would have happened if they had remained on their 2019 trend. After the lockdown, balances have remained stable, showing no sign of dissaving or reallocation towards other asset classes. Panel B shows a very similar pattern for liquid savings accounts: their balances have increased by 1.75% during the lockdown period and have not decreased after.[7]. In panel C, we report the evolution of total household debt: we see that the stock of household debt has decreased significantly, by about 2% in the aftermath of the covid crisis. This reflects the fact that household have used liquidity to pay back their debt. But it also driven by a decrease in the evolution of new credit lines, due to decreased consumption opportunities and the slowdown in the number of transactions in housing market. Finally panel D displays the evolution of mutual fund balances. It shows that the pandemic was initially met by a sharp de-

[7]Note that these balances are far larger than bank account balances. The overall contribution of each asset class to the evolution of total net financial wealth is given in Figure 5

cline in the value of mutual funds held by households, but that mutual funds balances have reached back their pre-crisis level by the end of August. These brutal evolutions are clearly driven by the evolution in asset prices. The pandemic shock triggered a sudden and global drop in stock prices and other asset prices. Interestingly there has been a quick recovery in asset prices following this initial crash: stock price indices are almost back to their pre-crisis level. This means that, once removing the effects of passive capital gains, there has not been much extra active savings in mutual funds so far.

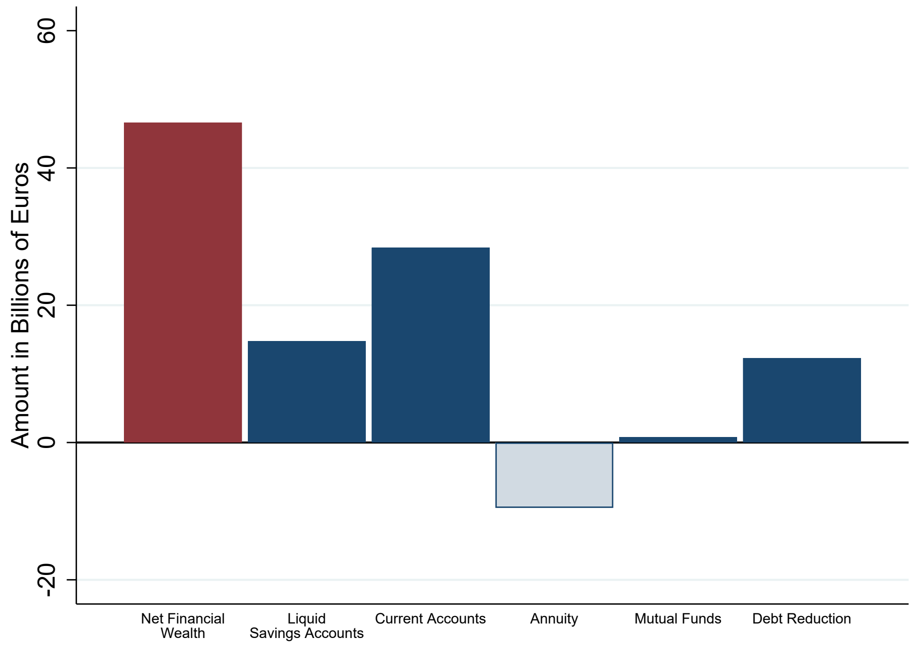
Figure 4: Detrended Evolution of the Different Components of Net Financial Wealth (2020)



Notes: The Figure reports the evolution of the different components of net financial wealth W_t as defined in equation (1). For each component W_t^k observed in month t, we deal with both seasonality and trend using the same methodology as in Figure 1. That is, we report the ratio $(W_t^{k,2020}/W_t^{k,2019})/(W_{Jan}^{k,2020}/W_{Jan}^{k,2019})$, and therefore, we measure the effect of the pandemic shock as the deviation from the 2019 trend. Panel A shows the evolution of bank account balances W_t^B. Panel B focuses on liquid savings, panel C reports the evolution of total debt including mortgage, panel D reports the evolution of mutual fund balances. See text for details.

In Figure 5, we summarize these findings by computing the contribution of each asset class to the evolution of total net financial wealth over the period January 2020 to August 2020. The left bar on the histogram corresponds to the excess net financial wealth of €5X billions generated during the covid crisis. The histogram shows that the bulk of this extra financial wealth has been held in liquid accounts (bank and liquid savings accounts). It also shows that the reduction in household debt has been an important contributor to the increase in aggregate net financial wealth of French households during the pandemic.

Figure 5: Contribution of Each Asset Class to Excess Total Net Financial Wealth Created Over the Period January 2020 to August 2020



Notes: The Figure reports the contribution of each asset class to the evolution of total net financial wealth W_t over the period January 2020 to August 2020. For each component W_t^k observed in month t, we deal with both seasonality and trend using the same methodology as in Figure 1. That is, we report the ratio $(W_t^{k,2020}/W_t^{k,2019})/(W_{Jan}^{k,2020}/W_{Jan}^{k,2019})$, and therefore, we measure the effect of the pandemic shock as the deviation from the 2019 trend. Panel A shows the evolution of bank account balances W_t^B. Panel B focuses on liquid savings, panel C reports the evolution of total debt including mortgage, panel D reports the evolution of mutual fund balances. See text for details.

4 Sectoral Heterogeneity

The richness of the CB data allows to document the large sectoral heterogeneity in the severity of the covid shock.

4.1 Durables

We start by focusing on expenditures on durable goods. We define durable goods as cars, motorcycles, home appliances, IT, furniture, and jewelry.[8] The dynamics of expenditures on durables is in important signal regarding the underlying mechanisms driving consumption dynamics. First, because, contrary to other goods or services, durables allow for intertemporal substitution. If the effect of the severe lockdown on consumption was entirely driven by incapacitation effects, then we should see almost perfect intertemporal substitution. And durable expenditures would catch up post lockdown the losses made during the lockdown period. But durable consumption is also an important signal regarding households' expectations and is often strongly correlated with cyclical variation in economic activity, dipping strongly in recessions. The reason is that durables are an important means of consumption insurance against the expectations of future shocks. In the face of a future expected shock, one can use durables to smooth consumption over time without having to incur new expenditures.

In Figure 6 below, we report in panel A the evolution of consumption expenditures on durables observed in the CB data following the same approach as in Figure 1 to account for trends and seasonality. The Figure shows that, after a very large decline during the lockdown period, expenditures on durable goods have bounced back significantly right after lockdown and have been at a significantly higher level than in 2019 ever since. Overall, this strong pattern of intertemporal reallocation of expenditures has enabled to recoup almost two thirds of the losses made during the lockdown period.

4.2 Hospitality

In panel B of Figure 6, we report, following a similar methodology, the evolution of expenditures in the hospitality sector, defined as sector codes "56", "90", "91" and "93" in the French NAF classification. The patterns are markedly different compared to panel A. We see that the hospitality sector has been severely impacted by the lockdown, but

[8] This corresponds to the following sectors in the French NAF classification of sectors: "451", "453","454", "474", "475", "4777".

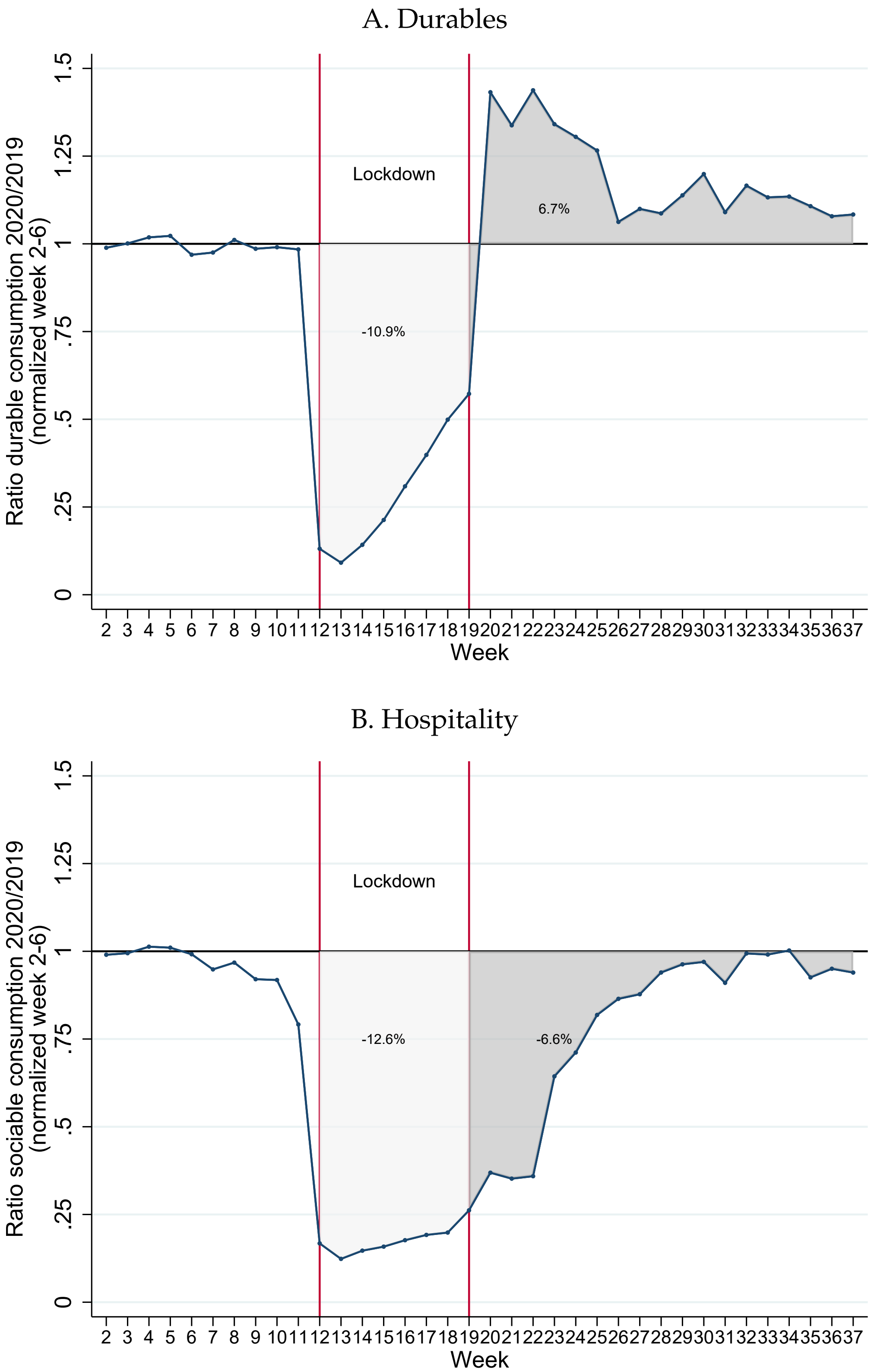
did not experience a quick rebound after. Various administrative restrictions have remained in place in these sectors throughout the summer months, such that in annual terms it has lost 6.6% of annual expenditures since the end of the lockdown. When added to the 13% annual expenditures already lost during the lockdown, this makes for a historic and dramatic loss for 2020. Furthermore, hospitality expenditures have been declining since the end of August, as new cases started to rise in France, prompting new administrative measures restricting consumption in these sectors.

4.3 Overall Heterogeneity Across Sectors

In Figure 7, we report the total annualized gains or losses in expenditures made by each sector during the lockdown period, and the post-lockdown period. Results provide a clear picture of the extreme heterogeneity in the severity of the shock across sectors, something that is quite unique compared to previous recessions. Overall, the majority of sectors was confronted with heavy losses in expenditures during the lockdown period, with only a few sectors doing better than in 2019. But interestingly, some sectors did compensate for these losses during the post-lockdown period with a significant rebound in expenditures (hardware stores, bookshops, etc). In contrast, some sectors continued to face extremely depressed expenditures (travel agencies, museums, leisure centers, etc).

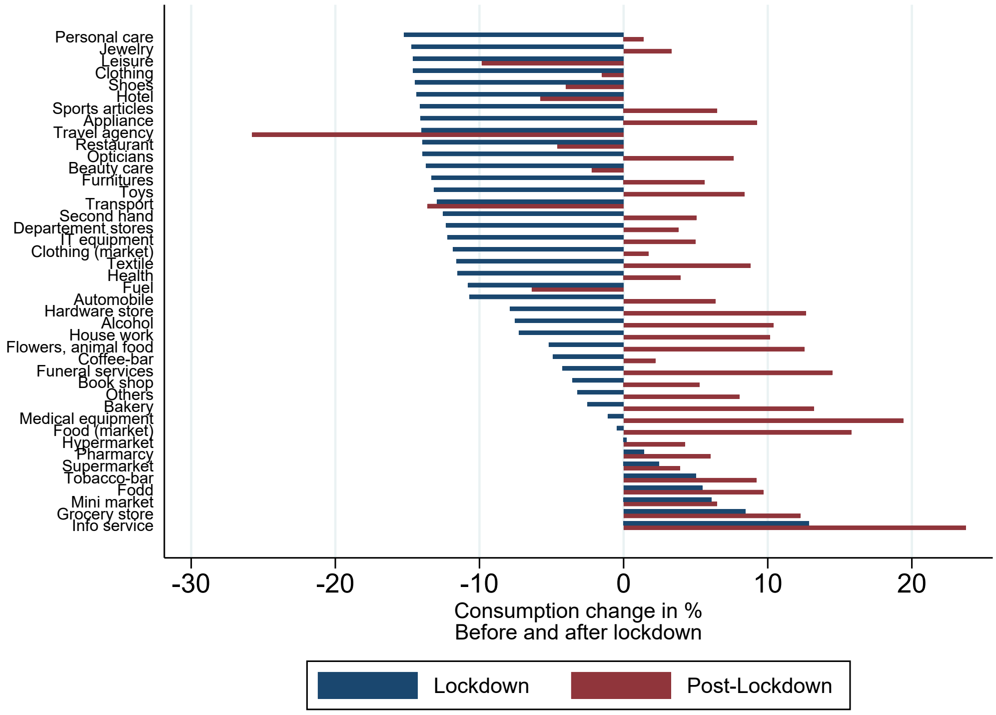
These results indicate that sectors face extremely heterogeneous prospects in terms of recovery, and different needs in terms of public policies. While some sectors have experienced temporary losses that did affect their liquidity but not their solvency in the near future, others have faced permanent losses, and cannot anticipate a recovery in terms of expenditures as long as the epidemic is not brought into control. These sectors are now facing extremely severe solvency issues, and their needs can only be addressed via targeted sectoral policies.

Figure 6: Evolution of Consumption Expenditures By Sector



Notes: The Figure reports the evolution of aggregate weekly credit card expenditures observed in the CB data following the same methodology as in Figure 1 for different sectors. The normalization procedures deals with both seasonality in expenditures, and the overall trend in expenditures over time. The graph therefore measures how consumption deviates from its 2019 level, once accounting for the general trend that would have occurred between 2019 and 2020 absent the pandemic. Durables correspond to sectors "451", "453","454", "474", "475", "4777" according to the French NAF classification of sectors. The hospitality sector corresponds to sectors "56", "90", "91" and "93".

Figure 7: Total Expenditure Change in Annual Terms by Sector During the Lockdown and Post-Lockdown Periods



Notes: The Figure reports the evolution of aggregate weekly credit card expenditures observed in the CB data by sector during the lockdown period (in blue) and post-lockdown period (in red). We follow the same normalization methodology as in Figure 1 to control for both seasonality and the overall trend in expenditures over time. We cumulate the difference between 1 and these normalized expenditures for each week during the lockdown and post lockdown periods. We then convert the cumulated difference in annual terms, to measure the overall losses or gains made during each period as a fraction of annual 2019 expenditures in each sector.

5 Distributional Effects

We now turn to documenting heterogeneity in the responses of household consumption and savings to the crisis.

We first rank households in the CM panel according to their level of total expenditures in 2019. The CM data does not enable us yet to measure income flows precisely, and total consumption expenditures offer a good proxy for the standard of living of a household pre-crisis.[9] In Figure 8, we show in panel A the evolution of total consumption expenditures for different deciles of the distribution of pre-crisis expenditures. The graph shows that households in the bottom of the distribution of pre-crisis expenditures experienced a smaller decrease in consumption during the lockdown, and a steeper rebound during the summer months. This finding of an overall larger decline in consumption for richer households is reminiscent of the results in Chetty et al. [2020]. Note that their results are based on correlations between aggregate card expenditures and average income across zip codes, while our approach is based on individual level variation in "income" levels.

Interpreting these differential consumption patterns is not straightforward. They may first reflect differential variations in income or in income expectations. But they may also be due to differential perceptions regarding the risk of getting infected or severely ill, perceptions which may ultimately affect consumption behaviors. Finally, they may also simply reflect differential incapacitation in the face of the restrictions (e.g. lockdowns, etc) put in place by the the government: individuals have the top end of the income distribution have usually a much larger share of their expenditures in sectors that have been shut down by the pandemic (travels, leisure, hospitality, etc.). It is important to understand which of these three main channels is driving consumption patterns to understand the distributional and welfare effects of the shock.

We start here by focusing on the role of income fluctuations and income expectations. Ideally, of course, we would like to be able to observe income, and its differential evolution across households. Unfortunately, we do not have (yet) a robust measure of income in the CM data. But by combining the patterns of evolution of consumption and household financial wealth in the CM data, we can get a good indication of what has happened to income, using households' budget constraint identity (2). In panel B of Figure 8, we report the evolution of total gross savings, defined as the sum of current account balances, all liquid savings account balances, and of all mutual funds balances held in the bank, for different deciles of the distribution of 2019 total expenditures. Once again, we take care of trends and seasonality, using the same approach as in panel A. The graph shows that the crisis has caused a decline of about 2% of

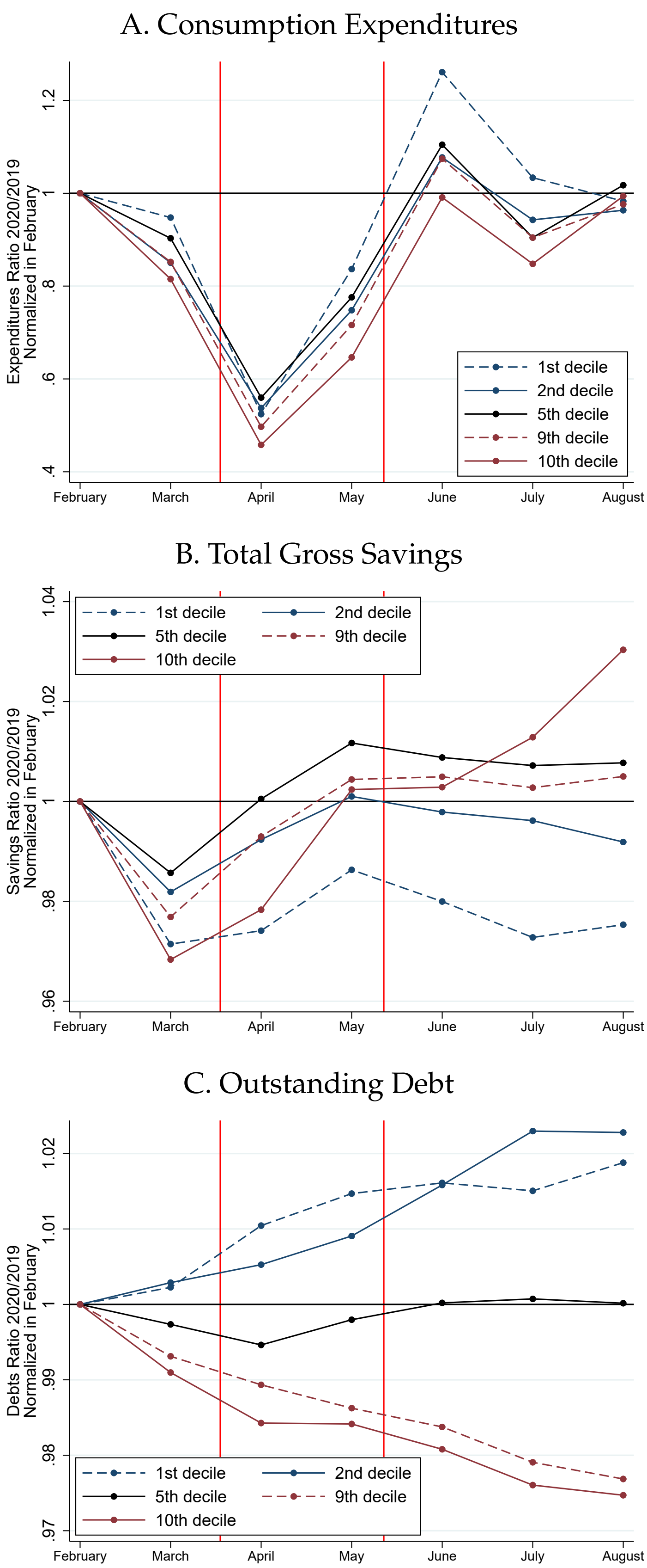
[9] Total expenditures are defined as credit card transactions, check payments and cash withdrawals.

the total gross financial wealth for the "poorest" households (i.e. the bottom deciles of the distribution of pre-crisis expenditures). For households in the middle of the distribution (5th decile), the crisis has created a small increase of about 1% of their gross financial wealth, after an initial dip in March, due to the crash in asset prices. Interestingly, households at the top end of the distribution saw a larger dip than other households in gross financial wealth in March, due to the larger fraction of their financial wealth held in risky assets. But after this dip, the situation reversed: as of August, households in the 10th decile have experienced the largest increase in financial wealth in percentage terms (i.e. of about 4%). This rebound reflects both the rebound in asset prices following the initial crash, but also the steady flow of savings maintained by these households since the start of the pandemic.

In panel C, we investigate the evolution of outstanding debt by deciles, and use the same approach as before to detrend the data and take care of seasonality. We find that poorest households have seen a significant increase in their outstanding debt since the start of the crisis. To the contrary, households at the top end of the distribution of pre-crisis expenditures have experienced a large decrease in the stock of their outstanding debt, reflecting movements both at the intensive margin (debt repayments), and extensive margin (fewer new debt contracts). Overall, the patterns reported in all three panels of Figure 8 suggest that households at the bottom of the distribution, experienced both a decline in consumption and a decline in their net financial wealth. Inverting their budget constraint's identity, this is direct evidence that they experienced a significant drop in income. Clearly, these households have been strongly affected by the pandemic crisis, and, contrary to households at the top end of the distribution, have not been able to create a buffer of savings during the lockdown.

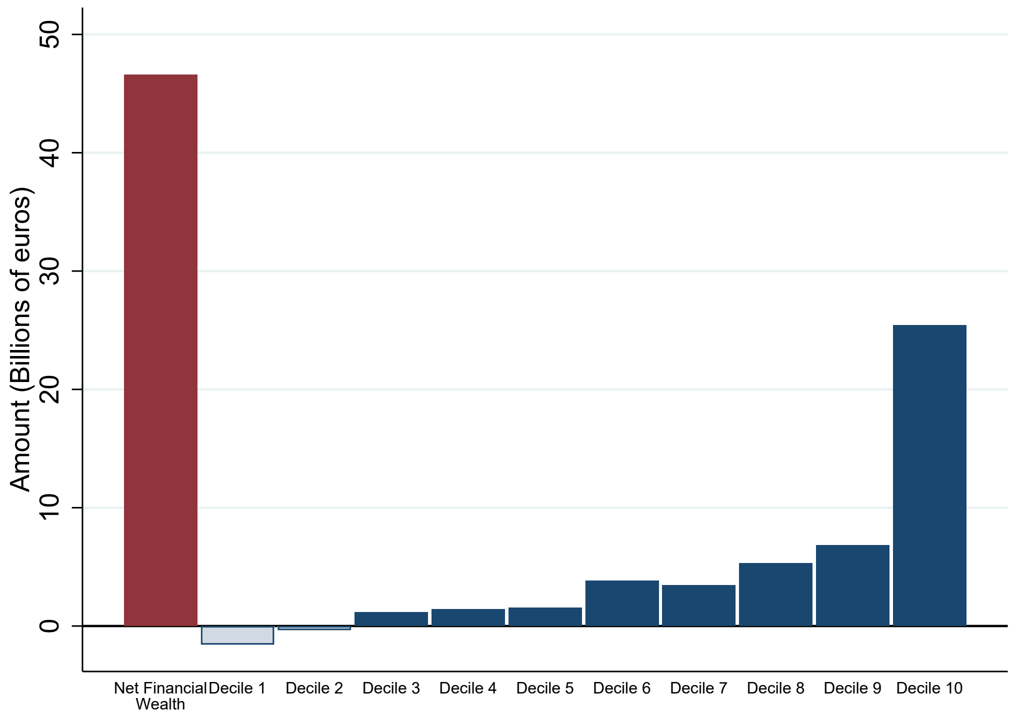
In Figure 9, we compute the contribution of each decile of pre-crisis expenditures to the excess growth in net financial wealth over the period February to August 2020. The graph shows that the contribution of the poorest deciles was negative, as they experienced a decline in their net financial wealth. It also shows that more than 70% of the €45 billions in excess wealth have accrued to the top two deciles. And 55% alone of this excess wealth went to the top decile. Given these top two deciles accounted for a little less than 45% of total net financial wealth before the pandemic, this suggests that the crisis has generated an increase in wealth inequality.

Figure 8: Dynamics of Consumption, Liquid Savings and Debt by Deciles of 2019 Total Expenditures



Notes: The figure reports the evolution of total expenditures (panel A), total gross savings (panel B) and outstanding debt (panel C) from the CM data. We break down the sample by deciles of 2019 total expenditures to proxy for differences across households in terms of income. In each panel, and for each decile, we detrend the data and take care of seasonality using the same methodology as in Figure 1. Total gross savings are defined as the sum of current account balances W_{it}^{B}, all liquid savings account balances W_{it}^{S}, and of all mutual funds balances W_{it}^{M} held in the bank.

Figure 9: Contribution to the "Excess" Growth in Net Financial Wealth by Deciles of Expenditures in 2019



Notes: The figure reports the contribution of each decile of pre-crisis expenditures to the excess growth in net financial wealth over the period February to August 2020, computed from the CM data. Excess growth is computed in Figure 3 as the deviation in observed net financial wealth compared to the counterfactual of the 2019 linear trend. It amounts to about €45 billions.

6 What Is Driving Consumption Dynamics?

We now investigate the role of three potential drivers of consumption dynamics during the pandemic. First, we focus on the role of income dynamics and income expectations. For this, we estimate marginal propensities to consume using the granularity of our data. Second, we explore the role of health risk. Finally, we measure the impact of restriction policies.

6.1 Income Dynamics & Marginal Propensities to Consume

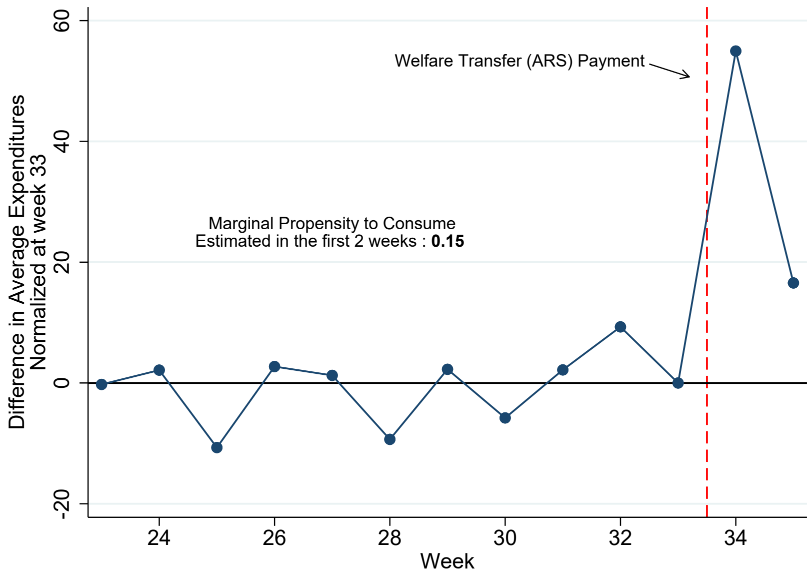
To evaluate the role of income dynamics in explaining consumption and savings dynamics, we focus on estimating marginal propensities to consume (MPC). MPCs measure the sensitivity of consumption to income changes and are therefore important to understand the aggregate demand effects of transfer and stimulus policies put in place during the crisis. Furthermore, MPCs reveal households' expectations about the future. The presence of strong precautionary saving motives for instance would translate into low MPCs, indicative that households prefer to use any extra income to build a buffer stock of savings in the face of uncertain income and employment dynamics. Finally and importantly, MPCs also help capturing the social value of transfers. Landais and Spinnewijn [forthcoming] show that, under particular assumptions, heterogeneity in MPCs can identify heterogeneity in the underlying price of raising an extra € of consumption. As a result, while consumption dynamics alone is a poor guide to evaluate the welfare consequences of a shock, heterogeneity in MPCs is key to measure the differential welfare impacts of such shocks, and determine the redistributive and social value of transfers.

Identifying MPCs To identify MPCs, we exploit eligibility criteria for a specific welfare transfer called the "Allocation de Rentree Scolaire" (ARS). This welfare transfer is a one-time payment made in August, just before the start of the school year, to families with children above 6 years old. The transfer is means-tested. This year, the regular amount was topped-up by an extra €100 payment, so that eligible families received €470 per child for children between six and ten years old. We focus on households in the CM panel with one or two children meeting the means-test requirement to receive the payments. We then create two groups from this subsample. The treatment group comprises households with just one child, whose age is between 6 and 10 years old, as well as families with two children, with one of them being between 6 and 10 years old and the other between 3 and 5 years old. The control group is made of households with just one child, whose age is between 3 and 5 years old, as well as families with two children, both of them being between 3 and 5 years old. The treatment group receives a €470 ARS payment on August 18th, while the control group does not receive any payment on this date. Identification relies on a standard diff-in-diff assumption of parallel trends.

Figure 10 shows the difference in average weekly expenditures between households in the treatment and control group, normalized to zero in week 33. The difference was extremely stable in the weeks preceding the ARS payment, lending credibility to our diff-in-diff identifying assumption. We see a sudden and sharp increase in consumption expenditures by households in the treated group in week 34, just after they receive the ARS welfare payment. When scaled by the value of the transfer (i.e. €470), this sharp increase in expenditures translates into a MPC estimate of .15 for the first two weeks. These findings are consistent with estimated expenditures responses to CARES Act stimulus payments in the US, from Chetty et al. [2020] (who use aggregate card transaction data), as well as from Baker et al. [2020] and Karger and Rajan [2020] who use individual transaction data. Note that the estimated MPCs from the latter two studies are slightly higher (around .2 to .25) but they both rely on samples primarily made of lower-income individuals (compared to the population eligible to ARS).

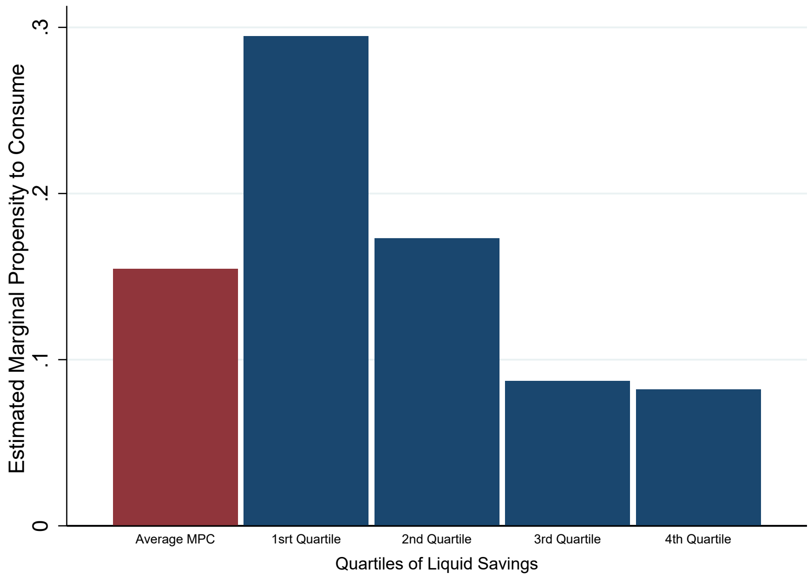
In Figure 11, we show the presence of strong heterogeneity in estimated MPCs. We split the estimation sample by quartiles of liquid savings, defined as the sum of current account balances W_{it}^{B}, all liquid savings account balances W_{it}^{S}, and of all mutual funds balances W_{it}^{M}. The graph shows that estimated MPCs are three times larger for households in the bottom quartile of liquid savings compared to households in the top quartile.

Figure 10: Estimating Marginal Propensity to Consume: Difference in Average Weekly Total Expenditures Between Households Eligible to ARS and Households Ineligible to ARS Based on the Child Age Cutoff



Notes: The graph reports the difference in average weekly expenditures between households in the treatment and control groups, normalized to zero in week 33. The treatment group is made of households with just one child above 6 years old and eligible to the ARS payment of €470 on August 18th. The treatment group is made of households with the same number of children, but with children below the 6 years old age cutoff to benefit from the payment. See text for details.

Figure 11: Estimated Marginal Propensity to Consume from the ARS Payment By Level of Liquid Savings



Notes: Panel reports the diff-in-diff estimate of the marginal propensity to consume from the ARS payment using the CM data. We split the estimation sample by quartiles of liquid savings, defined as the sum of current account balances W_{it}^{B}, all liquid savings account balances W_{it}^{S}, and of all mutual funds balances W_{it}^{M} held in the bank.

6.2 Health Risk

Time Series & Cross-sectional Geographical Evidence How much is consumption dynamics impacted by the increased health risk that people face due to the pandemic? The first natural approach is to look at time series and cross-sectional variation in the severity of the epidemic, and use this variation to estimate correlation with consumption expenditures. In Figure 12, we plot the evolution of ICU admissions in France against the evolution of aggregate daily card transactions in the CB data, using a 7-day moving average.[10] The graph shows the presence of a strong correlation in the time series between virus dynamics and aggregate consumption behaviors. In particular, the graph shows that aggregate consumption has started to falter since mid-September, as the second wave of the epidemic was gaining strength in France. Cross-sectional variation confirms the presence of a strong correlation between virus spread and aggregate consumption: in panel B, we display an binscatter of aggregate log CB consumption in September 2020 (relative to log aggregate CB consumption in September 2019) by "departement", against the number of average daily new confirmed cases in September by "departement".[11] The binscatter is residualized on a series of controls for observable characteristics at the departement level, including population size, density, occupational structure of the workforce, age structure of the population. The graph indicates clearly that departements in which the number of cases is the highest in September are also facing the lowest level of aggregate card transactions.

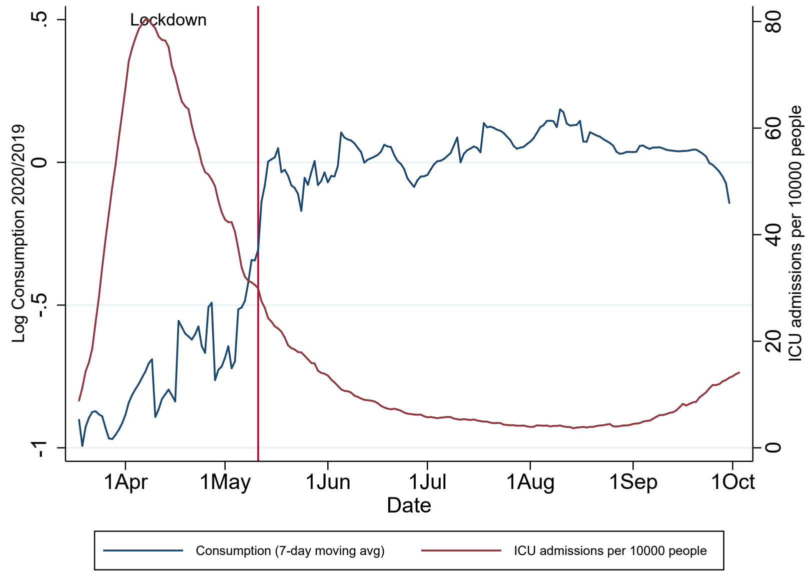
Evidence from Figure 12 clearly indicates that the steady and quick rebound of aggregate consumption observed in France during the Summer months is now at risk, and there is a clear slowdown of expenditures since mid-September, as the second wave is looming. However, it is hard to interpret the correlations from Figure 12 as direct evidence of a causal link between health risk and consumption dynamics, as there is a strong correlation in the time series and in the cross-section between the severity of the epidemic and restriction policies. To counter the rapid spread of the virus, the French government has indeed strengthened restrictions since early September, and enabled local jurisdictions to take targeted restrictions and lockdown measures.

[10] ICU admissions come from the official data series released by the French government on the "Sante Publique France" web portal.

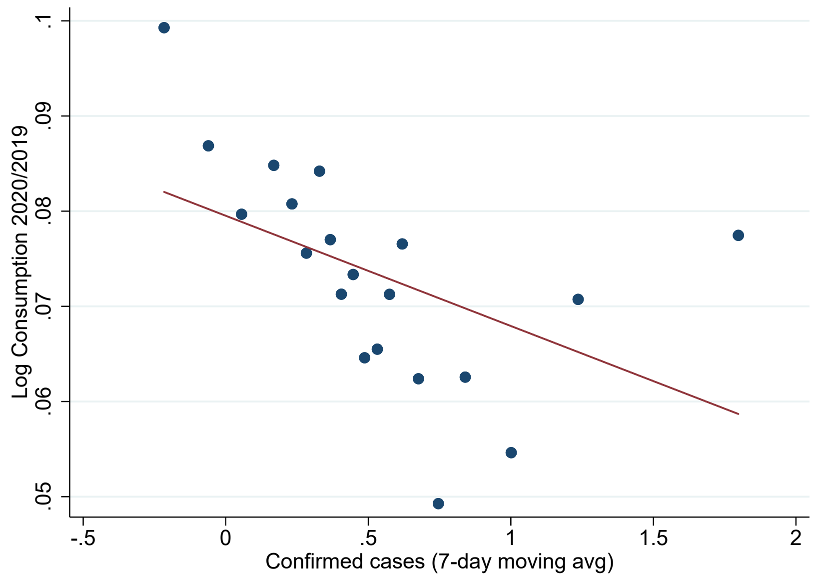
[11] A "departement" is a French political jurisdiction. There are about 100 "departements" in France. Numbers of daily new confirmed cases by departement come from the "Sante Publique France" web portal.

Figure 12: Health Risk & Consumption Dynamics

A. Time Series of CB Card Transactions & ICU Admissions



B. Cross-sectional Variation in New Cases
& CB Card Transaction by "Departement"



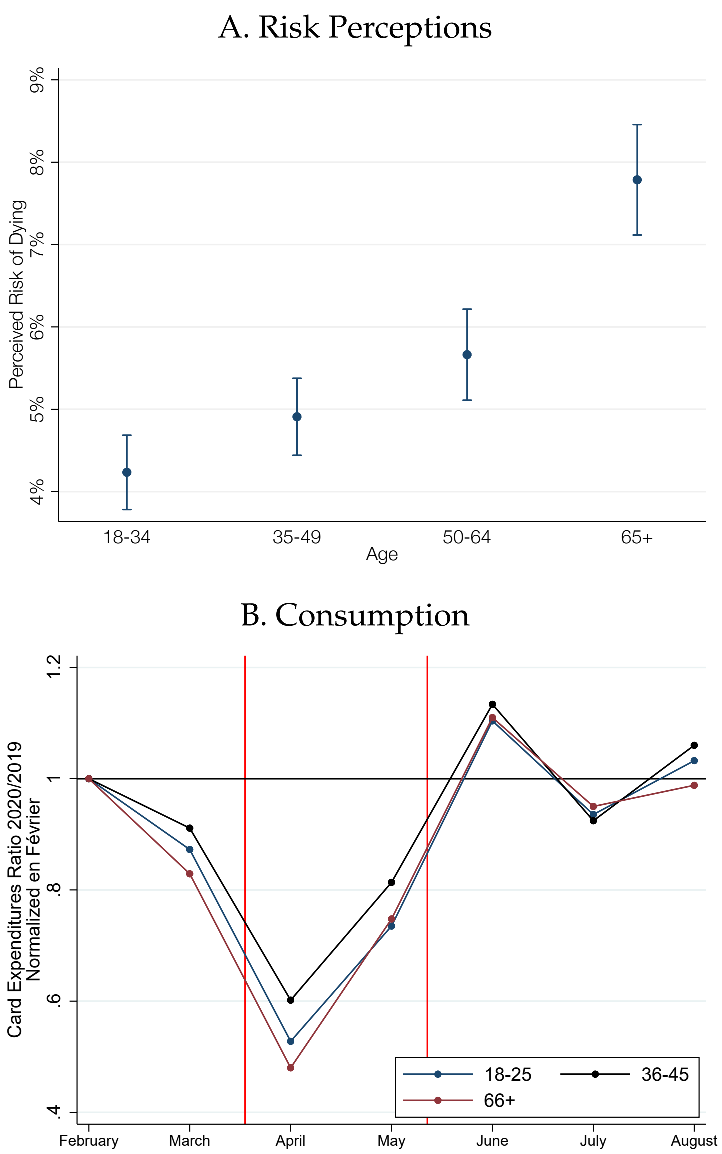
Notes: Panel A reports the evolution of ICU admissions (right axis) and of consumption in the CB data (left axis). Panel B is a binscatter of aggregate log CB consumption in September 2020 (relative to log aggregate CB consumption in September 2019) by "departement", against the number of average daily new confirmed cases in September by "departement". The data is first residualized on a series of observable characteristics at the departement level, including population size, density, occupational structure of the workforce, and age structure of the population. The health data comes from the dashboard of the web portal "Sante Publique France" of the French government.

Age Variation To try to identify the causal relationship between health risk and consumption dynamics, we examine heterogeneity in patterns of consumption across age groups. There has not been any age-specific restriction policies put in place during the pandemic, that may confound the correlation observed between age and consumption. Furthermore, there is a clear gradient in health risk by age, as older people are more likely to die from the new coronavirus. To identify first how risk perceptions varied by age, and correlate with actual risk, we use elicited risk perceptions of dying from the coronavirus from the DataCovid survey, which was conducted in June on a random representative sample of 5,000 individuals. Three insights emerge from this panel. First, the overall average elicited risk of dying strongly overstates the true actual risk of dying from the virus. Second, we find a strong gradient in elicited risk, with older people clearly perceiving their higher likelihood of dying from the virus. But thirdly, the gradient is smaller than the actual gradient in true risk. Epidemiological studies suggest that individuals above 65 years old are 4 to 5 times more likely to die from the virus than individuals below 40 years old. In the survey, we see that this gradient is only of about 2: older individuals believe on average to be about 2 times only more likely to die than 18-34 years old. This indicates that there is strong upward bias in risk perception in younger individuals, compared to older individuals.

In panel B, we investigate to what extent these differential percpetions translate into consumption dynamics. We use the CM data and plot the evolution of total expenditures for three age groups. We see that during the lockdown period, consumption of the elderly decreased significantly more than that of younger age groups. But interestingly, we see that as soon as the lockdown ended, consumption patterns reverted back to their 2019 levels for all age groups, without significant differences in consumption dynamics during the summer months. Note that if we break down consumption by sectors, we do find that the consumption structures of the elderly changed compared to younger age groups: the elderly are less likely to engage in consumption involving social interactions (restaurants, etc). Yet, these differences in structure do not seem to impact aggregate consumption levels, suggesting the presence of strong substitution across consumption types.

These results suggest that health risk perceptions may have been less consequential than restriction policies to explain, in the French context, the strong correlation between the dynamics of the epidemic, and that of consumption. To confirm this, we now turn to identifying the effect of restriction policies more directly.

Figure 13: Elicited Risk Perceptions and Consumption Dynamics By Age Groups



Notes: Panel A reports average elicited risk perceptions of dying from the coronavirus by age group. The data comes from the 8-th wave of the DataCovid survey, which took place in June, and surveyed a random representative sample of 5,000 French individuals. Panel B shows the evolution of consumption expenditures by age group in the CM data. We follow the same methodology as in Figure 1 to take care of seasonality and detrend the data.

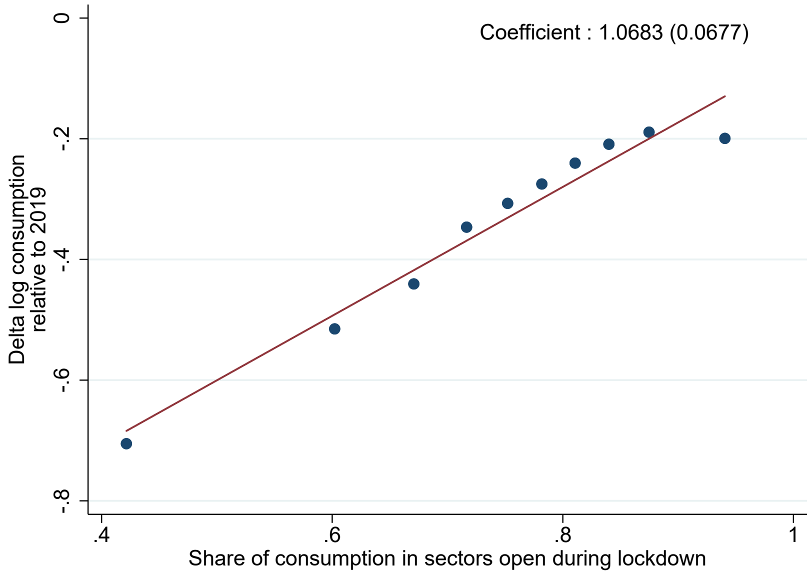
6.3 Lockdown & Restriction Policies

To investigate the effect of restriction and lockdown policies, we exploit geographical variation in the severity of the lockdown based on the structure of expenditures pre-crisis. For each sector, we compute an indicator variable equal to 1 if that sector ended up being closed by an administrative decree during the lockdown period.We compute for each ZIP code, using the CB data, the fraction of total expenditures made in 2019 in sectors that ended up remaining opened (i.e. not closed by decree) during the lockdown. This fraction represents our measure of exposure to the lockdown shock. In panel A of Figure 14, we correlate, using a binscatter, the change in average weekly card expenditures observed in the CB data during the lockdown period, in percentage term relative to 2019, and our measure of exposure to the lockdown shock, by ZIP code. We do residualize the data first on series of observable characteristics at the ZIP code level, including population size, density, occupational structure of the workforce, and age structure of the population.[12] We find a strong positive correlation between the two, indicating that in ZIP codes where the structure of expenditures was heavily tilted towards sectors that did close during the pandemic, the drop in expenditures has been more severe. Importantly, the estimated correlation is not statistically significantly different from 1, and the overall relationship lies almost exactly on the 45 degree line, which suggests an almost one for one mechanical relationship between consumption and sectoral closures. In panel B, we use detailed ZIP code level measures of unemployment available from the French Public Employment Service (Pole Emploi), and correlate the change in unemployment from February to June 2020 with our measure of exposure to lockdown policies. The binscatter is again residualized on ZIP code level characteristics. We find a strong relationship between lockdown exposure and unemployment growth: a ten percentage point increase in the pre-crisis share of total consumption expenditures in sectors that remained open during the lockdown correlates with a .2 percentage point decrease in the local unemployment rate. This large effect seems driven by the fact that sectors closed during the lockdown are predominantly labor intensive sectors (restaurants, retail, etc). Taken together this evidence suggests that restriction policies have a significant and first-order effect on consumption dynamics and as a consequence on labor market dynamics.

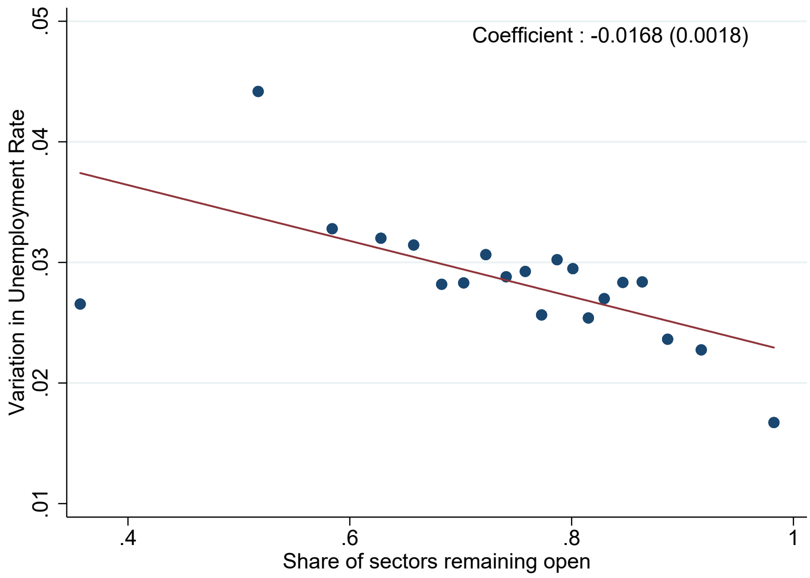
[12]These data come from the office of national statistics (INSEE) and are available at the municipality level.

Figure 14: The Impact of Lockdown Policies

A. Expenditures vs Exposure to Lockdown by ZIP Code



B. Unemployment vs Exposure to Lockdown by ZIP Code



Notes: Panel A is a binscatter of aggregate log CB consumption in the lockdown period in 2020 (relative to log aggregate CB consumption in the same weeks in 2019) by ZIP code, against our measure of exposure to lockdown policies, i.e. the fraction of total expenditures in the ZIP code in 2019 that was made in sectors that will not be closed by administrative decree during the lockdown period. Panel B is a binscatter of unemployment rate change between February and June 2020 by ZIP code, against our measure of local exposure to lockdown policies. In both binscatters of panels A and B, the data is first residualized on a series of observable characteristics at the ZIP code level, including population size, density, occupational structure of the workforce, and age structure of the population.

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APPENDIX

Data

Première banque à adopter le statut d'entreprise à mission, **Crédit Mutuel Alliance Fédérale** a contribué à cette étude par la fourniture de données de comptes bancaires sur la base d'un échantillon de ménages par tirage aléatoire. Toutes les analyses réalisées dans le cadre de cette étude ont été effectuées sur des données strictement anonymisées sur les seuls systèmes d'information sécurisés du Crédit Mutuel en France. Pour Crédit Mutuel Alliance Fédérale, cette démarche « s'inscrit dans le cadre des missions qu'il s'est fixé :

- contribuer au bien commun en œuvrant pour une société plus juste et plus durable : en participant à l'information économique, Crédit Mutuel Alliance Fédérale réaffirme sa volonté de contribuer au débat démocratique ;
- protéger l'intimité numérique et la vie privée de chacun : Crédit Mutuel Alliance Fédérale veille à la protection absolue des données de ses clients ».

Le **Groupement des Cartes Bancaires CB**, Groupement d'Intérêt Économique qui définit les modalités de fonctionnement du schéma de paiement par carte CB (physique ou dématérialisée dans le mobile) a également contribué à cette étude par la fourniture de ses données (agrégées) et par la possibilité de solliciter des traitements sur des données individuelles anonymisées dans un espace strictement sécurisé et dans le cadre de son partenariat avec la Chaire Finance Digitale. « Ce partenariat entre CB et le monde académique va permettre de développer de nouvelles filières de compétence. Il reflète aussi la démarche citoyenne et responsable de CB, qui a pour volonté de servir l'intérêt général et favoriser l'inclusion sociale et sociétale », déclare Philippe Laulanie, Directeur général de CB.

Representativeness of CM Sample

Table 1: DESCRIPTIVE STATISTICS: COMPARISON BETWEEN THE CM SAMPLE (WITH AND WITHOUT REWEIGHTING) AND THE FRENCH METROPOLITAN POPULATION

	(1)	(2)	(3)
	Raw Sample	Reweighted Sample Mean	Full Population (INSEE Data)
	Mean	Mean	Mean
Age (Percentage) :			
18-25	17.6	12.2	11.65
26-35	16.2	16.3	14.96
36-45	17	17.2	15.85
46-55	16.7	17.3	17.06
56-65	15.7	15.8	15.87
66+	16.7	21	24.61
Occupation (Percentage) :			
Farmers	0.3	0.6	0.8
Craftsmen, Traders and Company Head	4.6	9.1	3.5
Executives	8.9	13.8	10.1
Intermediate Professions	11.6	12.9	13.6
Employees	21.4	19.4	15.0
Workers	13.8	9.4	11.4
Retired	13.0	16.4	32.5
No Professional Activity	26.3	18.3	12.9
Family Status (Percentage) :			
Single	35.1	30.5	40.9
Married	36.6	39.4	43.0
Widower	4.7	6.3	7.5
Divorced	7.4	8.4	8.6
Civil Partnership	3.4	3.4	NA
French Department Code (The 3 most populated) :			
Nord (59)	2.1	3.99	3.99
Bouches du Rhone (13)	2.1	3.27	3.13
Seine Saint-Denis (93)	2.2	2.34	2.57

Figure 15: Aggregate Dynamics of Card Expenditures in CB & CM Data

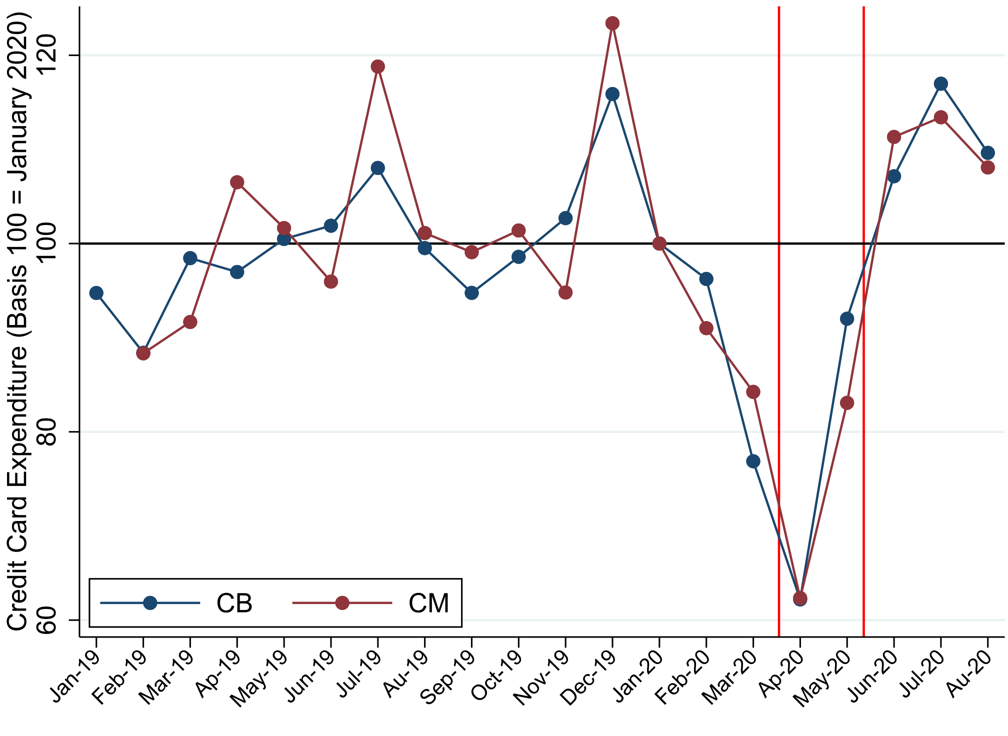
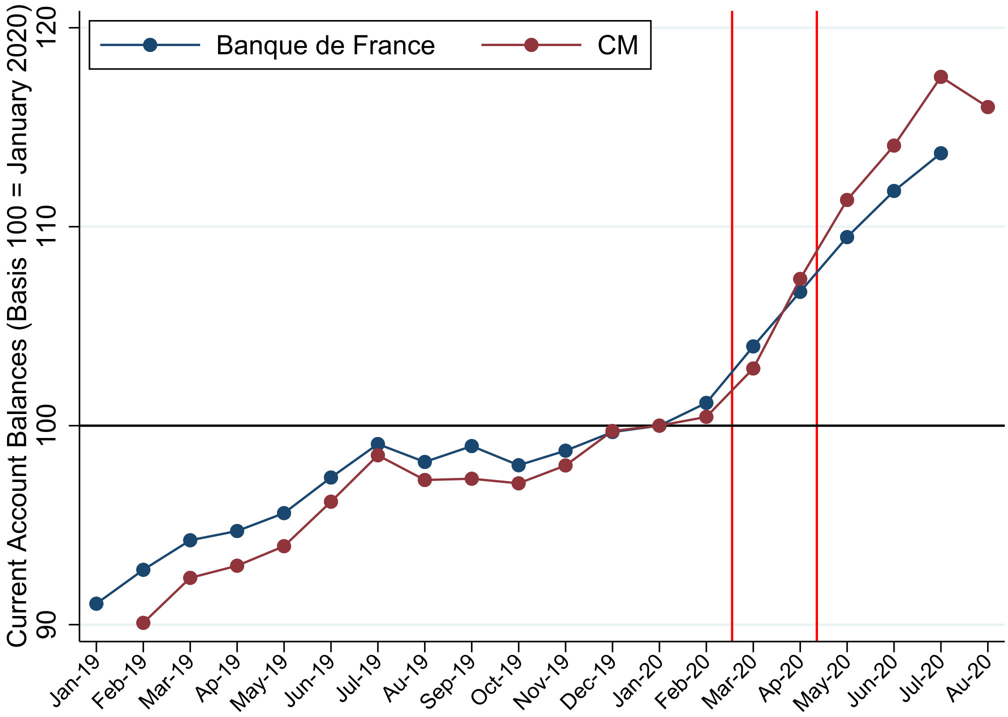


Figure 16: Evolution of Aggregate Balance of Liquid Bank Accounts: French Central Bank Data (Banque de France) vs CM Data



Substitution Across Payment Types

Figure 17: Evolution of Aggregate Monthly Expenditures in the CM Data For Different Payment Methods