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JEL Classification: D12, E21, G51

Keywords: real-time indicators, expenditure, Income, Access to finance

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Consumption in the time of Covid-19: Evidence from UK transaction data*

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Abstract

Using transaction data from a large Fintech company, we document a decline of 40% to 50% in the spending of British households during the Covid-19 crisis. The fall is concentrated in services such as retail, restaurants and transportation. The initial rise in on-line shopping and groceries purchases has been subsequently reverted. Income reductions have become far more frequent, with a median decline around 30%. The share of borrowers facing financing issues has increased significantly for both secured and unsecured lending. Consumption and income inequality have surged, with the most economically vulnerable groups experiencing the largest percentage decline. Mortgagors and higher earners in London record the most sizable pound change.

JEL classification: D12, E21 and G51.

Keywords: real-time indicators, expenditure, income, access to finance, inequality.

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1 Introduction

During the early stages of World War II, British mathematician Alan Turing designed 'The Bombe', a novel machine capable to rapidly intercept messages, quickly decode them, and thereby allow allied forces to react within hours rather than weeks. Turing's ingenuity brings to vivid life the speed of action required in times of crippling need and the necessary creative energy that is so often important to remedy crisis situations. The global pandemic created by the coronavirus is one such moment in time, where a Turing-style application might be given unprecedented consideration.

As much as epidemiologists and virologists have been battling with the unknowns of the health crisis, economists and policy makers have been battling with the unknowns of the economic crisis. An unfortunate common element of the two crises is the scarcity of reliable information to track – in real-time – the diffusion of the virus and the transmission of the associated economic shocks. A case in point are macroeconomic aggregates such as consumption, income and credit conditions – whether from national accounts, censuses or households and firms surveys – which typically are made available only with several weeks, if not months, of delays.

In the face of rapidly evolving conditions, the lags by which aggregate data are released make the design of fiscal and monetary policy a daunting task: bold interventions are very hard to calibrate without at least an educated guess of the breadth and depth of the economic crisis, as well as some knowledge of the most affected groups of households and firms. In this paper, we join an infant and very timely research effort to provide policy makers and academics with a set of quasi-real-time macroeconomic indicators to inform policy simulations and evaluate theoretical models.

We use detailed transaction-level data from one of the U.K.'s largest personal financial manager, Money Dashboard (MDB). The App is a real-time account aggregator that collates the financial transaction data of a user's current, credit and savings accounts, regardless of provider, within a single platform. Our sample spans the period from 1 January to 26 April 2020 and focuses on the more than 34,000 users who have consistently used the App over this period. This yields a sample of almost 8.5 million transactions. The granularity of the data allows us to construct weekly expenditure measures not only for non-durables, durables and services but also for a number of more detailed categories such as retail, restaurant, travel and transports. We are also able to look at the monthly figures for income, bank charges and mortgage payments.

Main findings. Our analysis highlights a few patterns. First, since the second week of March, actual consumer spending (i.e. not including imputed rents) has dropped by about 40% to 50%, with the largest decline recorded for services and non-durable goods. The change in durable goods expenditure has been relatively smaller but still significant, especially for vehicle purchases. Second, retail, restaurants and transportation have taken the most significant hit whereas the decline in travel & holidays has been quickly reverted. Similarly, the pick up in groceries has been short-lived, whereas on-line shopping and DIY have been enjoying enduring but reduced gains relative to the initial spike. Third, the largest expenditure changes occurred over the two weeks before March 23, when lockdown measures were implemented, and in particular during the week ahead of March 16, when social distancing policies were announced. Fourth, the share of users experiencing an income decline during the Covid-19 crisis has been significantly higher than before the crisis, with the median decline in overall income being around -30%. As for access to credit, March and April 2020 saw a significant increase in both the share of users incurring some form of bank charges (e.g. overdraft on their account) and the share of mortgagors experiencing a higher-than-20% decline in their regular monthly repayments. The rise in both shares might be suggestive of growing financial difficulties among British households. Households at the bottom of the consumption and income distributions have experienced the largest *percentage* decline, thereby causing a sharp increase in inequality. As for *pound* changes, we find a more pronounced decline among mortgagors and higher earners as well as in Greater London and the South East while Northern Ireland and Wales are the least affected areas.

Related literature. Our analysis is related to three recent and complementary papers, using transaction-level data to explore the changes in spending the first quarter of 2020 for three other countries. Baker et al. (2020) study the spending of U.S. households and report that the significant drops in consumption are associated with both the tightness of the regional social distancing policies and the political affiliation of the Fintech user. Carvalho et al. (2020) look at a large sample of households in Spain and focus on both the pervasive regional heterogeneity in the spending response to the lockdown and the distinction between on- and off-line sales. Andersen et al. (2020) explore a transaction level data from a large bank in Denmark and document a significant reduction in aggregate card spending. With these earlier and important studies on United States, Spain and Denmark, we share both the use of granular transaction-level data and the finding – for the United Kingdom – of a very significant decline in household expenditure.

The similarities of the consumption response in the three papers reduce possible external validity concerns. Unlike the papers exploring spending behavior in the US and Spain but similar to the Denmark study, we also look at income and borrowing. Furthermore, we study the effects on inequality and emphasize the distinctions across housing tenure groups and age as important dimensions of heterogeneity in the spending response to the Covid-19 crisis.[1]

Structure of the paper. The paper is organized in eight sections and two appendices. In Section 2, we describe the data source and report descriptive statistics for some main variables of interest. The findings on total household expenditure and several of its categories are presented in Section 3 whereas income and financing needs are the focus of Section 4. The focus of Section 5 is on consumption and income inequality. In Section 6, we look at heterogeneity across households by housing tenure, age, income whereas in Section 7 we present regional patterns. Section 8 concludes. Appendix A presents additional analyses and charts. In Appendix B, we provide details on the sample and variable construction as well as further descriptive information.

2 Data description

The data we use in this paper are provided by Money Dashboard (MDB), a free online personal financial management company operating in the U.K. Their main product is an App that gives its users the flexibility to link multiple accounts (current, savings or credit card accounts) and provides them with a set of tools for categorizing and keeping track of their spending. The number of users has increased significantly over time, from around 10,000 in 2012 to almost 145,000 by the end of 2019.

The raw dataset is composed of transactions. Every time a user utilizes their credit or debit card that is linked to the App, the transaction is collected with a time stamp, transaction description and the account that has been used. The users

[1] After having circulated the 5^{th} of May draft of our paper, we have been made aware of an independent and contemporaneous study by Chronopoulos, Lukas, and Wilson (2020) for the U.K., also using the MDB data. The analysis in Chronopoulos, Lukas, and Wilson (2020) is based on groceries, dining and drinking, alcohol and gambling expenditure and covers a period ending on the 7^{th} of April 2020. In contrast, we use data until April 26 and compare the weeks of 2020 with the corresponding weeks of 2019. In terms of variables, we cover most non-durable goods categories (including on-line shopping and recreation) as well as services (including travel and transportation) and durable goods. Furthermore, we track the evolution of income and financing needs for both secured and unsecured lending. Finally, we study consumption and income inequality, and document significant heterogeneity in the changes of the saving rate across households.

are anonymized as we only observe the partial postcode and the year of birth for each user, who is identified with a unique user reference number. As users can link more than one account, we can also observe different account reference numbers for each user.

We select users who consistently use the App throughout 2020. Specifically, we require each user to have at least 10 transactions per month in January, February and March, as well as to have spent at least £300 per month. For the same users, we also require them to have at least one transaction in April. Further, we follow the steps listed in Appendix B.1 to clean the data for outliers and discrepancies. The final dataset is composed of 34, 601 users and is made up of 8, 491, 166 transactions in the period between 1 January 2020 and 26 April 2020. Reassuringly, 33, 941 (or 98%) of these 34, 601 users have recorded their transactions with the MDB App since at least 1 January 2019.

The data provider has developed techniques to categorize transactions into almost 290 categories and thousands of merchants. These categories are as detailed as cinema, taxi, insurance, parking, dining out, mortgages etc, while merchants cover the most known businesses in the U.K., e.g. Tesco, Sainsbury's or Waitrose for groceries, Pret a Manger, Eat or McDonalds for take-away or snacks, and Amazon and eBay for on-line shopping. Similar to outflows, we observe incoming payments such as salary and interest income.

Users can apply their own tags to each transaction for e.g. electricity bills, groceries, restaurant or clothes purchases. When the user tag is missing, transactions are tagged by the company using their automatic algorithms. We use the expense categories and classified merchants to construct weekly measures of household spending and monthly measures of income and mortgage payments. The lists of categories in Table B.2 is used to create broader classifications of weekly expenditures for non-durable goods, durables goods, services and retail consumption.

The descriptive statistics of our sample are recorded in Table 1. On average, users link three bank accounts from two different banks to the App and have 61 transactions each month. The median net salary among the users is £2,663 and their median age is 37. For an average user, approximately a third of the total monthly expenses is on non-durable goods, and more than half of it is on services. Groceries account for about half of the non-durable expenses while spending on restaurants is on average £120 per month with a considerable dispersion within different percentiles. The average mortgagor faces over £1000 of monthly repayments and the average renters pays some £850 each month. In Appendix B.2, we present further information on the demographic and geographical features of the data. As shown in Figures B.1 and B.2, on average, Money Dashboard users are relatively young and more likely to be based in the Greater London area. Once we normalize the number of users by the population of the region they live in, however, the geographical distribution is more even (Figure B.3).

It should be noted that while our dataset contains information on users' ATM cash withdrawals, it only covers electronic transactions and payments. However, cash use among U.K. customers has been falling significantly in the last two decades: while in 2008 cash payments accounted for two thirds of all payments, in 2018 the share of cash payments has declined to 28%. As of 2019, 98% of adults holds a debit card while around 65% have a credit card. Due to the widespread use of contactless payments, the share of cash is predicted to fall further to 9% by 2028.[2] Hence, our dataset appears representative of the current transaction environment. Moreover, as we will discuss in the next section, some of our findings line up with the Office for National Statistics' March release of Retail Sales Inquiry on the changes in sales.[3]

Finally, there are two other important sources of information to track consumption in the U.K.: the Living Costs and Food Survey (LCFS) and the Understanding Society Survey (USS). In Appendix B.3, we provide details on the differences and similarities between our method and these more traditional sources. In short, two main advantages of the LCFS and the USS are that (i) their sample is representative of the British population and (ii) the recorded spending refers to both electronic and cash payments.

On the other hand, two main advantages of our method are (i) timeliness, as the data release comes with only a few days of delays since the end of the most recent week (as opposed to the six to twelve months of delay typically associated with the LCF and US surveys) and (ii) the data collection method, which being fully electronic and automated in real-time minimizes the type of serious non-classical measurement errors and recollection biases associated with diary records and retrospective interviews (see for instance Attanasio, Hurst, and Pistaferri (2014) and Pistaferri (2015)).

Furthermore, thanks to a large and loyal customer base who has been continuously using the App over the years and across the U.K., the MDB data have a panel dimension. This allows us to draw meaningful comparisons both over time and across many geographical areas. As for representativeness, we note that the

[2]U.K. Finance, Payment Markets Summary 2019, https://www.ukfinance.org.uk/sites/default/files/uploads/pdf/UK-Finance-UK-Payment-Markets-Report-2019-SUMMARY.pdf.

[3]Source: Office for National Statistics - Monthly Business Survey - Retail Sales Inquiry https://www.ons.gov.uk/businessindustryandtrade/retailindustry/bulletins/retailsales/march2020.

average expenditure shares across the different categories in the MDB data are similar to those reported in the LCFS and USS. We conclude that a real-time indicator of household expenditure from Fintech transaction level data could represent a useful complement to the well-established approaches based on survey data.

3 The household spending response to Covid-19

On March 23, the U.K. government announced nationwide lockdown measures. However, softer measures had been in place earlier. On March 15, elderly and people in vulnerable groups were asked to self isolate. On March 16, the government issued an advice against all non-essential travels and going to pubs, restaurants and cinemas, and closed schools until further notice. Starting from March 20, pubs, cafes, restaurants, bars and gyms were officially closed. In the mean time, most of the employers in the U.K., especially in Greater London, asked their employees to work from home whenever possible.[4] To evaluate the impact of these measures, their anticipation and more generally the effects of the uncertainty associated with the Covid-19 pandemic, in this section, we focus on the period from January to April 2020 and report first the pound changes in the broader classifications of household expenditure and then, we zoom on the sub-categories whose spending has changed most. We present the average spending across various categories in 2020 in comparison with the 2019 values.

3.1 Non-durable goods, services and durable goods

We begin our analysis with the main expenditure categories. These are reported in Figure 1 as the average weekly pounds spent on average by active MDB users. The solid blue lines refer to the nominal values in 2020 whereas the dashed red lines record the spending in the corresponding week of 2019 at 2020 prices. In practice, we have inflated the 2019 average weekly expenditure with the rate of month-on-month-in-the-previous-year CPI inflation for January, February and March 2020. As the CPI inflation rate for April 2020 has not yet been released at the time of writing, we inflate the spending in April 2019 with the annual CPI inflation rate between March 2019 and March 2020.

[4] Dingel and Neiman (2020) report that over 40% of the jobs in the U.K. can be performed at home while the Office of National Statistics (ONS) reports it as less than 30% of the workforce. Source: ONS Coronavirus and home-working in the U.K. labour market: 2019. https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/coronavirusandhomeworkingintheuklabourmarket/2019.

The rows in the first column of Figure 1 report, in order, (i) total expenditure,[5] (ii) total expenditure excluding recurring bills, (iii) services and (iv) services excluding recurring bills. The rows of the second column refers to the consumption of (i) non-durable goods, (ii) non-durable goods excluding recurring bills, (iii) non-durable goods excluding recurring bills and groceries, and (iv) durables. Recurring bills include regular payments such as utilities, insurance, council tax, TV license, gym membership, and phone, mobile and broadband bills, and are excluded from some of our broader measures of household consumption to emphasize the more discretionary spending.[6]

Comparing the last week of February (ending on 1 March) to the last week of March (ending on 29 March), total expenditure in the left panel of the first row has declined by over £150, from around £370 to about £220, before reaching a new low during the last week of April (ending on 26 April), close to £200. In the last week of April 2019, total expenditure was about the double, a touch above £400 a week. A similar story emerges for the right panel of the first row. From the last week of February to the last week of April 2020, non-durable goods consumption has declined of £40, from £150 to £110, whereas during the last week of April 2019, the average weekly spending was in excess of £160.

Excluding recurring bills in the second row, total expenditure drops from £300 in the last week of February to £175 during the last week of April, with the most visible decline recorded again in March. Relative to the last week of April 2019, this is a 50% decrease. Also the consumption of non-durable goods on the right chart of the second row is in April 2020 a fraction of what it was in the same week of April 2019, though its decline from February end seems more volatile. The reason is explained in the third row of the right column, which further removes groceries from non-durable spending: a fall of almost 50% is now clearly visible by comparing the last week of April 2019 and April 2020.

Finally, throughout the months of March and April 2020, services record almost a £100 drop in the third row, which corresponds to a £80 or a 45% fall once recurring bills are removed in the fourth row. On the other hand, no discernible patterns can be detected for durable goods expenditure in the fourth row of the right column, with a possible decline only towards the end of April, especially in comparison with the same week of the previous year.

[5]As detailed in Table B.2 and discussed in Section 3.4, in line with the consumption literature on Covid-19, our definition of total expenditure does not include actual or imputed rents.

[6]The beginning of each month is characterized by a significant spike in the expenditure on non-durable goods and services consumption, as can be seen from Figure A.1 due to recurring bills. Once these are excluded from the weekly expenditure of each category, the decline in consumption starting from the second week of March becomes smoother and thus more apparent.

Until now, we have mainly studied the intensive margin of consumption expenditure, tracking the evolution of average weekly expenditure in pounds. Another interesting exercise is to look at the extensive margin of expenditure, as measured by the number of transactions in a given category and a given week. In line with the evidence by Carvalho et al. (2020), we find that the number of transactions have decreased significantly. Figure A.2 in the Appendix shows the evolution of the number of transactions in our sample for the nondurables, durables and services categories, normalized to 100 in the second week of January for both years. Relative to April in the previous year, the number of transactions have fallen by over 60%. Interestingly, the fall turns out to be of similar magnitude in all three categories considered.

In summary, the largest decline in expenditure appears to have occurred during the second week of March 2020 and so earlier than the introduction of either social distancing policies (on March 16) or lockdown measures (on March 23). Throughout April, total expenditure and its broader subcategories remain significantly subdued and seem to have stabilized (or only slightly declined) relative to the historically unprecedented levels reached at the end of March 2020.

3.2 The most affected categories

In the previous section, we have documented that the largest expenditure changes occurred for services and, to a lesser extent, non-durable goods. In this section, we explore what drives the drop in services by looking at specific sub-categories. Furthermore, we also report the groups that recorded the largest gain in terms of pound change. The results of this exercise are reported in Figure 2, which sheds more light on households' spending behaviour by reporting the categories with the largest decline (in the left column) and the largest increase (in the right column). In Figure 2, the weeks of 2020 are displayed as blue solid lines and the weeks of 2019 as red dashed line.

Starting from the left column, retail expenses such as clothing, shoes, apparel, toys and books purchases in the first row fall after the first week of March. By April end, the drop is about £20 relative to the same week in 2020. Spending in restaurants in the second row declines consistently, with the average weekly amount falling from around £45 to £25 at the end of March, before raising to £32 by the end of April. The gap with the corresponding week of 2019 is about £15. Expenses on public transport, taxi, parking and fuel in the third row see a decline from a weekly average of £55 at the end of February to a weekly average of £42 at the end of April.

Travel expenses, which include hotels and flights, in the fourth row have suffered one of the largest declines in March. Cancellations of travel and holidays plans have started earlier than the lockdown measures: from the beginning of February to the end of March, the fall in travel spending has been more than 50%. Despite this, travel and holiday expenses reveal an uptick in the last week of March and throughout April as families have started to book holidays for later in the year and the weekly average spending at the end of April of this year is very close to the one during last year. This could indicate that consumers preserve hope of life going back to normal soon. Finally, recreation expenses (concert, theatre, cinema, museum, exhibition and sports events) have declined throughout March and further in April.

Moving to the right column, the first row reveals that on-line expenditures from Amazon and Ebay have been on the rise especially throughout March, virtually offsetting the pound decline in retail recorded in the same row but on the left column. Yet, our last data point is very close to what observed in the last week of April 2019. In the second row, it is easy to observe the stockpiling behaviour in groceries around the time of the introduction of the lockdown measures. The sharp spike in the third week of March, however, seems quickly reverted during the following week.[7] On average, the level of spending in April 2020 does not look too dissimilar from the one in April 2019. Households have increased significantly their weekly consumption of alcohol and tobacco in the third row, though there are early signs of a possible reversal in the last week of April.

The spending on DIY and home improvement, which includes gardening and repairs, has also gone up substantially but by the end of our sample it seems to have returned to the level of April 2019. Finally, spending on gambling in the fifth row has increased in February and March before falling sharply in April when the a regulation banning online credit card usage for gambling came into effect.[8]

Vehicle purchases. Large durable goods expenses occur infrequently and so, in the face of income uncertainty, households tend to postpone them as a precaution against future adversities. Among large durable goods expenses, earlier research has shown that vehicle purchases are associated with the largest marginal propensity to spend in the face of both positive income shocks, such as the tax rebates

[7]March 2020 alone has witnessed an extra almost £2 billions of grocery purchases most of which took place shortly before and after the lockdown. See for instance, among many others, Kantar Worldpanel at https://www.kantarworldpanel.com/en/PR/Covid-19-What-consumers-are-doing-with-extra-groceries.

[8]https://www.gamblingcommission.gov.uk/news-action-and-statistics/news/2020/Gambling-on-credit-cards-to-be-banned-from-April-2020.aspx.

of 2001 and 2008 in the U.S. analyzed by Misra and Surico (2014), and negative income shocks, such as the introduction of the 2011 property tax in Italy studied by Surico and Trezzi (2019).

In Figure 3, we report the average weekly spending on vehicles among MDB users who purchased one. Given the infrequent nature of these expenses, the time series for 2019 and 2020 are very volatile and March does not witness a significant difference between the two years. In contrast, since the first week of April, the weekly average value of vehicle purchases drops dramatically from an average of about £1500 weekly spending in 2019 to less than £500 pounds in April 2020, consistent with the most recent evidence on new car registration.[9]

3.3 Percentage changes

The results in Figure 1 and Figure 2 are about the level of pounds spent. To infer the percentage changes, one may wish to look at the spending growth rates between the end of February and the end of April 2020 as well as between the end of April 2019 and the end of April 2020. A simple way to visualize both of these growth rates is to normalize the values in some main charts of the previous figures by the spending of that particular category in the same week of each year. By doing so, all other weekly expenditure can be interpreted as a percentage of the spending in the reference week.

This is what we do in Figure 4 where we normalize all weeks to the expenditure in the second week of January, which is set equal to 100 both in 2019 and 2020. Apart from representing the start of the year and being the first week of our sample not contaminated by recurring bills, the second week of January 2020 is characterized by a level of spending very similar to the week ending with 8 March, which is the last week before the introduction in the U.K. of social distancing policies first and lockdown measures afterwards.

Two main results emerge from Figure 4. First, relative to the second week of January (and March) 2020, the last week of April 2020 records a decline of 45% for total expenditure and services (both excluding recurring bills) in the top and middle panel and a 25% drop in non-durable goods consumption in the bottom panel, with the largest falls occurring in March. Relative to the last week of April 2019, these declines become around 50% for total expenditure and services, and around 35% for non-durable goods consumption.

Finally, one may worry that seasonal factors make it hard to compare the spending during the last week of February to the one occurring in the last week of

[9] https://www.smmt.co.uk/vehicle-data/car-registrations/.

April. Accordingly, in Figure 5, we report also the growth rates in each spending category between the last four weeks of April 2019 and the last four weeks of April 2020. This comparison is particularly useful to control for seasonality as the time reference period is the same within the year.

The largest decline in Figure 5 is associated with discretionary expenses as measured by total expenditure excluding recurring bills, which records a drop in excess of 46%. This is evenly influenced by spending on services and non-durable goods consumption. The most hardly hit sub-categories are retail, restaurant and transportation, with declines between −26% and −30%. In contrast, we find a significant increase in the expenditure on Alcohol & Tobacco (+19%) and DIY/Home (+11%). Furthermore, the sharp rise in purchases related to Travel & Holidays and Groceries seen in March seems to have been reverted in April, who values are now relatively close to those witnessed in April 2020. On-line shopping is still 7% higher than in the same weeks of the previous year, though at lower levels than seen around late March/early April.

3.4 From fintech users' spending to national accounts concept

As discussed at length in Appendix B and the conclusions, our real-time consumption indicator complements rather than substitutes existing methods to measure household spending from survey data. Also, our expenditure indicator does not relate directly to (but complements) the concept of *household final consumption expenditures* in national accounts.

A main reason for why it is hard to link our real-time measure based on MDB users' spending to the national accounts concept is that the latter includes also actual rents for renters and imputed rents for owner occupiers.[10] In our data, we do observe actual rents for renters but of course we do not have a measure of imputed rents for homeowners.

A first step towards moving closer to the national accounts concept would be to add the actual rents paid by the renters in our sample to the total expenditure paid by all MDB users before computing a measure of average total expenditure

[10] As stated in the Coicop documentation (https://unstats.un.org/unsd/classifications/unsdclassifications/COICOP_2018_-_pre-edited_white_cover_version_-_2018-12-26.pdf), "persons who own the dwellings in which they live are treated as owning unincorporated enterprises that produce housing services that are consumed by the household to which the owner belongs. The housing services produced are deemed to be equal in value to the rentals that would be paid on the market for accommodation of the same size, quality and type. The imputed values of the housing services are recorded as final consumption expenditures of the owners. Imputed rentals normally include value for the use of the land on which the property stands, the dwelling occupied, and the fixtures and fittings for heating, plumbing, lighting, etc. Strictly speaking, the imputation refers to the value of goods or services involved and not to the expenditure itself."

with actual rents. Doing so, and focusing on the last four weeks of April 2020 relative to the last four weeks of April 2019, leads to a percentage decline of -39% (as opposed to -41.2% in Figure 5).

One might wish to go one step further and try to impute rental payments for owner occupiers. Unfortunately, the MDB data does not feature all the information necessary to do the imputation properly as in the national accounts. A simple approximation, however, is to add the average rent paid by the renters in our sample to the average total expenditure defined in Table B.2 and used in Figure 5, which does not include rents. By doing so, we effectively impute to all homeowner occupiers the same average rent paid by the renters in our sample. Using this approximate measure of imputed rents yields a percentage decline of about -29.1% between April 2019 and April 2020. It should be stressed that this back-of-the-envelope calculation is an approximation only and should be regarded with a grain of salt. Furthermore, including imputed rents prevents to appreciate the full extent of the decline in *actual* spending, which is of paramount importance to track household demand in times of crisis.

4 Income and financing needs

This section explores the effects of the pandemic on income and the potential increase in people's financing needs and cash hoarding. As we have seen in the previous section, fears about Covid-19 and social distancing measures are associated with a decline in household expenditure. On the other hand, the lockdown leads to the closure of a significant number of businesses and disrupts the flow of the labor market. There are two implications of this. First, some workers may have already lost their jobs. Second, free-lancers, self-employed, part-time and full-time employees may not be able to work at their desired level (and potentially productivity) during the lockdown, despite being still on the job. Both these circumstances may lead to a decline in income, which in turn may heighten the demand for short-term funds to support consumption. Finally, fears of disruption in the credit market or the payment system may lead some households to increase their cash holding.

4.1 The distribution of income changes

We start by exploring the changes in MDB users' income. There are two ways we can infer information on income in the data. First, users can choose to provide their yearly gross income range when they are registering with the App. If they choose not to, then the data provider can derive income range information based on an algorithm for the users who have the necessary underlying information in their transactions. Second, we can trace net monthly salary inflows into linked accounts. These transactions are tagged as main salary. Some users have other forms of income which we record as other salaries. MDB classifications have further categories for broader income measures, which we consider under overall income alongside the main and other salary.[11]

In Figure B.4, we report the yearly gross salary ranges derived from the MDB data. Most of the users earn a salary between £10K to £50K, with the most frequent range being around £20K to £30K. According to the ONS, the yearly median and mean gross income in the United Kingdom for the 2019 financial year are £29,600 and £35,900, respectively.[12] This suggests that the MDB dataset bears some representativeness of the British population. In the analysis below, we use the information from monthly net salary inflows to investigate the changes in monthly income in our sample.

In the Money Dashboard dataset, it is not possible to identify with certainty whether an individual has lost her job. The absence of salary information might also indicate changes in bank accounts that are linked to the App. Accordingly, we select the users whose overall income we can observe throughout the months of 2020. All other selection criteria remain the same as before, leading to a sample of 8,933 users. In each panel of Figure 6, we record key summary statistics about the distributions of the monthly income changes from January to April 2020. These statistics are reported in three sets of box plots and whiskers, for the percentage change (left column) and the pound change (right column) in income respectively. The thicker black horizontal bars refer to the median of the distribution while the box around the median reflects the interquartile range, i.e. 25^{th} and 75^{th} percentiles. The whiskers extend up to the maximum and the minimum values after eliminating some outliers.

The first row of Figure 6 reveals that the median change in the main salary between February and March 2020 is virtually of the same magnitude as the change between January and February, at a value approximately around zero. During the month of February, the income change distribution appears quite symmetric and concentrated: the frequency of income increases appears very similar to the frequency of income reductions and the inter-quantile range lies within the 5% (or £100) neighbourhood of the median value of zero. However, the picture

[11] Total income includes main salary, other salaries, secondary salaries, irregular income or gifts.

[12] Source: Office for National Statistics 2019 Average Income Report. https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/incomeandwealth/bulletins/householddisposableincomeandinequality/financialyearending2019.

changes abruptly moving from February to March, when only a small number of users experiences an income surge and the vast majority face an economically meaningful salary drop. The lower quartile becomes skewed towards lower negative values, around -10% and in excess of -£200. The whole distribution becomes asymmetric and the lower tail extends to percentage and pound changes that, in absolute value, are much higher than at the upper tail. The observations for April corroborates this trend, with a further left tail skewness characterized by the 25^{th} percentile value shy of -20% or around -£500.

A similar story emerges from the second row of Figure 6 about other salaries and in the last row focussing on overall income changes. The column on the left (right) refers to the percentage (pound) variations. Within each chart, the box plot and whiskers to the left, middle and right display respectively the income changes between January and February, February and March, and March and April. The latter is associated with a far more dispersed distribution than February, with an evident skewness caused by the far higher frequency of negative income changes. Among those experiencing a drop in April 2020, the median decline in overall income in the third row is just short of 30% or about £1000.

Extensive margin. In Figure 6, we have looked at the intensive margin, namely by how much income has declined in response to the Covid-19 shock. In Figure 7, we complement the previous analysis by focussing on the extensive margin. Unfortunately, we do not observe whether a user has been made furloughed or unemployed. However, a simple way of trying to infer that is to count the share of users for which we observe a percentage decline in either their main salary (left column) or their overall salary (right column) in excess of -50% (blue bars) or -80% (orange bars). The top row refers to all 6,388 and 8,933 users for whom we observe main and overall income respectively throughout 2020.

Figure 7 reveals a clear trend. The share of earners with significant income losses has ticked in March and then sharply risen in April for both thresholds. The largest increases are associated with overall income in the right panel of the first row, where the share of users facing a larger than 50% (80%) decline in income has increased from 7% (2%) in February to 16% (6%) in April. This evidence points to significant effects also on the extensive margin of the labor market.

4.2 Bank charges and mortgage payments

A reduction in income, whether temporary or permanent, is likely to make it more difficult for some households to meet their financial obligations or start new ones.

Furthermore, in such an environment, households might need additional funds to get by and finance consumption. In this section, we look at individuals who face higher bank charges and reduce their mortgage payments significantly from February to April.

In Figure 8, we organize the analysis on financing needs into two parts: the extensive margin (top panel) and the intensive margin (bottom panel). As for the extensive margin, the first row of the left column refers to the share of users facing bank charges – i.e. overdraft penalties, interest and late payment charges – and the first row of the right column records the share of mortgagors who have experienced a reduction in their payments larger than 20% (in absolute value). To ensure sample stability, we restrict our attention to users who have paid a bank charge in April and look at whether and how often they paid bank charges also in February and March.

The left chart in Panel A reveals that while in February around 35% of users faced bank charges, in March and April their shares have gone up by 2% and 4% respectively, exceeding 40% by the end of the sample. The right panel corroborates the evidence on tighter financial conditions by showing that the share of mortgagors with a payment reduction in excess of 20% (in absolute value) has almost doubled from February to March, moving from 4% to almost 8%, before peaking again in April, just short of 10%.[13]

Unfortunately, we have no information on the specific reason(s) behind such a significant drop in mortgage payments. While it is plausible to conjecture this may be due to the user entering in arrears, applying for a mortgage holidays or switching to an interest rate only product, we note that all these examples would represent the response to some form of heightened uncertainty and thus suggestive of possible financial troubles.[14]

It is also useful to look at the intensive margin of credit, which is the goal of Panel B. In each chart, we report the box plots for percent (left column) and pound changes (right column) in mortgage payments with respect to the previous month. The median value for percent changes and pound changes is zero in February but becomes negative in March and April. In February, many users made extra payments as the upper quartile is larger than the lower quartile (in absolute value).

[13] In the MDB dataset, mortgage payments are available for 5,968 users throughout 2020. Furthermore, in February 2020 there have been 1,378 mortgagors with a non-zero change in repayments while this group has expanded to 1,658 and 1,988 individual in March and April, respectively. The results on changes in mortgagors shares is robust to using a threshold of 10% or 30%.

[14] The share of 4% about mortgagors in possible financing difficulties in February 2020 is broadly consistent with the shares of mortgagors that have been in arrears during 2019 (see MLAR data from the Financial Conduct Authority, which are publicly available at https://www.fca.org.uk/data/mortgage-lending-statistics).

In March and April, however, the distribution becomes skewed towards the lower tail: half of the individuals who reduce their mortgage payments do so by more than 30%, for an average decline in excess of £300.

4.3 Cash

Heightened uncertainty, fears of not being able to access their own bank account, a possible failure of the payment system or simply a panic reaction to the unprecedented situation may nurture cash hoarding. We investigate this hypothesis in Figure 9, which reports the average weekly amount of ATM cash withdrawals. In a typical month before Covid-19 the average users would cash out about £100 a week. While we do not observe on which spending categories this cash is utilized, the recurrent withdrawals makes it plausible to conjecture that this also reflects some forms of spending, and therefore should be considered in addition to the amount spent through electronic transactions.

The main message from Figure 9 is that the start of the lockdown measures coincides with a significant 15% increase in cash holding. The upward trend continues also in April and by the end of the month is almost 20% larger than the average weekly amount withdrawn during the last week of February. Relative to April 2019, cash hoarding in April 2020 represents a 10% increase.

5 Inequality

In Section 3, we have documented a dramatic decline in total expenditure. In Section 4, we have reported a significant increase in the share of users facing a drop in earnings. In this section, we explore the implications of these findings for consumption and income inequality in the spirit of Attanasio, Hurst, and Pistaferri (2014) and Attanasio and Pistaferri (2016).

Two complementary ways of measuring dispersion or inequality are recorded in Figure 10, whose left column refers to total expenditure excluding recurring bills and whose right column displays the overall salary. These statistics are reported at weekly frequency for spending and at monthly frequency for income. The first row refers to the cross-sectional standard deviation across all users. The second row reads the ratio between the values at the 90^{th} and at the 10^{th} percentiles of the distribution of the variable of interest at each point in time. The third row displays separately the 90^{th}, median and 10^{th} percentile of the distribution of log consumption and log income. In the Appendix, we also report results based on the Gini coefficient.

Three main results emerge from Figure 10. First, consumption inequality has been relatively flat since the turn of the year but has increased significantly since the second week of March before reaching a new plateau around early April. The acceleration first and the flattening out after are visible through both measures, with some 20% increase using either the standard deviation or the 90^{th} to 10^{th} percentile ratio. Figure A.3 presents a milder rise based on the Gini coefficient. Second, income inequality also displays a sustained upward trend, though – relative to consumption inequality– this seems delayed and less pronounced, with only a modest rise in March 2020 but a very significant pick up during April 2020.[15] Third, in response to the Covid-19 shock, between March and Apri 2020, consumption inequality has increased more and earlier than income inequality, consistent with an important (if not predominant) role played by demand shocks. Furthermore, both measures of inequality are countercyclical. These findings are consistent with the evidence reported in Coibion et al. (2017) based on monetary policy shocks.

To investigate further the pick up in consumption and income inequality, the third row of Figure 10 zooms into the 90^{th}, 50^{th} and 10^{th} percentile of the consumption and income distribution. Two points are worth emphasizing about the two charts in this row. First, all three percentiles exhibit a decline over the months of March and April 2020. Second, however, the percentage fall in both consumption and income is far more pronounced among households in the bottom percentiles (i.e. p10), which by construction refer to the most economically vulnerable group in society as measured by lower levels of expenditure and earnings.

The spending and income variation across groups reported in Figure 10 suggests that there may be significant heterogeneity also in savings rates. This is explored in Figure 11, where we report the savings rate $(1 - \frac{c}{y})$, conditioning on the ex-ante distribution of income in February 2020.[16] We use total expenditure plus mortgage payments and rents for consumption and overall income as the measure of income. One caveat about these imputed savings rates is that we only observe electronic transactions. While only about 25% of UK payments take place in cash, this introduces an upward bias in the *level* of our imputed saving rates, especially among lower-income households who tend to use cash relatively more for their expenditure.

Bearing in mind this caveat about the *level* of the imputed saving rates, in Figure 11 we report the *evolution* of the saving rates over the first four months

[15]Figure A.4 reports the consumption inequality for nondurable and services consumption.

[16]To remove outliers, which can emerge from incomplete user accounts, we trim the bottom and top 2.5% of the savings rate distribution.

of 2020, conditioning on the (ex-ante) income distribution as of February 2020. The higher-income group is displayed as a green line, the lower-income group is depicted as an orange line, and the unconditional median is represented in blue. The heterogeneity is striking: while at the top and at the middle of the income distribution the saving rates increase gently before and during the Covid-19 crisis, at the bottom of the income distribution the saving rate declines sharply during April 2020, as the pound fall in earnings among low-income households is larger than the contraction in their expenditure.

In summary, the Covid-19 pandemic has triggered a sharp rise in consumption inequality first (towards the second half of March) and in income inequality later (during April). While expenditure and earnings have fallen for most users, the percentage decline has been heterogeneous, with the hardest hit group being households at the lower end of the consumption and income distributions. In the next sections, we complement the evidence in this section about percentage changes, with spending pound changes across the distribution of housing tenure status, age, income as well as regions of the United Kingdom.

6 Heterogeneity in individual characteristics

In this section, we exploit the richness of our data by focussing on three potentially important dimensions of heterogeneity in the response of household expenditure to the Covid-19 crisis: housing tenure (namely if a user owns a house outright, whether it does with a mortgage or they rent), age and income. In the next section, we explore the regional variation.

6.1 Housing tenure

As shown in Cloyne, Ferreira, and Surico (2020), British mortgagors fit well to the notion of wealthy hand-to-mouth households: they hold little liquidity (in the form, for instance, of saving on accounts and stock shares) relative to their income despite holding sizable illiquid assets. Furthermore, while mortgagors enjoy a good access to credit markets in normal times, a large share of their savings has been used as downpayment and a significant part of their monthly expenditure is pre-committed to repay the mortgage. This implies that this group of households may choose or be forced to reduce their consumption significantly whenever reoptimizing their financial portfolio (and, in particular how much equity to hold in the house) is costly or unfeasible.

In the MDB dataset, we do not observe housing tenure directly but we can infer it from users' transactions and whether they are tagged as mortgage or rental payments. There are several tags that include mortgage payments. To infer mortgagors, we combine transaction tags 'mortgages' and 'mortgage or rent'. Although the latter seems to be a vague category, a detailed text search in transaction descriptions show that more than 90% of these transactions are mortgage payments.

Rent payments can be inferred with more certainty and we use the tag 'rent' to construct the monthly series. The users who do not make neither mortgage nor rent payments are referred to as 'unidentified'. This would include more renters, outright owners and anyone else we cannot identify. Although uncertainty remains in the precise identity of this third group, for completeness we report also their response to the Covid-19 crisis.

This housing tenure classification strategy yields a sample of 37% of mortgagors, 21% of renters and 42% of unidentified users. As shown in Galeotti and Surico (2020) based on the representative sample of the British population available in the 2019 wave of the U.K. household longitudinal study 'Understanding Society', the actual shares for hosing tenure are likely to be closer to 30% for mortgagors, 32% for renters and 38% for outright owners. In other words, mortgagors seem slightly over-sampled in the MDB data whereas renters are significantly under-sampled.

With this caveat in mind, the top left panel of Figure 12 reports the average weekly total expenditure excluding recurring bills for each housing tenure group: mortgagors (blue solid line), renters (dotted green line) and unidentified (broken green line). The pound reductions range from £200 for mortgagors to £100 for renters. As households with mortgage debt tend to enjoy a higher level of both income and expenditure relative to the other groups, the percentage changes are homogeneous across housing tenure categorization.

To obtain an estimate of the contribution of each group to the aggregate (pound change) effects of the Covid-19 crisis, in the right column of Figure 12 we compute the overall pound decline in total expenditure excluding recurring bills in the whole sample and then calculate what is the share of that decline coming from each of the housing tenure group. More specifically, we first cumulate the pound decline in this spending category for all mortgagors, all renters and all unidentified users separately, and then report the ratio between the total pound decline in expenditure for each group and the total pound decline in the whole sample (i.e. summing this up across all housing tenure groups in the denominator).[17] The

[17]Computing the pound decline for each user requires us to condition on the users for whom we observe weekly expenditure for the last weeks of February and April. This leaves us with a total of

result of this accounting exercise by housing tenure are reported in the top right panel of Figure 12. The pie chart reveals that mortgagors account for about 40% of the overall pound decline in our sample, despite this group represents only 30% of the British population. This seems to suggest that the decline in aggregate consumer spending may be driven by households with debt.

6.2 Age

Another potentially relevant dimension of heterogeneity is age. Accordingly, in the second row of Figure 12, we split our sample depending on whether a user is in the top quartile of the age distribution (above 46 years or 'older' for a lack of a better term), in the bottom quartile (below 31, denoted as 'younger') or belongs to the 50% of users in the 'middle' of the other two groups, namely with age between 31 and 46 years old. While of course anyone in their late 40s or 50s can hardly be considered as old, the specific thresholds simply reflect the composition of the MDB sample as well as our desire to keep top and bottom groups of the same sample size in terms of number of users.

The left column shows that over the months of March and April 2020 both (i) users above 46 years old and (ii) the middle-age group have experienced an average weekly decline in total expenditure excluding recurring bills around £180. On the other hand, the consumption drop for the younger group was smaller, around £100.

The right column of the second row provides a decomposition of the consumption decline in our sample. If each group contributed to the pound decline in expenditure as much as they contribute to the number of users, we should observe shares of 25% for top and bottom groups and 50% for the middle-aged users. The results suggest that the contributions to the pound decline in expenditure from both the older and the middle-aged groups were higher that their users' share of 25% and 50% respectively. While older households account for around 29% of the total pound change decline in consumption, young users explain only 15% of the change recorded in our sample.

27,592 users. The housing tenure shares in this subsample are broadly in line with the shares on the entire sample; mortgagors and unidentified account for about 40% each and renters for about 20%. To ensure representativeness of the British population, we adjust the share of each group in our sample with the actual shares recorded in the 2019 wave of the 'Understanding Society' household longitudinal survey for the United Kingdom.

6.3 Income

British households differ markedly in their levels of earnings. As shown in Panel A of Table 1, the income of MDB users reflects such a variation and therefore can be exploited to investigate the heterogeneous consumption responses of households along the earning distribution. In line with the split in the previous section, the third row of Figure 12 groups users in three buckets, depending on whether their income is in the top quartile (blue solid line), bottom quartile (dotted green line) or second and third quartiles (dashed orange line) of the users' sample distribution.

The left panel reveals that the decline in expenditure is far more pronounced for users with annual net income above £50,000: between the last week of February and the last week of April 2020, this group has recorded an average weekly drop in total expenditure (excluding recurring bills) of around £250. In contrast, the consumption pound decline in the other two groups is only a fraction of the one among top earners, with an average drop of about £130.

In line with the other dimensions of heterogeneity, the right column of the third row converts the absolute pound changes for each group into a measure of the percentage contribution of each set of households to the overall pound decline in consumer spending in the sample. If the expenditure drops were proportional to the number of users in each bucket, we should expect a 25% contribution from the top and the bottom groups and a 50% contribution from the two quartiles in the middle of the income distribution. The evidence illustrated in the pie chart reveals, however, that this is not the case: the distribution of the expenditure pound decline is skewed towards households with higher income, which accounts for almost 40% of the overall contraction in consumption, despite representing only 25% of all users. The mirror images of this result is that each of the other groups account for a smaller share of the overall pound decline in expenditure than their respective users' shares.

In summary, the results of this section suggest that mortgagors and higher earners exhibit the largest spending drop in terms of pound value, but we find limited heterogeneity in the percentage decline across housing tenure, income and demographic groups. On the other hand, we have shown in the previous section that households at the bottom of the consumption and income distribution face the largest percentage decline. This suggests that significant heterogeneity may exist within each of the groups analysed in this section.

7 Regional patterns

It is often argued that London and the South East are different from the rest of England and the U.K. along a number of socio-economic dimensions. In this section, we therefore explore the geography of the Covid-19 economic crisis across the United Kingdom. In particular, we focus on total expenditure (excluding recurring bills) and, for each user in the sample, we compute the spending growth rate and pound change of expenses between the last week of February and the last week of April. Then, we calculate and report, in Figure 13, the median of the distribution of the individual growth rates and the pound change for every of the eleven regions of the United Kingdom.[18]

Three main results emerge from this exercise. First, on the left panel of Figure 13, the median decline in consumers' spending varies significantly across regions, being in the most affected area almost the double than in the least affected areas. Second, Northern Ireland and Wales experience the 'smallest' drop, with an average decline of -30% and -33% respectively. Third, in the South East and Greater London, the sudden stop in consumption has been larger than in the rest of the country: the capital is the most affected area with a median percentage decline of -57%, followed by the South East at around -50%. The right panel reveals that these percentage changes translate into a median decline in total weekly expenditures excluding bills of around £84 for the whole U.K., £107 for Greater London and £58 for Northern Ireland.

Finally, Figure 14 reports a more detailed geographical analysis using the first two digits of each user's home postcode to construct a heat map of the median percentage decline in total expenditure excluding recurring bills for 122 smaller areas across the four nations. Darker (lighter) shades represent larger (smaller) declines whereas the light grey denotes areas that do not satisfy the minimum requirement of fifty local users that we have imposed.

The heat map reveals pervasive heterogeneity in the economic costs both across the country and within the eleven regions of Figure 13, ranging in between -16% to -33% in a few locations in the Midlands, Wales, Belfast and the Scottish Highlands, and -56% to -65% in a handful of areas across Greater London, Hampshire, Berkshire, Surrey and Aberdeenshire.

[18] Unlike the average, the median is robust to the presence of outliers.

8 Conclusions

Covid-19 is the greatest health and economic crisis of our times. Despite the extraordinary global efforts among policy makers, health scientists and economists, many fundamental questions about its evolution remain unanswered. At the heart of this lies the difficulty to acquire real-time information that could help to decode the dynamics of the diffusion of the 'economic virus' and therefore design the optimal treatment to mitigate first and finally suppress its transmission to aggregate demand and aggregate supply. In this paper, we have shown how to construct a real-time indicator of economic activities using transaction data from a Fintech commercial provider, which we hope might contribute to that Alan Turing-type of Bombe machine to help solving the 'Enigma' of the Covid-19 economic crisis.

Looking at the few weeks before and after the start of the contagion in the U.K., we have documented an historically unprecedented decline in consumption over March and April 2020, driven by categories such as retail, restaurants and transportation. The largest part of this expenditure drop has occurred before the announcement of social distancing policies and lockdown measures. The number of income reductions has become significant, with a median decline around 30%. The share of users incurring bank charges, including those for overdrafts, has increased by 6% whereas the share of mortgagors with a decline in payments larger than 20% has more than doubled, from a value just above 4% in February to almost 10% in April. Consumption and income inequalities are on the rise, pushed by the large percentage decline among households at the bottom of each distribution. The consumption reduction in pounds has been more pronounced among mortgagors and high earners, who typically enjoy higher levels of income and expenditure. Greater London and the South East are the most affected regions whereas Wales and Norther Ireland are the least.

Our paper joins a new wave of research efforts to develop quasi real-time macroeconomic indicators that could timely inform and guide policy making and academic research in time of crisis. It is important to stress that the indicator proposed in this paper is not meant to substitute the still so-much-needed, fundamental role played by well-established projects such as the Understanding Society and the Living Costs and Food surveys in the United Kingdom and many others around the world. Rather, we hope our proposal might complement existing efforts by providing a new, early indicator for household expenditure that would precede significantly the data release of more traditional and comprehensive (but less timely) approaches. To fulfill this role and commitment fully, we intend to update the present analysis as soon as the data for the upcoming months become available. At a time in which the Bank of England is celebrating Alan Turing by launching a new £50 note, may his example inspire a novel research impetus to seek creative solutions to unprecedented problems.

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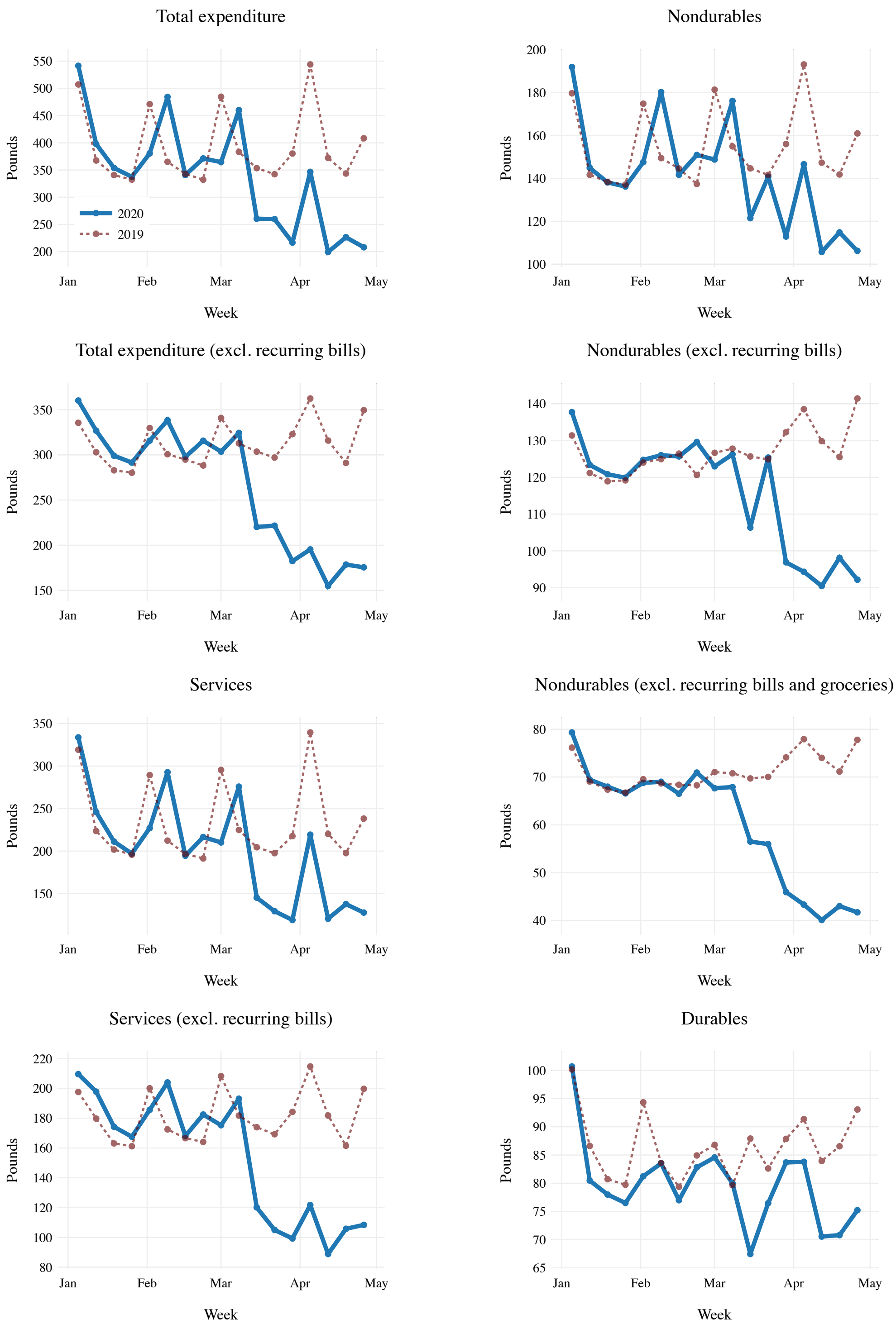
Table 1: Summary statistics

	Mean	$p10$	$p25$	$p50$	$p75$	$p90$
			User Characteristics			
#Banks	2.29	1.00	1.00	2.00	3.00	4.00
#Accounts	3.57	1.00	2.00	3.00	5.00	7.00
Age	39.21	26.00	31.00	37.00	46.00	55.00
Salary	3271.04	926.58	1689.88	2663.42	4175.85	6239.93
			Monthly Transactions			
#Transactions	71.06	26.00	41.00	63.00	92.00	125.00
Total expenditure	1526.27	400.92	690.94	1196.31	1971.38	2978.58
Nondurables	562.02	108.22	222.86	437.55	778.49	1180.04
Durables	155.95	7.63	19.49	56.70	158.56	389.00
Services	871.72	189.55	346.33	629.84	1090.25	1755.09
Groceries	288.73	35.54	96.69	217.13	415.20	642.48
Restaurant	119.70	14.00	34.97	80.28	158.52	267.32
			Monthly Mortgage and Rent Payments			
Mortgage payments	1045.45	311.78	529.90	852.68	1345.46	1994.01
Rents	855.21	104.00	363.53	660.99	1140.00	1750.00

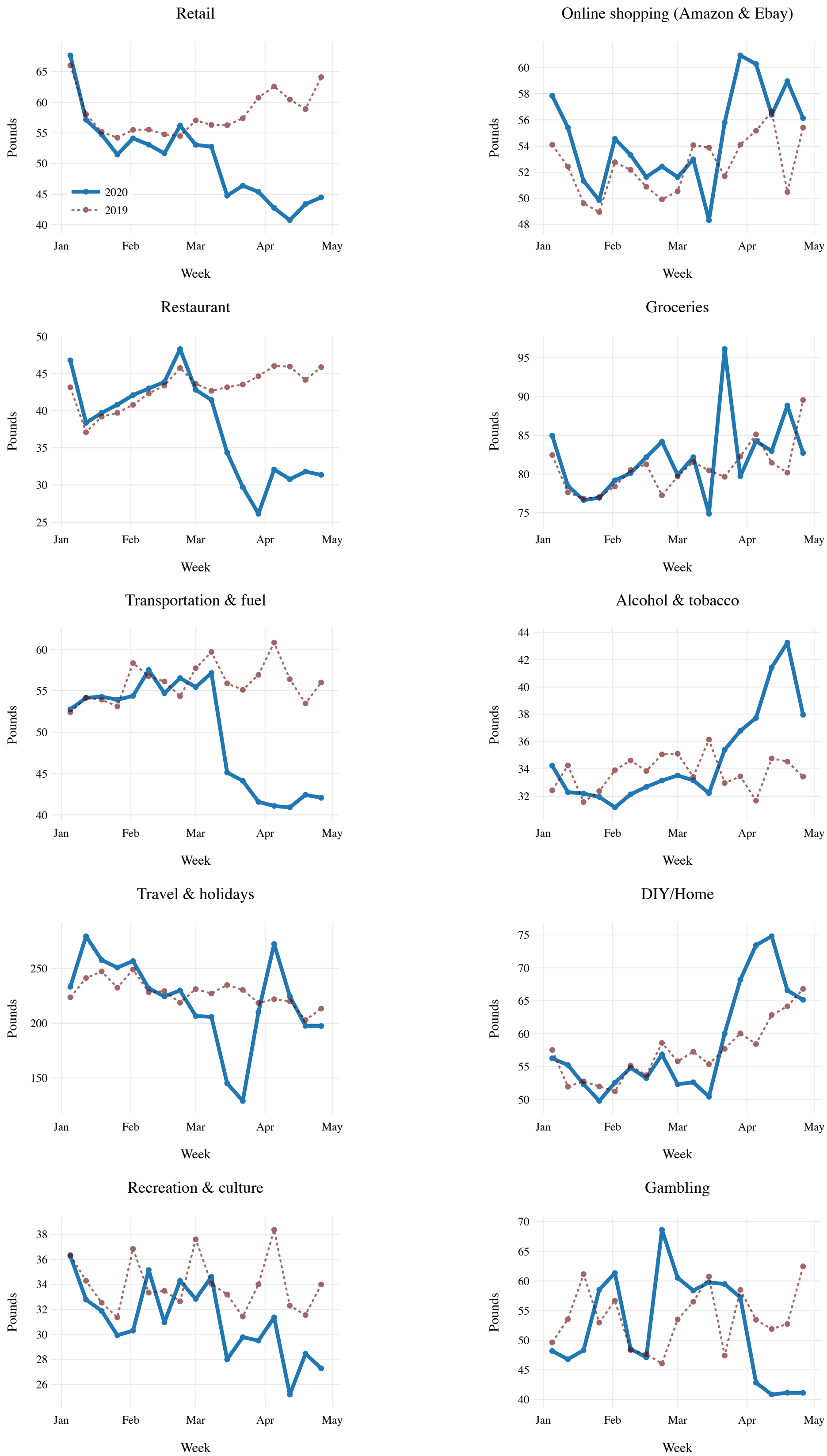
Note: Summary statistics on user characteristics (top panel), monthly transactions, salary and selected expense types (middle panel), mortgage and rent payments (bottom panel). The table reports the mean as well as 10, 25, 50, 75 and 90 percentiles. Salary, expenditure, and mortgage/rent payments refer to the period from January to March 2020.

Figure 1: Average weekly expenditures by broad categories



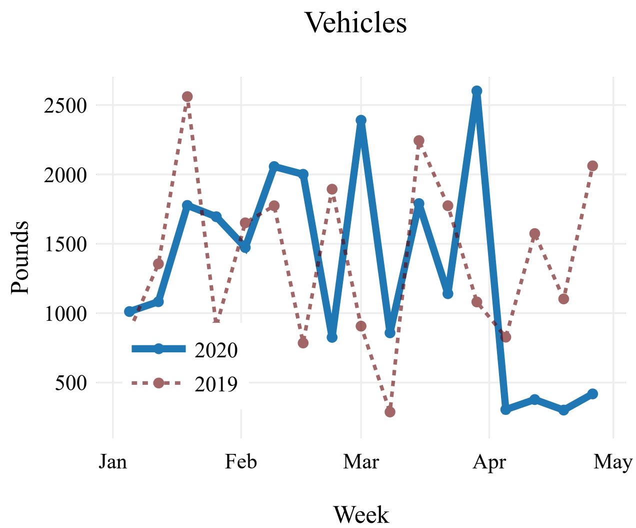
Notes: The figure shows the total average weekly expenditures in pounds, as well as weekly expenditures for a number of categories, including non-durable goods, services and durable goods (with and without recurring bills). 2019 values are represented in terms of 2020 values (April 2020 inflation rate has not been published at the time of writing this paper so March 2020 rate is used).

Figure 2: Average weekly expenditures by sub-categories



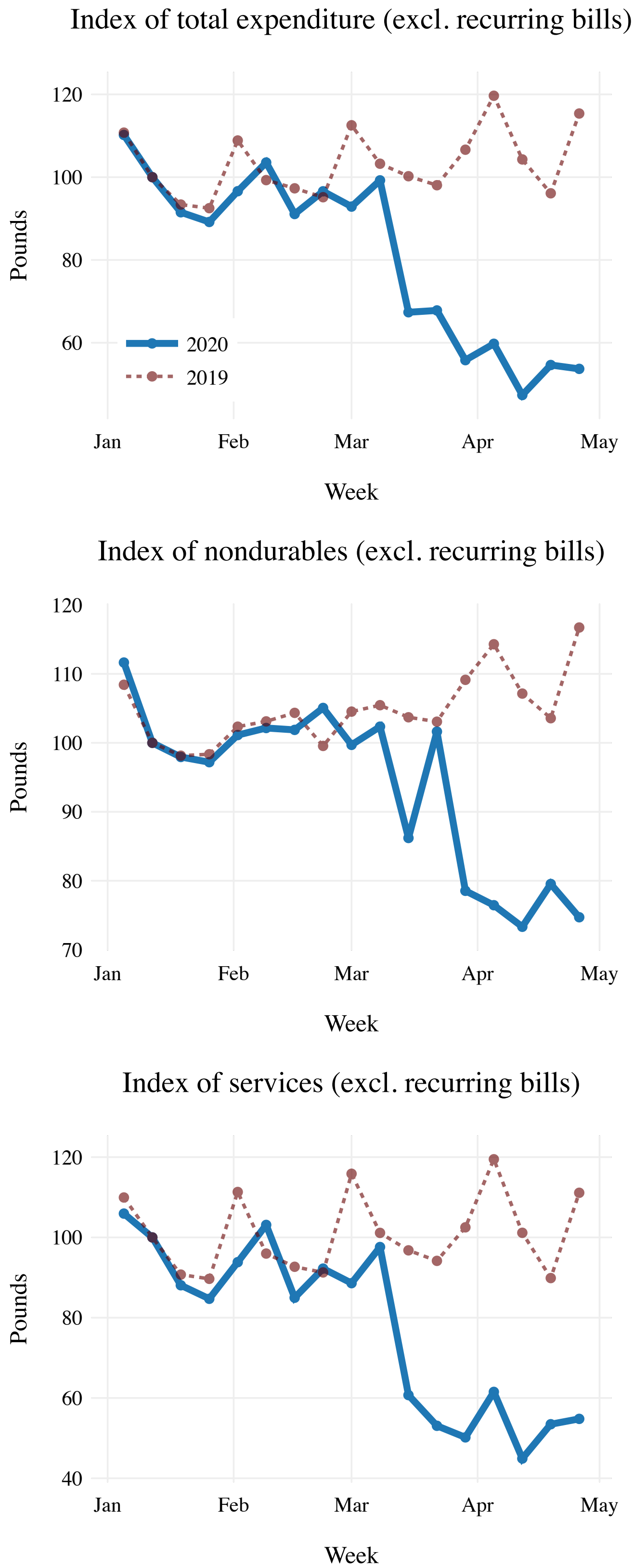
Notes: Average weekly expenditures in pounds for a number of subcategories of interest, namely, retail, online shopping (proxied by sales from Amazon and Ebay), restaurant, groceries, transportation and fuel, alcohol and tobacco, travel and holiday, DIY/Home, recreation and culture, and gambling. 2019 values are represented in terms of 2020 values (April 2020 inflation rate has not been published at the time of writing this paper so March 2020 rate is used).

Figure 3: Vehicle purchases and expenditure



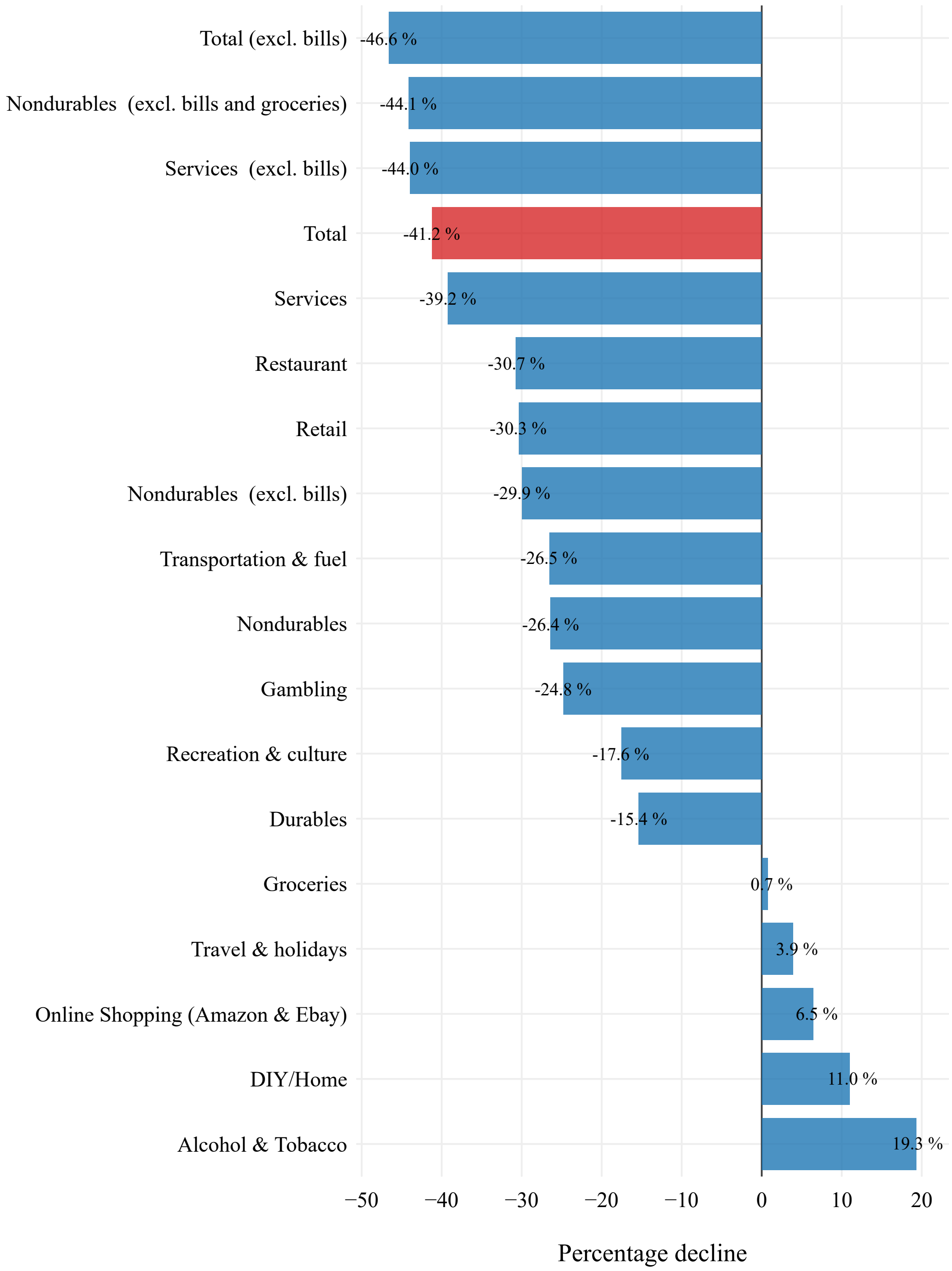
Notes: Average weekly expenditure in pounds on vehicles. 2019 values are represented in terms of 2020 values (April 2020 inflation rate has not been published at the time of writing this paper so March 2020 rate is used).

Figure 4: Indices of total, nondurable and services expenditures



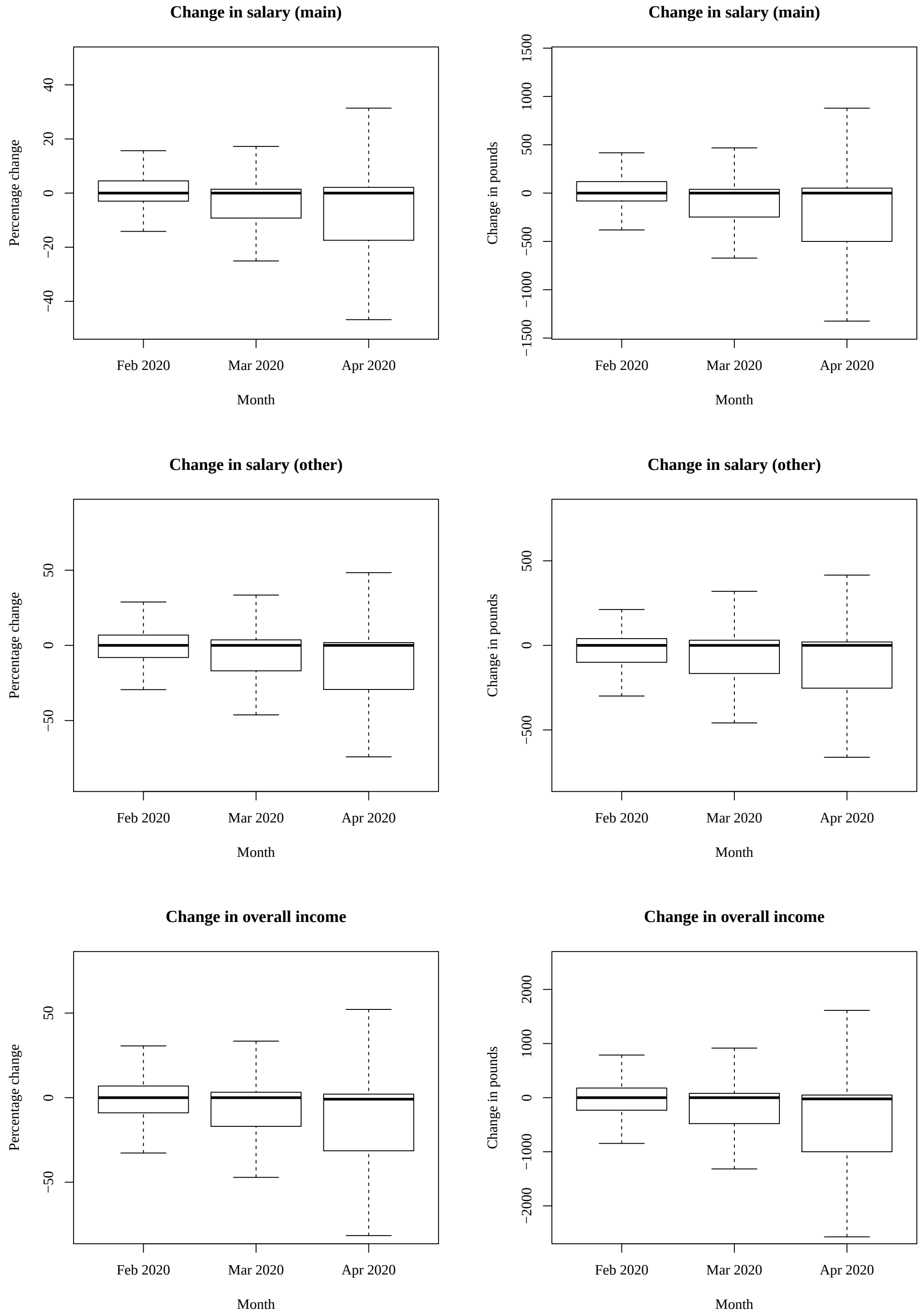
Notes: Indices of total, non-durable and services expenditures, excluding recurring bills. The indices are normalised to 100 in the second week of January.

Figure 5: Percent change in expense types from April 2019 to April 2020



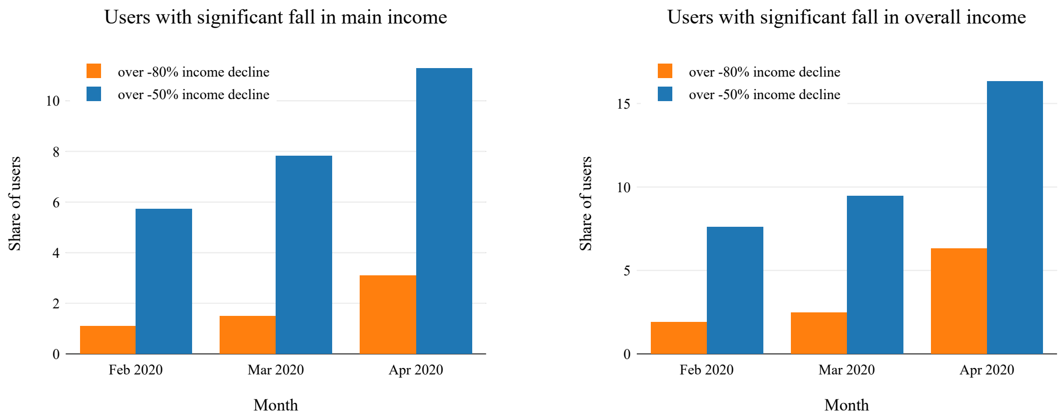
Notes: The figure records the percent change in average weekly expenditure from April 2019 to April 2020 for the expense types reported in Figures 1 and 2 in ascending order, from the largest decrease to largest increase.

Figure 6: Distribution of changes in income across months



Notes: Box plots of the change in income across months. We consider three different income definitions: the main salary, secondary and other salary, as well as overall income, which includes the first two as well as other irregular income. The left column shows the percentage change and the right column the change in pounds. The box shows contains the first quartile, median and second quartile. The whiskers are located at the smallest value between the maximum and the third quartile plus 1.5*IQR and the largest value between the minimum and the first quartile minus 1.5*IQR, respectively (IQR: interquartile range - the difference between the 25^{th} and 75^{th} percentiles).

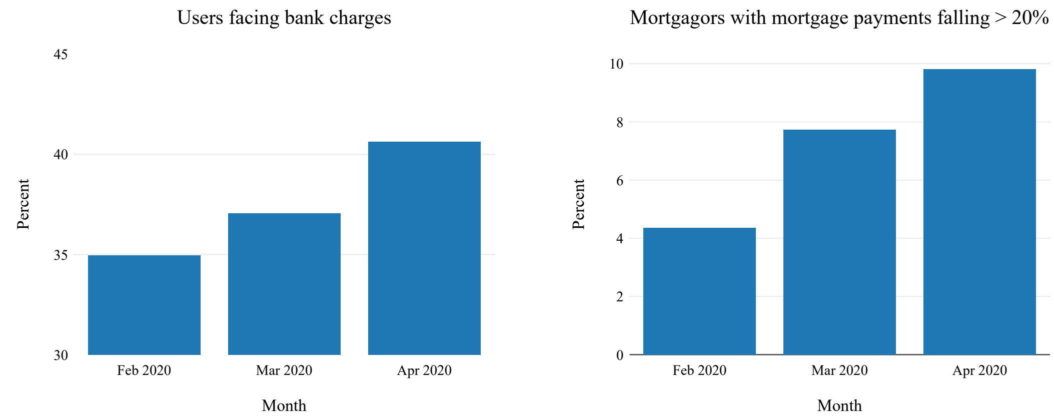
Figure 7: Share of users experiencing a significant income drop



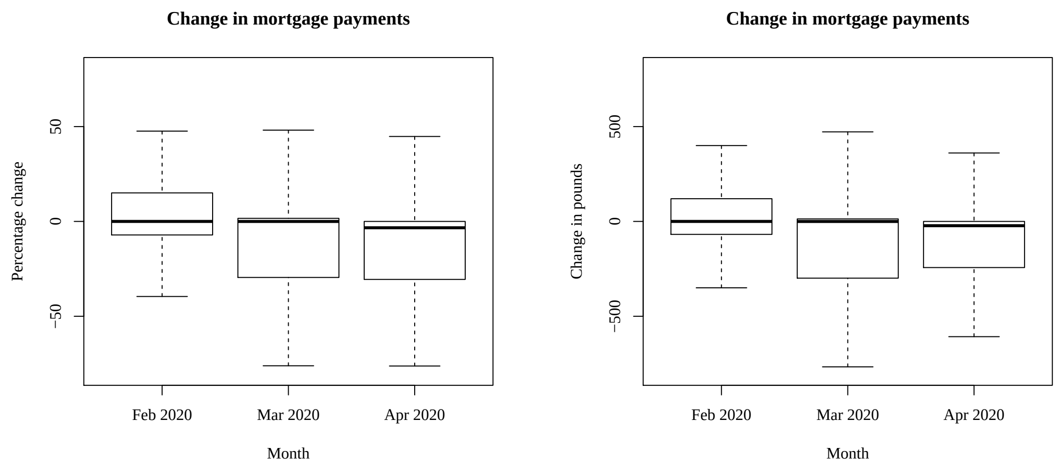
Notes: Share of users who observe a drop in income in excess of -80% and -50%, respectively (as a share of all users for which we consistently observe income throughout 2020). We use two definitions of income: main salary (left) and overall income (right).

Figure 8: Bank charges and mortgage payments

Panel A: Extensive margin

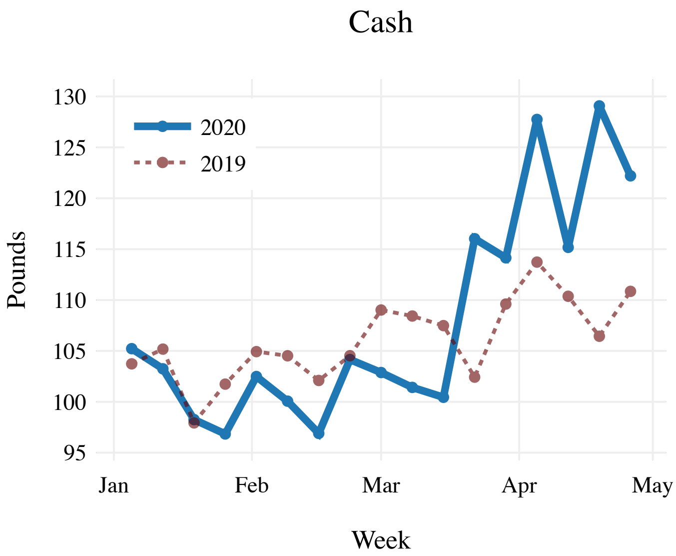


Panel B: Intensive margin



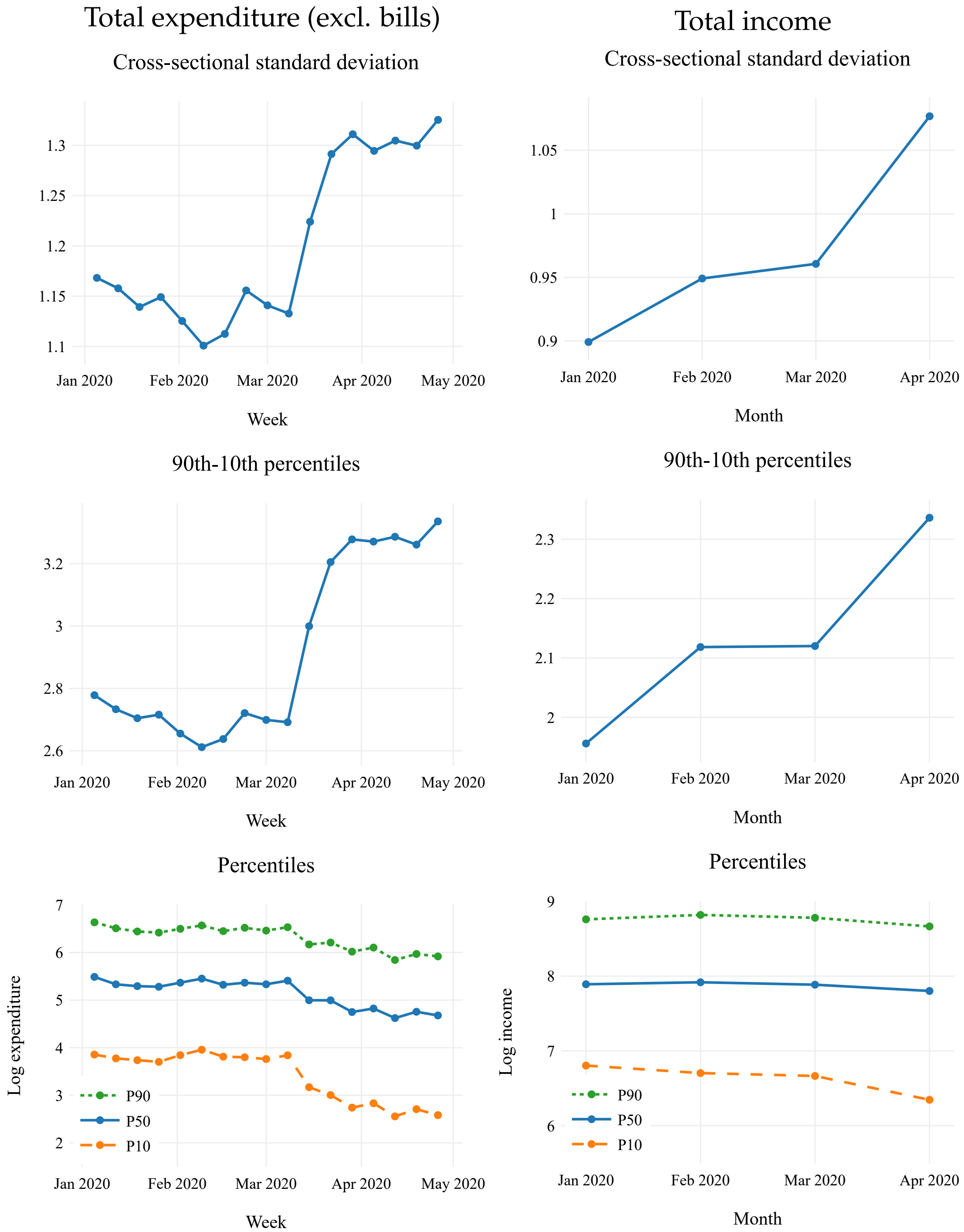
Notes: The figure shows changes in bank charges and mortgage payments across months. Panel A gives information on the extensive margin. It shows the share of users who face bank charges and the share of mortgagors with mortgage payments falling more than 20%. Panel B zooms in on mortgage payments and gives information on the intensive margin. It shows the distribution of the changes in mortgage payments across months, both in terms of percentage and pound change. The box shows contains the first quartile, median and second quartile. The whiskers are located at the smallest value between the maximum and the third quartile plus 1.5*IQR and the largest value between the minimum and the first quartile minus 1.5*IQR, respectively (IQR: interquartile range - the difference between the 25^{th} and 75^{th} percentiles).

Figure 9: ATM cash withdrawals



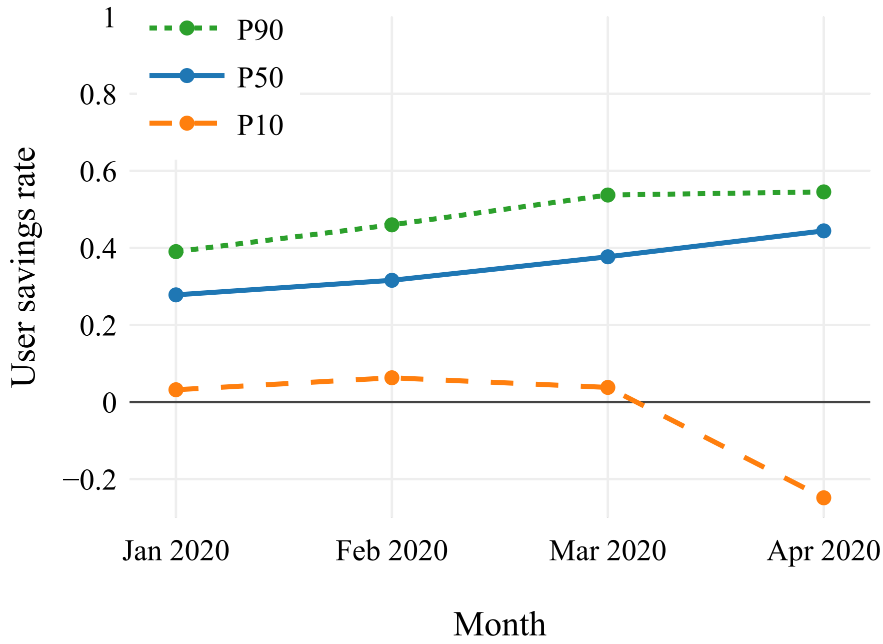
Notes: The figure shows the weekly average of cash withdrawals from ATMs in 2019 and 2020.

Figure 10: Consumption and income inequality



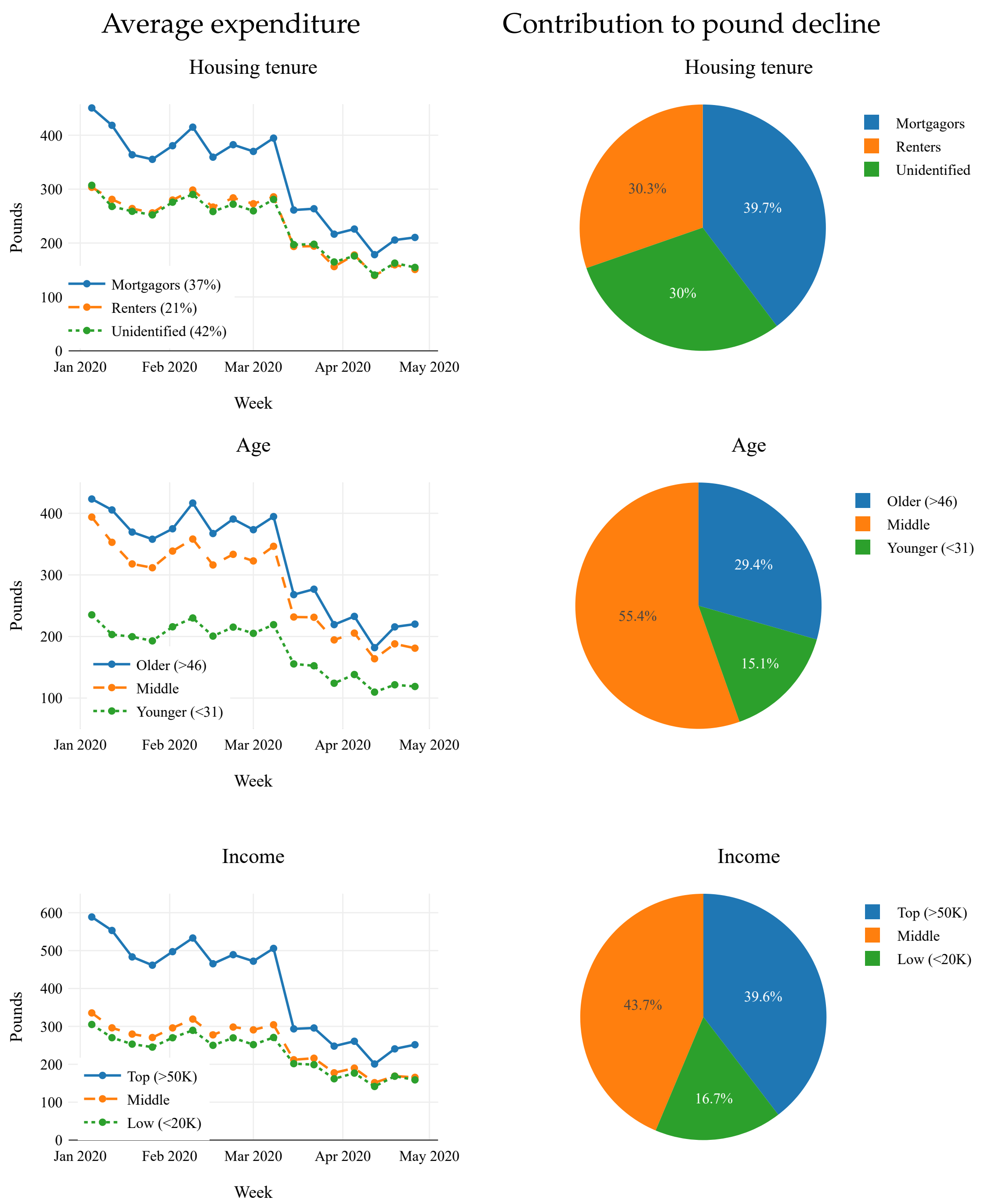
Notes: Consumption and income inequality as measured by the cross-sectional standard deviation (in logs) and the 90th-10th percentile ratio (in logs). Income refers to overall income, including irregular income, and consumption refers to total expenditure excl. recurring bills. The last panel also shows the median and the 10^{th} and 90^{th} percentiles of (log) consumption and income ex-ante distribution as measured in February 2020.

Figure 11: Savings rate



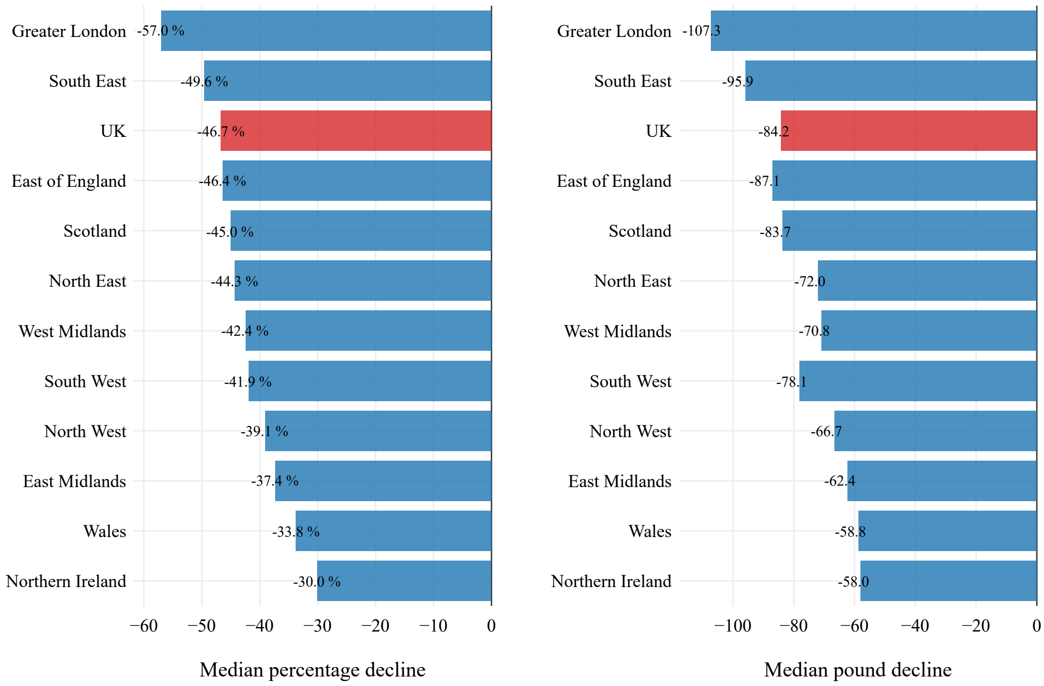
Notes: Imputed savings rates across the ex-ante income distribution as of February 2020. P50 refers to the unconditional median and P10 and P90 correspond to the median of the lower and the upper 10% of the income distribution, respectively. The savings rate is computed as $s = 1 - \frac{c}{y}$, where we use total expenditure plus mortgage and rent payments for consumption and overall income as the measure of income.

Figure 12: Heterogeneity by housing tenure, age and income



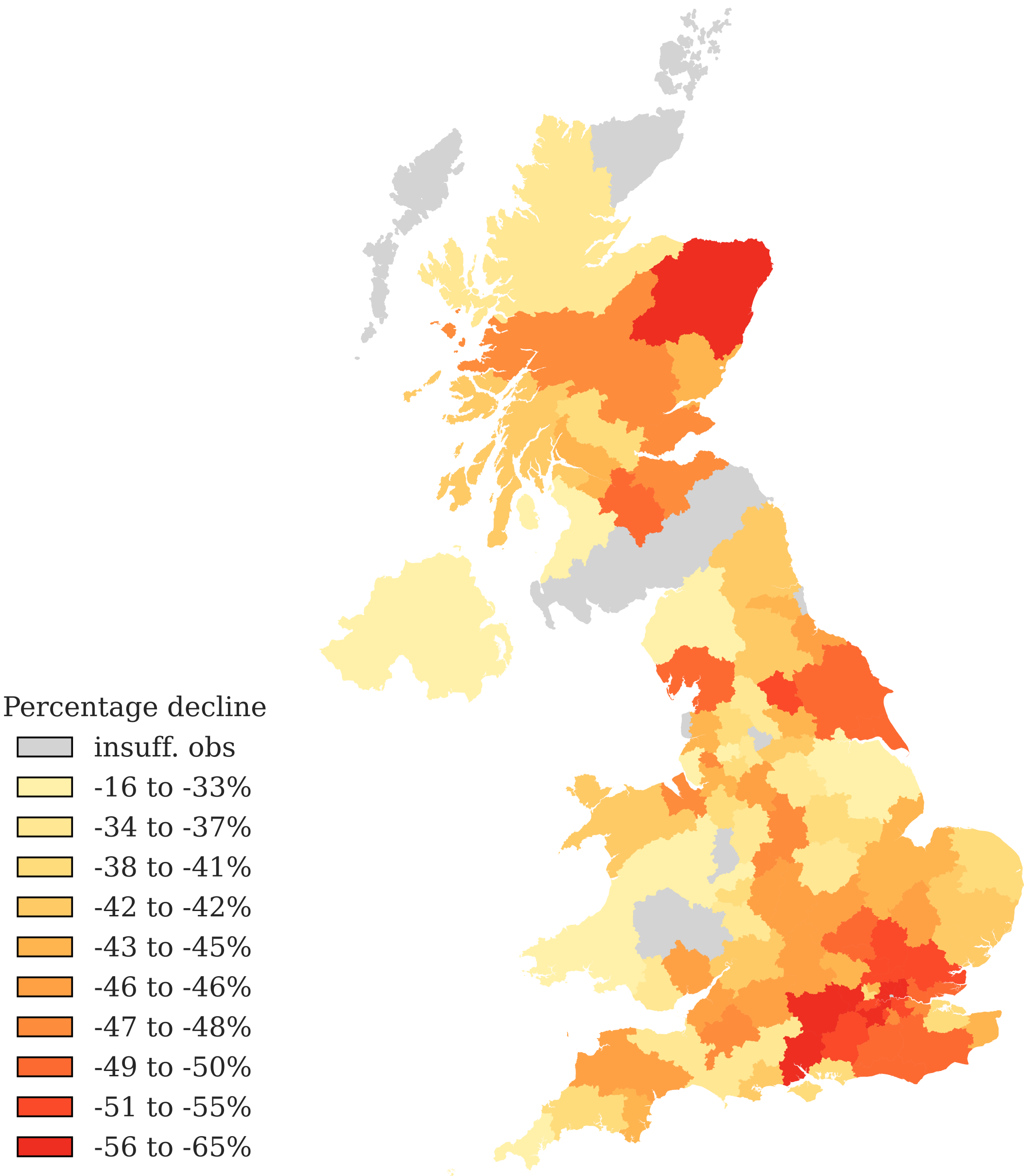
Notes: This figure shows the heterogeneity in spending behavior by housing tenure status, age and income. Left panel: Average total expenditure (excl. recurring bills). Right panel: Contribution of different groups to the decline (%) in total expenditure from the last week of February to the last week of April 2020.

Figure 13: Heterogeneity of the changes in spending across U.K. regions



Notes: Heterogeneity in spending behavior across different regions in the U.K. Left panel: percentage decline in total expenditure (excl. recurring bills) from the last week of February to the last week of April 2020. Right panel: decline in pounds. The regional changes are measured by the median of individual growth rate and pound changes.

Figure 14: Heatmap for the decline in total expenditure in the U.K.



Notes: Heatmap indicating the extent of the drop in total consumption expenditure (excl. recurring bills) in terms of percentage changes from the last week of February to the last week of April 2020 across different regions in the U.K.. The regional unit is at the area level. Darker areas indicate larger drops in spending. The regional changes are measured by the median of individual growth rate and pound changes.

Appendix

A Additional analysis and charts

Figure A.1: Recurring expenses

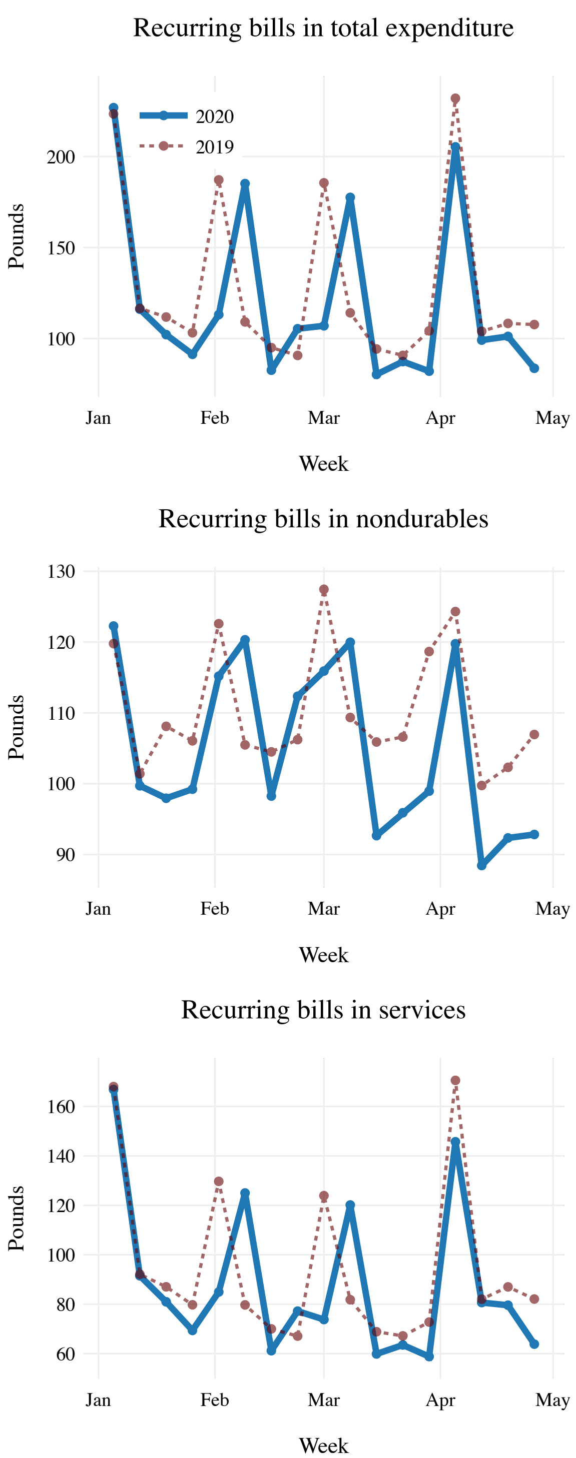
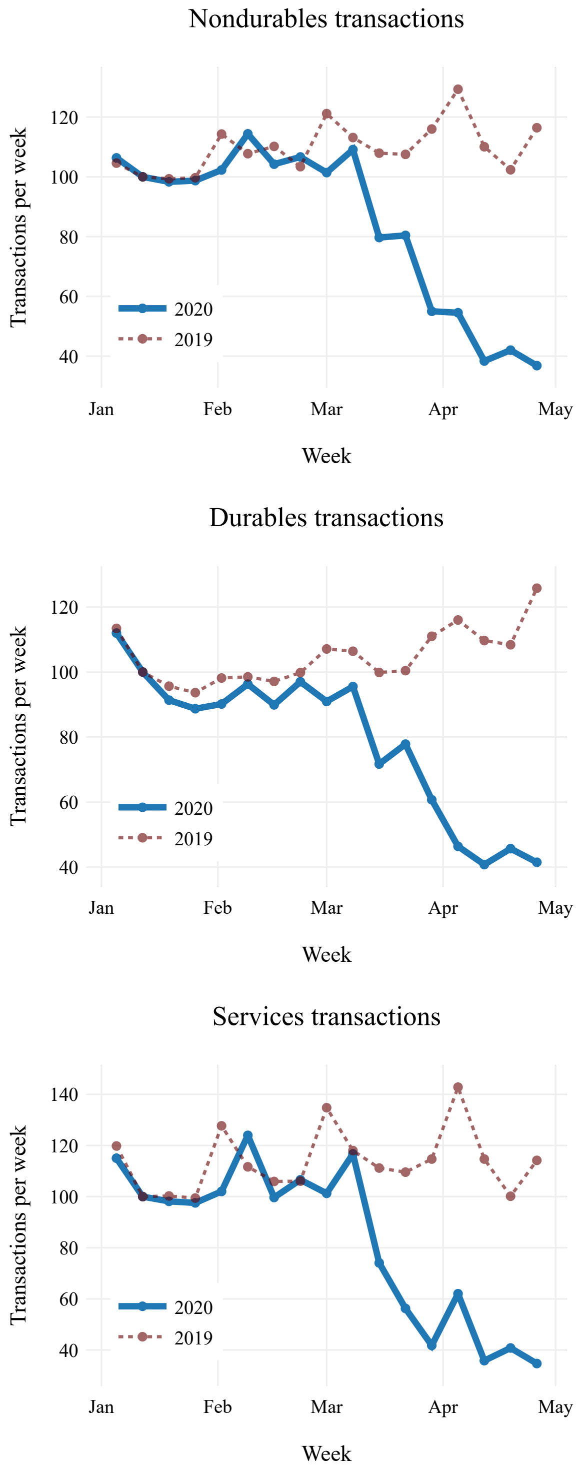
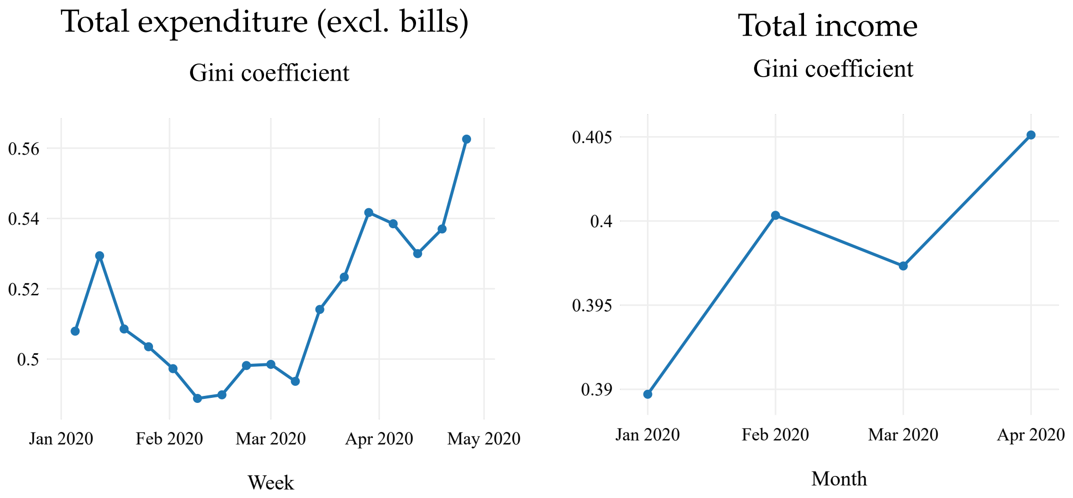


Figure A.2: Extensive margin for main expenditure categories



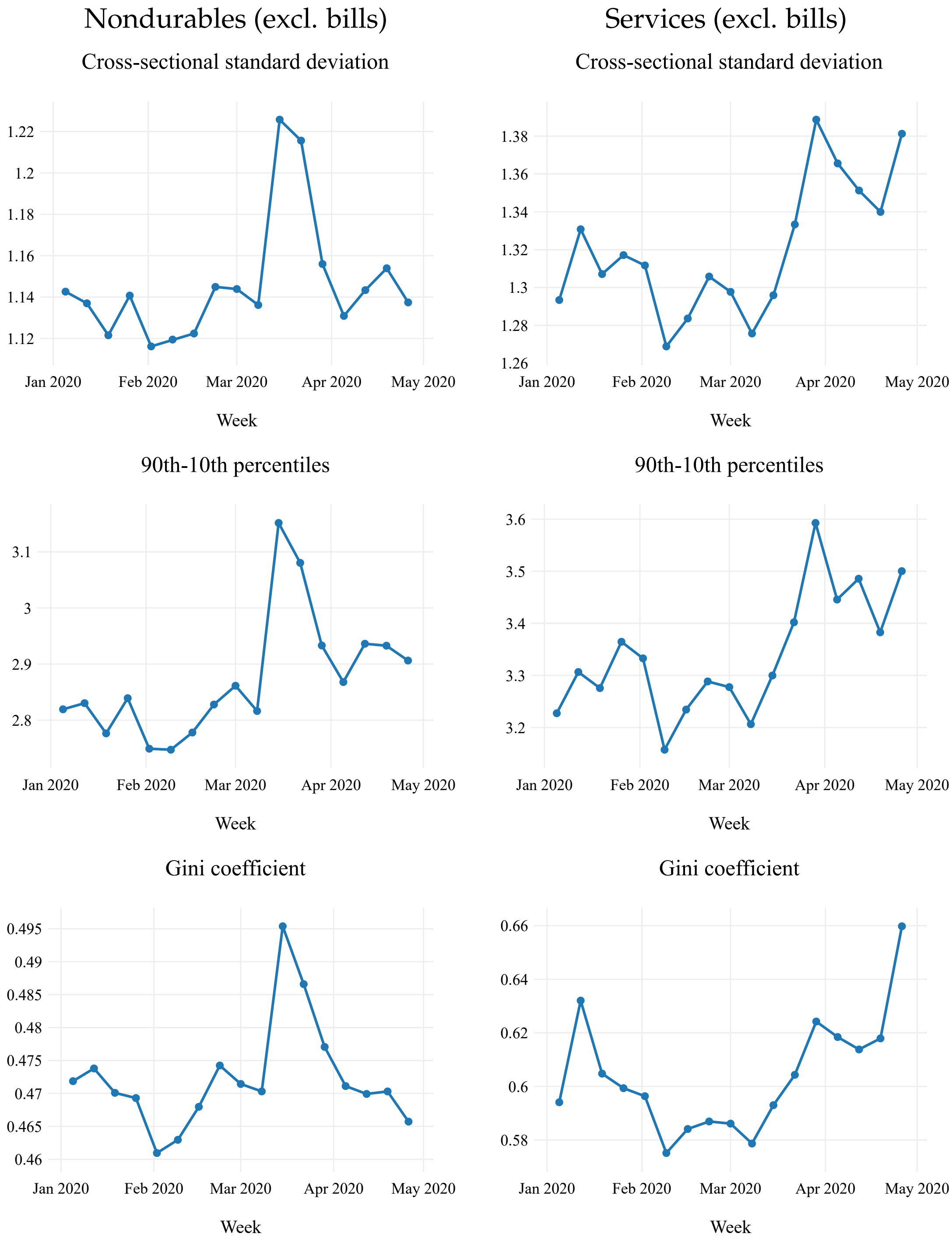
Notes: Extensive margin of nondurables, durables and services purchases as measured by weekly transactions, normalized to 100 in the second week of January 2020.

Figure A.3: Consumption and income inequality measured by the Gini coefficient



Notes: Consumption and income inequality as measured by the Gini coefficient (in levels). Income refers to overall income and consumption is total expenditure excl. recurring bills.

Figure A.4: Consumption inequality by category



Notes: Inequality in nondurables and services expenditure (excl. recurring bills) as measured by the cross-sectional standard deviation (in logs), the 90th-10th percentile ratio (in logs), and the Gini coefficient (in levels).

B Data appendix

B.1 Data cleaning

We follow simple rules to eliminate outliers and discrepancies in the raw data.

1. Drop expense amounts with 'no tag', transfers between different accounts and those smaller than £0.5 and larger than £50K.

2. Drop transactions above 99% percentile within each spending category to eliminate outliers.

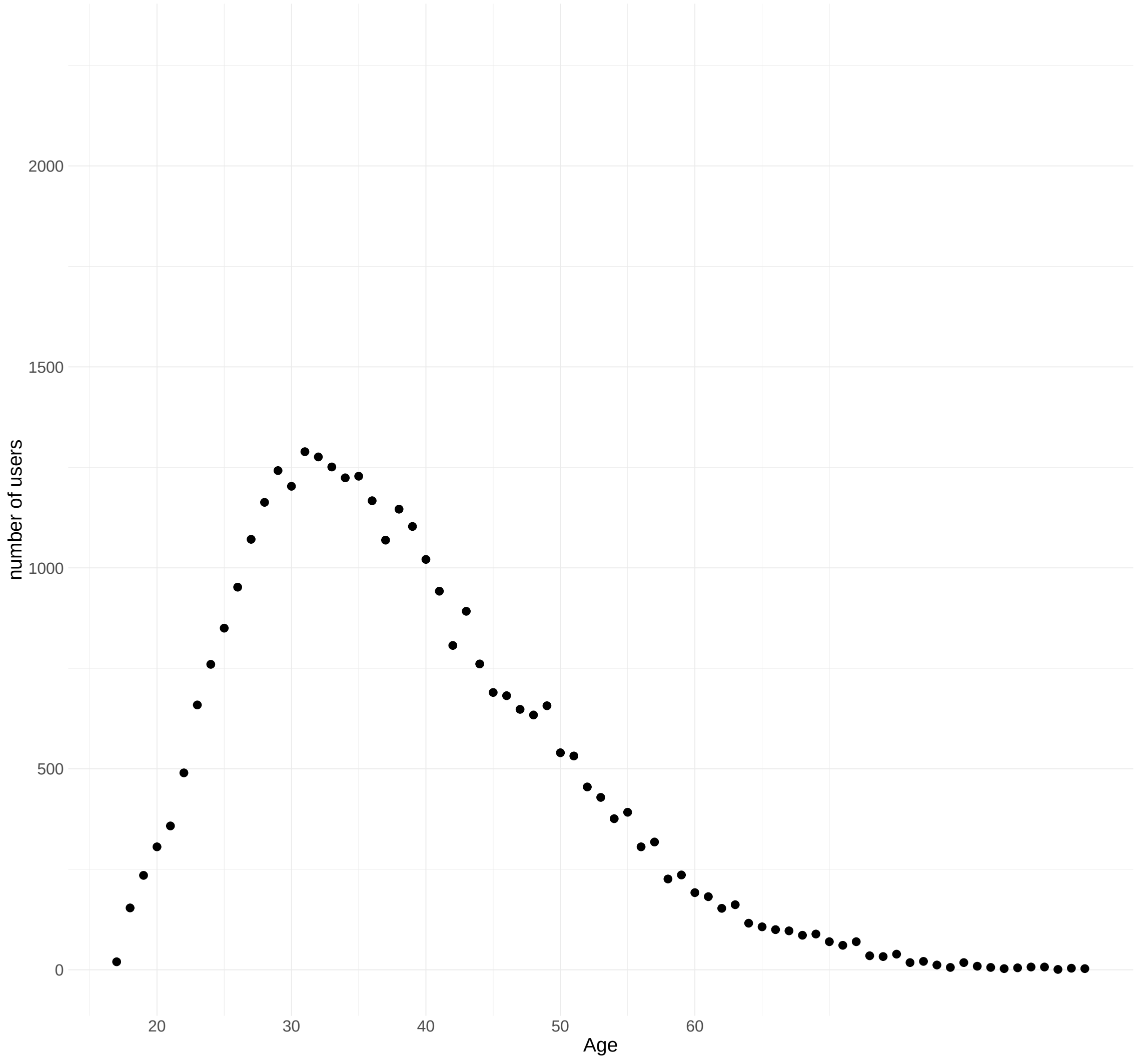
3. Keep users with sufficiently long history and those which have at least 10 transactions each week with at least the spending of £300 per month.

4. Drop salaries above 99% percentile and are implausibly low (below £10), and those users who have too many salary inflows in a given month.

B.2 Descriptive data information

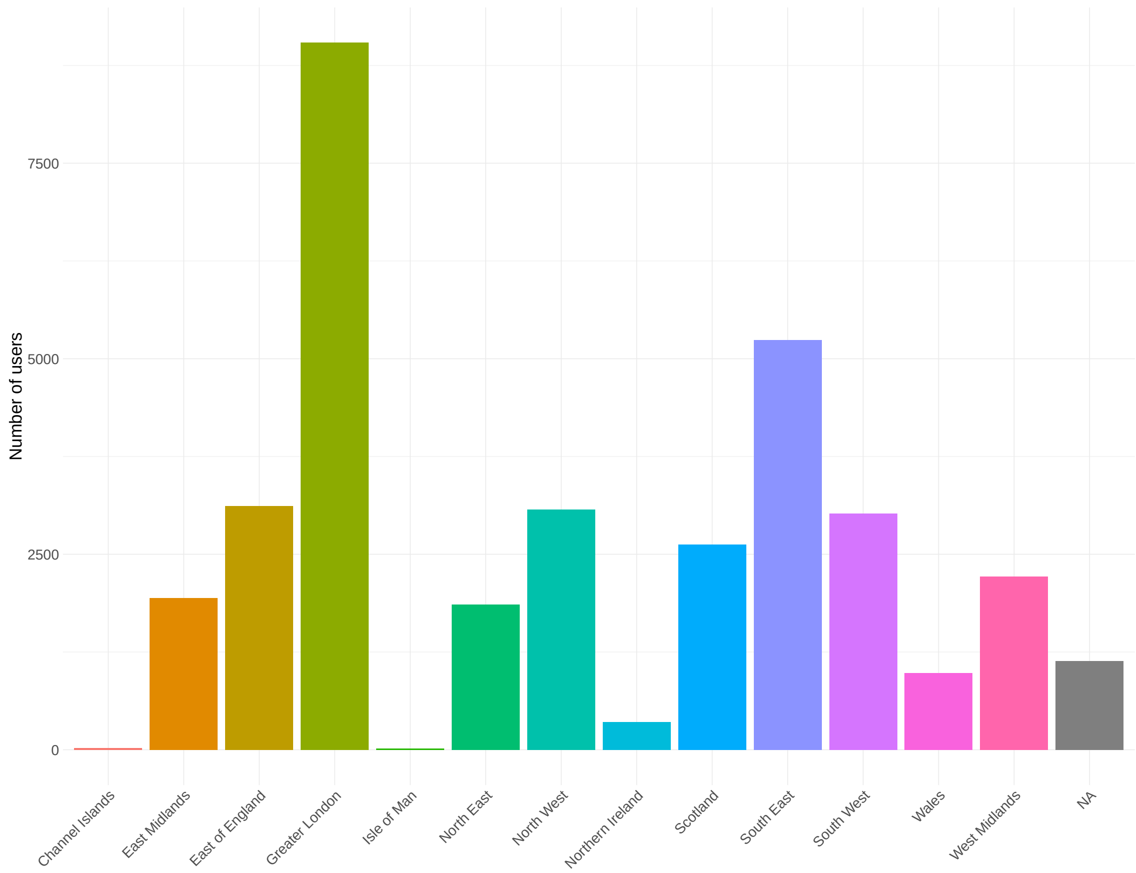
In this section, we plot different features of the data. Age profile of the users is presented in Figure B.1. Figures B.2 and B.3 present the number of users and the share of users with respect to the total population of the regions they live in. Table B.2 lists those expense types we used to construct nondurable, durable, services and retail consumption.

Figure B.1: Age profile of users



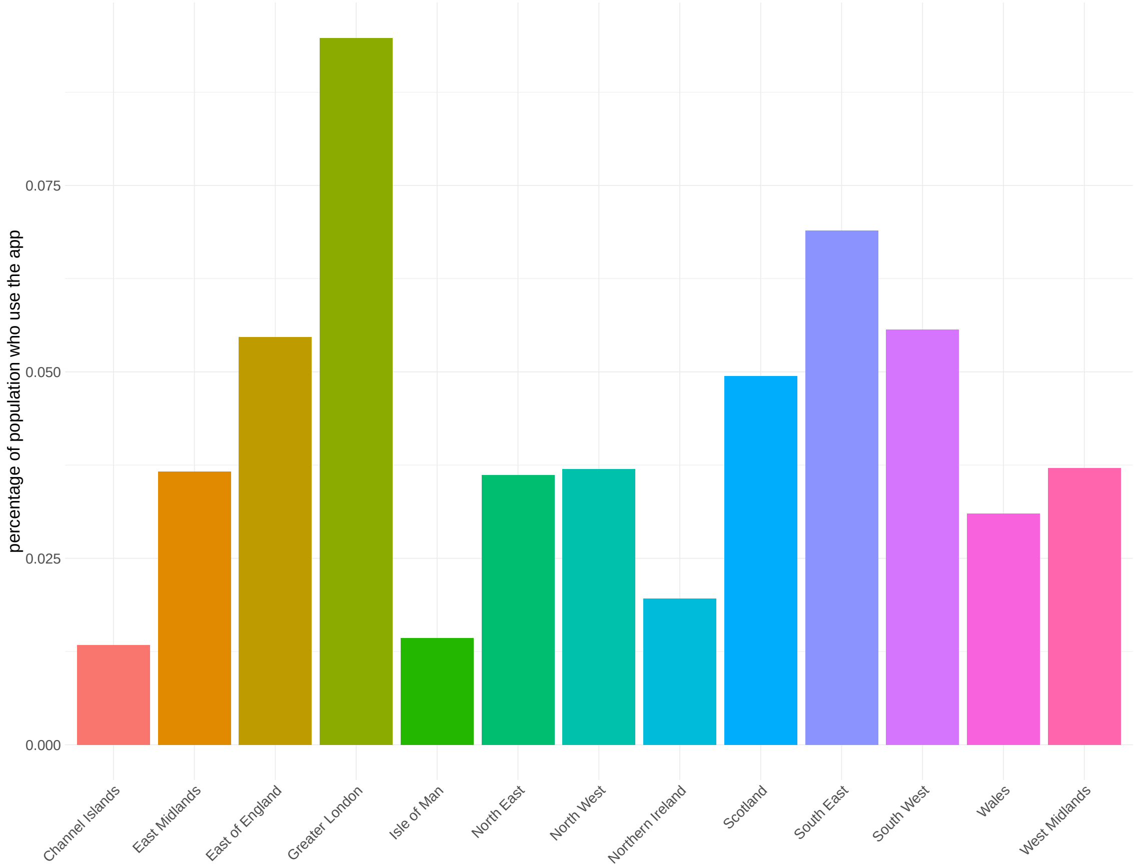
Note: Age profile of the users in the final dataset.

Figure B.2: Number of users by regions



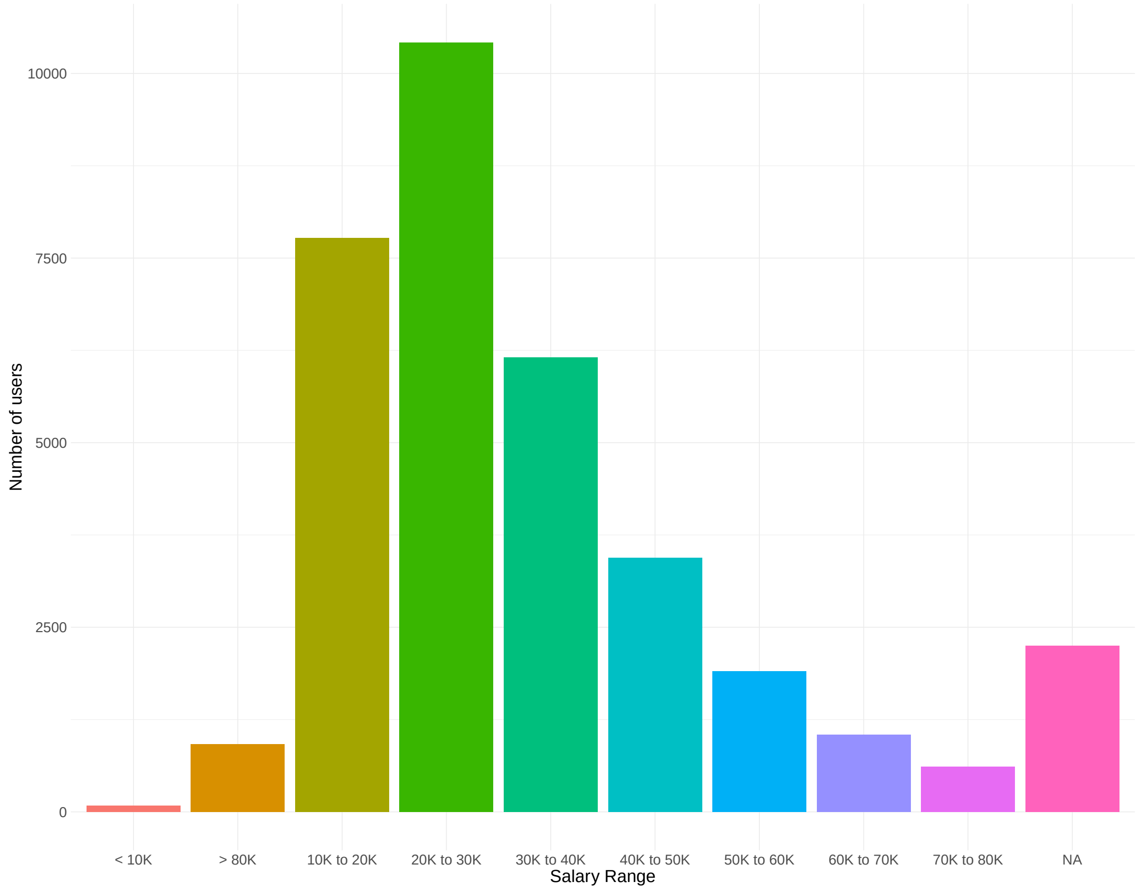
Note: Total number of users with respect to the regions they live in. NA: users with no postcode information.

Figure B.3: Number of users by regions normalized by region population



Note: Share of total number of users to the total population of the regions they live in. Excluding those with no postcode information.

Figure B.4: Derived income ranges of users



Note: Yearly income ranges of the users from the information they provide or the data provider infers from available user information. The information is either provided by the user or derived by the data provider.

B.3 Comparison of different spending indicators in the U.K.

There are two main information sources which inform both scholars and policy makers about how household expenditure evolves in the U.K.. The first is the Office of National Statistics' Living Costs and Food Survey (LCFS). This is a yearly survey whose results are released twelve months after the previous financial year ends.[1] The LCFS aims to understand consumption at the household level and reports the average weekly expenditure alongside comparisons with the previous financial years. The survey results feed into the calculation of consumer price indices and national output.

The second data source is the Understanding Society Surveys (USS), formerly conducted as the British Household Panel Survey.[2] This survey is conducted in multiple waves. As data collection and processing takes place for one wave, the other waves are taken to the development stage. The latest wave, Wave 9, has started in 2016 with the development phase. The data collection took place until the third quarter of 2019. Final data processing and documentation has been finalised in the second half of 2019 which allowed the results to be released in the last quarter of 2019.

In Table B.1, we compare our spending indicator with the information collected by the surveys by the ONS and Understanding Society. The first row discusses the release delay. To illustrate this, consider spending data that occurred during the month of March 2019. This information is collected by the MDB automatically and with no delay via the App and thus can be processed and released a few days after 31 March 2019, say – for sake of concreteness – by 3 April 2019. In contrast, the LFCS and USS releases come only after eleven and six-to-twelve months: for instance, data about March 2019 became publicly available on 19 March 2020 and in the month of December 2019 respectively.

Another relevant dimension of comparison is the frequency of data release. The MDB data allows us to observe every transaction that takes place on a daily basis and so we are able to generate weekly (and even daily) spending indicators. On the other hand, the data release of the ONS' Living Cost and Food Survey is yearly while the one of Understanding Society occurs at quarterly frequency.

As for method of data collection, it is worth emphasizing that the Fintech App minimizes measurement errors as both the exact amount, and the exact time

[1] The latest release for the financial year of April 2018 to March 2019 is in https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/expenditure/bulletins/familyspendingintheuk/april2018tomarch2019.

[2] Information on the methodology and the coverage of the Understanding Society Surveys can be found in https://www.understandingsociety.ac.uk.

and date of transaction are electronically recorded in real-time via the App. In contrast, the LCFS is based on a mixture of diary records (on smaller and more frequent expenses, especially groceries) and a retrospective interview (for larger and less frequent purchases) whereas the USS uses only a retrospective interview. As discussed by Attanasio, Hurst, and Pistaferri (2014) and Pistaferri (2015), retrospective interviews are subject to recollection biases and diary records typically suffer from severe non-classical measurement errors that may seriously compromise inference.

In terms of sample size, our MDB sample covers over 34,000 individuals with a growing user base while ONS and Understanding Society cover up to 6,000 households and 40,000 individuals, respectively. While the MDB data tend to over-represent younger consumers with higher earnings, it is not as representative of the British population as the other sources. We note, however, that the expenditure shares of all categories are very consistent with those obtained in the LCFS and USS.

It is useful at this point to discuss the means of payment. In the MDB data, we observe separately the amount of electronic payments and ATM cash withdrawals, though for the latter we do not know which category this is spent on. On the other hand, the LCFS and the USS include both electronic and cash payments. However, as discussed in Section 2, the share of cash transactions is less than a quarter of the total transactions and has been declining over time. Furthermore, the MDB data allows us a detailed coverage of different spending types. This is similar to the LCFS but different from the USS, which only covers some expenses types such as groceries, and alcohol and tobacco (but not other relevant categories such as transport, restaurant or travel).

All methods include information to explore regional heterogeneities as well as those arising from housing tenure, income and age. Finally, the unit of observations in the LCFS (and the USS) is a household, whose typically weekly expenditure is around £585. In contrast, the unit of observations in the MDB is a user, who through the App may be linking either individual or joint accounts, with the associated credit and debit cards. Accordingly, the average weekly spending in the MDB data is lower, around £385 and the average ATM cash withdrawal is about £100 a week.

In sum, all three methods and sources have advantages and disadvantages. The most appealing feature of our method is timeliness. As such, it may represent a useful addition that could complement the important role played by the LCFS and the USS, which are based on more representative samples of the British population.

Table B.1: Comparison of different consumption indicators

		Real-time Consumption Indicator Money Dashboard	**Office for National Statistics** Living Costs and Food Survey	**Understanding Society** The UK Household Longitudinal Study
Release delay		3 days	11 months after the financial year ends	6 months after data collection ends for the past 2 years
e.g. data for March 2019		*3 Apr 2019*	*19 Mar 2020*	*Dec 2019*
Frequency of data release		Weekly (Daily)	Yearly	Quarterly
Data collection method		Automated via the App	Diary and interview	Interview
Transactions type		Electronic payments & ATM cash withdrawals	Electronic & cash payments	Electronic & cash payments
Sample size		34,601 individuals	1,500 to 6,000 households	34,959 (Wave 9) - 40,000 (Wave 1) individuals
Representativeness		Partial	Full	Full
Spending categories	Nondurable	•	•	
	Durable	•	•	•
	Services	•	•	
	Retail	•	•	
	Groceries	•	•	•
	Alcohol and Tobacco	•	•	•
	Home	•	•	•
	Online shopping	•	•	
	Transport and Fuel	•	•	
	Restaurant	•	•	
	Travel	•	•	
	Recreation and Culture	•	•	
Heterogeneity	Geographical	•	•	•
	Housing Tenure	•	•	•
	Income	•	•	•
	Age	•	•	•

Notes: The table compares different sources of inferring consumption in the U.K.: real-time consumption indicator presented in this paper using Money Dashboard transaction level data; Office for National Statistics' Living Costs and Food Survey; Understanding Society UK Household Longitudinal Study.

Table B.2: Transaction categories for nondurable, durable, services and retail Consumption

	Nondurables	Durables	Services		Retail
1	Accessories	Antiques	Bank charges	Music	Appearance
2	Alcohol	Appliances or Electrical	Banking Charges	Nursery Fees	Art Supplies
3	Appearance	Art	Beauty treatments	Parking	Beauty products
4	Art Supplies	Art, Antiques or Other	Breakdown cover	Parking or Tolls	Birthday present
5	Beauty products	Caravan/Camping	Broadband	Payment Protection Insurance	Books / Magazines / Newspapers
6	Bills	Cycling	Child - Everyday or Childcare	Personal Training	Books & Course Materials
7	Birthday present	DIY	Childcare Fees	Pet Insurance	Child - Toys, Clubs or Other
8	Books / Magazines / Newspapers	Electrical equipment	Children - other	Pet training	Christmas present
9	Books & Course Materials	Furniture	Childrens Club fees	Phone (landline)	Clothes
10	Child - Clothes	Furniture, Furnishing, Gardens	Cinema	Phone or Internet	Clothes - Everyday or Work
11	Child - Toys, Clubs or Other	Garden	Clothing hire	Physiotherapy	Designer clothes
12	Christmas present	Gifts - other	Concert & Theatre	Postage / Shipping	Electrical equipment
13	Clothes	Home	Contents or Other Insurance	Public Transport	Eye care
14	Clothes - Designer or Other	Home and garden - other	Council Tax	Road charges	Flowers
15	Clothes - Everyday or Work	Home DIY or Repairs	Course and Tuition Fees	School fees	Gym Equipment
16	Clothes - other	Home electronics	Dental insurance	Service / Parts / Repairs	Home electronics
17	Coal/Oil/LPG/other	Household - other	Dental treatment	Social club	Kitchen / Household Appliances
18	Designer clothes	Jewellery	Device rental	Spa	Medication
19	Domestic supplies	Kitchen / Household Appliances	Dining and drinking	Sports Club Membership	Office Supplies
20	Electricity	Lighting	Dining or Going Out	Sports event	Personal Electronics
21	Energy (Gas, Elec, Other)	Musical Equipment	Driving Lessons	Take-away	Pet - Toys, Training, Other
22	Eye care	Personal Electronics	Dry cleaning and laundry	Taxi	Printing
23	Flowers	Soft furnishings	Education - other	Taxis or Vehicle Hire	Shoes
24	Food, Groceries, Household	Software	Enjoyment	Tradesmen fees	Software
25	Fuel	Vehicle	Entertainment, TV, Media	Transport	Sports Equipment
26	Games and gaming	Vehicle purchase	Flights	Transport - other	Stationery & consumables
27	Gas		Gambling	TV / Movies Package	Toiletries
28	Gas and electricity		Gambling account	TV Licence	Toys
29	Gifts or Presents		Going out - other	Vehicle hire	Workwear
30	Groceries		Gym Membership	Vehicle insurance	
31	Gym Equipment		Hairdressing	Vehicle Running Costs	
32	Hobby Supplies		Hairdressing, Health, Other	Vet	
33	Lifestyle - other		Health insurance	Web hosting	
34	Medical, Dental, Eye Care		Hire Purchase	Zoo/theme park	
35	Medication		Hobbies - other		
36	Office Supplies		Hobbies or Activities		
37	Personal Care - Other		Hobby Club Membership		
38	Pet - Everyday or Food		Holiday		
39	Pet - Toys, Training, Other		Holidays		
40	Pet food		Home appliance insurance		
41	Pet housing/care		Home insurance		
42	Pet toys		Hotel/B&B		
43	Pets - other		Income insurance		
44	Photography		Insurance		
45	Printing		Insurance - other		
46	Shoes		Life insurance		
47	Sports Equipment		Lunch or Snacks		
48	Stationery		Media bundle		
49	Stationery & consumables		Medical treatment		
50	Supermarket		Memberships		
51	Tobacco		Mobile		
52	Toiletries		Mobile phone insurance		
53	Toys		MOT		
54	Water		Motorbike Insurance		
55	Workwear		Museum/exhibition		

Notes: Transaction categories considered to construct non-durables, durables, services and retail expenditures in Section 2.

References

Attanasio, Orazio, Erik Hurst, and Luigi Pistaferri. 2014. "The Evolution of Income, Consumption, and Leisure Inequality in the United States, 1980–2010." *in Improving the Measurement of Consumer Expenditures*, NBER(C. Carroll, T. Crossley, and J. Sabelhaus (Eds.)): 100–140.

Pistaferri, Luigi. 2015. "Household consumption: research questions, measurement issues, and data collection strategies." *Journal of Economic and Social Measurement*, 1-4: 123–149.