Borrowing in Response to Windfalls

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November 18, 2019

Abstract

We use high-accuracy and comprehensive transaction-level panel data containing information on all spending, income, balances, and credit limits of a representative sample of the Icelandic population. We document that the marginal propensity to consume (MPC) out of small windfalls due to lottery payments, i.e., perfectly temporary unexpected income shocks, is larger than one for the average individual. Furthermore, we document that individuals who receive small windfalls increase their short-term unsecured consumer debt, such as overdrafts, in response. This borrowing response is prevalent for individuals having relatively little as well as a lot of liquidity, i.e., borrowing capacity. The larger-than-one MPCs are thus financed using expensive consumer debt that is then rolled over for a considerable period of time. For large windfalls we only observe small MPCs and no borrowing responses. We also document that individuals do not increase their savings in response to either small or large windfalls. Our findings point to overconsumption problems driving both high MPCs as well as large consumer debt holdings and are clean evidence against liquidity constraints as an explanation for high MPCs out of windfalls.

JEL classifications: E03, D03, D91, D14

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Fedra De Angelis Effrem and Andrea Marogg provided excellent research assistance. We are indebted to Meniga for providing and helping with the data.

1 Introduction

How do households respond to unanticipated transitory income shocks? What are the main drivers of heterogenity in the responses and what can they tell us about the use of high-interest unsecured consumer debt? A large literature in economics has studied the first of these questions and shown that people respond to transitory income shocks by increasing their spending, even though standard economic theory predicts that they should be saved almost entirely. However, the accumulation or paydown of consumer debt in response to transitory income shocks has been less widely studied.

In this paper, we are not only interested in spending responses but also in high-interest unsecured consumer debt. From 1945 to the second quarter of 2009, the amount of debt owed by households increased substantially in all developed countries. The increase in liabilities has been driven by both increasing mortgage debt (as a percent of real estate assets and as a percent of disposable personal income) but even more so by a substantial increase in consumer credit (Müller, 2018). Servicing their high-interest consumer debt is difficult and many consumers find themselves stuck in a cycle of expensive consumer loans. Furthermore, rolled-over high-interest consumer debt is difficult to rationalize under standard economic frameworks (Laibson et al., 2000; Georgarakos et al., 2014; Haliassos and Reiter, 2005). Understanding the underlying mechanisms of consumer debt accumulation and paydown is therefore important to understand households' finances because relatively little is known about what drives households' choices of debt types and levels.

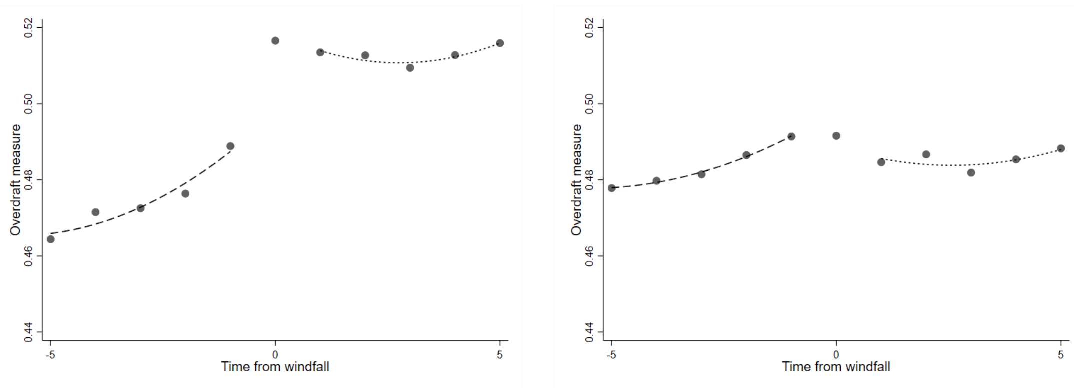
We use data from a personal finance platform in Iceland (a "financial account aggregator"), containing comprehensive transaction-level information on individual spending, income, account balances, and credit limits aggregated to the monthly level. This data source overcomes limitations in accuracy, scope, and frequency that have plagued the data used in previous studies (Olafsson and Pagel, 2018b). Other studies have exploited such data (see, e.g., Gelman et al., 2014; Baker, forthcoming) to generate measures of income and spending derived from the actual transactions and account balances of individuals in the US. Relative to US data, the Icelandic data we use has five main advantages: 1) utilizing Icelandic user data essentially eliminates the remaining limitation of app data – the absence of cash transactions – since Icelandic consumers almost exclusively use electronic means of payments, 2) the Icelandic app is marketed through banks thus covering a fairly broad fraction of the Icelandic population, 3) the spending and income data is pre-categorized allowing accurate predictions about the responses of different spending categories, 4) we observe all balances and credit limits of all accounts, and 5) individuals within households can link themselves but all accounts are personal.

We try to answer how individuals respond to windfall gains by exploiting two types of natural experiments. The first one is lottery winnings. We have information on how much individuals spend on lotteries and the gains reaped from them and the majority of the population participates in lotteries. The second one is repayments from banks in Iceland, resulting from a court ruling regarding loan recalculations. The Icelandic Supreme Court ruled on June 16, 2010, that loans indexed to foreign currency rates were illegal in cases involving private car loans. The decision meant that borrowers with such loans were only obliged to repay the principal in Icelandic krona even though initially the principal was tied to other currencies. In turn, banks had to repay some individuals' excess payments.

As pointed out by Fagereng et al. (2018), three econometric challenges need to be overcome in order to investigate how individuals respond to windfall gains. First, one needs to observe windfall gains and have information on whether they are anticipated or not as standard economic theories have different predictions for these two cases. Second, windfall income needs to be linked with household spending, balances, as well as other income. Third, in order to say something about long run effect and its dynamics, one needs longitudinal panel data. For the purpose of our study, we know whether windfalls are expected or not, we observe measurement-error free transaction data on all spending, income, and balances, our data covers 2011 to 2017, and its longitudinal nature allows us to include individual fixed effects in our estimations and thereby control for selection on all time-invariant (un)observable characteristics.

We split the transitory payments we observe by their median amount into small and large windfalls. Most interestingly, we document a marginal propensity to consume (MPC) out of small windfalls that is larger than one. In documenting this finding we follow other studies, such as Fagereng et al. (2018). However, Fagereng et al. (2018) deemphsized these larger-than-one MPCs because of data limitations. Furthermore, studying heterogeneity, we find that low and high liquidity individuals both display this behavior. The larger-than-one MPCs are financed by expensive short-term unsecured debt, such as overdrafts, which is then rolled over for a considerable period of time.

This main result can be easily seen in the raw data in Figure 1 showing the binned averages of an indicator for overdrawing individual checking accounts at least once per month in the five months before and after a small or large windfall. It can be clearly seen that individuals on average increase their borrowing in response to small windfalls.



Small windfall

Large windfall

Figure 1: Likelihood of overdrawing the checking account in the five months before and after small and large windfalls

Note: Raw data binned averages split by the median windfall amount of approximately $100.

In terms of broader implications, we think that our findings speak to a long-standing debate in the literature: are high MPCs driven by environmental constraints such as liquidity constraints as opposed to more behavioral motives such as overconsumption or subjective feelings of being rich. Borrowing in response to windfalls is clear evidence against the idea that high MPCs are driven by liquidity constraints. Our finding simply takes liquidity constraints as an explanation for high MPCs ad absurdum.

The 2015 American Household Credit Card Debt Study estimates the total credit card debt owed by an average U.S. household to be $15,762, which amounts to a total of $733 billion, and the average Icelandic household's amount borrowed is of similar magnitude. Such large high-interest debt holdings over longer periods of time are very hard to rationalize in standard economic models. For example, Laibson et al. (2003) argue that such debt holdings constitute a puzzle for standard life-cycle models in which fully rational agents would rather forgo the benefits of consumption smoothing than borrow at such high interest rates. Laibson et al. (2015) show that a model with hyperbolic discounting and illiquid assets rationalizes the amount of borrowing we see in U.S. data. However, for the calibration to work, the hyperbolic-discounting parameter has to be half of that commonly estimated in other domains (refer to, for instance, DellaVigna, 2009) and agents have to be fully naive, i.e., they must believe that they will not have any hyperbolic discounting problems but are perfectly rational in all future periods. There also exist rational models that generate some borrowing in response to permanent income shocks in the presence of illiquid assets (Kaplan and Violante, 2014). However, Kaplan and Violante (2014) assume the absence of transitory income shocks, to which any rational agent would respond by holding a small buffer of liquidity. Furthermore, they document that agents in the model bunch at zero borrowing when interest rates are high, such as the rates on credit cards or overdrafts, and only borrow (up to their credit limits) when interest rates are relatively low, such as the rates observed on home equity lines of credit.

Standard economic models say that credit demand is countercyclical and strongly negatively correlated with income shocks. We demonstrate this in the model by Laibson et al. (2015). The hyperbolic agents in the model, calibrated to match the real-world borrowing on credit cards that we see, decrease their likelihood to borrow as well as their amount borrowed in the event of positive transitory income shocks. The borrowing response we see in our data is clearly at odds with the predictions of this model. In fact, any economic model in which individuals have a concave utility function and thus want to smooth consumption will predict a clear negative correlation between borrowing and income. However, empirically we conclude that households may well increase their borrowing in response to a windfall and thus document an important discrepancy between theoretical and empirical results.

The paper is organized as follows: first, we briefly review the literature. In turn, we show theoretically that borrowing should be negatively correlated with transitory income shocks. We then provide background on the debt relief ruling as well as a data description and summary statistics. In turn, we present the main analysis and conclude.

2 Literature review

Many papers analyze individual spending responses to wealth shocks.[1] While many studies use consumption survey data, there exists several recent studies using administrative transaction-level data. Agarwal and Qian (2014) analyze Singaporean consumers' responses to a fiscal stimulus announcement and payout. The authors find a strong announcement effect of about 19% of the overall consumption response. These payments range from $78 to $702 per person which is in line with many of the lottery payments we observe. Closer to our debt relief experiment in magnitude are the exogenous wealth shocks examined by Kueng (2015) originating from the Alaska Permanent Fund. These anticipated pre-determined payments range from $692 to $3,722 per person. With an average Alaskan household size of 2.7, this amounts to a payment of up to $10,050 for a typical family. Using app data as we do, Gelman et al. (2015) and Baker and Yannelis (2015) examine how individuals respond to a temporary drop in income following the 2013 U.S. Federal Government shutdown. Federal government workers were subject to an unanticipated 40% decline in income, with no direct effect on permanent income. In a recent contribution, Cookson et al. (2019) study the long-run effects of unanticipated wealth shocks on the distribution of household debt. The authors again examine much larger payments than we do but also, directionally, find a larger debt response for small payments than large ones. However, the authors use credit report snapshots of balances as a proxy for credit card borrowing which may not perfectly accurately measure consumer debt that is actually rolled over. Finally, Baugh et al. (2014) study the effects of tax refunds using high-frequency transaction-level data. The authors also document very high MPCs but do not look at small payments specifically or consider that an increase in consumer debt that is driving high MPCs renders liquidity constraints implausible.

[1] Refer to Jappelli and Pistaferri (2010) for a survey of this literature.

Other empirical papers that examine transitory payments such as fiscal stimuli include Shapiro and Slemrod (1995), Shapiro and Slemrod (2003), and Parker (1999), among many others. Most of these studies, however, are using survey data that may contain measurement error because respondents may have little incentive to answer the questions accurately, may not understand the wording of the questions, or may behave differently in practice and forget their reported behavior. Moreover, such measurement error or noise in the data generated by surveys can increase with the length of the recall period (de Nicola and Giné, 2014). Additionally, surveys can produce biased (rather than merely noisy) data if respondents have justification bias, concerns about surveyors sharing the information, or stigma about their consumption habits (Karlan and Zinman, 2008).

Consumption and savings responses to lottery income are studied by Fagereng et al. (2018), Imbens et al. (2001), and Kuhn et al. (2011) among others. The first study uses yearly snapshots from the Norwegian tax register for over a decade. As mentioned Fagereng et al. (2018) also find larger-than-one MPCs for small prizes (below $1000) but deemphasize this finding due to data limitations.[2] The second study considers 500 winners of large prizes in a Massachusetts lottery and the last study considers a lottery in the Netherlands where households received prizes of 12,500 Euros. The Dutch findings stand out from most of the literature in that neither durable nor non-durable consumption responded by much. Furthermore, using Swedish wealth tax data, Cesarini et al. (2016) study effects of lottery winnings on health and child development and, using the same data, Briggs et al. (2015) study the effects of lottery winning on stock market participation.

Whether evidence from lotteries can be generalized to other income shocks is debatable

[2] The authors write that "winners of relatively small amounts tend to spend all they win, or even more than the prize itself. The mean estimate is 1.35 to the dollar won [...] we also see that the average debt response in this group is positive, suggesting that several of the low-prize winners top their prize up with credit or lower debt repayment. Surprisingly though, the estimated deposit coefficient is high too, and the sum of coefficients (minus debt) exceeds unity. This, together with the fact that all estimates in the lowest prize quartile come with relatively high standard errors, suggests that the exact point estimates in this group should be interpreted with caution."

(Crossley et al., 2016). We therefore, look at two sources of income shocks and compare the spending responses to the existing estimates in the literature. As we will discuss below, participation in betting activities, both state-run and organized by charitable organizations, is widespread in Scandinavian countries. Almost all the individuals we observe, participate in lotteries once in a while and our descriptive statistics reveal only minor systematic differences between participants and non-participants.

Given the small windfalls we focus on, our paper is related to the mental accounting literature that has shown that individuals may treat money from small windfalls differently than money out of salary income. Milkman and Beshears (2009) and Johnson et al. (2006) show that money coming as a windfall gain via coupons and tax rebates is consumed at a much higher rate than predicted by the standard economic model. Moreover, to name just a few studies on mental accounting, Hastings and Shapiro (2013) find that when gasoline prices rise, consumers substitute to lower octane gasoline to an extent that cannot be explained by income effects and thus reject the null hypothesis that households treat gas money as fungible with other income. Furthermore, Baker et al. (2006) find that dividends are consumed at a higher rate than capital gains and Beatty et al. (2014) show that the UK winter fuel payment, a cash grant, is disproportionally spent on heating.

To the best of our knowledge, no existing paper has emphasized the large and positive consumer debt response to small windfalls which allows us to comfortably rule out a long-standing explanation for high MPCs out of windfalls: liquidity constraints.

The theoretical literature that is informed by estimates of marginal propensities to consume (MPCs) out of windfalls is mostly comprised of incomplete markets models, as developed by Carroll (1997). In these models, households face uninsurable idiosyncratic labor income risk and a borrowing constraint. As a result, they acquire a buffer stock of capital in order to prevent the constraint from binding. The main determinant of household MPC then is their net wealth level. In turn, follow-up papers added a second illiquid asset to these models and argued that not the overall wealth level but the amount of liquid savings determines individual MPCs (Kaplan and Violante, 2014). Standard models with only one liquid savings vehicle have a hard time explaining high MPCs out of windfalls because agents spread the additional wealth over their entire lifetime and consume very little out of it. In contrast, models with liquid and illiquid savings as well as borrowing constraints generate high MPCs but only if transitory income shocks are otherwise assumed to be absent (if transitory income shocks are present, the agents would respond with holding a buffer of liquidity to smooth consumption). Alternative theoretical explanations for high MPCs and large consumer debt positions include overconsumption problems and time inconsistencies (Laibson et al., 2015) as well as agency problems within households (Bertaut et al., 2009; Olafsson and Pagel, 2018a).

In summary, relative to the existing literature, our study is characterized by 1) a large variance in the amounts of windfalls, 2) news about the payments that were unexpected arriving on a known date prior to the payments, 3) payments whose timing was unknown as the bank had to recalculate 30,000 loan contracts taking some time, 4) payments whose size individuals could find out from an online loan calculator, and 4) substantially smaller measurement error in spending responses with accurate disaggregated spending categories and other household characteristics including high-frequency balances and credit limit information. The categorization of our spending data allows us to draw a precise picture of what individuals spend on in response to such large payments and the observation of credit limits, overdraft limits, and balances allows us to analyze the debt paydown responses.

3 Theoretical background

We consider the same model as in Laibson et al. (2015) to formally illustrate the standard predictions of how borrowing responds to income shocks in a life-cycle model that successfully explains the extent of credit card borrowing via illiquid savings and naive hyperbolic discounting (see, Laibson, 1997; Kuchler and Pagel, 2015). Additionally, the model explains the existing evidence documenting a lack of consumption smoothing by showing that individual marginal propensities to consume out of transitory income shocks are very high (see Shapiro and Slemrod, 1995, among many other studies). Beyond illiquid assets and naive hyperbolic discounting preferences, the model features revolving high-interest credit, liquidity constraints, stochastic labor income, social security, child and adult household dependents, retirement, and mortality. The authors estimate the preference parameters using the method of simulated moments; in particular, the exponential discount function of a standard agent as well as the present-biased discount function of a hyperbolic-discounting agent. The authors show that the standard model of exponential discounting can be formally rejected in favor of hyperbolic discounting. Nevertheless, the hyperbolic discount factor the authors estimate is relatively low in comparison to typical estimates and assumptions in the micro literature (see, for instance DellaVigna, 2009, for a literature survey).

More specifically, Laibson et al. (2015) consider the following model.[3] The agent lives for $t = \{1, ..., T\}$ periods. Each period the agent optimally decides how much to consume C_t. Additionally, he decides how much to save in the liquid and illiquid assets. X_t represents the beginning of period t liquid asset holdings before receipt of period t income Y_t. If $X_t < 0$, then uncollateralized high-interest debt, i.e., credit card debt, was held between t and $t-1$ at an interest rate of R^{CC}. The agent also faces a credit limit in period t of λ times average income at age t. If the agent saves instead of borrows, he earns an interest R. The variable $Z_t \geq 0$ represents illiquid asset holdings at the beginning of period t, earning interest R^Z and providing consumption value. However, illiquid assets can be liquidated only with a proportional transaction cost, which declines with age $\kappa_t = \frac{1/2}{1+e^{t-50/10}}$. Let $I_t^X$and I_t^Z represent net investment into the liquid and illiquid assets so that the budget constraint is

[3]We thank the authors for kindly sharing their solution code.

given by

$$C_t = Y_t - I_t^X - I_t^Z + \kappa_t \min(I_t^Z, 0).$$

The consumer has constant relative risk aversion quasi-hyperbolic preferences and maximizes

$$\max_{I_t^X, I_t^Z} \{ n_t \frac{(\frac{C_t + \gamma Z_t}{n_t})^{1-\rho}}{1-\rho} + \beta E_t [\sum_{\tau=1}^{T-t} \delta^\tau (\prod_{j=1}^{\tau-1} s_{t+j}) (s_{t+\tau} \frac{(\frac{C_{t+\tau} + \gamma Z_{t+\tau}}{n_{t+\tau}})^{1-\rho}}{1-\rho} + (1 - s_{t+\tau}) B(X_{t+\tau}, Z_{t+\tau}))]\}$$

each period t subject to the budget constraint. Here n_t represents family size in period t, ρ is the coefficient of relative risk aversion, β is a hyperbolic discount factor, and δ is an exponential discount factor. The agent is fully naive in the sense that his period t self does not take into account that his period $t+1$ self is present-biased. $B(\cdot)$ incorporates the bequest motive in the death state which is represented by $s_t = 0$ instead of $s_t = 1$ when the agent survives. More details can be found in Laibson et al. (2015) and the model is solved by numerical backward induction. Laibson et al. (2015) estimate the environmental parameters of the model using data from the American Community Survey of the U.S. Census Bureau, the Survey of Consumer Finances, and the Panel Study of Income Dynamics and the preference parameters of this model to match the patterns of wealth accumulation and credit card borrowing over the life-cycle and we adopt the parameters of their best fit for the hyperbolic agent. In turn, we consider a standard agent by setting $\beta = 1$.

We simulate the life-cycle consumption paths of 10,000 agents and then run the equivalent of our empirical specification in the simulated data; i.e.,

$$\log(abs(X_{i,t}) | X_{i,t} < 0) = \alpha + \beta \log(Y_{i,t}) + age_{i,t} + \epsilon_{i,t}$$

where $log(abs(X_{i,t}) | X_{i,t} \leq 0)$ is the amount borrowed by agent i at age t (set to zero if the agent does not borrow) and $Y_{i,t}$ is the agent i's period t income that is subject to transitory shocks calibrated to include social security and unemployment benefits. Furthermore, to eliminate life-cycle effects, $age_{i,t}$ is a set of age or cohort fixed effects. Alternatively, we can use an indicator for whether or not agent i at time t borrows as the outcome variable as well as log consumption. Because all agents are the same in the sample of simulated data, this regression is equivalent to our empirical specification with individual fixed effects.

Of course, in reality, agents are heterogeneous, and to not all have the same preferences. That is why we report the regression results for two types of agents: a hyperbolic agent, whose preference parameters are estimated by Laibson et al. (2015) using a representative sample of the U.S. population, and also a standard agent who does not have a hyperbolic discounting problem. If one were to observe a mixed group of these two agents, the coefficients would be a combination of the ones displayed.

As we can see in Table 1, the likelihood and amount borrowed is strongly negatively correlated with transitory income fluctuations in the hyperbolic discounting model. We find that present-biased agents in the model are consumption smoothing as standard agents and use borrowing as a tool to smooth transitory income shocks. For the standard agent, we find directionally the same responses but this agent almost never borrows at the level of interest rates considered in this model. In fact, the standard agent only borrows 0.15% of the time.

4 Measuring windfalls, income, spending, and consumer debt

We follow Fagereng et al. (2018), Imbens et al. (2001), and Kuhn et al. (2011) in that we exploit information on lottery winnings of individuals to study how their consumption responds to windfall gains. As pointed out earlier, the most important difference between our settings and theirs in that we can link the information on lottery winnings to detailed, high-frequency, longitudinal information on spending. We will now discuss the measurement of windfall gains in the Icelandic setting and our measurement of consumption.

Because we analyze data from Iceland, nominal variables are measured in Icelandic Krona. The value in US dollars can be easily recovered by dividing by 100. There are 11,699 individuals in this data set which starts in November 2011 and ends in January 2017 (63 months), and we aggregate to a monthly panel with a total of 737,037 observations (for each of the 11,699 individuals, we observe 63 months).

Measuring Windfall Gains

Lottery winnings

Playing the lottery and gambling is very common in Iceland. Approximately 70% of Icelandic adults reported gambling at least once in the past year and 13% reported gambling weekly. The most common gambling forms included the lottery, scratch cards, and slot machines (Stefánsdóttir et al., 2015).

We observe 39,539 lottery winning payments which illustrates how common playing the lottery is. The reason is that many charities use lotteries to raise donations (lottery winnings related to charities which amount to 8,812 payments). Additionally, we observe 1,150 incidences of gambling gains and these windfalls are also quite sizable in magnitude.

Almost all the lottery purchases we observe are subscription lotteries. This is due to the fact that many charities sell tickets exclusively via subscriptions. Furthermore, those that do allow purchase of individual tickets provide strong incentives for subscription, e.g., individuals only pay for four draws per month even though there are sometimes five draws. That way individuals get four free draws per year for each subscription ticket. In addition, lottery companies often have a special lottery around Christmas that subscribers participate in automatically without paying extra.

Empirical evidence for this is shown in Figure 2 which shows the distribution of the number of individual's lottery ticket purchases as well as charges per month. If individuals are subscribers they are only charged once a month, independent of how many draws there are. Individuals would then have one lottery ticket charge per month if they have subscribed to one lottery, two if they have subscribed to two, etc. As we can see the number of charges per month is typically only one whereas the number of ticket purchases is typically one to three. Additionally, Figure 3 shows the number of lottery ticket purchases per month in which we see an increase in November, December, and January (as discussed part of that is due to extra lottery rounds during the winter months) but otherwise not too much variation.

In most cases, prizes are thus transferred automatically to the accounts of winners if they are subscribers. Therefore, subscribers do not have to worry about checking whether they won each time to make sure they do not miss a prize they may have won.

Debt relief ruling

Before the financial crisis, loans paid out and collected in Icelandic krona but indexed to foreign currencies were promoted aggressively by the Icelandic banks. In 2012, more than 10% of Icelandic households held car loans linked to foreign currencies, a legacy of the credit-fueled boom years when borrowers took advantage of lower interest rates on foreign-denominated loans while Icelandic rates were soaring. The exchange rate indexation of the loans meant that the total amount owed in Icelandic krona varied according to its exchange rate against the currencies in which the loan was issued. After the financial crisis, such loans left many diligent car and home owners with bigger debts than the original amount–despite paying their bills every month. What looked like a smart bet before the crisis turned into a nightmare afterwards, as the krona lost a third or more of its value against major currencies. This caused a sharp increase in repayment costs, adding to the pressure on recession-hit Icelandic households.

In February 2010, the Reykjavik District Court ruled that such loans are illegal. According to the legal precedent, exchange rate indexed loans should be turned into regular inflation indexed loans denominated in Icelandic krona. This meant that the (usually lower) interest rates that the parties had agreed up on were to be replaced by the ones of the Icelandic Central Bank. In December 2010 the Icelandic parliament passed a low (Act no. 151/2010) that stipulated that FX-linked loans were to be re-calculated. This meant that many consumers ended up owing higher interest on credit instalments they had already paid in the past. However, the principal was also re-calculated to a lower amount and some consumers received payments from the banks as a result of this.

Consumers were dissatisfied with the Central Bank interest being applied retroactively and this led to subsequent litigation. On 15 February 2012, the Supreme Court in Iceland passed a ruling (No.600/2011) that affected how the banks had recalculated the illegally FX-indexed loans. The ruling states that Act 151/2010, that the Icelandic Parliament passed in December 2010, instructing banks to recalculate FX-linked home mortgages, violates the provisions of the Icelandic constitution that protects the freedom to hold property, as the legislator cannot pass law that retroactively changes the rules on repayment of claims without adequate compensation, and that the re-calculation should be based the Central Bank interest.

This resulted in debt repayments to thousands of Icelandic households. The specific incidence of payments we observe were due to vehicle agreements by the major bank Landsbankinn. Because the bank needed to review around 30,000 loans, the first vehicle loans corrections based on this ruling were made in early July and the whole undertaking was completed by January 2015 even though we observe transfers based on recalculations as late as January 2017.

Measuring income, spending, and consumer debt

One of the main impediments that empirical studies of consumption are posed with is the lack of access to detailed longitudinal information on consumer spending. Thus far, researchers have mostly relied on information from household consumption surveys. (Johnson et al., 2006; Parker et al., 2013), e.g., employ the Consume Expenditure Survey (CEX) in the U.S., and Jappelli and Pistaferri (2014) the Survey on Household Income and Wealth in Italy. However, survey data suffer generally from small sample sizes, attrition, and can produce biased (rather than merely noisy) data if respondents have justification bias, concerns about surveyors sharing the information, or stigma about their consumption habits Karlan and Zinman 2008. Parker and Souleles (2017) compare spending measures based on self-reported survey data and observational data and conclude that the self-reported survey data, although informative, do not reliably measure quantitative spending.

One potential approach to overcome the lack of access to high-quality information on spending poses to research on spending behavior is to impute expenditure from information on income and wealth in administrative tax data (yearly snapshots). This approach has, e.g., been employed by Browning and Leth-Petersen (2003) using Danish register data, Eika et al. (2017) and Fagereng et al. (2018) using Norwegian register data, and Koijen et al. (2014) and Maggio et al. (2018) using Swedish register data. However, as pointed out by Baker et al. (2018), imputed spending can deviate from actual spending due to intra-year changes in asset values and composition. They show furthermore that the measurement errors vary across individuals of different types and income levels and are highly correlated with the business cycle.

The ideal solution to the problem of data availability is to get access to detailed longitudinal information on spending. The recent digitization of budgeting processes with financial aggregation services allow direct measurement of individual's spending in ways that were not previously possible. Using data from a financial aggregation and service app overcomes the accuracy, scope, and frequency limitations of the existing data sources of consumption and income as it is derived from actual transactions and account balances (see, e.g., Gelman et al., 2014; Baker, forthcoming). We follow this approach and discuss the data used in detail in the following section.

In this paper, we exploit data from Iceland generated by Meniga, a financial aggregation software provider to European banks and financial institutions. Meniga was founded in 2009 and is the European market leader of white-label Personal Finance Management (PFM) and next-generation online banking solutions, reaching over 50 million online and mobile banking users across 23 countries. Meniga's account aggregation platform allows bank customers to manage all their bank accounts and credit cards across multiple banks in one place and see all of them in a single location.

Anyone who has an online bank in Iceland can register at meniga.is in order to access the personal financial management (PFM) platform. Furthermore, the online banking interfaces of the three big Icelandic banks offer the software. The ones who do sign up agree to be a part of a sample for analytical purposes. In January 2017, the Icelandic population counted 338,349 individuals, of whom 262,846 were older than 16. At the same time, Meniga had 50,573 users, which is about 20% of the population above age 16. Because their service is marketed through banks, the sample of users is fairly representative. Each day, the software automatically records all the bank and credit card transactions, including descriptions as well as balances, overdraft, and credit limits. Additionally, the software collects demographic information such as age, gender, marital status, and postal code. Their data has already proven useful for studying, e.g., the spending responses of individuals to income arrivals (Olafsson and Pagel, 2018b), the drivers of individuals' attention to their personal finances (Olafsson and Pagel, 2017), and how expenditures and financial decisions change around retirement (Olafsson and Pagel, 2018c).

Individuals in Iceland use overdrafts as their main means of high-interest unsecured consumer debt. An overdraft occurs when withdrawals from a current account exceed the available balance. This means that the balance is negative and hence that the bank is providing credit to the account holder and interest is charged at the agreed rate. Virtually all current accounts in Iceland offer a pre-agreed overdraft facility, the size of which is based upon affordability and credit history. This overdraft facility can be used at any time without consulting the bank and can be maintained indefinitely (subject to ad hoc reviews). Although an overdraft facility may be authorized, technically the money is repayable on demand by the bank. In reality this is a rare occurrence as the overdrafts are profitable for the bank and expensive for the customer.

Definitions of variables

Total discretionary spending - Spending is pre-classified into 15 categories and aggregated to generate a monthly panel. The spending categories are groceries, fuel, alcohol,[4] ready made food, home improvement, transportation, clothing and accessories, sports and activities, pharmacies, media, bookstores, thermal baths, toy stores, insurances, and various subcategories of recreation (e.g., cinemas, gaming, gambling etc.). Total spending is the sum of the spending in all these categories and excludes all recurring spending, e.g., rent and bills. The data is pre-categorized by Meniga.

Necessary spending - Necessary spending is the sum of spending in grocery stores, gas stations and pharmacies.

Unnecessary spending - Unnecessary spending is the sum of spending in the alcohol, restaurants/take-outs, lottery, gambling, gaming, and cinema categories.

Cash - Cash is defined as the sum of checking and savings account balances, normalized by the average discretionary spending per day of individuals, i.e., we measure cash in consumption days.

Liquidity - Liquidity is defined as cash plus credit and overdraft limits minus credit card and overdraft balances, normalized by the average discretionary spending per day of individuals, i.e., we measure liquidity in consumption days.

[4] We can observe expenditures on alcohol that is not purchased in bars or restaurants because a state-owned company, the State Alcohol and Tobacco Company, has a monopoly on the sale of alcohol in Iceland.

Overdraft usage - We both look at whether individuals hold an overdraft in a given month, i.e., their checking account balance is negative at least once, and how many overdrawn checking accounts they have.

Overdraft interest payments - Overdraft interest is interest paid on the amount of overdraft individuals have. The overdraft interest rate varies with the Central Bank policy rate and is in the same ballpark as the interest on rolled over credit card debt. Individuals typically pay off their credit card in full and use overdrafts to roll-over debt. Overdraft interest payments should therefore be thought of as the costs of rolling over consumer debt. Figure 4 depicts the time series of overdraft interest and the short-term interest rate over our sample period.

Late fees - Fees assessed for paying bills after their due date.

Income - We observe the following regular income categories: child support, benefits, child benefits, interest income, invalidity benefits, parental leave, pension income, housing benefits, rental benefits, rental income, salaries, student loans, and unemployment benefits. In addition, we observe the following irregular income categories: damages, grants, other income, insurance claims, investment transactions, reimbursements, tax rebates, and travel allowances.

Descriptive statistics of windfall payments

Figure 5 shows the distribution of the total windfall amount. Table 2 contains detailed summary statistics of the different windfall sources and amounts relative to the incomes of the receiving individuals. Furthermore, Table 3 display the number of individuals receiving the different types of windfall payments under consideration and Tables 4 and 5 offer detailed comparison statistics of the individuals who receive windfalls versus those that do not as well as of the months in which individuals receive windfalls versus months that they do not receive windfalls.

For the purpose of our analysis, we only consider windfalls amounting to more than 2,000 ISK. The reason is that we want to have a minimum of economic importance in the size of the payments and responses. In turn, we refer to windfalls below median size as small and windfalls above median size as large. The median is 10,000 ISK. On average, individuals receive a rate of 1.663 small windfalls, i.e., 1,663 windfalls for 1,000 individuals, (4.671 if conditional on ever having a small windfall) and 7.350 large windfalls during the considered period.

5 Empirical Approach

We estimate how individuals respond to windfall gains by running regressions based on the following specification

$$y_{i,t} = \beta_0 + \beta_1 Windfall_{i,t} + \beta_2 X_{i,t} + \psi_t + \eta_i + \epsilon_{i,t} \tag{1}$$

where i is a household identifier, t is month-by-year, $y_{i,t}$ is the outcome under consideration—spending, use of consumer credit, or savings —of individual i at time t, $Windfall_{i,t}$ is the amount of windfall gains at time t. $X_{i,t}$ is a vector of controls, ψ_t are month-by-year fixed effects, and η_i is an individual fixed effect. The β coefficients thus measure by how much the individual outcome changes in response to windfall gains. The individual fixed effects control for all observable and unobservable time-invariant individual characteristics and the month-by-year fixed effects for all long-term trends, seasonal trends, and aggregate fluctuations over time.

We report both regression results from specifications including all individuals in our sample and only those individuals who received a windfall of the size under consideration at least once during our sample period. Because we include individual fixed effects, we identify within-individual when he or she receives a windfall payment in a given month versus not.

Nevertheless, by excluding individuals who never received a windfall, we exclude variation that may capture selection into playing the lottery versus not. Additionally, to exclude the size of the lottery payment as a potentially exogenous variable, we use windfall dummies in some specifications instead of windfall amounts.

Furthermore, when we take the indicator for overdrawing a checking account as the outcome variable, we use a logit regression model. As an alternative, when we take the number of overdrawn checking accounts as the outcome variable, we consider a linear probability model. Because most individuals have only one checking account, our results of this specification are thus very similar to a linear probability model and using an indicator for overdrawing as the outcome variable. Figure 6 shows the distribution of the number of overdrafts and savings accounts that individuals hold.

6 Results

6.1 Spending and borrowing responses to windfall gains

Tables 10 to 12 provide our empirical results. Table 10 shows the estimated MPC out of small and large windfall gains. It can be easily seen that the average MPC out of small windfalls is considerably larger than one. This has also been documented in previous papers such as Kueng (2015) and Fagereng et al. (2018), however, the authors did not emphasize their results as, because of different challenges with their data, the effect was not reliably estimated. Our data, in contrast, is high-frequency comprehensive spending data and we still find a MPC larger than one for the average person. The high MPC is not only found for individuals with low liquidity or low income. In contrast, we find it for all liquidity and income terciles as shown in Tables 7 and 8. Furthermore, Table 9 shows the effect split up by gender.

What we also see is a borrowing response to small windfalls but not for large windfalls, consistent with a MPC larger than one being financed by borrowing. Our borrowing measure is a dummy for whether individuals have an overdraft and the number of overdrafts. We use these measures of overdrafts rather than the overdraft amount because this variable is only part of our dataset for a shorter time period. Furthermore, the indicator of holding an overdraft is also a better measure than overdraft interest payments. Overdraft interest payments also reflect interest rates which may be different for each individual and vary over time in the aggregate but also on an individual basis. As individual interest rates are unobservable to us, we cannot control for individual-level variation in this measure that is not related to the amount borrowed. We see that the number of overdrafts is strongly correlated with the overdraft interest and the overdraft amount and thus we argue that it is a very good measure for the intensive margin of borrowing.

Table 10 shows the effects of small and large windfalls on the indicator for holding an overdraft and thus the increase in the probability of rolling over high-interest unsecured debt. We can clearly see that individuals are more likely to take on consumer debt in the months of receiving a small windfall explaining their ability to finance an MPC that is larger than one. Furthermore, Table 11 shows the same for the number of overdrafts in different checking accounts that individuals roll over.

Clearly, a high MPC financed via high-interest consumer debt discredits the notion that a lack of credit capacity or liquidity constraints cause such high MPCs in the first place.

It seems that there is some borrowing response to large windfalls but when we look one month ahead this response disappears while it stays the same for small windfalls. A potential explanation is that people might borrow just before receiving the windfall (but already know they will) but then use the windfall to pay back and that is why we do not see any lasting effects for large windfalls. In contrast, for the small windfalls it appears that individuals indeed borrow to finance their consumption and this increase in borrowing is persistent. Furthermore, the coefficients on current and lagged windfalls are almost the same, it thus appears as if, individuals roll over most of the amount borrowed.

The dynamics of spending and overdraft responses are further illustrated in Figure 7. We can see that the spending response is not statistically significantly different for small versus large windfalls whereas the overdraft response is statistically significantly larger for small windfalls. Furthermore, the overdraft response is persistent: after five months, if anything, the effect is larger than in the month of the actual windfall.

In contrast, we do not see a savings response to either type of windfalls (measured by the number of savings accounts) as shown in Table 12. This result can be taken at face value, i.e., individuals do not appear to save more at the external margin in response to windfalls, but also serves as a placebo check that the number of overdrawn checking accounts does not result from individuals linking more accounts or the like (which, however, would not be picked up anyway in our specification given that we control for individual fixed effects).

Finally, Figures 8 and 8 illustrate our results graphically as well as showing the estimated dynamics. These figures plot the fitted values for total spending as well as groceries and ready-made food in the months before and after the windfall. We can see that the level of spending jumps, especially for small windfalls, and then grows at the same rate as before. If we look at the percentage deviation of spending, we see an increase of 5% relative to individual's average spending.

We see large increases in spending in restaurants and groceries that are non-durable and non-lumpy expenditure categories. Finding large responses in these categories also addresses a potential explanation for the debt response due to lumpiness and Ss-rules of spending in combination with individuals needing a buffer stock of liquidity.

Furthermore, in Figure 8, we see financial outcomes and, in particular, consumer debt. As we saw in the raw data in Figure 1, consumer debt, as measured by an indicator for holding an overdraft, the number of overdrawn checking accounts, late fees, or paid overdraft interest, jumps up for small windfalls but not or not as much for large ones.

6.2 Heterogeneity

Let us now look into heterogeneity using 3D plots following Fagereng et al. (2018). We see in Figures 10 to 15 that the high MPC individuals are also the ones borrowing heavily to finance that consumption. This holds true for both the likelihood to borrow as measured by an indicator for rolling over high-interest unsecured consumer debt via overdrafts as well as for the number of overdrafted checking accounts individuals have.

Figures 10 and 11 show the heterogeneity in the MPC by the number of overdrawn accounts, the likelihood of overdrawing in general, and the likelihood of overdrawing in the same month as the windfall. Furthermore, Figure 13 breaks up the effects by gender and 14 by generation. Finally, Figure 15 highlights the effect of liquidity.

7 Conclusion

We use an accurate panel data set from a financial account aggregation app to evaluate how spending and use of consumer debt respond to wealth shocks of various sizes. These shocks originate from lotteries and a debt relief ruling that resulted in large repayments from banks to thousands of Icelandic households holding foreign exchange indexed car loans. To the best of our knowledge, this is the first paper using transaction-level high-frequency data to look beyond spending responses and investigate how individuals' personal finances are affected by wealth shocks. In particular, we are interested in how indebted households pay down debt and what is their marginal propensity to do so.

We document a MPC out of windfalls that is larger than one for a substantial fraction of the population following other studies, such as Fagereng et al. (2018). Fagereng et al. (2018), however, deemphasized this result because of data limitations. Furthermore, we find that most of the debt is rolled over, and, studying heterogeneity, we find that low and high liquidity individuals have such a high MPC. We argue that these findings invalidate the explanation that high MPCs are caused by liquidity constraints. After all, the high MPCs are facilitated by borrowing in the form of high-interest unsecured consumer debt.

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Table 1: The effect of income on borrowing and consumption in the model of Laibson et al. (2015)

	(1) Log of total borrowing	(2) Indicator for borrowing	(3) Log of total spending
Hyperbolic-discounting agent:			
log income	-3.918***	-0.386***	0.820***
	(0.0094)	(0.0006)	(0.0019)
Standard agent:			
log income	-0.0304***	-0.0038***	0.0372***
	(0.0005)	(0.0001)	(0.0009)
#obs	71,000	71,000	71,000
Age fixed effects	✓	✓	✓

This table shows the estimated effect of log income in the simulated data of the model in Laibson et al. (2015), featuring an illiquid asset, credit card borrowing, liquidity constraints, and stochastic labor income. The hyperbolic discounting agent borrows on average 35% of the time and the standard agent 0.15% of the time. Standard errors are within parentheses. Each entry is a separate regression.

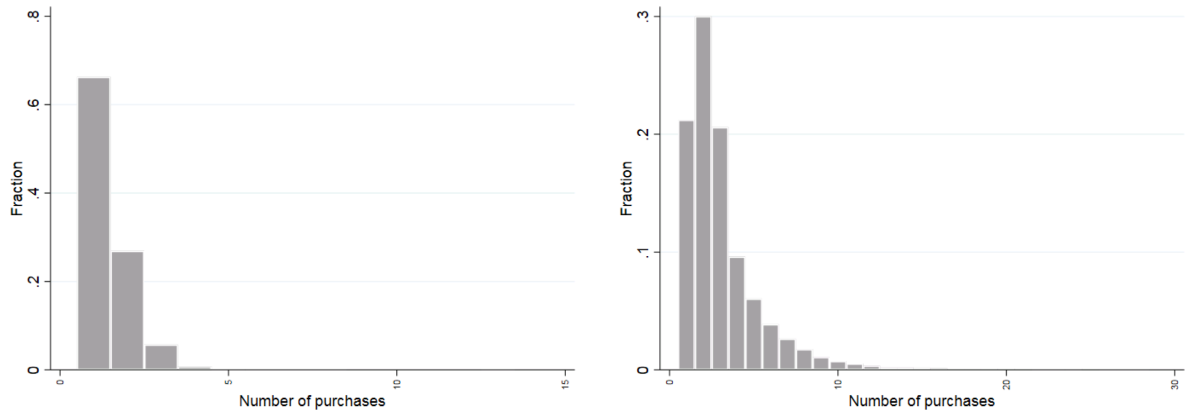


Figure 2: Distribution of the number of charity lottery charges and tickets purchases per month

Note: Raw data.

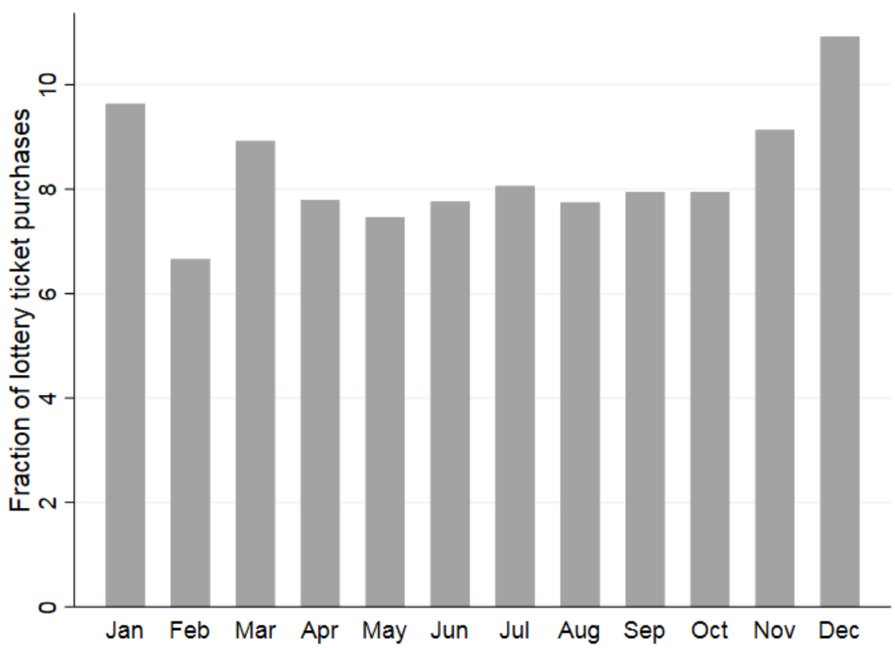


Figure 3: Distribution of purchases of lottery tickets across months

Note: Raw data.

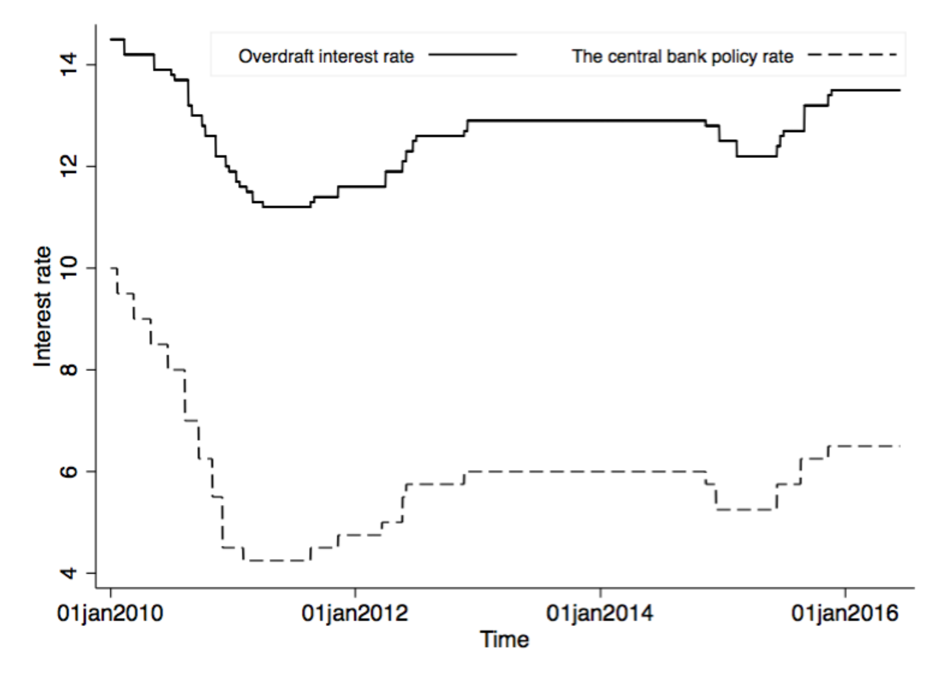


Figure 4: Trends of the Icelandic central bank policy interest rate and overdraft interest rate throughout the sample period

Note: Raw data, source, Central Bank of Iceland https://www.cb.is/.

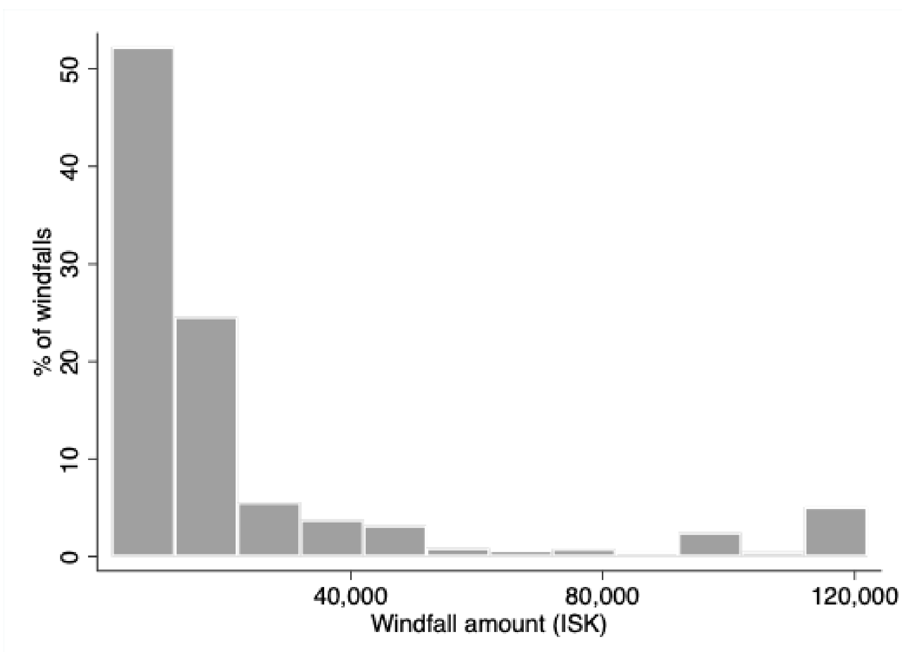


Figure 5: This histogram shows the distribution of the size of windfalls (winsorized at the 5% level and excluding windfalls below ISK 2000) in percent of observations. The unit of analysis is an individual x month. All values are inflation-adjusted (base = January 2017).

Note: Raw data.

Table 2: Summary statistics describing key windfall and other income variables in ISK (all variables are inflation adjusted, base = January 2017.

	Mean	SD	Min.	Max.	P25	P50	P75	P90	P95	#Obs.
Windfall category income:										
Loan write-off	100,661	213,593	8	2,358,316	683	1,846	108,711	326,704	533,739	1,654
Lottery (no charity)[1]	8,068	373,160	4	53,454,748	704	1,134	1,976	3,898	10,295	28,843
Lottery (charity)[2]	31,248	201,145	567	15,139,475	9,744	19,507	19,801	48,978	97,856	8,812
Lottery (total)	13,772	344,426	10	53,454,748	915	1,566	5,101	19,766	34,669	36,892
Gambling	74,730	162,985	130	2,583,362	9,281	28,169	77,423	181,668	283,871	1,150
Windfall income:										
Total windfall	19,234	337,369	8	53,454,748	902	1,699	9,265	22,661	49,402	39,539
Small windfall[3]	3,909	5,559	8	19,985	838	1,260	3,961	14,708	19,596	35,112
Medium windfall[4]	32,471	9,631	20,000	49,985	24,507	30,190	39,431	48,867	49,126	2,511
Large windfall[5]	282,726	1,508,394	50,000	53,454,748	86,259	102,165	217,009	490,147	745,966	1,916
General income:										
Total income[6]	482,405	398,491	1	2,356,979	240,822	397,264	616,855	933,185	1,220,362	628,036
Regular income[6]	472,163	384,863	1	2,272,298	239,879	389,992	601,529	910,140	1,187,615	620,680
Irregular income[6]	74,610	126,997	1	729,802	3,128	20,372	88,834	214,512	333,774	120,741
Salary[6]	467,366	384,718	1	2,265,930	237,828	386,687	595,811	902,817	1,181,646	577,685
Windfall-mean-total-income ratios:[8]										
Total windfall ratio	1.015	108.805	0.000	20,848	0.002	0.004	0.020	0.074	0.170	39,539
Small windfall ratio[7]	0.016	0.102	0.000	3	0.002	0.003	0.010	0.033	0.052	35,112
Medium windfall ratio	0.152	2.115	0.011	106	0.046	0.072	0.121	0.204	0.282	2,511
Large windfall ratio	14.014	487.337	0.029	20,848	0.166	0.298	0.611	1.332	1.976	1,916

Note: Unit of analysis is an individual x month. All zero values were excluded. [1]This category considers lotteries without a charity component. [2]This category considers lotteries with a charity component. [3]A small windfall is a non-zero windfall of less than ISK 20,000. [4]A medium windfall is a windfall of at least ISK 20,000 and less than ISK 50,000. [5]A large windfall is a windfall of at least ISK 50,000. [6]High values are winsorized at the 1% level. [7]High values are winsorized at the 0.1% level. [8]Ratios exclude zero values and the mean of total income exclude months with positive windfall earnings.

Table 3: Summary statistics describing the number of individuals receiving different types of windfalls.

	#Individuals	Percent
No windfall person	5,392	46.09
Windfall person	6,307	53.91
Total	11,699	100.00
No loan-write-off person	10,217	87.33
Loan-write-off person	1,482	12.67
Total	11,699	100.00
No lottery (no charity) person	5,030	43.00
Lottery (no charity) person	6,669	57.00
Total	11,699	100.00
No lottery (charity) person	5,045	43.12
Lottery (charity) person	6,654	56.88
Total	11,699	100.00
No lottery (total) person	2,886	24.67
Lottery (total) person	8,813	75.33
Total	11,699	100.00
No gambler	9,820	83.94
Gambler	1,879	16.06
Total	11,699	100.00

Note: Unit of analysis is an individual. For a given individual, the type of person does not vary over time. A given type of person is defined as a person who has ever received a positive amount of the respective windfall category, or, in terms of lottery and gambling, has ever spent a positive amount on that windfall category, over the whole observation period.

Table 4: Summary statistics: How windfall individuals differ from non-windfall individuals

	Non-windfall persons		Windfall persons		Difference	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Error
Demographics:						
Age	42.2	(12.4)	44.7	(11.9)	2.5***	(0.2)
Female	0.488	(0.500)	0.468	(0.499)	-0.020**	(0.009)
Spouse	0.114	(0.317)	0.103	(0.304)	-0.011*	(0.006)
Income:						
Total income[1]	375,781	(398,293)	441,224	(409,626)	65,443***	(945)
Regular income[1]	363,925	(385,910)	426,430	(396,525)	62,505***	(915)
Irregular income[1]	10,785	(55,088)	13,452	(60,972)	2,667***	(136)
Salary[1]	334,506	(383,604)	393,515	(395,523)	59,009***	(912)
Personal finances:						
Total financial cost	2,352	(8,217)	2,979	(8,051)	627***	(19)
Savings account balance	418,939	(2,317,544)	453,092	(5,138,368)	34,154**	(14,504)
Current account balance	270,713	(2,914,646)	222,054	(947,986)	-48,659***	(7,452)
Credit card balance	146,488	(872,441)	199,148	(2,292,624)	52,660***	(6,331)
Current account limit	268,882	(1,245,160)	346,081	(674,563)	77,199***	(3,480)
Credit card limit	476,088	(1,089,474)	614,843	(2,417,903)	138,755***	(6,824)
Overdraft interest	1,441	(4,194)	2,084	(5,142)	643***	(11)
Overdraft	178,818	(956,586)	231,408	(580,189)	52,589***	(2,758)
Cash	689,651	(3,753,401)	675,146	(5,261,228)	-14,506	(16,425)
Liquidity	1,288,139	(4,056,773)	1,436,948	(5,389,359)	148,809***	(17,112)
Cash (cons. days)	162.6	(836.2)	117.3	(752.1)	-45.4***	(2.8)
Liquidity (cons. days)	273.2	(851.3)	240.6	(764.6)	-32.5***	(2.9)
Late-payment interest	28.7	(273.8)	35.1	(318.7)	6.4***	(0.7)
Non-sufficient funds fees	26.6	(274.5)	30.5	(284.3)	3.9***	(0.7)
Late fees	855.4	(6,513.8)	829.6	(5,711.8)	-25.8*	(14.2)
Credit utilization	0.388	(0.278)	0.381	(0.260)	-0.007***	(0.001)
Total logins	0.924	(6.564)	1.163	(6.465)	0.239***	(0.015)
Total expenditure share:						
Necessities	0.423	(0.120)	0.431	(0.114)	0.008***	(0.002)
Groceries	0.282	(0.108)	0.283	(0.103)	0.001	(0.002)
Fuel	0.116	(0.078)	0.122	(0.073)	0.006***	(0.001)
Pharmaceuticals	0.025	(0.021)	0.025	(0.022)	0.000	(0.000)
Non-necessities	0.362	(0.129)	0.343	(0.117)	-0.019***	(0.002)
Clothes & accessories	0.082	(0.052)	0.075	(0.047)	-0.006***	(0.001)
Alcohol	0.035	(0.043)	0.034	(0.039)	-0.001	(0.001)
Ready made food	0.139	(0.088)	0.119	(0.075)	-0.020***	(0.002)
Recreation	0.051	(0.028)	0.049	(0.026)	-0.002***	(0.001)
Lottery	0.001	(0.003)	0.007	(0.014)	0.007***	(0.000)
Media	0.063	(0.045)	0.068	(0.045)	0.005***	(0.001)
Charities	0.002	(0.005)	0.003	(0.005)	0.000***	(0.000)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Regarding age, female, and spouse, the unit of analysis is an individual. Otherwise, unit of analysis is an individual x month. [1]High values were winsorized at the 1% level. Expenditure shares were calculated by dividing the individual-specific mean of a given expenditure category by the individual-specific mean of total expenditures. The unit of analysis is an individual. All variables are inflation-adjusted.

Table 5: Summary statistics: How windfall months differ from non-windfall months

	Non-windfall month		Windfall month		Difference	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Error
Income:						
Total income	404,364	(403,451)	529,208	(427,538)	124,844***	(2,093)
Regular income	391,846	(391,141)	499,517	(409,657)	107,671***	(2,027)
Irregular income	11,350	(56,524)	27,615	(82,784)	16,265***	(301)
Salary	360,785	(389,158)	463,933	(413,305)	103,148***	(2,019)
Personal finances:						
Total financial cost	2,652	(8,080)	3,372	(8,998)	720***	(42)
Savings account balance	428,183	(3,923,185)	574,499	(6,015,807)	146,316***	(29,881)
Current account balance	245,158	(2,154,658)	234,971	(933,006)	-10,188	(15,354)
Credit card balance	171,257	(1,814,681)	228,482	(1,224,508)	57,225***	(13,045)
Current account limit	306,292	(1,000,941)	372,603	(603,537)	66,310***	(7,174)
Credit card limit	539,683	(1,951,192)	717,238	(1,433,617)	177,555***	(14,065)
Overdraft interest	1,750	(4,715)	2,449	(5,111)	699***	(24)
Overdraft	204,899	(791,243)	240,531	(527,278)	35,632***	(5,686)
Cash	673,342	(4,508,619)	809,470	(6,127,607)	136,128***	(33,838)
Liquidity	1,348,070	(4,709,970)	1,670,944	(6,242,525)	322,874***	(35,254)
Cash (cons. days)	139.1	(805.0)	124.6	(570.2)	-14.6**	(5.8)
Liquidity (cons. days)	255.4	(818.5)	258.9	(586.0)	3.4	(5.9)
Late-payment interest	32.4	(301.3)	28.8	(253.1)	-3.6**	(1.5)
Non-sufficient funds fees	28.7	(279.6)	29.4	(283.3)	0.7	(1.4)
Late fees	840.2	(6,039.0)	864.3	(7,002.9)	24.1	(31.5)
Credit utilization	0.385	(0.270)	0.373	(0.246)	-0.012***	(0.002)
Total logins	1.034	(6.478)	1.376	(7.073)	0.342***	(0.034)
Expenditure dummies:						
Total expenditures	0.905	(0.293)	0.999	(0.038)	0.093***	(0.001)
Necessities	0.888	(0.316)	0.990	(0.099)	0.102***	(0.002)
Groceries	0.877	(0.329)	0.980	(0.139)	0.104***	(0.002)
Fuel	0.794	(0.405)	0.914	(0.280)	0.121***	(0.002)
Non-necessities	0.890	(0.312)	0.996	(0.060)	0.106***	(0.002)
Alcohol	0.455	(0.498)	0.538	(0.499)	0.083***	(0.003)
Groupon	0.047	(0.211)	0.077	(0.266)	0.030***	(0.001)
Lottery (no charity)	0.178	(0.383)	0.750	(0.433)	0.572***	(0.002)
Lottery (charity)	0.236	(0.425)	0.547	(0.498)	0.310***	(0.002)
Gambling	0.008	(0.087)	0.034	(0.181)	0.026***	(0.000)
Cinema	0.242	(0.428)	0.257	(0.437)	0.016***	(0.002)
Craftsmanship	0.046	(0.210)	0.057	(0.231)	0.010***	(0.001)
Recreational areas	0.092	(0.289)	0.102	(0.303)	0.010***	(0.001)
Sports & activities	0.155	(0.362)	0.178	(0.383)	0.023***	(0.002)
Swimming	0.106	(0.307)	0.109	(0.312)	0.004**	(0.002)
Home improvements	0.626	(0.484)	0.742	(0.438)	0.116***	(0.002)
Transportation	0.534	(0.499)	0.627	(0.484)	0.093***	(0.003)
Media	0.744	(0.436)	0.889	(0.315)	0.145***	(0.002)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dummies equal 1 if a given individual spent a positive amount on the given good in a given month. All variables are inflation-adjusted.

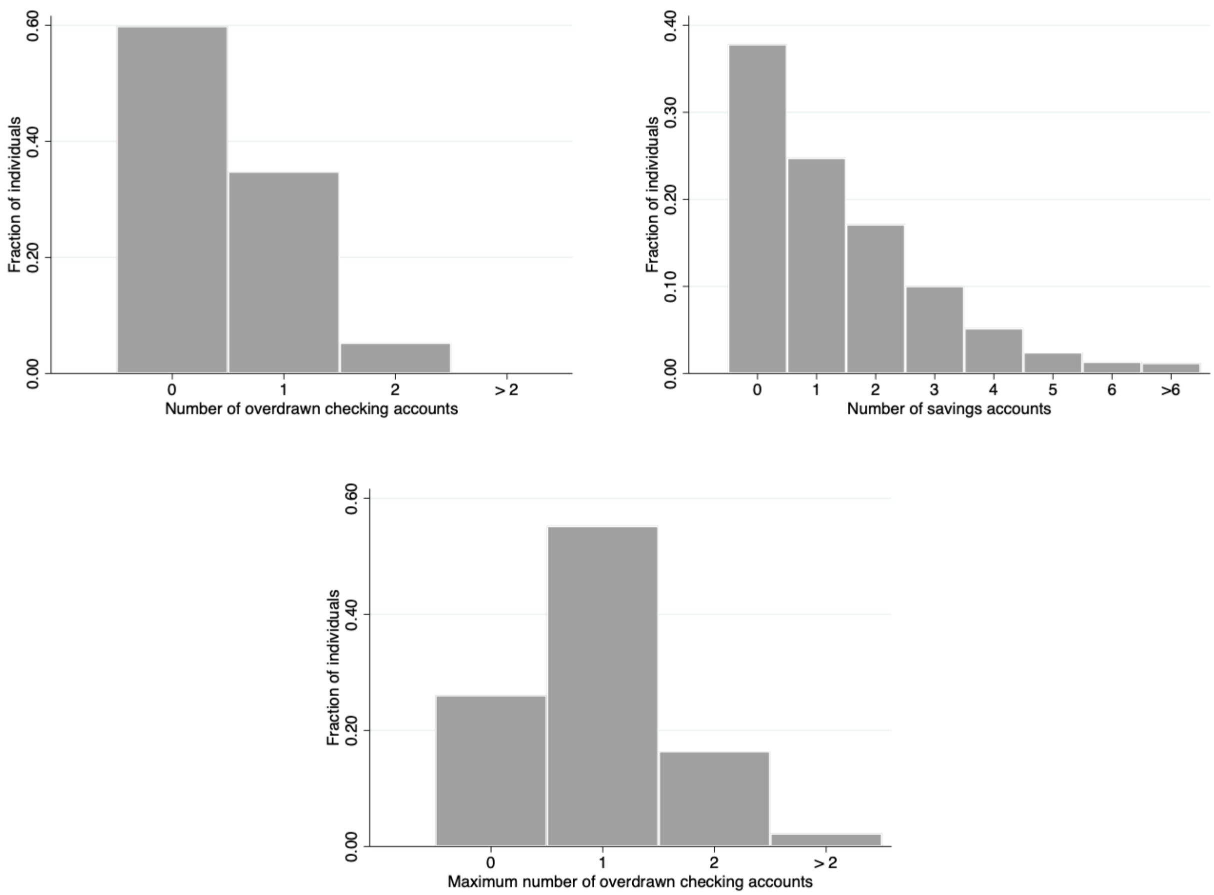


Figure 6: Distribution of the number of overdrafts and savings accounts that individuals hold
Note: Raw data.

Table 6: The effect of windfall gains on expenditure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total spending								
Windfall	0.023***							
	(0.003)							
Small windfall		2.002***		2.014***	2.317***		2.143***	
		(0.387)		(0.387)	(0.336)		(0.333)	
Large windfall			0.023***	0.023***		0.023***		0.022***
			(0.003)	(0.003)		(0.003)		(0.003)
R-sqr	0.042	0.042	0.042	0.042	0.049	0.050	0.063	0.061
#obs	737,037	737,037	737,037	737,037	262,395	237,447	262,395	237,447
#groups	11,699	11,699	11,699	11,699	4,165	3,769	4,165	3,769
month-by-year fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
individual fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
regular income	✓	✓	✓	✓			✓	✓

[a] * $p<0.1$, ** $p<0.05$, *** $p<0.01$ [b] This is the estimated effect of windfall gains of different sizes. Standard errors are clustered at the individual level and are within parentheses. Each entry is a separate regression. Columns (7) and (8) restrict the sample to individuals that have ever received a windfall of the type under investigation, i.e., a small or large one.

Table 7: The effect of windfall gains by liquidity terciles

	(1)	(2)	(3)	(4)	(5)	(6)
Total spending						
Small windfall	1.387**	2.642***	2.435***			
	(0.632)	(0.510)	(0.654)			
Large windfall				0.015***	0.073***	0.018***
				(0.003)	(0.008)	(0.006)
R-sqr	0.060	0.052	0.042	0.054	0.054	0.046
#obs	65,646	100,107	79,191	617,40	88,893	73,773
Liquidity tercile	1	2	3	1	2	3
month-by-year fixed effect	✓	✓	✓	✓	✓	✓
individual fixed effect	✓	✓	✓	✓	✓	✓

[a] * p<0.1, ** p<0.05, *** p<0.01 [b] This is the estimated effect of windfall gains of different sizes. Standard errors are clustered at the individual level and are within parentheses. Each entry is a separate regression. [c] Liquidity is defined as savings account balances plus credit limits plus checking account balances minus credit card balances and is normalized by individual average spending.

Table 8: The effect of windfall gains by income terciles

	(1)	(2)	(3)	(4)	(5)	(6)
Total spending						
Terciles of average income						
Small windfall	1.969***	1.929***	2.920***			
	(0.411)	(0.475)	(0.678)			
Large windfall				0.063***	0.015***	0.023***
				(0.010)	(0.004)	(0.004)
R-sqr	0.112	0.059	0.039	0.107	0.065	0.039
#obs	65,394	92,799	104,202	59,346	83,538	94,563
#groups	1,038	1,473	1,654	942	1,326	1,501
Terciles of income relative to own average income						
Small windfall	2.836***	0.816**	1.271*			
	(0.521)	(0.407)	(0.673)			
Large windfall				0.065***	0.015***	0.042***
				(0.015)	(0.002)	(0.009)
R-sqr	0.105	0.033	0.025	0.093	0.033	0.027
#obs	68,280	91,923	102,192	63,241	81,966	92,240
#groups	3,791	3,932	4,165	3,444	3,575	3,674
Income tercile	1	2	3	1	2	3
month-by-year fixed effect	✓	✓	✓	✓	✓	✓
individual fixed effect	✓	✓	✓	✓	✓	✓

[a] * p<0.1, ** p<0.05, *** p<0.01 [b] This is the estimated effect of windfall gains of different sizes. Standard errors are clustered at the individual level and are within parentheses. Each entry is a separate regression.

Table 9: The effect of windfall gains by gender

	(1)	(2)	(3)	(4)
Total spending				
	Men	Women	Men	Women
Small windfall	3.004***	1.567***		
	(0.522)	(0.411)		
Large windfall			0.025***	0.014***
			(0.003)	(0.005)
R-sqr	0.044	0.060	0.043	0.064
#obs	139,860	122,535	127,575	109,872
month-by-year fixed effect	✓	✓	✓	✓
individual fixed effect	✓	✓	✓	✓

[a] * p<0.1, ** p<0.05, *** p<0.01 [b] This is the estimated effect of windfall gains of different sizes. Standard errors are clustered at the individual level and are within parentheses. Each entry is a separate regression.

Table 10: Logit regressions - The effect of receiving a windfall gain on probability of holding an overdraft

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Probability of holding an overdraft								
Windfall	0.0920***							
dummy	(0.0203)							
Lagged windfall	0.0726***							
dummy	(0.0204)							
Small windfall		0.1007***		0.1029***	0.1280***		0.1212***	
dummy		(0.0240)		(0.0241)	(0.0240)		(0.0241)	
Lagged small		0.0873***		0.0883***	0.1165***		0.1124***	
windfall dummy		(0.0241)		(0.0242)	(0.0241)		(0.0242)	
Large windfall			0.0601*	0.0672*		0.0781**		0.0665*
dummy			(0.0351)	(0.0352)		(0.0351)		(0.0351)
Lagged large			0.0313	0.0370		0.0504		0.0445
windfall dummy			(0.0353)	(0.0354)		(0.0353)		(0.0353)
R-sqr								
#obs	470,642	470,642	470,642	470,642	179,118	162,378	179,118	162,378
#groups	7,591	7,591	7,591	7,591	2,889	2,619	2,889	2,619
month-by-year fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
individual fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
regular income	✓	✓	✓	✓			✓	✓

[a] * p<0.1, ** p<0.05, *** p<0.01 [b] This is the estimated effect of windfall gains of different sizes. Standard errors are clustered at the individual level and are within parentheses. Each entry is a separate regression. Columns (7) and (8) restrict the sample to individuals that have ever received a windfall of the type under investigation, i.e., a small or large one. [c] The average size of windfalls is 26,848, the average small windfall amounts to 2,883, and the average large windfall amounts to 81,084.

Table 11: The effect of windfall gains on the number of overdrafts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of overdrafts								
Windfall	0.0149***							
	(0.0026)							
Lagged windfall	0.0128***							
	(0.0026)							
Small windfall		0.0161***		0.0165***	0.0177***		0.0169***	
		(0.0030)		(0.0030)	(0.0032)		(0.0032)	
Lagged small windfall		0.0161***		0.0162***	0.0178***		0.0172***	
		(0.0030)		(0.0031)	(0.0032)		(0.0032)	
Large windfall			0.0101**	0.0112**		0.0103**		0.0092**
			(0.0044)	(0.0044)		(0.0046)		(0.0046)
Lagged large windfall			0.0043	0.0054		0.0046		0.0039
			(0.0044)	(0.0044)		(0.0047)		(0.0046)
R-sqr	0.015	0.015	0.015	0.015	0.012	0.013	0.014	0.016
#obs	715,790	715,790	715,790	715,790	256,308	232,128	256,308	232,128
#groups	11,545	11,545	11,545	11,545	4,134	3,744	4,134	3,744
month-by-year fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
individual fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
regular income	✓	✓	✓	✓			✓	✓

[a] * $p<0.1$, ** $p<0.05$, *** $p<0.01$ [b] This is the estimated effect of windfall gains of different sizes. Standard errors are clustered at the individual level and are within parentheses. Each entry is a separate regression. Columns (7) and (8) restrict the sample to individuals that have ever received a windfall of the type under investigation, i.e., a small or large one.

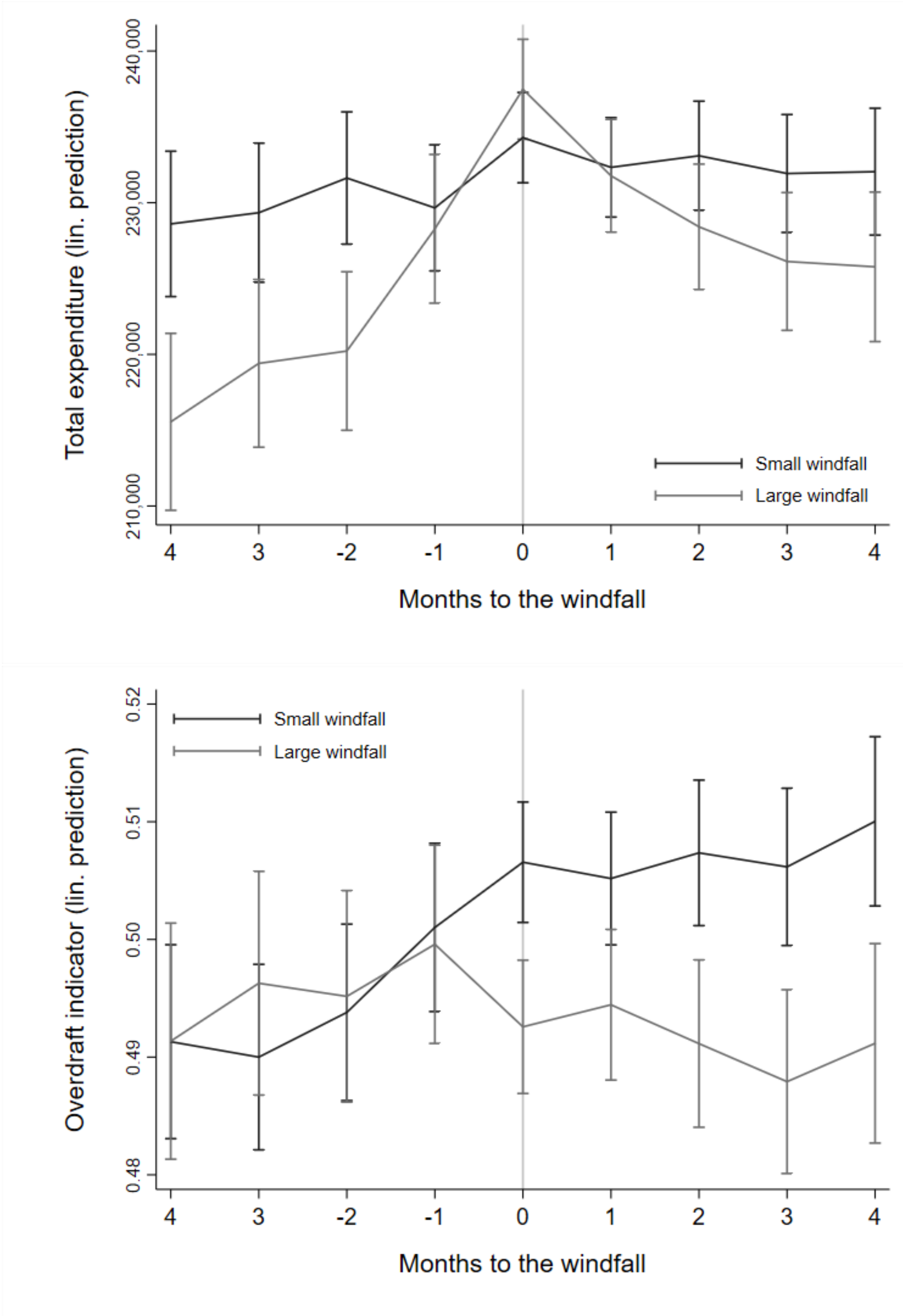
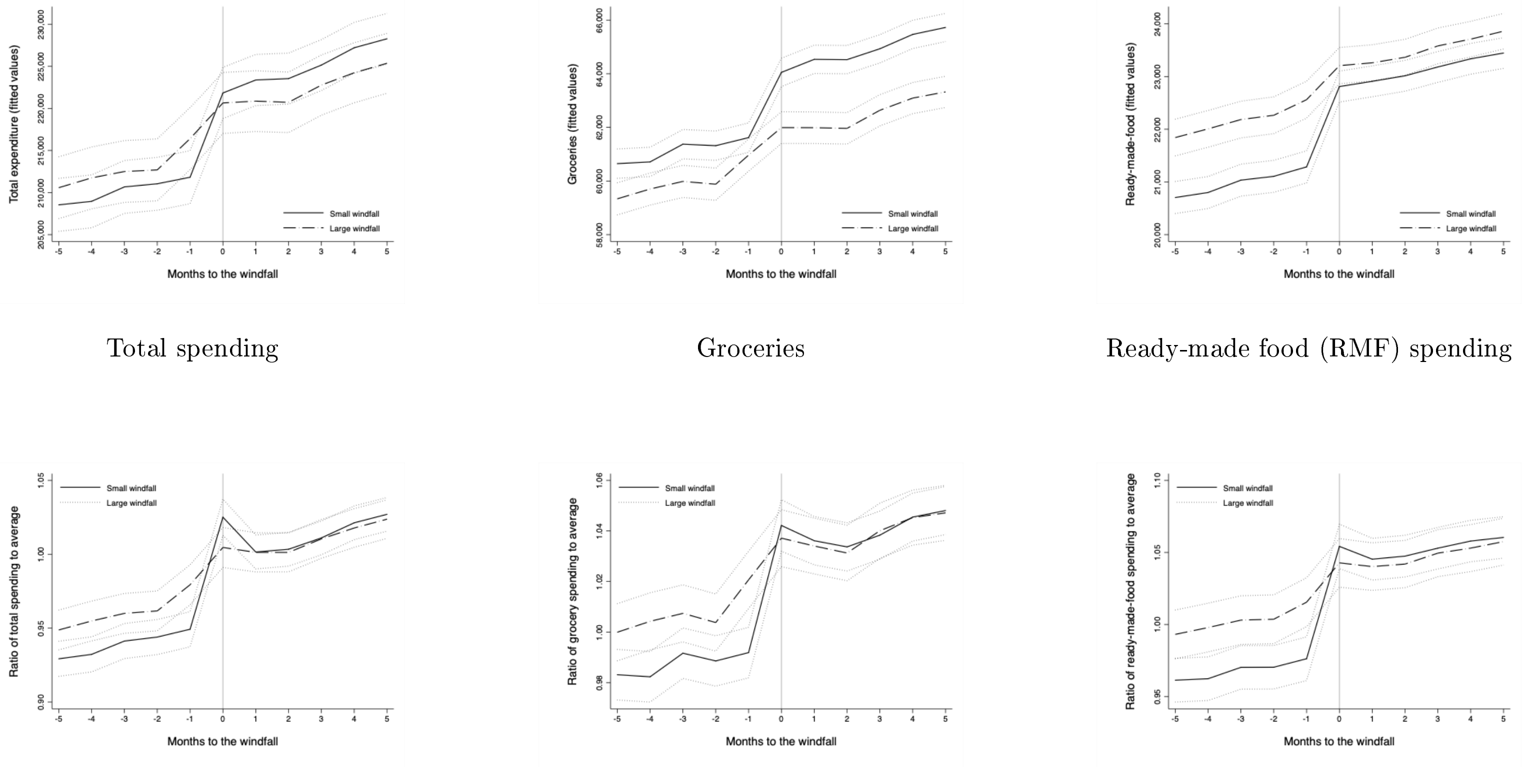


Figure 7: Linear predictions of spending and the likelihood of overdrawing checking accounts
Note: Linear predictions and 95% confidence intervals (clustered at the individual level) for different months before/after the windfall.

Table 12: The effect of windfall gains on the number of savings accounts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of savings accounts								
Windfall	0.0041							
	(0.0039)							
Lagged Windfall	0.0002							
	(0.0039)							
Small Windfall		0.0042		0.0043	0.0039		0.0039	
		(0.0046)		(0.0046)	(0.0048)		(0.0048)	
Lagged Small Windfall		-0.0004		-0.0004	-0.0008		-0.0008	
		(0.0046)		(0.0046)	(0.0048)		(0.0048)	
Large Windfall			0.0032	0.0036		0.0028		0.0028
			(0.0065)	(0.0065)		(0.0065)		(0.0065)
Lagged Large Windfall			0.0016	0.0015		0.0012		0.0012
			(0.0066)	(0.0066)		(0.0066)		(0.0066)
R-sqr	0.021	0.021	0.021	0.021	0.026	0.026	0.026	0.026
#obs	277,153	277,153	277,153	277,153	100,114	91,465	100,114	91,465
#groups	11,007	11,007	11,007	11,007	3,888	3,562	3,888	3,562
month-by-year fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
individual fixed effect	✓	✓	✓	✓	✓	✓	✓	✓
regular income	✓	✓	✓	✓			✓	✓

[a] * p<0.1, ** p<0.05, *** p<0.01 [b] This is the estimated effect of windfall gains of different sizes. Standard errors are clustered at the individual level and are within parentheses. Each entry is a separate regression. Columns (7) and (8) restrict the sample to individuals that have ever received a windfall of the type under investigation, i.e., a small or large one.



Total spending

Groceries

Ready-made food (RMF) spending

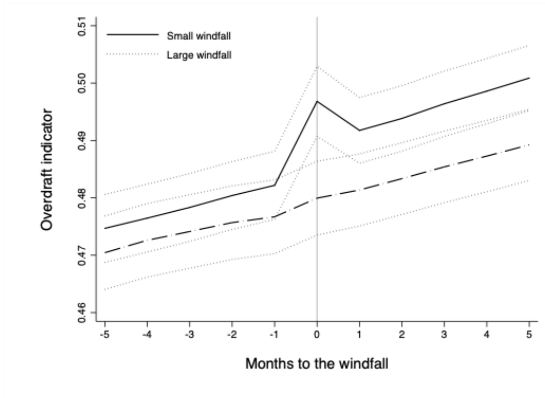
Deviation from average total spending

Deviation from average groceries spending

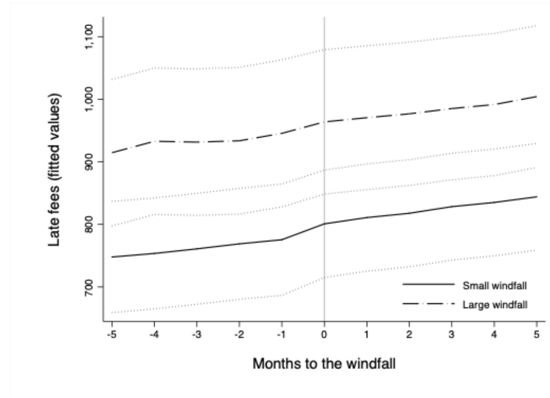
Deviation from average RMF spending

Figure 8: Fitted values for spending

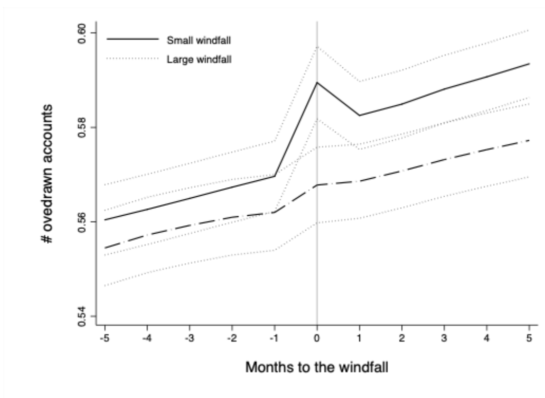
Note: Average fitted values and 95% confidence intervals (clustered at the individual level) at different months before/after the windfall controlling for individual and month-by-year fixed effects.



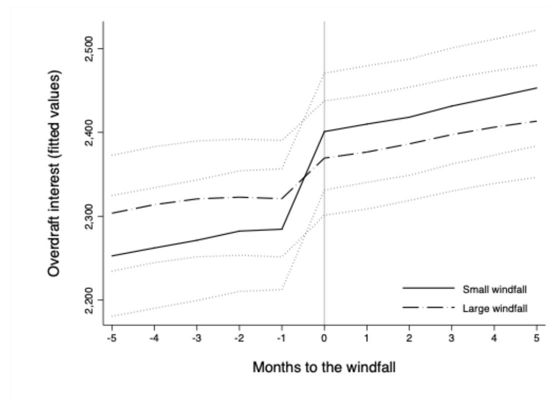
Overdraft indicator



Late fees



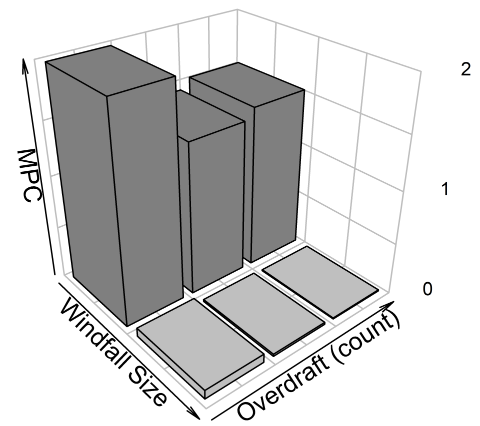
Overdraft count



Overdraft interest

Figure 9: Fitted values for different financial outcomes

Note: Average fitted values and 95% confidence intervals (clustered at the individual level) at different months before/after the windfall controlling for individual and month-by-year fixed effects.



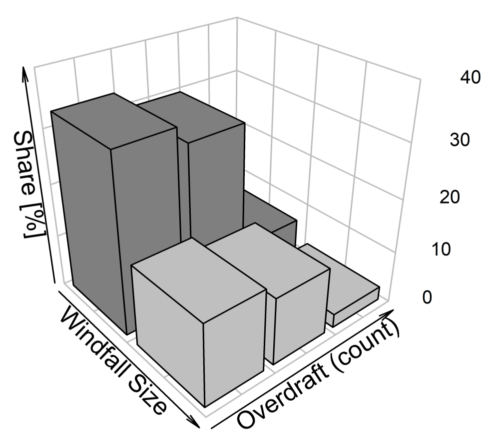


Figure 10: Heterogenous consumption responses to windfall gains by the number of overdraft accounts

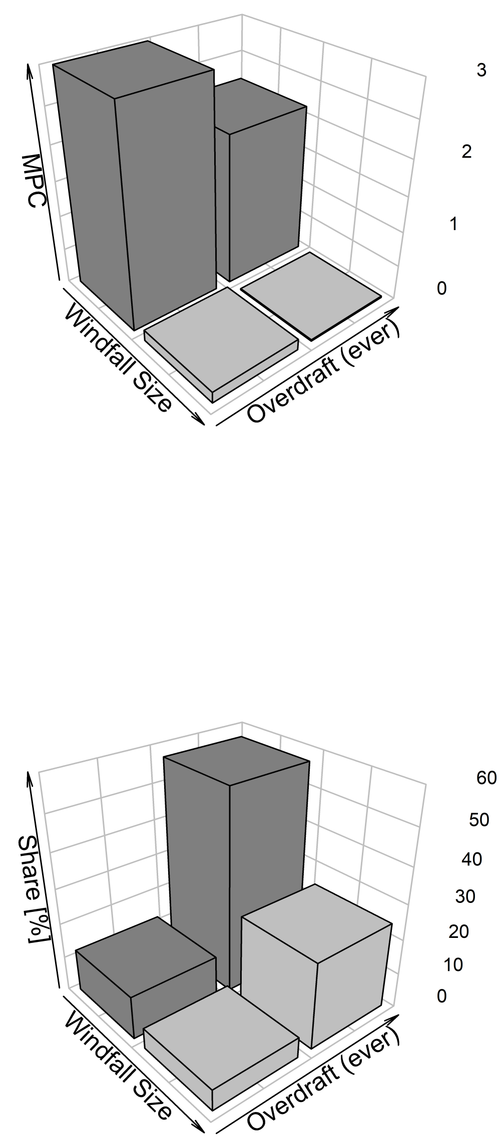
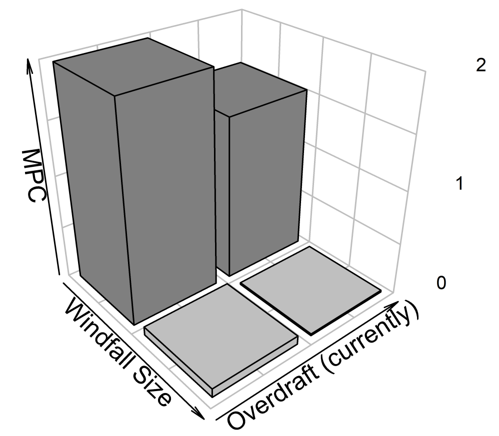


Figure 11: Heterogenous consumption responses to windfall gains by the probability of ever holding an overdraft during the period under consideration



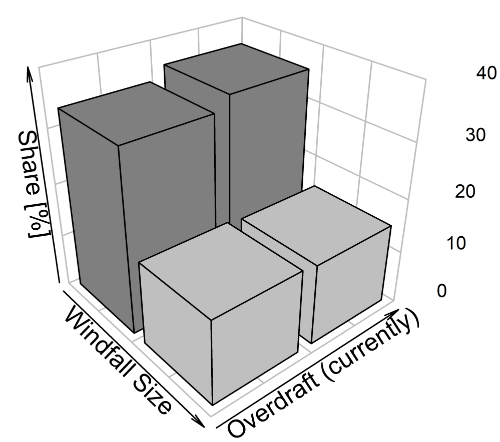
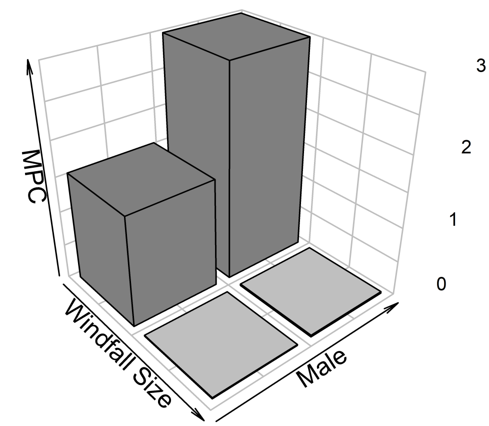


Figure 12: Heterogenous consumption responses to windfall gains by the probability of holding an overdraft currently



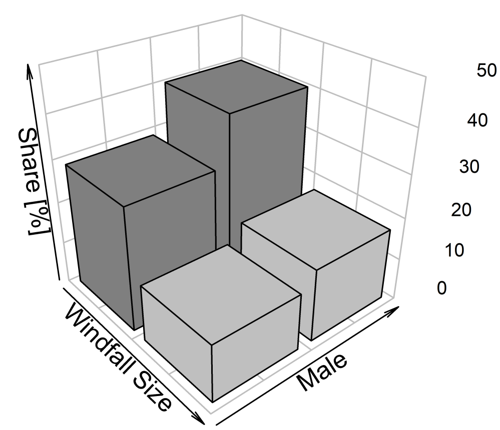


Figure 13: Heterogenous consumption responses to windfall gains by gender

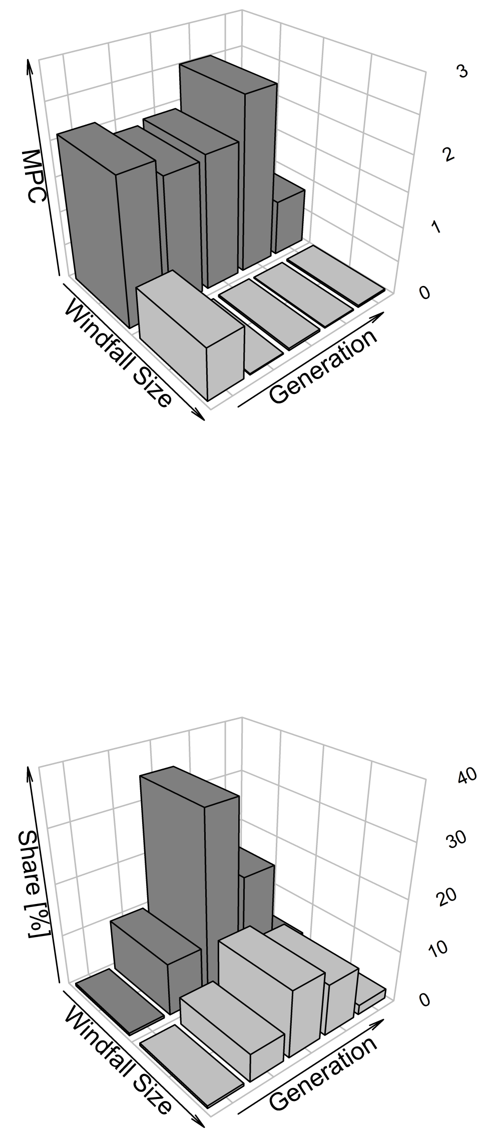


Figure 14: Heterogenous consumption responses to windfall gains by generation

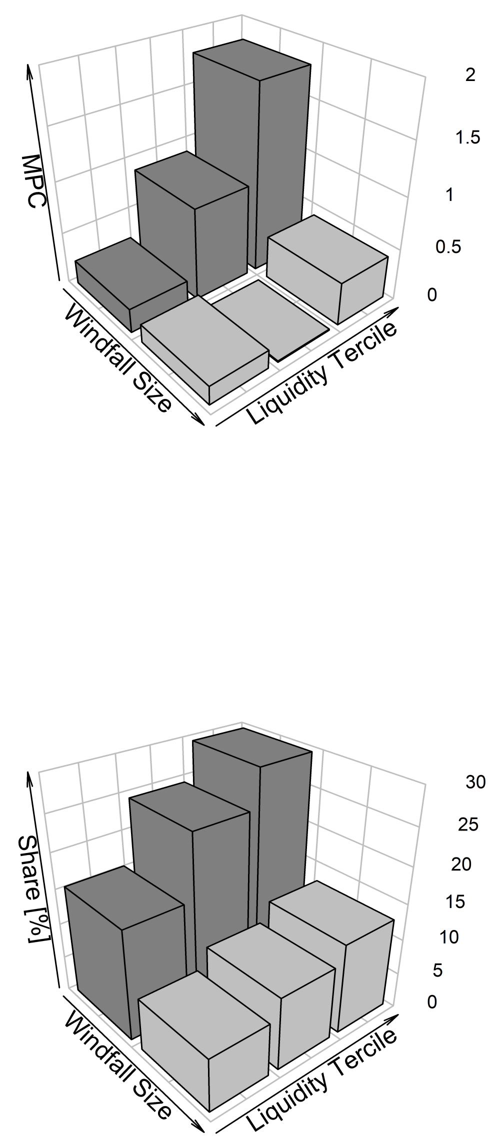


Figure 15: Heterogenous consumption responses to windfall gains by liquidity