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Personality-Augmented MPC: Linking Survey and Transaction Data to Explain MPC Heterogeneity by Big Five Personality Traits

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Personality-Augmented MPC

Linking Survey and Transaction Data to Explain MPC Heterogeneity by Big Five Personality Traits*

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Abstract

We investigate the link between Big Five personality traits and the marginal propensity to consume (MPC) for users of a German financial account aggregator app. We use 1,700 survey responses and transaction data of 56,000 app users to assess whether Big Five personality traits help explain MPC heterogeneity. We find that extraversion corresponds to an increase in consumption whereas agreeableness and neuroticism correspond to a decrease in consumption. We test this with trust and risk preferences and find that risk indicates more explanatory power in consumption response than the Big Five. Our findings help policy makers target individuals more efficiently.

Keywords: Marginal Propensity to Consume, Big Five Personality, Survey Data, Transaction Data

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1 Introduction

Consumption is a vital aspect of a functioning economy. Crises such as the Covid-19 pandemic or the 2008 financial crisis can lead to economic depression if not prevented by appropriate governmental intervention. To design appropriate measures, policy makers require a good understanding of consumption dynamics.

The marginal propensity to consume (MPC) is a key concept for consumption dynamics and a major metric for macro-economic analysis. It describes the share of incremental income that individuals spend on consumption as opposed to saving it.[1] The MPC features in a variety of economic contexts such as the widely known Keynesian multiplier (Keynes, 1936), and also in contemporary work like HANK-models for monetary policy (Kaplan et al., 2018), life-cycle models for distributional economics (Carroll et al., 2017), and fiscal policy (Jappelli and Pistaferri, 2014).

Before the 2008 financial crisis, MPC was mostly thought of as a homogeneous figure per country (Keen, 2021). As a consequence, distributional questions for income and wealth could be neglected. More recently, the focus has shifted on more re-distributional questions - particularly after the contributions by Piketty (2013) - and scholars have focused their studies on identifying and explaining heterogeneity in MPCs.

Early investigations into MPC heterogeneity followed from theoretical considerations (e.g., liquidity constraints and precautionary savings) and looked at hard economic variables such as income (Fagereng et al., 2021; Baker et al., 2020b), liquidity (Jappelli and Pistaferri, 2014, 2020; Baker et al., 2020b), and wealth (Ganong et al., 2020; Fagereng et al., 2021). Subsequently, also socio-demographic variables have been considered such as age (Mueller and Plug, 2006), education (Fagereng et al., 2021), race (Ganong et al., 2020), or political views (Baker et al., 2020a).

Our research aim is to extend the set of explanatory variables for MPC heterogeneity to the realm of psychological variables, particularly, the Big Five personality traits.[2] Big Five personality traits (Goldberg, 1990; Costa and McCrae, 1992) are a well accepted concept from the psychological liter-

[1] In the simplest form, an individual has only two options what to do with income: consume it or save it. In this simple case, the marginal propensity to consume (MPC) and the marginal propensity to save (MPS) add up to 1.

[2] Figure 1 on page 3 illustrates our intention to augment the conceptual framework by adding personality to the overall context of MPC decisions. Of the context-variables listed, the personality variable is most closely related to age. In our set-up, we focus exclusively on unanticipated and transitory income shocks from lottery payments, both small and large.

ature that measure human personality based on survey responses and map individuals along five personality dimensions: openness, conscientiousness, extraversion, agreeableness, and neuroticism (OCEAN).[3]

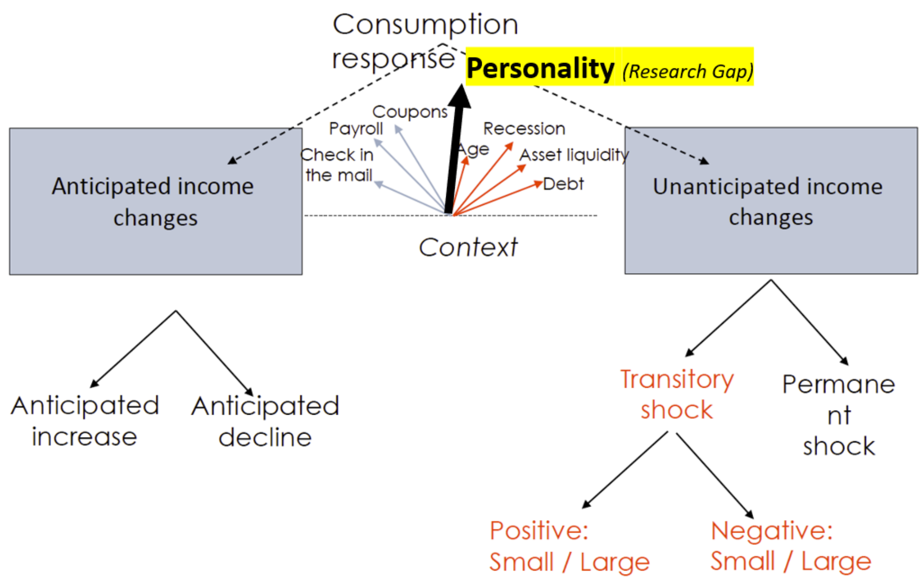

Figure 1: The role of personality in the consumption response. Illustration by Jappelli and Pistaferri (2017) with own augmentation.

For the last decades, psychological concepts have enriched economic analyses. Several Nobel Prizes have been awarded to behavioral economists for concepts related to decision-making under uncertainty, human judgement, and irrationality. More recently, economists (Heckman, 2011; Becker et al., 2012) have started to argue that the Big Five personality traits (Goldberg, 1990; Costa and McCrae, 1992) should be integrated more into economics along with the traditional concept of economic preferences. Likewise, psychologists have started using financial transaction data to relate and derive personality traits (Matz et al., 2016; Landis and Gladstone, 2017; Gladstone et al., 2019).

In this paper, we try to marry the MPC literature from economics with the personality literature from psychology by linking the economic concept of MPC heterogeneity to the psychological concept of Big Five personality traits.[4] Further, we test the precautionary savings motive (Jappelli and

[3]Please refer to Table 1 on page 8 for a description of the Big Five personality traits.

[4]We are not the first to investigate the link between personality and MPC. Katona (1951) argues that a personality explanation of consumption patterns would be desirable. And

Pistaferri, 2014) which states that individuals save not only to smooth consumption across the life cycle, but also to hedge against uncertainties. Additionally, we examine the Permanent Income Hypothesis Friedman (1957). This hypothesis postulates that transitory income changes do not affect consumption.

Establishing a link between MPC and Big Five personality traits, this leads us to formulate the following research question: Is MPC heterogeneity related to Big Five personality traits? I.e. do individuals with different Big Five personality profiles have different levels of MPC?

This research question is well embedded in the existing literature. Mueller and Plug (2006) find that higher earnings are associated with non-agreeableness, non-neuroticism, and openness. Jappelli and Pistaferri (2014) show that households with low liquidity have higher MPCs. With the assumption that high earnings correspond to high liquidity we combine these findings into the hypotheses that: agreeableness and neuroticism are associated with higher levels of MPC and openness is associated with lower levels of MPC.[5]

Mahalingam et al. (2014) find that low patience is related to high neuroticism, high extraversion, low conscientiousness, and low openness. With the assumption that low patience corresponds to high MPC we derive the hypotheses that: neuroticism and extraversion are associated with higher levels of MPC and conscientiousness and openness are associated with lower levels of MPC.

Balasuriya and Yang (2019) find that pension plan participation is positively correlated with conscientiousness and negatively with extraversion. With the assumption that pension plan participation implies lower levels of MPC we derive the hypotheses that: conscientiousness is associated with lower levels of MPC and extraversion with higher levels of MPC.

Landis and Gladstone (2017) show that low-income extraverts spend more on status. Assuming this holds for extraverts overall and status spending is related to higher levels of MPC we derive the hypothesis that: extraversion is associated with higher levels of MPC.

Wicks and Nelson (1967) conduct a small sample study in the 1960s among college students in the US, finding that there are significant differences in temperament if participants were grouped according to their MPCs. Our paper reconsiders these questions on MPC and personality long ago asked (and potentially meanwhile forgotten) and combines them with the technical possibility of utilizing survey and transaction data from users of a financial account aggregator.

[5]Throughout this study we make the assumption that personality correlations are linear. That is, for example, if non-agreeableness implies high earnings then agreeableness implies low earnings.

To answer our research question, we group and summarize the above mentioned findings and assumptions into the following five hypotheses:

- H_1: **Openness** corresponds to **lower** levels of MPC
- H_2: **Conscientiousness** corresponds to **lower** levels of MPC
- H_3: **Extraversion** corresponds to **higher** levels MPC
- H_4: **Agreeableness** corresponds to **higher** levels of MPC
- H_5: **Neuroticism** corresponds to **higher** levels of MPC

We cooperate with a German Financial Account Aggregator app from which we obtain two datasources: (i) responses to a survey that we designed and conducted with about 1,700 customers, and (ii) anonymized transaction data of customers participating in the survey. We check the representativeness of our transaction data with the samples from the German socio-economic panel (Goebel et al., 2019), the EVS (Destatis, 2019), and the European Household and Consumption Survey (ECB, 2020).

Our approach makes use of micro-data to investigate a key macro-economic measure. Additionally, we provide timely evidence on consumption attitudes and behavior of individuals in Germany. For our analysis, we combine approaches from the classical economic MPC literature with psychological aspects from the personality and personal finance literature. We do this in two parts:

First, we build upon the survey-driven MPC literature as in Jappelli and Pistaferri (2014) and relate it to personality scores obtained in the same survey. Figure 1 illustrates our intention to augment the conceptual framework by adding personality to the overall context of MPC decisions. Our set-up provides us with support for the hypothesis that extraversion is related to higher levels of MPC which is in line with the literature (Landis and Gladstone (2017)). Also, we use alternative explanatory measures such as risk and trust preferences and find support that especially risk is stronger related with consumption responses (Dohmen et al. (2011); Lusardi and Mitchell (2011)).

Second, we build on Olafsson and Pagel (2021) and extend their analysis of consumption responses after the receipt of lottery windfalls by the Big Five personality traits. Specifically, we take lottery windfalls[6] as exogenous

[6]Studying the consumption response to lottery windfalls also allows for a test of the permanent income hypothesis (Friedman, 1957), which would predict no significant effect on consumption for small (transitory) lottery gains.

shocks and identify which personality types consume the windfall differently once they receive their lottery winning. We find that individuals with pronounced agreeableness and neuroticism consume less and, thus, find support for the findings of other studies such as Airaksinen et al. (2021) and Brown and Taylor (2014).

The remainder of this study is structured as follows. Section 2 discusses the theoretical framework and literature, highlighting the concepts and importance of MPC and Big Five in economics and psychology. Section 3 features our data and methodology, presenting the survey and transaction data, discussing its representativeness, and stating the econometric models we use. Section 4 presents our results with subsections for results from survey and transaction data. In section 5 we discuss our results and conclude in section 6.

2 Literature Review and Theoretical Framework

Our study builds on several streams of literature, which we briefly introduce. First, economic literature on the marginal propensity to consume with a focus on heterogeneity. Second, psychological literature on personality with a focus on Big Five personality traits. Third and finally, we discuss how both strands are related to each other.

2.1 Marginal Propensity to Consume

The concept of MPC heterogeneity is very relevant for policy making because it allows to consider income and wealth distributions within societies. Before the 2008 financial crisis, MPC was mostly thought of as a homogeneous figure per country (Keen, 2021). The focus on more re-distributional questions has particularly evolved after the contributions by Piketty (2013). MPC dates back to Keynesian economics and can be broadly understood as the size of the Keynesian multiplier (Keynes, 1936). Vermeiren (2021) describes that poor and liquidity-constrained households have MPCs close to 1, meaning that they consume almost everything they earn. In the literature this is also referred to as 'liquid hand-to-mouth' (Olafsson and Pagel, 2018; Kaplan et al., 2014). On the other hand, in the case of wealthy households, current income does not affect consumption much and their related MPCs are close to 0 (Vermeiren, 2021). This is very important for policy making if its goal is to increase aggregate demand: giving EUR 1000 to a poor person will have a bigger boost on consumption than giving EUR 1000 to a rich person, because the poor person will consume a much larger fraction of the EUR 1000.

Plenty of recent studies try to explain heterogeneity in MPC[7].Jappelli and Pistaferri (2014) find for Italian data that households with poor liquidity (i.e. low cash-on-hand) have much higher MPCs than affluent households, which is in line with the concept of precautionary savings. Patterson et al. (2019) show that individuals with higher MPCs suffer more from recessions. Herman and Lozej (2021) show in a HANK model that MPC heterogeneity also relates to labor economics and the effectiveness of monetary policy.

Keen (2021) describes this anecdotally with how Bernanke (2010) criticized Irving Fisher's assessment of the Great Depression as a consequence of 'debt deflation'. Bernanke (2010) assumed that there are no large differences

[7] For instance, Fagereng et al. (2021); Ganong et al. (2020); Baker et al. (2020b,b); Jappelli and Pistaferri (2017).

in MPC between different societal groups. Therefore, 'debt deflation' should have had macro-economically no large impact because it only represented a redistribution of goods from debtors to creditors, which were assumed to have similar levels of MPC. Keen (2021) highlights that this argument falls apart if one does not postulate MPC homogeneity.

2.2 The Big Five Personality Traits

The Big Five personality traits (short: *Big Five*) describe a concept from the psychological literature that describes personalities of humans by the following five traits: openness, conscientiousness, extraversion, agreeableness, and neuroticism. An overview of the dimensions and their facets is provided in Table 1. They are derived from factor analysis of large scaled surveys and appear to be robust among different situations in and throughout life (Goldberg, 1990; Costa and McCrae, 1992). In the economic literature, they might be referred to or mentioned in line with *non-cognitive abilities*.

Big Five	Facets
Openness	Imagination, Artistic Interest, Emotionality, Adventurousness, Intellect, Liberalism
Conscientiousness	Self-Efficacy, Orderliness, Dutifulness, Achievement-Striving, Self-Discipline, Cautiousness
Extraversion	Friendliness, Gregariousness, Assertiveness, Activity Level, Excitement-Seeking, Cheerfulness
Agreeableness	Trust, Morality, Altruism, Cooperation, Modesty, Sympathy
Neuroticism	Anxiety, Anger, Depression, Self-Consciousness, Immoderation, Vulnerability

Table 1: Big Five and its Facets (borrowed from Schäfer (2016))

The concept of Big Five is widely accepted and frequently used in psychology and has been more recently frequently used in economic research. Bowles and Gintis (1976) pioneered[8] this work by assessing the relationship of personality and earnings in a long-term study of school development and labor market outcomes. Similarly, Mueller and Plug (2006) relate Big Five personality traits to earnings by using interviews conducted in 1992 with individuals that graduated from high school in 1957. Traits associated with higher earnings for men were non-agreeableness, non-neuroticism, and openness to experience. Women received on average higher earnings if they were conscientious and open to experience.

Heckman and Masterov (2007) use natural experiments around the Perry Preschool program[9] to establish that non-cognitive attributes such as personality have a great effect on socioeconomic achievements. Borghans et al.

[8]Before, there had been already other scholars that tried to combine psychology with economics. See, e.g., Katona (1951).

[9]The Perry Preschool program was was scientific experiment at an Elementary School in Michigan during the 1960s. Young children from backgrounds and neighborhoods with

(2008) provide an extensive overview of the existing literature on the intersection of personality psychology and economics and try to integrate Big Five personality traits into the classical economic paradigm of preferences.

Almlund et al. (2011) try to integrate personality psychology into economic models. In doing so, they provide a very exhaustive literature review and analysis. Heckman (2011) bridges the gap between personality psychology and economics. He provides a quick overview of several psychological frameworks around personality. Heckman et al. (2013) use data from the Perry Preschool Program to causally show that even personality traits were improved by this early-childhood program.

Becker et al. (2012) analyze psychological personality and economic preferences using three data sources: (i) laboratory experiments with students, (ii) their own representative sample of 1,000 German individuals, and (iii) the German Socio-Economic Panel Study (SOEP) with 14,000 individuals, representative for the German population. They do not find a strong overlap between personality and preferences. They hence view the two concepts as complementary to each other.

Gerhard et al. (2018) study personality and savings behavior. They use a 2013 representative sample of 3,382 UK households and finite mixture model to assess latent heterogeneity between two types of household classes in the UK: striving and established. They find that links between personality and savings behavior can also differ by type of class.

Balasuriya and Yang (2019) also discuss how Big Five personality traits can be linked to other psychological concepts used in economic research already. Low self-control often correlates with low conscientiousness, high neuroticism, and high extraversion (Costa and McCrae, 1992; Whiteside and Lynam, 2001; Aslan and Cheung-Blunden, 2012). High present-bias, i.e. low patience is often correlated with low conscientiousness and high extraversion (Ostaszewski, 1996; Hirsh et al., 2008; Manning et al., 2014; Mahalingam et al., 2014).

Furthermore, Rustichini et al. (2012) argue and demonstrate on a dataset with 1000 US truckers that including personality traits into economic models increases their predictive power.

However, it is important to mention that the concept of the Big Five personality traits is subject to criticism. E.g., Mischel (1968) disregards

high risks of school failing were randomly allocated into two groups. One group, the program group, received a high-quality preschool education, while the other group, the control group, did not. The lives of the individuals in these two groups have been closely monitored since then and compared to each other such that inferences about the group differences due to the program could be drawn.

personality concepts in general and argues instead for a situative view. According to him there are no stable personalities and choices depend to a large extent on the situation. According to the economic literature, the Big Five are prone to measuring errors and research needs to be cautious with hasty conclusions due to possible reversed causality (Borghans et al., 2008; Heckman, 2011). However, such issues have been overcome in several studies (e.g., Heckman et al. (2006)).

Psychologists have recently started making use of digital footprints that are available through digitization (Matz et al., 2016; Landis and Gladstone, 2017; Gerhard et al., 2018; Gladstone et al., 2019; Weston et al., 2019). Particularly, financial footprints stemming from transaction data are of interest to study consumption and savings patterns among individuals.

Matz et al. (2016) study consumption behavior and happiness. They use 6 months of transaction data for 625 customers of a UK-based bank and an online survey, which included the BFI-10 (Rammstedt and John, 2007) for personality estimation and the SWLS (Diener et al., 1985) for estimating life satisfaction, in late 2014. They find a match between participants' personalities and purchased products. They also find that participants with a high personality-product match observed higher life satisfaction figures.

Landis and Gladstone (2017) study consumption among extraverts. They use 12 months of transaction data for 718 customers of a UK-based bank and an online survey to assess personality with the BFI-10 and some questions on self-control and materialism. They asked 50 Amazon MTurk workers to assess spending categories by status. They find that extraverts, particularly those with low income, spend significantly more on status-categories than introverts.

2.3 Linking Big Five Personality Traits to MPC

Several psychological studies have illuminated spending behaviour with the concept of Big Five personality traits. Spending behavior itself is directly linked to MPC so that we provide a link of both concepts.

Psychological studies that related spending behavior with the Big Five personality traits tried to identify different consumption patterns among different personality types. As for example, Gerhard et al. (2018), Gladstone et al. (2019) and Tovanich et al. (2021) infer the personality traits from spending behavior on a dataset with matched survey and transaction data of bank customers by applying machine learning techniques. Other work go even further, such as Ebert et al. (2020), and relate spending behavior not only by personality types but also by surrounding peer groups.

However, there are also studies in economics that use the Big Five personality traits to explain financial decision-making. As for example, Brown and Taylor (2014) use survey data from the British Household Panel Survey and find that certain personality traits have influences on household finances. Gerhard et al. (2018) try to explain household savings behaviour with a representative sample of the UK population and identify links to psychological characteristics, such as the Big Five.

The availability of new data sources such as financial account aggregators makes it possible to validate the existence and robustness of the Big Five. To our knowledge, the first studies that use such data to explain spending behaviour and, thus, explain MPC, are Baugh et al. (2014) and Gelman et al. (2014). In the case of Baugh et al. (2014), tax rebates were identified to test theories on consumption such as myopic behavior and precautionary savings motive. On the other hand, Gelman et al. (2014) analyzed consumption responses after the receipt of anticipated incomes. Newer studies go further and analyze payday responses in such datasets (e.g., Olafsson and Pagel (2017), Olafsson and Pagel (2021), Gelman (2021)), consumption responses of policy measures (e.g., Baker and Yannelis (2017) and Baugh et al. (2021)) or of unexpected income shocks such as lottery windfalls (Olafsson and Pagel (2021)) or spending behaviour and income across households with different levels of debt and credits Baker (2018).[10]

Overall, we see that both strands are well established while Big Five personality traits are not directly linked to the concept of MPC. To our knowledge, however, there is no study that provides a link between the two. Strategically, we nest personality traits in well-defined models that estimate MPCs and examine precautionary trading motives. Joint behavioral beliefs and preferences are risk, trust, patience and self-control that both strands have in common. In our study we focus on risk and trust due to data availability to interlink the two. Doing so, we expect significant coefficients of the personality traits which are helping us to answer our research question whether there indeed exists a link to the concept of MPC.

Relevance of Big Five personality traits for Policy Making

A key challenge is that personality traits are not easily observable for the policy maker at an individual level. Nonetheless, there is knowledge about aggregate distributions of personality traits in populations such that further knowledge on personality can be useful for good policy making (e.g. to raise

[10]For a survey of the literature on transaction data, see Baker and Kueng (2021).

awareness about adverse behavior related to specific personality traits). Also, policy makers can measure this by the use of representative samples and revealed behavior.

Only a few studies have analyzed consumption decisions of individuals with respect to their personality traits and policy measures. Balasuriya and Yang (2019) discuss the role of personality traits in financial decision-making in light of pension decision-making in the UK. They use data from the UK Household Longitudinal Study. Their main findings are that conscientiousness is positively correlated with participation in a pension plan and extraversion negatively. Schäfer (2016) investigate what influence personality traits have on retirement saving patterns in Germany. And Wicks and Nelson (1967) conduct a small sample study in the 1960s among college students in the US finding that there are significant differences in temperament if participants were grouped according to their MPCs. Mangiavacchi et al. (2021) use the data from the SOEP to identify different personality profiles among different consumption categories.

Overall, it is worth mentioning that for policy makers it might be hard to directly elicit the Big Five of individuals. Still, this study shows us that it is important to look at the MPC as a higher dimensional measure that is driven by much more individual characteristics than only income for instance. The application of the Big Five persoanlity traits demonstrates that we still can learn that there is much more MPC heterogenity among individuals.

3 Data & Methodology

In this section, we describe our dataset that involves survey and transaction data that we receive from a German financial account aggregator app. First, we explain which specificities such financial account aggregators involve. Second, we describe our datasets, starting with the survey where we describe how the Big Five personality traits and the survey-based MPCs were elicited. Finally, we summarize the transaction data. Lastly, we introduce our model with which we rigorously identify consumption responses among different personality traits.

3.1 Financial Account Aggregator

The digitization of different areas of life also reached the private financial budget planning. There are several companies that provide services that help private households and individuals to (i) optimize financial behavior, (ii) reduce debt, and (iii) aid with the management of subscriptions. Such a service is called 'financial-account aggregator'[11] (hereafter FAA). FAAs process and aggregate all in- and out-going cash flows from different accounts. Doing so, they reveal aggregate income and spending among different categories to provide a unified overview of the financial situation. Such FAAs make use of the EU Payment Services Directive (PSD2) to receive their customers' data entrusted with other financial service providers.

For this study, we cooperate with a German company that provides an FAA app. We conduct a survey among their customers which allows us to match survey and transaction data and reveal behavioral consistencies and discrepancies among what the customers said in the survey compared to their actual behavior visible in their transaction data. Data from such FAAs has been used in several recent studies.[12] Our data sample stemming from this app is similar to data used in comparable studies such as Olafsson and Pagel (2021) or Gelman et al. (2014).

[11] There are studies that use different names such as 'online personal finance website' (Baker and Yannelis, 2017), 'linked financial account data' (Baker, 2018) or 'personal finance management software' (Olafsson and Pagel, 2018).

[12] An exhaustive list of studies using data from FAAs to analyse consumption responses: Agarwal et al. (2007); Baker (2018); Baker and Yannelis (2017); Baugh et al. (2014, 2021); D'Acunto et al. (2019); Gelman et al. (2014); Kuchler and Pagel (2021); Olafsson and Pagel (2021, 2018, 2017). An exhaustive literature overview on studies using financial transaction data in general is provided by Baker and Kueng (2021).

3.2 Survey

In the app of our partnering FAA, about 56,000 customers were activated for the survey, i.e., a notification card with an invitation to the survey was displayed in the app. Yet, only customers who opened the app could see the notification. The activated customers that were invited to the survey had already been pre-selected by the company based on their prior activity in the app [13]. Hence, we did not need to rely on an 'activity test' as mentioned by Olafsson and Pagel (2021).

The participation to the survey over time and the response rates are depicted in figure A.1 and B.2 in the appendix. The overall field phase of the survey lasted from 9 August, 2021, until 17 September, 2021. It started with a test phase where we tested the customers' response behavior for measurement errors. During the test phase, no monetary incentivization was applied, i.e., participation to the survey was completely voluntary. As of 27 August, the actual field phase started where established customers were activated in charges (first charge on 27 August, second charge on 6 September, etc.). We incentivized by randomly drawing fifty EUR 20 Amazon vouchers among the participants. Since 10 September, we further activated an additional sample including new customers. The overall sample size is n=1,771. The winning respondents were drawn on 17 September, 2021.

After filtering out (i) non-completed surveys, (ii) surveys with missings in the responses, (iii) surveys with total response durations longer than 60 minutes, and (iv) duplicated participations, we end up with a cleaned net sample size of n=1,334.[14]

The descriptive statistics of the final dataset are presented in Table 2. In the upper part of the table, we depict the descriptive statistics of the survey. We see that on average the respondents are 34 years old and 60 percent are male.[15]

To assess self-reported MPC-scores, we follow the HFCS (ECB, 2020) and pose the question:

'Imagine you receive money unexpectedly from a lottery equal to your monthly net income. What would you do with that money over the next 12 months?'

[13]E.g., customers should be active during the past 6 month.

[14]For a detailed overview of the response rates with completed surveys, refer to table B.2 in the appendix on page 45.

[15]Unfortunately, our cooperation partner is not able to retrieve information on age and gender for all customers but only for 72% and 89%, respectively. For further details, see Table B.3 in the appendix.

The respondents should choose between the options:

'0% consuming and 100% saving',

'25% consuming and 75% saving',

'50% consuming and 50% saving',

'75% consuming and 25% saving', and

'100% consuming and 0% saving'.[16]

The reported MPC that we based our survey question on is very similar to the one of ECB (2020). The two main differences in our survey compared to the HFCS are: (i) simpler language and (ii) a discrete option scale instead of a continuous scale. For details, see a comparison of the two survey questions asked in the appendix.

We elicit the Big Five personality traits similarly to Landis and Gladstone (2017) using the well-established 10-item version of the Big Five Inventory (BFI-10) developed by Rammstedt and John (2007). The advantage of this module is its brevity and compactness which helps us to avoid premature survey drop-outs. We do not survey established behavioral predictors such as self-control and materialism (like Tovanich et al. (2021)), but the Big Five personality traits are closely linked to these. Nevertheless, we elicited risk and trust preferences (i.e., risk attitude and general trust).

We follow Matz et al. (2016) and standardize, i.e. subtract the mean and divide by standard deviation, the Big Five personality traits to facilitate its interpretation. Doing so, a score larger than 1 indicates a strong manifestation of a personality trait and smaller than -1 is associated with a low level of the trait, respectively.

3.3 Transaction Data

The transaction data we use is comparable to the FAA dataset used in Olafsson and Pagel (2021) and Matz et al. (2016), which is a rich dataset at the most granular transaction level. We observe different information on each transaction such as amount, receiver, whether the transaction was collected automatically or not, account id, number of total transaction to receiver, etc.

Additionally, we receive a transaction category, which is high-level, and feature categories such as: income, cash, work and education, food and

[16] Refer to the appendix on page 46 for the actual question in German.

	N	Mean	SD	Min	p25	Median	p75	Max
survey data								
dummy 1=male, 0=female	1185	.614	0.487	0	0	1	1	1
Age	960	34.523	10.059	17	27	33	40	77
Risk attitude	1334	3.853	1.546	1	3	4	5	7
General Trust	1334	3.934	1.375	1	3	4	5	7
Reported MPC (Lottery)	1333	.354	0.230	0	.25	.25	.5	1
Openness	1334	3.324	0.698	1	3	3.5	4	5
Conscientiousness	1334	3.503	0.618	1	3	3.5	4	5
Extraversion	1334	3.089	0.502	1	3	3	3.5	5
Agreeableness	1334	3.115	0.707	1	2.5	3	3.5	5
Neuroticism	1334	2.935	0.584	1	2.5	3	3.5	5
openness (standardized)	1334	-.014	1.002	-3.349	-.479	.239	.957	2.392
conscientiousness (standardized)	1334	-.008	1.010	-4.098	-.83	-.013	.804	2.438
extraversion (standardized)	1334	-.006	1.009	-4.21	-.185	-.185	.821	3.84
agreeableness (standardized)	1334	.004	1.003	-2.994	-.868	-.159	.55	2.677
neuroticism (standardized)	1334	-.012	1.004	-3.334	-.758	.1	.959	3.534
transaction data								
Nbr. current accounts	1334	2.333	1.918	1	1	2	3	27
Avg. current account balance	1333	3548.83	7869.701	-8552	460	1204	3193	80109
Number of depot accounts	1334	.723	1.247	0	0	0	1	12
Avg. income	1334	2428.352	1950.113	15.649	1268.696	2027.228	3034.028	23134.672
Total avg. monthly expenditures	1334	62.863	1685.951	-28893.957	-91.385	15.51	234.159	20679.721
Avg. monthly transaction	1334	56.154	26.428	11.051	38.378	51.012	67.959	204.758
Avg. cash withdrawals	1334	-276.81	423.185	-5921.178	-332.494	-160.583	-68.891	163.824
Avg. expenditures education/vocation	1334	-14.478	40.856	-533.491	-11.817	-.118	0	0
Avg. expenditures drugstore	1334	-24.37	32.019	-347.008	-33.005	-13.116	-3.723	0
Avg. income	1334	2428.352	1950.113	15.649	1268.696	2027.228	3034.028	23134.672
Avg. finances	1334	-767.646	1671.540	-19305.629	-769.927	-249.882	-60.243	820.5
Avg. expenditures leisure/entertainm	1334	-94.944	292.945	-10030.676	-106.092	-61.881	-34.37	201.158
Avg. health expenditures	1334	-38.769	92.825	-1649.101	-36.486	-16.343	-6.056	0
Avg. pet expenditures	1334	-9.092	23.307	-248.272	-5.258	0	0	0
Avg. children expenditures	1334	-33.107	111.871	-1882.419	-10.501	0	0	0
Avg. foodstuff	1334	-207.16	173.750	-1573.685	-278.815	-162.081	-80.262	0
Avg. vacation expenditures	1334	-70.717	155.693	-3507.569	-84.732	-28.158	-3.617	0
Avg. shopping expenditures	1334	-288.606	245.260	-4870.644	-359.153	-237.916	-142.214	0
Avg. other expenditures	1334	-2585.404	11750.279	-305330.31	-2323.08	-1105.475	-506.05	-24.391
Avg. other receipts	1334	3423.456	16590.947	.667	721.525	1489.268	3128.463	492203.47
Avg. expenditures on savings/pension	1334	-395.865	6888.491	-249626.92	-208.25	-30.755	0	5247.702
Avg. mobility expenditures	1334	-78.445	141.974	-1761.494	-79.928	-39.189	-16.883	.262
Avg. insurance expenditures	1334	-214.553	366.171	-7378.271	-248.133	-114.141	-45.062	218.707
Avg. living and household	1334	-594.362	483.311	-6142.285	-822.218	-502.361	-246.518	0
Total avg. monthly expenditures	1334	62.863	1685.951	-28893.957	-91.385	15.51	234.159	20679.721
Avg. monthly transaction	1334	56.154	26.428	11.051	38.378	51.012	67.959	204.758
received lottery windfall	1334	.141	0.348	0	0	0	0	1
received small lottery windfall	1334	.096	0.295	0	0	0	0	1
received large lottery windfall	1334	.092	0.289	0	0	0	0	1
count lottery windfall	1334	.537	2.512	0	0	0	0	39
# received small lottery windfal	1334	.272	1.273	0	0	0	0	16
# received large lottery windfal	1334	.265	1.551	0	0	0	0	25
observed months	1334	43.441	16.663	20	35	47	47	263
dummy 1=no missing months in obs	1334	.085	0.279	0	0	0	0	1

Note: In panel transaction data, positive (negative) values indicate account inflows (outflows). We have filtered the data by individuals who (1) completed the survey, (2) who provided all information on Big Five, (3) completed the survey in less than 60 minutes and (4) participated to the survey only once. Note that we do not observe age and gender for all individuals. Refer to Table B.3 in the appendix for for more information on sample construction.

Table 2: Descriptive statistics of survey and transaction data

drinks, finances, leisure and entertainment, health, pets, children, shopping, savings, mobility, insurances, living and household, and other receipts and expenditures.[17] All categories were labeled by the company automatically based on amount, intended purpose, receiver, date, frequency of transaction, and customer discretion.[18] We lack transaction information on intended purpose and on some receiver names as some of them are censored or not delivered by the financial service providers. Both, however, are not relevant for us as we still receive information on the transaction category. We list the descriptive statistics of the transaction data in Table 2. Note that negative numbers indicate outflows from accounts and positive numbers are inflows.

We now describe how we prepare our final dataset when matching survey with transaction data. We initially look at individuals for whom we observe both, survey and transaction data, which amounts to 2,163 individuals. First, we remove all customers that did not complete the questionnaire.[19] This leaves us with 1,771 observations. After excluding observations with missings in the Big Five personality traits and focusing on transaction data with valid dates, we end up with 1,454 observations. Next, we drop observations in the month of November 2021, because it is not fully covered and focus on transactions in the period from January 2000 through October 2021. The number of customers reduces to 1,352. Finally, we restrict our sample by customers with at least ten transactions per month and a minimum monthly salary of EUR 200. Our final sample amounts to 1,335 distinct customers. The customers in our sample have, on average, an income of about EUR 2,400, about EUR 3,500 as current account balance, and 2.3 accounts connected to the FAA app. Note that information on age and gender is not always provided by the financial institutions such that the final sample size might change in analyses with both information. We provide a clear sample construction of all above mentioned filters in Table B.3 in the appendix.

Lottery Windfalls

Analyzing lottery windfalls is a useful and common procedure to infer MPCs and, thus, investigate how individuals respond to unexpected and

[17] We were also provided a more detailed subcategory which is more granular and amounts to almost 140 levels which are, however, less useful as most of those categories are empty as they appear to be rarely used.

[18] The app provides the opportunity to the customer to correct wrong labels or to assign labels herself, i.e. an optional human-in-the-loop / feedback-loop.

[19] We define completeness by the filters: (i) non-completed surveys, (ii) surveys with missings in responses, (iii) surveys with total response duration longer than 60 minutes, and (iv) duplicated participations.

exogeneous income shocks.[20]

Similar to Olafsson and Pagel (2021), we only consider windfalls above EUR 25 to guarantee a minimum economic impact. After winsorizing at the 99th percentile, we end up with 191 individuals of our final sample of 1,335 who received a lottery windfall (about 13.6%). On average, individuals received lottery windfalls of about EUR 158. The median is EUR 52.95, the minimum is EUR 25 and the maximum is EUR 11,597.15. We provide a histogram of lottery windfall size and number in Figure A.22 in the appendix. Both distributions are characterized by fat tails and are comparable to those in Olafsson and Pagel (2021). One might consider that the occurrence of lottery windfalls is rare. However, we point out that in our study we look at lottery windfalls from different kinds of games such as gambling, prize drawing, sports bets, etc. This is quite common in Germany as about half of the German population participates in lottery gambles on a regular basis as can be seen in Figure A.24 in the appendix.

Representativeness

To investigate the German representativeness of the sample used in our study, we compare several statistics of gender, age, and monthly net income with representative datasets such as the German Socio-Oeconomic Panel (SOEP, Goebel et al. (2019)), the German sample of the Household Finance and Consumption Survey (HFCS, ECB (2020)) and the 'Einkommens- und Verbraucherstichprobe' (in English: Income and Consumption Sample of Germany, Destatis (2019)). Also, we cross-check common economic preferences such as risk attitude and trust and compare the Big Five personality traits that have been elicited in the SOEP, too.

For gender, we find in our sample for 2019 that males are slightly overrepresented: while the SOEP has a 50% gender balance, in our sample we observe about 60% male.

In 2019, we observe in our sample slightly younger age cohorts compared to the SOEP. Particularly, in the SOEP, half of all participants are 45 years old or younger and in our sample this group accounts for 86%.

For monthly net income, we find in our sample for 2019 that average net income is overall slightly higher compared to the SOEP. Namely, about 2,400 Euros in our data compared to about 2,200 Euros in the SOEP, both in 2019. Regarding the income distribution, we observe higher incomes across all

[20] An unexhaustive list of studies that analyzed lottery windfalls: Fagereng et al. (2021); Olafsson and Pagel (2021); Fagereng et al. (2018); Kuhn et al. (2011); Imbens et al. (2001).

income quintiles. The differences are, however, not high and range between 100 to 400 Euros.

For monthly net income by age cohort, we find in our sample for 2019 that wealthy individuals are over-represented among the age cohorts of 35 and older.

Further details on the comparison of the distributions can be found in the appendix, starting on page 55 with Figure A.7.

For the EVS, we compared food consumption in 2018 with our reported food and drinks spending.[21] Our variable is, on average, at EUR 140 per month, and therefore similar to various measures of the EVS for per-capita food expenditures on different household sizes.

Additionally, we compare the self-reported MPC in our survey with the self-reported MPC in the HFCS (ECB, 2020) for Germany. We display both histograms in Figure A.20 in the appendix. On first sight, it seems that both distributions are rather different because the responses in the ECB (2020) spike in the first and third category whereas the responses to our survey are centered around the second category. However, when comparing the means of both distributions, they are equal (means: $\text{MPC}_{survey} \approx 25\%$, $\text{MPC}_{HFCS} \approx 25\%$). Therefore, we consider our responses somewhat consistent with the ECB (2020).

Overall, our sample exhibits relatively young individuals that are slightly more often male and but have similar incomes as the common surveys which are representative for the German population. Using our sample, we can enrich our knowledge of MPC heterogeneity and its extension to the Big Five personality traits.

3.4 Model

In this section we present three models with which we link the Big Five personality traits to the consumption response or MPC, respectively. The first model evaluates the self-reported MPC that was elicited in the survey. The next two models examine consumption responses that we observe in transaction data. By interpreting the results of the three models, we evaluate the five hypotheses and, ultimately, give provide an answer to the research question. On top, we assess precautionary savings motives and permanent

[21] The EVS lists food, drink, and tobacco consumption. The definition of food consumption in our sample contains: supermarket, other groceries expenses, other food and drinks expenses, restaurants, food delivery, grocery-subscription, canteen expenses, and drinks store.

income hypothesis through the channels income and savings that we directly observe from transaction data.

Self-reported MPC and Big Five personality traits

First, we start with the self-reported MPC and regress it via OLS with following specification:

$$MPC_i = \beta_0 + \beta_1 log(income_i) + \beta_2 log(savings_i) + \gamma BigFive_{i,j} + \delta X_i + \epsilon_i \quad (1)$$

i stands for individual, $BigFive_{i,t}$ include the j=5 personality traits and $X_{i,t}$ is a vector of controls in which we include the behavioral preference, risk and trust. With this specification we are identifying drivers of the self-reported MPC to reveals whether individuals' responses are in line with what we observe in their actual behavior in terms of observed transaction data.

Consumption responses in transaction data and Big Five personality traits

In a second step, we lean on Parker (2017) and investigate the consumption responses around the lottery windfall by conducting the following pooled OLS regression. We use this specification to control for unobserved heterogeneity over time and to analyze also time-invariant effects such as the Big Five personality traits which would be, for instance, absorbed in a fixed-effects regression:

$$y_{i,t} = \beta_0 + \beta_1 Windfall_{i,t} + \beta_2 BigFive_{i,j} + \sum_{s=-L}^{L} \beta_{4,t+s} D_{i,t+s} + \beta_5 X_{i,t} + \epsilon_{i,t}, \quad (2)$$

where i stands for individuals, t for month, $y_{i,t}$ is the independent variable and measures total consumption of individual i in month t. Furthermore, $Windfall_{i,t}$ measures the lottery windfalls and β_1 is the respective MPC out of lottery windfalls; $D_{i,t}$ is a dummy that is 1 for each month in the L=3-month-window around the lottery windfall; $BigFive_{i,t}$ include the j=5 personality traits and $X_{i,t}$ is a vector of controls in which we include age, gender, income, savings, risk, and trust. With this cross-sectional specification, we examine whether the individuals indeed respond in the month of the receipt of lottery windfall while identifying effects among the Big Five.

In a next specification, we follow Olafsson and Pagel (2021) and build on our extension by incorporating the Big Five personality traits. We do this by including dummies of the Big Five that are 1 if the trait is strongly pronounced[22]:

$$y_{i,t} = \alpha_i + \beta_{i,t} Windfall_{i,t} + \gamma_{i,t} BigFive_{i,j} \times Windfall_{i,t} + \delta_{i,t} X_{i,t} + \tau_t + \epsilon_{i,t} \quad (3)$$

where α_i and τ_t represent individual and monthly fixed-effects, $\beta_{i,t}$ is the measure of MPC from lottery windfall, $y_{i,t}$ is the dependent variable and measures again total consumption, $X_{i,t}$ is a vector of controls where we include income and savings, and, ultimately, $\gamma_{i,t}$ is the coefficient of the interaction term with which we identify whether a certain personality trait is related to weak or strong consumption when the lottery windfall arrives. We conduct for each personality trait j a separate regression so that we end up with five separate models. With this specification, we focus on the average impact of the arrival of the lottery windfall on spending and investigate which individuals with certain pronounced personality respond more or less strongly to the arrival of the lottery windfall. For instance, individuals with strong conscientiousness are expected to respond less to the windfall compared to individuals with strong extraversion or neuroticism.

[22]Specifically, we code the dummies for each trait =1 if the respective z-score is larger than 0.

4 Results

To answer our research question, we proceed in two steps. First, we relate the Big Five personality traits to the self-reported MPC from the survey. Second, we look at the transaction data and examine consumption responses of lottery windfalls in relation to the Big Five. We look at the results of both sections to evaluate our five predefined hypotheses.

4.1 Self-reported MPC and Big Five Personality Traits

We show in Figure 2 a heatmap of self-reported MPC among each Big Five personality trait to examine heterogeneity among both concepts. Specifically, we show the share of individuals that fall in a certain cell in the heatmap. The darker the color the higher the share. We see that MPC scores are mainly distributed around the means of each Big Five score, namely around 3.0. Additionally, we observe that, e.g., conscientiousness is slightly distorted to the right which is in line with Tovanich et al. (2021) and indicates a potential self-selection issue: surveys are more often answered by individuals with higher conscientiousness levels. Additionally, we see that, e.g., extraversion is highly concentrated at the mean, 3.0, whereas agreeableness shows more variation. As the traits are unevenly distributed, we apply z-standardization to make the traits comparable. For latter analysis, we also focus on extreme values and generate dummies if traits are strongly pronounced.

Subsequently, we look at the correlations in Table 3 of the Big Five personality traits and the MPC scores. Overall, we see small correlations between the MPC scores and the z-standardized personality scores. Correlations are negative for openness and conscientiousness and positive for agreeableness. These numbers hint that there is support for our hypotheses. For robustness check, we also look at the preference measures, risk and trust, to identify possible alternative channels that might trigger MPC or consumption responses in general. Also, we compare the results with the literature to examine

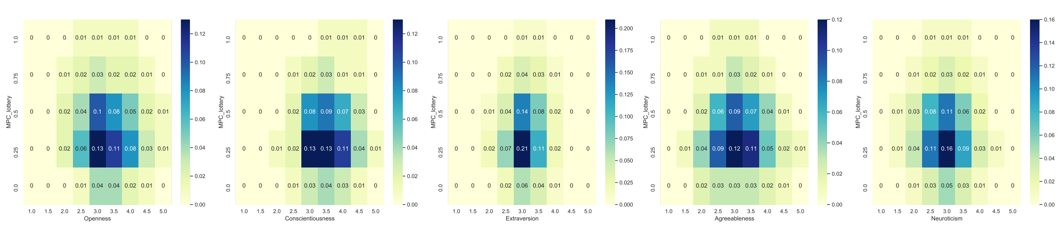

Figure 2: Heatmaps of self-reported MPC and Big Five personality traits

	openness	conscientiousness	extraversion	agreeableness	neuroticism
openness	1,000	0,064	0,078	0,082	0,010
conscientiousness	0,064	1,000	0,079	0,117	0,158
extraversion	0,078	0,079	1,000	0,060	0,129
agreeableness	0,082	0,117	0,060	1,000	0,069
neuroticism	0,010	0,158	0,129	0,069	1,000
self-reported MPC	-0,052	-0,034	-0,046	0,051	0,000
risk	0,117	0,003	0,016	0,068	0,029
trust	-0,021	-0,053	-0,005	0,276	0,009

Table 3: Correlation of self-reported MPC to z-standardized personality scores

whether our data is comparable. For instance, Dohmen et al. (2011) find that risk is positively correlated to openness and extraversion and Lusardi and Mitchell (2011) also find that investors with high openness are more willing to take risks. Likewise, trust is positively correlated with agreeableness Borghans et al. (2008).

In a next step, we conduct regression analysis using OLS where we regress self-reported MPCs on the Big Five scores while controlling for income, savings, and preference measures. The results are presented in Table 4.

In the first column, we regress self-reported MPC on the Big Five personality traits. Here, note that the coefficient of openness is significantly negative and that of agreeableness is significantly positive. This is plausible for agreeableness as it is linked with altruism, friendliness, and straight-forwardness. It is also in line with Balasuriya and Yang (2019) since individuals with low levels of agreeableness tend to save too little.

Regarding openness it seems implausible, at first sight, that individuals with a pronounced openness trait have a lower MPC. As openness is related to risk preferences, it would imply that risky individuals are saving more. However, in the context of the precautionary savings motive, these individuals hedge themselves against income shocks, and, thus, compensate their risky behavior.

The relation of openness and risk preference is also visible. The effect of the significantly negative coefficients of openness is passed through to risk in the third column. This is in line with Dohmen et al. (2011) stating that the Big Five personality traits do not eliminate the effects of risk. In other words, the Big Five alone do not fully capture risk preferences.

Additionally, we see that in the second and third column also savings indicates a significantly negative coefficient. This is in line with the MPC score as both are directly linked to each other: if individuals have high savings, their MPC must be lower, and vice versa.

Differently than expected, we do not see significant effects of the other

Big Five personality traits. As MPC is directly linked to impatience (e.g., Fagereng et al. (2021)) and conscientiousness is related to it likewise (e.g., Manning et al. (2014); Mahalingam et al. (2014)), we expected to see a negative effect of conscientiousness to self-reported MPC. We assume that, similar to risk and openness, Big Five personality traits lack to some extend explanatory power of MPC heterogeneity.

	(1)	(2)	(3)
	OLS	OLS	OLS
	self-reported MPC	self-reported MPC	self-reported MPC
log(income)		0.00265	0.00329
		(0.00821)	(0.00811)
log(savings)		-0.00620**	-0.00576**
		(0.00261)	(0.00259)
openness	-0.0117*	-0.0113*	-0.00884
	(0.00653)	(0.00649)	(0.00651)
conscientiousness	-0.00809	-0.00891	-0.00847
	(0.00697)	(0.00689)	(0.00693)
extraversion	-0.00995	-0.01000	-0.00984
	(0.00639)	(0.00638)	(0.00635)
agreeableness	0.0140**	0.0131**	0.0122*
	(0.00654)	(0.00654)	(0.00683)
neuroticism	0.00181	0.00219	0.00268
	(0.00652)	(0.00650)	(0.00653)
risk			-0.0201***
			(0.00654)
trust			0.00756
			(0.00686)
Constant	0.353***	0.342***	0.336***
	(0.00629)	(0.0613)	(0.0605)
Observations	1,334	1,334	1,334
R-squared	0.009	0.013	0.021

Note: All measures of Big Five and risk and trust are z-standardized.
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: OLS self-reported MPC on Big Five and other measures

4.2 Consumption response to lottery windfalls and Big Five

In this section, we answer the research question about the relation of MPC and personality by investigating how individuals with different personalities react differently to the receipt of lottery windfalls. First of all, we investigate graphically whether individuals increase total consumption at the arrival of windfalls. In Figure 3, we show the monthly means of total consumption from 4 months prior to 4 months after the lottery windfall receipt. Small lottery windfalls are displayed as solid line and large lottery windfalls are dashed. Before the month 0, total consumption is roughly about 3,000 Euros, but after the lottery windfalls arrives, total consumption jumps up to over 4,000 Euros and returns back in the months afterwards. We clearly see that the higher the lottery windfall, the more is consumed in the month of arrival and, especially, one month afterwards where total consumption peaks in the case of large lottery windfalls.

Overall, we indeed see that individuals increase their consumption which gives us certainty that our data is comparable to the data used by Olafsson and Pagel (2021). Additionally, the reproduced results of the FE model of Olafsson and Pagel (2021) also demonstrate that the responses exhibit clear significant coefficients for large lottery windfalls (see Table B.8 in the appendix).

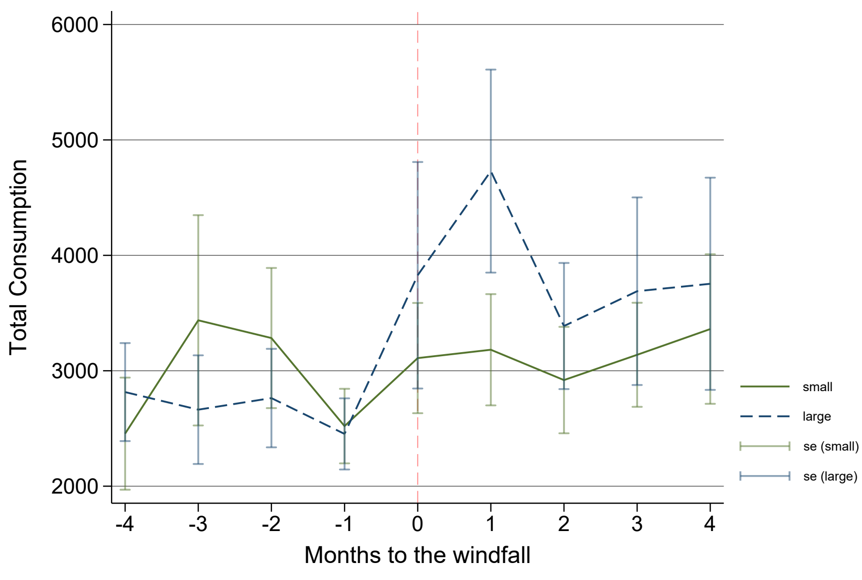

Figure 3: Revealed MPC of Total Consumption after Lottery Windfalls

The results of the pooled OLS specification that we use to examine consumption responses in relation to the Big Five personality traits are presented in Table 5.

In the first column, we include only the controls and the dummies of the 3-month-window around the month when the individuals receive the windfall. We see that all controls are significant: income, savings, age, and the male dummy are related to total consumption; and are in line with several studies (e.g., Agarwal et al. (2007); Olafsson and Pagel (2021); Jappelli and Pistaferri (2014)) - except for the male dummy. We assume that the over-representation of males in our sample who receive lottery windfalls is higher than for females.[23] Additionally, as shown by Handa et al. (2009), females spend indeed less than men as they have higher control over their budgets.

Noticeably, in this specification, the amount of lottery windfall turns out to be insignificant. We explain this by the following three points. First, we include dummies that control already for the month in which the lottery windfall arrives. Second, we conduct pooled OLS on a sample where we observe many months per individual but the lottery windfall only occurs in very few months. Third, as we see in Figure 3 and in the significant dummy in t+1, we see that the lottery windfall rather affects the subsequent month. Putting all this together, the effect of the size of the windfall vanishes. Additionally, we take a closer look at this when conducting the fixed-effects specification where we specifically focus on changes over time.

In the next column, we include the Big Five personality traits. Here, soley extraversion indicates a significant coefficient. Landis and Gladstone (2017) and Mahalingam et al. (2014) also find that extroverted individuals tend to spend more today and argue that these individuals try to uphold their desire for status.

In the third column, we also include risk and trust to control for alternative channels. Indeed, we see here that the preference for risk indicates a highly significant and positive coefficient: risk-seeking individuals consume much more money. On first sight, this seems contradictory to Dohmen et al. (2011). However, such individuals with high levels of risk preference tend to earn much higher incomes (Ströing et al. (2016)) and are able to build higher levels of precautionary savings. Having higher incomes and savings, these individuals have more liquidity and as a result tend to consume more.[24]

The results of the fixed-effects regression are presented in Table 6. In each of the five columns we include an interaction between the lottery windfall and a dummy for each of the the Big Five personality traits, which are 1 if

[23]We observe about 3/4 of all lottery windfall winners to be male.

[24]For this, we provide three graphs in the appendix to display income, savings, and total consumption by the risk measure in Figure A.5. All three figures indicate an increasing relation with risk.

	(1) Pooled OLS total consumption	(2) Pooled OLS total consumption	(3) Pooled OLS total consumption
income	0.0785***	0.0762***	0.0708***
	(0.0220)	(0.0211)	(0.0187)
savings	0.249**	0.230**	0.233**
	(0.104)	(0.110)	(0.106)
age	62.46***	76.33***	79.43***
	(23.01)	(23.38)	(20.62)
male dummy	1,365***	1,429***	940.8**
	(404.5)	(401.0)	(395.6)
lottery windfall amount	0.184	0.126	0.309
	(0.649)	(0.642)	(0.625)
D_{t-3}	454.5	478.1*	421.5
	(277.6)	(277.4)	(275.4)
D_{t-2}	115.4	130.8	89.03
	(262.8)	(269.3)	(272.2)
D_{t-1}	190.6	230.6	209.5
	(235.0)	(234.5)	(237.2)
D_t	243.7	247.8	184.8
	(249.5)	(249.1)	(246.5)
D_{t+1}	957.4*	996.4*	1,026**
	(505.6)	(510.7)	(512.0)
D_{t+2}	148.3	128.7	150.1
	(248.3)	(240.2)	(246.0)
D_{t+3}	151.4	143.8	113.3
	(207.4)	(206.5)	(207.8)
openness		-252.4	-212.5
		(265.4)	(258.9)
conscientiousness		183.9	37.95
		(242.7)	(260.2)
extraversion		420.3**	403.5**
		(174.3)	(163.8)
agreeableness		46.94	-79.97
		(266.1)	(214.3)
neuroticism		175.6	47.10
		(251.6)	(252.1)
risk			604.7***
			(224.4)
trust			130.1
			(186.6)
constant	-891.3	-1,483	-1,312
	(930.4)	(956.2)	(858.0)
Observations	1,728	1,728	1,728
R-squared	0.115	0.128	0.148

Note: the lags and leads of lottery windfalls represent dummies where lottery windfall t+3 is the base category.
Clustered standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 5: Pooled OLS regression of total consumption

	(1) FE total consumption	(2) FE total consumption	(3) FE total consumption	(4) FE total consumption	(5) FE total consumption
lottery windfall amount	0.802***	0.581**	1.052**	0.812***	0.806***
	(0.128)	(0.289)	(0.410)	(0.135)	(0.133)
income	0.129***	0.129***	0.129***	0.129***	0.129***
	(0.0420)	(0.0420)	(0.0420)	(0.0420)	(0.0420)
savings	0.00401	0.00401	0.00402	0.00401	0.00401
	(0.00265)	(0.00265)	(0.00265)	(0.00265)	(0.00265)
high openness x lottery windfall	-0.243				
	(1.416)				
high conscientiousness x lottery windfall		0.298			
		(0.354)			
hig extraversion x lottery windfall			-0.351		
			(0.412)		
high agreeableness x lottery windfall				-0.808***	
				(0.297)	
high neuroticism x lottery windfall					-0.657*
					(0.339)
constant	2,333***	2,334***	2,333***	2,334***	2,334***
	(126.0)	(126.0)	(126.0)	(126.0)	(126.0)
Observations	39,550	39,550	39,550	39,550	39,550
users	1,328	1,328	1,328	1,328	1,328
R-squared	0.391	0.391	0.391	0.391	0.391
month FE	YES	YES	YES	YES	YES
user FE	YES	YES	YES	YES	YES

Clustered standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6: Fixed-effects regression of total consumption on Big Five dummies indicating high scores interacting with lottery windfall

the trait is strongly pronounced. Further, we include the amount of lottery windfall, income, and savings as controls. First of all, the coefficient of lottery windfalls is highly significant in each of the specifications which clearly shows that individuals indeed increase consumption. Moreover, we see that only the interactions of lottery windfalls with agreeableness and neuroticism in column (4) and (5) are significant.

In the case of agreeableness, the coefficient is negative which indicates that strongly agreeable individuals tend to increase consumption after the receipt of lottery windfalls. This stands in clear contrast to the results of the regression on self-reported MPC (Table 4) where we saw a clear positive coefficient. We explain this by the fact that such strongly altruistic and moral individuals overall tend to 'give' and rather spend money if they were asked what they would do but by looking at their revealed behavior they strongly reduce consumption. They restrict themselves in terms of amount of spending as from a moral point of view they feel bad receiving high lottery windfalls so that they ultimately compensate the amount won by reduced consumption (Airaksinen et al. (2021)).

Furthermore, the interaction between neuroticism and lottery windfalls has a negative coefficient. In the context of precautionary savings, this can be explained by the fact that strongly neurotic individuals feel stronger uncertainty of the future so that they rather spend less and instead save the extra gained money from the lottery (e.g., Brown and Taylor (2014)).

To our own surprise, we do not see any significance for conscientiousness: we would have expected that individuals with such pronounced trait would clearly adjust consumption. However, we assume that no significant coefficient is still valid as conscientious individuals are aware of potential misbehavior of over-consuming lottery windfalls so that they do not react at all.

Overall, we do not find any support for the hypotheses except for extraversion which corresponds in the pooled OLS specification to increased consumption, thus, higher MPC (H_3). Instead, the underlying findings show reversed results for agreeableness (H_4) and for neuroticism (H_5). For the remaining traits, openness and conscientiousness, we do not find any results (H_1 and H_2). In the next section we continue with discussing our results and evaluate how robust these are.

5 Discussion

In this section, we first discuss the results of the previous chapter and suggest a link of MPC and the Big Five personality traits in the context of the precautionary savings motive. Afterwards, we mention several limitation of our study to highlight considerations of our findings.

In the first part of our analysis, where we explained self-reported MPC with the Big Five personality traits, we find support for two of our hypotheses: openness corresponds to lower levels of MPC (H_1) and agreeableness to higher levels (H_4). This finding is in line with the literature (e.g., Mueller and Plug (2006); Mahalingam et al. (2014)). In the case of openness, however, we see strong explanatory power through risk which itself is correlated with openness. The relation between openness and risk was substantiated by Becker et al. (2012). Therefore, we confirm H_1 with restrictions.

For the remaining traits we observe no significant effects. In the case of conscientiousness, we explain it by the fact that we see a relatively high fraction of individuals that exhibit this trait strongly. We assume that, as such people are rather dutiful, thoughtful, and prudent, they do not react in either direction with their MPC (neither lower nor higher MPC). Furthermore, we see potential issues when trying to link the Big Five as we lack important measures such as patience (e.g., Dohmen et al. (2011); Fagereng et al. (2021)) and self-control (e.g., Aslan and Cheung-Blunden (2012); Baugh et al. (2021)) as these measures stand in stark relation to both, MPC and the personality traits.

Additionally, we see some issues with surveying MPC. We expect that surveys do not fully capture real circumstances and individuals cannot project the surveyed experiment to real life situations so that results from surveys should be considered with caution as several studies have mentioned. Such issues were also mentioned in Olafsson and Pagel (2021) or Parker and Souleles (2019), for instance.

Comparing the results from regressing self-reported MPC to those where we regressed total consumption, we see that they are not in line with each other. In the analysis of the self-reported MPC, agreeableness seemed to play a decisive role. On the other hand, in the analysis of total consumption, agreeableness, extraversion and neuroticism were significant drivers. Putting both together, we point out that both results are only comparable with restrictions. The results from self-reported MPC are not only presenting real-life circumstances, but also the results from total consumption are not one-to-one mirroring MPC as we proxy it through consumption only.

To our knowledge, there is no study that actually suggests a measure for MPC deduced from transaction data. As MPC is a measure that relates consumption to savings[25] we therefore apply the simple heuristic of soley measuring consumption to indicate that individuals have high MPCs. We argue that this procedure is still valid in our case as self-reported MPC clearly frames individuals to their consumption behaviour.

Additionally, the results from the fixed-effects specification are interpreted differently (Brambor et al., 2006) as with the interaction term of personality trait and lottery windfall we measure only conditional effects on total consumption. That is, among individuals with strongly pronounced agreeableness or neuroticism, lottery windfalls are associated with an decrease in total consumption. In the pooled OLS specification, we only see that the extraversion is positively significant and, thus, measures the unconditional relation of an increase in this trait and consumption. Therefore, we conclude that (i) extraversion is related to an increase in consumption and (ii) individuals with strong agreeableness or neuroticism who receive high lottery windfalls reduce consumption.

The choice of pooled OLS is debatable as it delivers inconsistent estimators if the error term is correlated to regressors due to unobserved heterogeneity. Therefore, we have applied several robustness tests as mentioned in Gormley and Matsa (2014) to find support for our model specification. As, for example, the Hausman test did reject the null hypothesis that the preferred model is a random effects model. We, finally, also use a fixed-effects model of the second specification as our applied tests for heteroscedasticity and endogeneity suggested to use this model. Also, we conduct all regressions with clustered standard errors to still account for heteroscedasticity and we further tested for multi-collinearity by examining variance inflation factors of the regressors as suggested by O'brien (2007) and there are no issues.

When linking MPC and the Big Five personality traits through the behavioral preference measures, risk and trust, it turned out that risk is a stronger predictor for consumption behavior than the Big Five personality traits. We explain this by the fact that risk preferences are indeed a decisive measure as Dohmen et al. (2011) and Becker et al. (2012) have shown. The authors also point out that time preferences, thus impatience, are key measures, which we were not able to elicit.

Nevertheless, we confirm relations between the MPC and Big Five personality traits that are not captured by risk preferences: namely, extraversion,

[25] For simplicity, we only relate consumption and savings but obviously, debt are an third channel individuals might think of when they allocate lottery windfalls.

agreeableness, and neuroticism. In the case of trust, we do not observe any significant effects which we assess as plausible as to our knowledge no relevant connection to consumption or savings behavior is available.

One can argue that Big Five personality traits are endogenously related to lottery participation. In case one would like to entertain this thought, it could still be argued that some lottery participation might not be self-selected: for instance, the lottery windfalls we observe in the data also cover windfalls of different kinds of games such as sports gambling, postal code lotteries, lotteries from supermarkets and banks, lotteries from charities, etc. (see Table B.13 for an overview). This mitigates concerns for self-selection of individuals to some extend. Also, similar to Olafsson and Pagel (2021), we control for individual fixed-effects that might explain self-selection behavior into lotteries. Lastly, the participation is relatively common as almost half of the German population participate in lottery gambles on an annual basis (see Table A.24).

Issues related to self-selection into the app might also distort the analysis of personality traits. For example, individuals who use personal finance management apps can be seen as conscientious per se because they are already interested in optimizing their finances. However, we argue that financial account aggregators also attract especially such individuals who lack conscientiousness because the app is marketed as tool to avoid typical financial errors (e.g., overdraft, missing savings for a rainy day). Also, in our analysis we focus on certain sub-samples that have pronounced personality traits (e.g. in the fixed-effects specification in Table 6). It turns out that the results are not distorted towards conscientiousness so that we assume that this is a rather irrelevant issue.

Third, the app might also attract rather young people as they are digitally more socialized. Indeed, app users are much younger than the overall population. As we have demonstrated in the descriptive section, our sample rather represents the young population in Germany and therefore, we can still add value among this specific cohort.

The usage of data of an financial account aggregator (FAA) app entails several difficulties regarding data quality. We do not observe much relevant information, such as demographics (education, employment or marital status), debt, or household situation (e.g., shared account, household members, etc.). In the literature, this is a commonly known issue (e.g., Olafsson and Pagel (2021, 2018); Gelman et al. (2014); Matz et al. (2016)).

Nevertheless, we would like to highlight the granularity and completeness of transactions we observe with which we can mitigate several issues that come up with alternative data, such as with survey data. For instance, Parker and Souleles (2019) clearly point out that using survey data does not fully project individuals' actual behavior and might contain measurement errors, just to name two common issues among many others. On the other hand, relying soley on transaction data does not help in understanding individuals' beliefs and preferences. In our set-up we see both, revealed and reported behaviour with which we can clearly observe what individuals in our sample say and actually do.

6 Conclusion

The purpose of this study is to gain insights whether there exists a link between the marginal propensity to consume (MPC) and the Big Five personality traits. We answer this question by formulating hypotheses for each of the personality traits and relate consumption responses directly to them through findings in the literature. To test the hypotheses, we use data from a German company that provides a mobile app with financial account aggregator (FAA) services. This data contains (i) responses to a survey we conducted in Fall 2021 and (ii) transaction data of up to 5 years for users of the app that can be mapped to the survey responses.

By our analysis of MPC and the Big Five personality traits, we combine two strands of literature. First, economic literature, which has often incorporated psychological concepts, but has not done that yet for MPC and personality. Second, psychological literature, which has started using transaction data in computational psychology to explain financial behavior or derive personality from it, but has not considered the concept of MPC yet.

Overall, we conduct regression analyses with (i) self-reported MPCs and (ii) total consumption we observed in the transaction data. In each of the regression specifications we include the Big Five personality traits and evaluate our formulated hypotheses. In our methodology, we mainly follow Tovanich et al. (2021) and Olafsson and Pagel (2021). This contains appropriate data cleaning, descriptive statistics, and rigorous regression settings. In the latter, we focus on lottery windfalls which are specified as exogenous transitory income shocks and are directly identified in the transaction data.

Of our hypotheses, we cannot reject hypothesis H_3, leading to our conclusion that extraverts are indeed increasing total consumption and, thus, exhibit high MPCs. This finding is in line with Landis and Gladstone (2017). However, we find reversed results as expected for H_4 and H_5, agreeableness and neuroticism. Both of them lead to reduced total consumption and smaller MPCs which are in line though with Airaksinen et al. (2021) and Brown and Taylor (2014), but not with our initial hypotheses. Finally, we conclude that the precautionary savings motive is indeed visible for individuals with pronounced agreeableness or neuroticism as they shift consumption towards savings. Different than the permanent income hypothesis suggests, we do see that individuals with the personality traits extraversion, agreeableness, or neuroticism react after they receive a transitory income shock.

By and large, we point out that our analysis is limited to some extend.

Particularly, regarding representativeness of the full Germany population and self-selection concerns into the app. Additionally, there are concerns regarding alternative measures such as impatience, wealth or assets with which we could provide further evidence of personality-driven MPC. Finally, there are also concerns regarding potential endogeneity issues with the Big Five and our measure of the exogenous shock.

Nonetheless, we provide insights into MPC heterogeneity that is by far much more complex than the large literature on MPC to date has stated and is not only limited to observables such as income, wealth, debt, age, etc. (see Figure 1). Future research might provide further evidence that personality traits are indeed linked to MPC by including all these known facets. Policy makers could use this information to effectively aim for desired consumption or savings behavior knowing of a heterogeneity in personality types.

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Appendices

A Additional descriptives statistics

	N	Mean	SD	Min	p25	Median	p75	Max
lottery windfall	670	157.945	523.577	25	34	52.95	107.44	11597.15
lottery windfall small	343	36.715	8.687	25	29.9	34.5	44.2	54.5
lottery windfall large	327	285.107	728.559	54.6	75	111.6	251.1	11597.15
total consumption	39501	-2726.997	4369.019	-28481.529	-2848.9	-1328.91	-621.35	0
cash	27420	471.675	1638.861	.08	100	215	460	111600
savings	39501	550.638	15486.227	0	0	0	163	1604547.1
education & vocation	39501	-16.23	100.240	-8211	0	0	0	81.65
income	39501	3000.964	3832.635	200.01	1589.63	2384.62	3638.17	433789.16
drugstore	39501	-27.379	51.456	-1259.43	-35.4	0	0	.01
food & drinks	39501	38.064	72.712	0	0	10	49.68	2895.59
foodstuff	39499	239.946	255.560	0	54.7	172.08	346.23	6342.03
leisure and entertainment	38993	109.091	1040.899	0	18	53.99	121.95	193680.16
vacation	39445	82.226	490.360	0	0	0	0	60116.77
shopping	39415	321.683	734.509	0	60.86	182.72	402.89	100993.34
finances	39501	-914.69	6127.071	-527219.19	-694.41	-212.06	-10	95326.828
health	39493	46.977	217.806	0	0	0	26.2	9492.81
pets	39501	10.169	51.039	0	0	0	0	1883.3
children	39501	38.569	268.045	0	0	0	0	44581
savings & pension	39501	-457.564	15496.875	-1602397.1	-150	0	0	61612.559
mobility	39501	-92.729	789.590	-44990	-60.05	0	0	424.6
insurances	39501	-251.872	633.350	-40729.09	-293.68	-108.56	-16.85	16667.039
living & household	39501	-694.828	803.820	-23179.08	-940.55	-551.39	-176.02	3390.07
other expenditures	39501	2826.465	21639.547	0	234.16	727.24	1951.25	1987333.9
other receipts	39501	3032.828	28499.898	0	148.41	673.51	2013.52	2186557
monthly positive total	39501	7014.531	30295.193	204	2307.87	3738.9	6687.91	2213697
monthly negative total	39501	-6951.779	32780.500	-2435517	-6479.57	-3605.14	-2154.16	0
monthly absolute total	39501	13966.31	62364.677	239.38	4563.63	7409.59	13344.82	4482866.5
transactions per month	39501	62.798	36.547	1	38	55	79	813

Note: Positive (negative) values indicate account inflows (outflows). Here, we have filtered individuals only by (1) completed surveys, (2) availability of all Big Five information, (3) survey completeness within 60 minutes, and (4) by non-duplicates.

Table B.1: Descriptive statistics of transactions of all customers with spending categories

B Survey

The participations to the survey over time are depicted in Figure A.1. The overall field phase of the survey proceeded from August 9 until September 17 and started with a test phase where we tested the customers' response behavior for measurement errors. During the test phase, we did not apply any monetary incentivisation, i.e., we asked for voluntary participation to the survey. Since August 27, the actual field phase started where we activated established customers in charges (first charge on August 27, second charge on September 6, etc.). When participating to the survey, we incentivized them to automatically participate to a prize drawing of 50 20 Euro Amazon vouchers. Since September 10, we further activated an additional sample which includes new customers. The overall net sample size is n=1,771. The winning respondents were drawn on the September 17. After filtering (1) non-completed surveys, (2) surveys with missings in responses, (3) surveys with total response durations longer than 60 minutes and (4) duplicated participations, we end up with a cleaned net sample size of n=1,7662.

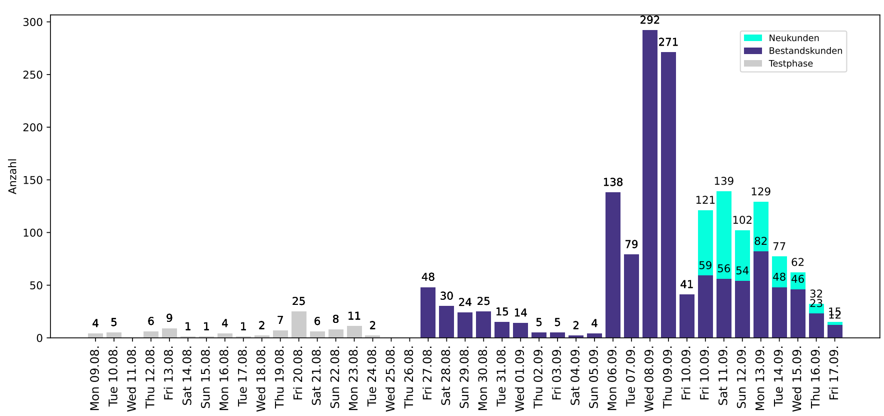


Figure A.1: Survey participation of completed surveys over time

We also included softer MPC questions in the survey, which were maybe answered more intuitively by the respondents. The correlations are in Table B.4.

	overall activated customers	all customers		customers with completed questionnaires		
	number	number	response rate	number	dropout rate	response rate
all	ca. 56,000	2163	3,86%	1771	18,12%	3,16%
survey test phase	ca. 5,000	118	2,36%	92	22,03%	1,84%
established customers*	ca. 45,000	1684	3,74%	997	40,80%	2,22%
new customers*	ca. 6,000	359	5,98%	297	17.27%	4,95%

*: respondents were incentivated with 10 Euros Amazon-vouchers.
Note: We define completedness by the four filters: (i) non-completed surveys, (ii) surveys with missings in responses, (iii) surveys with total response durations longer than 60 minutes, and (iv) duplicated participations.

Table B.2: Suvey response rates

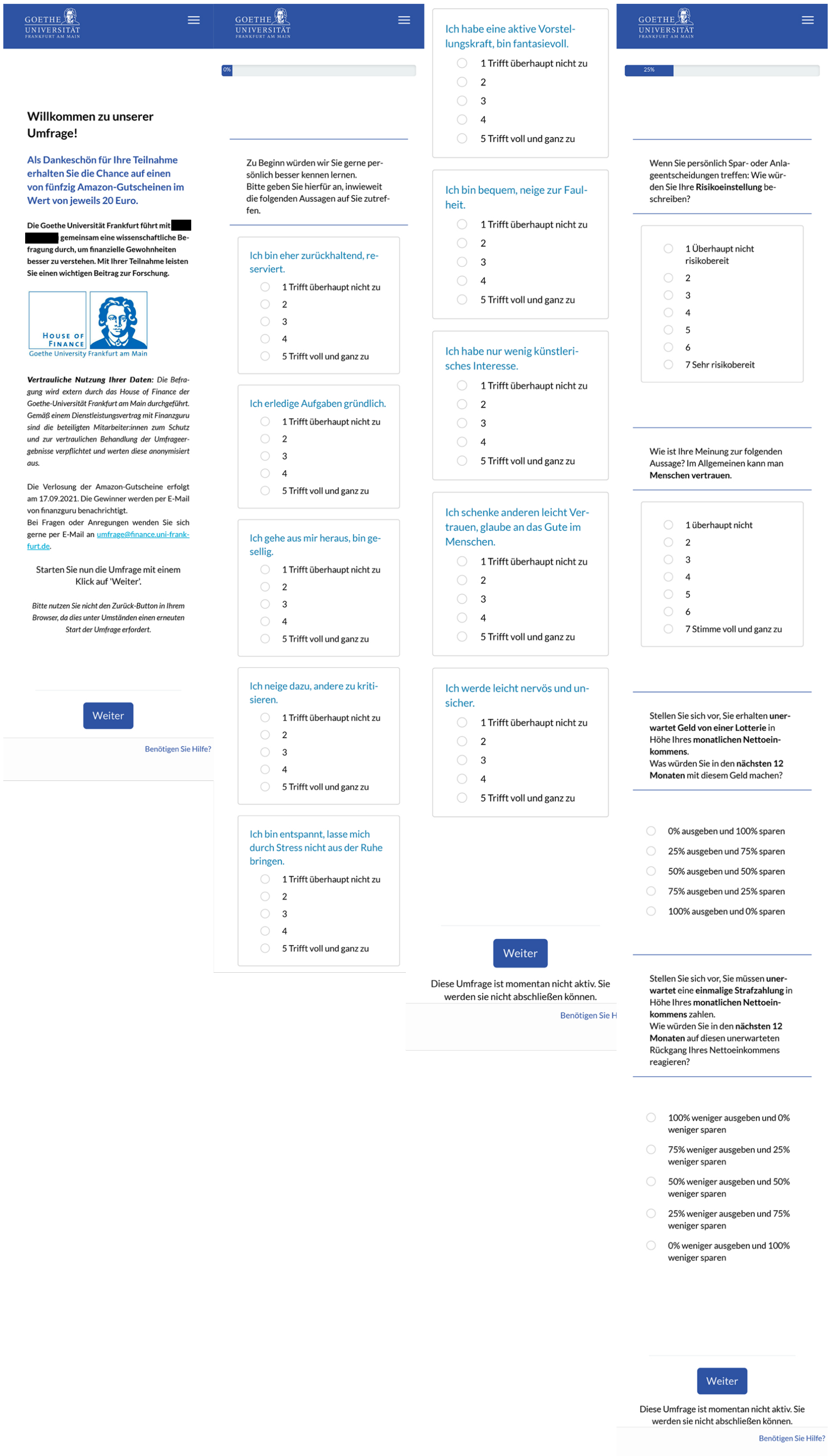
filter	sample size
- customers who were activated to the survey	ca. 56,000
- customers who participated to the survey	2,163
- customers who completed survey*	1,771
- customers with valid transaction dates only	1,770
- customers with non-missing information on Big Five Traits	1,454
- customers with transaction period of min. 12 months (2000m1 to 2021m10)	1,352
- customers with min. 10 transactions per month	1,352
- customers with min. 200 Euros income	1,335
final sample	**1,335**
- customers with available information on gender (i_male)	1,186
- customers with available information on age	961
- customers with available information on both, gender and age	879

*: We define completed surveys by four filters: (i) non-completed surveys, (ii) surveys with missings in responses, (iii) surveys with total response durations longer than 60 minutes, and (iv) duplicated participations.

Table B.3: Sample construction

	openness	conscientiousness	extraversion	agreeableness	neuroticism
have been adviced recently	0,018	-0,079	-0,035	0,002	-0,014
fin.decision: I do rather spend	-0,017	0,071	0,018	0,113	0,019
fin.decision: have long-term fin. plan	0,078	-0,071	-0,014	-0,058	-0,023
fin.decision: forgo today for cons. tomorrow	0,074	0,017	0,006	-0,010	-0,032
fin.decision: do irrational purchases	0,002	0,098	-0,001	0,097	0,044
fin.decision: always looking for cheaper subscriptions	0,034	-0,061	0,008	0,015	0,000
fin.decision: always postpone	-0,037	0,087	-0,017	0,096	0,090
fin.decision: feel exhausting	-0,043	0,049	0,000	0,059	0,086
fin.decision: loss aversion	-0,063	0,056	0,022	0,006	0,055
fin.decision: anxious	-0,046	0,096	0,047	0,064	0,089

Table B.4: Correlation of self-reported financial decision making attitudes to z-standardized Personality Scores


GOETHE UNIVERSITÄT FRANKFURT AM MAIN

Willkommen zu unserer Umfrage!

Als Dankeschön für Ihre Teilnahme erhalten Sie die Chance auf einen von fünfzig Amazon-Gutscheinen im Wert von jeweils 20 Euro.

Die Goethe Universität Frankfurt führt mit [redacted] gemeinsam eine wissenschaftliche Befragung durch, um finanzielle Gewohnheiten besser zu verstehen. Mit Ihrer Teilnahme leisten Sie einen wichtigen Beitrag zur Forschung.

HOUSE OF FINANCE Goethe University Frankfurt am Main

Vertrauliche Nutzung Ihrer Daten: *Die Befragung wird extern durch das House of Finance der Goethe-Universität Frankfurt am Main durchgeführt. Gemäß einem Dienstleistungsvertrag mit Finanzguru sind die beteiligten Mitarbeiter:innen zum Schutz und zur vertraulichen Behandlung der Umfrageergebnisse verpflichtet und werten diese anonymisiert aus.*

Die Verlosung der Amazon-Gutscheine erfolgt am 17.09.2021. Die Gewinner werden per E-Mail von finanzguru benachrichtigt.
Bei Fragen oder Anregungen wenden Sie sich gerne per E-Mail an umfrage@finance.uni-frankfurt.de.

Starten Sie nun die Umfrage mit einem Klick auf 'Weiter'.

Bitte nutzen Sie nicht den Zurück-Button in Ihrem Browser, da dies unter Umständen einen erneuten Start der Umfrage erfordert.

Weiter

Benötigen Sie Hilfe?

GOETHE UNIVERSITÄT FRANKFURT AM MAIN

0%

Zu Beginn würden wir Sie gerne persönlich besser kennen lernen. Bitte geben Sie hierfür an, inwieweit die folgenden Aussagen auf Sie zutreffen.

Ich bin eher zurückhaltend, reserviert.
1 Trifft überhaupt nicht zu
2
3
4
5 Trifft voll und ganz zu

Ich erledige Aufgaben gründlich.
1 Trifft überhaupt nicht zu
2
3
4
5 Trifft voll und ganz zu

Ich gehe aus mir heraus, bin gesellig.
1 Trifft überhaupt nicht zu
2
3
4
5 Trifft voll und ganz zu

Ich neige dazu, andere zu kritisieren.
1 Trifft überhaupt nicht zu
2
3
4
5 Trifft voll und ganz zu

Ich bin entspannt, lasse mich durch Stress nicht aus der Ruhe bringen.
1 Trifft überhaupt nicht zu
2
3
4
5 Trifft voll und ganz zu

Ich habe eine aktive Vorstellungskraft, bin fantasievoll.
1 Trifft überhaupt nicht zu
2
3
4
5 Trifft voll und ganz zu

Ich bin bequem, neige zur Faulheit.
1 Trifft überhaupt nicht zu
2
3
4
5 Trifft voll und ganz zu

Ich habe nur wenig künstlerisches Interesse.
1 Trifft überhaupt nicht zu
2
3
4
5 Trifft voll und ganz zu

Ich schenke anderen leicht Vertrauen, glaube an das Gute im Menschen.
1 Trifft überhaupt nicht zu
2
3
4
5 Trifft voll und ganz zu

Ich werde leicht nervös und unsicher.
1 Trifft überhaupt nicht zu
2
3
4
5 Trifft voll und ganz zu

Weiter

Diese Umfrage ist momentan nicht aktiv. Sie werden sie nicht abschließen können.

Benötigen Sie H

GOETHE UNIVERSITÄT FRANKFURT AM MAIN

25%

Wenn Sie persönlich Spar- oder Anlageentscheidungen treffen: Wie würden Sie Ihre **Risikoeinstellung** beschreiben?

1 Überhaupt nicht risikobereit
2
3
4
5
6
7 Sehr risikobereit

Wie ist Ihre Meinung zur folgenden Aussage? Im Allgemeinen kann man **Menschen vertrauen.**

1 überhaupt nicht
2
3
4
5
6
7 Stimme voll und ganz zu

Stellen Sie sich vor, Sie erhalten **unerwartet Geld von einer Lotterie** in Höhe Ihres **monatlichen Nettoeinkommens.**
Was würden Sie in den **nächsten 12 Monaten** mit diesem Geld machen?

0% ausgeben und 100% sparen
25% ausgeben und 75% sparen
50% ausgeben und 50% sparen
75% ausgeben und 25% sparen
100% ausgeben und 0% sparen

Stellen Sie sich vor, Sie müssen **unerwartet** eine **einmalige Strafzahlung** in Höhe Ihres **monatlichen Nettoeinkommens** zahlen.
Wie würden Sie in den **nächsten 12 Monaten** auf diesen unerwarteten Rückgang Ihres Nettoeinkommens reagieren?

100% weniger ausgeben und 0% weniger sparen
75% weniger ausgeben und 25% weniger sparen
50% weniger ausgeben und 50% weniger sparen
25% weniger ausgeben und 75% weniger sparen
0% weniger ausgeben und 100% weniger sparen

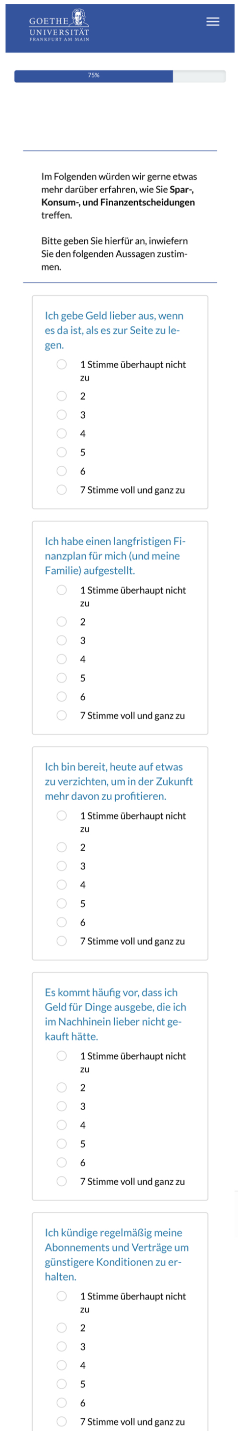
Weiter

Diese Umfrage ist momentan nicht aktiv. Sie werden sie nicht abschließen können.

Benötigen Sie Hilfe?

Figure A.2: Survey Mobile Version (page 1-3)

Figure A.3: Survey Mobile Version (page 4-6)



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75%

Im Folgenden würden wir gerne etwas mehr darüber erfahren, wie Sie **Spar-, Konsum-, und Finanzentscheidungen** treffen.

Bitte geben Sie hierfür an, inwiefern Sie den folgenden Aussagen zustimmen.

Ich gebe Geld lieber aus, wenn es da ist, als es zur Seite zu legen.

- 1 Stimme überhaupt nicht zu
- 2
- 3
- 4
- 5
- 6
- 7 Stimme voll und ganz zu

Ich habe einen langfristigen Finanzplan für mich (und meine Familie) aufgestellt.

- 1 Stimme überhaupt nicht zu
- 2
- 3
- 4
- 5
- 6
- 7 Stimme voll und ganz zu

Ich bin bereit, heute auf etwas zu verzichten, um in der Zukunft mehr davon zu profitieren.

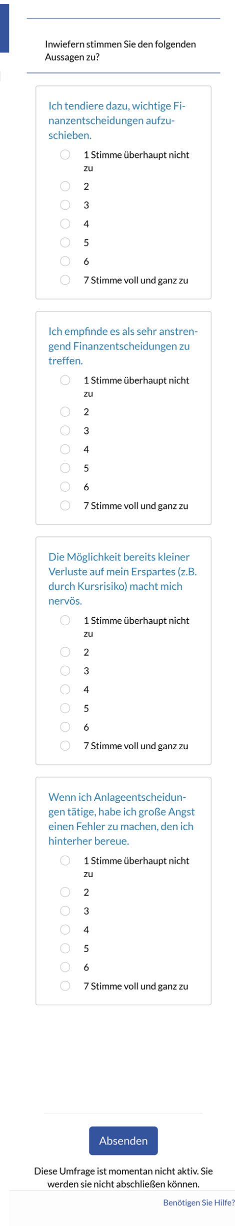
- 1 Stimme überhaupt nicht zu
- 2
- 3
- 4
- 5
- 6
- 7 Stimme voll und ganz zu

Es kommt häufig vor, dass ich Geld für Dinge ausgebe, die ich im Nachhinein lieber nicht gekauft hätte.

- 1 Stimme überhaupt nicht zu
- 2
- 3
- 4
- 5
- 6
- 7 Stimme voll und ganz zu

Ich kündige regelmäßig meine Abonnements und Verträge um günstigere Konditionen zu erhalten.

- 1 Stimme überhaupt nicht zu
- 2
- 3
- 4
- 5
- 6
- 7 Stimme voll und ganz zu



Inwiefern stimmen Sie den folgenden Aussagen zu?

Ich tendiere dazu, wichtige Finanzentscheidungen aufzuschieben.

- 1 Stimme überhaupt nicht zu
- 2
- 3
- 4
- 5
- 6
- 7 Stimme voll und ganz zu

Ich empfinde es als sehr anstrengend Finanzentscheidungen zu treffen.

- 1 Stimme überhaupt nicht zu
- 2
- 3
- 4
- 5
- 6
- 7 Stimme voll und ganz zu

Die Möglichkeit bereits kleiner Verluste auf mein Erspartes (z.B. durch Kursrisiko) macht mich nervös.

- 1 Stimme überhaupt nicht zu
- 2
- 3
- 4
- 5
- 6
- 7 Stimme voll und ganz zu

Wenn ich Anlageentscheidungen tätige, habe ich große Angst einen Fehler zu machen, den ich hinterher bereue.

- 1 Stimme überhaupt nicht zu
- 2
- 3
- 4
- 5
- 6
- 7 Stimme voll und ganz zu

Absenden

Diese Umfrage ist momentan nicht aktiv. Sie werden sie nicht abschließen können.

Benötigen Sie Hilfe?

GOETHE UNIVERSITÄT FRANKFURT AM MAIN

Vielen Dank für Ihre Teilnahme!

Ihre Antworten wurden gespeichert. Sie nehmen nun automatisch an der Verlosung der Amazon-Gutscheine teil. Die Verlosung erfolgt am 17.09.2021. Die Gewinner werden per E-Mail von finanzguru benachrichtigt.

Sie können die Seite nun schließen.

Benötigen Sie Hilfe?

Figure A.4: Survey Mobile Version (page 7-8)

C Additional materials on MPC in survey and transaction data

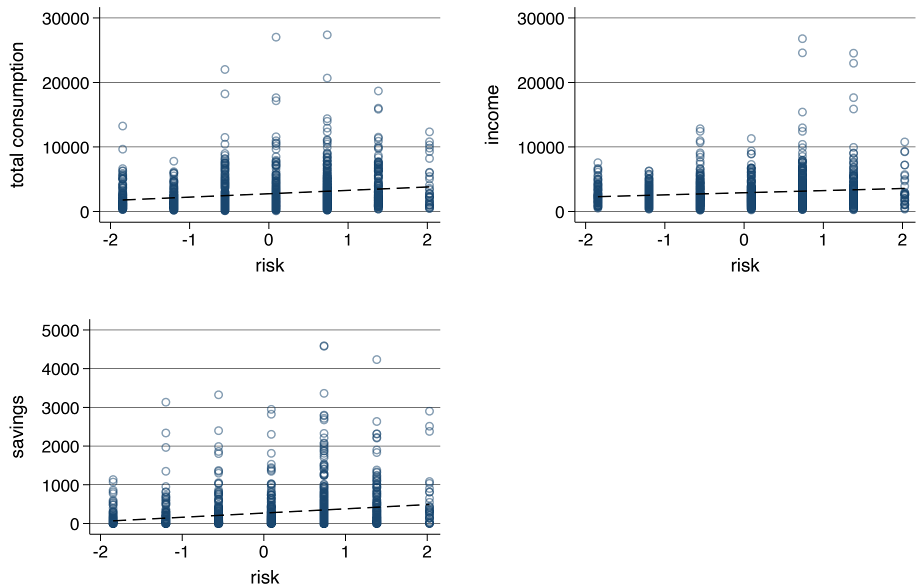


Figure A.5: Scatter plot of individuals' consumption, income and savings by risk preference

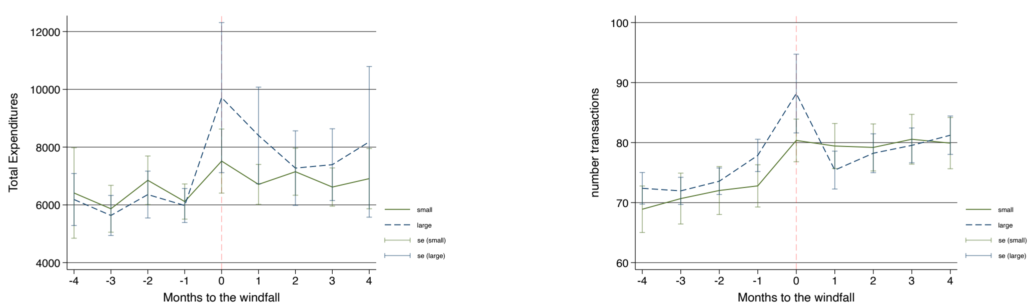


Figure A.6: Revealed MPC of total expenditures and number of monthly transactions as alternative measure after lottery windfalls

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
	risk	risk	risk	risk
openness		0.113***	0.112***	0.0821**
		(0.0294)	(0.0291)	(0.0344)
conscientiousness		-0.0148	-0.0100	-0.0293
		(0.0274)	(0.0273)	(0.0321)
extraversion		0.00238	-0.000793	-0.0165
		(0.0277)	(0.0272)	(0.0331)
agreeableness		0.0595**	0.0342	0.0173
		(0.0289)	(0.0305)	(0.0367)
neuroticism		0.0253	0.0265	0.00932
		(0.0285)	(0.0284)	(0.0340)
age	-0.0174***			-0.0174***
	(0.00350)			(0.00351)
male dummy	-0.674***			-0.649***
	(0.0676)			(0.0681)
log(income)	0.0880**			0.0785*
	(0.0414)			(0.0418)
trust			0.103***	0.142***
			(0.0316)	(0.0381)
self-reported MPC			-0.387***	-0.311**
			(0.122)	(0.142)
constant	0.204	-0.00239	0.134***	0.377
	(0.283)	(0.0271)	(0.0504)	(0.291)
Observations	879	1,335	1,334	878
R-squared	0.133	0.018	0.035	0.164

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.5: Regression results of risk on z-standardized Big Five Personality Traits

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
	trust	trust	trust	trust
openness		-0.0377	-0.0478	-0.0617*
		(0.0297)	(0.0296)	(0.0362)
conscientiousness		-0.0827***	-0.0809***	-0.0464
		(0.0278)	(0.0276)	(0.0327)
extraversion		-0.0127	-0.0124	-0.0282
		(0.0292)	(0.0288)	(0.0346)
agreeableness		0.290***	0.282***	0.255***
		(0.0304)	(0.0304)	(0.0366)
neuroticism		0.00328	0.00149	0.0276
		(0.0304)	(0.0303)	(0.0362)
age	0.000615			0.00497
	(0.00353)			(0.00344)
male dummy	0.000955			0.0404
	(0.0685)			(0.0705)
log(income)	0.0371			0.0186
	(0.0434)			(0.0413)
risk			0.0967***	0.142***
			(0.0296)	(0.0387)
self-reported MPC			0.122	0.138
			(0.120)	(0.145)
constant	-0.324	-0.00709	-0.0507	-0.399
	(0.303)	(0.0262)	(0.0514)	(0.299)
Observations	879	1,335	1,334	878
R-squared	0.001	0.086	0.095	0.097

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.6: Regression results of trust on z-standardized Big Five Personality Traits

	(1) OLS log(income)	(2) OLS log(income)	(3) OLS log(income)	(4) OLS log(income)
age	0.0364***		0.0370***	0.0370***
	(0.00287)		(0.00304)	(0.00301)
male dummy	-0.226***		-0.187***	-0.188***
	(0.0511)		(0.0549)	(0.0546)
openness		0.0547**	0.0256	0.0259
		(0.0218)	(0.0252)	(0.0252)
conscientiousness		-0.0662**	-0.000933	-0.000568
		(0.0272)	(0.0322)	(0.0324)
extraversion		-0.0258	-0.0234	-0.0224
		(0.0244)	(0.0275)	(0.0276)
agreeableness		-6.73e-05	0.0110	0.0104
		(0.0248)	(0.0272)	(0.0273)
neuroticism		-0.0206	0.0121	0.0116
		(0.0237)	(0.0243)	(0.0244)
risk			0.0500**	0.0510**
			(0.0254)	(0.0256)
self-reported MPC				0.0491
				(0.107)
constant	6.366***	7.511***	6.328***	6.314***
	(0.106)	(0.0227)	(0.115)	(0.128)
Observations	879	1,335	879	878
R-squared	0.217	0.012	0.222	0.222

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.7: Regression results of log income on z-standardized Big Five Personality Traits

	(1) FE total consumption	(2) FE total consumption	(3) FE total consumption	(4) FE total consumption
small & large lottery windfall	0.796***			
	(0.128)			
small lottery windfall		2.991		3.437
		(7.740)		(7.759)
large lottery windfall			0.789***	0.794***
			(0.122)	(0.125)
income	0.129***	0.129***	0.129***	0.129***
	(0.0421)	(0.0421)	(0.0421)	(0.0421)
Constant	2,335***	2,336***	2,335***	2,334***
	(126.2)	(126.5)	(126.2)	(126.5)
Observations	39,550	39,550	39,550	39,550
R-squared	0.391	0.391	0.391	0.391
User FE	YES	YES	YES	YES

Table B.8: Regressions following Olafsson and Pagel (2021) with fixed effects.

	(1) FE total expenditures	(2) FE total expenditures	(3) FE total expenditures	(4) FE total expenditures
small & large lottery windfall	1.489***			
	(0.180)			
small lottery windfall		0.663		1.500
		(11.02)		(11.05)
large lottery windfall			1.488***	1.489***
			(0.176)	(0.178)
income	0.297***	0.297***	0.297***	0.297***
	(0.106)	(0.106)	(0.106)	(0.106)
Constant	4,939***	4,943***	4,940***	4,939***
	(317.0)	(316.9)	(317.0)	(317.0)
Observations	39,550	39,550	39,550	39,550
R-squared	0.472	0.471	0.472	0.472
User FE	YES	YES	YES	YES

Table B.9: Regressions following Olafsson and Pagel (2021) with fixed effects and total expenditures as dep.var.

	(1) FE numb. transactions	(2) FE numb. transactions	(3) FE numb. transactions	(4) FE numb. transactions
small & large lottery windfall	0.00832			
	(0.00551)			
small lottery windfall		0.153***		0.157***
		(0.0348)		(0.0346)
large lottery windfall			0.00797	0.00817
			(0.00530)	(0.00543)
income	0.000590**	0.000591**	0.000589**	0.000592**
	(0.000268)	(0.000268)	(0.000268)	(0.000268)
Constant	60.50***	60.47***	60.50***	60.45***
	(0.804)	(0.805)	(0.804)	(0.806)
Observations	39,550	39,550	39,550	39,550
R-squared	0.719	0.718	0.719	0.719
User FE	YES	YES	YES	YES

Table B.10: Regressions following Olafsson and Pagel (2021) with fixed effects and number of transactions as dep.var.

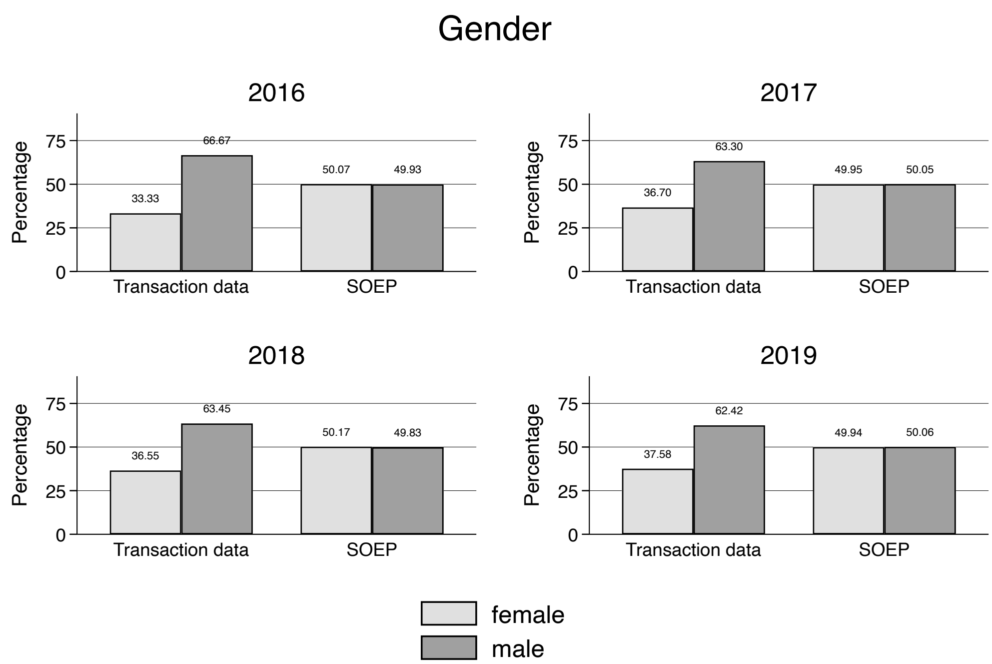
	(1) FE savings	(2) FE savings	(3) FE savings	(4) FE savings
small & large lottery windfall	-0.0171			
	(0.0235)			
small lottery windfall		1.413		1.402
		(1.268)		(1.267)
large lottery windfall			-0.0203	-0.0185
			(0.0248)	(0.0240)
income	0.0180*	0.0180*	0.0180*	0.0180*
	(0.00962)	(0.00962)	(0.00962)	(0.00962)
Constant	205.1***	204.5***	205.1***	204.6***
	(28.85)	(28.84)	(28.85)	(28.84)
Observations	39,550	39,550	39,550	39,550
R-squared	0.431	0.431	0.431	0.431
User FE	YES	YES	YES	YES

Table B.11: Regressions following Olafsson and Pagel (2021) with fixed effects.

	FE total consumption
lottery windfall t-1	0.149
	(0.195)
lottery windfall t-2	0.217
	(0.186)
lottery windfall	0.803***
	(0.139)
lottery windfall t+1	-0.0666
	(0.210)
lottery windfall t+2	0.0747
	(0.307)
income	0.119***
	(0.0405)
savings	0.00413*
	(0.00245)
Constant	2,380***
	(122.8)
Observations	34,245
R-squared	0.401
small+large lotteries	YES
user FE	YES

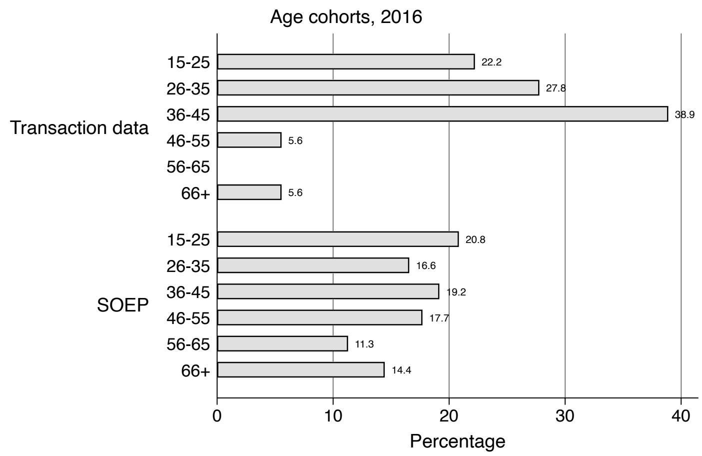
Table B.12: Fixed-effects regression with lottery windfall lags and leads

D Investigation of representativeness



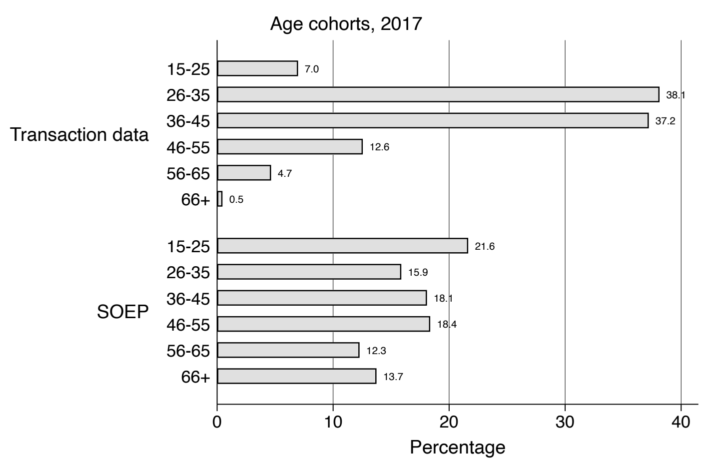
Source: German Socio-Economic Panel, v.36.
Data: SOEP: n=48,410, transaction data: n=1,286.

Figure A.7: Share of Male and Females in transaction data versus SOEP



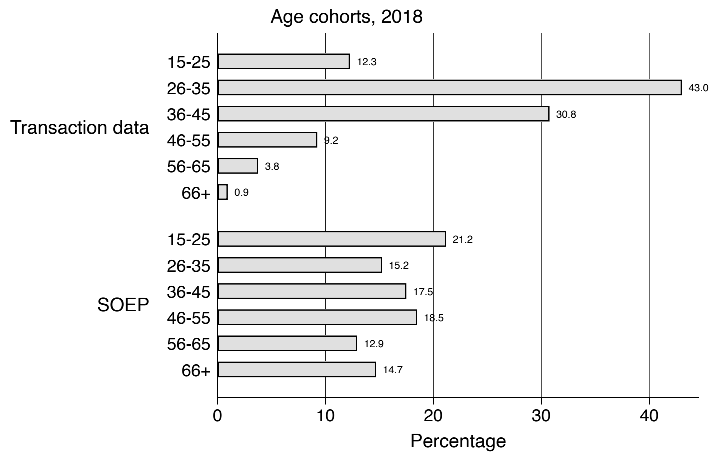
Source: German Socio-Economic Panel, v.36.
Data: SOEP: n=29,751, transaction data: n=14.

Figure A.8: Percentage shares of age cohort in transaction data versus SOEP, 2016



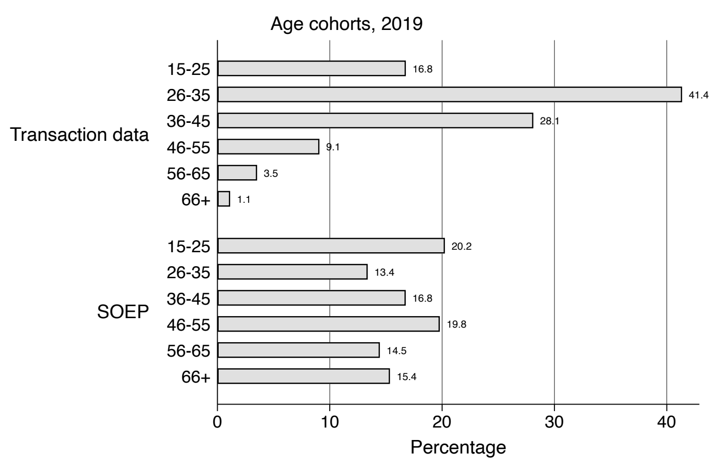
Source: German Socio-Economic Panel, v.36.
Data: SOEP: n=30,173, transaction data: n=202.

Figure A.9: Percentage shares of age cohort in transaction data versus SOEP, 2017



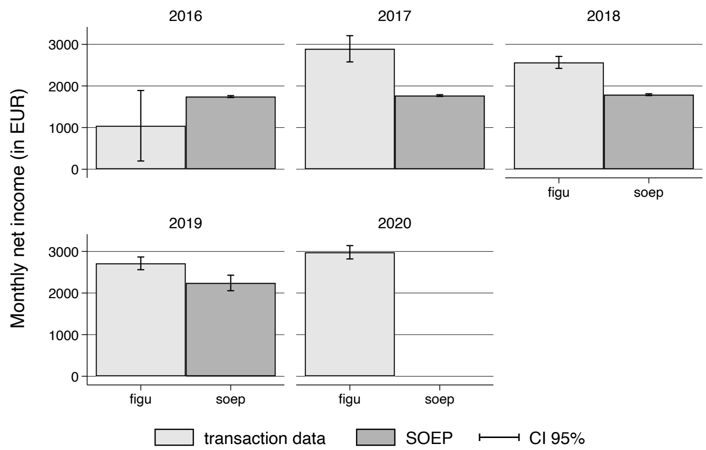
Source: German Socio-Economic Panel, v.36.
Data: SOEP: n=30,911, transaction data: n=326.

Figure A.10: Percentage shares of age cohort in transaction data versus SOEP, 2018



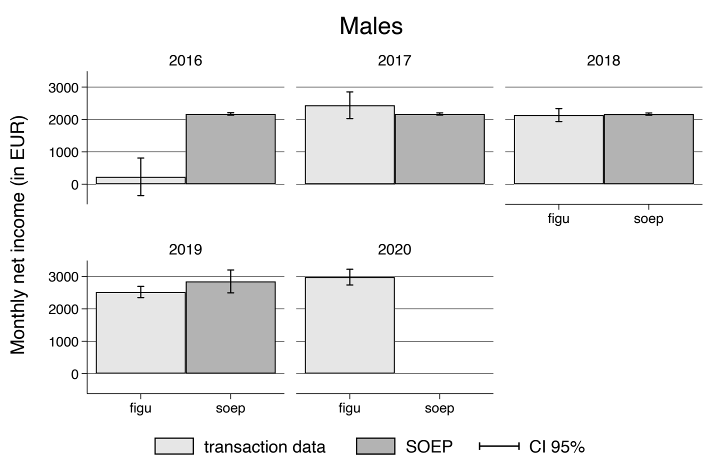
Source: German Socio-Economic Panel, v.36.
Data: SOEP: n=30,576, transaction data: n=255.

Figure A.11: Percentage shares of age cohort in transaction data versus SOEP, 2019



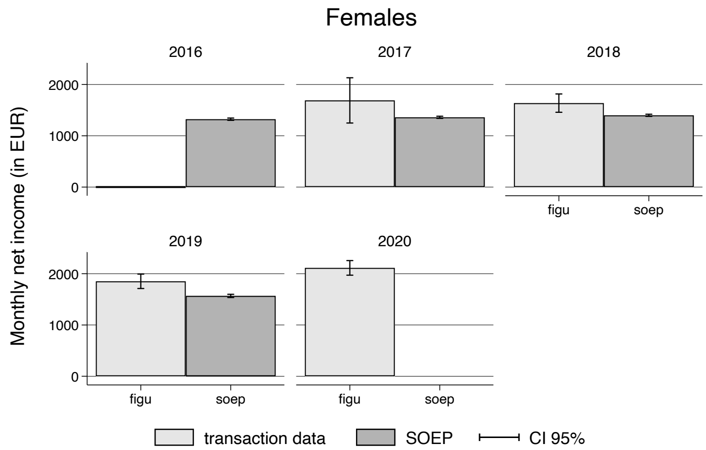
Source: German Socio-Economic Panel, v.36.
Data: SOEP: n=45,853, transaction data: n=1,741.

Figure A.12: Mean monthly net incomes in transaction data versus SOEP, 2016-2020



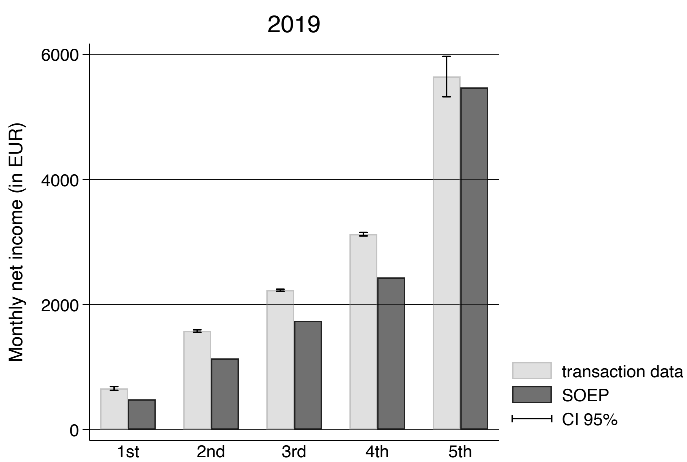
Source: German Socio-Economic Panel, v.36.
Data: SOEP: n=22,952, transaction data: n=779.

Figure A.13: Mean monthly net incomes in transaction data versus SOEP, 2016-2020, by males



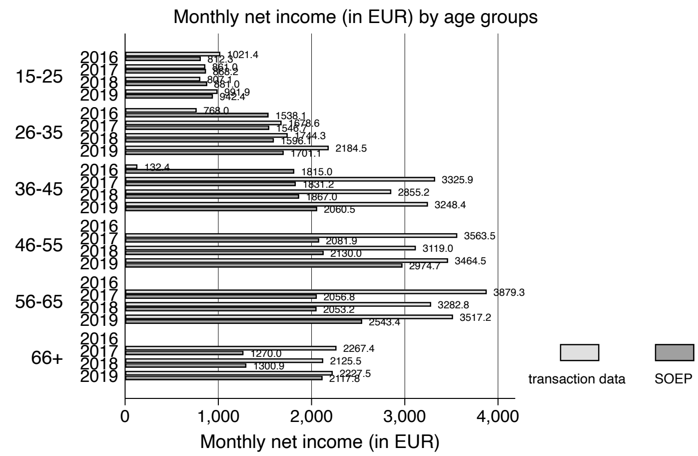
Source: German Socio-Economic Panel, v.36.
Data: SOEP: n=22,901, transaction data: n=507.

Figure A.14: Mean monthly net incomes in transaction data versus SOEP, 2016-2020, by females



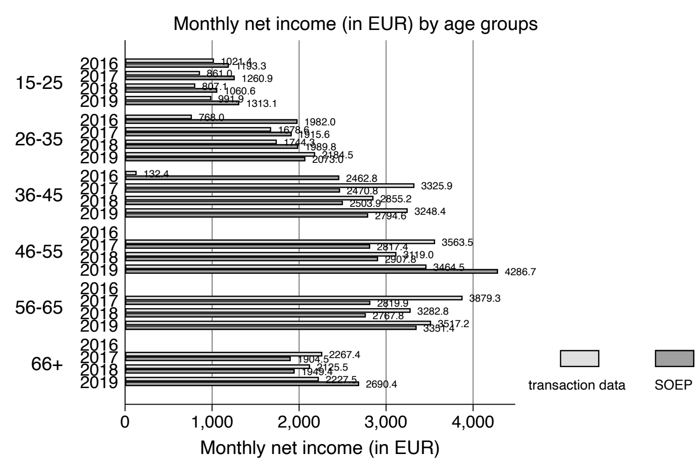
Source: German Socio-Economic Panel, v.36.
Data: SOEP: n=30,380, transaction data: n=1,741.

Figure A.15: Monthly net incomes in transaction data versus SOEP, 2019, by income deciles



Source: German Socio-Economic Panel, v.36.
Data: SOEP: n=27,959, transaction data: n=1,020.

Figure A.16: Monthly net incomes in transaction data versus SOEP, 2016-2019, by age cohorts



Source: German Socio-Economic Panel, v.36.
Data: SOEP: n=12,616, transaction data: n=1,020.

Figure A.17: Monthly net incomes in transaction data versus SOEP, 2016-2019, by age cohorts, high educated individuals only

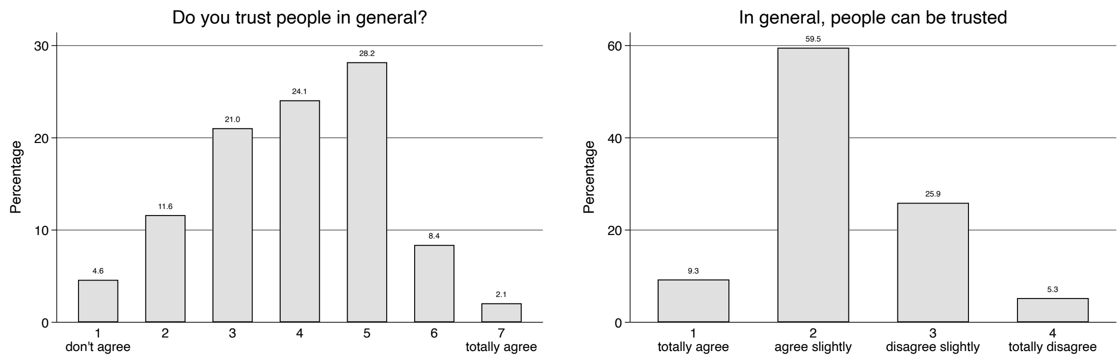


Figure A.18: Elicited trust in transaction data versus SOEP
Source: German Socio-Economic Panel, v.36.
Data: SOEP: n=30,306, transaction data: n=1,455.

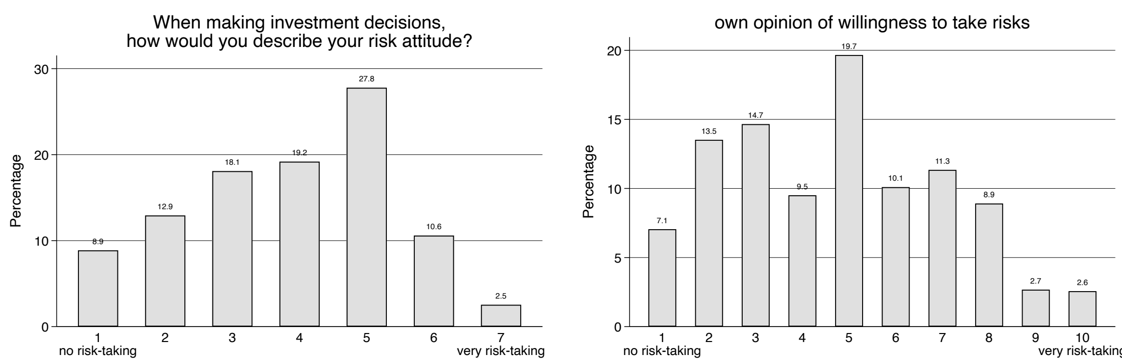


Figure A.19: Elicited risk in transaction data versus SOEP
Source: German Socio-Economic Panel, v.36.
Data: SOEP: n=30,306, transaction data: n=1,455.

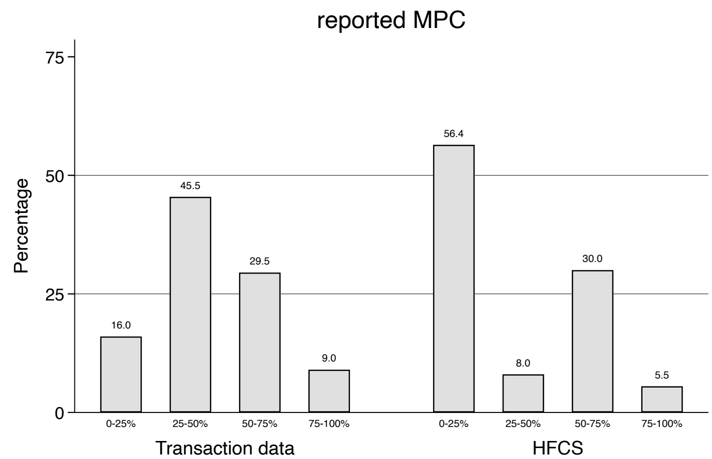


Figure A.20: Reported MPC, survey versus HFCS
Source: Household Finance and Consumption Survey, 2017.
Data: HFCS, Germany: n=24,700, transaction data: n=1,454.

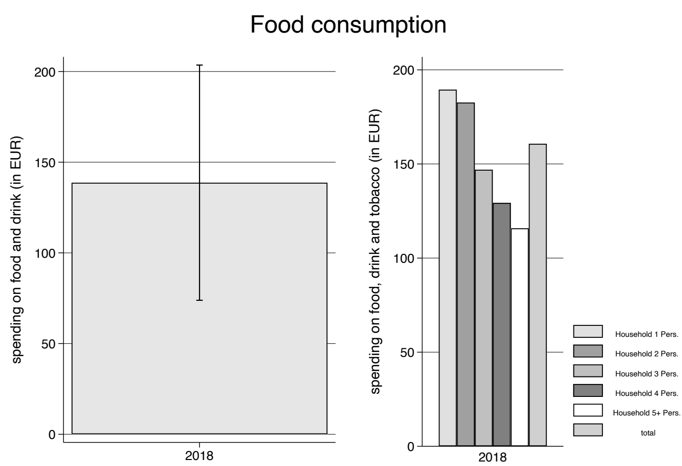


Figure A.21: Food consumption, survey versus EVS
Source: Einkommens- und Vermögensstichprobe (EVS), Destatis, 2018.
Data: EVS, 2018: n=40,683, transaction data: n=1,741.

E Lotteries and lottery windfalls

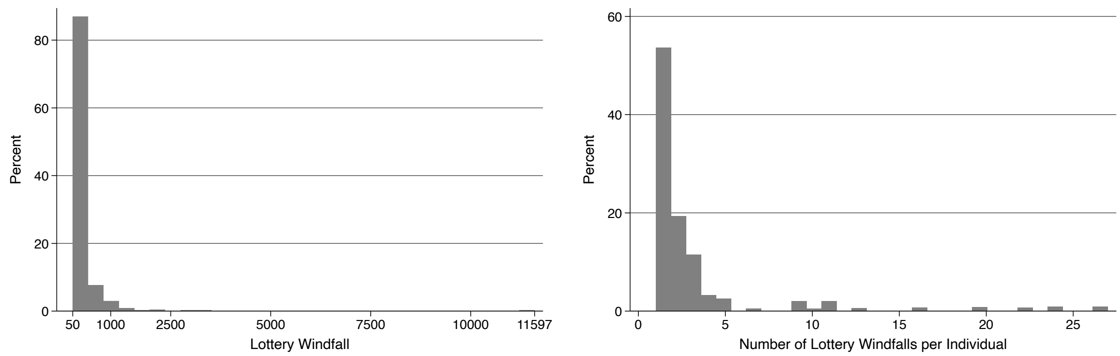


Figure A.22: Amount and number of lottery windfalls
Data: transaction data of surveyed individuals.

receiver	count
AKTION_MENSCH	28
DEUTSCHE_KLASSENLOTTERIE_BERLIN	22
LOTTO24	9
LOTTOHELDEN_DE	48
LOTTOLAND	1
LOTTO_BADEN_WUERTTEMBERG	20
LOTTO_BAYERN	14
LOTTO_HAMBURG	4
LOTTO_HESSEN	12
MEGAPIXEL_ENTERTAINMENT	5
POSTCODE_LOTTERIE_DT	3
SACHSENLOTTO	7
TIPICO	56
TIPP24_DE	9
TOTO_LOTTO_NIEDERSACHSEN_GMBH	75
WESTLOTTO	86
unkown	340

Data: raw transaction data of surveyed individuals
after dropping lottery windfalls at a cutoff of 25 Euros.

Table B.13: Observed lottery types of lottery windfall transactions

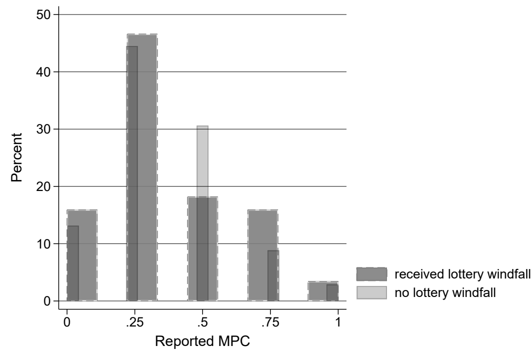


Figure A.23: Reported MPC by (non-)lottery winners
Data: transaction data of surveyed individuals.

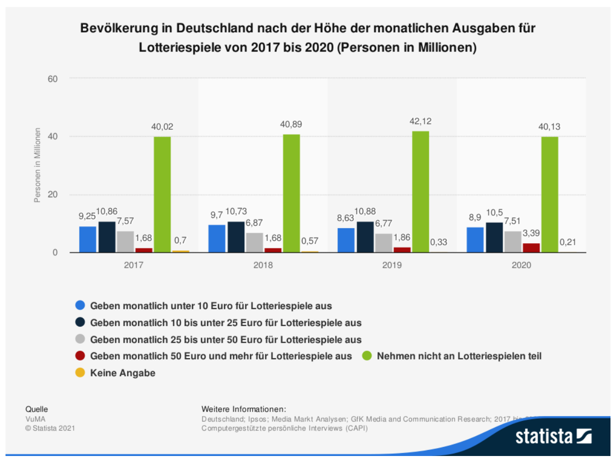


Figure A.24: Lottery Gambling in Germany
Data: VuMA.

mainCategory	subCategory	consignors
leisure & entertainment	lottery	unknown
leisure & entertainment	lottery	AKTION_MENSCH
leisure & entertainment	lottery	BET_AT_HOME_COM
leisure & entertainment	lottery	B_WIN
leisure & entertainment	lottery	CIGO
leisure & entertainment	lottery	COMMERZBANK_AG
leisure & entertainment	lottery	DEUTSCHE_FERNSEHlottery
leisure & entertainment	lottery	DEUTSCHE_KLASSENlottery_BERLIN
leisure & entertainment	lottery	EDEKA
leisure & entertainment	lottery	FABER_KG
leisure & entertainment	lottery	FABER_LOTTO_GMBH
leisure & entertainment	lottery	FABER_LOTTO_SERVICE_GMBH
leisure & entertainment	lottery	HILLSIDE_SHA
leisure & entertainment	lottery	HIT
leisure & entertainment	lottery	KLARNA_AB
leisure & entertainment	lottery	LEO_VEGAS_GAMING
leisure & entertainment	lottery	LOTTO24
leisure & entertainment	lottery	LOTTOHELDEN_DE
leisure & entertainment	lottery	LOTTOLAND
leisure & entertainment	lottery	LOTTO_BADEN_WUERTTEMBERG
leisure & entertainment	lottery	LOTTO_BAYERN
leisure & entertainment	lottery	LOTTO_HAMBURG
leisure & entertainment	lottery	LOTTO_HESSEN
leisure & entertainment	lottery	MARKTKAUF
leisure & entertainment	lottery	MEGAPIXEL_ENTERTAINMENT
leisure & entertainment	lottery	N26
leisure & entertainment	lottery	NEOLOTTO
leisure & entertainment	lottery	POSTCODE_lottery_DT
leisure & entertainment	lottery	SACHSENLOTTO
leisure & entertainment	lottery	SPARKASSE
leisure & entertainment	lottery	STAATLICHE_lottery_EINNAHME_BOESCHE
leisure & entertainment	lottery	STAATLICHE_lottery_EINNAHME_GLOECKLE_OHG
leisure & entertainment	lottery	SVM_EUROPA
leisure & entertainment	lottery	TIPICO
leisure & entertainment	lottery	TIPP24_DE
leisure & entertainment	lottery	TOTO_LOTTO_NIEDERSACHSEN_GMBH
leisure & entertainment	lottery	WESTLOTTO

Table B.14: List of selected transaction consignors in transaction data

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No. 347	Andrej Gill, Florian Hett, Johannes Tischer	Time Inconsistency and Overdraft Use: Evidence from Transaction Data and Behavioral Measurement Experiments
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No. 345	Florian Heider, Roman Inderst	A Corporate Finance Perspective on Environmental Policy
No. 344	Steffen Eibelshäuser, Fabian Smetak	Frequent Batch Auctions and Informed Trading
No. 343	Alessandro Di Nola, Leo Kaas, Haomin Wang	Rescue Policies for Small Businesses in the COVID-19 Recession
No. 342	Alperen A. Gözlügöl, Wolf-Georg Ringe	Private Companies: The Missing Link on The Path to Net Zero
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No. 339	Vincent Lindner, Sandra Eckert, Andreas Nölke	Political Science Research on the Reasons for the (non) Adoption and (non) Implementation of EMU Reform Proposals: The State of the Art
No. 338	Elsa Massoc	Fifty Shades of Hatred and Discontent Varieties of Anti-finance Discourses on the European Twitter (France, Germany, Italy, Spain and the UK)
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