

# Untangling the credit card debt puzzle – persistence, reaction to new liquidity and intra-household optimization

*Erkki Vihriälä\**

*April 29, 2019*

## **Abstract**

This paper makes three new observations on the credit card debt puzzle describing the simultaneous holding of high-interest credit and low-interest liquid assets. First, it documents the persistence of belonging to the puzzle group at the monthly frequency. Due to missing the imperfect persistence, the prevailing method of extrapolating from a cross-section such as the SCF overestimates the costs of puzzle behavior for the typical household. Second, a natural experiment reveals that an offer of new cheap liquidity is accepted only by a minority of puzzle households, and there is no evidence that the offer increases exit from the puzzle group. Therefore, theories relying on liquidity and precautionary borrowing concerns are not sufficient to account for the phenomenon. Third, the prevalence and persistence of puzzle behavior is significantly lower at the individual than at the household level. In addition, the intra-household distribution of liquid assets and unsecured borrowing influences the probability of accepting the offer of new cheap liquidity. Therefore, part of the puzzle group reflects a classification mistake due to the (incorrect) implicit assumption of perfect intra-household financial optimization.

**Keywords:** household finance, credit card debt puzzle, intra-household optimization

**JEL codes:** D13, D14, D91, E21

---

\*University of Oxford (erkki.vihrialala@economics.ox.ac.uk)

# 1 Introduction

Why do many households simultaneously use high-interest credit and hold low-yielding liquid assets? Across different vintages of the Survey of Consumer Finances (SCF), the share of such households is around 30 percent in the US as noted first by Gross and Souleles (2002). That these households do not use liquid assets to repay credit card debt in order to economize on interest costs has been labeled the *credit card debt puzzle*<sup>1</sup>.

Are the costs of this behavior sufficient to earn the label *puzzle*? Zinman (2007) argues that for most households the costs are not prohibitive: managing liquidity more aggressively would allow fewer than 10 percent of US households with a credit card to save more than 10 dollars a month. Still, a minority of households would be able to save a non-trivial amount by using liquid assets to pay down unsecured credit. The failure to do so has inspired a number of theories attempting to explain the behavior.

Firstly, Zinman (2007) and Telyukova (2013) argue that cash is inherently more liquid than untapped credit, which creates a demand for cash for transaction purposes. Also related to liquidity management, credit card borrowing can be rationalized by precautionary motives if consumers fear that banks will reduce or cancel their untapped credit lines when they would be needed (Fulford (2015), Gorbachev and Luengo-Prado (2016), Druedahl and Jørgensen (2018)). Thirdly, Lehnert and Maki (2002) highlight that at least part of the credit card debt could be explained by strategic bankruptcy considerations. Fourthly, self-control problems could rationalise co-holding as a strategy to reduce available credit at purchase time if the

---

<sup>1</sup>Sometimes also referred to as co-holding puzzle (Gathergood and Weber (2014)), particularly when not restricting analysis to only include credit card debt. Due to its prevalence, I stick in this paper to the term credit card debt puzzle.

impulsive “spender” does not have access to liquid savings (Bertaut and Haliassos (2001), Bertaut et al. (2009), Gathergood and Weber (2014)). Choi and Laschever (2018) add to the ‘behavioral’ explanations for the puzzle by studying the effects of the “Big Five” personality traits on co-holding. Finally, low financial literacy has not received much support as an explanation as the puzzle group does not stand out as particularly financially illiterate or uneducated (see e.g. Gathergood and Weber (2014) and Gorbachev and Luengo-Prado (2016)).

Despite earlier contributions, there are still gaps in the literature due to both data limitations and a lack of policy experiments to evaluate the proposed theories. For instance, we do not know (i) how persistent puzzle behavior is due to lack of high-frequency panel data; (ii) whether households would leave the puzzle group if offered sufficient liquidity; or (iii) how the intra-household distribution of liquid assets and borrowing impacts the puzzle. This paper contributes on these fronts using a new Finnish dataset with information on hundreds of thousands of individuals and households at a monthly frequency combined with evidence from a unique policy experiment.

First, I show that the existing literature exaggerates the costs of belonging to the puzzle group for the typical household because it relies on yearly cross-sections such as the SCF or other low-frequency data. The exaggeration is due to an extrapolation bias when missing the imperfect persistence of puzzle behavior revealed by the monthly panel. As an example, in my data only 40 percent of households satisfying the puzzle criteria in January 2015 do so for the full year. Exit from the puzzle group is particularly pronounced in the first few months: only around 75 percent of households remain in the puzzle group after two months.

Second, I exploit a natural experiment that provided certain puzzle households access to a new and cheaper source of liquidity through a free option to stop mortgage amortization payments for up to 12 months. Theories relying on the liquidity advantage or precautionary borrowing motive would imply a strong implicit demand for the new credit line, because the median mortgage interest rate was almost six percentage points lower than the unsecured credit rate for puzzle households (1.3 vs. 7.1 %). However, only one quarter of puzzle households accept the offer, which is seemingly at odds with the liquidity preference and precautionary borrowing hypotheses. Not being aware of the offer, despite the large marketing campaign, is not a sufficient explanation for low demand, because a minority accept the offer even among eligible households that include an employee of the bank. Finally, using a difference-in-difference analysis by mortgage status, I do not find effects of access to new liquidity on exit from the puzzle group.

Third, I provide empirical evidence on the role of intra-household dynamics, which has been understudied previously due to data limitations. The standard approach of defining the puzzle at the household level contains an implicit assumption of unitary household financial optimization. However, the accountant-shopper models of Bertaut and Haliassos (2001) and Bertaut et al. (2009) can be interpreted as a strategic game between two separate individuals. I provide supporting empirical evidence that in multi-adult households (i) the puzzle is considerably less prevalent at the individual than at the household level; (ii) conditional on puzzle group membership, the persistence is much lower at the individual than at the household level; (iii) the distribution of deposits and unsecured borrowing within households entitled to the bank's new liquidity offer impacts their acceptance probability. Therefore

part of the households classified in the puzzle group can be accounted for by an erroneous application of the unitary model.

The paper is structured as follows. In Section 2, I define the credit card debt puzzle criteria and introduce the data. In Section 3, I document the persistence in membership of the puzzle group. In Section 4, I present results on the effects of the new liquidity offer for which a subset of puzzle households was eligible. In Section 5, I show that puzzle membership is considerably less prevalent and persistent at the individual level, and that the distribution of debt and assets among household members affects the probability to accept the offer of additional cheap liquidity. Section 6 concludes.

## **2 Definitions and data**

This section first provides a definition of the credit card debt puzzle used in this paper. Second, it presents the Finnish proprietary bank data. Finally, it documents the sample selection procedure and the overall puzzle share in the data.

### **2.1 Puzzle definition**

The simplest definition would classify any household with simultaneous positive holdings of liquid assets and revolving credit card debt in the puzzle group. That seems unreasonable though, because very low levels of co-holding carry negligible costs and can merely reflect differential timing of expenditure and income flows. Therefore, to classify a household in the puzzle group, it seems reasonable to require simultaneous holding of (i) non-negligible

balances of interest-accruing credit card debt and (ii) liquid assets above some buffer.

Another issue is how to define the asset and borrowing subsets underlying the puzzle. I opt here to consider all balances in checking and savings accounts with no or only limited withdrawal restrictions as liquid assets. In terms of the puzzle, there is nothing particular about credit card debt in relation to other unsecured borrowing at similar interest rates. Therefore, in defining the puzzle, this paper also considers non credit card unsecured borrowing.

Consequently, the baseline puzzle criteria at the household level are:

1. Have interest-accruing unsecured credit above 500 EUR
2. Have deposit balances above 1500 EUR
3. Have deposit balances greater than monthly net income

The first criterion ensures that borrowing is not negligible. The second allows for a fixed minimum liquid buffer. The last condition takes into account the fact that households with a larger income have greater liquid asset needs due to their higher expenditure levels. These criteria are similar to those employed by many other papers in the literature, although they tend to be at the stricter end of the spectrum.

## **2.2 Data**

The data used in this study comes from one of the largest banks in Finland. I have customer-level data on assets, debts, income and card expenditure. Most of the data is available at a monthly frequency for three years (2014–2016). I can link customers belonging to the same household using the household identifier variable provided by the bank.

The main variables I observe are:

**Unsecured credit balances:** I observe interest-accruing balances on credit cards and other unsecured borrowing from the bank. In addition to credit cards, the bank offers two different unsecured borrowing products. The first of these is a flexible credit line that can be used repeatedly. The second is a traditional credit contract designed for a single purchase. Nominal interest rate margins on both credit cards and these two unsecured borrowing products are quite similar (in the 5 to 10 percent range). The most common product has a an interest margin of 7 percent. Total interest on all the products is the margin rate + 3 month Euribor, but the latter was very close to zero during the sample period. None of the products preclude full or partial prepayment of the loan balance. Therefore, I lump all unsecured borrowing together when defining the puzzle group.

**Liquid asset balances:** I include in liquid assets balances on all checking and savings accounts that do not have any or only limited withdrawal restrictions<sup>2</sup>. These deposits could be used flexibly to repay unsecured borrowing balances. The nominal yield on these assets during the sample period (2014–2016) was very close to zero.

**Net income:** I observe net income flows to bank accounts from the employer or from the government. The measure is unlikely to capture all net income, but the levels seem reasonable and there is high correlation (0.65) with taxable *gross* income for 2015 observed from administrative data.

---

<sup>2</sup>Checking accounts have no restrictions. Some of the savings accounts have restrictions on the number of free withdrawals per year (typically four). However, these savings accounts also have yields very close to zero percent over the sample period. Therefore, keeping funds on them is arguably ‘puzzling’ in the spirit of the credit card debt puzzle if there is a meaningful probability to have to borrow at the unsecured credit rate.

## 2.3 Sample selection and overall puzzle share

The pool of customers at the bank is large and diverse, which is important for the representativeness of the results. For instance, in the mortgage market the market share of the bank is around 1/3. The bank also has branches in all parts of the country. It is possible to also weigh the sample using e.g. geographic identifiers, although this is not currently done.

A concern with using data from a single financial institution is that I miss information on the customers' other banking activities. One mitigating factor is that the bank has a loyalty scheme that strongly encourages households to concentrate their full financial portfolio (assets, debts, insurance) at the bank. Still, there are a significant chunk of customers that are only loosely tied to the bank. Therefore, the criteria to be included in the sample population are:

1. Household needs to have an adult
2. Household needs to have a credit card issued by the bank
3. No household member has stated another bank as their main financial service provider
4. Household needs to have regular card expenditures using cards issued by the bank through 2014–2016
5. Household needs to regularly receive income payments to their bank account

Based on these criteria, the main sample consists of 519,940 households. Table 1 presents descriptive statistics both on the full sample and the subset of households that satisfy the puzzle conditions in the baseline month of January 2015. This baseline month is selected because it predates the liquidity offer that the bank made to a part of its customers in February 2015.



I find that 13 percent of households belonged to the puzzle group in January 2015. The fraction satisfying the criteria is secularly rising from 2014 to 2016 and ranges from 11 percent to 16 percent at a monthly level (Figure 1). These numbers are a lower limit for the true puzzle share because notwithstanding the sample selection process, there are residual cash holdings, deposits and unsecured credit at other financial institutions that I do not observe. This study does not focus on the detailed characteristics of households in the puzzle group, which has been extensively documented in the existing literature. Still, Table 2 reports the puzzle share by age and income quintiles in January 2015. It reinforces previous findings that puzzle behavior is not restricted to a few population subgroups.

### **3 Persistence and costs of puzzle membership**

The existing literature has faced difficulty in studying how persistent puzzle behavior is due to lack of high-frequency panel data. This section shows that persistence is far from perfect at the monthly level. Therefore, calculation of costs based on an extrapolation from a cross-section such as the SCF overstates yearly costs for a typical household belonging to the puzzle group.

#### **3.1 How persistent is puzzle membership?**

The only hard evidence in the existing literature on the persistence of the phenomenon is from Gorbachev and Luengo-Prado (2016)<sup>3</sup>. They present transition probabilities between

---

<sup>3</sup>In addition, the SCF includes a survey question on whether households typically pay off their credit card balance.

waves 2004, 2008 and 2012 of the National Longitudinal Survey of Youth (NLSY). Using their ‘strict’ criteria for the puzzle, which approximate criteria used in this paper, they show that around 40 percent of puzzle households remain in the puzzle group in two subsequent waves.

I find that persistence is far from perfect even within the year using my monthly panel. Figure 2 panel A depicts the survival share of households that satisfy the puzzle conditions in a given baseline month in the subsequent months. To measure an average survival share, panel B plots the results for all households satisfying puzzle conditions at some point during January 2014 to December 2015. The survival share here includes households who drop out of the puzzle group in one month but return to it later. The average survival share is 73 percent after 3 months, 67 percent after 6 months and 62 percent after 12 months.

A different way to measure persistence is to calculate the distribution of puzzle months over the next year conditional on satisfying the puzzle criteria in a given month. This is done for the baseline month of January 2015 in Figure 3. The mean is 8.5 months and the median 10 months. Only 40 percent of households satisfying the puzzle criteria in January 2015 do so for the whole year.

The imperfect persistence signifies that a cross-section such as the SCF does not yield an accurate picture of the degree of puzzle behavior over the whole year. As I show next, extrapolating from a cross-section overstates the yearly costs of puzzle behavior for a typical household classified in the puzzle group at a point in time.

### 3.2 Effect of persistence on costs of puzzle behavior

This section calculates how the degree of persistence affects the estimated costs of puzzle behavior. I calculate yearly costs for the baseline group satisfying the puzzle conditions in January 2015 in two scenarios: (i) under the assumption that yearly costs are proportional to the costs from co-holding in January 2015; (ii) by considering the actual deposit and unsecured credit balances during the rest of 2015. In case persistence of significant co-holding is imperfect, the first approach that is implicitly used by the existing literature exaggerates the costs for a typical household in the puzzle group.

The costs of puzzle behavior are calculated as the foregone savings in interest costs from using liquid assets to pay down unsecured credit following Zinman (2007).

$$costs = \min(\text{deposits}, \text{unsecuredCredit}) * (r_{\text{unsecuredCredit}} - r_{\text{deposits}}) \quad (1)$$

Overall, the yearly costs are fairly low (Table 3). The median cost if I extrapolate from January 2015 balances is 128 EUR and the actual cost for the median household is 113 EUR. At the 90th percentile these costs are 351 EUR and 310 EUR respectively, but given that the puzzle share is 13 percent, these costs only pertain to little over 1 percent of all households.

There are two caveats to the level of costs calculated here. Firstly, I do not observe cash or deposits and borrowing at other financial institutions. Although the sample restrictions are aimed to study a population that conducts most of their financial business at the bank in question, the results are still a lower bound for total costs. Secondly, other costs of unsecured borrowing products like billing and account fees can form a substantial fraction of the ‘true’

costs of unsecured credit, especially for fairly small balances. However, I do not assume here that puzzle households would completely stop unsecured borrowing or abolish their credit card accounts to avoid these costs. If they were to do so, the savings potential would be consequently larger. These fixed fees range from 60 to 98 EUR per year per unsecured borrowing product used under the assumption of positive borrowing in each month. Finally, unsecured borrowing can generate penalty fees for late payments etc.

Although there is uncertainty about the level of costs, the relative difference depending on whether the extrapolation method or actual costs are considered is likely to be less affected by the concerns above<sup>4</sup>. The extrapolation method overstates the costs of puzzle behavior for 70 percent of households belonging to the puzzle group in January 2015.

## 4 Reaction to new liquidity

Attempts to solve the puzzle have emphasised the differential liquidity of deposits versus untapped credit or the precautionary borrowing motive (Telyukova (2013), Fulford (2015), Druedahl and Jørgensen (2018)). These theories would predict strong implicit demand for cheaper additional liquidity. I use a natural experiment to show that acceptance of new and cheaper liquidity is relatively low in the puzzle group. In addition, there is no evidence that the offer would have increased the rate of exit from the puzzle group. Liquidity-based theories do not therefore seem sufficient to explain the puzzle.

---

<sup>4</sup>This is the case as long as outside activity (unsecured borrowing and liquid assets) is proportional to the activity at the bank in question.

## 4.1 New liquidity offer

In February 2015, the bank made a surprise offer to all of its mortgage customers. They could stop mortgage amortization payments for up to 12 months without fees or conditions. For instance, a household paying 500 EUR/month in amortization could obtain an additional 6 000 EUR of liquidity by accepting this offer.

The bank's offer was very salient during the application window. It was accompanied by a significant marketing push via social media and through normal bank-customer interaction. The offer also made national news on the day of the launch and there were multiple follow-up reports during the five month application window (until end of July). For instance the main national newspaper, Helsingin Sanomat, had the payment flexibility offer as their lead article the day after the offer launch (Helsingin Sanomat, February 6th 2015 edition). The main term used to describe the policy ("lyhennysvapaa") returns 26 articles published during the application window in Helsingin Sanomat's digital archive<sup>5</sup>. Visibility was not restricted to print media because the offer received also wide coverage by the national broadcasting company Yle.

This experiment generates a test of demand for additional cheap liquidity among puzzle households. The offer should be very enticing because whereas the median nominal interest rate on unsecured borrowing was 7.1 percent, the median mortgage interest rate was 1.3 percent for households in the puzzle group just before the liquidity offer was announced.

The offer can also be used to test if access to new liquidity had an effect on exit from the puzzle group or the degree of unsecured borrowing. The identification strategy is to

---

<sup>5</sup><https://www.hs.fi/haku/>. The search was made on the 20th of March 2019.

compare the behavior of puzzle households *with* a mortgage at the bank (=treated) to that of puzzle households *without* a mortgage at the bank (=control). A caveat is that some competitor banks also made similar offers to their mortgage customers in 2015. Therefore, some households in my control group may have had a mortgage at one of the competitor banks and would have been also ‘treated’. However, as detailed in the sample selection section, I focus on households that used the bank that I have data for as their main financial service provider. In addition, the campaigns of other banks were not as salient, and therefore for the subset of control households that may have been eligible for similar offers, the treatment intensity was weaker.

## **4.2 Acceptance rate of liquidity offer**

Table 4 presents the acceptance rate of the new liquidity offer by different subgroups of the January 2015 puzzle population holding a mortgage at the bank. Out of the total puzzle group of 67,499 households, 43,283 have a mortgage at the bank.

Overall, the acceptance rate is around a quarter. Predictably, the acceptance rate increases with the amount of unsecured borrowing but is only around 30 % even in the top quartile. There is no connection between the acceptance rate and total months spent in the puzzle group in 2015. The relatively low acceptance rate is therefore not explained by most households exiting the puzzle group very quickly and therefore having no need for the liquidity.

This is a surprising finding, which seems to be at odds with the liquidity preference and precautionary borrowing hypotheses for the puzzle. Both theories argue that households value

liquidity so much that they are willing to borrow at the unsecured credit rate. Therefore, they should also surely want to borrow at a considerably lower rate, if only to repay their higher interest debt whilst keeping equal or greater liquidity<sup>6</sup>. However, only a clear minority of puzzle households choose to do so.

Notwithstanding the major advertising campaign, there might still be a worry that many households were not really aware of the offer. However, I can identify households in the puzzle group who held a mortgage and that included an *employee* of the bank (N = 1,831). These households should have been extremely likely to be knowledgeable about the campaign. Among these employee-households, the acceptance is still only 40 %<sup>7</sup>.

### 4.3 Difference-in-difference analysis of effects of new liquidity

In addition to the acceptance rate, it is possible to study if the liquidity offer was associated with an increase in the exit probability from the puzzle group or a decrease in the level of unsecured credit.

First, Figure 4 provides graphical evidence of the overall probability of belonging to the puzzle group by mortgage status before and after the liquidity offer for the group of households that satisfied the puzzle conditions in January 2015. As a reminder, the liquidity offer was introduced in February 2015 so it is exogenous from the perspective of decisions made up to January 2015.

---

<sup>6</sup>Non-acceptance cannot be explained by the offer forcing “too much” liquidity on the households, because the overwhelming majority of mortgages are adjustable-rate and have no restrictions on extra amortization payments.

<sup>7</sup>Employee-households are somewhat more likely to be classified in the puzzle group than regular customers over the sample period. For instance, in January 2015 their puzzle rate is 16 % versus 13 % among all customers.

There is no difference in the exit probability of mortgagors and the exit probability of households not eligible for the offer during 2015. The comparison is sensible, because the likelihood of belonging to the puzzle group in the months leading up to the offer is very similar between the two groups. Finally, mortgage households seem to be, if anything, somewhat *more* likely to belong to the puzzle group during 2016.

Figure 4 does not control for any other variables that may differ systematically between mortgage and non-mortgage households and that might affect the probability of exiting the puzzle group. Therefore I run a binary regressions at the household-month level where the dependent variable takes the value 1 if the household belongs to the puzzle group in a given month and 0 otherwise. The difference-in-difference specification is:

$$\begin{aligned} \mathbb{1}_{\text{puzzle},h,m} = & \gamma_{pre} \mathbb{1}_{m < \text{Jan}2015} + \beta_{pre} \mathbb{1}_{m < \text{Jan}2015} * \mathbb{1}_{\text{mortgage}} + \\ & \gamma_{post} \mathbb{1}_{m > \text{Jan}2015} + \beta_{post} \mathbb{1}_{m > \text{Jan}2015} * \mathbb{1}_{\text{mortgage}} + \\ & \mathbb{X}_h + \epsilon_{h,m} \end{aligned} \tag{2}$$

, where  $h$  refers to the household,  $m$  to the month and  $\mathbb{X}_h$  refers to household-level control variables<sup>8</sup>. The specification tests whether following the offer the exit rate for mortgage households is larger than for non-mortgage households ( $\beta_{post} < 0$ ). It also tests for equality of pre-trends ( $\beta_{pre} = 0$ ) as a validity check of the difference-in-difference approach. The baseline month is January 2015 when by definition all sample households belonged to the puzzle group.

---

<sup>8</sup>Level of deposits and uncollateralised borrowing, number of adult males and females, number of children, average age of adults, municipality, net income and card expenditure.



The panel used to estimate the regression spans from January 2014 to December 2016.

The regression results for exit probability are presented in Table 5. No specification finds quantitatively significant differential exit rate for households eligible for the liquidity offer.

The fact that  $\hat{\beta}_{pre} \approx 0$  underpins the assumption of common pre-trends.

In addition to exit, I can study effects of the liquidity offer on the level of unsecured credit conditional on continuing to borrow. For this purpose, I change the dependent variable in equation (2) to  $\log(\text{unsecuredCredit})$ . Results for this specification are presented in Table 6. Again, there is no evidence for mortgagors reducing unsecured credit after the liquidity offer. On the contrary, households eligible for the offer on average have higher levels of unsecured credit in the post-offer period.

In summary, (i) only a minority of puzzle households eligible for new cheap liquidity accept the offer, (ii) there is no evidence for increased exit from the puzzle group as a result of the liquidity offer; (iii) households eligible for the offer do not as a group reduce unsecured credit faster in the post-offer period. Consequently, the results of this section signal that strategic liquidity/precautionary borrowing motives are unlikely to be a sufficient explanation for the credit card debt puzzle.

## 5 Role of incomplete intra-household optimization

The prevailing method of defining the puzzle at the household level implicitly assumes unitary household decision-making. This section studies whether the intra-household distribution of borrowing and deposits matters. I find that puzzle behavior is considerably less likely at

the individual than at the household level in households with multiple adults. Furthermore, conditional on belonging to the puzzle group, persistence of membership is lower at the individual level. The intra-household distribution of borrowing and deposits also influences the probability of accepting the offer of new cheaper liquidity. Part of the puzzle group therefore reflects an inappropriate application of the unitary household model. This can be interpreted as supporting evidence for the relevance of a (multi-person) accountant-shopper model à la Bertaut et al. (2009).

## 5.1 Prevalence of puzzle at individual vs. household level

I start this section by comparing the prevalence of the puzzle at the household and individual level in households with multiple adults. The purpose is to study in how large a proportion of household puzzle observations the puzzle criteria are satisfied only due to pooling household resources. Conversely, the results reveal in how many household puzzle observations there is at least one member that satisfies the puzzle conditions individually.

I do not employ the *deposits larger than one month's net income* criterion in the puzzle definition in this analysis. This allows for division of labor between paid work and shopping responsibilities within the household. Therefore, the household and individual are classified in the puzzle group if they have over 500 EUR of unsecured credit and over 1500 EUR of deposits. The qualitative results are unchanged if also the income criterion is used.

The puzzle share is on average 9.6 *percentage points* lower at the individual than at the household level (Figure 5). In relative terms, the puzzle share is 43 *percent* lower. This means

that in almost half of multi-adult household puzzle observations the puzzle criteria are only met due to considering household resources as pooled<sup>9</sup>.

The impact of within-household distribution of assets and borrowing has not been documented in the existing literature due to relying on data sources that aggregate financial variables at the household level. To the best of my knowledge, the only other paper that considers intra-household dynamics is Choi and Laschever (2018). They find that the “Big Five” psychological characteristics of both members of a couple impact the probability of belonging in the puzzle group. In addition, they document that the puzzle likelihood is impacted by income inequality and the level of agreeableness within the couple. However, their study also has to rely on aggregated financial variables and hence cannot provide a similar quantitative breakdown.

## 5.2 Persistence of individual vs. household puzzle membership

Conditional on satisfying the puzzle conditions in a given month, is there a difference in the persistence of puzzle membership at the household and individual level? If individuals are quicker to move out of the puzzle group than households as a whole, it may be a signal that financial optimization is better performed at the individual than at the household level. This would also be consistent with conflicts of interest sustaining co-holding at the household level.

Persistence is indeed much lower at the individual level. Figure 6 panel A depicts the average survival share in the puzzle group conditional on belonging to the puzzle group at some point

---

<sup>9</sup>Though we focus here on coordination within multi-adult households, the puzzle share is also considerably lower in single-adult than multi-adult households.

in January 2014 through December 2015. The survival rate for *households* after 12 months is approximately 75 percent whereas it is barely over 50 percent for *individuals*. Another way to study the difference in persistence is to compare the distribution of total puzzle months in 2015 conditional on being a member of the puzzle group in January 2015 (panel B). A *household* satisfies the puzzle conditions in 9.4 months on average over 2015. The same figure for an *individual* is only 7.4 months.

### **5.3 Intra-household distribution of deposits and borrowing: effect on acceptance of new liquidity offer**

A final test of the unitary household model is whether the distribution of deposits and unsecured credit impacts the household decision to accept the liquidity offer. The idea is to compare the acceptance probability between households with similar amounts of total deposits and unsecured credit but varying distribution across household members. If there is clear division within the household to a saver and a spender, the saver might want to prevent the household from applying for the liquidity offer to preclude the spender from over-consuming.

I operationalise the test as follows. For each individual mortgagor belonging to a multi-adult household, I derive information on both individual characteristics of the mortgagor, individual characteristics of the partner, and common household characteristics (e.g. number of children). Then I estimate a linear probability model with a dependent variable that takes the value 1 if the mortgagor accepts a freeze on at least one of her mortgages and 0 otherwise.

The underlying idea is to test whether the personal financial situation of one of the partners is more influential on the mortgage freeze decision than the situation of the other. This requires me to define who is the primary and who is the secondary partner. With individual mortgages, it is straightforward to regress the freeze decision on individual financial variables of both the mortgagor (primary partner) and her co-habitant (secondary partner).

The issue is somewhat fuzzier with joint mortgages for which both are liable: how to define the primary and secondary partners in this case? I opt to follow the bank classification, whereby it registers one of the individuals as the primary mortgagor. In the case of joint mortgages, the primary mortgagor is more likely to be male (69 percent of cases), has higher deposits (median 1418 EUR versus 938 EUR for the partner) and more unsecured credit (median 1091 EUR versus 641 EUR for the partner)<sup>10</sup>.

It is important to note that to obtain the freeze on a joint mortgage, both debtors need to agree to it. On the other hand, for decisions regarding individual mortgages the partners do not need to consult each other. This would lead to the hypothesis that couples with a joint mortgage would tend to behave more according to the unitary model than couples with individual mortgages.

The main regression specification is:

---

<sup>10</sup>These figures pertain to the sample of multi-adult households that have positive deposit and unsecured credit balances in January 2015.

$$\begin{aligned}
\mathbb{1}_{\text{freeze},p,h} = & \sum_{b=1}^{10} \gamma_b \text{totalUnsecuredCreditBin}_{h,b} + \sum_{b=1}^{10} \theta_b \text{totalDepositsBin}_{h,b} + \\
& \beta_1 \text{totalUnsecuredCreditShare}_{p,h} + \beta_2 \text{totalDepositsShare}_{p,h} + \\
& \Omega \mathbb{X}_h + \epsilon_{p,h}
\end{aligned} \tag{3}$$

The subscript  $p$  refers to a given partner with a mortgage in household  $h$ . The key variables are `totalDepositsShare` and `totalUnsecuredCreditShare`, which measure the share of the (primary) mortgagor in total household variables. If the distribution of deposits and consumer credit played no role in the decision to accept the freeze, estimates for both  $\beta_1$  and  $\beta_2$  should be close to 0 and insignificant. On the other hand, if the (primary) mortgagor has more weight in the household decision, then  $\beta_1 > 0$  and  $\beta_2 < 0$ . I.e. the acceptance probability is higher if the primary mortgagor accounts for a larger share of total household unsecured borrowing or has a smaller share of total household deposits. All regressions control for the *level* of total household deposits and unsecured credit as well as other household characteristics  $\mathbb{X}_h$ <sup>11</sup>.

The unitary model is rejected in terms of unsecured credit when estimating equation (3) using my baseline sample (Table 7, model 1), which includes all two-adult households that held both positive deposits and unsecured credit in January 2015. However, quantitatively the effect on freeze acceptance is moderate. Having all unsecured borrowing be due to the partner reduces the probability of freeze acceptance by 3.3 percentage points (or 12 percent in relative terms) compared to the case where all unsecured borrowing is due to the (primary)

---

<sup>11</sup>Number of adults and children, average age of adults, municipality, mortgage value, size of amortization payment, mortgage interest rate, property value, net income level, card purchase level.

mortgagor. Results are similar if I concentrate on two-adult households that satisfied the puzzle criteria in January 2015 (model 2).

However, the distribution of debts and assets seems to matter considerably for households with exclusively individual mortgages (model 4). For these households, having all unsecured borrowing be due to the partner reduces the probability of freeze acceptance by 7.8 percentage points (or 34 percent in relative terms) compared to the case where all unsecured borrowing is due to the mortgagor. The effect of deposit distribution is also sizeable. On the other hand, coefficient estimates for households with only joint mortgages (model 3) are small in absolute value and the coefficient on the deposit share even has a positive sign<sup>12</sup>.

The difference in intra-household optimization by mortgage contract type is probably due both to (a) the requirement of collective agreement to obtain a freeze for joint mortgages; and (b) self-selection of couples into joint/individual mortgage pools depending on their desired level of financial mutualization. It remains an open question, therefore, to what extent the null result for households with joint mortgages is explained by the contractual details of the offer versus a mutual desire for financial pooling.

## 6 Conclusions

For seemingly sub-optimal financial behavior to earn the label *puzzle*, it should entail significant costs. This paper's first finding of imperfect persistence of puzzle group membership lends

---

<sup>12</sup>Note that a small minority of households have both joint and individual mortgages. I exclude these households from models 3 and 4. That is why the sum of observations in models 3 and 4 is smaller than in model 1. Results are unchanged if I include these households in both samples.

more support to the original observation by Zinman (2007) that only few households in the puzzle group would save substantially through more aggressive liquidity management. In addition, to the extent that the phenomenon is transitory, it leaves room for corresponding explanations for the puzzle, such as time-varying levels of attention to household finances.

Secondly, the underlying assumption of intra-household optimization significantly impacts the share of households classified in the puzzle group and the magnitude of the puzzle. However, it is debatable why pooling of financial balance sheets should be the benchmark or why its failure should be considered *puzzling* (see e.g. Chiappori and Mazzocco (2017)). This paper adds to the evidence that intra-household distribution of financial assets and liabilities does matter.

Thirdly, the relatively low uptake of additional cheaper liquidity makes it difficult to argue that preference for liquidity or a precautionary borrowing motive would be sufficient to explain the phenomenon. Particularly the latter theory relies on sophisticated awareness and advance planning, which is difficult to reconcile with simultaneous refusal to accept credit at a lower interest rate. That said, it can be that both channels are more important in the US than in Finland. US households may have a higher demand for liquidity e.g. due to differences in payment methods, and they can be subject to higher credit limit variability.

Finally, anchoring as well as optimization frictions in the form of inertia and inattention could partly explain co-holding but have not been discussed rigorously in the literature. On the one hand, Keys and Wang (2016) document the substantial propensity of households to anchor monthly credit card payments to the default minimum. The behavior is unlikely to be driven by simply low liquid assets given the borrowers' reaction to changes in minimum



payment formula and the fact that low payments are common across different household types. On the other hand, inertia and inattention are considered important for explaining e.g. sluggish mortgage refinancing (Andersen et al. (2015)) with considerably larger stakes than co-holding. Therefore, it would not seem unreasonable that these frictions would also matter for the credit card debt puzzle.

## References

- Andersen, Steffen, John Y. Campbell, Kasper Meisner Nielsen, and Tarun Ramadorai (2015) “Inattention and Inertia in Household Finance: Evidence from the Danish Mortgage Market,” Technical Report 21386, National Bureau of Economic Research, Inc.
- Bertaut, Carol C. and Michael Haliassos (2001) “Debt Revolvers for Self Control,” Technical report.
- Bertaut, Carol C., Michael Haliassos, and Michael Reiter (2009) “Credit Card Debt Puzzles and Debt Revolvers for Self Control,” *Review of Finance*, Vol. 13, pp. 657–692, URL: <https://academic.oup.com/rof/article/13/4/657/2886494>, DOI: <http://dx.doi.org/10.1093/rof/rfn033>.
- Chiappori, Pierre-Andre and Maurizio Mazzocco (2017) “Static and Intertemporal Household Decisions,” *Journal of Economic Literature*, Vol. 55, pp. 985–1045, URL: <https://ideas.repec.org/a/aea/jeclit/v55y2017i3p985-1045.html>.
- Choi, Hwan-sik and Ron A Laschever (2018) “Credit Card Debt Puzzle and Noncognitive

- Ability,” *Review of Finance*, Vol. 22, pp. 2109–2137, URL: <https://academic.oup.com/rof/article/22/6/2109/3970879>.
- Druehdahl, Jeppe and Casper Nordal Jørgensen (2018) “Precautionary Borrowing and the Credit Card Debt Puzzle,” *Quantitative Economics*, Vol. forthcoming.
- Fulford, Scott L. (2015) “How important is variability in consumer credit limits?” *Journal of Monetary Economics*, Vol. 72, pp. 42–63, URL: <http://www.sciencedirect.com/science/article/pii/S0304393215000057>, DOI: <http://dx.doi.org/10.1016/j.jmoneco.2015.01.002>.
- Gathergood, John and Jörg Weber (2014) “Self-control, financial literacy & the co-holding puzzle,” *Journal of Economic Behavior & Organization*, Vol. 107, pp. 455–469, URL: <http://www.sciencedirect.com/science/article/pii/S0167268114001231>, DOI: <http://dx.doi.org/10.1016/j.jebo.2014.04.018>.
- Gorbachev, Olga and María José Luengo-Prado (2016) “The Credit Card Debt Puzzle: The Role of Preferences, Credit Risk, and Financial Literacy,” SSRN Scholarly Paper ID 2826962, Social Science Research Network, Rochester, NY.
- Gross, David B. and Nicholas S. Souleles (2002) “Do Liquidity Constraints and Interest Rates Matter for Consumer Behavior? Evidence from Credit Card Data,” *The Quarterly Journal of Economics*, Vol. 117, pp. 149–185, URL: [http://econpapers.repec.org/article/oupqjecon/v\\_3a117\\_3ay\\_3a2002\\_3ai\\_3a1\\_3ap\\_3a149-185..htm](http://econpapers.repec.org/article/oupqjecon/v_3a117_3ay_3a2002_3ai_3a1_3ap_3a149-185..htm).
- Keys, Benjamin J. and Jialan Wang (2016) “Minimum Payments and Debt Paydown in Consumer Credit Cards,” *NBER Working Paper*, Vol. 22742, URL: <https://www.nber.org/papers/w22742>.

Lehnert, Andreas and Dean M. Maki (2002) “Consumption, debt and portfolio choice: testing the effect of bankruptcy law,” Finance and Economics Discussion Series 2002-14, Board of Governors of the Federal Reserve System (U.S.).

Telyukova, Irina A. (2013) “Household Need for Liquidity and the Credit Card Debt Puzzle,” *The Review of Economic Studies*, Vol. 80, pp. 1148–1177, URL: <https://academic.oup.com/restud/article/80/3/1148/1571542>, DOI: <http://dx.doi.org/10.1093/restud/rdt001>.

Zinman, Jonathan (2007) “Household Borrowing High and Lending Low Under No-Arbitrage,” *Mimeo*.

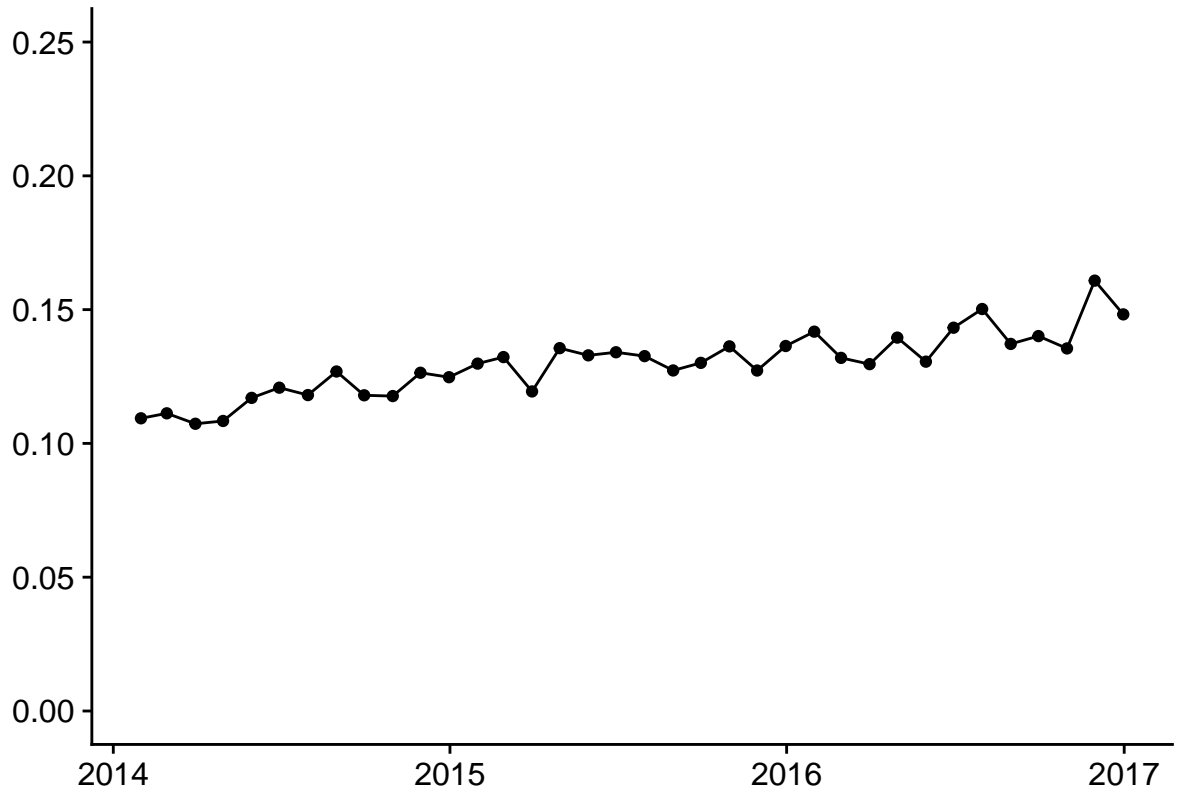
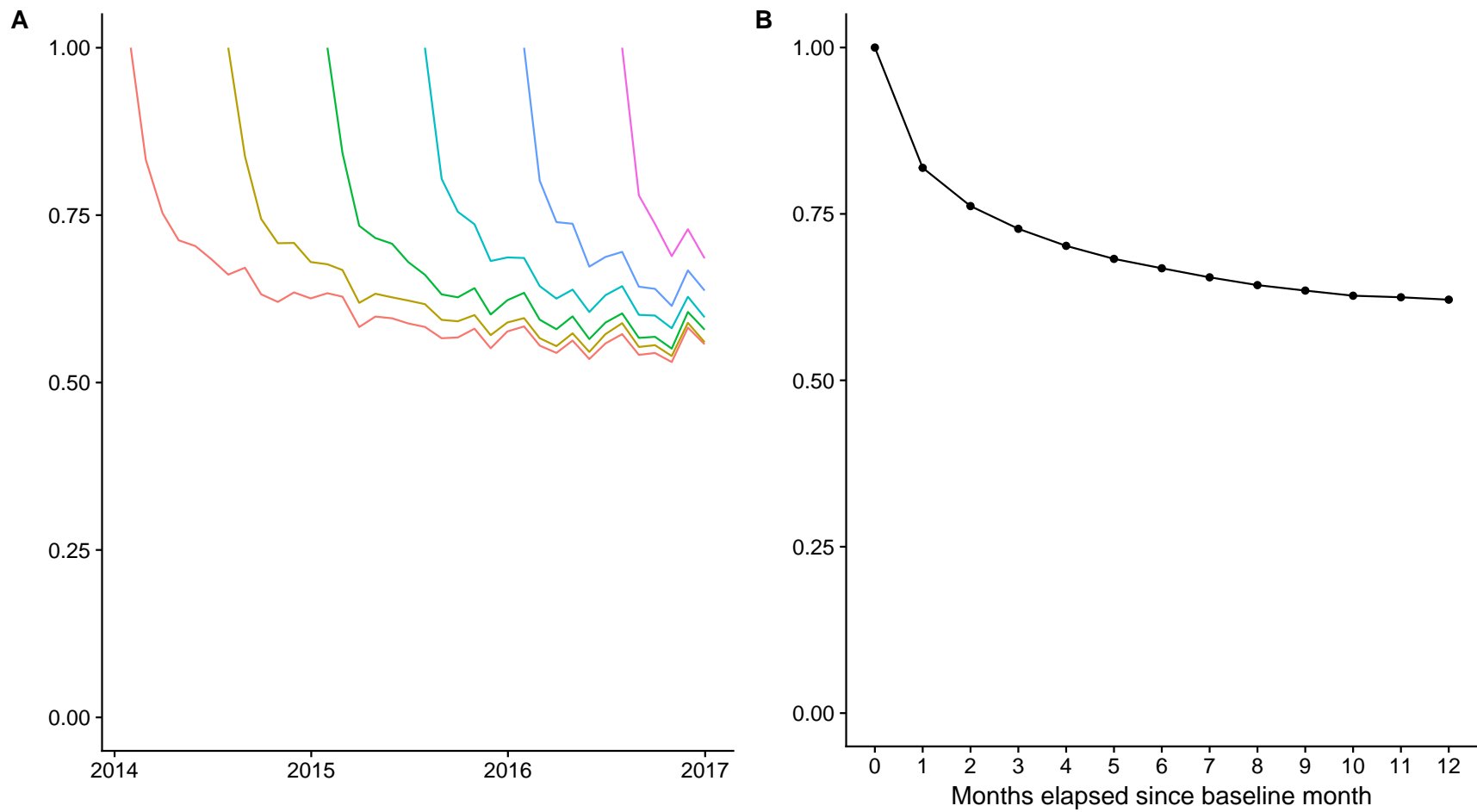


Figure 1: Share of households satisfying puzzle conditions by month



Note: Panel A presents the survival share of households that satisfy the puzzle criteria in the baseline months of January and July in 2014, 2015 and 2016. Panel B depicts the average survival share for households that satisfy the puzzle criteria at some point during January 2014 to December 2015.

Figure 2: Share of initial puzzle group satisfying puzzle conditions by month

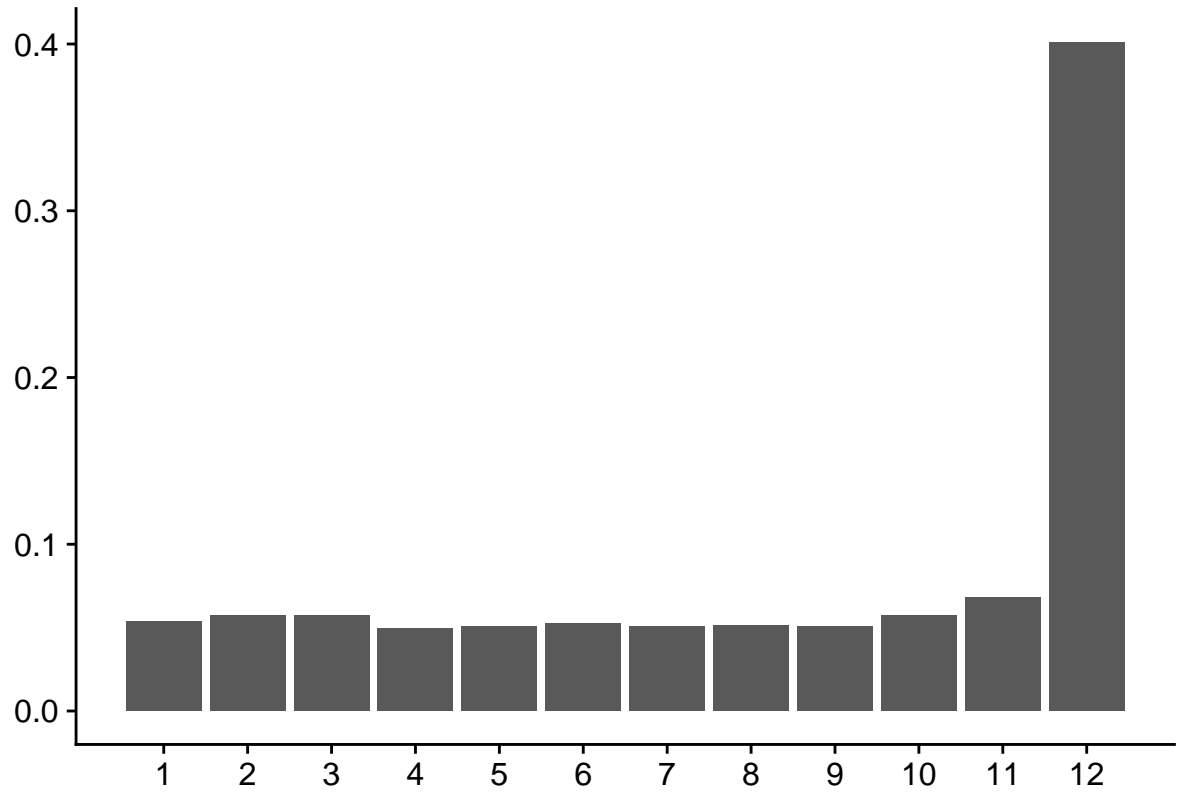


Figure 3: Distribution of puzzle months in 2015 for households in puzzle group in January 2015

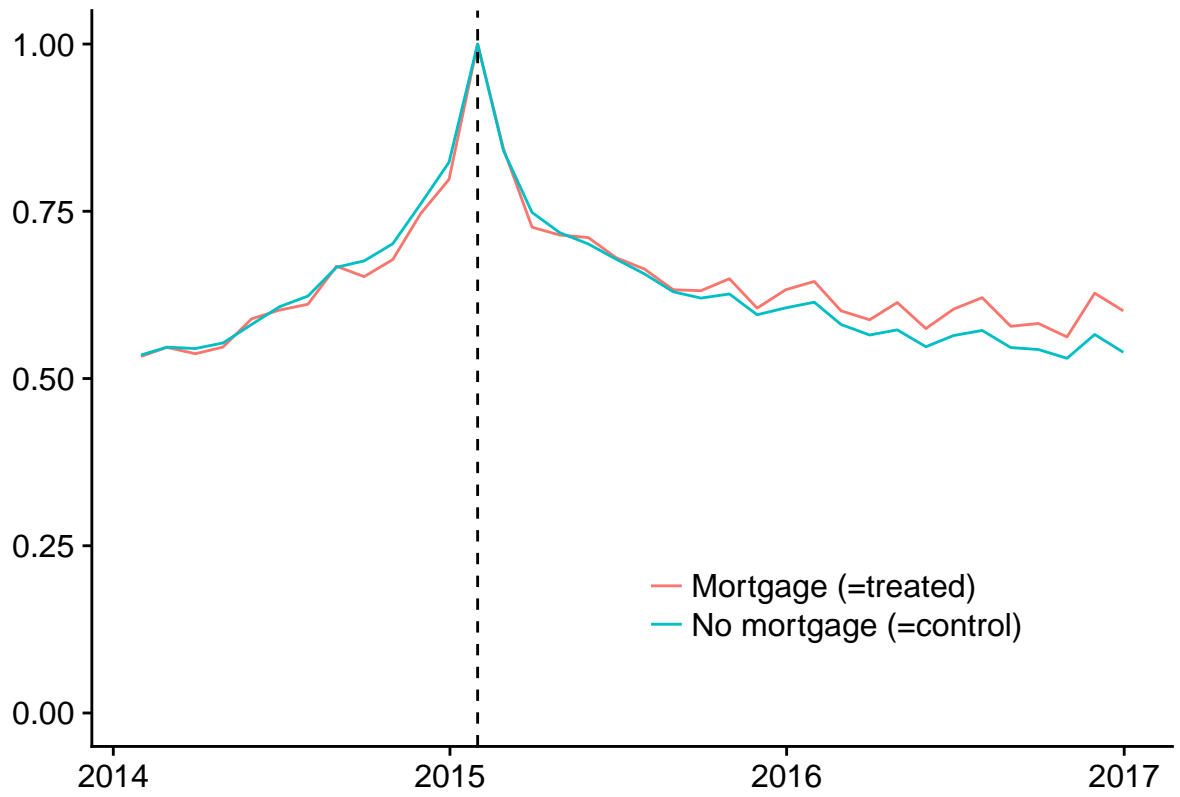
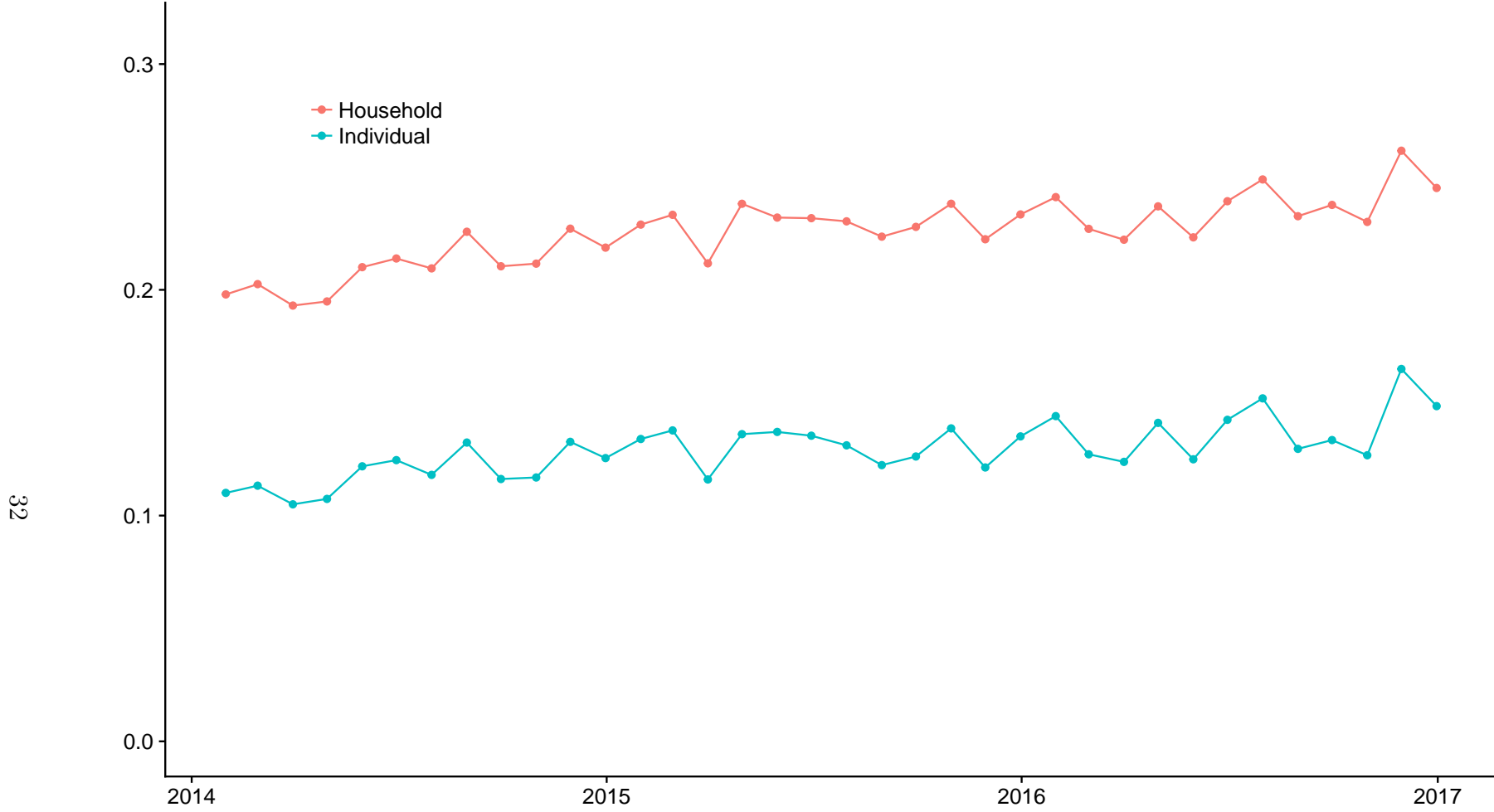


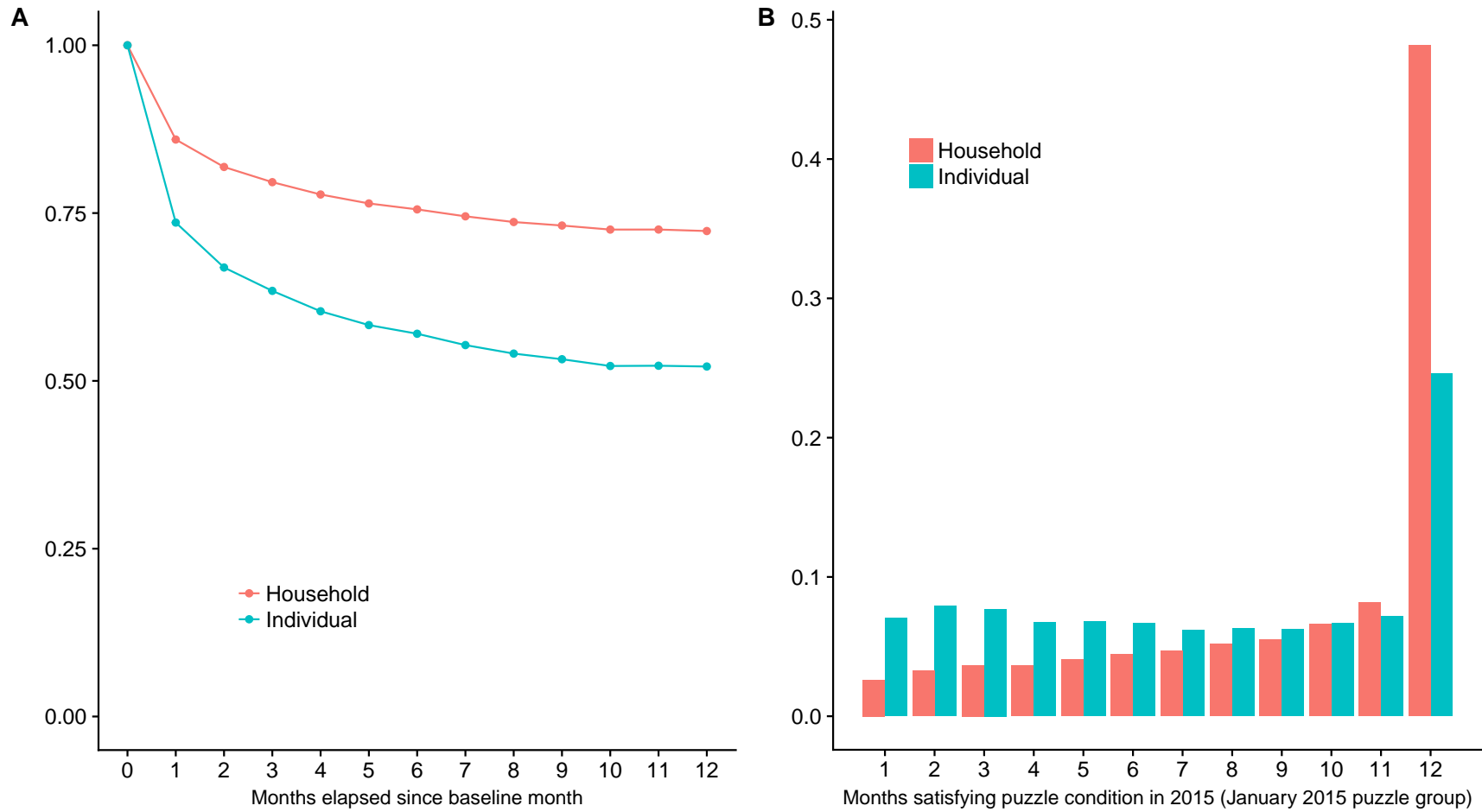
Figure 4: Survival share of January 2015 puzzle households by mortgage status



Note: The figure plots the share of multi-adult households satisfying the puzzle conditions at the household level (red line). It also plots the proportion of these same households where at least one individual satisfies the puzzle conditions (blue line). The difference in the two proportions is accounted for by multi-adult households where the puzzle conditions are met only if liquid assets and unsecured credit are aggregated across household members. This puzzle definition does not employ the deposits larger than one month's net income criterion to allow for division of labor between paid work and shopping responsibilities.

Figure 5: Prevalence of puzzle at individual vs. household level in multi-adult households





Note: Panel A depicts the average survival share for households/individuals that satisfy the puzzle criteria at some point during January 2014 to December 2015. Panel B calculates the number of months in 2015 that households/individuals spend in the puzzle group conditional on satisfying the puzzle criteria in January 2015. Both figures are based on the sample of multi-adult households.

Figure 6: Persistence of puzzle group membership: individual versus household

Table 1: Sample descriptives, January 2015

	N	Mean	Q0.1	Q0.25	Q0.5	Q0.75	Q0.9
<b>Full sample</b>							
Deposits	519,940	22,751	634	2,315	8,313	24,771	56,868
Unsecured credit	519,940	1,035	0	0	0	1,016	3,615
Co-holding	519,940	534	0	0	0	526	1,794
Net income	519,940	3,300	1,371	1,954	2,776	4,106	5,410
<b>January 2015 puzzle</b>							
Deposits	67,499	15,626	2,837	4,511	7,972	16,220	33,051
Unsecured credit	67,499	2,795	694	1,009	1,854	3,626	6,227
Co-holding	67,499	2,486	694	1,009	1,829	3,258	5,187
Net income	67,499	3,374	1,481	2,097	3,038	4,377	5,548

<sup>a</sup> Co-holding is equal to the minimum of deposits and unsecured credit.

Table 2: January 2015 puzzle share by group

	Net income quintile					
	All	Q1	Q2	Q3	Q4	Q5
<b>Age quintile</b>						
All	0.13	0.11	0.12	0.12	0.15	0.15
Q1	0.14	0.13	0.13	0.13	0.15	0.15
Q2	0.17	0.18	0.17	0.17	0.18	0.16
Q3	0.16	0.15	0.15	0.16	0.17	0.16
Q4	0.12	0.09	0.11	0.11	0.13	0.13
Q5	0.07	0.05	0.06	0.07	0.09	0.13

Table 3: Cost of puzzle behavior at household level for January 2015 puzzle group

	N	Mean	Q0.1	Q0.25	Q0.5	Q0.75	Q0.9
Extrapolated yearly costs	67,498	170.41	49.09	71.41	128.15	223.82	350.62
Actual yearly costs	67,498	147.16	32.86	60.57	112.62	195.37	309.88
Actual to extrapolated ratio	67,498	0.91	0.40	0.66	0.89	1.05	1.32

<sup>a</sup> The table presents two estimates of the yearly costs of puzzle behavior for households satisfying the puzzle criteria in January 2015. Both estimates are based on the interest rate difference between liquid assets and unsecured borrowing and the amount of liquid assets that could be used to reduce debt [equation (1)]. The first estimate, 'Extrapolated yearly costs', assumes that yearly costs are proportional to balances of liquid assets and unsecured borrowing in January 2015. The second estimate, 'Actual yearly costs', uses data on actual deposit and unsecured borrowing balances in each month during 2015. The final row, 'Actual to extrapolated ratio', is based on calculating the ratio of the two cost measures for each household.

Table 4: Acceptance rate of liquidity offer among January 2015 puzzle group

	January 2015 unsecured credit bin				
	All	Lowest quartile	Second quartile	Third quartile	Top quartile
<b>Puzzle months in 2015</b>					
All	0.25	0.19	0.23	0.27	0.31
1 to 3	0.26	0.19	0.26	0.30	0.36
4 to 6	0.25	0.19	0.24	0.30	0.32
7 to 9	0.26	0.20	0.25	0.29	0.32
10 to 12	0.24	0.19	0.21	0.25	0.29

Table 5: Effect of liquidity offer on exit from puzzle group: January 2015 puzzle households

	<i>Dependent variable:</i>		
	Member of puzzle group (0/1)		
	(1)	(2)	(3)
preDummy	-0.36*** (0.002)	-0.35*** (0.002)	-0.36*** (0.002)
preDummyMortgage	-0.01*** (0.003)	-0.03*** (0.003)	-0.01*** (0.003)
postDummy	-0.38*** (0.002)	-0.37*** (0.002)	-0.38*** (0.002)
postDummyMortgage	0.02*** (0.003)	0.002 (0.003)	0.02*** (0.003)
Household controls	No	Yes	No
Household FEs	No	No	Yes
Unique households	67,407	67,407	67,407
Observations	2,426,652	2,426,652	2,426,652

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

The table presents estimation results for different specifications of equation (2). Model (1) does not include any controls or fixed effects. Model (2) controls for January 2015 amounts of deposits and uncollateralised borrowing, the number of adult males and females, number of children, average age of adults, municipality, net income and card expenditure. Model (3) replaces household controls by household fixed effects. The data is a panel from January 2014 to December 2016 which follows all households that satisfied the puzzle criteria in January 2015. The dependent variable takes the value 1 if the household belongs to the puzzle group in a given month and 0 otherwise. January 2015 is the baseline month because it preceded the bank's liquidity campaign for mortgage households that started in February 2015.

Table 6: Effect of liquidity offer on unsecured borrowing: January 2015 puzzle households

	<i>Dependent variable:</i>		
	log(unsecuredCredit)		
	(1)	(2)	(3)
preDummy	-0.21*** (0.01)	-0.13*** (0.003)	-0.16*** (0.004)
preDummyMortgage	0.18*** (0.01)	-0.01*** (0.004)	0.0004 (0.004)
postDummy	-0.22*** (0.01)	-0.15*** (0.004)	-0.19*** (0.004)
postDummyMortgage	0.23*** (0.01)	0.04*** (0.005)	0.05*** (0.005)
Household controls	No	Yes	No
Household FEs	No	No	Yes
Unique households	67,407	67,407	67,407
Observations	2,190,527	2,190,527	2,190,527

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

The table presents estimation results for a variation of equation (2) where the dependent variable is changed to log(unsecuredCredit). Model (1) does not include household controls or fixed effects, i.e. it measures the average difference in borrowing levels between mortgagors and non-mortgagors before and after the freeze campaign. Model (2) controls for the number of adult males and females, number of children, average age of adults, municipality, net income and card expenditure. Model (3) replaces household controls by household fixed effects. The data is a panel from January 2014 to December 2016 which follows all households that satisfied the puzzle criteria in January 2015. January 2015 is the baseline month because it preceded the bank's liquidity campaign for mortgage households that started in February 2015.

Table 7: Liquidity offer acceptance: role of intra-household distribution of deposits and unsecured credit

	<i>Dependent variable:</i>			
	Freeze acceptance (0/1)			
	(1)	(2)	(3)	(4)
depositShare	−0.005 (0.005)	−0.006 (0.007)	0.015*** (0.006)	−0.043*** (0.009)
unsecuredCreditShare	0.033*** (0.004)	0.037*** (0.005)	0.013*** (0.004)	0.078*** (0.006)
Sample	All two-adult	Puzzle	Joint mortgage	Individual mortgage
Freeze share	0.28	0.23	0.29	0.23
Unique individuals	79,674	31,106	56,462	19,664
Unique households	70,303	27,174	52,674	15,945
Household controls	Yes	Yes	Yes	Yes
Observations	79,674	31,106	56,462	19,664

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

The table presents estimation results of equation (3) with varying samples. Model (1) includes all two-adult households with positive deposits and uncollateralised borrowing and a mortgage in January 2015. Model (2) includes the subset of households in Model (1) that satisfied the puzzle criteria in January 2015. Model (3) includes the subset of households in Model (1) that had only joint mortgage(s). Finally, Model (4) includes the subset of households in Model (1) that had only individual mortgage(s). The dependent variable takes the value 1 if the (primary) mortgagor accepts a freeze on one of his/her mortgages during the campaign period. The unit of observation is an individual primary mortgagor within a two-adult household. If there are multiple primary mortgagors within a household (due to multiple joint mortgages with different primary mortgagors or multiple individual mortgages), the same household is represented in the data twice. All models control for the total amount of deposits and unsecured borrowing, the number of adults and children, average age of adults, municipality, mortgage value, size of amortization payment, mortgage interest rate, property value, net income level, card purchase level.