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David Coyne, Itzik Fadlon and Tommaso Porzio

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Measuring Valuation of Liquidity with Penalized Withdrawals*

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June 2022

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We propose using penalized withdrawals from retirement savings accounts, identified from U.S. tax records, as a revealed-preference tool to analyze households' valuation of liquidity. A simple dynamic model formalizes the notion that the prevalence of withdrawals can be used to characterize American households' valuation of liquidity over time and space. Over time, we find that declines in household income lead to sudden, large, and persistent jumps in the probability of penalized withdrawals, providing evidence that shocks are imperfectly insured and that households have high valuation of liquidity. Across space, we show that both local economic conditions and persistent household characteristics play an important role, with the average valuation of liquidity being higher in financially underdeveloped areas as well as in black communities, consistent with them being marginalized from the credit market. Applying our tool to the Great Recession, we further find that more affected areas saw larger increases in penalized withdrawals, likely driven by tightening of local credit conditions. Overall, our analysis offers a new tool to study the valuation of liquidity, and our results point to sizable welfare gains from social insurance policies targeted at both households and locations over time.

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1 Introduction

In a world with no borrowing constraints, households should smooth their marginal utility of consumption almost perfectly over time, with the remaining variation being purely driven by aggregate shocks and permanent changes in their income or consumption profiles. In practice, however, households are only imperfectly insured as they do not have access to sufficient liquidity from formal or informal lending institutions (Parker 1999; Johnson et al. 2006). As a result, the degree to which marginal utility today differs from expected marginal utility tomorrow—or, simply, the valuation of liquidity—would typically vary across households at any point in time. Such variation implies resources are misallocated, lending the possibility of large welfare gains from directing funds to households with higher valuations of liquidity or from helping them borrow from households who have lower valuations today.

To harvest these welfare gains, we need to empirically identify differences in the valuation of liquidity, which is a difficult task due to two challenges. First, the valuation of liquidity is not directly observed in the data, and relying on available consumption data is problematic. In fact, detecting fluctuations in consumption is neither sufficient nor necessary to infer that a household is imperfectly insured: preferences may themselves change over time, possibly as a function of economic and life circumstances, and lead consumption to fluctuate. Second, the valuation of liquidity is an equilibrium object determined not only by household-specific shocks, which affect their demand for funds, but also by the available supply of credit, which is itself a function of market-level economic conditions and household-specific factors. As a result, observing shocks to income, or even directly to demand for liquidity, is not sufficient to characterize the equilibrium valuation of liquidity. Doing that would further require detailed knowledge of the available supply of credit.

In this paper, we offer a revealed-preference approach that overcomes these challenges and allows us to characterize how the valuation of liquidity by American households varies across time and space. We leverage a simple insight: households who are willing to take up pricey borrowing reveal a high valuation of consumption today versus consumption tomorrow. They thus have a high valuation of liquidity. The logic rests on the simple notion that observing a household purchasing a good at a given price (here, borrowing at a given interest rate) implies that the household values the good by at least its price.

In practice, the implementation of this revealed-preference approach requires a credit product that possesses two characteristics: (1) wide availability to households (allowing for comprehensive analysis and for households to reveal their preferences); (2) observable price (to serve as the benchmark against which preferences are revealed). In addition, a product with uniform pricing has important value added: it allows comparable assessments across

time (to assess effects of changing economic conditions), across space (to assess variation across geographical locations), and across observable types of households (to assess disparities by uncovering differential access to alternative cheaper sources of credit).

Our starting point in this paper is to notice that penalized withdrawals from retirement savings accounts stand as a common credit “product” that is close to ideal: it is widely available to households, and it has an observable and constant marginal price (the 10 percent penalty). Based on this idea, we use U.S. administrative tax records for American households from 1999-2018 to characterize their valuation of liquidity.

To motivate our approach, we first provide descriptive empirical analysis on penalized withdrawals. Overall, we find evidence that households widely use them to mitigate short-run needs for liquidity. We show that households are more likely to withdraw when experiencing negative income shocks and that they withdraw sizable sums, partially offsetting the income declines. We also complement our tax data with information from the Health and Retirement Study (HRS), and we find that the modal household that withdraws funds prematurely uses the distributions for current spending.¹ Finally, in our tax data, we find that households withdraw only infrequently and that typical penalized withdrawals are not linked to account closures (so that households are at an interior solution). These last two pieces of evidence are consistent with households optimally deciding to use their retirement savings account to access liquidity and less with some leading behavioral interpretations (myopia, mental accounting, and narrow bracketing) driving the observed patterns in penalized withdrawals.

Informed by the data, we develop an analytical framework to formalize the idea that penalized withdrawals can be used as a revealed-preference tool to characterize the valuation of liquidity. The model provides a tight mapping between withdrawal behavior and equilibrium valuation of liquidity, and it clarifies the importance of designing an empirical strategy that considers both demand and supply drivers of liquidity needs. The model also highlights a crucial caveat of our approach common to all revealed-preference exercises, namely, that it needs to rely on households’ ability to optimize since we use their behavior to back out their preferences.² Reassuringly, the descriptive evidence on penalized withdrawals supports the view that households are indeed optimizing on this margin.

We then proceed to characterize empirically Americans’ valuation of liquidity and its determinants. We begin by investigating how the equilibrium valuation of liquidity at the household-level is affected by plausible shocks to their demand for funds. We do so by studying major financial household events—specifically, unemployment and large income

¹This is also consistent with the fact that households report in surveys that penalized withdrawals is an important means of self-insurance (Lusardi et al. 2011).

²Revealed-preference exercises are pervasive in the literature. See, for example, Chetty (2008) or, more recently Atkin et al. (2021), Porzio et al. (2021), and, in a setting close to ours, Choukhmane (2019).

declines—that could lead to sudden increases in the demand for liquidity. We find that these adverse shocks lead to sudden and persistent increases in penalized withdrawals, implying that these leading life-cycle shocks are only partially insured. In terms of magnitudes, we find that a 20 percent decline in household income leads 9 percent of households to make a penalized withdrawal. Remarkably, we find that even households with plausibly large wealth holdings are imperfectly insured and see their valuation of liquidity spike as a result of income shocks, although, as expected, to a lesser extent.

The event study results imply that households face an inelastic supply of credit since their equilibrium valuation of liquidity changes when demand shifts. These results motivate us to investigate the supply-side determinants of the valuation of liquidity. The household-level supply of liquidity is plausibly determined by the local environment to which a household is exposed (including formal institutions and social informal support), for which we proxy with geographic location, and by the characteristics that govern access to credit (such as the household’s credit score). We leverage the variation in the average annual share of households that have a penalized withdrawal across commuting zones (CZs) to study the determinants of the supply of credit. To do so, we postulate an AKM-style model (Abowd et al. 1999) as a basis for our statistical investigation in two related analyses: a standard movers design, and a correlational study using the estimated household and location fixed effects.

First, the movers design quantifies the share of the geographic variation attributed to location itself. We find clear changes at the time of the move, which then balance out with a high degree of persistence. The patterns show that permanent location characteristics strongly pass-through to household withdrawals and that place effects can explain about a third of the overall spatial variation in penalized withdrawals that we have found. We interpret this result through the lens of our framework as evidence that when households move to locations with a worse local supply of credit, they have to rely more on penalized withdrawals for liquidity. We provide a series of investigations that support this conclusion, by corroborating the validity of the movers design in identifying the location pass-through and by studying other candidate explanations.

Next, we estimate the location and household fixed effects, flexibly controlling for household economic conditions, and we then explore correlates with regional differences using CZ-level social and economic characteristics. This exercise sheds light on potential drivers of the systematic heterogeneity across households and locations in the access to credit, i.e., in the supply of liquidity. In line with our interpretation of the findings, we find a strong correlation with the location component (and not with the household component) when considering measures of local credit insecurity and median home values (as high home values can provide collateral). We then investigate correlations with the percent of black residents

in a given community, motivated by the literature suggesting that black households might be marginalized from the credit market (Derenoncourt et al. 2021; Bartscher et al. 2021). We find a persistent relationship with the household fixed effects, suggesting that households in black communities indeed have limited access to credit. We find similar patterns for another traditionally disadvantaged household type, that of single mothers.

Finally, we apply our tool to a study of the Great Recession, a leading episode that could have engendered severe worsening of local credit in the most affected locations. We find clear evidence that the more affected commuting zones, as measured by unemployment increases, have seen a larger increase in penalized withdrawals. We decompose the overall effect into a direct component (driven by a household’s income and employment status) and an indirect component (plausibly through local credit market spillovers) by flexibly accounting for household-level economic circumstances. We find that about two-thirds of the overall effect can be attributed to the indirect component, suggesting that the impact of aggregate local unemployment on the valuation of liquidity operates mainly through a credit crunch, hence through a decrease in the local supply of liquidity.

Overall, our work introduces penalized withdrawals as a powerful yet overlooked tool that carries information on the valuation of liquidity among American households. We find that local supply of credit is a key determinant of household valuation of liquidity, identifying an important channel by which location shapes behavior and welfare. Our results also provide strong motivation for enriching the targeting of social insurance from primarily household circumstances to also locations over time. Doing so could generate promising welfare improvements. Moreover, underscoring its relevance, our analysis shows that we can use penalized withdrawals as a dynamic tool to monitor the local valuation of liquidity across households and to guide richer targeting schemes for the large and growing government programs that provide social insurance protection.

Related Literature. The interest in the valuation of liquidity spans several fields, including public finance and macroeconomics, and encompasses the analysis of insurance and capital market inefficiencies, liquidity constraints and households’ ability to smooth marginal utility, and the optimal design of social insurance (see, e.g., Zeldes 1989; Parker 1999; Souleles 1999; Johnson et al. 2006; Card et al. 2007, and the review by Chetty and Finkelstein 2013). To this broad literature, we make three main contributions.

Our first contribution is to propose and validate a new tool to assess household valuation of liquidity, which overcomes previous measurement challenges. First, consumption is hard to measure: data are usually partial, measurement requires accounting for the flow value of durable goods, and it necessitates the use of economies of scale in household production

technology.³ Second, a fundamental challenge in welfare evaluations is the need to translate household behaviors to normative values by estimating households’ preferences, in a way that allows for heterogeneity as well as for state dependence (Landais and Spinnewijn 2021).⁴ Our approach overcomes these two challenges by relying on a margin—the choice of making a penalized withdrawal—which is both observable *and* directly reveals information on the underlying valuation of liquidity that is robust to any preference specification and state dependence.

Our second contribution is to offer a comprehensive analysis of the anatomy of variation in the valuation of liquidity across the U.S., identifying the underlying driving forces. In doing so, we contribute to several sub-strands of the literature. To the rich body of work showing that households are imperfectly insured against adverse economic shocks (specifically unemployment) by analyzing changes in consumption or income,⁵ we offer a direct assessment of fluctuations in the valuation of liquidity that is robust to the possibility that preferences are directly affected by employment status. That is, we provide a direct look at under-insurance and the valuation of liquidity in the short run and in the long run, freely allowing for consumption-leisure complementarities and any other form of state dependence in preferences. To the growing work showing the key role of location in determining well-being in the U.S., from education, to intergenerational mobility, to health,⁶ we add another important economic channel—credit and liquidity—by which location shapes behavior and welfare. Relatedly, in their recent work, Keys et al. (2020) analyze geographic variation in financial distress (focusing on collections, defaults, and bankruptcy), which could offer a look into some particular channels by which the variation in the valuation of liquidity in the U.S. that we analyze could be explained. To the work on racial disparities in consumption smoothing in response to shocks (such as Ganong et al. 2020), we contribute novel evidence that households in areas with a high percentage of blacks reveal a high valuation of liquidity and may be excluded from alternative credit channels. Lastly, to the extensive work on the Great Recession,⁷ we offer new insights by providing clear evidence on the dynamics of local valuation of liquidity and showing a quantitatively large role for a market spillover effect.

Our third contribution is to provide a new set of moments on the relationships between

³Recognizing the significant challenges involved in analyzing consumption data, recent work has developed new methods based on studying labor supply behavior (e.g., Shimer and Werning 2007; Chetty 2008; Landais 2015; Hendren 2017; Fadlon and Nielsen 2019).

⁴See also discussions in, e.g., Finkelstein et al. (2009, 2013), Chetty and Finkelstein (2013), and Coyne et al. (2019).

⁵See, for example, Sullivan and Von Wachter (2009); Kolsrud et al. (2018); Schmieder et al. (2018); Ganong and Noel (2019); Gerard and Naritomi (2021); Landais and Spinnewijn (2021).

⁶See, for example, Chetty and Hendren (2018a,b); Finkelstein et al. (2016, 2021).

⁷See, for example, Chodorow-Reich (2014); Chodorow-Reich et al. (2019); Yagan (2019)

economic shocks and valuation of liquidity that are informative for the emerging quantitative macro literature with heterogeneous agents.⁸ Our results strongly support the notion that even wealthy households may be liquidity constrained (Kaplan et al. 2014), and they offer a new set of targeted moments and external validation tests for quantitative exercises. For the same reasons explained above, targeting directly our moments on the valuation of liquidity, hence on distortions in the Euler equation, has the key advantage, relative to moments on consumption and income, that it is robust to different preference specifications and state dependence. This is even more important given the recent evidence that preference heterogeneity is central to properly accounting for the joint distribution of household level changes in income and consumption.⁹

Finally, we note that we are certainly not the first to study early withdrawals from retirement savings accounts, which have been a major policy concern for their potential effect on financial security at older ages. There is, in fact, work specifically focused on understanding overall leakages from retirement accounts and how they may react to economic circumstances. Two papers, in particular, are very related as they study how leakages increase after negative income shocks (Goodman et al. 2021) and the aggregate patterns of potential leakages around the Great Recession (Argento et al. 2015). Relative to this work, and beyond our broader empirical contribution, we differ by our focus on dissecting penalized distributions rather than overall leakages, and, most importantly, by the theoretical insight linking the act of making a penalized withdrawal to the valuation of liquidity and its determinants. Whereas early withdrawals have obvious implications for the soundness of the old-age pension system, our core conceptual contribution is to notice that early withdrawal behavior carries valuable information for our understanding of the broader financial environment in which households operate over the life cycle.

Structure of the paper. Section 2 discusses the institutional details of penalized withdrawals and describes our data. Section 3 introduces a conceptual framework to formalize the link between penalized withdrawals and household valuation of liquidity as well as to guide the empirical analysis. We then turn to our main empirical analysis: Section 4 studies household-level events and the valuation of liquidity; Section 5 studies local market supply of liquidity and households' access to credit based on spatial analysis; and Section 6 studies the evolution of local valuation of liquidity during the Great Recession. Section 7 discusses policy implications of our results, and Section 8 concludes.

⁸See, for example, Krueger et al. (2016); Kaplan et al. (2018); Auclert (2019); Auclert et al. (2020); Laibson et al. (2021).

⁹See Parker (2017); Aguiar et al. (2020)

2 Institutional Background, Data, and Motivating Facts

We begin by describing how penalized withdrawals work institutionally, introducing our dataset, and explaining how we measure penalized withdrawals for the U.S. population. We then use the data to investigate whether households rely on penalized withdrawals from their retirement savings accounts as a source of short-term liquidity.

2.1 Institutional Setting

Many financial savings instruments require that money is held for a specified period of time or until a certain date. These include vehicles such as Health Savings Accounts (HSAs), Certificates of Deposits (CDs), and, most prominently, retirement savings accounts—either employer-sponsored 401(k)s or private Individual Retirement Accounts (IRAs). Within these retirement accounts, holders may withdraw funds “early” but must pay a penalty when doing so. Specifically, in the U.S., holders of retirement accounts must pay a penalty of 10 percent (above and beyond their income tax liability) for withdrawals that occur prior to age 59.5. The presence of this penalty provides us with the underlying basis of our approach as we will elaborate.

Some early withdrawals are exempt from tax penalties due to the reason for withdrawal. An exemption is granted for the following events: account rollovers (e.g., across employers or from 401(k) to an IRA upon a job separation); permanent disability; death of account holder (allowing spouses to withdraw with no penalties); funds used for higher education; unreimbursed medical costs over 10 percent of the household’s adjusted gross income (AGI); first time home purchase; and separation from employment for those over age 55.¹⁰

To put penalized withdrawals in context, it is useful to describe the different ways in which U.S. households can access credit in the short run. Using data from the 2009 TNS Global Economic Crisis survey, Lusardi et al. (2011) examine households’ ability to come up with \$2,000 within 30 days if the need arises. They find that penalized withdrawals are perceived by many households as a relevant liquidity tool. The different methods and the share of households who expects to use each method (given in parentheses) are: savings (52.4), family (29.6), work more (22.9), credit cards (20.9), sell possession (18.8), liquidate retirement investments even if penalty is required (11.1), pawn assets (7.7), friends (7.4), unsecured loan (7.1), home equity line of credit (HELOC)/second mortgage (4.3), payday/payroll advance loan (3.6), liquidate investments (2.3), sell home (0.4).

¹⁰For more details, see IRS website at <https://www.irs.gov/retirement-plans/plan-participant-employee/retirement-topics-tax-on-early-distributions>.

2.2 Data

We describe our dataset, the sample restrictions, and the variables used in the analysis.

Data sources and sample construction. We use U.S. administrative tax records based on a 10 percent random sample of U.S. tax filers from 1999-2018 aggregated to the household level. Specifically, we select 10 percent of individuals based on the last 4 digits of their Social Security Number (SSN). We then pull tax records for taxpayers who report those SSNs on Form 1040 (income tax return) for either the primary filer or the spouse. In cases where spouses indicate that they are married filing separately, we combine their data to build a single household return comparable to those married filing jointly. Once we have constructed these households, we create a consistent panel for them throughout our data’s time range. We enrich the data from income tax returns with data from information returns filed by third parties (e.g., Form W-2, Form 1099-R, etc.).

For the core, analysis we restrict our sample to households who have an individual in the age range 45-59 as a primary filer. Throughout our analysis, when we use the term “age of the household” we always refer to the age of the primary filer. This age range condition allows us to focus on prime-age households who are likely to have retirement accounts and for whom this tool is more relevant, which we verify below. We identify households as having a retirement account in a given year if up to that year (within our sample period of 20 years) they report making a contribution to a 401(k) or an IRA account on Form W-2 or Form 5498, or if they have outstanding balances in IRA accounts as reported on Form 5498. Households can contribute to 401(k) accounts if such accounts are offered to them by their employer, and every household can contribute to an IRA account whenever they have earned income. We later restrict the analysis only to households who have a retirement account. As we show below, this restriction only drops a small share of households among our age group. Our overall sample consists of approximately 10.5 million households.

Variable definitions. The key outcome we study is penalized withdrawals from retirement savings accounts (401(k)s/IRAs) prior to age 59.5 with a penalty of 10 percent. We observe whether households took a distribution from the Form 1099-R (Box 1). We know whether or not the distribution was subject to the 10 percent penalty based on the distribution code reported on Form 1099-R (Box 7).

While there are several codes that correspond with penalized withdrawals, it is possible that a distribution coded as penalized on Form 1099-R is not ultimately penalized. For example, account administrators might not know the reason for withdrawal, and, without any additional input from the account owner, they might mark a distribution as penalized. However, if the account owner qualified for an exception but did not report this exception

to the fund manager, they would not necessarily be liable for the 10 percent penalty. There are also some exemptions that are correctly reported with the code “no known exception” but may not be subject to the 10 percent penalty, including withdrawals for unreimbursed medical expenses.

To account for these cases, we rely on the following tax rule. Taxpayers are given the opportunity to correct these potential discrepancies by filing Form 5329, which is *required* for all taxpayers who do not owe the 10 percent penalty on the entire amount of reported penalized early distributions. On Form 5329, taxpayers can claim the amount of early distributions that are not subject to the 10 percent penalty due to hardship exceptions, along with the specific appropriate exception on Line 2. In doing so, Form 5329 reports the corrected amount of the 10 percent penalty owed in Line 4. As such, for those taxpayers who file Form 5329, we further correct the amount of early penalized distributions extracted from Form 1099-R based on the information reported on Form 5329. There is no change for taxpayers who do not file Form 5329, since the default if a taxpayer does not file this form is to pay the 10 percent penalty on the entire amount of reported early distributions.

For the household’s economic circumstances, we rely on Form 1040. We define the household’s overall income as the household-level Adjusted Gross Income (AGI) minus the amount of penalized withdrawals. AGI includes earnings, capital income, retirement income, and taxable Social Security benefits. Labor supply outcomes are based on earnings, where we define employment as having positive earnings in a given year.

Additional information we use includes the following. We gather annually-reported location information based on the address provided on Form 1040. We extract information on outstanding IRA balances from Form 5498, which indicates the fair market value of all IRA accounts (Box 5). This value includes all investments in the account at year end on December 31, where account trustees and custodians are responsible for ensuring that all IRA assets (including those not traded on established markets or not having a readily determinable market value) are valued annually at their fair market value. Finally, we use Form 1099-G (unemployment benefits) to define unemployment events; we extract capital income from Schedule D of Form 1040 when we study variation by household capital income; and we extract employer ID (EIN) from Form W-2 to identify job switch events.

2.3 Four Motivating Facts on Penalized Withdrawals

We begin our look into the data by exploring patterns to shed light on when and how households use penalized withdrawals. We note that whereas some of these investigations can already have normative implications, the analysis we conduct here is purely in the realm of descriptives. We take this as a first step since little is known about the behavior of

taking penalized withdrawals itself. We will then provide the framework that injects direct normative interpretation and proceed with empirical analysis that aims to establish causal relationships. With that in mind, in this section, we will document four sets of facts that describe how households use penalized withdrawals, which will end up providing evidence in support of the hypothesis that penalized withdrawals are used as self-insurance for short-run liquidity needs.

Fact 1: Most households have retirement accounts. Figure 1 shows the prevalence of retirement savings accounts across U.S. households, by age and income, focusing on all households whose primary filer is between ages 25 and 70. Panel (a) shows that, for our selected age group (ages 45-59), almost 90 percent of households have at least one account. Panel (b) shows that, among households with income above the median (marked by the vertical line), almost everyone has an account. Accounts are instead less prevalent, as expected, for lower-income households. Nonetheless, even among the households with low levels of annual income, e.g., between \$10,000 and \$20,000, approximately half have an account. Overall, we conclude that retirement accounts are highly prevalent in the economy and that most American households have access to this form of short-term liquidity. We note that the high prevalence rate is reflective of our analysis unit of interest, that is, a household, whereas we could have expected lower prevalence rates if our analysis pertained to individuals.¹¹

As mentioned, from now on, we restrict the analysis to households that have a retirement account and whose primary filer's age is between 45 and 59.

Fact 2: Penalized withdrawals are widely used but infrequently. Next, Figures 2a and 2b show that penalized withdrawals are widely used by households throughout the age and income distributions. Within our age group, almost 10 percent of households make a penalized withdrawal in any given year. Penalized withdrawals are prevalent across the age distribution, but they fall, as expected, after age 55, when separation from employers becomes an exempted event. They are also prevalent across the income distribution, along with a declining frequency as household income increases. This is consistent with the idea that higher-income households have alternative cheaper sources of short-run liquidity to insure against economic shocks. Finally, we notice that most of the distributions are from 401(k) accounts, but a non-negligible fraction is from IRA accounts, a feature of the data that we leverage below.

Importantly, penalized withdrawals are not concentrated among a few households. Rather,

¹¹An additional reason prevalence is so high is our focus on filers. We show in Appendix Figure B.1 that overall prevalence shifts downwards (though still only moderately) when non-filers are included.

they are a prevalent liquidity tool across the whole population. Figure 2c shows the distribution of the number of years a household has taken a penalized withdrawal—almost half of the households observed for 15 consecutive years in our sample take a penalized withdrawal in at least one year. Moreover, the typical household withdraws infrequently, consistent with the hypothesis that they are using penalized withdrawals as a tool to access liquidity when the need arises. Finally, Figure 2d shows, among households who do make a withdrawal in some period, the distribution of subsequent periods within our data frame the household has made additional withdrawals. We provide two versions of this distribution for different definitions of “periods,” one that uses one-year periods and another that uses three-year periods (to allow for a longer period of “consecutive” liquidity needs). The figure displays large masses at zero, consistent with penalized withdrawals reflecting temporary financial constraints that require short-run liquidity.

Fact 3: Withdrawn amounts are sizable, yet accounts are not fully depleted.

Figure 3a shows the CDF, across all years and households for whom we observe a penalized withdrawal, of the dollar amounts of positive penalized distributions. The typical withdrawal is approximately \$5,000 (and most of the mass is within \$1,000 and \$20,000). These amounts are sizable and sufficient to provide substantial short-term liquidity relief for most households. For example, they could substantially mitigate the earnings losses upon unemployment which we find to be around \$20,000. The same figure also shows the CDF of positive amounts of any distribution (either penalized or subject to exceptions as described in Section 2.1). As expected, we notice that average penalized distributions are lower, consistent with the idea that households limit the amount withdrawn due to the presence of the marginal penalty.

As we next show, penalized withdrawals are usually not associated with an account closure, and they typically deplete only a relatively small fraction of the available funds. This evidence is consistent with the interpretation that they are the result of households withdrawing the necessary amount of money to self-insure a shock (i.e., they are in an interior solution) rather than closing old or secondary accounts, which could have been, in principle, a concern. To show this, we provide two exercises that exploit two features of the data: (i) for IRA accounts (but not for 401(k)s), we observe outstanding balances, and (ii) we can separate the distributions from IRAs using a designated checkbox on Form 1099-R. We restrict attention to households who have an IRA account at time $t - 1$ and who make a penalized withdrawal from an IRA account between periods $t - 1$ and t .¹² We first plot in

¹²As can be seen in Figures 2a and 2b, while most of the penalized withdrawals are made from 401(k) accounts, almost 1 percent of the households in our sample make a withdrawal from an IRA account in each period. This prevalence of withdrawals from IRAs should be considered relative to the baseline of share of households who have an IRA accounts as displayed in Figure 1.

Figure 3b the share of households who have no IRA balances left at the end of time period t as a function of the balance at time $t - 1$. This share is consistently below half throughout the account balance distribution, and, as expected, it shows a declining relationship with substantially lower rates if we focus on households who have non-trivial amounts of money in their accounts. Second, in Figure 3c, we compute, for those households that do not fully deplete their accounts, the ratio of the penalized distributions at time t out of the household's IRA balance at time $t - 1$, and we plot its CDF. We find that the median withdrawal depletes approximately 25 percent of outstanding IRA balances. Overall, the evidence shows that most households partially withdraw from their accounts and are therefore within an interior solution with respect to their withdrawal decision margin.

Fact 4: Penalized withdrawals are strongly associated with income losses. Lastly, Figure 4 shows that households who make a penalized withdrawal are more likely to have suffered an income loss. We plot the CDF of annual income changes, separating households according to whether they are making a penalized withdrawal in a given year. Among households who make a penalized withdrawal, almost 60 percent have experienced an income loss. Moreover, they are more likely to have experienced large income losses. For example, they are twice as likely, relative to households who have not made a penalized withdrawal, to have suffered an income loss larger than 50 percent.

2.4 Taking Stock

Taken together, the four facts just shown provide evidence that households use penalized withdrawals as a mean to mitigate short-run needs for liquidity. They are more likely to withdraw when experiencing negative income shocks, and they withdraw sizable sums of money that can relax short-run liquidity constraints. Overall, the evidence strongly motivates us to use penalized withdrawals as a revealed-preference tool to characterize the needs and valuation of liquidity across American households.

Yet, before moving forward with the analysis, we discuss and address two potential concerns with our approach: first, in our main dataset, we cannot observe how households use their funds, and hence we cannot directly show that they are used for self-insurance; second, any revealed-preference approach must rely on the assumption that agents are maximizing at the margin.

Evidence from Health and Retirement Study (HRS). We complement our data with information on premature withdrawals among American families from the Health and Retirement Study (HRS). Despite small samples, the key benefit from doing so is that households are asked to provide the reasons they withdrew funds prematurely. To get closest to

our population, we use survey waves 7-14 which cover the years 2004-2018, and we restrict the sample to respondents who have defined contribution pension plans and are of ages 45-59. The survey does not separate penalized from non-penalized withdrawals, so we provide statistics that pertain to any withdrawal that occurs prior to age 59.5 upon which the penalty is waived.

We rely on two main questions in the HRS, which relate to a household's experience between consecutive waves that are typically two years apart. The first question pertains to withdrawals and asks: "Not including any money you rolled into an IRA, not including any money you used to purchase an annuity. How much money in total did you 'withdraw'/'receive in payments' 'since you left that business or employer'/'since we last talked to you in [Previous Wave Interview Month] [Previous Wave Interview Year]'?" The second question pertains to the usage of withdrawn funds and asks: "What did you do with the money?" where respondents can choose among the options: bought durables (house, car, etc.), spent it, saved/invested, paid off debt, rolled into IRA, gave it away, other, as well as don't know and refuse to answer. The information on the usage of withdrawals that we use is based on the first usage indicated by the household.

Table B.1 summarizes these statistics. Panel (a) first provides the distribution of amounts of balances in defined contribution accounts and withdrawals from them, with numbers that are broadly in line with total withdrawals in Figure 3 from the tax data. Second, the taxonomy of uses of funds from early withdrawals in panel (b) aligns well with the notion that these funds are used for concurrent expenditure needs, corroborating the indirect evidence we have provided from the tax data.

Possible Behavioral Interpretations. Revealed-preference approaches rely on households' ability to optimize on the margin investigated. The regularities we have seen so far are closely consistent with various predictions of a model by which households optimize on the margin of taking penalized withdrawals. Still, it is important to assess the degree to which alternative potential explanations could drive the observed behavior. Indeed, economists justify the existence of illiquid accounts, either fully illiquid such as Social Security or partially illiquid such as 401(k)s/IRAs, with a trade-off between taste shocks (e.g., a realization of a real consumption need) and present biases that may lead them to over-consume (Amador et al. 2006; Beshears et al. 2020; Fadlon and Laibson 2021). In fact, one traditional rationale for government intervention in retirement savings (particularly in the form of Social Security) has been that some individuals lack the foresight to save for their retirement years (Diamond 1977; Feldstein 1985). In our context, the main concern is that the observed behavior could be generated purely by behavioral biases, such as narrow

bracketing (e.g., Thaler 1999), mental accounting (e.g., Read et al. 1999), or myopia/present bias (e.g., Laibson 1997; O’Donoghue and Rabin 1999), and may not convey information on the underlying valuation of liquidity. Reassuringly, as we next discuss, the evidence just presented is not consistent with these interpretations.¹³

First, the fact that most households withdraw sizable amounts and that the penalized withdrawals are only infrequently linked to the closure of a specific account mitigate the concern that withdrawals are mainly driven by narrow bracketing considerations, whereby households do not integrate their entire portfolios into their decision making (e.g., Thaler 1999). With narrow bracketing, in contrast, we could expect withdrawals to be the result of households disregarding some small amounts left in isolated accounts, which they then might close down without direct link to their actual liquidity needs. Second, under mental accounting (e.g., Read et al. 1999), households’ behavior would involve some assignment of activities to specific accounts, thereby potentially avoiding the liquidation of funds that are mentally designated for consumption later in the future. In contrast, we have seen that withdrawals are prevalent across the whole population, and we will show they are increasingly used exactly when large income losses occur. Third, if penalized withdrawals were driven by myopic behavior among a particular share of the population with present bias, we would expect to observe that most of the withdrawals are due to repeated take-up by the same set of households. Instead, Figure 2c clearly shows that withdrawals are rare for any given household and widespread across the population, consistent with the idea that they are optimal responses to economic shocks. While the data are inconsistent with the particular margin of penalized withdrawals being driven by myopia, some households are, naturally, present-biased, and the infrequency of penalized withdrawals certainly does not preclude their presence. However, in such a case, observing a penalized withdrawal would still inform us about the relative valuation of liquidity in a given period among optimizing present-biased households, in light of the properties of their value functions developed in Maxted (2020).

3 Conceptual Framework

We next develop a simple theoretical framework with two goals. The first goal is to formalize the idea that the choice of making penalized withdrawals is informative of households’ valuation of liquidity. This will provide the mapping between withdrawal behavior and valuation with an explicit layout of the underlying assumptions. The second goal is to motivate our empirical analysis by illustrating how the valuation of liquidity is an equilibrium object

¹³Of course, while the evidence is inconsistent with these behavioral explanations governing the results, they could still naturally play a role.

determined by both the local supply of credit and the demand for liquidity.

3.1 Model Setup

We consider the problem of a household i , who lives in region z and chooses consumption over the life cycle. The household earns income in each period, $y_{i,t}$, which can be used for consumption, $c_{i,t}$, or saved in either a liquid asset or a retirement savings account for future consumption. The household also receives a share φ of earnings that is directly deposited into the retirement savings account by the employer.

To finance consumption, the household can get funds from the available liquid assets, borrow liquid assets paying an additional marginal cost $\rho_{i,z}$, so that for each dollar borrowed only $1 - \rho_{i,z}$ dollars are available for consumption, or withdraw from the retirement savings account. The cost $\rho_{i,z}$ is specific to household i and location z in which the household resides. It is a perceived shadow cost of funds, which captures the expected optimal borrowing choices across alternative sources of funds that are available for, and known to, the household. Therefore, $\rho_{i,z}$ is a reduced-form measure of the local, household-specific, supply of credit, as perceived by household i .

If the withdrawal from the retirement savings account is done before a statutory retirement age (denoted as time t^*), the household has to pay a marginal penalty τ , so that, for each dollar withdrawn, only $1 - \tau$ dollars are available for consumption. Due to the penalty τ , we refer to the retirement savings account as the illiquid account. We denote the balances in the liquid and illiquid accounts at the beginning of period t by $a_{i,t}$ and $k_{i,t}$, and we let $\Delta a_{i,t}$ and $\Delta k_{i,t}$ represent the net flows within these accounts across time periods.

We denote by $h_{i,t}$ the household's full history by period t , and we let the flow utility be indexed by history, that is: $u(c_{i,t}; h_{i,t})$. This flexibility offers three advantages: (1) Dynamically, it allows the utility function to be history dependent, for example, as a function of marital status, fertility choices, or employment history and status (which also captures consumption-leisure complementarities and consumption complementarities across household members). (2) Cross-sectionally, since $h_{i,t}$ varies across households, it allows the utility function to be household specific—i.e., different households might get different utility from the same level of consumption. (3) It freely allows for state dependence in preferences, hence permitting important cases when the demand for liquidity could be driven by household shocks that also affect preferences for consumption (e.g., severe health shocks). This level of flexibility highlights a strength of our approach—we directly reveal valuation of liquidity from household behavior without having to rely on structural assumptions that map behaviors to preferences.

We define $V_t(a_{i,t}, k_{i,t}; h_{i,t})$ to be the value of the problem at time t for household i with

history $h_{i,t}$, liquid asset $a_{i,t}$, and illiquid asset $k_{i,t}$. The household's optimization problem can then be written as:

$$V_t(a_{i,t}, k_{i,t}; h_{i,t}) = \max_{\Delta k_{i,t}, \Delta a_{i,t}} u(c_{i,t}; h_{i,t}) + \beta E_t [V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})]$$

subject to:

$$\begin{aligned} c_{i,t} &= (1 - \varphi) y_{i,t} - \Delta k_{i,t} - \Delta a_{i,t} + \tau \Delta k_{i,t} \mathbb{I}_{(\Delta k_{i,t} < 0)} \mathbb{I}_{(t < t^*)} + \rho_{i,z} \Delta a_{i,t} \mathbb{I}_{(a_{i,t} < 0)} \mathbb{I}_{(\Delta a_{i,t} < 0)} \\ a_{i,t+1} &= (1 + r) [a_{i,t} + \Delta a_{i,t}] \\ k_{i,t+1} &= (1 + r) [k_{i,t} + \Delta k_{i,t} + \varphi y_{i,t}] \end{aligned}$$

where β is the discount factor. It is important to emphasize one feature of this formulation—the value functions are indexed by time and by the household history since they vary both across time and across households even conditional on the state variables.

3.2 Equilibrium Valuation of Liquidity

We next define our main object of interest, the value that a household assigns in equilibrium to an extra unit of liquidity, relative to a benchmark world with an undistorted Euler equation.

Definition 1: Equilibrium Valuation of Liquidity. *The equilibrium valuation of liquidity for household i at time t consuming c_t is given by*

$$\theta_{i,t}(c_{i,t}; h_{i,t}) \equiv u'(c_{i,t}; h_{i,t}) \left(E_t \left[\frac{\partial V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})}{\partial a_{i,t+1}} \right] \right)^{-1} (\beta (1 + r))^{-1}$$

which is the ratio between the marginal value of a liquid dollar today (in terms of consumption) at consumption level c_t and the expected value of a marginal liquid dollar tomorrow.

The following lemma builds some intuition on $\theta_{i,t}(c_{i,t}; h_{i,t})$ by showing its value in different benchmark scenarios. Proofs for all Lemmas are provided in Appendix A.

Lemma 1: Benchmarks for the Equilibrium Valuation of Liquidity. *The equilibrium valuation of liquidity for household i at time t and for any history $h_{i,t}$ satisfies:*

1. *If credit markets are perfect – i.e., $\rho_{i,z} = 0$ – then $\theta_{i,t}(c_{i,t}; h_{i,t}) = 1$.*
2. *If the household saves in the liquid asset – i.e., $\Delta a_{i,t} > 0$ – then $\theta_{i,t}(c_{i,t}; h_{i,t}) = 1$.*
3. *If the household borrows from the liquid asset – i.e., $\Delta a_{i,t} < 0$ – then $\theta_{i,t}(c_{i,t}; h_{i,t}) \geq \frac{1}{1 - \rho_{i,z}}$.*

A few comments are in order. First, notice that even in the presence of perfect credit markets, the household's consumption may fluctuate over time, for example, as a function of changes in household circumstances, consumption needs, or preferences. Yet the valuation of liquidity must be equal to 1 since the household Euler equation must be undistorted as households can save and borrow with no limits at the same interest rate r . This underscores a challenge in the analysis of fluctuations in consumption to recover information on fluctuations in marginal valuation, which we overcome with our revealed-preference approach. Second, households that save also have valuation of liquidity equal to 1, suggesting that, just as in the case of perfect credit markets, they are perfectly smoothing marginal utility over time in expectation at time t .¹⁴ Finally, if a household is borrowing from the liquid asset, the valuation of liquidity is a function of the shadow cost of funds. In fact, if we could observe each household's shadow cost of funds, $\rho_{i,z}$, this would directly inform us of the household's valuation of liquidity; intuitively, if you are willing to borrow at a high interest rate, your marginal valuation of funds today must be at least as large. However, in practice, researchers do not directly observe $\rho_{i,z}$ since this value captures not only the specific interest rate that each household may pay on a credit card or bank loans, but it is also a summary of all the available means of credit that each household may or may not have access to. Our approach overcomes this information hurdle by relying on revealed preferences based on a credit product whose marginal price is known for all households. The fact that this price is uniform also allows us to conduct comparisons across households, time, and space.

As Lemma 1 remarks, $\theta_{i,t}(c_t; h_{i,t})$ is a useful equilibrium object, which conveys important information both on households' utility and on the underlying credit markets. Indeed, it directly informs of the value that a given household assigns, at a specific point in time and given the credit resources available, to the relaxation of their credit constraint. At the same time, however, it is very hard to directly measure $\theta_{i,t}(c_t; h_{i,t})$ in the data for several reasons. First, we do not observe u' , which poses the major traditional challenge of preference identification (see, e.g., Chetty and Finkelstein 2013). Second, it requires data on the consumption aggregate c_t , which should include comprehensive consumption data on both durable and non-durable goods. It also necessitates estimation of scale economies in consumption in the context of households, in order to translate consumption utility into per capita terms as the required moment for welfare analysis (see, e.g., Fadlon and Nielsen 2019). Third, even if we could observe $u'(c_t; h_{i,t})$, it is even harder to compute the expected value

¹⁴It is important to notice that this result does not imply that the *realized* ex-post marginal utility is constant over time. For example, in the presence of precautionary savings due to prudence (Carroll 1997), $\theta_{i,t}(c_t; h_{i,t})$ would be equal to 1 as long as a household saves, yet consumption (and, accordingly, the marginal utility) may fluctuate over time as a function of household level income shocks.

of a dollar tomorrow, $E_t \left[\frac{\partial V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})}{\partial a_{i,t+1}} \right]$ since this requires knowledge of households' expectations about future income and consumption needs.

The main contribution of this paper is to offer an indirect, revealed-preference approach that conveys important information on our object of interest $\theta_{i,t}(c_t; h_{i,t})$ and bypasses the stated challenges. As we explain below, we rely on penalized withdrawals as a tool to recover direct information on $\theta_{i,t}(c_t; h_{i,t})$ and thus also indirectly gather information about local credit conditions, or $\rho_{i,z}$ in our model. Before we do so, it is convenient to define another useful theoretical object that represents the relative value of funds in the liquid and illiquid accounts.

Definition 2: Relative Value of Illiquid Dollars. *The value of an illiquid dollar relative to a liquid dollar is the ratio between the expected marginal values of an illiquid and a liquid dollar tomorrow:*

$$\pi(h_{i,t}) \equiv \frac{E_t \left[\frac{\partial V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})}{\partial k_{i,t+1}} \right]}{E_t \left[\frac{\partial V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})}{\partial a_{i,t+1}} \right]}.$$

The next lemma characterizes how this value behaves in equilibrium.

Lemma 2: Bounds and Special Cases of the Relative Value of Illiquid Dollars.

The relative value of an illiquid dollar satisfies $\pi(h_{i,t}) \in [1 - \tau, 1]$. Furthermore, for all $h_{i,t}$, $\pi(h_{i,t}) = 1$ if either $t = t^$ or if the perceived probability that a household makes a penalized withdrawal or borrows from the liquid account is zero in the window $(t, t^*]$.*

The upper bound is due to the fact that both accounts offer the same interest rate and that, at time t^* , the illiquid account becomes liquid. As a result, while funds in the illiquid accounts are generally less valuable due to the withdrawal penalty τ , they are equally valuable for a household that, with probability 1, will not make a withdrawal before time t^* .¹⁵ For this same reason, $\pi(h_{i,t}) = 1$ if the household expects with certainty not to pay a penalty (for example, because it is time t^*) since in this case the household expects all the illiquid dollars to become liquid *before* they will withdraw them.¹⁶ The lower bound, instead, is due to optimal household behavior. If the bound does not hold, then it would be

¹⁵In practice, illiquid accounts may pay higher interest rate. Assuming that the two accounts offer similar interest rate simplifies the analysis. Yet, the main insights do not hinge on this assumption. In fact, observing a penalized withdrawal would be an even stronger signal of liquidity needs if a household not only has to pay a penalty, but also forgoes the higher interest gains.

¹⁶For the value of funds to be identical in the two accounts (i.e. $\pi(h_{i,t}) = 1$), we need to condition on those households that do not expect to borrow from the liquid account before t^* . If a household expects to borrow, then funds in the liquid account are more valuable as they could prevent the household from paying the marginal cost of borrowing $\rho_{i,z}$.

optimal for a household to transform one marginal illiquid dollar into $1 - \tau$ liquid dollars, until $\pi(h_{i,t}) = 1 - \tau$.

3.3 Penalized Withdrawals and Valuation of Liquidity

A core goal of the model is to formalize the idea that observing households making a penalized withdrawal reveals information on their valuation of liquidity; a task to which we turn in the next lemma.

Lemma 3: Withdrawals and Equilibrium Valuation of Liquidity. *If a household withdraws from the illiquid account at time $t < t^*$, then $\rho_{i,z} > \tau$ and:*

$$(1) \quad \theta_{i,t}(c_{i,t}; h_{i,t}) \geq \left(\frac{1}{1 - \tau} \right) \pi(h_{i,t}).$$

The intuition for this result is straightforward if we first consider the last period before retirement age (so that it is time t^* and $\pi(h_{i,t^*}) = 1$). If a household can freely withdraw funds from the illiquid account next period but still decides to withdraw today paying a penalty τ , then we can infer that the household does not have access to cheaper credit and that it values a marginal dollar by at least as much as the penalty they have to pay on it.

This simple insight applies more broadly but needs to be refined. As Lemma 3 shows, in general, we need to also consider that the marginal valuation of liquid and illiquid funds may vary, as captured by the term $\pi(h_{i,t})$. If the illiquid funds become liquid next period (i.e., $t = t^*$), or if the household does not expect to make further withdrawals until retirement, then $\pi(h_{i,t}) = 1$, and thus, the simple insight applies exactly. Nonetheless, even in the case with $\pi(h_{i,t}) < 1$ (so that $\pi(h_{i,t}) \in [1 - \tau, 1)$), penalized withdrawals reveal a relatively high equilibrium valuation of liquidity in excess of the undistorted benchmark. First, the fact itself that illiquid dollars are less valuable than liquid dollars implies that liquidity is valuable for household i since they expect to make penalized withdrawals throughout their life cycle, i.e., the liquid account itself is not sufficient to provide self-insurance. Second, notice that, for $\pi(h_{i,t})$ to be at its lower bound $1 - \tau$, it has to be that at time t the household knows with certainty that at $t + 1$ they will withdraw with penalty all their illiquid savings. As a result, in general $\pi(h_{i,t}) > 1 - \tau$, which implies that observing a penalized withdrawal signals high equilibrium valuation of liquidity at time t .

Importantly, as we have shown empirically in Section 2, most households make penalized withdrawals only infrequently: conditional on withdrawing at least once, more than 50

percent of households make only one penalized withdrawal.¹⁷ This result suggests that the insights from the simple benchmark (of $\pi(h_{i,t}) = 1$) are likely to hold as the empirically relevant ones.

3.4 Towards an Empirical Implementation

Lemma 3 describes how observing a given household withdrawing at a point in time provides information on their equilibrium valuation of liquidity. In practice, in our empirical specifications we consider linear probability models for the probability of making a withdrawal or, alternatively, the share of households that make a penalized withdrawal given some observed characteristics. Lemma 4 formalizes how these observable empirical objects relate to the model's primitives, thus concluding the theoretical analysis and motivating our empirical investigation.

Lemma 4: Probability of Making a Penalized Withdrawal. *Define $\mathbb{S}(\rho_{i,z}) \equiv \mathbb{I}_{\rho_{i,z} > \tau}$, and $\mathbb{D}(h_{i,t}) \equiv \mathbb{I}_{\theta_{i,t}(y_{i,t} + a_{i,t}; h_{i,t}) > (\frac{1}{1-\tau})\pi(h_{i,t})}$. Then the indicator variable for the event that household i with history $h_{i,t}$ in region z makes a penalized withdrawal is*

$$(2) \quad \underbrace{\sigma_z(h_{i,t})}_{\text{Withdrawal Event}} = \underbrace{\mathbb{S}(\rho_{i,z})}_{\text{Supply}} \times \underbrace{\mathbb{D}(h_{i,t})}_{\text{Demand}}$$

Further, define a set \mathcal{I}_t of households with certain observable characteristics at time t . Then the share of these households in region z who make a penalized withdrawal, $\Sigma_{z,t}(\mathcal{I}_t) \equiv \int \sigma(h_{i,t}) dF_{z,t}(h_{i,t}|\mathcal{I}_t)$, can be written as

$$(3) \quad \underbrace{\Sigma_{z,t}(\mathcal{I}_t)}_{\text{Share of Withdrawals}} = \underbrace{\int \mathbb{S}(\rho_{i,z}) dG_z(\rho_{i,z}|\mathcal{I}_t)}_{\text{Local Supply of Credit}} \times \underbrace{\int \mu(h_{i,t}) \mathbb{D}(h_{i,t}) dF_{z,t}(h_{i,t}|\mathcal{I}_t)}_{\text{Local Demand for Liquidity}}$$

where $G_z(\cdot|\mathcal{I}_t)$ is the distribution for these households over cost of capital in region z ($\rho_{i,z}$), $F_{z,t}(\cdot|\mathcal{I}_t)$ is the distribution over all their histories ($h_{i,t}$), and $\mu(h_{i,t}) \equiv \frac{\mathbb{S}(\rho_{i,z})}{\int \mathbb{S}(\rho_{i,z}) dG_z(\rho_{i,z}|\mathcal{I}_t)}$ is a weighting factor to capture the possible correlation between demand and supply drivers of withdrawals.¹⁸

Equation (2) shows that, for a household to make a penalized withdrawal, two conditions must apply: (i) the household does not have access to cheaper available funds (weak *supply*

¹⁷Lemma 3 points out that households that make a penalized withdrawal must have $\rho_{i,z} > \tau$, which implies that they will also never borrow from their liquid assets but will rather rely on penalized withdrawals (unless they have exhausted all their illiquid funds, which is atypical in practice).

¹⁸To understand the notation, recall that $h_{i,t}$ includes all household information, hence also their shadow cost of capital $\rho_{i,z}$.

of credit); (ii) the household needs to borrow in order to smooth the value of consumption over time, as captured by the fact that, without borrowing, their valuation of liquidity is higher than what could be achieved by making a penalized withdrawal (strong *demand* for liquidity).¹⁹

Equation (3) then aggregates equation (2), summing over the population of households with certain characteristics \mathcal{I}_t . The equation shows that, at each point in time, the share of households with given characteristics making a penalized withdrawal is a function of their local supply of credit and demand for liquidity. The first term in the equation measures the local supply, by calculating the share of households who face cost of capital more expensive than the penalty τ , hence those who face limited supply of credit. The second term in the equation captures the local demand, by summing over all the households who would have, if they consumed all their income and liquid savings, a valuation of liquidity higher than $\left(\frac{1}{1-\tau}\right) \pi(h_{i,t})$. Equation (3) offers a structural counterpart to the empirical objects that we are going to use in our empirical analysis in Sections 4, 5, and 6.

From Model to Data. Before turning to the data, it is important to remark how this section has set the foundation for the empirical analysis. We are not going to bring the model structurally to the data. Rather, the model provides the foundation for the empirical regressions, and it maps them into objects that have a clear theoretical meaning. In particular, two equations lead and motivate our empirical analysis. Equation (1) motivates us to study penalized withdrawals: while we are not interested in leakages from retirement accounts per se, penalized withdrawals are a signal that reveals a high valuation of liquidity, which is difficult to measure directly. Equation (3) shows that a high valuation of liquidity could be driven by either demand forces or supply forces, and it motivates us to leverage the empirical variation to unpack both drivers as follows. *Section 4* will study household level events. By following a set of households over time, with the vast majority staying in the same location, we aim to keep constant the local supply of credit and identify life cycle events that affect the *demand* for liquidity of a set of households.²⁰ This maps to $\mathbb{D}(h_{i,t})$ and primarily uses variation in $y_{i,t}$. *Section 5* instead will study the determinants of local *supply* of credit (governed by $\rho_{i,z}$ and maps to $\mathbb{S}(\rho_{i,z})$), and it will unpack them into components that are specific to locations (Γ_z) and components that are specific to households (α_i). In particular,

¹⁹Notice that this is slightly different from the condition in Lemma 3. Lemma 3 was only considering households that make a penalized withdrawal, while we here consider all households, some of whom may end up having in equilibrium valuation of liquidity lower than $\left(\frac{1}{1-\tau}\right) \pi(h_{i,t})$ due to borrowing from their liquid assets.

²⁰In practice, we will show that the results are almost identical if we limit the analysis to the households who remain in the same commuting zone around the specific events that we study, such as becoming unemployed.

postulating that the shadow cost of capital is a function of a household component and a location component (specifically, $\rho_{i,z} = \alpha_i + \Gamma_z$), a simple movers design that includes a rich set of controls to account for variations in the demand for liquidity (to the extent possible) can unpack the local supply of credit. We will additionally study how these components vary as a function of observable characteristics. Finally, *Section 6* will consider an extended version of the model in which, conceptually, we allow the location component of supply of credit to vary over time, $\Gamma_{z,t}$. It will study how $\Gamma_{z,t}$ has been dynamically affected by the Great Recession and translated to valuation of liquidity.

4 Household Events and Valuation of Liquidity

In this section, we study how changes in the demand for liquidity at the household level lead to changes in their valuation of liquidity. Conceptually, we are interested in tracing how shifts in the demand for liquidity lead to movement along the supply function and, hence, to changes in the equilibrium valuation of liquidity. Doing so allows us to learn the extent to which household level shocks are insured by the credit market. In a world with perfect markets, households face a horizontal supply curve at the prevailing interest rate, so that an upward shift in demand for liquidity would be absorbed by more borrowing without leading to a change in its equilibrium valuation. In the language of Equation (3), $\int \mathbb{S}(\rho_{iz}) dG_z(\rho_{iz}|\mathcal{I}_t)$ would be equal to 0, in which case any change in demand would not lead to a change in penalized withdrawals. Instead, as long as some households face restricted supply of credit—that is, $\int \mathbb{S}(\rho_{iz}) dG_z(\rho_{iz}|\mathcal{I}_t) > 0$ —we should observe that an increase in household level demand would lead to an increase in withdrawals and, accordingly, in the valuation of liquidity.

Many types of shocks may affect the demand for liquidity at the household level. In practice, given the nature of our data, the main candidates to investigate in our setting are household level events that affect income, such as unemployment and job changes. We study both within a similar event study framework, which we now describe.

Estimating Equation. Our event study estimating equation takes the form:

$$(4) \quad y_{i,t} = \sum_{r \neq -2, r=-5}^{r=10} \beta_r \times I_r + x_{i,t} \lambda + \alpha_i + \varepsilon_{i,t},$$

where $y_{i,t}$ is an indicator for a penalized withdrawal for household i at time t , $x_{i,t}$ is a full set of age fixed effects for the primary-filer and (cyclical) calendar year fixed effects, and

α_i are household fixed effects.²¹ We let $r(i, t)$ denote the year relative to the event timing for household i at time t , so that $I_r = \mathbb{I}_{r(i,t)=r}$ represent a set of relative time indicators. We take the baseline year to be -2 to capture changes in trends that could happen toward the realization of the event. We plot β_r around different events to trace the evolution of households’ withdrawal behavior, where we are interested in capturing behavioral responses to the realization of the event as well as in anticipation of the event to evaluate the full dynamics of the valuation of liquidity. We note that the year -1 coefficient can incorporate anticipation but also potential effects of the onset of an event, given the annual frequency of the data at the end of a calendar year and the defined timing of the event. For example, households who experience a large decline in income (which we take to be at least 20 percent) between the end of period 0 and period -1 would be assigned a “large income decline” event at 0, but the process of a decline in income could have already (and likely) began throughout the year -1 .

Next, we use this empirical framework to study the dynamics of household penalized withdrawals around the events of unemployment, income changes, and job-to-job moves.

4.1 Unemployment Event

As a first step, we focus on household unemployment events. We define unemployment as the first period we observe at least one of the household members receiving unemployment benefits.

Results and Interpretation. Panel (a) of Figure 5 plots the event study coefficients β_r for this event. It shows that, as the event approaches, there is some increased take-up of withdrawals, which is then followed by a large spike in penalized withdrawals in the year of the event. Through the lens of our model, it implies that the share of households with high valuation of liquidity more than doubles at the onset of the event, relative to the constant of 8.3 percentage points (pp) that can be attributed to $t = -2$. While the large increase declines relatively quickly over subsequent periods, there is still some elevated take-up in the years that follow. Overall, the cumulative use of penalized withdrawals in the five years following the unemployment event amounts to 20 pp.

The findings of large and persistent increases in penalized withdrawals signal that unemployment leads to a large increase in the valuation of liquidity. Unemployment shocks are therefore far from being perfectly insured, and, in fact, our analysis suggests that existing unemployment subsidies are not sufficient to smooth marginal utility of consumption. As

²¹In the samples on which we run these regressions, we include all households to help with identification of non-event coefficients and we accordingly add to $x_{i,t}$ a dummy for households who do not experience an event.

a result, more generous social insurance policies would be, purely from a marginal utility smoothing perspective, welfare improving. Of course, in practice, we would need to weigh these benefits against potential costs, such as financial externalities through effects on employment.

The findings are consistent with the literature on the effects of unemployment on earnings and consumption, which has shown large declines in consumption in the short run with lingering effects on earnings in the long run.²² Unlike these assessments of income or consumption, however, our investigation of the valuation of liquidity is robust to the possibility that preferences are themselves affected by employment status. This could be the case, for example, if employment leads to different consumption needs, such as the classic substitution to cooking meals at home while unemployed and the reduction in time and monetary costs involved in commuting.

Heterogeneous Effects. We can use our approach to explore how different types of households vary in the degree to which they are insured against unemployment. Doing so allows to both shed new light on the household level determinants of valuation of liquidity and to validate our approach by exploring how some of our results that relate to existing literature are consistent with previous findings.

Motivated by the large peak in withdrawals that occurs at the time of the unemployment event (panel (a) of Figure 5), we focus on this particular moment as a natural measure of household-level self-insurance, and we show how it varies as a function of different observable characteristics.²³

First, in panel (b) of Figure 5, we study how the responses may vary by the age of the primary filer. Prior to age 55, when job separations become eligible for non-penalized withdrawals, we find a gradient with respect to age in withdrawal probability upon unemployment.²⁴ The evidence is consistent with the idea that older households, who had more time to accumulate a buffer stock of savings, may be more resilient to shocks and have lower

²²See, e.g., Sullivan and Von Wachter (2009); Kolsrud et al. (2018); Schmieder et al. (2018); Ganong and Noel (2019); Gerard and Naritomi (2021).

²³In what follows, when the characteristics are observed at the household level (i.e., age and capital income), we present heterogeneity results from a regression that simultaneously includes these categories, as well as additional household level controls: home ownership (an indicator based on claimed property tax or mortgage interest deductions from Schedule A and mortgage information from Form 1098), a dummy for whether the primary filer is married, the number of dependents, and the average household income based on information from all years within our data range.

²⁴As discussed, our analysis is done at the household level. As a result, even if the primary filer is older than 55, the secondary filer could be younger than 55, hence still being ineligible to make non-penalized withdrawals. This explains why we still see a positive mass of withdrawals with penalty after age 55. Relatedly, in Appendix Figure B.3 we report the unemployment event study estimates for observations with primary filers younger than 55 to account for the change in withdrawal rules at that age.

liquidity needs.²⁵

Second, in panel (c) of Figure 5, we study how the responses may vary with households' capital income, which is the best available measure in our data of household wealth. We split households into those with negative, zero, or positive capital income, and we bin the ones with positive capital income into four groups. In the non-negative range, we find evidence that is closely consistent with our revealed-preference interpretation of withdrawing with penalties—households with access to alternative financial means that can provide liquidity have lower increases in the valuation of liquidity, likely due to lower residual uninsured risk.²⁶ While the differences across households are sizable, it is worthwhile to notice that even households in the top quartile of capital income display a meaningful increase in penalized withdrawals when experiencing the event. Considering that those households have an average capital income close to \$40,000 per year, this result strongly corroborates the notion that even wealthy households might be liquidity constrained (e.g., Kaplan et al. 2014).

Third, we turn to geography-based differences. We focus on two dimensions of heterogeneity across locations which we will show in Section 5 to be particularly relevant. The first is the Credit Insecurity Index, which is a measure developed by the Federal Reserve Bank of New York for assessing American communities' credit health and well-being (Hamdani et al. 2019). The second is the share of black households living in a location, which allows us to explore the hypothesis that black communities might be marginalized from the credit market (Ganong et al. 2020). Panels (d) and (e) of Figure 5 show that, in both cases, the results confirm our priors—households either in areas with worse Credit Insecurity Index or in communities with a higher share of black households are less able to self-insure against unemployment shocks and, hence, have a higher valuation of liquidity. The magnitudes are economically relevant—locations in the fifth quintile of the Credit Insecurity Index have approximately 25 percent more penalized withdrawals than those in the first, and locations in the fifth quintile of the share of black households have approximately 15 percent more penalized withdrawals than those in the first.

Of course, all the heterogeneity results discussed here are purely correlational, and it is naturally difficult to tease apart the exact mechanism leading to the documented patterns. Nonetheless, we believe that the analysis shows the potential of using penalized withdrawals to shed light on the candidate determinants of households' ability to self-insure shocks and

²⁵Another possible interpretation in line with our conceptual framework is that the gradient is driven by intertemporal substitution as households are approaching an age in which they can withdraw without paying a penalty.

²⁶The somewhat lower levels of withdrawals at the region of negative capital income could be reflective of the notion that these households still have better access to capital markets as compared to households that are unlikely involved in capital markets altogether (those with zero capital income).

their liquidity needs. Even more, the heterogeneity analysis is directly informative for targeting households with a higher valuation of liquidity along observable/measurable dimensions (e.g., age, wealth, location, and race), which are the exact moments we have assessed and are independent of the mechanism that drives the differences.

4.2 Income Changes and Job-to-Job Moves

Next, we look at income changes, both with and without concordant job switches. We first look at large income losses as an event, which we define as a first period we observe a household experiencing a decline in overall income of more than 20 percent (relative to a previous year). Panel (a) of Figure 6 displays the event study coefficients, showing a large increase in withdrawals—and hence in the valuation of liquidity—upon the event. This suggests that income shocks, just as unemployment events, are far from being formally fully insured and that households have to rely on some self-insurance through penalized withdrawals to a large degree.

We then dig deeper into variation in income changes. To do so, we calculate for each household in a given year, the deviation of their income flow from their average income within our data period. Panels (c) and (d) of Figure 6 plot the behavior of penalized withdrawals—take-up and amounts, respectively—as a function of income deviations. We additionally split households by whether a member of the household switched jobs that year. This is because job changes themselves, as displayed in panel (b) of Figure 6, lead to increased take-up.²⁷

Panels (c)-(d) of Figure 6 reveal a clear pattern. First, we find a strong gradient with respect to income losses. Larger income losses lead to a higher frequency of withdrawals with a large increase of more than 19 pp by those with the largest losses. This supports our underlying model where penalized withdrawals are used as means of short-run self-insurance. Second, we find stark asymmetry around zero, where behavior completely flattens in the income increases domain. This is consistent with the self-insurance hypothesis, and it rules out alternative explanations. Specifically, it is inconsistent with the notion of strategic withdrawals for tax purposes as driving the penalized withdrawals behavior. In that case—that is, if households withdrew funds with penalty differentially as their current marginal tax rate

²⁷This could be driven by several factors such as increases in the valuation of liquidity in the transitional period, as well as alternative considerations such as salience or simply choosing to cash out if the balance is negligible. Recall that we exclude account rollovers which are just mechanical transfers of funds and could be common upon job separation. That said, upon job separation, low balances below a certain threshold can be automatically paid out in cash to the departing employee, with thresholds of \$5,000 prior to 2005 and \$1,000 thereafter. (Note that amounts between \$1,000 and \$5,000 can be automatically rolled over into an IRA post-2005.) To account for negligible balances and these automatic passive penalized distributions, Appendix Figure B.4 replicates all our event study analyses but where the outcome variables are indicators for taking penalized withdrawals that are higher than given thresholds.

changes—we would expect to observe some degree of a gradient in the entire income changes domain. Third, we note that even households experiencing positive income changes make non-negligible penalized distributions, with average withdrawal amounts close to 1 percent of average income. This result suggests that, as long as households are maximizing on the margin (as the evidence pointed to in Section 2), the equilibrium valuation of liquidity is not only driven by income shocks, but it is also driven by changing consumption needs through expenditure shocks (such as health shocks, child-related expenses, etc.). As a result, even perfectly insuring households against negative income shocks would still be likely insufficient to achieve marginal utility smoothing over time.

Summary. Overall, the analysis of household events shows large increases in the valuation of liquidity upon adverse financial circumstances. This result reveals that households face constrained supply of credit, so that shifts in demand for liquidity significantly impact their equilibrium valuation of liquidity. Additionally, the analysis corroborates the underlying hypothesis of our model that withdrawals represent needs for liquidity, here driven by increases in demand.

5 Local Supply of Credit and Valuation of Liquidity

Section 4 has shown that households are only imperfectly able to self-insure—events that negatively affect their income lead them to make penalized withdrawals. In the language of our leading equation (3), we learned that households face a limited supply of credit, $\int \mathbb{S}(\rho_{iz}) dG_z(\rho_{iz}|\mathcal{I}_t) > 0$, which induces some of them to rely on withdrawals in the face of income shocks. Given this result, it becomes natural and important to investigate the determinants of the local supply of credit and how it varies across households and locations.

In an ideal case, one would want to know the full schedule of credit supply and the corresponding shadow costs of capital for each household. This would require data on all the credit instruments available to each particular household and their direct and indirect costs. With these data, one could then study how credit access varies across household characteristics and locations, thus providing useful evidence to optimally target liquidity injections across households of different types and who live in different locations. To the best of our knowledge, however, such rich data are essentially impossible to build, as we rarely observe the full set of available credit vehicles (e.g., informal lending among family members) and it is challenging to quantify the cost of borrowing.

In this section, we overcome this challenge by leveraging our revealed-preference tool combined with an empirical design able to shed light on the determinants of the supply of credit. To do so, we rely on spatial variation. Geographic heterogeneity is an interesting

dimension of heterogeneity per se, as it captures the local credit environments to which households are exposed. Importantly, it also allows us to sidestep a limitation of our dataset, namely, that it includes limited demographics at the individual level. We proceed in three related steps: (i) we show that there are large differences in penalized withdrawals across locations, thus justifying us to study and rely on this source of variation; (ii) we then use a standard movers design to quantify the share of the variation attributed to the location itself, where location captures the local environment to which a household is exposed; (iii) finally, we use estimates of location effects and average household effects by location and study how they correlate with a battery of observables at the location level that could govern or mediate the valuation of liquidity.

Large Variation across Regions. As a first step of our analysis, we simply plot the average annual share of households that have a penalized withdrawal by commuting zones (CZs). Panel (a) of Figure 7 displays a map of these averages. We find large differences across regions, with a mean of 8.6 percentage points and a standard deviation of 1.8 percentage points. This variation could capture either differences across locations in demand for liquidity, for example due to a higher unemployment rate, or differences in the local supply of credit. The local supply of credit could itself be driven either by characteristics of the individuals inhabiting that location, such as average household credit score, or by true location effects, due to the local environment to which a household is exposed, including traditional financial institutions (such as banks) as well as local social networks and informal support (such as religious organizations). These three components can be decomposed using a standard statistical model with income controls and household and location fixed effects. This model, which we describe below, will guide our analysis in the whole section.

Statistical Model. We use the following statistical model for household behavior:²⁸

$$(5) \quad y_{i,z,t} = \alpha_i + \Gamma_{z(i,t)} + x_{i,t}\lambda + \varepsilon_{i,t}.$$

In this specification, $y_{i,z,t}$ is the penalized withdrawal outcome for household i in commuting zone (CZ) z at time t . α_i is a household fixed effect. $\Gamma_{z(i,t)}$ are location fixed effects determining the household's outcome, where $z(i,t)$ indexes the location of household i in year t . $x_{i,t}$ is a vector of potential time-varying controls, including indicators for age of primary filer, (cyclical) calendar year fixed effects, and household-level economic conditions. As is well known, this specification is identified off movers across CZs, and it requires a sufficient

²⁸We adopt the model from Abowd et al. (1999) and Finkelstein et al. (2016) adjusted to our setting.

amount of mobility to get statistically sound estimates (see Andrews et al. 2008).

5.1 Movers Design

The second step of our analysis is to use a movers design to establish whether and to what degree the large spatial variation shown in panel (a) of Figure 7 is due to persistent characteristics of the local environment. Specifically, we analyze outcomes of households who have moved across CZs, and we use the difference in intensity of early withdrawal behavior between the household’s original location and new location as the source of variation. We discuss the identifying assumption and its validity below.

To proceed, we further develop the statistical model in equation (5). For household i , whose location changed from z_0 to z_1 , we denote by Δ_i the difference in average propensity of taking penalized withdrawals between the destination CZ and the origin CZ: $\Delta_i \equiv y_{z_1} - y_{z_0}$, where $y_z \equiv E[y_{i,z,t}]$ is the average taken over all time periods and all households in location z . Empirically, we include in these averages only households that are non-movers to attain “leave-out” means. Δ_i is the sum of the differences in the locations’ and households’ contributions to the observed share of withdrawals across households.

Next, we denote the difference across location z_0 and z_1 that is attributable to location effects as: $\theta \equiv \frac{\Gamma_{z_1} - \Gamma_{z_0}}{y_{z_1} - y_{z_0}}$. We define $r(i, t)$ as the period relative to the household’s move, and we let $I_{r(i,t)>0}$ denote an indicator for time periods after the move. For households who move, we can rewrite equation (5) as:

$$y_{i,t} = \alpha_i + \Gamma_{z_0} + \theta I_{r(i,t)>0} \Delta_i + x_{i,t} \lambda + \varepsilon_{i,t},$$

where θ is our parameter of interest. It represents the average change in households’ withdrawals in the years following the move, relative to the overall difference between the new and old location means; in short, under the identifying assumption, it captures the variation in overall household behavior across CZs attributable to location.

Estimating Equation. A direct empirical analogue for the latter equation, which estimates the mean effects in the post-move years, takes a standard difference-in-differences form:

$$(6) \quad y_{i,t} = \mu_i + \theta \times Post_{i,t} \times \Delta_i + x_{i,t} \lambda + \varepsilon_{i,t},$$

where $\mu_i = \alpha_i + \Gamma_{z_0}$. Here, $Post_{i,t}$ is an indicator variable that equals 1 in the post-move years and equals 0 in the pre-move years. The vector $x_{i,t}$ includes a full set of primary-filer age fixed effects, (cyclical) calendar year fixed effects, potential household-level economic

outcomes as controls, as well as the baseline variable $Post_{i,t}$.²⁹

We take an extended version of this equation to the data, to allow for flexible interactions with time with respect to the event, and we estimate the following equation:

$$(7) \quad y_{i,t} = \mu_i + \sum_{r \neq -2} \beta_r \times I_r + \sum_{r \neq -2} \theta_r \times I_r \times \Delta_i + x_{i,t} \lambda + \varepsilon_{i,t},$$

where $I_r = \mathbb{I}_{r(i,t)=r}$ are indicators for time relative to the move. To be consistent with the previous section, our baseline period is taken to be two years prior to the move ($r = -2$). The event study specification in equation (7) allows us to test for parallel trends in the pre-period (based on θ_r for $r < -1$) and to investigate dynamics in location effects in the post-period (based on θ_r for $r > 0$). Robust standard errors are clustered at the origin CZ level.

Results and Interpretation. Figure 8 displays the θ_r coefficients from the estimation of equation (7). As a baseline estimation, we run the analysis on a balanced sample of households for whom the data range covers information from at least period -3 to period $+5$. We start with a specification in which the vector $x_{i,t}$ includes primary-filer age fixed effects and (cyclical) calendar year fixed effects. Panel (a) of Figure 8 first shows that there are no differential pre-trends across households who move to differential intensity locations, in support of the design as we discuss below. Second, the figure shows clear changes at the time of the move, which then balance out with a high degree of persistence for the analysis period. This shows that permanent location characteristics pass-through to household withdrawals. In the post-move years (periods 1 to 5) the coefficients average to 0.34. Through the lens of the statistical model above, this result implies that place effects can explain about a third of the overall spatial variation that we have found in penalized withdrawals. This is one of our main findings, and it highlights that the local environment is a crucial determinant of valuation of liquidity, thus calling for place-based policies as powerful welfare-enhancing instruments.

Our interpretation of this result is that when households move to locations with worse local supply of credit, they have to rely more on penalized withdrawals for liquidity. We next provide a series of empirical checks that lead to this conclusion. In particular, we investigate the validity of the movers design in identifying the location pass-through, we explore leading threats to identification, and we study the potential role of other explanations or mechanisms for the patterns we found.

²⁹Note that Δ_i is absorbed by the household fixed effect.

First, we consider our identifying assumption that households who experience differential intensity changes in local propensity to withdraw following the move (i.e., Δ_i) have withdrawal behavior that would run parallel in the absence of the move. Put differently, our design requires that households’ underlying trends in withdrawals do not systematically differ by Δ_i . The standard testable implication of this assumption is whether there are differential trends in the pre-move period across households with differential Δ_i . Reassuringly, we show that there are virtually no differential trends across differentially treated households in the years prior to the move across the specifications that we study (using data up to 5 years prior to the move; see, e.g., panel (b) of Figure 8). This alleviates concerns that households who switch to higher or lower intensity locations might be on different withdrawal trajectories, and provides support for our empirical design.

Another aspect to consider is that mover designs cannot account for shocks that both differ across households with varying treatment intensity Δ_i and align exactly with the timing of moves. We therefore ask: can the results be explained by differential changes to household economic conditions interacted with timing of move to differentially intense locations? Two pieces of evidence are inconsistent with this notion. We re-estimate equation (7) for an extended window that runs from year -5 to $+10$ (on an unbalanced sample of households). In panel (b) of Figure 8, we find a high degree of persistence for up to 10 years in the estimates for the role of location, θ_r . This is in contrast to the effects of household-level shocks that have been shown above to be transitory with clear dissipating dynamics. Similarly, Appendix Figure B.5 shows a comparable pattern of transitory dynamics for the move event itself, as captured by the “event study” coefficients of β_r in equation (7). These combined findings are hard to reconcile with patterns in pass-through being driven by shocks aligned with the time of move. We note that the moderate decline in the estimates in the extended window of post-move years is attributable to attrition and return moves (see panel (a) of Appendix Figure B.6). They attenuate the persistence in the effects since we assign a household the same destination location for the entire post-move period (whether they subsequently moved or not because these behaviors could be endogenous to the event). Panel (b) of Appendix Figure B.6 illustrates this point: when we scale the estimates by the share of movers still at the assigned destination, the dynamics flattens out. We then directly account for household-specific economic conditions that could change around the move and, potentially, in a differential way across locations with varying degrees of withdrawal intensity. We run specifications that include flexible (endogenous) economic controls: unemployment, wage earnings, and gross income, with lagged, current, and lead values, including interactions of all these variables with time with respect to the move. The results show that the estimates hardly change, in terms of either dynamics or magnitudes. See panel (a) of Figure 9.

Second, it is possible that a learning mechanism can drive the results, where households learn about withdrawals from peers when they move to a higher intensity location. To test this hypothesis, we focus on households who had already used this liquidity tool and made a penalized withdrawal in the pre-move periods. Albeit with naturally less precision due to the additional constraint (and with increased noise in the longer horizon region where there are less households), panel (b) of Figure 9 shows the results are very similar, suggesting that a learning mechanism is not driving our findings.

Third, an additional explanation could be tax optimization, whereby households' penalized withdrawal behavior is governed by their marginal tax rate. We have already seen evidence inconsistent with this conjecture in the analysis of household events where we find no gradient in the region of positive income changes. To further investigate it in the context of moves, we add controls for a location's top marginal tax rate (that varies over state and time) flexibly interacted with time relative to the move. The small attenuation in estimates in panel (c) of Figure 9 suggests that a tax motive mechanism might play at most a minor role.

Fourth, we consider that potential limited mobility bias may affect AKM models such as the one in specification (5). To address this concern, we split the sample randomly, and we re-estimate the movers design on each sample separately. If mobility bias is a major concern, then reducing the sample, hence the amount of mobility, should affect the results. Panel (d) of Figure 9 provides the findings. We find that the splits display patterns similar to the baseline results and that they do not show a systematic deviation from baseline (ruling out there could be a consistent bias). Thus, our benchmark results are not subject to limited mobility bias, in line with a high prevalence of moves in our dataset that spans many households and years and with our choice of relatively large geographic areas.

5.2 Interpreting Differences in the Supply of Credit

The previous subsection showed that, within the large systematic spatial variation in Figure 7, location characteristics explain approximately one third of the total variation, with the rest being driven by the characteristics of households. Moreover, since the pass-through estimates hardly change at all when we flexibly control for changing household economic conditions, the evidence suggests the remaining variation across location attributed to households is not the result of differences in their demand for liquidity but rather systematic differences in their access to credit, that is, a supply-side factor. Motivated by this evidence, the third and final step of our analysis in this section is to shed light on the potential drivers of these supply-side components, both those that pertain to households within a location and those that pertain to locations themselves.

To do so, we return to the statistical model in equation (5) to provide us with separate estimates for the location fixed effects, Γ_z , and the household fixed effects, α_i . In this estimation, we flexibly control for household-level economic outcomes: unemployment, wage earnings, and gross income, with lagged, current, and lead values. Having estimated this equation’s coefficients, panel (b) of Figure 7 maps the location effects, which capture the local market-level supply of credit. We notice that there is substantial variation across locations (standard deviation of 2.3 pp), corroborating that it is worthwhile to study them and see how they are correlated with key socio-economic indicators. For the household fixed effects, since our data include limited demographic information, we take averages of α_i by location to study how α_i varies across households’ characteristics. We then use the location-level averages of the characteristics of households living there to investigate whether there is persistent inaccessibility to credit for particular groups. Panel (c) of Figure 7 confirms that the averaged household fixed effects vary considerably by location (standard deviation of 2.75 pp), thus justifying our empirical approach.

For both location fixed effects and averaged households fixed effects, we investigate correlations with a battery of CZ-level characteristics which are taken (unless noted otherwise) from Chetty et al. (2016). Figure 10 reports all the normalized beta coefficients from a series of univariate OLS regressions, while Appendix Figures B.7 and B.8 include all the corresponding scatter plots. We focus here on discussing several characteristics which display particularly strong correlations with our model estimates.

Location Effects. We start by discussing the most notable correlations with the location fixed effects. We consider the Credit Insecurity Index, which is a measure developed by the Federal Reserve Bank of New York for assessing American communities’ credit health and well-being (Hamdani et al. 2019). We find that areas with a higher Credit Insecurity Index exhibit higher propensities of using penalized withdrawals, consistent with lower availability of alternative sources of credit. We also consider the correlation with a location’s median house value. We find that locations with higher home values display less reliance on withdrawals, consistent with the notion that high home values can provide collateral, reducing risk in the credit market. A lower risk in the credit market would then decrease the interest rate faced by individuals, effectively increasing the local supply of liquidity and limiting the needs of households to rely on penalized withdrawals.

Household Effects. Next, we turn to the household fixed effects. To begin, it is worthwhile to notice that the factors emphasized above, in particular, the Credit Insecurity Index, do not correlate strongly with household fixed effects. In other words, locations with worse

credit security are not typically inhabited by households who would have worse access to credit irrespective of their location.

Instead, household fixed effects most notably correlate with measures of racial composition—households who live in communities with a high percentage of black residents are significantly more likely to make a penalized withdrawal irrespective of their current location. How should we interpret this result? Withdrawals are a financial instrument that, conditional on having a retirement account, does not discern across households. The heterogeneity across types of households can thus reveal their differential access to alternative means of credit. In our case, the evidence is consistent with more limited access to credit among households in black communities. These households reveal a high valuation of liquidity, suggesting they may be marginalized from the credit market, which is also in line with recent results in Ganong et al. (2020) who show that black households are less able to smooth consumption.

This provides an important aspect that could help guide place-based policies aimed at increasing equity in the access to credit. That said, we want to note that, due to the nature of our data, it is impossible to discern, with certainty, whether this disparity is driven by the lack of access to credit by black households themselves or by non-black households living in black communities. Still, two pieces of evidence lead us to conclude that the former is the more likely explanation. First, the location effects are uncorrelated with the share of blacks, which implies that when households randomly drawn from the distribution move into an area with a high share of blacks, we do not see their penalized withdrawals increasing on average. Second, we repeat the entire analysis at finer geographic units; in particular, we run specification (5) at the 5-digit ZIP code level and project α_i onto their ZIP code. We then use the resulting estimates to run regressions of household fixed effects and ZIP code fixed effects on the share of black households within the ZIP code, while controlling for CZ fixed effects. As shown in Figure B.7, the point estimates are remarkably similar: the empirical correlations across CZs are very similar to those within CZs across ZIP codes.³⁰

Finally, we note that similar patterns also hold when we explore a location’s percent of children living with single mothers, which represent another classic example of economically-disadvantaged households. Our results suggest that single mothers may also have limited access to credit within their communities.

³⁰It is relevant to notice that due to spatial segregation, there is a lot of variation both across CZs and within CZs across ZIP codes in the share of black population, see Appendix Figure B.9.

6 Valuation of Liquidity During the Great Recession

Localities can encompass both stable components, such as institutions, and time-varying components, such as aggregate shocks and changing economic conditions. In Section 5, we have focused on characterizing the stable component of location in determining valuation of liquidity. In this final piece of our empirical analysis, we consider locations as an evolving entity and study their dynamic evolution during a leading episode that could have led to a severe worsening of local credit, the Great Recession.

Estimating Equation. We estimate specifications of the following event study type:

$$(8) \quad y_{i,z,t} = \sum_{r \neq 2006, r=2000}^{r=2017} \beta_r \times I_r + \sum_{r \neq 2006, r=2000}^{r=2017} \theta_r \times I_r \times Treat_z + \Gamma_z + \alpha_i + x_{i,t}\lambda + \varepsilon_{i,t}.$$

In this equation, I_r are calendar year indicators, running from years 2000 to 2017, where year 2006 is taken to be the baseline year; $x_{i,t}$ is a full set of primary-filer age fixed effects, (cyclical) calendar year fixed effects, and potential household-specific economic controls; Γ_z are the commuting zone fixed effects; and α_i are household fixed effects. $Treat_z$ is the treatment intensity of location z in terms of unemployment shock. Specifically, we utilize the measures from Yagan (2019), which calculate the change in a commuting zone’s unemployment rate between the years 2007 and 2009. Our parameters of interest are θ_r , which capture the relative change in behavior in a locality that is exposed to a 1 percentage point larger local unemployment shock.

Results and Interpretation. The solid line in Figure 11 plots the θ_r estimates from equation (8). The figure first shows that locations, who were about to be hit differentially by the Great Recession, were on similar trajectories prior to the event. Then, the figure reveals that commuting zones more severely affected by the Great Recession, as measured by unemployment increases, have seen a larger increase in penalized withdrawals and, hence, in the local valuation of liquidity. The response peaks around the height of the Great Recession with an effect of 0.374 pp in local penalized withdrawals per 1 pp local unemployment shock in year 2009. Calculating the cumulative effect from 2007-2012 of the probability of taking a penalized withdrawal, we find an increased propensity of 1.36 pp for a 1 pp rise in CZ unemployment.

Interestingly, at their peak, the flow effect of a locality-level unemployment shock is about 4 times as large as the direct effect of a household-level unemployment shock that we have estimated (0.374 vs. 0.095). This suggests that the effect of a 1 pp of local unemployment

on the valuation of liquidity is about one-quarter due to increases in household demand and about three-quarters due to decrease in local supply. In light of these patterns, we break down the cumulative impact of the Great Recession into a direct effect (through, e.g., the specific household’s income and employment) and an indirect effect (through market-level spillovers) by flexibly accounting for household-level economic circumstances. Specifically, we add as controls unemployment, wage earnings, and gross income, with lagged, current, and lead values, as well as their interactions with calendar year dummies. The estimates are reported in the dashed line in Figure 11. We find that at its peak in 2009, the indirect impact amounts to 0.286 pp. The cumulative indirect effect from 2007-2012 amounts to 1.07 pp, which is about three-quarters of the overall cumulative effect of the Great Recession. Our findings are therefore consistent with a tightening of local credit conditions for all workers in distressed locations.

Overall, the Great Recession provides a leading example of how evolving local circumstances can have an important role on American households’ need for and valuation of liquidity, not only directly but also through market spillovers.

7 Policy Implications

Our findings have two main related policy takeaways. First, there could be meaningful welfare improvements from enriching the targeting of social insurance policies and sections of the tax code that affect liquidity. Richer policies could depend on households’ specific economic conditions (addressing their demand for liquidity), on locality (e.g., by improving a community’s access to credit), as well as on time and local economic conditions (e.g., by inter-temporal reallocation of the same funds). Second, our work stresses that we can indeed use penalized withdrawals as a practical dynamic tool to monitor the evolving local valuation of liquidity and guide such richer targeting.

There is a variety of ways in which this targeting could happen through the social insurance system or the tax code. Most immediately, the tax penalty itself could become a function of household-level, location-level, and aggregate-level economic conditions. Indeed, tax penalties are already waived in the tax code for several qualified household-level events (such as spousal death) that are believed to increase households’ liquidity needs. Moreover, Congress has recognized premature withdrawals as a potential avenue for liquidity and has adjusted this price in the wake of major events that caused shocks to liquidity among American taxpayers. Specifically, localized exceptions have been offered in the past for some natural disasters, including Hurricane Katrina. Most recently, in 2020, Congress waived penalties on withdrawals of up to \$100,000 from qualified retirement accounts for COVID-19-related purposes.

Our analysis points to welfare gains from these adjustments. It suggests that systematic price adjustments to the cost of funds within savings accounts through the tax code could provide additional welfare improvements. For example, the tax penalty may be especially burdensome on lower-income taxpayers who already face relatively higher prices in credit markets. Policymakers could then consider tailoring the penalty amount to a taxpayer’s income level, especially around events predictive of penalized withdrawals.

Additionally, the tool developed in this paper can serve to identify targets for other location-level incentives aimed at equalizing access to financial services across communities. For example, a program similar to Empowerment Zones (EZs), which allowed businesses in economically distressed areas to receive employment tax credits, could be implemented to specifically target the financial services sector in financially underdeveloped communities that have residents with high liquidity needs based on our findings.

Finally, our findings provide a precursor for potential welfare gains from new financial products and the coming regulation of these markets. With the large spatial variation in available credit that we have uncovered, easy-access financial technology (FinTech) solutions have the potential to reach out to households in need of credit who live in financial deserts with limited traditional credit means, allowing for more equitable access to credit nationwide.

8 Conclusion

This paper introduces conceptually and validates empirically penalized withdrawals from retirement savings accounts as a robust tool that carries information on households’ valuation of liquidity. We use this tool to characterize the anatomy of equilibrium valuation of liquidity among American families and offer several new findings. First, we find that households’ valuation of liquidity spikes at adverse income events with some lingering effects over several years, suggesting that households are far from being well-insured. Second, we show that the valuation of liquidity is strongly affected by location-specific characteristics that may affect the supply of available credit and that some communities—specifically those with a high percentage of black households—seem to display higher liquidity valuation, suggesting they may have limited access to alternative credit channels. Third, we find that local supply can substantially change over time as a function of aggregate shocks, such as in the case of the Great Recession.

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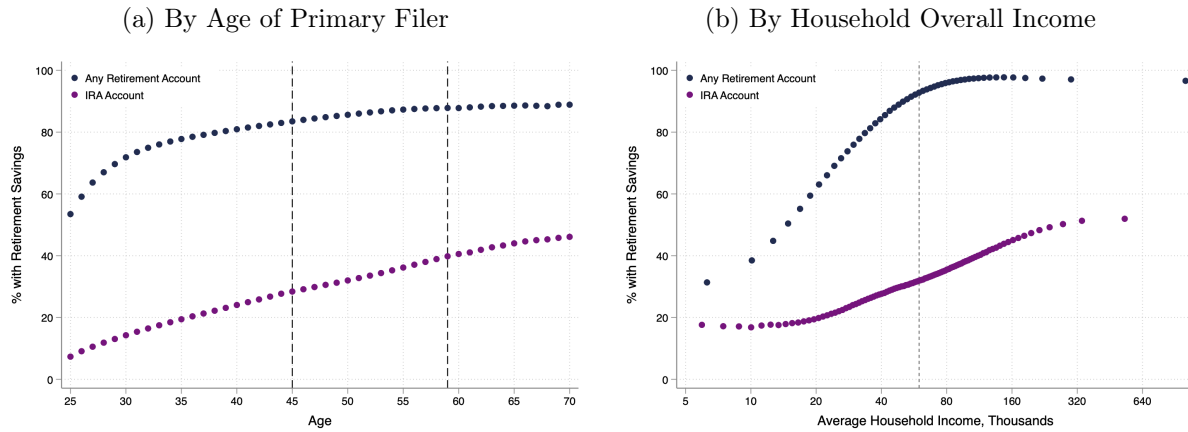
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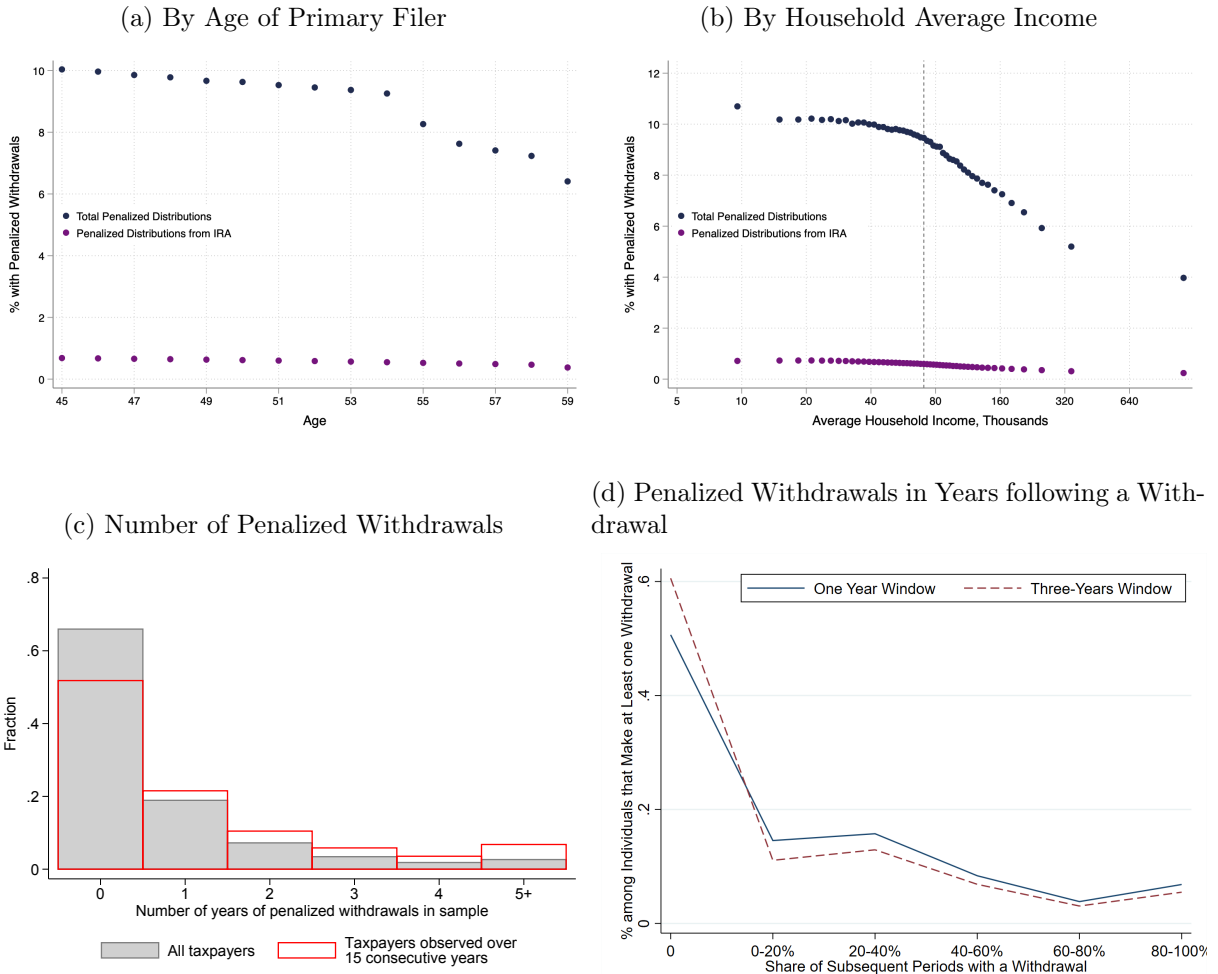
Figures

Figure 1: Prevalence of Accounts



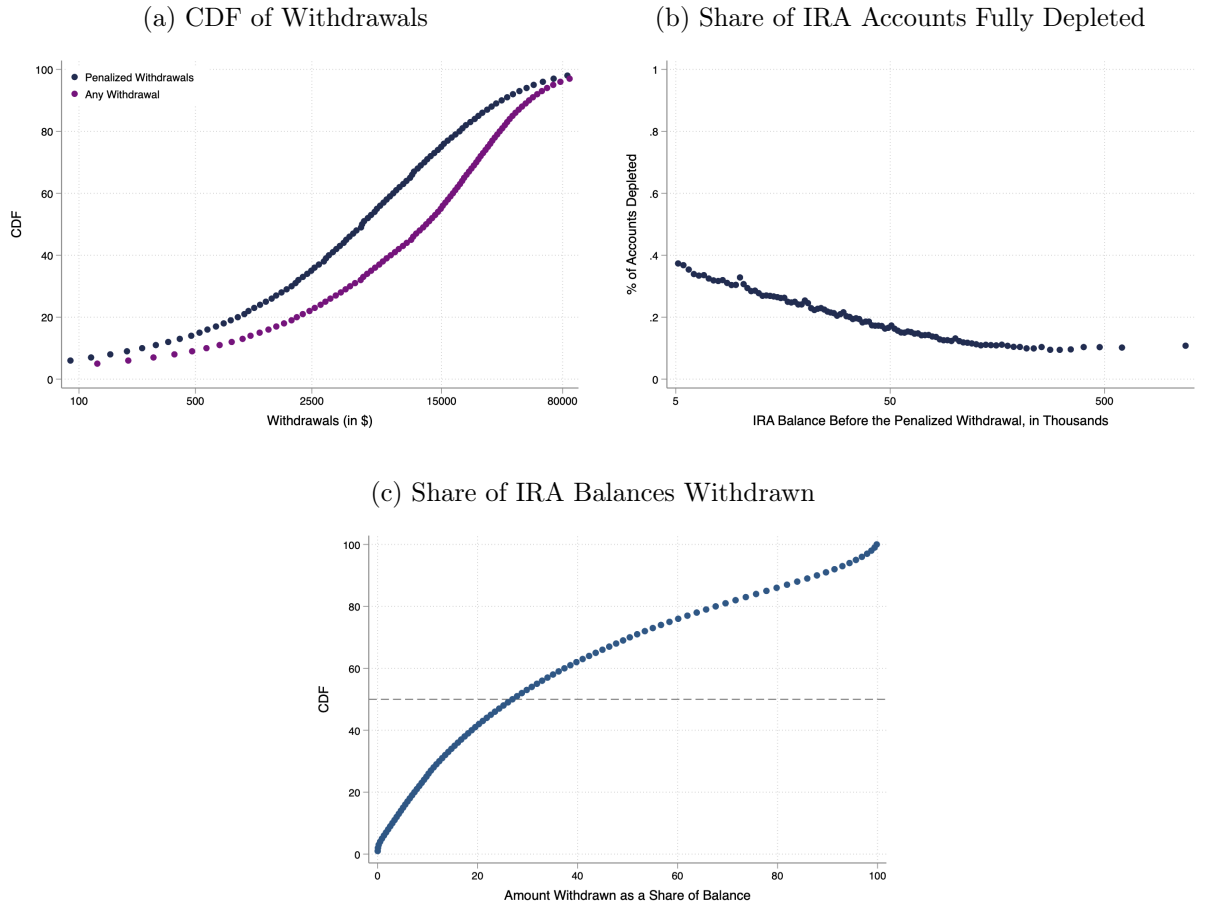
Notes: These figures illustrate the prevalence of retirement accounts. Panel (a) plots the share of households with retirement accounts by age. Panel (b) plots the share of households with retirement accounts by average household income (where the vertical line marks the median value in our sample). We identify households as having accounts in a given year if, up to that year within our sample period of 20 years, they have made a contribution to 401(k)/IRA accounts or have balances in IRA accounts for which balances are reported in the tax information. We include in the figures information on both any type of account (401(k)/IRA) and IRA accounts only.

Figure 2: Prevalence of Withdrawals



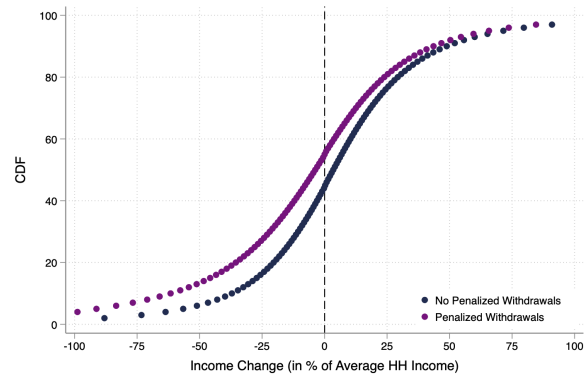
Notes: These figures illustrate the prevalence of penalized withdrawals, calculated as the share of households that make a penalized withdrawal within the year, averaged across all years in our data. Panel (a) plots the share of households with a penalized withdrawal by age. Panel (b) shows the distribution of annual withdrawals by household income (where the vertical line marks the median value in our sample). Panels (a) and (b) show both the total penalized distributions and those from IRA accounts only. Panel (c) shows the distribution of the number of years a household has taken a penalized withdrawal. Panel (d) shows, among households who make a withdrawal in some period, the distribution of subsequent periods within our data frame the household has made additional withdrawals. We provide two versions of this distribution for different definitions of “periods,” one that uses one-year periods and another that uses three-year periods (to allow for a longer period of “consecutive” liquidity needs).

Figure 3: Amounts of Penalized Withdrawals



Notes: These figures illustrate the distribution of withdrawal amounts and their relationship with balances in retirement accounts before the withdrawal. Panel (a) shows the overall CDF of amounts of penalized withdrawals and compares it with the overall CDF of amounts of withdrawals of any kind. Panels (b) and (c) focus on households who have an IRA account and make a penalized withdrawal from such an account. Panel (b) first computes, among this group, the share of households who have fully depleted their IRA account after the withdrawal. Panel (c) then shows, only for those households that do not fully deplete their IRA accounts, the CDF of the ratio of the amounts of penalized withdrawals to the previous IRA balances.

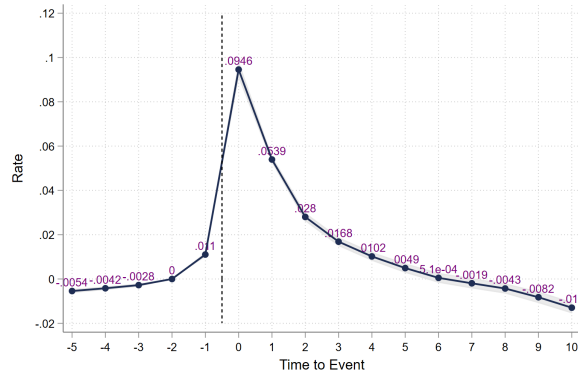
Figure 4: Penalized Withdrawals and Income Changes



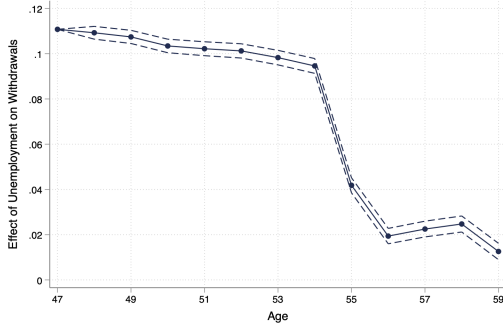
Notes: This figure plots the CDF of annual income changes, separating households according to whether they made a penalized withdrawal in a given year.

Figure 5: Unemployment Event

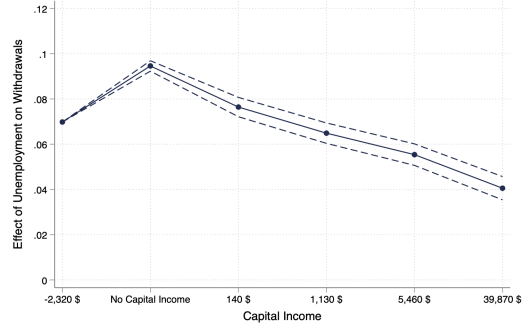
(a) Frequency of Penalized Withdrawals



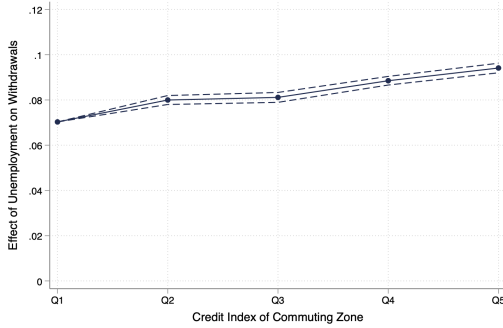
(b) Event Response by Age



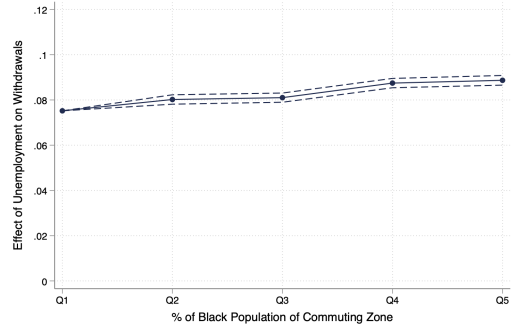
(c) Event Response by Household Capital Income



(d) Event Response by Local Credit Insecurity Index

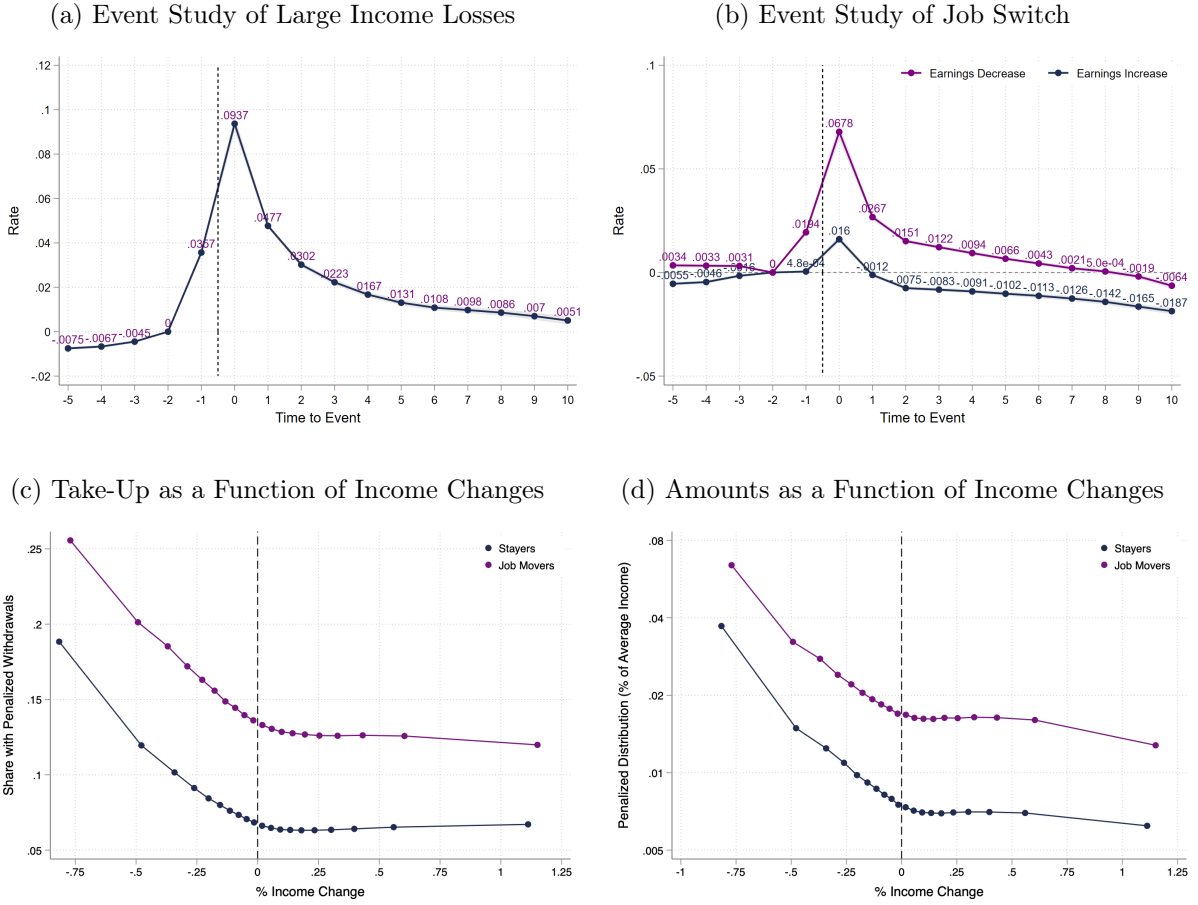


(e) Event Elasticity by % of Black Population in Locality



Notes: This figure studies penalized withdrawals around the event of household unemployment, defined as the first period we observe at least one of the household members receiving unemployment benefits. Panel (a) plots the event study coefficients from specification (4). Panels (b)-(e) show how the point estimates at time 0 (i.e., at the onset of the unemployment event) vary as a function of age, household capital income, Credit Insecurity Index, and % of black population in the commuting zone (CZ) in which the household resides at the time of the shock. For the characteristics we observe at the household level—i.e., age and capital income—we present heterogeneity results from a regression that simultaneously includes these categories, as well as additional household-level controls: home ownership (an indicator based on property tax payments from Schedule A and mortgage debt from Form 1098), a dummy for whether the primary filer is married, the number of dependents, and the average household income based on information from all years within our data range. In panel (c), we split households into those with negative, zero, or positive capital income, and we bin the ones with positive capital income into four groups. On the x-axis, we then plot the average capital income within the corresponding bin. The Credit Insecurity Index and % of black population of the CZ are computed as described in Section 5 and binned in quintiles weighted by CZ population.

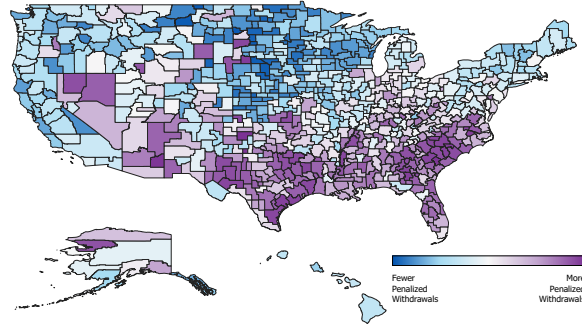
Figure 6: Income Changes and Penalized Withdrawals



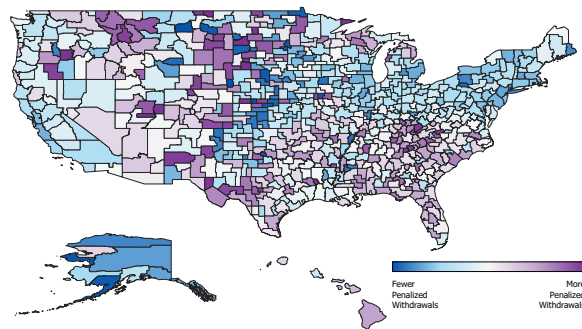
Notes: This figure studies penalized withdrawals around changes in household income. Panels (a)-(b) plot the event study coefficients for different household-level events using specification (4). Panel (a) studies the event of a large income loss, which we define as a first period we observe a household experiencing a decline in overall income of more than 20 percent (relative to a previous year). Panel (b) studies the event of a job switch. It focuses on the sample of households for whom we see a change in employer from period $t - 1$ to period t without an episode of being on unemployment benefits. We then split households by whether the employee experienced an earnings increase or an earnings decrease upon the switch. In panels (c) and (d), we calculate, for each household in a given year, the deviation of their income flow from their average income within our data period, and we then plot the behavior of penalized withdrawals—take-up and amounts, respectively—as a function of income deviations.

Figure 7: Location-Based Withdrawals

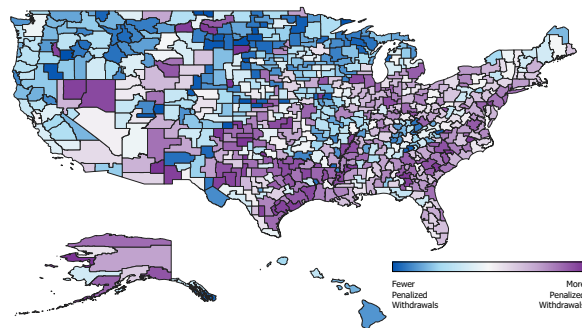
(a) Overall Variation



(b) Location Fixed Effects



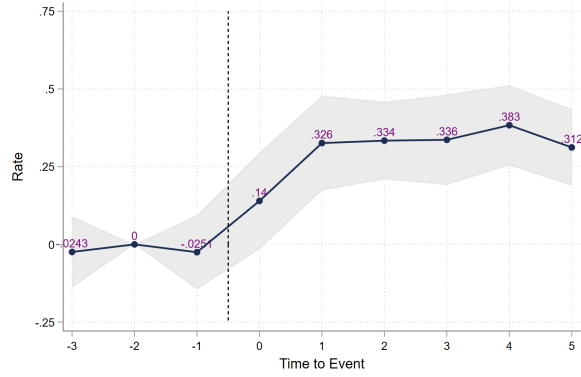
(c) Household Fixed Effects



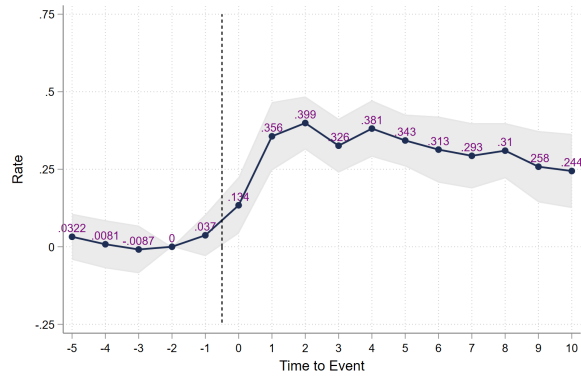
Notes: This figure plots a map of the average annual share of households that have made a penalized withdrawal by commuting zones (CZs). Panel (a) plots overall variation. Based on estimation of equation (5) with household-level economic controls, panel (b) plots a map of the location fixed effects, Γ_z , and panel (c) plots a map of the household fixed effects, α_i , collapsed at the CZ level. The economic controls include unemployment, wage earnings, and gross income, with lagged, current, and lead values.

Figure 8: Movers Design

(a) Balanced Panel

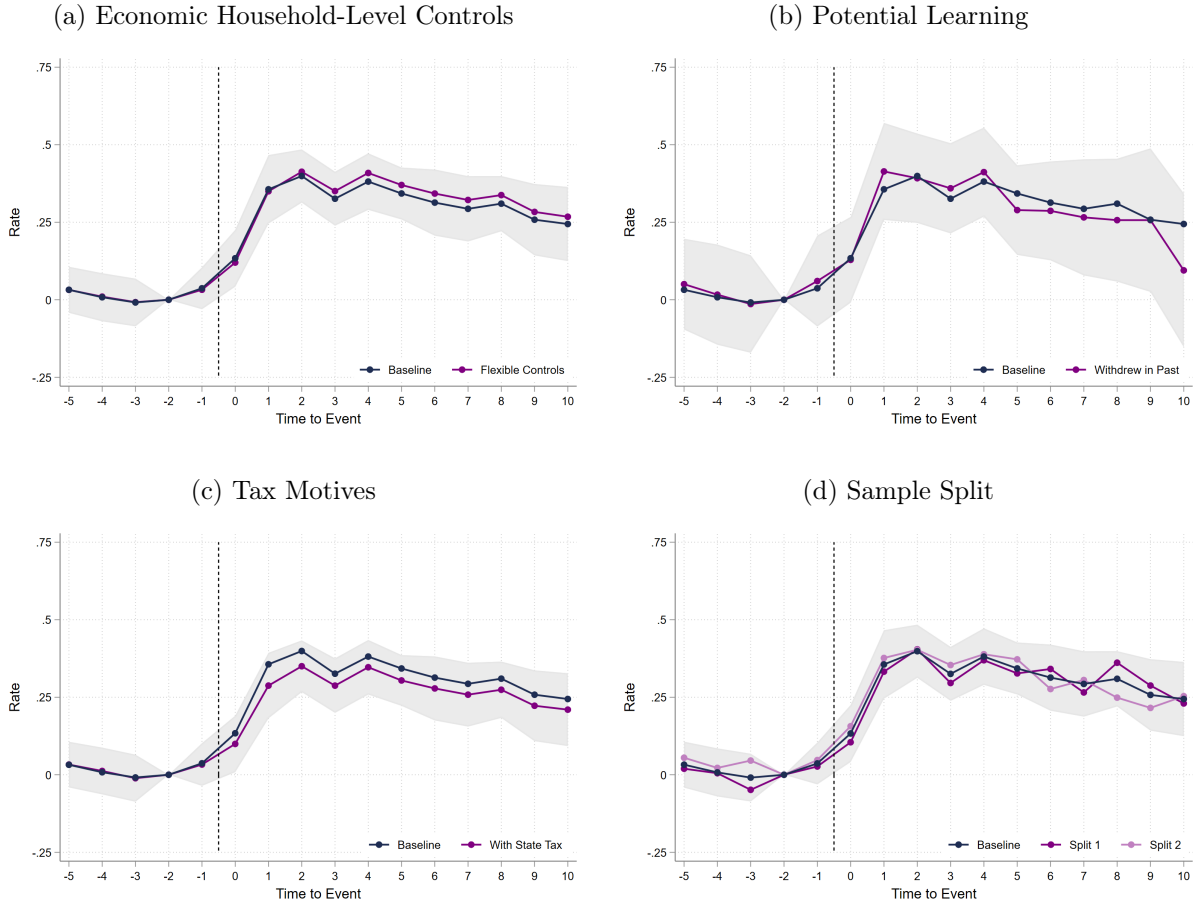


(b) Extended Horizon



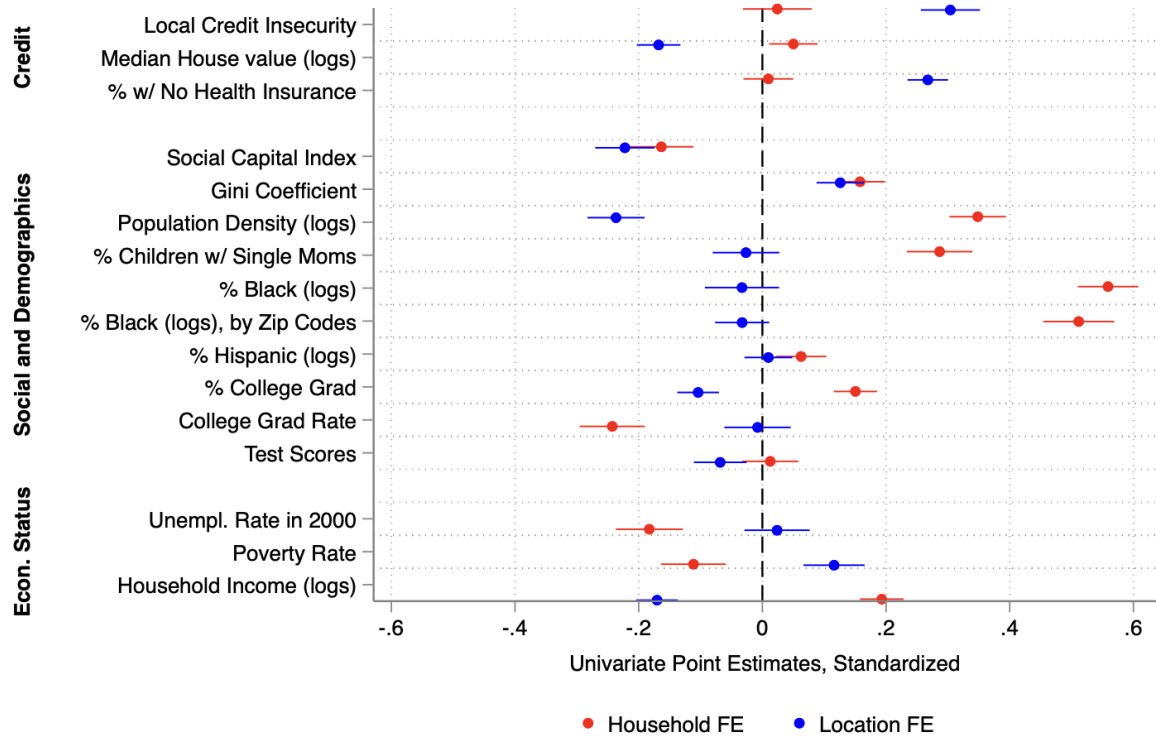
Notes: These figures display estimates for the share of spatial variation in withdrawals that can be attributed to location, using the movers design specification of equation (7). Panel (a) shows the estimates from a balanced panel of households we observe in the window $[-3, +5]$ years around the move. Panel (b) shows the estimates from an unbalanced panel of households on an extended time window that spans the years $[-5, +10]$ around the move. We include as controls household fixed effects, a full set of primary-filer age fixed effects, and (cyclical) calendar year fixed effects. Robust standard errors are clustered at the origin CZ level.

Figure 9: Movers Design—Robustness



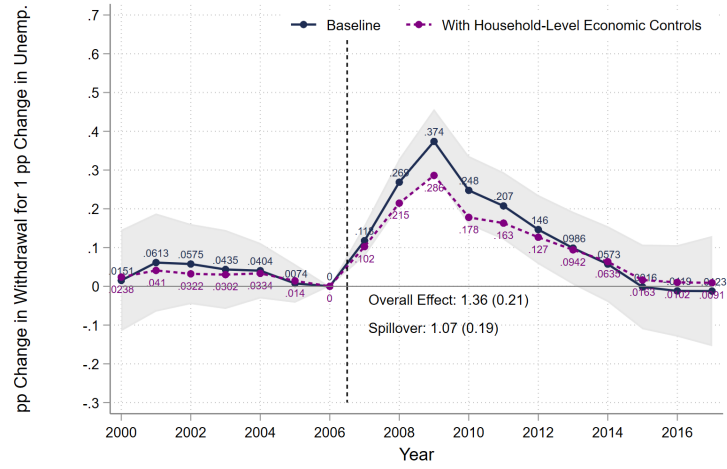
Notes: These figures display different estimates for the share of spatial variation in withdrawals that can be attributed to location, using the movers design specification of equation (7). The figures provide a series of investigations that study the validity of the movers design in identifying the location pass-through, explore leading threats to identification, and study the potential role of other explanations or mechanisms for the patterns we found. Panel (a) runs a specification that includes flexible (endogenous) economic controls: unemployment, wage earnings, and gross income, with lagged, current, and lead values, including interactions of all these variables with time with respect to the move. Panel (b) studies a learning mechanism, by focusing on the sample of households who had already made a penalized withdrawal in the pre-move periods. Panel (c) tests the explanation of tax optimization, by including controls for a location’s top marginal tax rate (that varies over state and time) flexibly interacted with time relative to the move. Panel (d) tests for limited mobility bias, by splitting the sample randomly and re-estimating the movers design on each sample separately. In all estimations, we include as controls household fixed effects, a full set of primary-filer age fixed effects, and (cyclical) calendar year fixed effects. Robust standard errors are clustered at the origin CZ level.

Figure 10: Correlations with Location-Level Withdrawals (All Indicators)



Notes: This figure displays correlations of the regional differences across CZs, as estimated using equation (5), with CZ-level social and economic characteristics. We display correlations of these characteristics separately for the location fixed effects, Γ_z , and for the household fixed effects, α_i , collapsed at the CZ level.

Figure 11: Penalized Withdrawals and Local Unemployment during the Great Recession



Notes: This figure displays estimates of the effect of the Great Recession on penalized withdrawals, using the specification in equation (8). It provides estimates for the relative change in behavior in a locality that was exposed to a 1 percentage point larger local unemployment shock.

Online Appendix (not for Publication)

A Proofs of Theoretical Results

We prove all the Lemmas of Section 3 by characterizing in steps the solution of the model.

We start from the recursive formulation of the problem

$$V_t(a_{i,t}, k_{i,t}; h_{i,t}) = \max_{\Delta k_{i,t}, \Delta a_{i,t}} u(c_{i,t}; h_{i,t}) + \beta E_t [V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})]$$

subject to:

$$\begin{aligned} c_{i,t} &= (1 - \varphi) y_{i,t} - \Delta k_{i,t} - \Delta a_{i,t} + \tau \Delta k_{i,t} \mathbb{I}_{\Delta k_{i,t} < 0} \mathbb{I}_{t < t^*} + \rho_{i,z} \Delta a_{i,t} \mathbb{I}_{(a_{i,t} < 0)} \mathbb{I}_{(\Delta a_{i,t} < 0)} \\ a_{i,t+1} &= (1 + r) [a_{i,t} + \Delta a_{i,t}] \\ k_{i,t+1} &= (1 + r) [k_{i,t} + \Delta k_{i,t} + \varphi y_{i,t}]. \end{aligned}$$

First, notice that the household would never deposit into the illiquid account, since it pays the same interest rate as the liquid account but it leads to a penalty in the case of a withdrawal, hence it is strictly dominated as a savings instrument. For this same reason, we know that $\frac{\partial V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})}{\partial k_{i,t+1}} \leq \frac{\partial V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})}{\partial a_{i,t+1}}$ with equal sign if and only if the household knows with certainty that they are not going to make a penalized withdrawal nor borrow from the liquid account (which would entail them paying the marginal cost $\rho_{i,z}$) before date t^* . In this latter case, all dollars deposited in the illiquid account will become liquid with certainty and would not be useful before t^* since the household is not expecting to need liquidity from any source before t^* . As a result, $\frac{\partial V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})}{\partial k_{i,t+1}} = \frac{\partial V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})}{\partial a_{i,t+1}}$.

Next, take the first order conditions with respect to $\Delta k_{i,t}$ and $\Delta a_{i,t}$, taking into account that the derivative is different depending on whether the values of this choice variables are positive or negative (and excluding the non-relevant case $\Delta k_{i,t} > 0$) to get:

$$\begin{aligned} \{\Delta a_{i,t} > 0\} : \quad & u'(c_{i,t}; h_{i,t}) \left(E_t \left[\frac{\partial V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})}{\partial a_{i,t+1}} \right] \right)^{-1} (\beta(1+r))^{-1} = 1 \\ \{\Delta a_{i,t} < 0\} : \quad & u'(c_{i,t}; h_{i,t}) \left(E_t \left[\frac{\partial V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})}{\partial a_{i,t+1}} \right] \right)^{-1} (\beta(1+r))^{-1} \geq \frac{1}{(1 - \rho_{i,z})} \\ \{\Delta k_{i,t} < 0\} : \quad & u'(c_{i,t}; h_{i,t}) \left(E_t \left[\frac{\partial V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})}{\partial k_{i,t+1}} \right] \right)^{-1} (\beta(1+r))^{-1} \geq \frac{1}{1 - \tau}. \end{aligned}$$

Lemma 1 and the second part of Lemma 2 are derived directly from the first order conditions, the definition of $\theta_{i,t}(c_{i,t}; h_{i,t})$, and the argument we just made on the relationship between $\frac{\partial V_{t+1}}{\partial k_{i,t+1}}$ and $\frac{\partial V_{t+1}}{\partial a_{i,t+1}}$.

Next, we show that $\pi(h_{i,t}) \in [1 - \tau, 1]$, thus concluding the proof of Lemma 2. The upper

bound follows again immediately from the discussion above and the definition of $\pi(h_{i,t})$. To prove the lower bound we proceed by contradiction. Assume that the household is maximizing and that $\pi(h_{i,t}) < (1 - \tau)$. Next, build an alternative strategy by withdrawing one dollar from the illiquid account, pay the penalty τ , and transferring $(1 - \tau)$ dollars in the liquid account. This deviation generates a total change in the household's value of the problem given by

$$-E_t \left[\frac{\partial V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})}{\partial k_{i,t+1}} \right] + (1 - \tau) E_t \left[\frac{\partial V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})}{\partial a_{i,t+1}} \right],$$

which would be bigger than 0 if $\pi(h_{i,t}) < 0$. We have thus found a welfare enhancing deviation and reached a contradiction.

We now turn to Lemma 3. First, we show that if $\rho_{i,z} \leq \tau$, then the strategy of never making a penalized withdrawal is optimal. Consider any period in which the household would like to consume more than their income and assume that the household uses funds from the liquid account. Now, consider a deviation from this strategy in which the households withdraws one illiquid dollar, pays the penalty τ , has $1 - \tau$ more available dollars, and can thus withdraw $\frac{1-\tau}{1-\rho_{i,z}}$ fewer liquid dollars and still keep the consumption constant. This deviation would lead to a change in total future value given by

$$-E_t \left[\frac{\partial V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})}{\partial k_{i,t+1}} \right] + \frac{1 - \tau}{1 - \rho_{i,z}} E_t \left[\frac{\partial V_{t+1}(a_{i,t+1}, k_{i,t+1}; h_{i,t+1})}{\partial a_{i,t+1}} \right]$$

which is positive if and only if

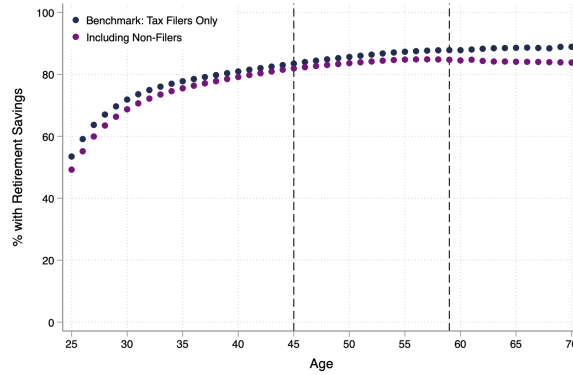
$$\pi(h_{i,t}) > \left(\frac{1 - \tau}{1 - \rho_{i,z}} \right).$$

Therefore, this deviation cannot be welfare improving if $\rho_{i,z} \leq \tau$. This is because if the household expects to never make a penalized withdrawal with probability one (as they do on the optimal path given that when $\rho_{i,z} \leq \tau$ relying on liquid funds is always cheaper than making a penalized withdrawal), then $\pi(h_{i,t}) = 1$. The second part of Lemma 3 is derived directly from the first order conditions and the definitions of $\pi(h_{i,t})$ and $\theta_{i,t}(c_{i,t}; h_{i,t})$.

Finally, Lemma 4 is derived from properly defining supply and demand and summing Lemma 3 over any set of households \mathcal{I}_t .

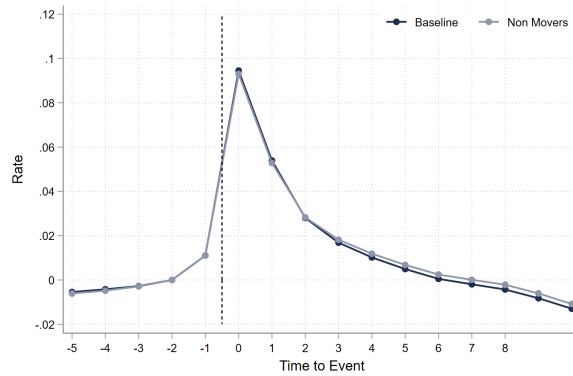
B Appendix Figures

Figure B.1: Prevalence of Accounts: Inclusion of Non-Filers



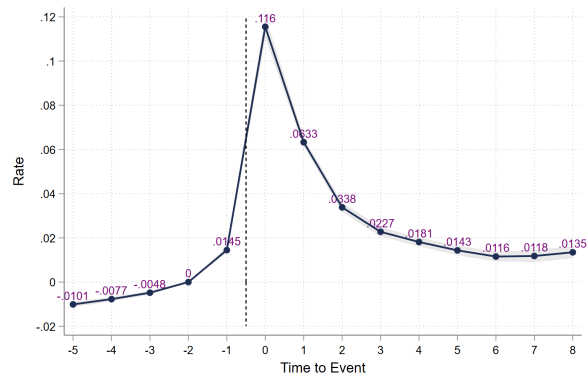
Notes: This figure illustrates the prevalence of retirement accounts by age. We compare our benchmark sample of households that file tax returns to a more inclusive sample, which combines in households that do not file tax returns. The figure shows that households that do not file tax returns are less likely to have a retirement savings account.

Figure B.2: Unemployment Event: Households that Stay in the Same CZ



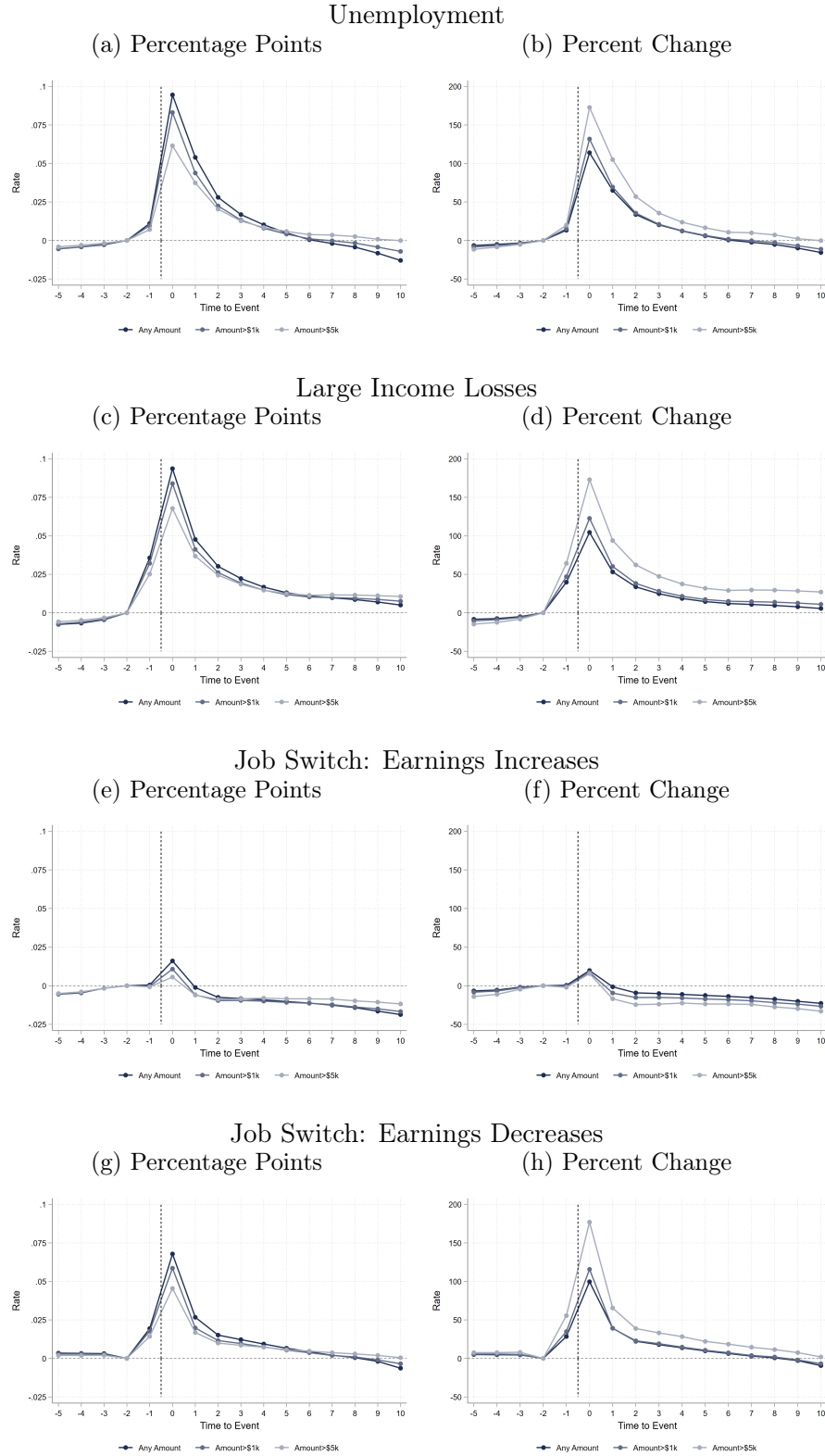
Notes: This figure plots the event study coefficients from specification (4) for the event of unemployment, as defined by the first period we observe at least one of the household members receiving unemployment benefits. We compare the overall sample to a restricted sample in which we include only households that do not change their commuting zone around the event. Specifically, we only consider households that are in the same commuting zone (CZ) in periods -1 and 1.

Figure B.3: Unemployment Event: Primary Filers Younger than 55



Notes: This figure plots the event study coefficients from specification (4) for the event of unemployment, as defined by the first period we observe at least one of the household members receiving unemployment benefits. We include observations of primary filers younger than 55.

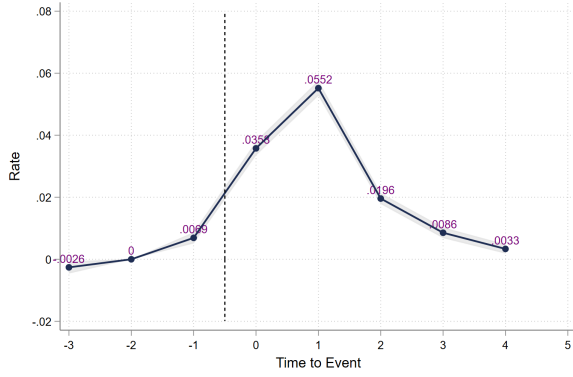
Figure B.4: Event Studies by Amount Withdrawn



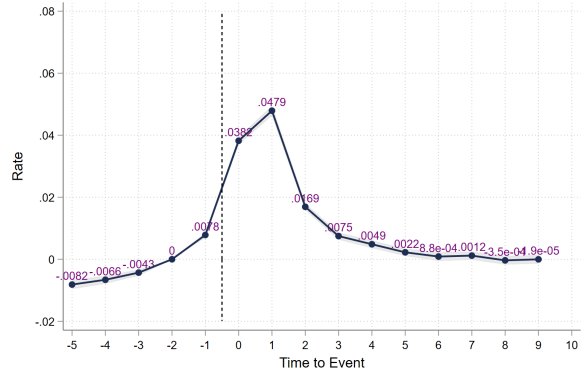
Notes: This figure plots the event study coefficients from specification (4) for the events of unemployment, large income loss, job switch with earnings increases, and job switch with earnings decreases. We study indicators for making penalized withdrawals of different amount thresholds: any amount, more than \$1,000, and more than \$5,000. For each event, the left panel reports estimates in percentage points, and the right panel reports these estimates in percent changes relative to the respective baseline levels at period $t = -2$.

Figure B.5: Event Study Estimates around the Move Event

(a) Balanced Panel

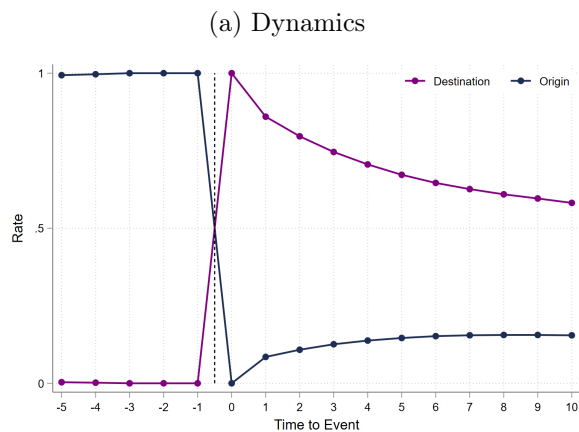


(b) Extended Horizon

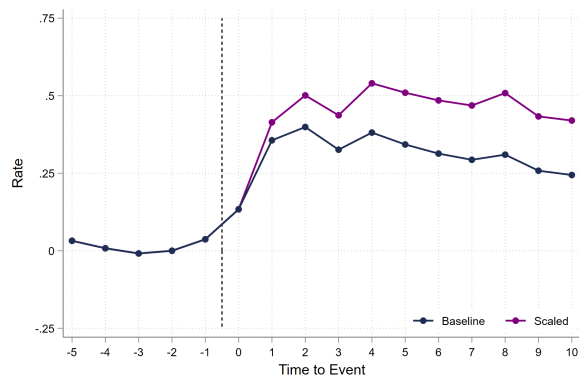


Notes: These figures display estimates for the event study coefficients of a move (β_r) from the estimation of equation (7).

Figure B.6: Movers Design—Attrition and Return Moves

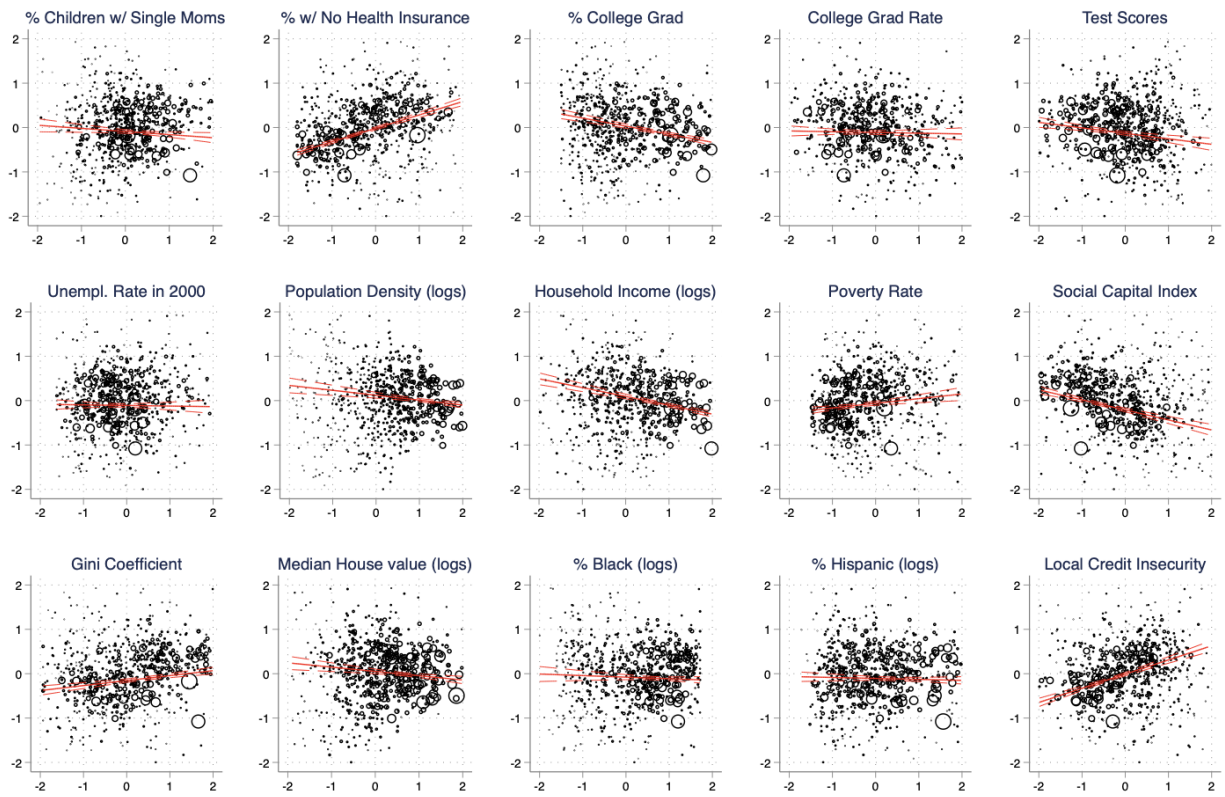


(b) Pass-Through Scaled by Movers Still in Destination



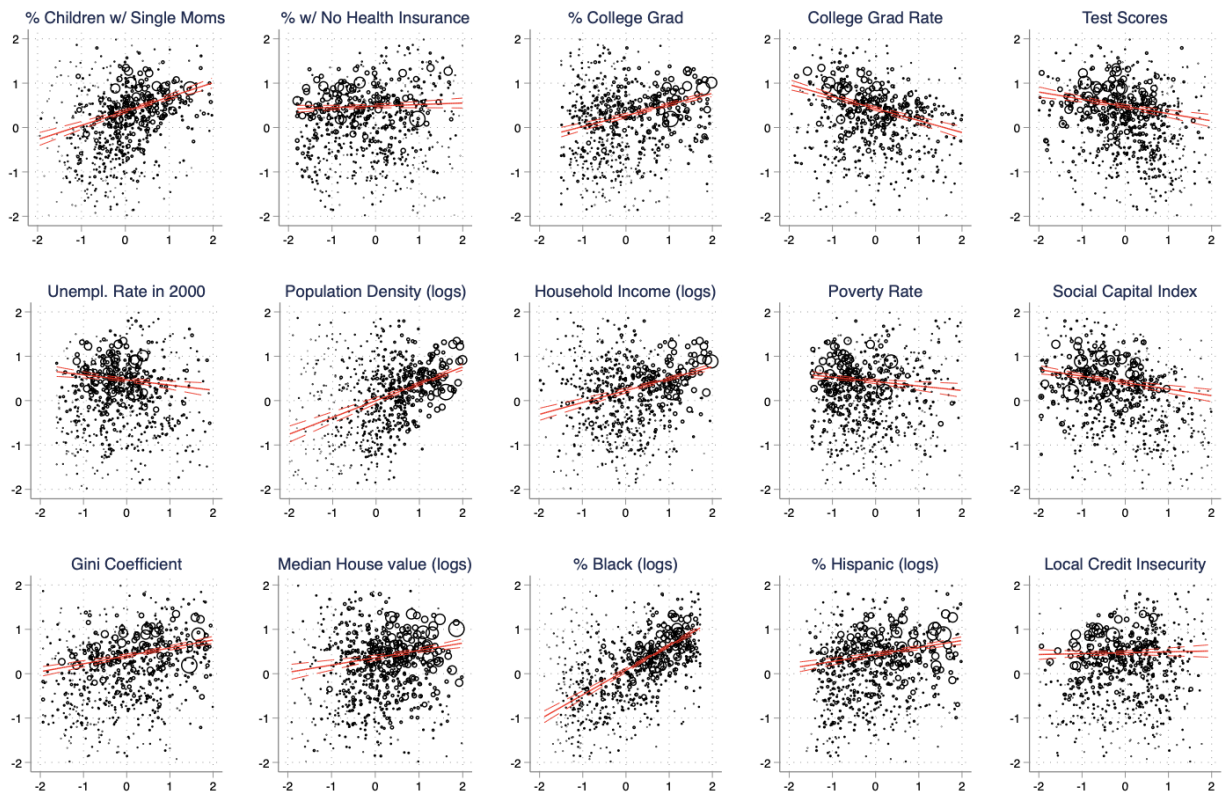
Notes: This figure provides additional analyses in support of the movers design. Panel (a) displays indicators for a household’s geographic location around the move. In the movers design, we assign a household the same destination location for the entire post-move period. In this figure, we display indicator variables for whether, in a given period, the household remains in the assigned destination unit and whether the household returns to the assigned origin unit. Panel (b) scales the estimates for the movers analysis from panel (b) of Figure 8 by the share of movers still at the assigned destination.

Figure B.7: Correlations with Location Fixed Effects (All Indicators)



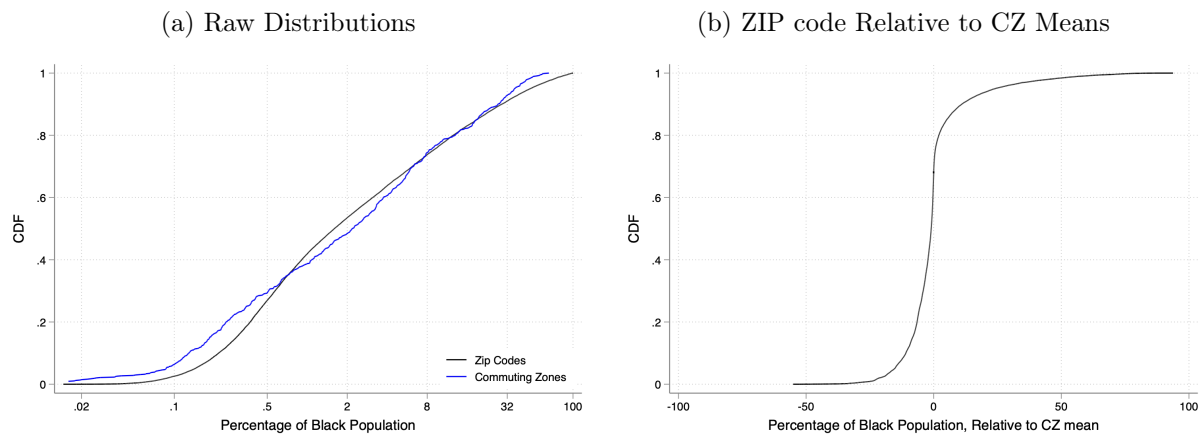
Notes: These figures display correlations of the location fixed effects, Γ_z , as estimated using equation (5), with CZ-level social and economic characteristics.

Figure B.8: Correlations with Households Fixed Effects (All Indicators)



Notes: These figures display correlations of the household fixed effects, α_i , as estimated using equation (5) and collapsed at the CZ level, with CZ-level social and economic characteristics.

Figure B.9: CDFs of Share of Black Households by Commuting Zones and ZIP Codes



Notes: These figures display cumulative density functions (CDFs) for the share of black households. Panel (a) displays CDFs across commuting zones (CZs) and across 5-digit ZIP codes, and panel (b) displays the CDF across 5-digit ZIP codes relative to the commuting zone means (panel (b)).

Table B.1: Health and Retirement Study (HRS): Defined Contribution Accounts

(a) Distribution of Amounts of Balances and Withdrawals

	Mean	10th	25th	50th	75th	90th	Number of Obs.
Balances	108,856	2,695	10,000	40,000	123,625	300,000	6,368
Withdrawals	34,834	2,000	3,975	10,000	30,000	60,000	1,647

(b) Use of Withdrawals

	Number of Obs.	Percent
Bought durables	238	15
Spent it	532	34
Saved/invested	185	12
Paid debt	442	28
Rolled into IRA	50	3
Gave it away	0	0
Other	86	5
Don't know	14	1
Refused	24	2
Total	1,571	100

Notes: This table displays summary statistics for the use of defined contribution accounts based on the Health and Retirement Study (HRS). We use HRS data from waves 7-14, which cover the years 2004-2018. The sample is restricted to respondents who have defined contribution pension plans and are of ages 45-59. We rely on two main questions in the HRS, which relate to a household's experience between consecutive waves that are typically two years apart. The first question pertains to withdrawals and asks: "Not including any money you rolled into an IRA, not including any money you used to purchase an annuity. How much money in total did you 'withdraw'/'receive' in payments 'since you left that business or employer'/'since we last talked to you in [Previous Wave Interview Month] [Previous Wave Interview Year]'?" The second question pertains to the usage of funds and asks: "What did you do with the money?" where respondents can choose among the options: bought durables (house, car, etc.), spent it, saved/invested, paid off debt, rolled into IRA, gave it away, other, as well as don't know and refuse to answer. Information on usage of withdrawals is based on the first usage indicated by the household.