The Consumption Response to Realized Capital Gains: Evidence from Mutual Fund Liquidations*

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Abstract

Using data from a large German retail bank, we investigate how individual consumption responds to realized capital gains. Investors can decide when to liquidate their assets. To address this concern, we investigate consumption when mutual funds close and investors face forced liquidation of their assets. We estimate that the marginal propensity to consume (MPC) out of one dollar received from a forced sale is approximately 11% over the following 30 days. We also find that the MPC is lower in recessions and decreasing in interest rates. These findings are difficult to reconcile with the theoretical predictions of a standard life-cycle portfolio-choice model.

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1 Introduction

Fluctuations in stock prices should significantly affect households' savings and consumption decisions; after all, stock and mutual fund holdings represent a significant fraction of household financial wealth – comparable to the stock of housing wealth. On the other hand, unlike housing wealth, stockholdings are very volatile and fluctuations are seen as transitory by individuals. Moreover, stocks and funds are very liquid instruments, much more so than housing wealth, and can be easily monetized any time when consumption needs arise.

A standard life-cycle portfolio-choice model predicts that the marginal propensity to consume (MPC) out of fluctuations in stock prices should be close to zero and more or less constant across age and income as well as the business cycle and interest regimes. In contrast, heterogeneous agent models or models in which stock prices are partly predictable imply differences in the MPCs for groups of different ages and incomes as well as over business cycles. Furthermore, in richer models, monetary policy and the interest rate regime affects the MPC out of capital gains. Despite a sizable theoretical literature making clear predictions about how individuals respond to changes in the value of their stockholdings, empirical evidence remains scarce.

Clearly, estimating the marginal propensity to consume out of stock price changes, realized or not, is difficult. Aggregate fluctuations in stock prices are endogenous with respect to other macroeconomic shocks, such as income growth and consumer confidence. Therefore, the relationship between aggregate consumption and stock price fluctuations will be overestimated due to common shocks. Common shocks are arguably less problematic when utilizing individual-level data and computing abnormal returns. This way, one could sensibly estimate the marginal propensity to consume out of unrealized capital gains or irregular dividends. However, if one were to look at realized capital gains, there are clear-cut endogeneity problems present. When individuals decide to liquidate stockholdings, they either decided to consume more or rebalance.

To investigate the effect of capital gains on individual investor consumption, we use a unique panel dataset on the daily trading of 103,000 private investors in Germany spanning the years 1999 to 2016. We precisely measure each individual's daily activity by his or her log in and trading behavior as well as all of his or her transactions in the settlement, checking, and savings accounts. In this sample, we see the forced sales from 8,510 mutual fund closures from 2003 to 2016 identified by their International Securities Identification Number (ISIN).[1]

We estimate the effects of forced liquidations on consumption using a simple cross-sectional design, which straightforwardly estimates the average MPC. We find that individuals, on average, consume approximately 11% of their funds after the forced sale event. Following **?**, **?** document a very high MPC out of dividends, around 35%, relative to MPCs out of unrealized capital gains that range from 13% for the bottom 50% of the wealth distribution (who own less than 7% of overall stockholdings) to a flat 5% for the remainder. Thus, our estimate for realized capital gains is much closer to the MPC out of dividends than that of unrealized capital gains. This finding suggests that the high MPC out of dividends is because of the liquidation event rather than optimization of life-cycle income profiles. **?** argue that the estimated MPC of 5% is consistent with near-rationality in life-cycle models. However, our finding says that the MPC is low only because the capital gains have not been realized. If these capital gains had been realized, then the MPC may be higher. As an alternative specification, we consider a panel regression of consumption on liquidations.

We thus argue that the baseline level of our estimated MPC is much too high to be consistent with a standard life-cycle model, which predicts the MPC out of capital gains to be very close to zero. Furthermore, in our setting, i.e., liquidations of capital gains, there is no immediate wealth shock in a strict sense. Such an absence of a wealth shock is true for dividends too: stock market wealth falls by exactly the amount liquidated. For this reason, as well, the MPC out of forced liquidations should be zero. However, if individuals substitute intertemporally, are myopic, or face transaction costs, our estimated MPC is close to the actual MPC out of capital gains. Our estimated MPC of 11% over 30 days is similar to the documented high MPC out of dividends (**??**) and fiscal stimulus payments (**???**); both of which should be close to zero in a standard life-cycle model, as the wealth implications are either zero or small and transitory. Overall, we thus again document that whenever individuals are handed cash, they consume a sizable chunk of it (**?**).

We also explore how the MPC varies for different ages and income levels as well as over the

[1] In **?**, we study the subset of mutual fund closures that are not imputed focusing on how much individual reinvest out of these liquidations when they either result in a gain or loss relative to the initial investment.

business cycle and across interest rate regimes. We find a higher MPC for young and high-income investors, the former appears consistent while the latter is inconsistent with standard life-cycle portfolio-choice models. Moreover, we find that the MPC is much lower in recessions, which is also surprising from a standard model perspective. In terms of the interest rate regime, we find that the MPC is lower when the baseline interest rate is lower. We also discuss to which extent new macroeconomic models that incorporate heterogeneity **?**, among many others can explain these differences in our estimates.

By estimating the consumption response to realized capital gains, this paper contributes to the literature linking stock market wealth with consumption, which includes studies employing aggregate and regional variation (e.g. **?**, **?**, and **?**).[2] However, endogeneity concerns are likely to affect the interpretation of the estimates in these existing studies, as they use aggregate data and cannot distinguish between the direct effect of changes in stock wealth on consumption and the fact that stock prices are a leading indicator of economic growth and reflect consumer sentiment. There also exist studies employing household-level data but lack disaggregated data on households' actual stock holdings (e.g. **?** and **?**). Specifically, **?** uses CEX data and shows that stockholder's consumption responds strongly to changes in dividend payments but not to changes in stock prices. They also provide suggestive evidence that this behavior is driven by mental accounting. Unfortunately, even the estimates in studies using household-level data can be upward biased to the extent that there exist shocks that increase the household stock wealth but also have a direct effect on household consumption (for instance, an employee receiving stocks as part of her compensation).

? use disaggregated household consumption and asset holdings data from the Swedish wealth registry. They instrument contemporaneous stock market returns with those returns that the household would have had if it were not to change its stock allocation. The authors can take advantage of very granular data and its coverage of the entire population of Sweden to document heterogeneity across wealth groups and that even the consumption of households in the top percentiles of financial wealth is ten times more responsive to dividend payments than to capital gains. However, the Swedish data may contain measurement error in both imputed consumption as well as imputed

[2]See **?** for a survey of the literature.

capital gains when stocks appear in individuals' year-end portfolios but their actual purchase prices cannot be recovered from the data.

As mentioned, to estimate the MPC out of realized capital gains rather than unrealized capital gains not only offers a source of exogenous variation of liquidations, but it may also estimate an actual MPC out of stock market wealth – if individuals are inert or face transaction costs which prevents them from liquidating assets, even though, in principle, our shocks are pure liquidation shocks and do not have wealth implications. Nevertheless, we here follow a literature estimating MPCs out of cash-flow shocks or events in which no actual wealth shock occurs. For instance, **?** estimate the MPC out of dividends that do not imply a wealth shock as in the event of any dividend payout the stock price decreases by the same amount. Moreover, the tax rebate literature, **????**, either considers wealth shocks that are, in principle, just future tax obligations (abstracting from redistribution), or simply rearrangements of tax obligations, which thus do not have wealth implications either. Furthermore, even if there occurs redistribution, the wealth shock is small and transitory. To test the predictions of a life-cycle model or permanent income hypothesis by looking at simple liquidation shocks is thus not unusual. Thus, this paper relates to the extensive literature on household consumption in response to current and future income shocks, such as **?**, **?**, **?**, **?**, **?**, among others.

2 Data and summary statistics

Our data set stems from clients of one of the largest online banks in Germany. We have daily information regarding logins (from 2012 onwards), trades, and portfolio holdings of approximately 103,000 customers as well as all balances and transactions of each investor's other accounts at the online bank from 1999 to 2016. We keep only private investors that reside in Germany and obtain data on customer demographics such as gender, age, occupation, and zip code location. In online banks, silent attribution is a common phenomenon, as usually there is no charge for having an account. Therefore, in order to not analyze accounts of investors who stopped trading, we require that individuals execute at least 1 trade per year. An advantage of our data set is that we can exclude quasi-automatic trades, such as savings plan transactions. Additionally, trading decisions in our sample are not moderated by any influence from third parties, such as financial advisers. To further ensure that our sample includes only self-directed online consumers, we exclude trades from limit orders, because this type of transactions do not reflect current trading decisions of investors. For each trade, we obtain detailed information on the security such as asset class, risk class, issuer, and issue date.

Our sample is not representative for the German population as a whole; less than half of Germans are invested into equities, either directly or indirectly. However, it is a relatively representative sample of self-directed retail investors in Germany. Our sample does not comprise the entirety of the bank's customer base, but a roughly 10 percent sample of all customers. The bank did not pick the sample of retail investors by trading frequency but rather chose a random subsample of all bank users who held a brokerage account. In that sense, our sample is representative for individuals in Germany holding an investment portfolio at a major bank. The average age of investors is 53 and the median age is 52. 16.9 percent of our sample is female and 83.1 percent is male. Brokerage clients are generally expected (**?**) and found to be more sophisticated than the overall population (**?**). The same is true for our sample: 6 percent of our investors hold a doctoral degree, which is higher than average in the German population (**?**, 1.1%,).

Investors own portfolios that are worth 55,854ï¿œ, on average. These descriptive statistics are comparable to those reported by household finance studies using US-data (**?**). In addition, we compare average portfolio values to official statistics in Germany. The Deutsche Bundesbank (2013) reports the average portfolio value of a German stock market investors to be around 48,000 Euros. This value seems comparable to the average values we observe in our sample. Additionally, we compare portfolio holdings to self-reported wealth and gross annual household incomes for those investors who reported these data. Since income is reported in several ranges, we use the midpoint of each range as a proxy for investor income. The self-reported wealth measure is close to the actual portfolio holdings we observe which is reassuring as it means the average client does not have another brokerage or major savings accounts. The mean ratio of the average portfolio value (over the entire sample period) to annual income is 1.3. For comparison, the ratio of total financial assets to gross household income in the German population is about 1.1 (**??**).

The information on fund closures was obtained from the Bundesverband Investment und Asset Management e. V. (BVI). The BVI is the point of contact for politicians and supervisory authorities on all issues related to the German Capital Investment Code (Kapitalanlagegesetzbuch, KAGB), and represents the interests of the German fund industry at national and international level. Beyond the information from the BVI, we can also look at situations in which many individuals sell the same fund and in turn the fund is never traded or held again by any individual in the sample. In practice, an ISIN is assumed to be a forced sale if the difference between average daily sell transactions and sell transactions on the last of trading of the ISIN in the database is larger than 10 to identify other mutual fund closures in our data that are not recorded by the BVI, such as mutual fund closures before 2006. We observe another 1,369 fund closures roughly evenly distributed between 1999 and 2016 as can be seen in Figure 1. Moreover, in Figure 2, we display the day of month and the day of week of all fund closures.

[Insert Figure 1 and 2 about here]

The SPIVA US Scorecard 2017 documents that over a 15-year period, 58% (48%) of equity (fixed income) funds were merged or liquidated and states that the main reason is continued poor performance. **?**, the forerunners of mutual fund termination studies, found that US mutual fund disappearance is a function of lagged relative returns, relative fund size, fund expenses, and fund age. **?** argue that the importance of returns depends on the age and style of the fund and show that beyond returns also expenses, turnover, the S&P 500, and the short-term interest rate matter for mutual fund closures. **?** shows that total returns are more important than risk-adjusted returns in explaining mutual fund termination. When we perform a kitchen-sink regression in a linear probability model of mutual fund closures, we find that returns and size decrease the probability to close a fund but overall fund closures are not explained well by observables. After all, mutual fund are fairly diversified and thus mostly determined by market conditions and there is no clear evidence for manager skill **?**, among many other studies. In any case, for identification it matters whether investors can choose to invest into to-be-closed funds endogenously. We feel that is unrealistic and thus consider liquidations as plausibly exogenous.

Of those 1,369 fund closures, we observe 8,510 forced sales, i.e., individuals affected by the mutual fund closures (double-counting if individuals are affected multiple times). If we just count the number of distinct investors affected than it is 6,484 portfolio IDs. Most forced sales happen in 2008 and are roughly evenly distributed in the other years, as can be seen in Figure 3.

[Insert Figure 3 about here]

Table 1 shows detailed summary statistics for our forced sales events including the holding periods before closure, the purchase and selling share prices, and the average value and return of the forced sales.

[Insert Table 1 about here]

Table 2 shows detailed summary statistics of assets under management for all funds that did not close and funds that were closed. The row last total assets refer to the last value of total net assets right before closure of the closed funds or the total assets at the last observation for the non-closed funds. Furthermore, Table 3 shows the raw return performance of all and the closed funds from 2 years up to 1 day prior to the closing date. It can be seen that the closed funds did not necessarily perform much worse than the remaining universe of funds. In fact, in the raw return numbers there does not appear to be a clear pattern in terms of the decision to keep a fund alive or not. The size of the fund appears a more important factor than the performance.

[Insert Tables 2 and 3 about here]

Finally, Table 4 shows detailed summary statistics for our universe of investors relative to those affected by the fund closures, i.e., holding funds that were closed, and relative to those affected by the fund closures and ultimately forced to sell. It can be seen that the three samples of investors look very similar in terms of demographics and income.

[Insert Table 4 about here]

Figure 4 shows the average amounts (in Euros) of all fund liquidations per year. We can see that the average amounts are quite substantial ranging from 6,000ï¿œ to 10,000ï¿œ. Clearly, the fund liquidation does not represent a wealth shock, but they are quite substantial liquidation shocks. As discussed in the introduction, we follow a large literature estimating MPCs out of cash-flow shocks that do not go hand-in-hand with an actual wealth increase.

[Insert Table 4 about here]

3 Methodology

Cross-sectional regression specification

We consider a simple cross-sectional approach. The cross-sectional regression is specified as follows:

$$\Delta Y^i_{j,j+\tau} = \alpha + \beta F^i_j + \gamma m_j + \theta y_j + \epsilon^i_j \tag{1}$$

where $\Delta Y^i_{j,j+\tau}$ is the sum of the outcome variable of interest for investor i at the time of the forced sale event j to $j+\tau$, F^i_j is the forced sale affecting investor i at time j, m_j is a month fixed effect, and y_j is a year fixed effect. We consider two bandwidths τ: five or thirty days since the day that the money arrives in individual's accounts. Because the forced sale is exogenous to individual investors, other control variables are not necessary but may increase precision. Furthermore, we adjust standard errors for heteroskedasticity.

When investors make a trade or a position gets liquidated, then there occurs a transfer to the settlement account (Verrechnungskonto). The settlement account is an account dedicated for making trades and automatically opened when individuals open a portfolio. It pays some interest and is federally insured. We thus consider the following outcome variables: 1) transfers to the portfolio via purchases of securities (reinvestment), 2) transfers to the checking account within in the bank (consumption), 3) transfers to the savings account within the bank (savings), and 4) transfers outside of the bank (residual transfers). All the variables are transfers and thus flow variables. The coefficients can thus be interpreted as the share of wealth reinvested or saved or, as a residual, consumed.

We argue that everything that is not reinvested or saved is consumed. Thus, consumption equals the transfers into the checking account in addition to all transfers from the settlement account outside the bank. We argue that it is unlikely that individuals have a second brokerage accounts or additional savings vehicles as banking with multiple banks is discouraged in the German credit score system. Furthermore, individuals want to dedicate one brokerage account as their main one to receive the tax-free allowance of capital gains.

Panel regression specification

As an alternative, we can consider a panel regression approach. The cross-sectional regression is specified as follows:

$$Y_{i,t} = \alpha_i + \phi_t + \beta F_{i,t} + \gamma L_{i,t} + \theta D_{i,t} + \epsilon_{i,t} \tag{2}$$

where $Y_{i,t}$ is the measure of consumption at time t. α_i is an individual fixed effect and ϕ_t is a time fixed effect. In turn, $F_{i,t}$ is the forced sale affecting investor i at time t, $L_{i,t}$ are non-forced sale of investor i at time t, and $D_{i,t}$ are dividends or other liquidations received by investor i at time t. Because the forced sale is exogenous to individual investors, other control variables are not necessary but may increase precision. Furthermore, we cluster standard errors at the individual level as common in individual-level panel regressions.

To improve on our previous measure of consumption, treated as a residual, we can use a more direct measure of consumption in the panel regression approach: transactions that are flagged as either ATM withdrawals or point-of-sale (POS) transactions, i.e., when individuals swipe their debit card in stores.

4 Results

Cross-sectional regression results

Table 5 shows the estimation results for the share of liquidity consumed (i.e., transferred into the checking account or transferred out of the settlement account), reinvested, or transferred to the savings accounts in the thirty days after individuals received their liquidity from the forced sales

(Specification (1)). Furthermore, we show the share of liquidity that remained in the settlement account as well as the overall difference between the money that the online bank held at the time of the liquidation versus thirty days later.

[Insert Table 5 about here]

We find that, on average, individuals consume around 11% of the liquidation amount and reinvest 54% of their newly found liquidity within thirty days. Furthermore, we find that 30% is transferred into savings accounts. This implies a very high MPC on the quarterly or annual level, which is in the same ballpark as the estimates of **?** and **?** for the MPC out of dividends but much higher than their estimates for the MPC out of unrealized capital gains. When we look at five versus thirty days we find qualitatively and quantitatively similar results.

We want to compare the estimated coefficients in response to forced sales to the estimated coefficients for young and old individuals. Standard portfolio-choice models with stochastic labor income predict that the share invested into risky assets is decreasing in age but the MPC may be increasing or decreasing in age depending on how much wealth increases in age. We thus estimate the same specification for two groups of investors – those above the median age of 51 and those below. The estimation results for the forced sales interacted with a dummy for young and old investors for thirty days can be found in Table 6.

[Insert Table 6]

In summary, we find that young investors consume more and reinvest less. They thus have a higher MPC than old investors, which would be predicted by a life-cycle model if the income effect (younger investors are typically poorer) outweighs the age effect (older investors should have a higher MPC as they die earlier). Overall, the estimation results line up sensibly across different specifications such as using five days instead of 30 days or controlling for additional fund characteristics or calendar fixed effects. Furthermore, when we interact with a dummy for over 65 years old, we find similar effects.

Furthermore, we want to understand how the estimation results differ for high-income versus low-income investors. Here, we use only those investors who provide, self-reported, income statistics which halves the sample size. The results with interactions for above-median, i.e., 60,000 Euro annual income, versus below-median income investors for thirty days can be found in Table 7.

[Insert Table 7]

In summary, we find that low-income investors have a lower MPC than high-income investors as they reinvest a smaller share of their wealth. That low-income investors thus consume less out of fluctuations in their stock market wealth is not consistent with standard life-cycle portfolio-choice models. The results line up sensibly when we split investors into three instead of two income groups.

We also want to compare the estimated coefficients in response to forced sales to the estimated coefficients across business cycles and interest rate regimes. With respect to business cycles, standard portfolio-choice models predict that the share consumed should be higher in recessions (see, for instance, **?**). We thus estimate the same specification but interact the liquidation events with whether or not the period has been declared a recession by the European Central Bank (ECB) or the National Bureau of Economic Research (NBER). The estimation results for the forced sales interacted with the recession dummies for thirty days can be found in Table 8.

[Insert Table 8]

Across different specifications and also when we use the National Bureau of Economic Research (NBER) definition of a recession, we find that investors consume a larger share of their funds in a boom versus a recession and reinvest a smaller share. Again, this is not necessarily consistent with standard life-cycle portfolio-choice models featuring business cycles. Instead it appears as positive consumer sentiment leads people consume more in booms and individuals appear contrarian as they reinvest more in recessions.

Finally, we estimate the coefficients in response to forced sales across interest rate regimes. With respect to the baseline level of risk-free interest, standard portfolio-choice models predict that the share invested should be higher in low-interest rate environments. We thus estimate the same specification but interact the liquidation events with whether or not the period has been characterized by interest rates hitting the zero lower bound (ZLB). The estimation results for the forced sales interacted with a ZLB dummy for thirty days can be found in Table 9.

[Insert Table 9]

Across different specifications, we find results that suggest that the share reinvested is much higher during the ZLB period. Again German investors appear contrarian or are reaching for yield in low-interest rate environments. This result is consistent with the standard portfolio-choice model with stochastic labor income. Agents in this model invest more because their expected labor income is discounted at a lower rate and thus increases relative to their stock market investment. To align their capital allocation with their optimal portfolio share they thus invest more into the stock market.

Panel regression results

Table 10 shows the estimation results when we instead use ATM withdrawals and POS transactions as our measure of consumption in the panel regression analysis represented by Specification (2). The first column shows the panel regression results of ATM withdrawals and POS transactions normalized by their own average, i.e., the average deviation in ATM and POS, aggregated to the weekly level on a dummy for an exogenous liquidation in that week controlling for individual, year, and week-of-year fixed effects for the subsample of main clients only. We can see that individuals on average consume 13% more in a week in which they are subject to a forced sale. The second column does the same but also controls for the amount of the liquidation which does not affect the coefficient. In turn, the third to fifth columns regress the absolute values of different measures of consumption on the liquidation amount controlling for individual, year, and week-of-year fixed effects for the subsample of main clients only. The third column uses all net outgoing wires plus ATM plus POS transactions as the variable for total spending. The fourth column uses all net outflows including buys into the portfolio as the outcome variable. The fifth column uses the absolute value of ATM and POS transactions estimating an (insignificant) coefficient of 2%. This coefficient is quantitatively similar when we use a salary inflow instead of the exogenous liquidation as the regressor. These results thus confirm that individuals consume substantially more, in the same magnitude as receiving an additional salary payment, when they are subject to a forced sale.

[Insert Table 10]

Robustness

We find consistent effects throughout specifications and sample splits that line up sensibly. The cross-sectional specification basically treats the population as similar and conducts an experiment in which individuals are chosen at a point in time to give them their investment back. Thus, we identify a pure cross-sectional effect of individuals receiving more versus less liquidity back. We do not think that our results are specific to the year 2007 and 2008 (although we have a lot of observations in that year) because we include year fixed effects in all our regressions and thus do not identify off of individuals being forced out of funds in year 2007 versus other years. It is important to note though that 2007 was before the financial crisis which started in 2008. Many of the forced sales in 2007 are due to the closures of a few funds that the investors of this particular bank were invested in. The reason that these funds closed were due to a large German bank closing an arm of their operations that white-labeled funds for our online bank which were marketed through their clients. Thus, a chunk of the variation in our sample is because of fund closures that are not due to small niche funds or underperformance. In any case, while we acknowledge that underperformance is probably a main driver of fund closures, we do not think individuals would choose to invest into a fund because they expect it to underperform and then close, which is our identifying assumption.

We argue that the liquidation event is exogenous to the retail investors that happen to invest into that fund. We think that it is unlikely retail investors would deliberately choose to invest into a certain fund because they expect it to be closing. Moreover, we think that the liquidation amount, as determined by the initial investment into the fund, is unrelated to the fact that the fund later happens to close. However, the return of the initial investment is potentially jointly determined by market factors that also determine whether individuals want to reinvest at a higher or lower rate at the time of event closure. Thus, while the initial investment and the closure date is exogenous, the return of the initial investment may be subject to an omitted variables problem that also determines individual's propensity to reinvest (for instance, sentiment or market conditions). When we control for fund fixed effects in the unconditional cross-sectional regression, we also effectively control for the time and market as well as all other contemporaneous conditions at the time of the fund closures. Still, we can additionally control for the market return, in the past three or twelve months, and obtain the same result, as well as we can control for individual's portfolio returns, in the past three or twelve months, and obtain the same result.

Quality of the consumption data

We observe transaction categories from the transactions system that allows us to pinpoint ATM withdrawals, (international) POS transactions, (repeated, automated, international) wires, interest and dividend payments, (portfolio) fee payments, tax payments, check payments, salary transfers, cash deposits, social security payments as well as security purchases and sales as well as Fx-trading transactions. However, we have no spending categories such as groceries and we are limited in the sense that we cannot know for certain whether an individual has other bank accounts or portfolios. Nevertheless, using ATM withdrawals and POS transactions or ATM plus POS plus wires as a measure of spending may give us a relatively accurate picture of spending. To assess the quality of our spending data, we compare the spending responses to paydays to those that have been documented in the literature using transaction-level spending data that is more thoroughly categorized (**???**). When we replicate the analysis in **?** and **?**, i.e., plotting the daily deviation in spending around paydays for three income groups, we obtain very similar pictures in terms of magnitudes and tightness of the estimates (as can be seen in Figure 5). Furthermore, when we look at the daily consumption response out of dividends and forced sales due to mutual fund liquidations, we find very similar responses to those in **?** as can be seen in Figure 6.

[Insert Figures 5 to 6 about here]

Tax implications of forced sale events

In Germany, capital gains are taxed at the same rate as dividends and interest payments and the tax is subtracted at the source, i.e., in the event of a capital gains realization, the funds that arrive in the settlement account are already after tax funds. Since 2009, the capital gains tax (Abgeltungssteuer) is 25% plus solidary addition (Solidaritï¿œtszuschlag) (5.5% of the capital gains tax) and church tax (Kirchensteuer) (8 or 9% of the capital gains tax) which amounts to approximately 28% in total. Furthermore, there is an initial allowance (Freibetrï¿œge) of 801ï¿œ for singles and 1.602ï¿œ for married couples. Individuals can specify their main brokerage such that the capital gains tax will not be subtracted unless the initial sum is exceeded (Freistellungsauftrag). Furthermore, if capital losses are realized before capital gains, then the capital gains tax will be automatically lowered by the realized losses. For stocks and funds that were bought before the 1st of January 2009, the sale does not initiate the automatic capital gains tax subtracted at the source. Before 1st of January 2009, capital gains and dividends were taxed at the personal income tax rate, which can amount up to 42%. For stocks and funds bought but not sold before 1st of January 2009, any capital gains will remain tax free until the end of 2017 and tax free up until 100,000ï¿œ from January 2018 on. In summary, for all practical concerns, the capital gains tax is thus taken at the source and all funds individuals receive are after-tax.

5 Life-cycle portfolio-choice model

We now assess the qualitative and quantitative predictions of a standard life-cycle model with stochastic labor income and portfolio choice. This exercise aims to provide a basis for thinking about our results and empirically distinguishing between standard versus non-standard preferences for participation, portfolio shares, consumption, and wealth accumulation over the life cycle.

To validate the model quantitatively, we feed in the estimated labor income profile and aim to match the average empirical life-cycle profile of non-participation and portfolio shares using household portfolio data of the Survey of Consumer Finances (SCF) from 1992 to 2007. Figure 7 displays the empirical life-cycle profiles for participation and portfolio shares as well as labor income. Participation, portfolio shares, and income are all hump shaped over the life cycle.[3] Furthermore, we can compare the model's quantitative predictions about consumption and wealth accumulation

[3] In this data, I control for time and cohort effects using a technique that solves the identification problem associated with the joint presence of age, time, and cohort effects with minimal assumptions (?). This technique is of special importance in this context because the life-cycle profiles of participation and shares are highly dependent on the assumptions the age-time-cohort identification is based on (as made clear by ?).

to the empirical profiles from the Consumer Expenditure Survey (CEX).

The agent lives for $t = \{1, ..., T\}$ periods and is endowed with initial wealth W_1. Each period the agent optimally decides how much to consume C_t out of his cash-on-hand X_t and how to invest the remaining funds $A_t = X_t - C_t$. The agent has access to a risk-free investment with return R^f and a risky investment with i.i.d. return R_t. The risky investment's share is denoted by α_t such that the portfolio return in period t is given by $R_t^p = R^f + \alpha_{t-1}(R_t - R^f)$. Additionally, the agent receives labor income in each period t given by $Y_t = P_t N_t^T = P_t e^{s_t^T}$ with $s_t^T \sim N(0, \sigma_Y^2)$ stochastic up until retirement $T - Ret$ and P_t a deterministic profile that we estimate from SCF data. Accordingly, the agent's maximization problem in each period t is given by

$$max_{C_t}\{u(C_t) + E_t[\sum_{\tau=1}^{T-t} \beta^\tau u(C_{t+\tau})]\}$$

subject to the budget constraint

$$X_t = (X_{t-1} - C_{t-1})R_t^p + Y_t = A_{t-1}(R^f + \alpha_{t-1}(R_t - R^f)) + P_t e^{s_t^T}.$$

We solve the model by numerical backward induction and additional details on the numerical backward induction solution is provided in **?**.

To assess the quantitative performance of the model, we calibrate the structural parameters governing the environment and preferences, $\mu, \sigma, \sigma_Y, G, r^f, R, T, \beta,$ and θ, in line with the literature. For an annual investment period, the literature suggests fairly tight ranges for the parameters of the log-normal return and we match these by estimating $\hat{\mu} - \hat{r}^f = 6.33\%$, $\hat{\sigma} = 19.4\%$, and the log risk-free rate, $\hat{r}^f = 0.86\%$, using value-weighted CRSP return data. Moreover, the life-cycle consumption literature suggests fairly tight ranges for the parameters determining stochastic labor income: labor income is log-normal, characterized by shocks with variance σ_Y, a probability of unemployment p, and a trend G that we roughly match by estimating $\hat{\sigma}_Y = 0.1$, $p = 1\%$, and $\hat{G}_t$ from the SCF data. We abstract from permanent income shocks because **?**, **?**, and more recently **?**, argue that household income processes are well approximated by a deterministic trend and a transitory shock. Labor income is correlated with the risky asset with a coefficient of approximately 0.2 following **?** among others. Moreover, because 25 is chosen as the beginning of life by **?**, we choose $\hat{Ret} = 11$ and $\hat{T} = 54$ in accordance with the average retirement age in the US according to the OECD and the average life expectancy in the US according to the UN. In turn, we choose $\beta = 0.96$ and $\theta = 8$ to match the empirical profile of portfolio shares in the SCF data, the profiles for portfolio shares, income, and consumption can be found in Figure 8. As the agent is second-order risk averse, he will always participate in the stock market but portfolio shares are as low as in the data because we choose a fairly high coefficient of risk aversion θ. The profiles are decreasing in the end of life because the agent's expected labor income is decumulating. The profiles are increasing in the beginning of life because the labor income profile is increasing initially and the agent is prudent such that increasing expected labor income makes labor-income and stock-market risks more bearable.[4]

Figure 9 displays consumption as a function of cash-on-hand for each year before retirement over the life-cycle. We can see that the marginal propensity to consume is higher for agents approaching retirement as less many years are left to save for. Furthermore, because the agent's utility function is prudent, the consumption functions are concave, which implies that the marginal propensity to consume out of an additional unit of cash-on-hand is increasing for lower levels of consumption. Therefore, in a recession, the standard agent will always have a higher propensity to consume out of his capital gains. In terms of age, the increased MPC due to lower wealth may or may not offset the decreased MPC due to a long life ahead and the predictions are less clear-cut. In turn, Figure 9 displays the consumption function for a higher level of the interest rate that is very low in the baseline model. Here, we do not see large quantitative differences, the MPC is marginally lower in the high-interest environment, as determined by a substitution versus income effect.

Additionally, we can run a standard consumption regression in the simulated data: $\Delta log(C_{it}) = \alpha + \beta \Delta log(CapR_{it}) + \epsilon_{it}$ holding age constant for four groups of savings A_{t-1} that represents all accumulated wealth invested in the risky or risk-free assets in this model. As we can see in Table 11. We chose a cross-section on old agents, age 60, to increase the MPC out of capital gains. However, even for older agents, the MPC out of capital gains is very close to zero. Moreover, it decreases

[4] **?** and **?** show that portfolio shares can be increasing at the beginning of life when income growth is high for high levels of risk aversion in the standard model.

in wealth but only ever so slightly. Thus, we feel that the level and amount of variation in our estimated coefficients are not matched by the life-cycle model and classic motivations contained in it. However, this is not surprising, as we are splitting the sample based on an endogenous variable, income or wealth, and many characteristics are different among rich versus poorer individuals leading to considerable heterogeneity in the estimates.

6 Conclusion

Using a large sample of transaction-level data on all asset holdings, spending, and income from a German retail bank, this paper explores how individual consumption responds to realized capital gains. Our identification strategy exploits mutual fund closures, which are arguably exogenous to individual characteristics. We find that individuals reinvest a large part of their newly found liquidity immediately. However, the MPC out of realized capital gains is much higher than that out of unrealized capital gains and in the ballpark of the high MPC documented for dividends (**??**). We further explore how the MPC out of realized capital gains varies across age, income, business cycle, and interest rate regime. We find a higher MPC for younger investors and low-income investors, which appears consistent with standard life-cycle portfolio-choice models. However, we also find that the MPC is much lower in recessions which is surprising from a standard model perspective.

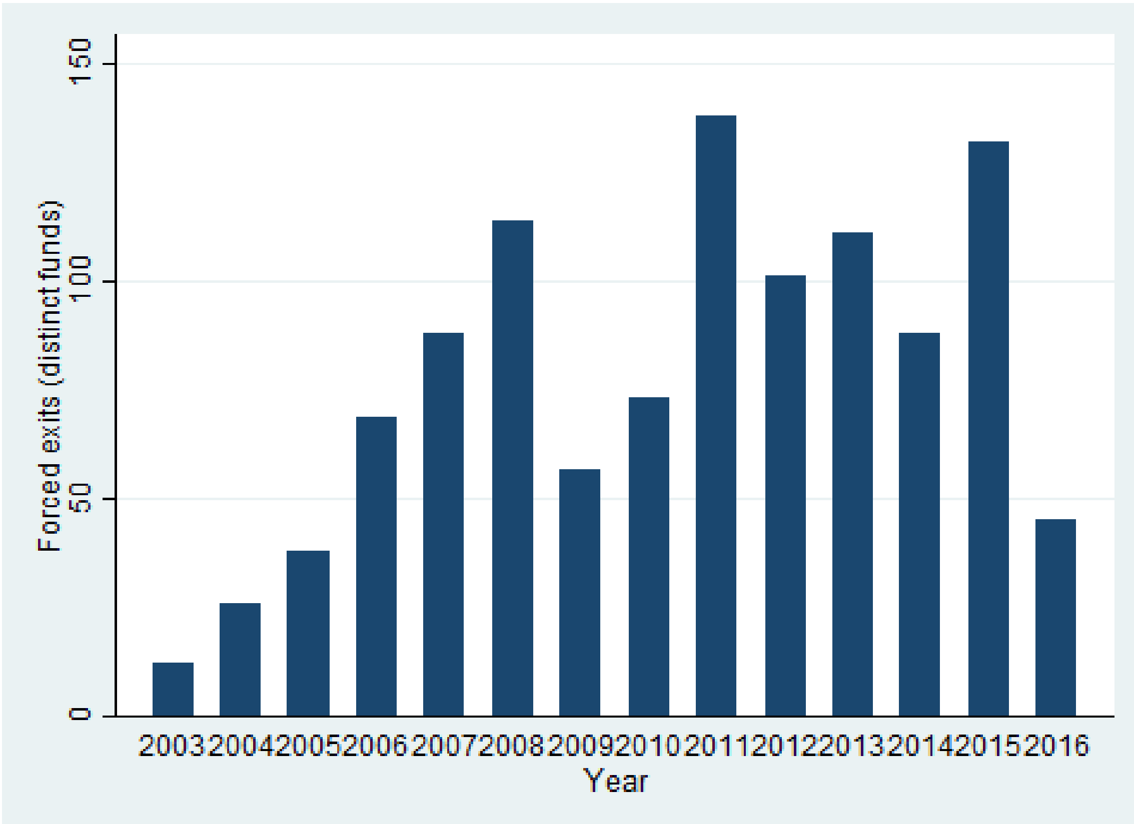

Figure 1: Number of mutual funds closures, as identified by the International Securities Identification Number (ISIN), per year over the period 1999 to 2016.

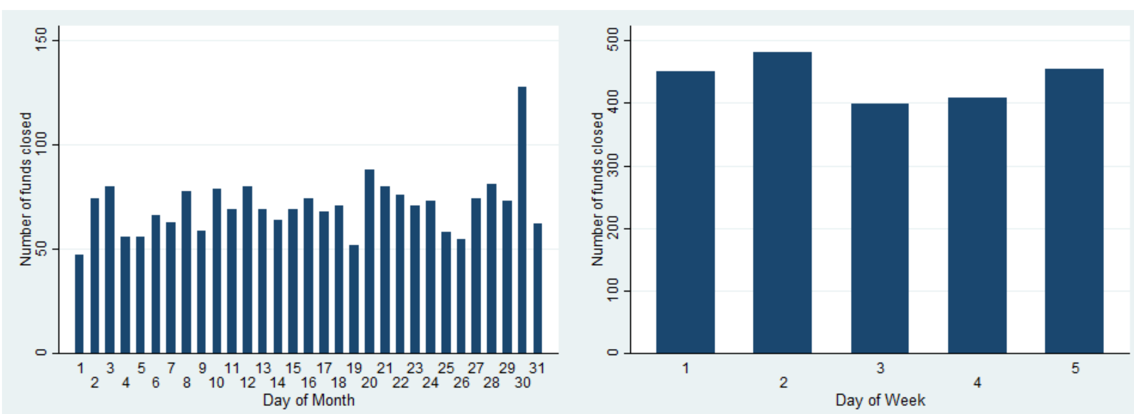

Figure 2: Number of mutual funds closures, as identified by the International Securities Identification Number (ISIN), per day of month and per day of week (0=Sunday to 6=Saturday).

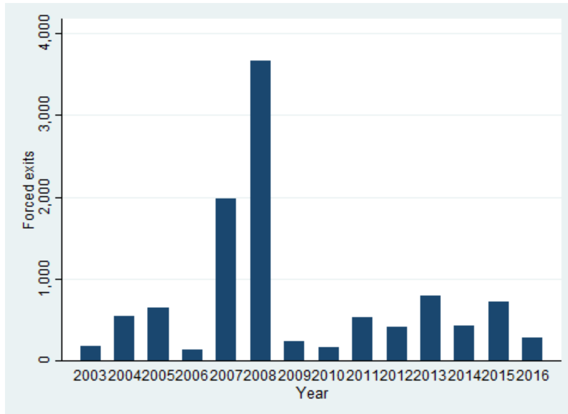

Figure 3: Number of forced sales, i.e., number of individuals affected by each fund closure (double-counting), per year over the period 1999 to 2016, and number of distinct investors affected per year.

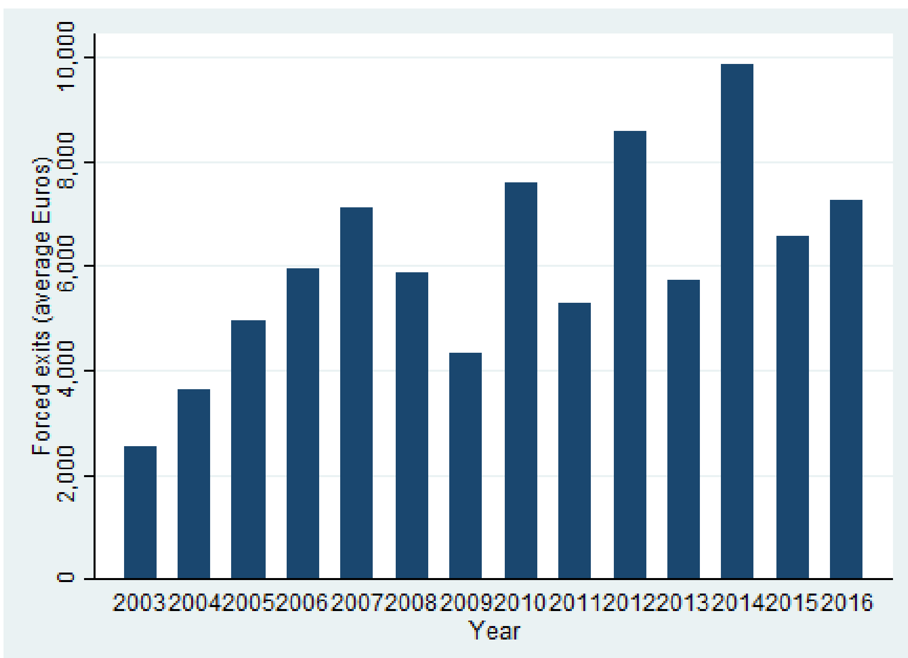

Figure 4: Average amounts of forced sales per year over the period 2006 to 2016.

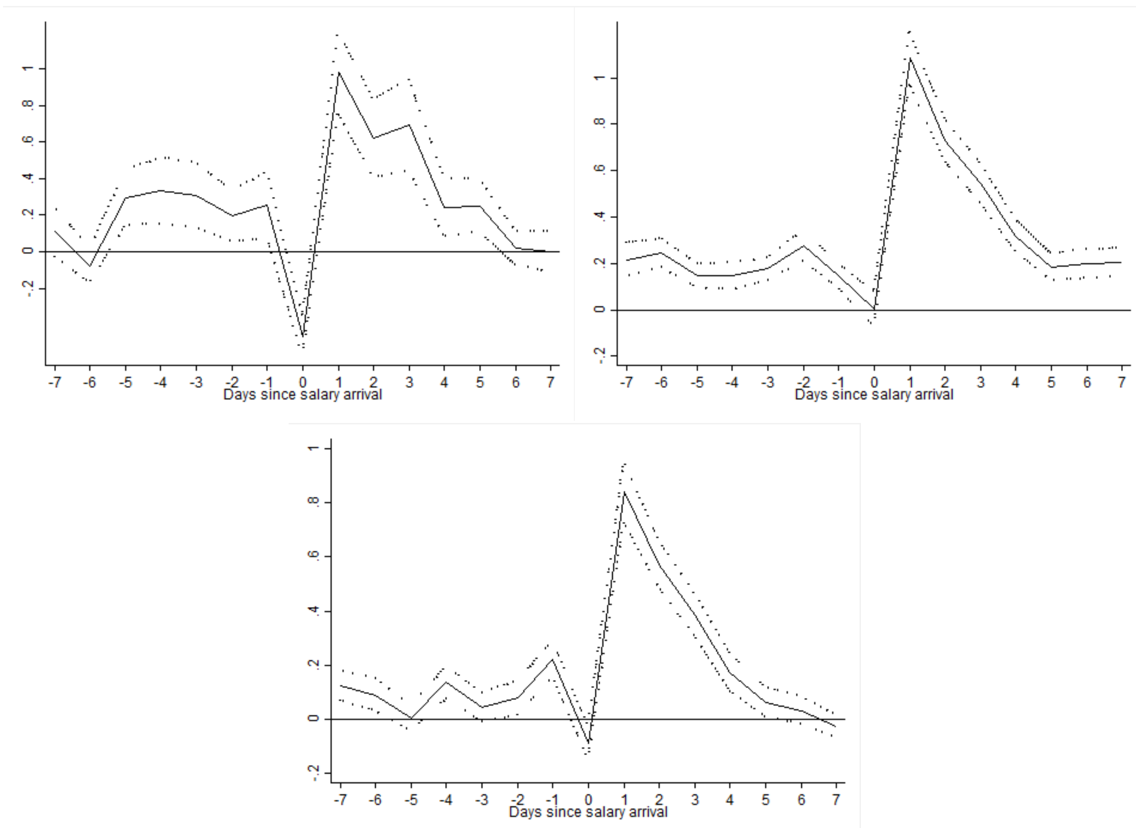

Figure 5: Payday responses of ATM withdrawals and POS transactions in the two weeks around salary receipt for three terciles of income (lowest tercile on the upper left)

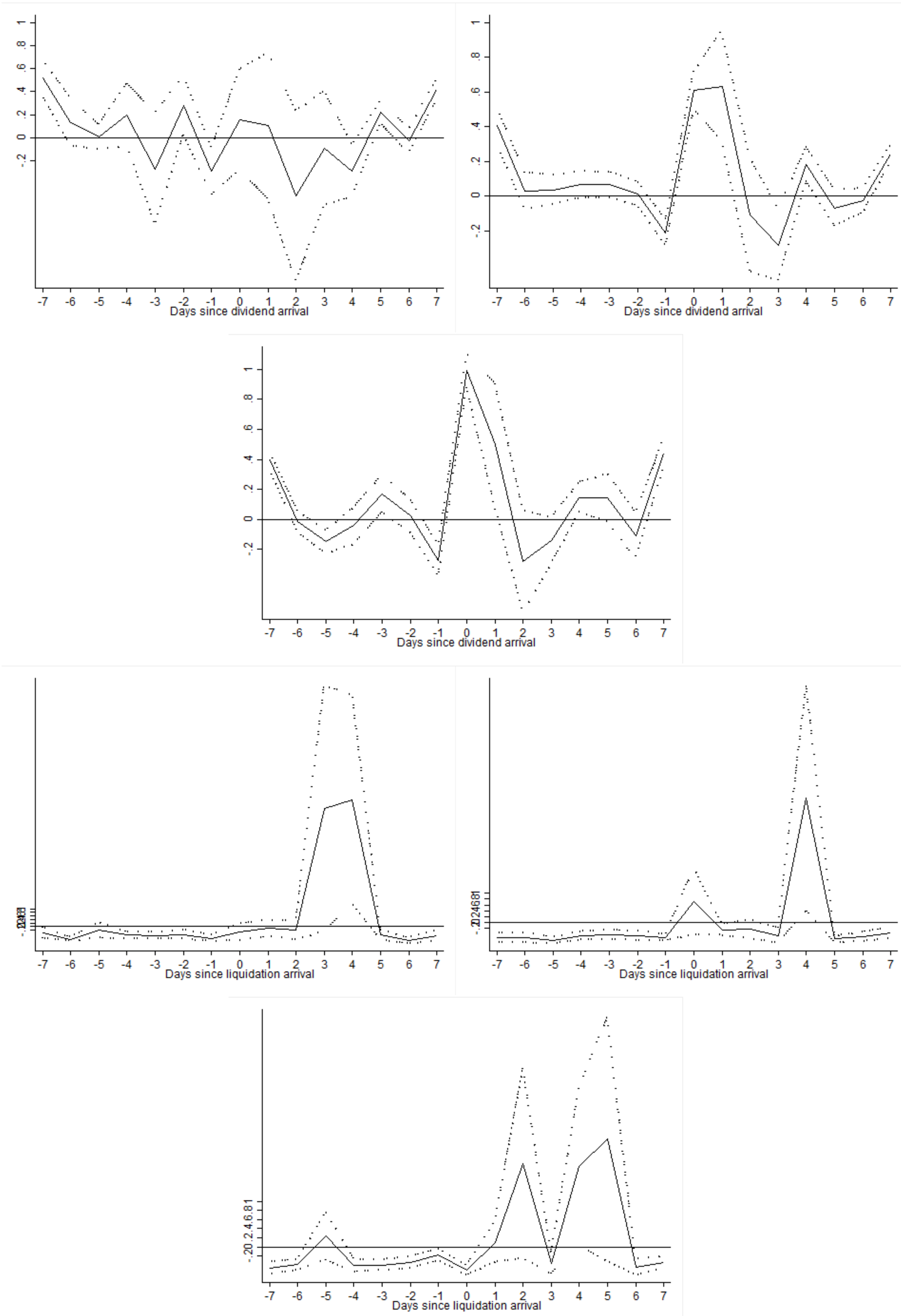

Figure 6: Responses of ATM withdrawals and POS transactions in the two weeks around receipt of dividends (upper) and liquidations from mutual fund closures (lower) for three terciles of income (lowest tercile on the upper left)

Table 1: Summary statistics for the forced sales events of all fund closures

	mean	standard deviation	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
holding period before closure	818	640	129	308	680	1,242	1,764
purchase share price	155	871	8.4	18	47	92	155
forced selling share price	77	337	7.6	13	48	77	114
value of forced sell	4,729	10,288	313	817	2,160	5,055	10,516
return of fund investment	-.064	.42	-.63	-.29	-.019	.15	.37
observations	19,029						

Table 2: Summary statistics for all funds and all closed funds

	mean	standard deviation	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
all funds							
mean total assets	1.3e+09	1.9e+10	688,887	5222079	2.5e+07	1.1e+08	5.7e+08
min total assets	3.0e+08	4.0e+09	100	70,800	2051500	1.5e+07	7.8e+07
max total assets	3.1e+09	5.1e+10	1600000	1.1e+07	5.5e+07	2.6e+08	1.4e+09
last total assets	1.8e+09	4.2e+10	62,300	1586300	1.3e+07	8.3e+07	4.9e+08
observations	51,859						
closed funds							
mean total assets	1.5e+08	1.1e+09	4562695	1.3e+07	3.5e+07	1.0e+08	2.5e+08
min total assets	3.3e+07	1.5e+08	266,170	1582050	6916000	2.4e+07	6.6e+07
max total assets	4.0e+08	4.5e+09	9028200	2.5e+07	7.2e+07	2.1e+08	5.5e+08
last total assets	7.8e+07	6.3e+08	726,816	3363050	1.2e+07	3.8e+07	1.2e+08
observations	1,960						

Table 3: Performance statistics for all funds, all closed funds, and all merged funds

Fund type		N	125 tading days before		250 trading days before		500 trading days before	
			Mean	SD	Mean	SD	Mean	SD
Alternatives	All	2,472	-3.06%	35.35%	-2.53%	15.77%	-2.41%	10.28%
	Deleted	21	6.76%	17.12%	5.76%	13.96%	5.56%	12.47%
Bond	All	193,397	-2.66%	13.94%	-3.20%	9.65%	-3.97%	6.68%
	Deleted	319	-1.42%	33.82%	-1.73%	17.96%	-2.49%	9.61%
Commodity	All	1,654	11.21%	45.11%	9.42%	25.43%	7.68%	13.69%
	Deleted	16	4.64%	18.27%	6.46%	11.75%	7.67%	9.57%
Equity	All	694,019	-1.06%	38.46%	-2.76%	26.29%	-4.46%	17.39%
	Deleted	702	2.99%	38.26%	0.79%	26.00%	-2.34%	17.27%
Balanced Fund	All	231,318	-2.82%	20.73%	-3.12%	13.67%	-3.57%	9.10%
	Deleted	327	1.38%	15.33%	0.84%	11.71%	-0.14%	10.30%
Money Market	All	5,822	-1.80%	8.72%	-2.12%	5.65%	-1.85%	3.94%
	Deleted	61	-0.03%	9.25%	-0.95%	6.65%	-0.48%	3.64%
Other	All	7,490	2.67%	28.53%	1.83%	20.31%	0.89%	15.64%
	Deleted	174	-1.81%	15.76%	-1.41%	10.84%	-1.35%	7.69%
Real Estate	All	26	4.42%	19.42%	4.01%	12.25%	2.34%	8.87%
	Deleted	4	-1.48%	2.32%	-1.94%	1.33%	-1.62%	2.44%

Table 4: Summary statistics for all individuals, all affected individuals, and affected individuals who were ultimately forced to sell (income and risk aversion are self-reported in brackets)

	mean	standard deviation	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
all individuals							
male	.84	.37	0	1	1	1	1
age	52	13	35	43	51	60	69
PhD educated	.067	.25	0	0	0	0	0
account tenure	12	3.8	7	11	11	12	18
risk aversion	3.4	1.6	1	1	4	5	5
income	50,338	24,741	10,000	30,000	50,000	80,000	80,000
observations	107,164						
affected individuals							
male	.84	.36	0	1	1	1	1
age	53	12	39	45	52	60	69
PhD educated	.089	.28	0	0	0	0	0
account tenure	13	3.4	11	11	11	15	19
risk class	3.7	1.4	1	3	4	5	5
income	53,440	24,397	10,000	30,000	50,000	80,000	80,000
observations	28,610						
affected individuals forced to sell							
male	.84	.37	0	1	1	1	1
age	53	11	40	45	52	60	68
PhD educated	.089	.29	0	0	0	0	0
account tenure	13	3.3	11	11	11	13	19
risk class	3.6	1.4	1	3	4	5	5
income	54,161	24,073	10,000	30,000	50,000	80,000	80,000
observations	16,920						

Table 5: Estimation results from forced liquidations of fund closures after 30 days

	consumption	outflows into portfolio	outflows into savings	staying in settlement	outflows out of bank
liquidation	0.1059***	0.5408***	0.2788**	0.0745	0.0050
	(0.0295)	(0.0776)	(0.1184)	(0.1261)	(0.0300)
year fes	✓	✓	✓	✓	✓
month fes	✓	✓	✓	✓	✓
observations	10,742	10,742	10,742	10,742	10,742
R-squared	0.0185	0.0659	0.0133	0.0086	0.0067

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

Table 6: Estimation results from forced liquidations of fund closures after 30 days – young versus old investors

	consumption	outflows into portfolio	outflows into savings	staying in settlement	outflows out of bank
liquidation × young	0.1800***	0.4031***	0.1890	0.2280	-0.0434
	(0.0530)	(0.1513)	(0.2305)	(0.2279)	(0.0790)
liquidation × old	0.0749**	0.5987***	0.3165**	0.0100	0.0254
	(0.0321)	(0.0800)	(0.1266)	(0.1389)	(0.0185)
year fes	✓	✓	✓	✓	✓
month fes	✓	✓	✓	✓	✓
observations	10,742	10,742	10,742	10,742	10,742
R-squared	0.0202	0.0676	0.0135	0.0092	0.0073

	consumption	outflows into portfolio	outflows into savings	staying in settlement	outflows out of bank
liquidation × under 65	0.1385***	0.5310***	0.3269*	0.0036	-0.0233
	(0.0384)	(0.0940)	(0.1699)	(0.1754)	(0.0419)
liquidation × over 65	0.0443	0.5594***	0.1877***	0.2086**	0.0587**
	(0.0280)	(0.1151)	(0.0646)	(0.1020)	(0.0255)
year fes	✓	✓	✓	✓	✓
month fes	✓	✓	✓	✓	✓
observations	10,742	10,742	10,742	10,742	10,742
R-squared	0.0198	0.0660	0.0135	0.0092	0.0075

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

Table 7: Estimation results from forced liquidations of fund closures after 30 days – low versus high income investors

	consumption	outflows into portfolio	outflows into savings	staying in settlement	outflows out of bank
liquidation × low income	0.0637**	0.7209***	0.1872*	0.0282	0.0673*
	(0.0296)	(0.1646)	(0.0975)	(0.1565)	(0.0397)
liquidation × high income	0.1815***	0.3955***	0.1995	0.2235	-0.0364
	(0.0572)	(0.1335)	(0.1721)	(0.1730)	(0.0583)
year fes	✓	✓	✓	✓	✓
month fes	✓	✓	✓	✓	✓
observations	5,792	5,792	5,792	5,792	5,792
R-squared	0.0275	0.0566	0.0199	0.0170	0.0146

	consumption	outflows into portfolio	outflows into savings	staying in settlement	outflows out of bank
liquidation × low income	0.0749**	0.7126***	0.1915*	0.0209	0.0765*
	(0.0307)	(0.1664)	(0.0990)	(0.1590)	(0.0402)
liquidation × medium income	0.1257	0.5731***	0.1263**	0.1749*	-0.0015
	(0.0779)	(0.1244)	(0.0601)	(0.1007)	(0.0231)
liquidation × high income	0.3435***	0.1076	0.3090	0.2398	-0.1171
	(0.1090)	(0.3213)	(0.4935)	(0.4766)	(0.1596)
year fes	✓	✓	✓	✓	✓
month fes	✓	✓	✓	✓	✓
observations	5,403	5,403	5,403	5,403	5,403
R-squared	0.0460	0.0646	0.0207	0.0167	0.0188

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

Table 8: Estimation results from forced liquidations of fund closures after 30 days interacted with ECB and NBER recessions

	consumption	outflows into portfolio	outflows into savings	staying in settlement	outflows out of bank
liquidation	0.0147	0.8939***	0.0816***	0.0098	-0.0086
× ECB recession	(0.0212)	(0.0341)	(0.0298)	(0.0171)	(0.0207)
liquidation	0.1136***	0.4369***	0.5460**	-0.0965	0.0072
× boom	(0.0386)	(0.1364)	(0.2587)	(0.2742)	(0.0584)
year fes	✓	✓	✓	✓	✓
month fes	✓	✓	✓	✓	✓
observations	9,777	9,777	9,777	9,777	9,777
R-squared	0.0176	0.1248	0.0142	0.0026	0.0064

	consumption	outflows into portfolio	outflows into savings	staying in settlement	outflows out of bank
liquidation	0.0153	0.8948***	0.0794***	0.0105	-0.0098
× NBER recession	(0.0213)	(0.0342)	(0.0298)	(0.0172)	(0.0208)
liquidation	0.1128***	0.4367***	0.5475**	-0.0970	0.0083
× boom	(0.0385)	(0.1364)	(0.2589)	(0.2744)	(0.0583)
year fes	✓	✓	✓	✓	✓
month fes	✓	✓	✓	✓	✓
observations	9,777	9,777	9,777	9,777	9,777
R-squared	0.0175	0.1248	0.0143	0.0026	0.0064

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

Table 9: Estimation results from forced liquidations of fund closures after 30 days interacted with interest rate regime

	consumption	outflows into portfolio	outflows into savings	staying in settlement	outflows out of bank
liquidation × positive interest	0.1645** (0.0661)	-0.0400 (0.1283)	0.3086 (0.2073)	0.5669*** (0.2170)	0.0263 (0.0396)
liquidation × zero lower bound	0.0719*** (0.0241)	0.8781*** (0.0617)	0.2615* (0.1434)	-0.2115 (0.1417)	-0.0073 (0.0408)
year fes	✓	✓	✓	✓	✓
month fes	✓	✓	✓	✓	✓
observations	10,742	10,742	10,742	10,742	10,742
R-squared	0.0195	0.0962	0.0133	0.0155	0.0068

	consumption	outflows into portfolio	outflows into savings	staying in settlement	outflows out of bank
liquidation	0.1863*** (0.0508)	0.1593 (0.1185)	0.4164* (0.2151)	0.2380 (0.2200)	0.0067 (0.0519)
liquidation × zero lower bound	-0.1804*** (0.0545)	0.8563*** (0.1399)	-0.3089 (0.2190)	-0.3670 (0.2316)	-0.0038 (0.0549)
year fes	✓	✓	✓	✓	✓
month fes	✓	✓	✓	✓	✓
observations	10,742	10,742	10,742	10,742	10,742
R-squared	0.0227	0.0939	0.0144	0.0102	0.0067

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

Table 10: Estimation results from forced liquidations of fund closures in panel regression specification

	ATM + POS deviation	ATM + POS deviation	spending	all net outflows	ATM + POS
liquidation dummy	0.1278*	0.1273*			
	(0.0668)	(0.0669)			
liquidation dummy	-0.0377	-0.0381			
one week lag	(0.0468)	(0.0468)			
liquidation dummy	-0.0034	-0.0037			
two week lag	(0.0486)	(0.0486)			
liquidation dummy	0.0597	0.0593			
three week lag	(0.0638)	(0.0638)			
liquidation		-0.0000	0.5127**	0.4129	0.0200
		(0.0000)	(0.2333)	(0.2518)	(0.0176)
individual fes	✓	✓	✓	✓	✓
year fes	✓	✓	✓	✓	✓
week fes	✓	✓	✓	✓	✓
observations	772,996	772,996	795,103	795,103	795,103
R-squared	0.0296	0.0296	0.0005	0.0003	0.0124
# main clients	15,017	15,017	15,480	15,480	15,480
salary			0.0657***	0.0626***	0.0180***
			(0.0181)	(0.0181)	(0.0043)

Standard errors clustered at the individual level in parentheses *** p<0.01, ** p<0.05, * p<0.1

Figure 7: Empirical profiles of participation, portfolio shares, and labor income over the life cycle.

Figure 8: Simulated profiles of portfolio shares, consumption, and labor income over the life cycle. Agents receive stochastic labor income and income from the risky return investment.

Figure 9: Consumption as a function of cash-on-hand for each year before retirement over the life cycle in a low-interest and high-interest environment.

β Parameter Estimation Results

	old agents			
	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$
estimate	0.0023	0.0020	0.0020	0.0011
t-statistic	(9.45)	(12.34)	(12.34)	(2.17)

Table 11: Simulated regression results of consumption growth on capital gains of the cross-section of agents at age 60 for four groups of savings.