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

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Abstract

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 estimate the marginal propensity to consume (MPC) out of one dollar received from a forced sale event and find that it is approximately 30%. We explore how the MPC varies in age and income as well as over the business cycle and across interest rate regimes. We find a higher MPC for low-income investors, which appears consistent with standard life-cycle portfolio-choice models, though we do not find any differences in the MPC for young versus old investors. We also find that the MPC to be lower in recessions and decreasing in interest rates, which is surprising from a standard model perspective.

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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 could be 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 representative agent economy predicts that the marginal propensity to consume (MPC) out of fluctuations in stock prices should be 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 across business cycles. Furthermore, monetary policy and the interest rate regime may affect 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 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 log in and trading behavior and see the forced sales from a sample of mutual fund closures. More specifically, we obtain the

International Securities Identification Number (ISIN) and dates of 8,510 mutual fund closures from 1999 to 2016.

We estimate the effects of forced liquidations on consumption using a simple cross-sectional design. Alternatively, we can use a fixed-effects approach to compare the same individuals before and after the forced liquidations. In that case, we effectively employ an Event study or a Regression Discontinuity in Time (RDiT) design. The deployment of RDiT faces an number of challenges primarily due to its reliance on time-series variation for identification, which is different from the canonical cross-sectional designs of standard regression discontinuity (RD) designs. We argue that our setting is addressing all these challenges because we use high-frequency, high-accuracy, transaction-level data for different short bandwidths of time around a number of events alleviating concerns due to time-series trends and time-varying confounds. However, we find results consistent with the identification approach with cross-sectional variation, which straightforwardly estimates the average MPC out of forced liquidations for different age and income groups and across interest rate regimes and the business cycle.

We find that individuals on average consume approximately 20% to 30% of their funds after the forced sale event. Furthermore, we explore how the MPC varies for different ages and income levels as well as over the business cycle and across interest rate regimes. Following Baker et al. (2006), Maggio et al. (2017) 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 mental accounting rather than optimization of life-cycle income profiles. Maggio et al. (2017) 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 would be higher.

Furthermore, we find a higher MPC for low-income investors, which appears consistent with standard life-cycle portfolio-choice models. However, we do not find a difference with respect to young versus old investors. Moreover, we find that the MPC is much lower in recessions, which is 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 higher.

By estimating the consumption response to realized capital gains, this paper contributes to the literature linking stock prices with spending, which includes studies employing aggregate and regional variation (e.g. Davis et al. (2001), Dynan and Maki (2001), and Case et al. (2005)).[1] 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. Parker (1999) and Baker et al. (2007)). Specifically, Baker et al. (2007) uses CEX data and shows that stockholders' 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 a 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).

Maggio et al. (2017) use disaggregated data and an identification strategy based on previous portfolio shares to ensure that the relation between household consumption and capital gains is not spurious. Moreover, the authors can take advantage of very granular data and its coverage of the entire population of Sweden to document important 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 contains some measurement error in both imputed consumption as well as capital gains when stocks appear in individuals' year-end portfolios and are held so that their actual purchase prices cannot be recovered from the data.

By estimating MPCs, this paper belongs to the extensive consumption literature, such as John-

[1] See Poterba (2000) for a survey of the literature on stock market wealth and consumption.

son et al. (2006), Agarwal and Qian (2014), Olafsson and Pagel (2016), Jappelli and Pistaferri (2014), Jappelli and Pistaferri (2000), among others. Individual's marginal propensity to consume out of realized and unrealized capital gains is an important object in macro and macro-finance models. The marginal propensity to invest is not simply the reverse of the marginal propensity to consume, but of independent interest as individuals can invest into many different asset classes. Two recent papers, Briggs et al. (2015) and Andersen and Nielsen (2011), estimate the marginal propensity to invest into stocks using administrative data and large wealth shocks but focus on first-time participants. In contrast to these two papers, we focus on stock-market participants' marginal propensities to invest out of forced liquidations using high-frequency transaction-level data.

2 Data and Summary Statistics

Our data set stems from one of the largest online banks in Germany. 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 all customers who are not self-directed. Further, we exclude transfers among personal accounts, saving plans and trades from limit orders, because this type of transactions do not reflect current trading decisions of investors. Moreover, we obtain data on customer demographics such as gender, age, and occupation as well as detailed information on traded securities such as asset class, risk class, issuer or issue date of a security.

We thus get information on a daily basis 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. Moreover, 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.

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, 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 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]

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]

3 Methodology

Regression specification

We consider two approaches, one "conditional cross-sectional" regression and one "unconditional panel" regression. The conditional cross-sectional regression is specified as follows:

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

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.

Outcome variables

When investors make a trade or a position gets liquidated, then there occurs a transfer to the settlement account (Verrechnungskonto). We thus consider the following outcome variables: 1) transfers to the portfolio via purchases of securities (investment), 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. To take care of outliers, we log all outcome variables as well as the liquidation variable. The coefficients can thus be interpreted as the share of wealth reinvested or saved or, as a residual, consumed.

4 Results

Empirical results

Table 5 shows the estimation results for the share of liquidity reinvested, transferred to savings accounts, and transferred to checking accounts in the five days after individuals receive their liquidity from the forced sales.

[Insert Table 5 about here]

We find that, on average, individuals reinvest 70% to 80% of their newly found liquidity within a few days either back into the portfolio or transferred into savings accounts. This implies a MPC of 20% to 30%, which is in the same ballpark as the estimates of Baker et al. (2006) and Maggio et al. (2017) for the MPC out of dividends but much higher than their estimates for the MPC out of unrealized capital gains. Furthermore, Table 6 show the same estimation results for the share of liquidity reinvested, transferred to savings accounts, and transferred to checking accounts in the thirty days after individuals receive their liquidity from the forced sales. The results for five versus thirty days look qualitatively and quantitatively similar.

[Insert Table 6 about here]

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 either five or thirty days can be found in Tables 7 and 8.

[Insert Tables 7 and 8 about here]

The estimation results line up sensibly across different specifications. In summary, we find that young investors reinvest a similar share of their wealth and thus have a similar MPC as old investors.

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 either five or thirty days can be found in Tables 10 and 9.

[Insert Tables 10 and 9 about here]

The estimation results line up sensibly across different specifications. In summary, we find that low-income investors reinvest a smaller share of their wealth and thus have a higher MPC than high-income investors. That low-income investors thus consume more out of fluctuations in their stock market wealth is in line with standard life-cycle portfolio-choice models.

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, Kaplan and Violante, 2014). 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). The estimation results for the forced sales interacted with a recession dummy for either five or thirty days can be found in Tables 11 and 12.

[Insert Tables 11 and 12 about here]

Across different specifications and also when we use the National Bureau of Economic Research (NBER) definition of a recession, we find that investors reinvest a larger share of their liquidity and thus have a lower MPC in recessions. This is not necessarily consistent with standard life-cycle portfolio-choice models featuring business cycles.

Finally, we estimate the coefficients in response to forced sales across interest rate regimes. With respect to the baseline leven 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 either five or thirty days can be found in Tables 13 and 14.

[Insert Tables 13 and 14 about here]

Across different specifications, we find results that suggest that the share reinvested is much lower during the ZLB period, that said, our results lack statistical power. For that reason, we also interact the liquidation events with the level of the interest rate over the sample period. The results can be found in Tables 15 and 16.

[Insert Tables 15 and 16 about here]

In these tables, we confirm that a higher interest rate has a positive impact on the share of liquidity reinvested, which is consistent with a lower MPC in high interest rate environments.

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 (Solidaritätszuschlag) (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 (Freibeträge) of 801€ for singles and 1.602€ 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 100,000€ from January 2018 on. Overall, the capital gains tax is thus taken at the source and all funds individuals receive are after-tax.

5 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 (Baker et al., 2006; Maggio et al., 2017). 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.

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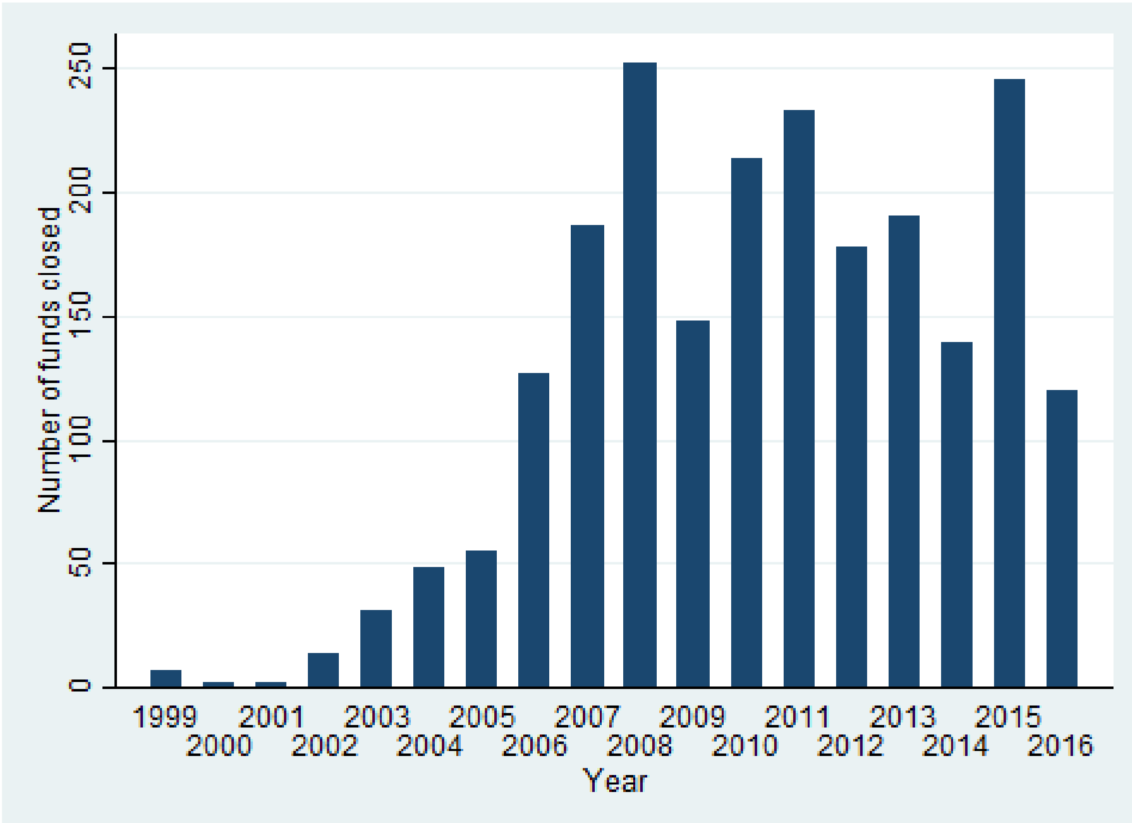

Figure 1: Number of mutual funds closures, as identified by the International Securities Identification Number (ISIN), per year over the period 1999 to 2016.

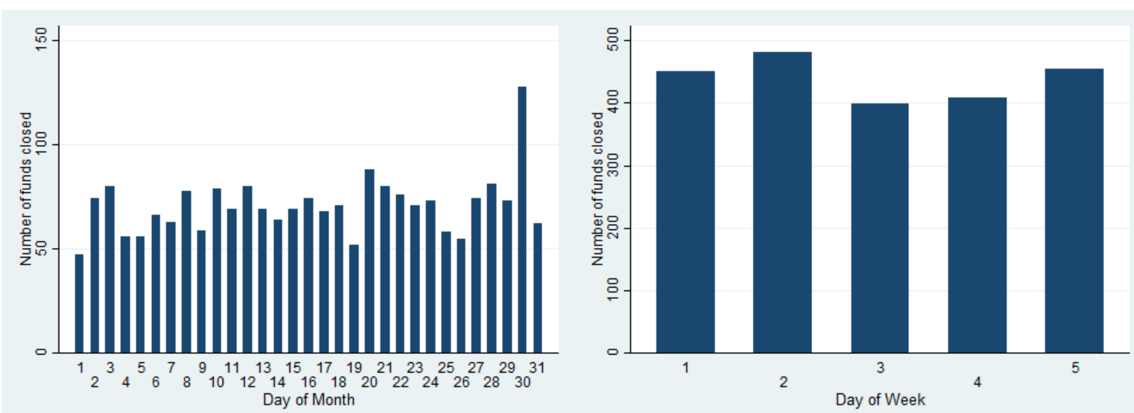

Figure 2: Number of mutual funds closures, as identified by the International Securities Identification Number (ISIN), per day of month and per day of week (0=Sunday to 6=Saturday).

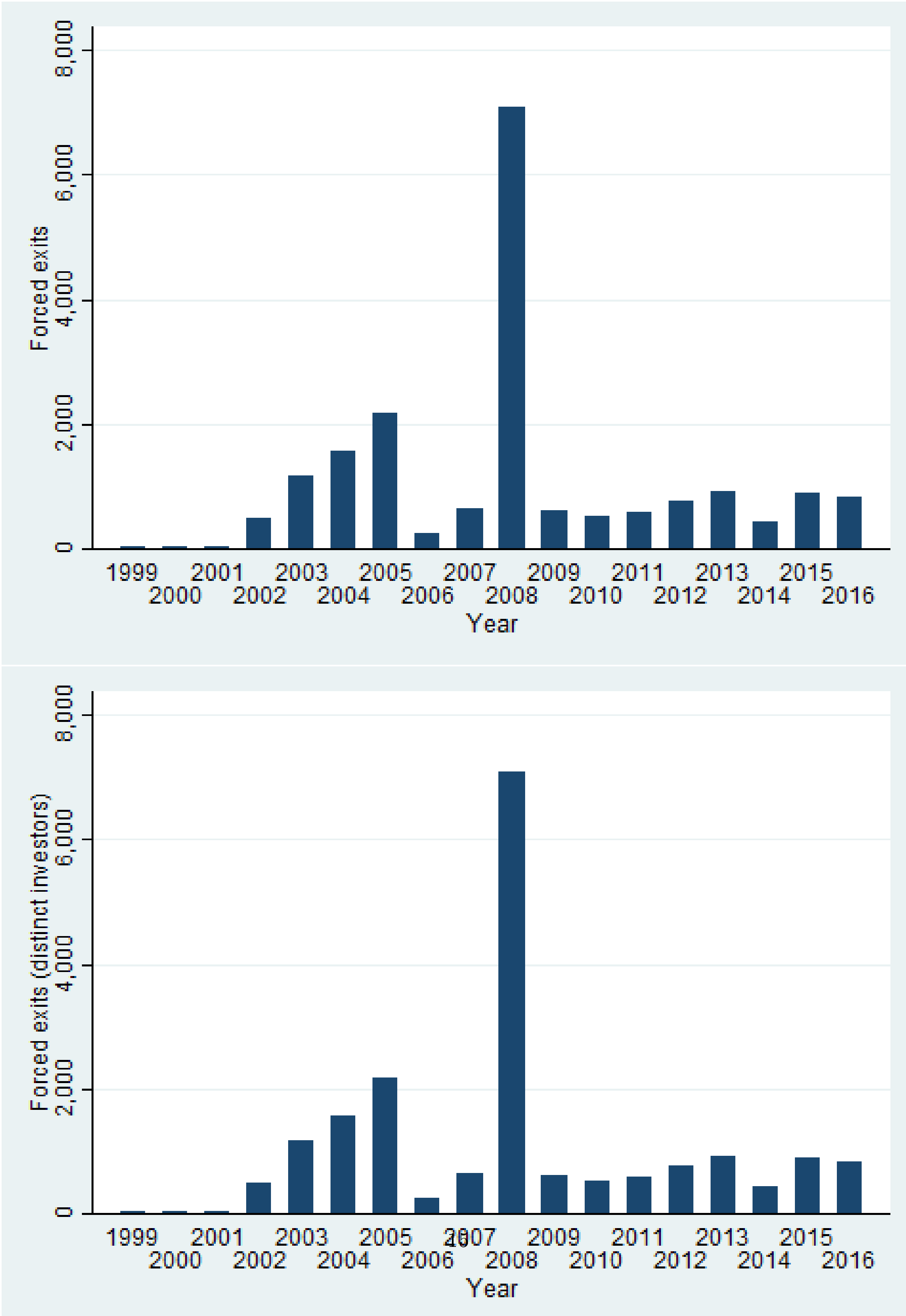

Figure 3: Number of forced sales, i.e., number of individuals affected by each fund closure (double-counting), per year over the period 1999 to 2016, and number of distinct investors affected per year.

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 and all closed funds

Fund type		N	125 trading days before		250 trading days before		500 trading days before		1 trading day before	
			Mean	Median	Mean	Median	Mean	Median	Mean	Median
Alternatives	All	2472	-0.031	-0.018	-0.025	-0.016	-0.024	-0.021	0.021	0.000
	Deleted	21	0.068	0.049	0.058	0.042	0.056	0.032	0.682	0.200
Bond	All	193397	-0.027	-0.024	-0.032	-0.024	-0.040	-0.036	-0.023	0.000
	Deleted	319	-0.014	-0.012	-0.017	-0.014	-0.025	-0.020	0.162	0.000
Commodity	All	1654	0.112	0.085	0.094	0.068	0.077	0.081	-0.547	-0.118
	Deleted	16	0.046	0.045	0.065	0.039	0.077	0.065	0.049	-0.114
Equity	All	694019	-0.011	-0.082	-0.028	-0.081	-0.045	-0.072	0.105	0.000
	Deleted	702	0.030	-0.062	0.008	-0.053	-0.023	-0.054	0.283	0.000
Mixed Assets	All	231318	-0.028	-0.042	-0.031	-0.043	-0.036	-0.039	-0.028	-0.034
	Deleted	327	0.014	-0.006	0.008	-0.014	-0.001	-0.014	-0.022	0.000
Money Market	All	5822	-0.018	-0.008	-0.021	-0.012	-0.018	-0.017	-0.025	0.000
	Deleted	61	0.000	-0.009	-0.009	-0.014	-0.005	-0.009	0.066	0.000
Other	All	7490	0.027	-0.005	0.018	-0.009	0.009	-0.010	0.012	0.000
	Deleted	174	-0.018	-0.022	-0.014	-0.022	-0.013	-0.018	0.181	0.000
Real Estate	All	26	0.044	-0.016	0.040	-0.018	0.023	-0.016	0.009	0.000
	Deleted	4	-0.015	-0.017	-0.019	-0.021	-0.016	-0.024	0.512	0.000

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 5 days

	share outflows into portfolio	share all other outflows	share outflows into savings	share outflows into checking
liquidation	0.6120***	-0.0071	0.1138***	0.0040
	(0.0417)	(0.0336)	(0.0270)	(0.0041)
year fes	✓	✓	✓	✓
month fes	✓	✓	✓	✓
observations	8,510	8,510	8,510	8,510
R-squared	0.3200	0.0176	0.0341	0.0052

Table 6: Estimation results from forced liquidations of fund closures after 30 days

	share outflows into portfolio	share all other outflows	share outflows into savings	share outflows into checking
liquidation	0.5391***	0.0243	0.1859***	0.0031
	(0.0474)	(0.0470)	(0.0362)	(0.0063)
year fes	✓	✓	✓	✓
month fes	✓	✓	✓	✓
observations	8,510	8,510	8,510	8,510
R-squared	0.1984	0.0291	0.0323	0.0044

Table 7: Estimation results from forced liquidations of fund closures after 5 days interacted with age

	share outflows into portfolio	share all other outflows	share outflows into savings	share outflows into checking
liquidation*young	0.6183***	-0.0016	0.0989***	0.0031
	(0.0444)	(0.0356)	(0.0286)	(0.0042)
liquidation*old	0.6110***	-0.0079	0.1161***	0.0042
	(0.0416)	(0.0336)	(0.0269)	(0.0042)
year fes	✓	✓	✓	✓
month fes	✓	✓	✓	✓
observations	8,510	8,510	8,510	8,510
R-squared	0.3200	0.0176	0.0346	0.0052

Table 8: Estimation results from forced liquidations of fund closures after 30 days interacted with age

	share outflows into portfolio	share all other outflows	share outflows into savings	share outflows into checking
liquidation*young	0.5387***	0.0526	0.1737***	0.0005
	(0.0501)	(0.0495)	(0.0384)	(0.0066)
liquidation*old	0.5392***	0.0200	0.1878***	0.0035
	(0.0473)	(0.0470)	(0.0362)	(0.0063)
year fes	✓	✓	✓	✓
month fes	✓	✓	✓	✓
observations	8,510	8,510	8,510	8,510
R-squared	0.1984	0.0297	0.0325	0.0046

Table 9: Estimation results from forced liquidations of fund closures after 5 days interacted with income

	share outflows into portfolio	share all other outflows	share outflows into savings	share outflows into checking
liquidation*low	0.2970*	0.0303	0.2476	0.0001
	(0.1707)	(0.0740)	(0.2234)	(0.0010)
liquidation*high	0.7416***	-0.0517	0.2221*	0.0005
	(0.1953)	(0.0438)	(0.1149)	(0.0008)
year fes	✓	✓	✓	✓
month fes	✓	✓	✓	✓
observations	4,656	4,656	4,656	4,656
R-squared	0.0473	0.0170	0.0216	0.0085

Table 10: Estimation results from forced liquidations of fund closures after 30 days interacted with income

	share outflows into portfolio	share all other outflows	share outflows into savings	share outflows into checking
liquidation*low	0.4876***	0.0517	0.1438***	0.0022
	(0.0642)	(0.0632)	(0.0502)	(0.0097)
liquidation*high	0.5012***	-0.0127	0.1900***	-0.0004
	(0.0647)	(0.0635)	(0.0500)	(0.0095)
year fes	✓	✓	✓	✓
month fes	✓	✓	✓	✓
observations	4,656	4,656	4,656	4,656
R-squared	0.1837	0.0341	0.0373	0.0080

Table 11: Estimation results from forced liquidations of fund closures after 5 days interacted with ECB recession

	share outflows into portfolio	share all other outflows	share outflows into savings	share outflows into checking
liquidation*norecession	0.4517***	-0.0807*	0.1766***	0.0047
	(0.0593)	(0.0477)	(0.0378)	(0.0032)
liquidation*recession	0.8643***	0.0203	0.0969***	0.0014
	(0.0540)	(0.0428)	(0.0366)	(0.0014)
year fes	✓	✓	✓	✓
month fes	✓	✓	✓	✓
observations	7,650	7,650	7,650	7,650
R-squared	0.3420	0.0227	0.0398	0.0057

Table 12: Estimation results from forced liquidations of fund closures after 30 days interacted with ECB recession

	share outflows into portfolio	share all other outflows	share outflows into savings	share outflows into checking
liquidation*norecession	0.4146***	-0.0272	0.2302***	0.0025
	(0.0648)	(0.0630)	(0.0488)	(0.0058)
liquidation*recession	0.8451***	0.0624	0.2087***	-0.0022
	(0.0614)	(0.0629)	(0.0496)	(0.0030)
year fes	✓	✓	✓	✓
month fes	✓	✓	✓	✓
observations	7,650	7,650	7,650	7,650
R-squared	0.2135	0.0353	0.0374	0.0080

Table 13: Estimation results from forced liquidations of fund closures after 5 days interacted with interest rate regime

	share outflows into portfolio	share all other outflows	share outflows into savings	share outflows into checking
liquidation*noZLB	0.7324***	0.0027	0.0997***	0.0026
	(0.0423)	(0.0346)	(0.0286)	(0.0027)
liquidation*ZLB	0.2735***	-0.0345	0.1536***	0.0080
	(0.0560)	(0.0513)	(0.0416)	(0.0085)
year fes	✓	✓	✓	✓
month fes	✓	✓	✓	✓
observations	8,510	8,510	8,510	8,510
R-squared	0.3263	0.0177	0.0344	0.0053

Table 14: Estimation results from forced liquidations of fund closures after 30 days interacted with interest rate regime

	share outflows into portfolio	share all other outflows	share outflows into savings	share outflows into checking
liquidation*noZLB	0.6349***	0.0123	0.1643***	0.0017
	(0.0485)	(0.0495)	(0.0386)	(0.0044)
liquidation*ZLB	0.2700***	0.0578	0.2468***	0.0071
	(0.0683)	(0.0693)	(0.0561)	(0.0126)
year fes	✓	✓	✓	✓
month fes	✓	✓	✓	✓
observations	8,510	8,510	8,510	8,510
R-squared	0.2017	0.0292	0.0327	0.0044

Table 15: Estimation results from forced liquidations of fund closures after 5 days interacted with level of interest rate

	share outflows into portfolio	share all other outflows	share outflows into savings	share outflows into checking
liquidation	0.1751***	-0.0235	0.1834***	0.0092
	(0.0675)	(0.0592)	(0.0463)	(0.0100)
liquidation*interest	0.1905***	0.0072	-0.0304**	-0.0023
	(0.0219)	(0.0183)	(0.0150)	(0.0026)
year fes	✓	✓	✓	✓
month fes	✓	✓	✓	✓
observations	8,510	8,510	8,510	8,510
R-squared	0.3276	0.0176	0.0348	0.0053

Table 16: Estimation results from forced liquidations of fund closures after 30 days interacted with level of interest rate

	share outflows into portfolio	share all other outflows	share outflows into savings	share outflows into checking
liquidation	0.1943**	0.0792	0.1704***	0.0082
	(0.0777)	(0.0767)	(0.0590)	(0.0145)
liquidation*interest	0.1503***	-0.0240	0.0068	-0.0022
	(0.0250)	(0.0253)	(0.0200)	(0.0037)
year fes	✓	✓	✓	✓
month fes	✓	✓	✓	✓
observations	8,510	8,510	8,510	8,510
R-squared	0.2017	0.0292	0.0327	0.0044