Who Sold During the Crash of 2008-9?
Evidence from Tax-Return Data on Daily Sales of Stock

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Abstract: We examine individual stock sales from 2008 to 2009 using population tax return data. Individuals sold stocks more intensely in the days following episodes of market tumult, and the increase was concentrated among older investors and those with the highest incomes. The share of sales by the top 0.1 percent of income recipients and other top income groups rose sharply following the Lehman Brothers bankruptcy and remained elevated throughout the financial crisis. Tumult-driven sales were not concentrated in any one sector, but mutual fund sales responded more strongly than stock sales. Additional analysis suggests that gross sales in tax return data are informative about unobserved net sales.

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Introduction

Periods of turmoil in stock markets—such as September 2008 in the wake of the Lehman Brothers bankruptcy—are associated with large declines in prices, abnormally high intra-day price volatility, and high trading volume. Market commentary often characterizes these periods as "sell-offs." As always, there is a buyer for every seller, so investors as a group cannot all be sellers. What may be happening instead during these instances is that some investors sell out, leaving the remaining investors to bear the risk of stock ownership. Such a reallocation of asset ownership among heterogeneous investors is consistent with the high level of trading activity observed during such periods. Little is known, however, about the characteristics of the investors that are prone to sell in the midst of market turmoil.

Understanding heterogeneity in investors' propensity to sell is an important first step towards explaining asset price movements during these extreme periods. Premia for bearing risk (Bollerslev and Todorov 2011; Martin 2015) and for providing liquidity (Nagel 2012) are sharply elevated following market tumult episodes. One potential reason is that a part of the investor population pulls out of the market during times of market turmoil, which leaves a smaller set of investors holding aggregate stock market risk. Empirical evidence on whether such sudden shifts in stock ownership exist has so far remained largely elusive due to lack of data.

We use administrative data from the Internal Revenue Service, consisting of billions of third-party reports on all sales of stock in United States taxable individual accounts, to investigate, at a daily frequency, which individuals sold stocks and mutual funds during the tumultuous market events of 2008 and 2009. The data are extracted from the universe of (anonymized) tax returns filed with the Internal Revenue Service (IRS), and allow us to match asset sales reported for capital gains taxation purposes with some demographic information on each taxpayer. While we do not observe asset purchases in these tax records, we present indirect evidence from dividend receipts and a supplementary brokerage account data set suggesting that individuals with high levels of gross sales are also, to a substantial extent, net sellers of stocks.

We focus our analysis on 2008 and 2009, and further zoom in on the period immediately following the bankruptcy of Lehman Brothers in September 2008. In our baseline analyses, we measure market tumult with lagged daily changes in the VIX index. The VIX index is a measure of (risk-adjusted) expected market volatility and it is commonly used as a proxy for market tumult and as a crisis indicator (see Adrian and Shin 2010; Longstaff 2010; Nagel 2012). Since we focus on stock sales, and hence on a *change* in investors' stock holdings, which should be triggered by a *change* in the market environment, our tumult measure is based on changes in the VIX index. During our sample period, stock market returns are typically strongly negative on days when the VIX rises, and we interpret VIX changes as a broad proxy of market turmoil rather than a narrow measure of volatility.[1]

We find that the total selling volume of all individual taxpayers rises strongly in response to a rise in the VIX. However, this effect is heavily concentrated among investors with certain demographic characteristics. First, investors at the very top of the income distribution—both the top 1 percent and even the top 0.1 percent—have a much greater propensity to sell during times of market tumult than investors in the rest of the income distribution. Second, older investors, close to or beyond the typical retirement age, are more likely to sell in response to a rise in the VIX than younger investors.

The strong reaction of older investors is in line with predictions of life-cycle portfolio choice models with labor income. The presence of non-tradable labor income stream typically

[1] We obtain similar results with negative lagged daily market index returns as alternative tumult proxy instead of VIX.

induces agents to take higher risks, while fixed consumption commitments have the opposite effect (Chetty and Szeidl 2007). For older investors, the present value of labor income is small relative to committed consumption and they have less scope to make up losses by adjusting future labor income (Chai et al. 2011). As a consequence, their capacity to bear stock market risk is reduced following the asset price declines and the rise in risk associated with market tumult episodes. We also examine a number of taxpayer characteristics that could be associated with housing-consumption commitments, such as the presence and amount of a mortgage interest deduction, and zip-code-level house price growth in 2007, but we do not find heterogeneity in selling volume related to these.

Our finding of a positive relationship between of income and tumult-induced selling is more surprising in light of life-cycle portfolio choice theory. Consumption commitments or subsistence levels should, presumably, be less relevant for individuals with very high income, putting them, relatively, in a better position to bear risks during market tumult. However, at the daily frequencies that we study in this paper, differences in information processing could be an additional source of heterogeneity. In an asymmetric information setting, Barlevy and Veronesi (2003) show that rational uninformed investors may find it optimal to pull out of the market during panic episodes. Thus, it is conceivable that high-income investors' reaction to market tumult is a sophisticated response aimed at avoiding adverse selection.[2] Overconfidence in market-timing abilities could reinforce this behavior. High-income investors are more prone to overconfidence (Graham, Harvey, and Huang 2009) and they also pay greater attention to their portfolios (Sicherman et al. 2016).

[2] Moreover, recent work by Moreira and Muir (2016) suggests that temporarily reducing stock market exposure following burst of high volatility may in fact be a utility-improving timing strategy.

A behavioral explanation that is consistent with both the income- and age-related heterogeneity is based on the disposition effect, i.e., the tendency of investors to avoid selling stocks with accumulated losses (Shefrin and Statman 1985; Odean 1998). Prior evidence in Dhar and Zhu (2006) and Calvet, Campbell, and Sodini (2009) indicates that the disposition effect is stronger for younger investors and those with lower wealth. This earlier work studies decisions at the individual stock level and does not directly address reaction to market-wide movements. However, since tumult episodes in our sample period are typically associated with negative market returns, the number of stocks with accumulated losses in investors' portfolios should typically rise and this should inhibit selling by disposition-prone investors.

The disposition effect explanation also fits with differences in tumult-sensitivity of directly-held stock sales and sales of mutual funds. We find that taxpayers' mutual fund sales volume is more sensitive to changes in the VIX than is sales volume of directly-held stocks, consistent with earlier research showing that the disposition effect is absent for delegated assets such as mutual funds (Chang, Solomon, and Westerfield 2016). Furthermore, the age- and income-related heterogeneity of the sales response to VIX changes is almost entirely due to sales of directly held stocks, while we do not find much of this heterogeneity for mutual fund sales, consistent with the absence of a dampening disposition effect for mutual funds.

The data we analyze are, in a number of ways, substantially better than the data sets that have been studied up to now. Existing studies of investor responses to market movements and changes in risk use data either from investor surveys (Guiso et al. 2013; Hudomiet et al. 2011; Shiller 1987), from non-randomly selected samples of portfolio holdings data (Dorn and Weber 2013; Hoffmann et al. 2013; Weber et al. 2012; Barrot et al. 2016), administrative data from Sweden that are available only at annual frequency (Calvet et al. 2009), or data on institutional investor portfolios (see Ben-David, Franzoni, and Moussawi (2012); Cella et al. (2013) for the crisis in 2008; see Brunnermeier and Nagel (2004); Griffin et al. (2011) for the Nasdaq crash in 2000). Our data let us investigate, for the first time, the population of U.S. taxable investors as a whole at a daily frequency.

The data set is not perfect, though. The data set covers only reported taxable sales, but not purchases of stocks and mutual funds. Additional analyses show, however, that there is a strong relationship between gross selling, which we observe, and net selling (i.e., sales minus purchases), which we do not observe. First, we examine data from a discount brokerage that reports both gross and net sales (Barber and Odean 2000). We find a very strong positive relationship between gross and net sales. Furthermore, net sales of brokerage customers rise with changes in the VIX in similar ways as the gross sales of taxpayers in our data. Second, in the IRS data, we examine changes in dividend income reported on individual tax returns. Here we find a strong negative relationship between gross sales in a given year (e.g. 2008) and the change in dividend income from the previous year (2007) to the subsequent year (2009). Despite coming from different sources and time periods, the quantitative results from discount brokerage data and from changes in dividend income on tax returns are highly consistent with one another, suggesting that $1 of gross sales corresponds to about $0.33 in net sales.

Another shortcoming of the data set is that we do not observe sales in non-taxable accounts, such as Individual Retirement Accounts. We analyze data from the 2007-2009 panel of the Survey of Consumer Finance, which contains data on wealth in taxable and non-taxable accounts, including pensions and trusts. We find that the share of wealth in taxable accounts is relatively higher for individuals at the top of the income distribution, and for older individuals. These facts rule out the concern that our main findings are driven by older and higher-income people holding a disproportionately small share of their equities in taxable accounts. Additionally, net sales in taxable accounts between the 2007 and 2009 waves of the survey are strongly related to total net sales, suggesting that our analysis of sales in taxable accounts are informative about total asset holdings. Overall, our evidence therefore indicates that market tumult leads to a concentration of stock ownership among a smaller pool of investors.

Our study connects to a number of recent papers that have started to shed light on the reaction of different types of investors to the market turmoil during the financial crisis. The evidence from existing studies is mixed, possibly because samples used in these studies are small and selective. Dorn and Weber (2013) find that customers of a large German retail bank kept their overall equity allocations quite stable, but they withdrew from actively managed mutual funds, which could be related to our finding that U.S. taxpayer mutual fund sales volume is more sensitive to changes in VIX than stock sales are. Barrot et al. (2016) find that customers of a French brokerage also withdrew from mutual funds, but they increased their exposure to directly held stocks. Hoffmann et al. (2013) find that the brokerage customers in their sample did not reduce the risk of their portfolios during the height of the crisis, even though, temporarily, their risk tolerance dropped and they expected lower returns and higher risk. In contrast, Weber et al. (2012) find substantial changes in risk taking associated with changes in subjective perceptions of risk and return during this period in a survey of U.K. online brokerage customers. Similarly, Guiso et al. (2013) find that both a qualitative and a quantitative survey-based measure of risk aversion increased following the experience of the crisis, but they do not find much predictable cross-sectional heterogeneity in the change in risk aversion. Although certainly of interest, the small and selected nature of the samples in these studies limits the extent to which one can learn about heterogeneity between demographic groups and how much one can generalize from these findings. We turn now to describe the much more comprehensive data we examine, our research design and its theoretical underpinning, and finally our results.

2. Data

This section describes the confidential administrative data and publicly available data we use, and provides summary statistics and match rates across different data sources.

2.1 Tax Return Data

We use two types of tax-return data on U.S. individuals trading in taxable accounts. The primary source of data is third-party information assembled by brokerages and provided to the IRS and taxpayers on Form 1099-B.[3] The raw data set contains all Form 1099-B's for trades occurring between January 1, 2000 and December 31, 2012. For any covered financial asset sold in this period, Form 1099-B provides the sale price and date, the Committee on Uniform Security Identification Procedures (CUSIP) number identifying the asset, an anonymized version of the taxpayer identification number (TIN), which for an individual seller is a Social Security number, along with several less relevant items.[4]

The second source of information we can link to asset sales is demographic information from individual income tax returns (Forms 1040) and other records. These include, among other details, age and gender (from Social Security records), number of dependents, whether the individual takes a mortgage interest deduction, and the ZIP code of the filing address. We also observe a variety of income measures, including wages and salaries, dividends, interest payments, retirement benefits, and net income from self-employment, many of which are supported by third-party information.

[3] For a current year 1099-B, see www.irs.gov/pub/irs-pdf/f1099b.pdf.

[4] For some assets acquired after January 1, 2011, Form 1099-B also lists the date of acquisition, the cost basis, the capital gain or loss, and whether the capital gain is short-term or long-term. We do not use this information in this paper.

Our data set offers several important advantages over existing work. We have daily transaction data, as do Odean (1998) and Hoffman et al. (2013). However, our enormous sample size permits estimation of trading behavior at a daily frequency with substantial precision. Our data are unique in measuring activity across all taxable accounts; the aforementioned studies use data from a single brokerage house. Our data are also unique in containing several income-source variables, as well as many other taxpayer characteristics.

Because we only observe activity in individual taxable accounts, if individuals' propensity to sell off assets during times of turmoil systematically differs between non-taxable retirement accounts and taxable accounts, our results will be limited in scope, because they are only informative about the latter. Second, we observe gross sales, but not purchases, so we cannot provide direct evidence on "net sales;" we do, however, observe annual dividend income, which is related to stock ownership. We address these issues at length in Section 5.

2.2 Match Rates and Aggregate Statistics

Table 1 provides details of our data selection process and sample statistics. We start with the population of 1.4 billion 1099-B's in tax years 2008 and 2009, representing $37 trillion in total trading volume. There were about 22 million distinct taxpayers (individuals and institutions) in 2008, and about 21 million distinct taxpayers in 2009. After eliminating non-trading days and partial trading days, negative trade amounts and seemingly erroneous and very large trades, we are left with 1.4 billion 1099-Bs and $36 trillion of volume.[5] Next, we keep only sales related to individual taxpayers, substantially reducing our sample to 870 million transactions and $9.6 trillion in volume; the excluded trades are largely executed by entities such

[5] Specifically, we discard data from a trivial number of 1099-Bs (under 10) that are clearly errors (single sales of stock in the tens of billions of dollars) and several large sales apparently related to a single event in a single state. Many large trades remain in our sample; from 2007 to 2009, there are over 13,000 sales over $10 million and over 140 sales over $100 million. We verified as valid by hand a random set of these transactions.

as partnerships, corporations, and trusts.[6] Of these 1099-Bs that have a valid Social Security Number as a TIN (individual taxpayers), we discard trades entered into by minors (those under 18), leaving 861 million 1099-Bs in the sample, representing $9.5 trillion in volume. Although many different assets are subject to 1099-B reporting, we focus on stocks and stock mutual funds, represented by 273 million 1099-Bs and $6.8 trillion in trading volume. Until Section 6.2, when we examine differences in selling behavior between stock shares and mutual funds, we refer to individual stocks and stock mutual funds collectively as stocks. Finally, because our main income measure derives from average income over the period 2000 to 2007, we retain only transactions in 2008 and 2009 for taxpayers who appear as the taxpayer or spouse on at least one Form 1040 from 2000 to 2007. This leaves us with a final sample of $6.8 trillion in trading volume across 2008 and 2009—$3.7 trillion in 2008, and $3.1 trillion in 2009. Our total trading volume of $3.8 trillion in 2008 compares to the estimate of $2.2 trillion from the Sales of Capital Assets (SOCA) sample in 2008 (Wilson and Liddell 2013).[7] Additional summary statistics on the final sample are presented in Appendix Table A.1.

On average, 1099-B sales volume amounts to about 6 percent of total equity market sales volume as reported by CRSP.. Given estimates that about 73 percent of U.S. equity trading in our sample period is done by computer-driven, high-frequency (HF) traders,[8] a 6 percent coverage rate implies that our data covers the sales volume of a substantial fraction—about 22 percent—of non-HF trading. Because HF traders typically close their positions at the end of each day, they

[6] If a demographic group is unusually likely to execute trades through such entities, we might be mis-stating the relative sensitivity of these groups' overall sales. Cooper at al. (2015) provide evidence about the ultimate owners of pass-through entities, suggesting that they are substantially more concentrated among high earners.

[7] See https://www.irs.gov/pub/irs-soi/08in03soca.xls. A number of factors might account for the difference between the universe of 1099-B transactions and the sample in the SOCA data assembled by the Statistics of Income Division of the IRS. For 2008, SOCA estimates are based on a sample of 58,521 taxpayers (Wilson and Liddell 2013). Further, based on conversations with IRS staff, we believe that the data in the SOCA is based on when a return is filed, as opposed to when a trade is executed. Further, the SOCA study only records a limited number of short-term trades (500) per taxpayer, due to the costliness of transcribing Schedule D data.

[8] See MacKenzie (2009), which references estimates by the Tabb Group, a consulting firm.

are better viewed as intermediaries that hold temporary positions rather than investors that add risk-bearing capacity to the market. For a study like ours that focuses on who is ultimately bearing stock market risk, the sales volume of HF traders is not particularly relevant. The non-HF part of sales volume of course also includes the sales volume of mutual funds, hedge funds, and other non-HF institutional investors. We are therefore likely capturing a substantial part of individual investors' sales volume. Further, we observe no evidence that our coverage of individual trading volume relative to the entire market is time-varying. See the online Appendix for more details.

2.3 Market Turmoil and the Financial Crisis

To proxy for market tumult, we use the Chicago Board Options Exchange Volatility Index (VIX), obtained from the Center for Research in Security Prices (CRSP). The VIX index measures the implied volatility of stock prices based on option contracts sold on the S&P 500 stock index with a one-month maturity.[9] Because it is based on option prices, it is a forward-looking measure of investor uncertainty. It reflects the expected S&P 500 stock-index return volatility at a one-month horizon as well as the risk premium that investors are willing to pay to insure against shocks to volatility over this horizon. The VIX is widely used in academic studies as a measure of tumult in stock markets and the financial system more generally (see, for example, Adrian and Shin (2010), Longstaff (2010), and Nagel (2012)).[10] For purposes of presentation, we divide VIX by 100 throughout and make any transformations on this re-scaled

[9] The VIX calculated based on the S&P 500 is highly correlated with reasonable alternatives such as the VIX based on the Dow Jones Industrial Average or the NASDAQ, with rank correlations in excess of 0.95 between each pair of these measures over our sample period.

[10] The VIX is, to be sure, not the only reasonable measure of market tumult, one alternative being the lagged negative market return. Below we show that our qualitative conclusions about investor heterogeneity in their response to market tumult are preserved if we use this alternative measure.

variable, and often analyze the logarithm of the VIX. Unless noted otherwise, we examine behavior only on full trading days.[11]

Since we focus on stock sales, and hence on a change in investors' stock holdings, which should be triggered by a change in the market environment, our tumult measure is based on changes in the VIX index. Since the level of the VIX is highly persistent at a daily frequency, daily changes are quite close to unexpected innovations.

Figure 1 plots the evolution of the VIX at a daily frequency. In Panel A of Figure 1, we plot the VIX, in logs and levels, from 2008 to 2009. Until mid-2008, the VIX was low relative to levels seen during the crisis. Starting in the second week of September 2008, the VIX increased dramatically, from 0.23 on September 8 to 0.80 on October 27.[12] Panel B of Figure 1 displays the VIX from September to November 2008. On the day of the Lehman Brothers bankruptcy (September 15, 2008), the VIX increased by 24 percent.[13] The following day, American International Group (AIG) avoided bankruptcy after receiving an $85 billion loan from the Federal Reserve Bank of New York. The next major increase in the VIX occurred on September 29, the day on which Citigroup agreed to purchase Wachovia, the Federal Open Market Committee (FOMC) expanded swap lines with several other central banks, and the U.S. House of Representatives rejected legislation from Treasury on the purchase of troubled assets. On October 14, Treasury announced the Troubled Asset Relief Program (TARP), and VIX increased considerably on the following day. Ten days later, VIX reached a new peak, when National City Bank was purchased by PNC. Almost a month later, on November 18, executives of three large U.S. auto companies testified before Congress and requested TARP funds,

[11] For 2008-2009, the half-trading days are 7/3/2008, 11/28/2008, 12/24/2008, 12/26/2008, 7/2/2009, 11/27/2009, and 12/24/2009. The market is fully closed on weekends and holidays. See http://www1.nyse.com/pdfs/closings.pdf.
[12] A VIX value of 23 (scaled to 0.23) means that option prices imply that a one standard deviation movement in the S&P 500 is 23 percent of the current index level over the next year, and 6.6 percent ($=23/\sqrt{12}$) over the next month.
[13] This narrative is based on the account in https://www.stlouisfed.org/financial-crisis/full-timeline.

triggering an increase in the VIX that began to turn around only on November 21. The VIX peaked on November 20 (at 0.81), and then began to decrease toward pre-crisis levels.

3. An Econometric Model of Who Sells

We hypothesize that there is heterogeneity in the willingness of different groups of investors to hold on to stocks during times of turmoil. To investigate this hypothesis, we begin by developing an analytical framework, which we draw on to guide our empirical analysis and to address two important questions. First, to what extent can we use data on stock and mutual fund gross sales to infer the unobserved net trades (sales minus purchases)? Second, how does market clearing—that is, the fact that the average investor can neither buy nor sell on net—affect our analysis?

Conceptually, we split investors' trades into two categories with different trading motivation: (i) "reallocation" trades that aim to change the overall wealth allocation to stocks, and (ii) "selection" trades that aim to change the composition of the stock portfolio, but not the overall wealth allocation to stocks. If we could observe net trades, we would not have to worry about the selection trades, because they cancel when netting purchases and sales.

Consider individual i in investor group g. We assume that the dollar amounts of shares bought or sold by this individual on trading day t for reallocation and selection reasons can be represented by four independent Poisson random variables with the following time-varying intensities:

	Reallocation	Selection
Sales (S_{it})	$\sigma_\lambda \lambda_t W_i$	$\sigma_\eta \eta_t W_i$
Purchases (B_{it})	$\sigma_\lambda \lambda_t^{-1} W_i$	$\sigma_\eta \eta_t W_i$

where λ_t and η_t are positive random variables with unit time-series mean and variance; σ_λ and σ_η are constants. Conditional on the intensities, the four types of trades are independent. Over time, however, they can be correlated if λ_t and η_t have correlated time-variation. The same factors that drive sales also generally drive purchases, but the effects are in the same direction for selection trades (hence they offset when netting) and in the opposite direction for reallocation trades (hence they add when netting). All intensities are proportional to the investor's wealth W_i to capture the fact that wealthier investors are likely to trade higher dollar amounts. We view W_i as slowly moving relative to the time-variation in trading intensities, so that we can think of it as roughly constant for the purposes here. Wealth and the intensities can differ across investor groups, but to reduce clutter we do not use a g-subscript.

Aggregating across a large number of individuals within some group, with $S_t \equiv \sum_i S_{it}$, $B_t \equiv \sum_i B_{it}$, and $W \equiv \sum_i W_i$, and, in the case of purchases, applying a first-order Taylor approximation around the (unit) mean of λ_t yields[14]

$$S_t / W \approx \sigma_\lambda \lambda_t + \sigma_\eta \eta_t , \tag{1}$$

$$B_t / W \approx 2 \sigma_\lambda - \sigma_\lambda \lambda_t + \sigma_\eta \eta_t. \tag{2}$$

We can express net sales, $T_t = S_t - B_t$, as

$$T_t / W \approx 2 \sigma_\lambda (\lambda_t - 1), \tag{3}$$

Thus, sensibly, a higher λ_t implies higher net sales, while η_t has no impact on net sales. Taking expectations,

$$\mathrm{E}[S_t / W] = \mathrm{E}[B_t / W] = \sigma_\lambda + \sigma_\eta, \tag{4}$$

$$\mathrm{E}[T_t / W] = 0. \tag{5}$$

[14] We use the fact that the sum of Poisson random variables is also Poisson with intensity equal to the sum of the intensities. Further, for a large intensity ψ, the Poisson distribution is approximated very well with a lognormal distribution with parameters μ = log ψ and $\sigma = 1/\psi$. In our case, by summing across a very large number of individuals the intensity is so big that the variance is negligibly small relative to the mean. Stochastic variation in trading volume therefore originates only from stochastic variation in the intensities.

The sum $\sigma_\lambda + \sigma_\eta$ therefore represents average trading volume measured as a percentage of wealth.

We specify intensities as follows. The intensity of reallocation trades on day t depends on two factors: First, it depends on changes in the investor's risk aversion, pessimism, or "panic" since the previous day, which we summarize in Δx_t. Second, it depends on Δp_t, the log change in the value of the stock market index. More precisely,

$$\lambda_t = \exp(b\,\Delta x_t + d\,\Delta p_t) \approx 1 + b\,\Delta x_t + d\,\Delta p_t, \tag{6}$$

where $E[\Delta x_t] = 0$ and $E[\Delta p_t] = 0$ and the second (approximate) equality follows from a first-order Taylor approximation around these expected values. The inclusion of the Δp_t term allows the model to account for that part of an individual's desired change in the allocation to stocks due to price changes rather than trading that changes the quantities of assets held. In eq. (6), the $b\Delta x_t$ term reflects the trades the individual would want to undertake if prices remained unchanged and the $d\Delta p_t$ term reflects the offset due to price changes. We use Δp_t here to capture two effects associated with price changes that work in the same direction: A decline in stock prices reduces the investor's share of wealth allocated to stocks and it may be associated with a rise in expected returns. Both imply a reduced inclination to sell.

For the market to clear in aggregate, T_t must sum to zero in the investor population. Our empirical study focuses on individual investors, and for this sub-group, T_t can be non-zero. For the investor population as a whole, however, the market-clearing condition combined with (3) and (6) requires that $\Delta p_t = -(B/d)\,\Delta x_t$, where B is the $\sigma_\lambda W$-weighted average of b in the investor population.

Because we do not observe T_{it} in the tax-return data, we work with data on gross sales. Taking logs of (1), applying a first-order approximation around the means of λ_t and η_t, combining with (6), and using our result $\Delta p_t = -(B/d)\,\Delta x_t$, we obtain

$$\log(S_t) \approx \mu + \sigma_\lambda (\sigma_\lambda + \sigma_\eta)^{-1} (b - B)\, \Delta x_t + \sigma_\eta (\sigma_\lambda + \sigma_\eta)^{-1}(\eta_t - 1)\,, \qquad (7)$$

where $\mu = \log(\mathrm{W}) + \log(\sigma_\lambda + \sigma_\eta)$.

This model clarifies a few important points. First, as eq. (7) shows, an individual investor sells if his or her inclination to reduce stock holdings in response to tumult is stronger than for the average investor, i.e., $b > B$. In contrast, for the average investor, adjustment can only take place through changes in prices and equilibrium expected returns rather than adjustment of quantities. As a consequence, we cannot identify the level of b, but rather only cross-sectional differences $b - B$. In other words, we can identify the extent to which a subset of the investor population reacted more strongly or more weakly than did the average investor. For example, if we look at the taxpayers in our sample as a whole, we can identify the extent to which they reacted differently from the average investor in the entire investor population.

Second, going from a dependent variable expressed as fraction of wealth as in (1) to a dependent variable expressed in logs, the coefficients get scaled by $(\sigma_\lambda + \sigma_\eta)^{-1}$, i.e., by the reciprocal of expected trading volume (in terms of fraction of wealth traded). Thus, multiplying the effect of Δx_t on $\log(S_t)$ with an estimate of average trading volume yields an estimate, to a first-order approximation, of the effect on S_t / W.

Third, since we do not observe whether a sale of a stock is a selection trade or a reallocation trade, we have to leave η_t as unobserved in the residual. To the extent that Δx_t and η_t are positively correlated (e.g., during times of tumult investors' reduce their stock holdings overall, but they also re-shuffle the composition of their stock portfolio more than they do in times of calm markets), this will make the coefficient in a regression of log S_t on Δx_t an upward biased estimate of the effect on net sales. Ideally, we would like to estimate the (infeasible) regression of T_t / W on Δx_t. In Section 5, we use the brokerage account data of Barber and Odean

(2000) to estimate the effect of using gross sales rather than net sales. We find that gross sales and net sales are strongly positively correlated and the coefficient in regressions of $S_t\,/W$ on Δx_t is about three times higher than the coefficient in a regression of T_t/W on Δx_t. Thus, our estimates based on gross sales from tax return data should be adjusted downward by a factor of three if one wants to estimate the likely effect on net sales. Section 5 also presents an analysis of dividend receipts, which provides additional indirect evidence of a link between gross sales and net sales.

In our baseline specification, we proxy for changes in investors' desire to sell stock, Δx_t, with ΔV_{t-1}, the change in the log of the VIX index from day t-2 to t-1. Let $\Delta x_t = \Delta V_{t-1} + u_t$, where u_t represents other unobserved components of Δx_t that are orthogonal to ΔV_{t-1}. Projecting log gross sales from (7) on ΔV_{t-1}, we get

$$\log(S_{gt}) = \beta_g \Delta V_{t-1} + \alpha_g + \delta_t + \varepsilon_{gt}\ , \qquad (8)$$

where ε_{gt} is a composite residual that contains a u_t-related component as well as the part of the η_t-related term in (7) that is orthogonal to ΔV_{t-1}; we add g-subscripts to emphasize that we are looking at a sub-group of investors.

We estimate (8) with ordinary least squares. The key parameter of interest is β_g, which measures how gross sales of group g respond to the lagged change in log VIX. As discussed above, estimates of β_g likely reflect the response of reallocation as well as selection trades. We include group fixed effects, α_g, to absorb time-invariant differences in μ across groups, and we include date fixed effects, δ_t, to absorb sales determinants that affect all groups. Because we include date fixed effects, we normalize β_g to equal zero for one group of taxpayers in each regression. Throughout, we use Newey-West standard errors that allow for autocorrelation in the residual ε_{gt} up to a maximum of 10 days.

4. Evidence on Investor Selling Behavior

This section presents the main results on investor heterogeneity in the propensity to sell stock during periods of high market volatility. We present graphical evidence on the shares of sales—as a fraction of total sales volume reported on Form 1099-B—attributable to particular groups of taxpayers. We also examine these phenomena in a regression context, estimating regressions based on equation (8).

We begin by establishing basic facts about the relationship between aggregate sales behavior and movements in the VIX. As discussed in Section 3, because net sales must add up to zero for all investors in aggregate, the higher the aggregation level that we use, the less likely it is that the observed stock sales reflect net sales (that reduce investors' stock holdings) rather than selection trades (that change the composition of investors' stock portfolios). However, individual taxpayers do not constitute the entire investor population. For example, endowments, pension funds, or mutual funds that have flexibility to alter their stock market exposure could take the other side of individual taxpayer stock sales.

Table 2 presents the results of regressing the log of the amount of stocks sold on changes in lagged log VIX, both for 2008 and 2009 and separately for September through November of 2008. In columns 1 and 3, we examine only the one-day lag, while in columns 2 and 4 we report the sum of the estimated coefficients on the first ten lags of log VIX. Over the 2008-2009 period, a ten-percent increase in the VIX (i.e., an increase in log VIX of 0.0953) is associated with 3.3 percent more selling the next day, and 47.3 percent more over the next ten trading days. Focusing on the three months from September to November 2008 during which the financial turmoil peaked, the one-day effect is very similar, and the ten-day is almost one and a half times as large. As columns 2 and 4 show, the ten lags of log VIX also explain a substantial portion of the time-variation in log sales volume, especially during the height of the financial crisis: In the September to November 2008 time window, the R-squared is 54%.

This initial analysis shows that market tumult, as measured by the VIX index, induces individual taxpayers to engage in a substantial amount of stock sales during the following days. To understand the reasons for these stock sales, we now look at the data in a more disaggregated way and study heterogeneity in selling behavior.

4.1 Heterogeneity by Quantiles of Pre-Crisis Average Adjusted Gross Income

We first examine how the propensity to sell assets during the crisis relates to traders' income. We focus on average adjusted gross income (AGI) over the eight years prior to the period we study, from 2000 to 2007. We do not use income from 2008 onwards because it can be influenced by sales of stock in the period we are studying.[15] We divide the population of individual tax return filers into five groups to study heterogeneity by pre-2008 average AGI. We select groups such that each group accounts for a roughly similar share of total sales volume in the 1099-B data. The precise quantiles used to generate the groups should not substantially affect the results. More broadly, though, this approach implies that we are focusing much more on differences in trading behavior between individuals in the top percentiles of AGI than on differences between individuals in the "middle class" part of the AGI distribution. For example, our bottom group contains individuals all the way up to the 75th percentile of AGI and this group's sales volume is most strongly influenced by its relatively wealthier members close to the 75th percentile cutoff than by those lower down the AGI ranks who tend to hold smaller

[15] In cases where taxpayers did not file a tax return in a given year (if, for example, the taxpayer has very low income)—we use income only in the years it is available. We use AGI rather than taxable income because the latter subtracts below-the-line deductions that are arguably better thought of as consumption expenditures (i.e., itemized deductions such as charitable contributions and home mortgage interest payments, personal and dependency exemptions, etc.). AGI does subtract "above-the-line" deductions such as alimony payments.

portfolios. Since our focus is on understanding the contribution of various demographic groups to aggregate sales volume, this tilt towards higher-income taxpayers is appropriate.

Figure 2 presents the main results for heterogeneity by income in stock sales during the sample period. Panel A depicts the daily share of total 1099-B sales volume attributable to each group, for 2008 and 2009. Panel B normalizes the shares from Panel A by their average value from 2008 to 2009 in order to facilitate visual interpretation of how the shares change over time. For the most part, the shares are stable until September of 2008. Starting in September, though, the share of sales volume attributed to the top 0.1 percent of income recipients rises sharply until the beginning of 2009, at which time the top-income share drops continuously through mid-March, when it levels out. As must be true mechanically, the behavior of the other shares on average mirrors these patterns, with the most striking behavior among the lowest of the income groups, those below the 75th percentile. Plainly, sales by the top 0.1 and top 0.1-1 percent responded more strongly to the events of the financial crisis than sales by other groups. We also observe an increase in the top 0.1 percent share during the very last days of 2008, which we attribute to a greater propensity of these individuals to "harvest" capital losses to offset realized capital gains. These observations are consistent with our proposed explanation for the structural change occurring at the beginning of 2009: having sold large amounts of stock during the crisis and the loss-harvesting period at the end of 2008, very-high-income traders had sold a significant amount of their stock in individual taxable accounts by 2009. As a result, their share of sales volume fell, and did not recover until the last quarter of 2009, when the time series in Panel B of Figure 2 converge back to their pre-crisis (normalized) values.

Regression analysis tells a similar story. Table 3 presents the results of regression analyses of the association between sales volumes of these income groups with measures of volatility using the methodology described above, for several alternative measures of volatility. Specifically, we report the estimated β_g coefficients from eq. (8), where g denotes an AGI group. The left-out group in these regressions is sales by individuals in the bottom 75 percent of the income distribution, so these coefficients are estimates of the degree to which traders in a given AGI group tend to sell more than the bottom 75 percent in periods of higher tumult. As suggested by Figure 2, these coefficients are largest in magnitude, positive, and strongly statistically significant for the top 0.1 percent group. The share of stock sales by the top income group move up when the lagged change in VIX rises, relative to the lowest income group. The results are qualitatively similar when examining all of the trading days in 2008 and 2009 (columns 1 and 2) or focusing on just September through November of 2008 (columns 3 and 4): the estimated coefficients are positive and significant, although smaller in magnitude. They are even smaller and difficult to distinguish statistically from zero for the other two groups. Table A.4 shows that the results are quantitatively similar when we use the change in log VIX or the change in VIX as our measure of volatility, and Table A.5 shows the results are similar if we use the negative market return as a measure of market tumult.

Heterogeneous responsiveness to volatility by income persists well beyond the first day after an increase in volatility. Columns 2 and 4 of Table 3 show the sum of the estimated coefficients on the first ten lagged differences of VIX. Indeed, the 10-day effect is approximately ten times larger than the one-day-after effect, suggesting no let-up in the effect over the first two weeks. Appendix Table A.6 provides more detail on the lag structure, showing the differential effect on the top 0.1 percent income group gradually weakening in magnitude after ten trading days, but remaining statistically significant for more than twenty days; a similar pattern appears for the next two highest income groups.

To get a sense of the magnitude of the effects documented in Table 3, consider the following exercise. The estimate for the top 0.1 percent in column 1 suggests that a 10 log point (or 10.5 percent) increase in the VIX on date t is associated with a 3.3 percent increase in sales volume for the top 0.1 percent of earners relative to the bottom 75 percent.[16] The 25 percent increase in the VIX on the day of the Lehman Brothers collapse is therefore associated with a change in sales volume of the top 0.1 percent of 7.9 percent more than the change for the bottom 75 percent. When we account for the typical dollar amounts of sales volume in the top 0.1 percent, this effect corresponds roughly to $142 million (0.079*$1.8 billion) more stock sales by this group on September 15, 2008 alone. Proceeding similarly, the results from the ten-day specification in column 2 of Table 3 suggest that the Lehman collapse led roughly to $1.7 billion more gross stock sales by the top 0.1 percent than the bottom 75 percent over the ten days following collapse. Next, we scale these numbers by a factor of three to convert gross sales to net sales (see Section 5). We finally obtain that the elevated sensitivity of the top 0.1 percent relative to the bottom 75 percent corresponds to net sales by the top 0.1 percent of $47 million one day after the Lehman collapse and $567 million over the ten-day period following the collapse.

4.2 Heterogeneity by Age and Retirement Status

In this section, we report results for heterogeneity by characteristics related to aging and retirement. First, we consider age. Figure 3 depicts shares of sales in a fashion similar to Figure 2, dividing taxpayers into age groups rather than income groups. We define age as of December 31, 2008 for all individuals in the 1099-B sales data, based on records from the Social Security Administration. Panel A depicts shares of sales for selected age groups. Panel B normalizes these shares for ease of visual comparison. We observe that older individuals, especially those

[16] Appendix Table A.1 provides the summary statistics used in this calculation.

over the age of 60, were substantially more prone to sell during the crisis. In the regression analysis by age, tabulated in Table 4, we observe that individuals over the age of 60 are more likely to sell following increases in the VIX, both over the full two-year period (columns 1 and 2) and September to November 2008 (columns 3 and 4). The coefficients for the 60+ age group in columns 1 through 4 of Table 4 are statistically significant, and roughly comparable in magnitude to the coefficients for the top 0.1 percent AGI group in Table 3, although the persistence over a ten-day period is less marked for the age 60+ group than it is for the top 0.1 percent income group.

Figure 4 examines whether retirees are more prone to selling in times of tumult than non-retirees, where we proxy for retirement status by whether any Social Security income is reported on individuals' tax returns. It plots the share of sales by individuals with retirement income, relative to total sales reported on Form 1099-B—note that because there are only two groups in this analysis, one share completely characterizes the heterogeneity. Regression results in Table 5 indicate that households with retirement income were significantly more likely to sell assets during the crisis in late 2008 and 2009 than were households without retirement income.

4.3 Heterogeneity by Selected Other Household Characteristics

Figure 5 reports shares of asset sales by percentiles of the dividend income distribution. We use the same percentile categories (0-75, 75-95, etc.) we used for the AGI distribution, but we do not split individuals in the top 0.1 percent of the distribution out from everyone else to facilitate the visual comparisons. Panel A depicts the shares themselves; the shares are roughly comparable although, because dividend income is more unequally distributed than AGI, the share of sales is shifted towards the top of the dividend income distribution relative to AGI. Panel B depicts normalized shares, revealing a higher tendency to sell during the crisis among individuals in the top 1 percent of the dividend income distribution, and to a lesser degree the top 5 percent. Table 6 reports the coefficients for the regression version of this analysis. The VIX interaction coefficients on the top 1 percent and the top 1-5 percent are statistically significant and quite large, and indeed are larger than the estimated coefficients on top AGI percentiles in Table 3.

Figure 6 and Table 7 report results using as a measure of financial sophistication whether an individual had positive partnership or S-corporation income prior to 2008 (whether they have income reported on Line 32 of Schedule E). We observe that the share of sales by these individuals increases significantly during the crisis, and that it is significantly more responsive to changes in VIX. However, the relationship between market tumult and sales by sophisticated individuals is weaker than many others studied here, and not significantly different from sales by others during the narrower period of September-November 2008.

4.4 Heterogeneity Non-findings

We also investigated whether the relationship of volatility varied by other aspects of investors: gender, marital status, region, state, presence and amount of a mortgage interest deduction, 2007 zip-code level house price growth, and the frequency with which individuals traded in prior years. We did not find any noteworthy effects, with the exception that the relationship of trading volume to volatility is apparently higher for those in the third, and possibly second, quartile of trading frequency. This finding suggests that sensitivity to volatility is concentrated among investors who adjust their portfolios relatively often, but not day traders. Appendix Tables A.7 through A.14 provide the details of these exercises.

4.5 Multi-Dimensional Heterogeneity: Income and Age

A natural question is whether the strong association of volatility sensitivity to income is at least partly reflecting other investor characteristics that are correlated with income. To examine this, we define group-day volume by income and one of several other characteristics, and estimate the coefficient on the interaction between our measure of lagged change in VIX and an indicator for the income-by-other characteristic group. We also include income-by-other characteristic fixed effects and date fixed effects.

The results suggest that our two most striking findings, those involving income and age, are statistically distinct from one another. Table 8 presents results for average AGI and age. Panel A examines trades from 2008-2009, and Panels B presents results for September to November 2008 only. The coefficients from Panel A are plotted graphically in Figure 7. In general, we find that the responsiveness to tumult increases in AGI for each age group, and increases in age for each AGI group.

5. Evidence that Gross Sales are Informative about Net Sales

So far we have interpreted the evidence from gross sales volume in taxable accounts as indicative of a likely similar (although quantitatively perhaps accentuated) behavior of net sales across all accounts. This section presents evidence in support of this assumption using three supplemental data sets. To examine whether gross sales track net sales, we use detailed daily trading data from discount brokerage accounts, and we examine the evolution of dividend income in tax-return data. To examine whether sales in taxable accounts track total sales of equities, we use detailed wealth data in the Survey of Consumer Finance.

5.1 Gross and Net Sales in Discount Brokerage Data

We begin by analyzing the Barber and Odean (2000) data set of daily trades in a discount brokerage account from 1991 to 1996.[17] In the brokerage account data, we can observe both gross sales and net sales (i.e., gross sales minus purchases). We eliminate option trades and trades in fixed-income mutual fund shares. The resulting sample largely comprises trades in domestic common stock and equity mutual fund shares, but it also includes small amounts of trades in such assets as ADRs, Canadian stocks, REITs, and preferred shares. This sample contains roughly 1,000 individual trades per day.

For each trading day, we calculate two aggregate sales numbers for the whole brokerage account sample. The first is the amount of net sales, T_{gt}, which is simply the aggregate dollar amount (positive for sales, negative for purchases) added across all brokerage customers each day. The second is the amount of gross sales, S_{gt}, which includes only the dollar amount of sales across all brokerage customers. The latter gross sales number corresponds to the sales numbers that we get from the tax-return data. We further observe the aggregate value of brokerage customers' portfolios at the beginning of each month (including all assets, not just stocks and stock mutual funds), and we express T_{gt} as a percentage of this aggregate portfolio value.[18]

We first replicate our baseline regressions with the brokerage account data. Column 1 in Table 9 shows the results from a regression of log gross sales volume in taxable accounts—the equivalent to 1099-B sales volume in the tax-return data—on the change in the log VIX index. In addition to the lagged one-day change in the log VIX index, we also include the contemporaneous change. In the tax-return data, the contemporaneous change in log VIX is not significantly related to sales volume but, as Table 9 shows, brokerage account customer sales are

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[17] We thank Terry Odean for allowing us to access these data.

[18] We take the absolute value of each position in the calculation of the portfolio value; that is, short positions enter with a positive value. We do this because we want to scale trading activity variables with the gross size of an investor's portfolio rather than the net equity of the portfolio.

strongly related to both the contemporaneous and lagged change in log VIX. The magnitude of the combined effect is about 4-to-5 times as big as the effect in the tax return data. Both of these findings are sensible: discount-brokerage customers are more likely to react to same-day news and trade more actively than the average taxpayer is. For our purposes, the relevant take-away is that the tax return data and the brokerage account data tell the same story about the direction and the order of magnitude of the relationship between changes in log VIX and gross sales volume.

Column 2 presents the most important piece of evidence from the brokerage account data. Here we use net sales (which we do not observe in the tax-return data) as the dependent variable and gross sales (which we do observe in the tax-return data) as the explanatory variable, both expressed as a percentage of the portfolio value. The results show that there is a very strong relationship between these two variables. A gross sale of one percent of the portfolio value is associated with a net sale of 0.34 percent. The adjusted R^2 of approximately 27 percent also indicates that there is a strong relationship between gross sales and net sales.

Columns 3 and 4 compare regressions on log VIX changes with gross sales and net sales as dependent variables, both expressed as a percentage of portfolio value. As we discussed in Section 3, a comparison of the estimates from these two regressions can help us estimate to what extent a rise of gross sales in times of market tumult also implies a rise in net sales. We find that the coefficient estimates with gross sales are about two to three times as big as with net sales. This finding is the basis for our suggestion in Section 4 that one can get a rough estimate of the effect on net sales by dividing the coefficient in the gross sales regression by three. More broadly, the estimates in columns 2 to 4 suggest that the gross sales from the tax return data are informative about the unobserved net sales.

Unlike the tax-return data, the brokerage account data also contains trades in non-taxable (IRA and Keogh) accounts. This allows us to check whether in tumultuous times the behavior of investors in non-taxable accounts is fundamentally different. We find that they are not. The results reported in column 5 are quite similar to the results for taxable accounts in column 1. Thus, it seems that the results from our analysis of taxable trades in tax-return data could also carry over to some extent to non-taxable accounts.

Finally, column 6 looks at the taxable accounts restricted to customers with large portfolios, defined as those above the 80th portfolio value percentile. This is an imperfect way to approximate the high-AGI sample in the tax-return data. Based on the point estimates, the relationship with the VIX index changes is slightly stronger than in column 1, but the difference is not statistically significant and the magnitude of the difference is much smaller than in our AGI-based sample splits in the tax return data. Part of the reason could be that the value of the brokerage-house portfolio is not as good a measure of wealth and income as is AGI in the tax-return data. Moreover, the brokerage customers are a rather special selected sample that likely differs from the average taxpayer on a number of dimensions. We also repeated the regressions in column 3 and 4 with the large-portfolio sample (untabulated). We find that the estimated coefficients on log VIX changes are slightly higher than those reported in columns 3 and 4.

5.2 Changes in Dividend Income

Next we present evidence that annual gross sales by a given individual are associated with decreases in dividend income reported on that individual's tax return (Form 1040 Schedule B). Intuitively, one can think of qualified[19] dividend income as a rough proxy for the amount of

[19] A qualified dividend is one that is taxed at the preferential lower tax rate. Regular dividends paid out to shareholders of for-profit U.S. companies are usually qualified. There are minimum holding periods around ex-dividend days, and dividends paid out by, for example, real estate investment trusts and master limited partnerships do not qualify.

stocks held in an individual's portfolio. If gross sales are associated with net sales, then an individual's portfolio should contain less stock after a year of high gross sales, and thus the individual's dividend income should decrease.

We run simple regressions of the change in dividend income from year t-1 to year t+1 on gross sales in year t, where t is either 2008 or 2009.[20] We restrict the sample to individuals receiving dividends in year t-1, and we winsorize gross sales and dividend income changes at the 1 and 99 percent levels to eliminate the effect on the results of some obvious data errors.[21]

Table 10 reports the results of this analysis. In columns (1) and (2), we document a statistically significant relationship between gross sales and decreases in dividend income. To assess whether the coefficient we estimate is reasonable and consistent with the analysis of the discount brokerage data in Table 9, consider $1 of gross sales on some day. The earlier analysis suggested that $1 of gross sales corresponds on average to $0.33 of net sales on the same day. Suppose that the $0.33 reallocated from stocks on that day is not reallocated back to stocks within one year. Then the decrease in dividend income will be roughly $0.33 times the dividend yield in the individual's portfolio. For the average individual, we expect the dividend yield to be somewhere near the S&P 500 dividend yield of 2 percent. In this case the drop in gross sales would be about $0.33*0.02 = $0.0066. This number is nearly identical to our estimated coefficients, which are 0.0065 and 0.0068.

A number of assumptions are implicit in the above reasoning. Our interpretation requires that changes in dividend yields from t-1 to t+1 should be reasonably unrelated to gross sales, and to the share of gross sales that pass through to net sales. For example, the first condition fails if

[20] We have also estimated regression specifications with transformed versions of the same dependent and independent variables, including logarithmic specifications and those in which all variables are scaled by adjusted gross income. In all instances, the qualitative results are the same. We prefer the specifications reported here because their interpretation is relatively straightforward.

[21] The results are nearly identical if we also exclude individuals with zero gross sales in the given year.

individuals disproportionately sell dividend-paying stocks, and the second fails if individuals' selection trades transfer assets away from high-dividend-paying stocks and towards low-dividend paying stocks. While this analysis is an imperfect test of the relationship between gross and net sales for the reasons described above, we believe the most plausible explanation for the strong negative association between gross sales in year *t* and changes in dividend income from *t-1* to *t+1* is that gross sales are associated with net sales, especially given that the magnitude of the coefficients so closely aligns with this interpretation.

We also use changes in dividend income to test an implicit assumption above, that the relationship between gross sales to net sales is invariant across groups. Specifically, if this implicit assumption is satisfied, the relationship between dividend income changes and gross sales should be roughly constant across groups. Columns (3) and (4) of Table 10 report the results of this test for AGI groups: we interact the specification in columns (1) and (2) with the AGI groups used in Section 4. The negative coefficients on the interaction between gross sales and high-AGI group membership suggests that individuals in the higher-AGI groups have a *higher* rate of pass-through from gross to net sales than people in the bottom 75 percent of the income distribution. While there may be heterogeneity in pass-through rates, heterogeneity of the kind suggested by these results would actually *strengthen* our interpretation of the results in Section 4 that high-income groups disproportionately sold out of the stock market during the financial crisis. The interpretation of the regressions in columns (3) and (4) in terms of pass-through rates from gross to net sales is subject to similar caveats about dividend yields described in the previous paragraph.

5.3 Taxable and Non-Taxable Accounts

We next provide suggestive evidence that our inability to observe activity in non-taxable accounts does not confound the qualitative results described in Section 4, using data from the 2007-2009 panel of the Survey of Consumer Finances. This data set contains detailed information on wealth for 3,857 households interviewed in late 2007 and late 2009, and the survey deliberately oversamples high-wealth individuals (see Bricker et al, (2011) for an overview). Importantly, the data allow us to examine separately wealth in taxable accounts, which includes directly held stock, mutual funds, and hedge funds, and wealth in non-taxable accounts, where the latter includes tax deferred retirement accounts, trusts, other managed assets, and annuities.[22] Using this data, we construct measures of 1) equities held in taxable accounts, 2) equities in all accounts, 3) net sales or purchases of equities in taxable accounts, and 4) net sales or purchases of equities in all accounts.[23]

How might our inability to observe non-taxable accounts influence our results? The percent change in an individual or group's overall equity holdings sold in response to an uptick in volatility (our principal parameter of interest) depends on (1) the percent change in their taxable equities, (2) the share of overall equities held in taxable accounts, and (3) the relative intensity of their stock trading in taxable accounts. Our main results suggest that (1) is higher for high-income groups. A comparison of (1) alone, however, could be misleading if higher-income individuals hold a smaller share of wealth in taxable accounts and/or they execute more of their equity sales in their taxable accounts.

Figure 8 plots the share of wealth held in taxable accounts by income group (Panel A) and age group (Panel B). We use similar group definitions as elsewhere in the paper, but because of data limitations we use income in 2007 rather than average AGI from 2000-2007 and, due to

[22] The data do not include wealth held by foundations controlled by an individual.
[23] To be comparable with the IRS data, we consider a transaction in the SCF to be taxable if it would lead to a reported sale on a 1099-B linked to an individual taxpayer.

power concerns, we group the top 0.1 percent of the income distribution with the rest of the top 1 percent. Examining these graphs rules out the first potential pitfall, that higher income individuals hold a smaller share of wealth in their taxable accounts. Indeed, the opposite is true: high-income people hold a higher share of their wealth in taxable accounts, perhaps due to the limits on contributions to tax-deferred retirement accounts. The same is true of older individuals, as shown Panel B of Figure 8. These facts on their own suggest that the heterogeneity in responses to market tumult is likely higher than what we document.

Although our results are clearly not driven by differences in the share of wealth held in taxable accounts, it could still be the case that higher-income individuals conduct much more of their volatility-driven net sales in taxable accounts, while lower-income individuals mix their activity between taxable and non-taxable accounts. This could cause our results to be misleading, as the overall sales of lower-income individuals would be higher than what we measure, and maybe not that different from the high-income individuals.

To address this second problem, we regress across the individuals in the SCF the change in total stock holdings between 2007 and 2009 on the change in stock holdings in taxable accounts, with and without an interaction with income group indicators. When calculating these changes, we adjust the stock holdings in 2009 for the change in the Wilshire 5000 Total Market Stock Index between the survey dates in 2007 and 2009. The remaining change in stock holdings equals approximately the amount of stocks bought or sold. This exercise is similar in spirit to the regression comparing gross and net sales in Table 9 (column 2), but we here compare net taxable sales and total net sales. If individuals conduct all their trading in taxable accounts and no trading in non-taxable accounts, or if trading in non-taxable accounts is uncorrelated with trading in taxable accounts, the slope coefficient in such a regression would be around one: a dollar in net taxable sales is associated with a dollar in total sales. If selling in taxable and non-taxable accounts is positively correlated, this coefficient would be larger than one. Another possibility is that individuals tend to sell in taxable accounts when they buy in non-taxable accounts, in which case the coefficient would be less than one. The main caveat to this approach is that not all variation in net sales in these data is a response to market tumult, although to be sure a large amount of activity between 2007 and 2009 was driven by the tumult of the financial crisis.

Table 11 reports the results of the regression. The slope coefficient is 0.92; this estimate is statistically different from zero ($p < 0.001$) but not from one ($p \approx 0.37$). When we include interactions for income groups in column 2, we find that the group interaction terms are all statistically insignificant, and the point estimates are relatively small relative to the overall effect.[24] Thus, we find no evidence that the relative trading activity in taxable versus non-taxable accounts confounds our main results. These results also rule out that gross sales in taxable accounts over this period were primarily due to shifting assets from taxable to non-taxable accounts (in which case the estimated coefficient would be zero). To be sure, this exercise is suggestive rather than dispositive, as due to data limitations it does not directly analyze the response of equity holdings in various accounts to tumult, but rather the overall variation in equity holdings.

6. Which Stocks Were Sold?

Thus far, we have focused on heterogeneity in individual investors in the propensity to sell corporate stock during times of market tumult. In this section, we add another dimension to the analysis: the propensity of investors to sell off different assets during times of crisis.

[24] If we include interactions for age groups, the point estimates for interactions are also small and statistically insignificant.

To perform this analysis, we group sales from the Form 1099-B microdata based on the reported CUSIP number of the asset sold, and the date of sale. We restrict ourselves, as before, to sales by individuals, using the TIN on the 1099-B and on individual tax returns. The result is a CUSIP-day panel dataset. To preserve anonymity, we exclude CUSIP-days on which fewer than ten individuals sold a particular asset, which eliminates just under 0.1 percent of the total sales volume in the original dataset. We add to the dataset information on these assets from Wharton Research Data Services, including stock returns, Standard Industrial Classification (SIC) codes, CRSP sales volume, and the S&P 500 VIX used throughout the paper. The methods we use to analyze this data are similar to the ones employed in Section 4, except that we examine heterogeneity by asset characteristics instead of by taxpayer characteristics.

As a check on the quality of the CUSIP-day panel dataset, we estimated a regression of log individual sales volume from 1099-B data for a given CUSIP-day on log CRSP volume for that CUSIP-day, including stock fixed effects. The estimated coefficient on log CRSP volume was roughly 0.81, suggesting that a ten percent increase in CRSP volume for a given CUSIP is associated on average with an 8.1 percent increase in taxable individual sales for that CUSIP.

6.1 Sector

We first focus on the sector of the companies whose stock was sold. We use the Fama-French 12-industry (FF12) classification system, which classifies each stock into one of 12 sectors based on the Standard Industrial Classification (SIC) code (Fama and French, 1997). We aggregate sales in these 12 sectors and then show the evolution over time of shares of total individual sales in various sectors, as we did in Figures 2 through 6. Given the nature of the financial crisis, we are interested particularly in the sales of stock of firms in the financial sector. We thus disaggregate sales in the financial sector into finer groups at times, using the Fama-

French 48-industry classification system, in order to focus on more narrowly defined sectors in finance.

Figure 9 depicts the evolution of shares of stock sales within selected sectors. Panel A depicts the share of total individual sales in each of the FF12 sectors. The two largest sectors are finance, with 46 percent of total sales on average over the two-year period, and business equipment, with 20 percent. The share of sales in the finance sector increases markedly during March of 2008, during which Bear Stearns nearly failed and subsequently was bought out by JPMorgan Chase with the assistance of the Federal Reserve Bank of New York. The finance-sector share falls following the Bear Stearns acquisition, but increases shortly thereafter and remains elevated until the end of 2009. We observe a marked short-term increase in the finance share during the height of the crisis in September 2008.

The definition of the finance sector we use in Panel A is broad, grouping together firms in banking and trading as well as insurance. In Panels B and C, we report shares of sales volume using sector definitions that separate firms in banking and trading firms from those in insurance.[25] We also include manufacturing and consumer durables, two sectors that reflect firms in the so-called "Main Street" part of the economy, as opposed to the "Wall Street" firms in finance. The evolution of shares using these groupings is depicted in Panel B of Figure 9. The banking and trading subset of the finance sector is much larger than the insurance subset, but both exhibit elevated sales shares relative to non-finance stocks around key dates like the Bear Stearns acquisition and the Lehman Brothers collapse. The overall share of sales in banking and trading remains elevated from the last quarter of 2008 to the end of 2009, likely due to the uncertainty created by the financial crisis.

[25] The FF12 Finance sector also includes a very small number of firms in the real estate sector, consisting of less than one percent of total sales in the FF12 Finance category. Note that prominent firms such as Merrill Lynch and Lehman Brothers are (were) classified as trading firms.

In Panel C of Figure 9 we plot the shares from Panel B, normalized according to the mean share from 2008-2009 in each sector. The large differences in scale between sectors means that some caution is warranted in interpreting this figure: our normalization will cause changes in shares that constitute a smaller share of overall sales to appear more volatile when we plot normalized shares. We observe, in addition to the response of the financial shares to the collapse or near-collapse of several large firms mentioned above, an elevated share of sales in consumer durables throughout the last three quarters of 2009, elevation in the share of sales in insurance in fall of 2008, and another jump in the share of sales in insurance in late August through mid-September of 2009. This pattern is also apparent if we just plot sales in these sectors on their own, but it is masked in the previous figures due to the relatively small shares of trading in these categories. We attribute the increase in the consumer durables share to the market's increasing concern that the financial crisis might have a very large effect on Main Street. The fall 2008 spike in sales of insurance companies' shares is likely related to the woes of AIG, which in its second quarter filing on August 6 updated its total losses to $26.2 billion and aggregate collateral to $16.5 billion, and on September 15 had its credit rating downgraded, forcing another $14.5 billion in collateral. On September 16, the Federal Reserve authorized the New York Fed to lend AIG up to $85 billion through a revolving credit facility in return for a 79.9 percent equity stake.

We next examine whether individual sales of stock in different sectors respond differently to overall market tumult using regressions similar to those in Section 4, but with an asset characteristic as the "group" variable in the regressions instead of a taxpayer characteristic. Table 12 reports the results of this analysis. We document little sectoral heterogeneity in the responsiveness of sales to tumult using just one lagged difference in log VIX, with the possible exception of sales in chemicals, energy, and utility. However, examining 10 days of lagged differences uncovers significant heterogeneity by sector, with business equipment, chemicals, consumer non-durables, energy, finance, and utilities all much more responsive to tumult than consumer durables (the left-out industry). Although sales in financial stocks clearly respond to specific events and are strongly related to tumult, we find no evidence that sales in finance respond significantly more strongly to changes in the overall VIX than sales in many other sectors.

6.2 Mutual Funds versus Individual Shares

Here, we compare the relationship of sales of stock with that of sales of assets in mutual funds. We are motivated in part by the finding of Chang, Solomon, and Westerfield (2016), who find that the disposition effect that could explain many of our results is stronger for individual stocks than delegated accounts like mutual funds, and by Dorn and Weber (2013), who find that German retail brokerage customers tended to pull out of mutual funds during the crisis. Barrot et al. (2016) report a similar finding with data from a French retail brokerage.

Overall, the results do suggest that individuals disproportionately sold off assets in mutual funds during the crisis. Figure 10 depicts the share of total individual sales (for any asset class subject to 1099-B reporting) in either individual stocks or mutual funds from 2008 to 2009. We observe that the share of sales of mutual fund assets increases noticeably during the financial crisis, from roughly 20 percent of all sales to 30 to 40 percent, and then falls gradually during the latter three quarters of 2009. Consistent with this observation, we report regression estimates in Table 13 suggesting that direct sales of stocks are less sensitive to market tumult than sales of mutual fund assets. The difference is significant at the 5 percent significance level using just one day of lagged differences of log VIX, but not statistically different from zero when we use 10 days of lagged differences.[26]

Finally, we examine in Table 14 whether the heterogeneity in the relationship between changes in VIX and sales volume we have documented above holds for both direct sales of stock and sales of mutual funds. The answer is no. The rich were more likely to sell directly-held following market tumult, but this relationship do not hold for sales of mutual funds. This is consistent with the disposition effect (a reluctance to sell stocks with accumulated capital losses) being (i) weaker for delegated assets such as mutual funds and (ii) stronger for lower-income people. As a consequence, the disposition effect dampens the sales of directly-held stocks by lower-income taxpayers, but not their sale of mutual fund shares, which is consistent with the pattern shown in Table 14.

Those over the age of 60 were more likely to sell in volatile periods, and this continues to hold for sales of directly-held stocks. For mutual fund sales the picture is unclear, but, at a minimum, there is no clear-cut evidence that older investors were more prone to increase mutual funds sales in response to a rise in the VIX (the picture stays unclear if we add multi-day lags of VIX changes).

7. Conclusions

In this paper we have investigated which types of individuals sell stocks, and which kind of stocks are sold, during periods of turmoil in stock markets. To do this we use administrative data from the Internal Revenue Service consisting of billions of third-party reports on all sales of stock in United States taxable individual accounts, to understand which individuals sold out

[26] Differences in the effect of tumult on sales volume between stocks and mutual funds fade much more quickly than in the by-taxpayer-group analysis, with the effect beyond two days of lagged differences being approximately zero. This explains why the 10-day effect here is more difficult to distinguish from zero statistically than the 1-day effect.

during the tumultuous market events of 2008 and 2009. On many dimensions, this data set is vastly superior to the kinds of data that have been brought to bear heretofore on these questions.

We begin by developing a statistical model that frames to what extent we can use data from tax returns on gross sales (which may include trades that reshuffle the portfolio between different stocks) to infer unobserved net sales (sales minus purchases, i.e., the overall reduction in stock holdings). We confirm, based on a supplementary data set on brokerage accounts from Barber and Odean (2000) and an analysis of the relationship of gross sales to changes in dividends received, that gross sales are indeed strongly related to net sales. The model further clarifies that data on sales can only identify differences between investor groups in their tendency to reduce stock holdings in response to turmoil. After all, the average investor can neither buy nor sell on net. For this reason, the objective in our study is to uncover differences between taxpayers and the investor population as a whole and differences between groups of taxpayers.

The unique advantage of our data is that we can identify for each sale exactly who sold what security on each day, and characterize the sellers by the demographic information available on income tax returns and matched Social Security data. We see that, starting in September 2008, the share of sales volume attributed to the top 0.1 percent of income recipients rises sharply until the beginning of 2009. The same is true of the share of sales by those over the age of 60. These observations are confirmed by regression analyses that show that the relationship of volume to recent market tumult, as measured by changes in the VIX index, is higher for the top 95-99, 99-99.9, and 99.9-100 income percentiles over the period 2008 to 2009. In multi-dimensional analysis, both income and age are separately related to tumult sensitivity of sales volume. Other aspects of investors—gender, marital status, region and state of residence, presence and amount of a mortgage interest deduction, and 2007 zip-code-level house price growth—are not related to the tumult sensitivity of stock sales. Although sales in financial stocks clearly respond to specific events, we find no evidence that sales in finance responded more strongly to changes in the VIX than sales in other sectors.

Overall, our results show that there is substantial heterogeneity in investors' responses to market tumult. An explanation of market movements during these episodes likely needs to take into account these shifts in risk-bearing capacity. The data support theories that emphasize reduced willingness to take risk among investors close to or in retirement. More difficult to explain is the tendency of high-income investors to sell in response to market tumult. Perceived market-timing skills of financially more sophisticated investors could play a role. There could also be a connection to the disposition effect—the tendency of investors to hold on to stocks with accumulated losses—as the groups that we find are less likely to sell are also those that previous research has identified as having stronger disposition effects. We encourage future research to further examine why individuals at the very top of the income distribution are especially prone to sell stock during tumultuous times.

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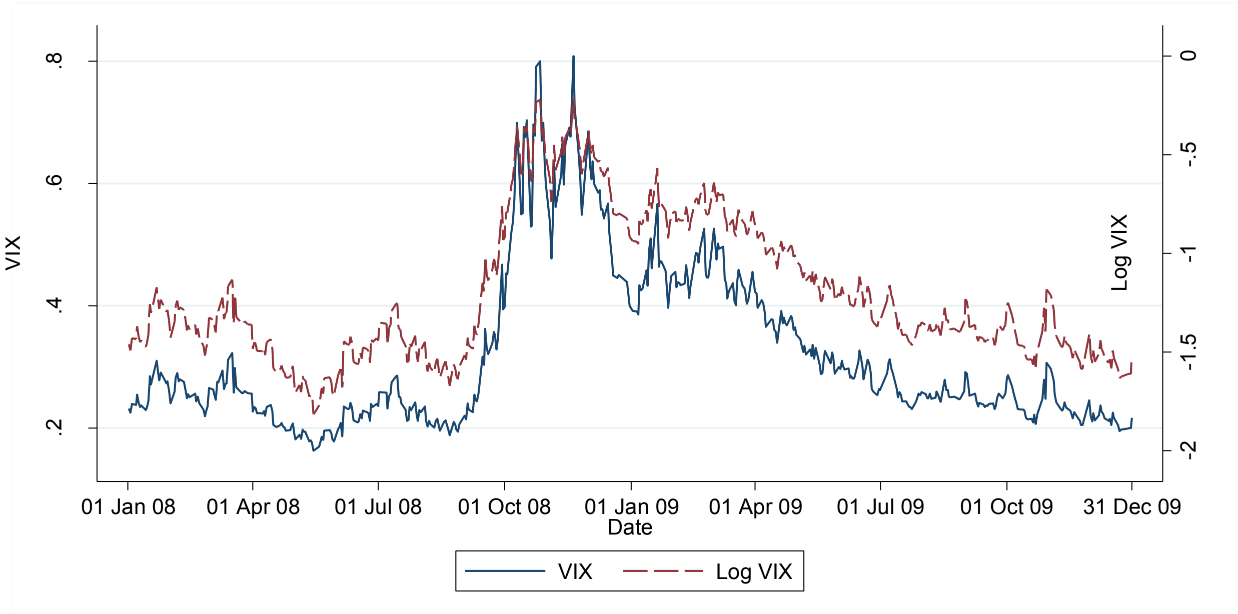
Figure 1. Stock Market Volatility (VIX S&P 500) Over Time

Panel A. 2008-2009



Panel B. September-November 2008

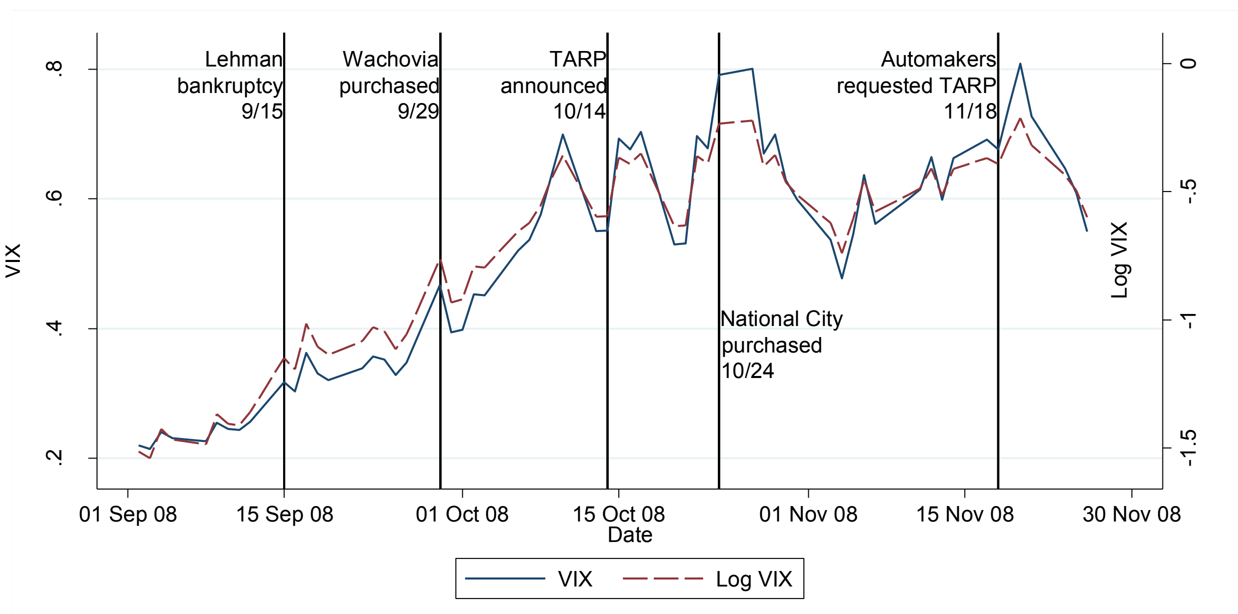
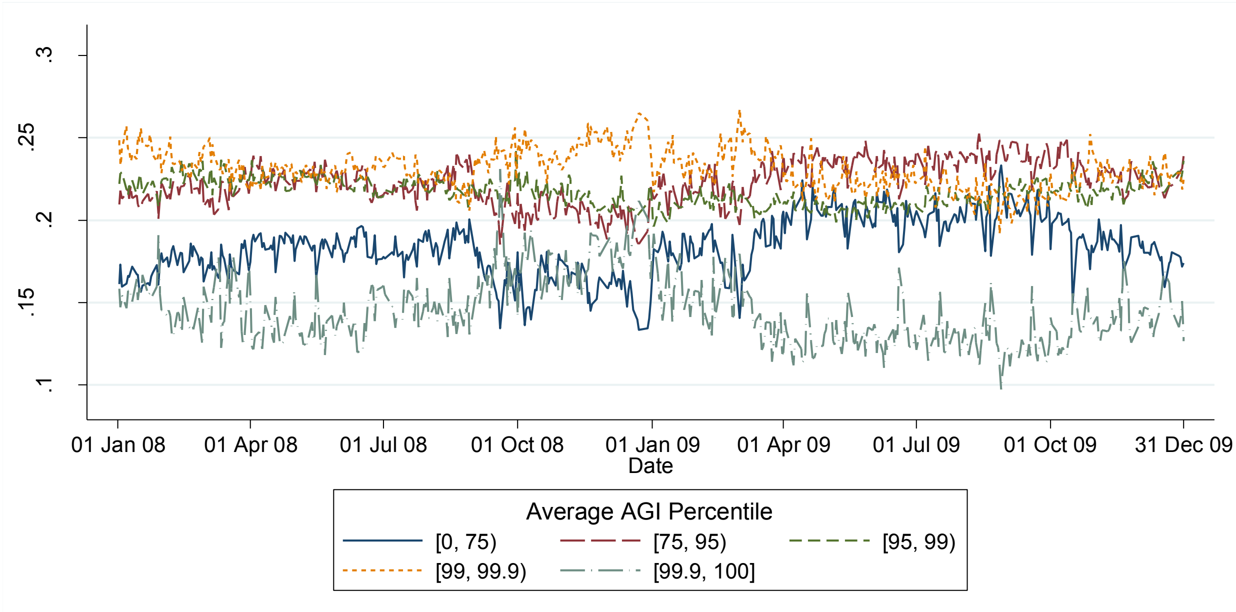


Figure 2. Shares of 1099-B Sales Volume by Average Adjusted Gross Income Percentiles

Panel A. 2008-2009



Panel B. 2008-2009, Normalized by Average Share of Trading Volume from 2008-2009

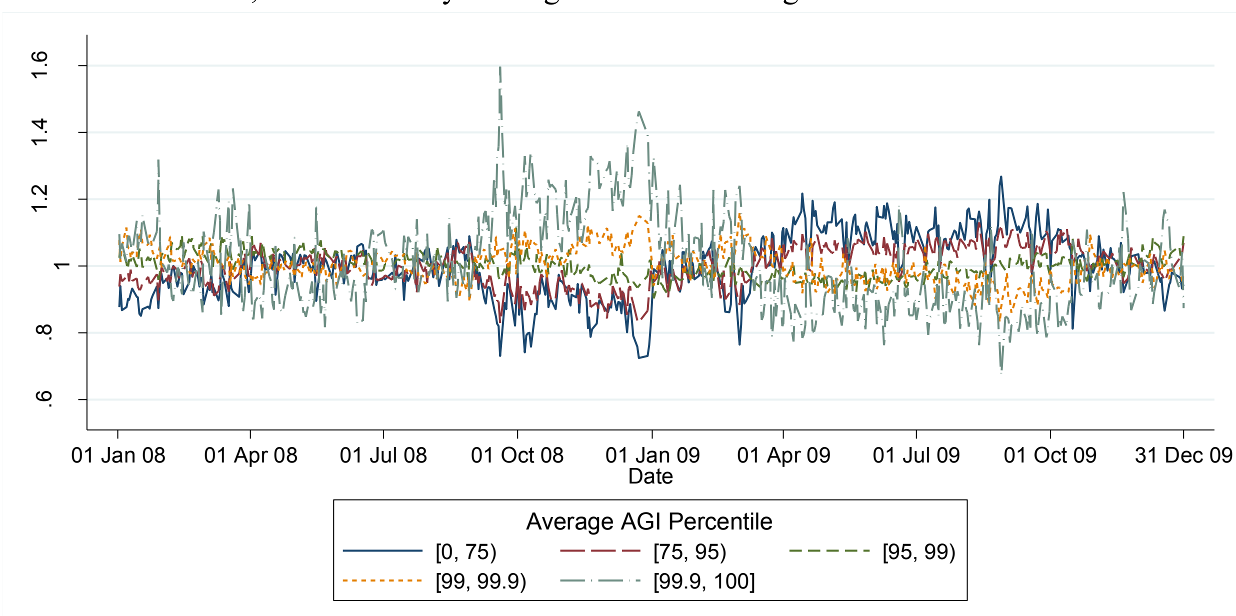
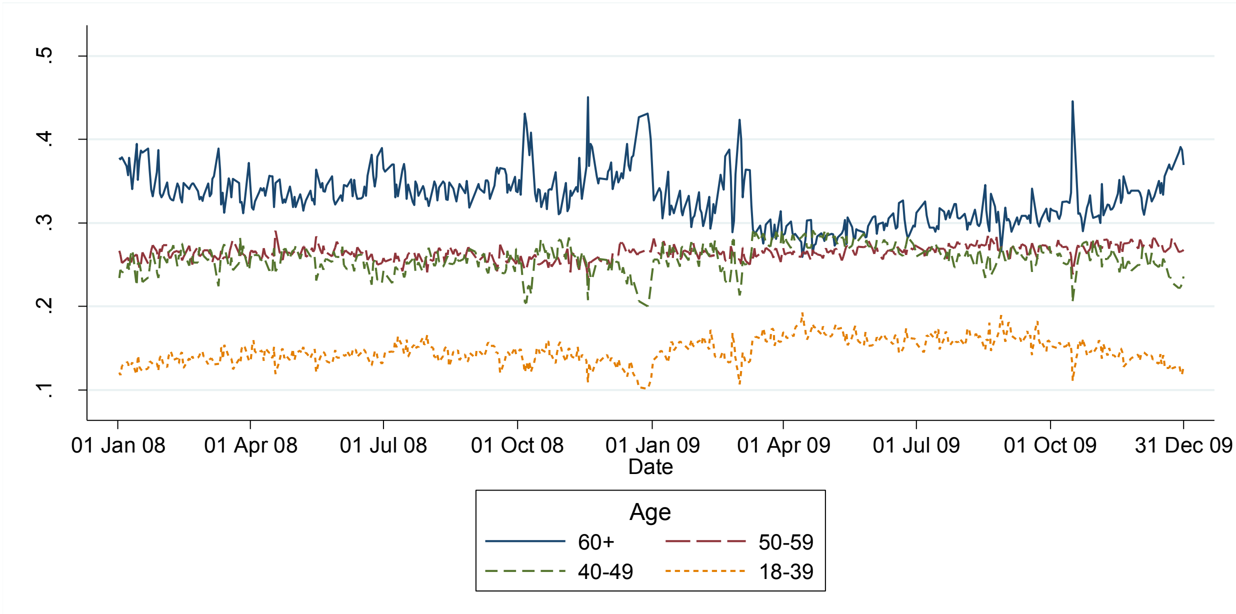


Figure 3. Shares of 1099-B Sales Volume by Age

Panel A. 2008-2009



Panel B. 2008-2009, Normalized by Average Share of Trading Volume from 2008-2009

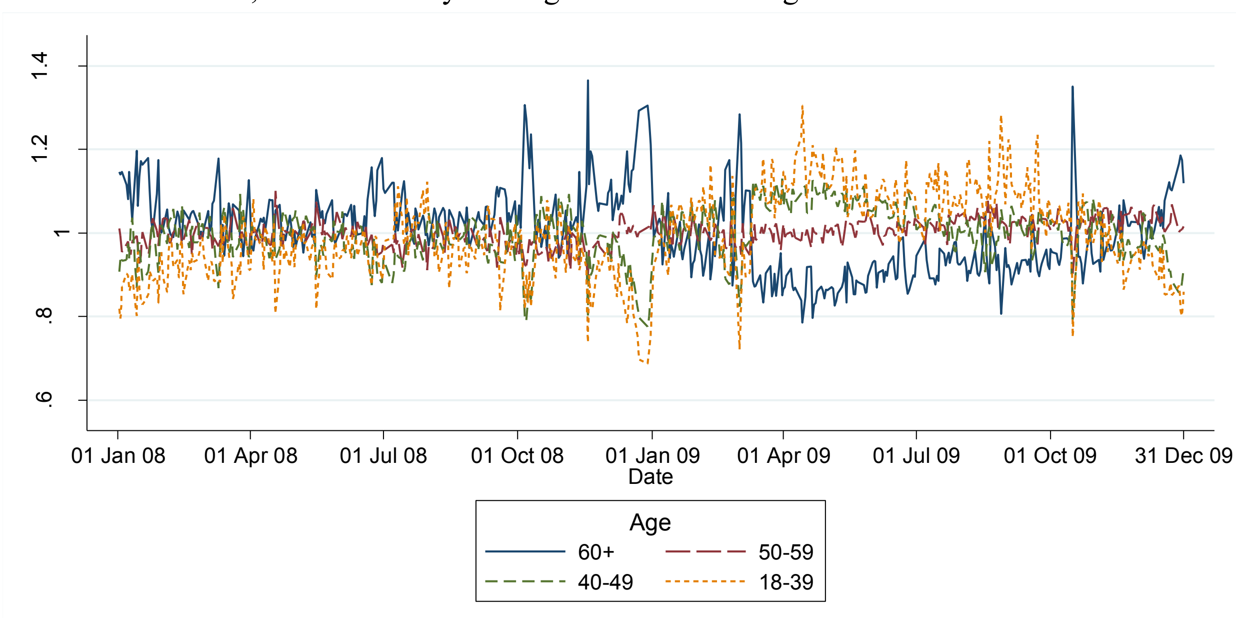


Figure 4. Share of 1099-B Sales Volume, Taxpayers Receiving Social Security Income, 2008-2009

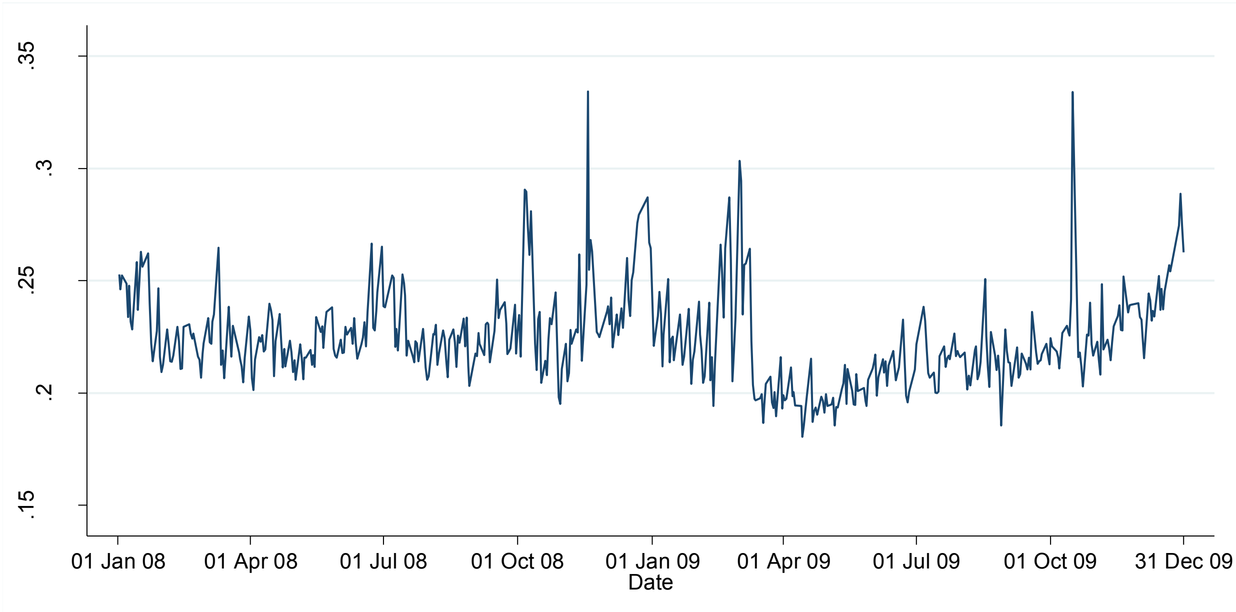
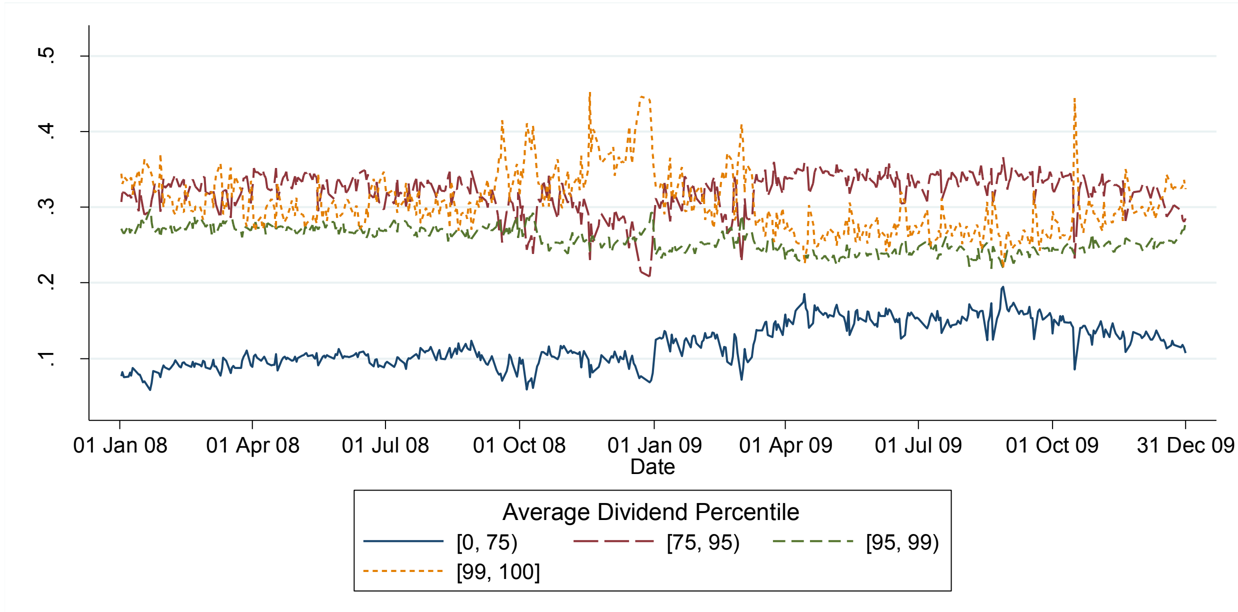


Figure 5. Shares of 1099-B Sales Volume by Average Dividend Income Percentiles

Panel A. 2008-2009



Panel B. 2008-2009, Normalized by Average Share of Trading Volume from 2008-2009

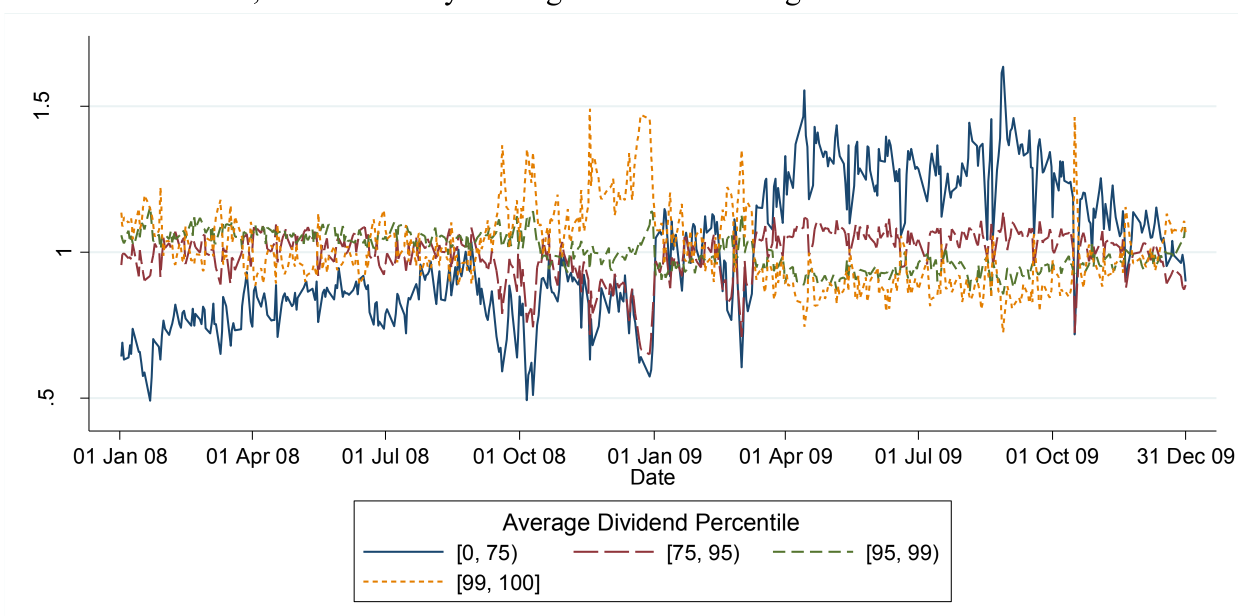


Figure 6. Share of 1099-B Sales Volume, Taxpayers Receiving Positive Partnership or S-Corporation Income before 2008

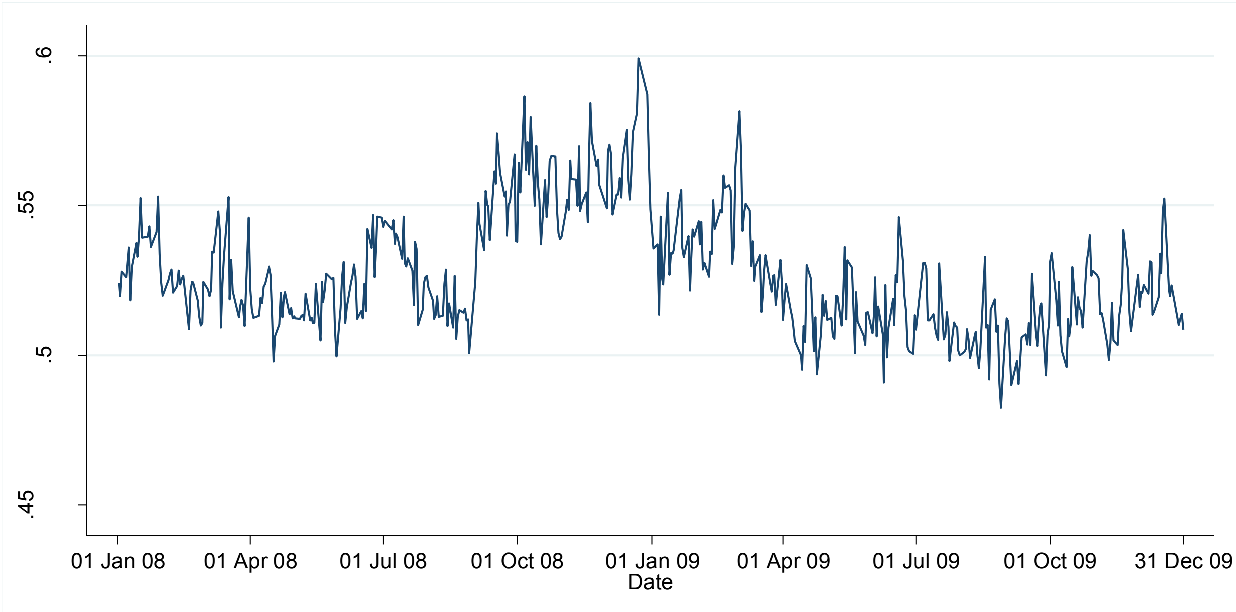
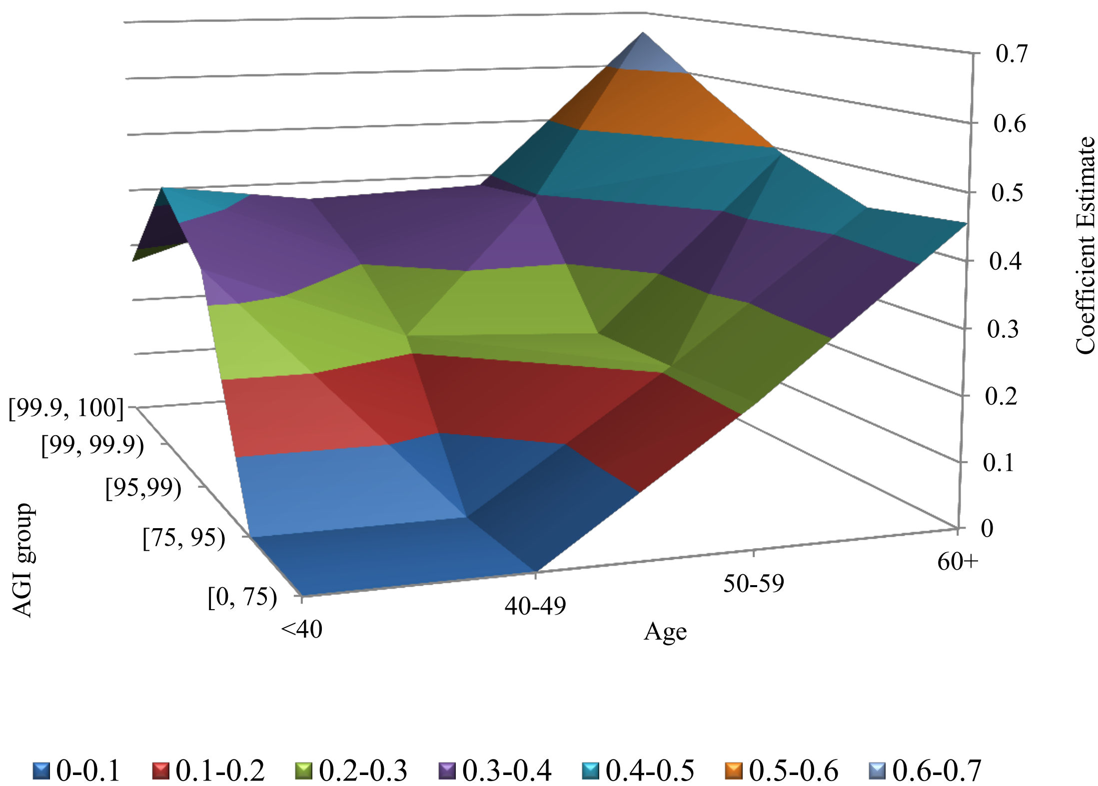


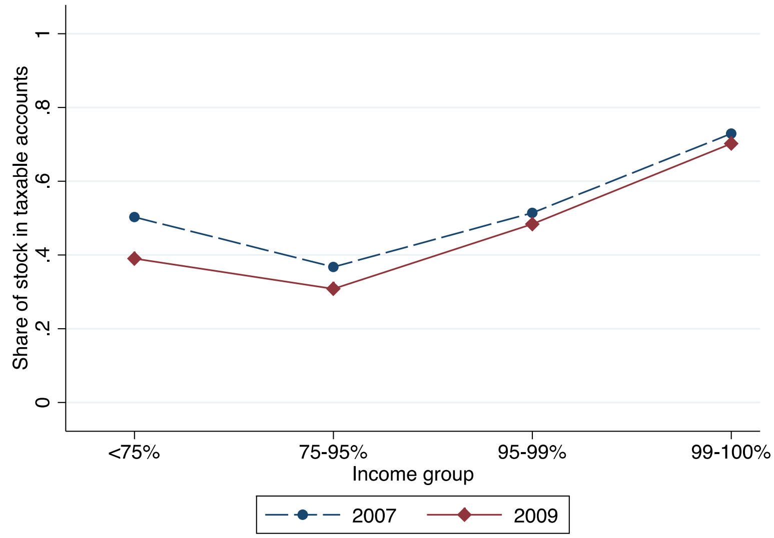
Figure 7. Heterogeneity by Income and Age in Sales Response to Market Tumult



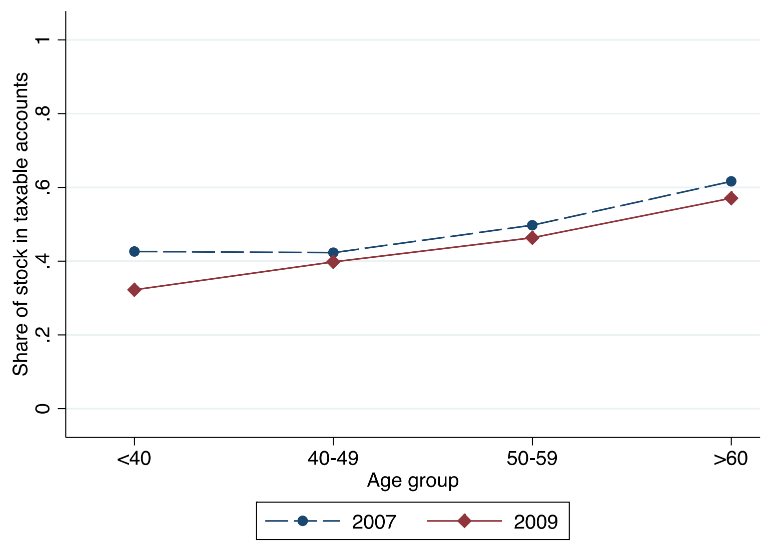
Notes. This graph depicts the coefficients in the regressions documented in Panel A of Table 8.

Figure 8. Share of Wealth in Taxable Accounts by Income and Age

Panel A. By Income Group



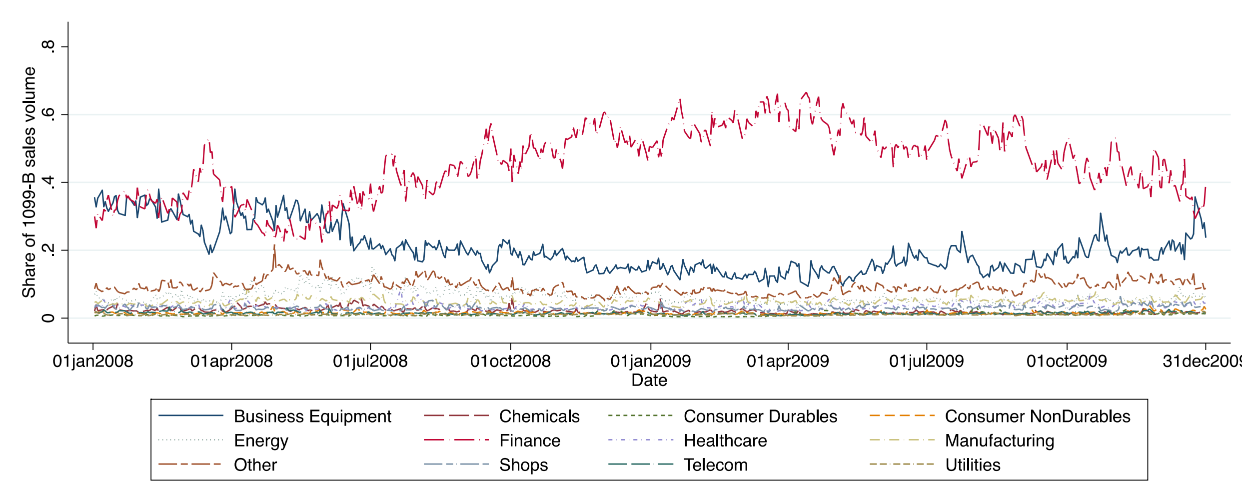
Panel B. By Age Group



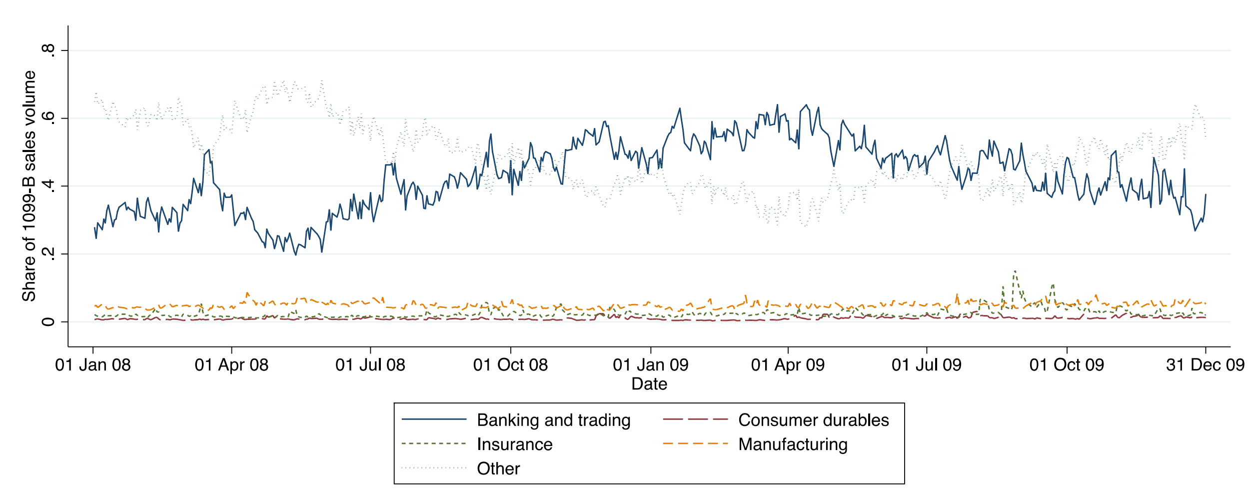
Notes. The data for this analysis come from the 2007-2009 panel of the Survey of Consumer Finance. Income groups and age groups are defined based on income and age reported in the 2007 wave of the survey. We calculate the shares by dividing the total equities (stocks and mutual funds) held in taxable accounts in each group by the total equities held in any account in the same group.

Figure 9. Shares of Individual 1099-B Stock Sales by Sector

Panel A. Shares in Fama-French 12-Industry Classification of Stocks, 2008-2009



Panel B. Shares in Financial Sectors and Selected Non-Finance Sectors, 2008-2009



Panel C. Shares in Financial Sectors and Selected Non-Finance Sectors, 2008-2009, Normalized

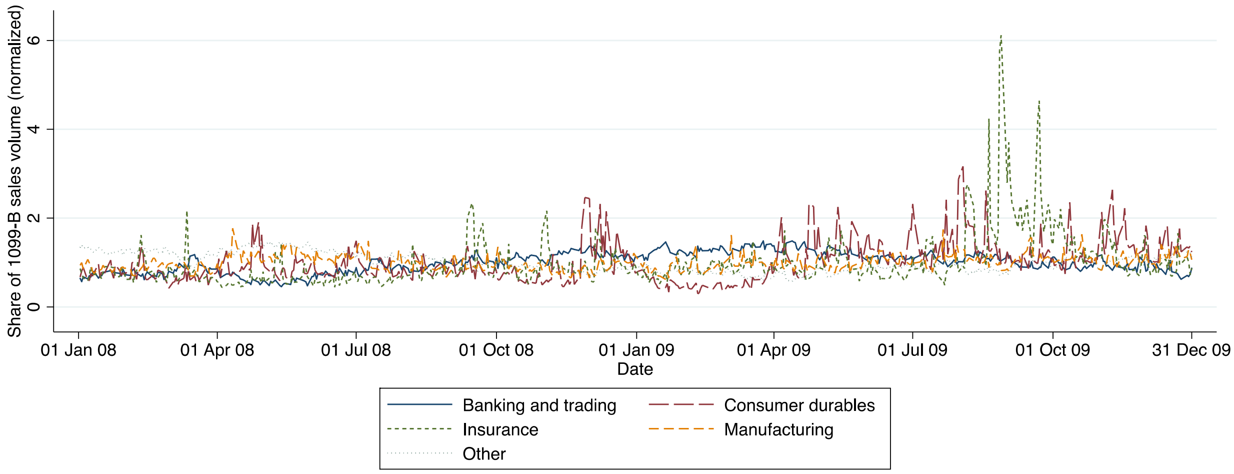


Figure 10. Sales of Stock versus Sales of Mutual Funds

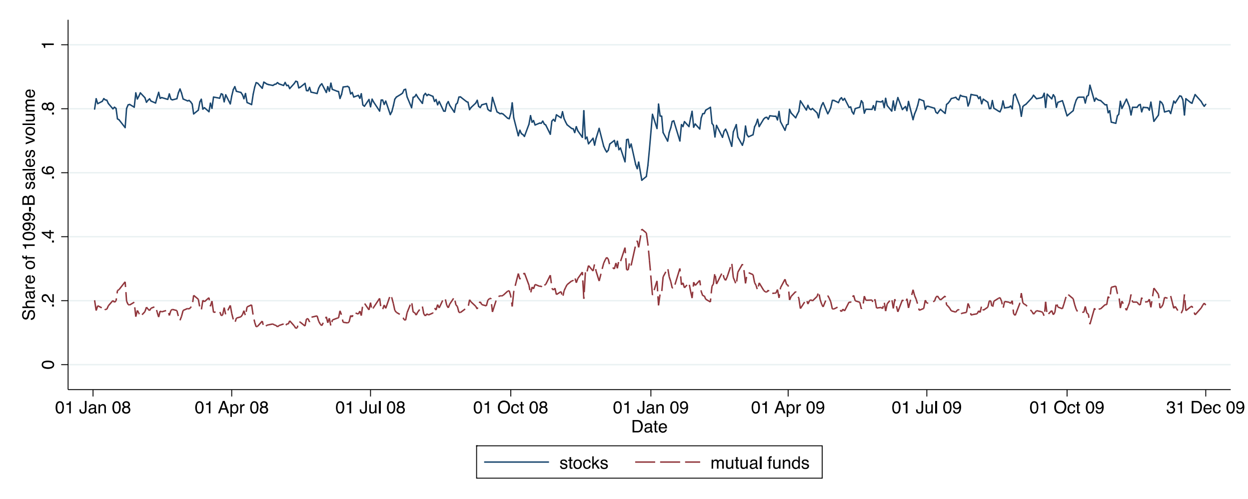


Table 1. Sample Selection

Sample Restriction	Transactions	Dollar Volume
All 1099-Bs in 2008-2009	1,432,614,704	$ 37,180,571,687,408
Non-trading and partial days eliminated	1,427,880,785	$ 37,101,171,401,512
Eliminate negative and trades over $2 billion	1,411,432,043	$ 36,283,816,476,155
Individual Taxpayers	870,141,589	$ 9,574,862,035,508
Taxpayers age over 17	861,220,943	$ 9,547,946,596,246
Stocks and Stock Mutual Funds	273,524,098	$ 6,793,511,903,794

Notes. Full trading days are defined as days with positive CRSP trading volume, less days marked as partial trading days. Age of the taxpayer is determined as of December 31, 2008. Stocks are defined as assets where the first two characters of US_CFI_CODE from the cusip.issue database on WRDS are ES (common equity) or EP (preferred shares).

Table 2. Overall Sales Response to Market Tumult

Dependent variable: log 1099-B sales volume, USD				
	Sample Period			
	2008-2009		September - November 2008	
Number of 1-day lagged differences:	1	10	1	10
	(1)	(2)	(3)	(4)
Change in log VIX	0.346**	4.964***	0.349***	7.183***
	(0.135)	(1.115)	(0.131)	(1.179)
Observations	498	498	62	62
R-squared	0.01	0.16	0.03	0.54

Notes: 1-day lagged difference is the difference between the lagged and twice lagged value (t-1 and t-2). Columns 2 and 4 report sums of 10 1-day lagged differences (for t-1 and t-2, t-2 and t-3,…, t-10 and t-11). Newey-West standard errors (10-day lag) in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3. Heterogeneity by Income in Sales Response to Market Tumult

Dependent variable: log 1099-B sales volume, USD
Reported coefficient: interaction between change in log VIX and average AGI percentile indicator

	Sample Period			
	2008-2009		September - November 2008	
Number of 1-day lagged differences:	1	10	1	10
	(1)	(2)	(3)	(4)
[99.9, 100]	0.327***	3.798***	0.224**	2.640***
	(0.110)	(1.408)	(0.103)	(0.666)
[99, 99.9)	0.255***	2.310***	0.147**	1.500***
	(0.072)	(0.884)	(0.072)	(0.501)
[95,99)	0.146**	1.895**	0.152*	1.427***
	(0.071)	(0.865)	(0.080)	(0.504)
[75, 95)	0.076	0.732	0.100	1.223**
	(0.077)	(0.955)	(0.066)	(0.495)
Group-day observations	2,490	2,490	310	310
R-squared	0.91	0.92	0.96	0.97

Notes: All regressions include day and income-group fixed effects. 1-day lagged difference is the difference between the lagged and twice lagged value (t-1 and t-2). Columns 2 and 4 report sums of 10 1-day lagged differences (for t-1 and t-2, t-2 and t-3,…, t-10 and t-11). Omitted category is taxpayers with average income in [0, 75). Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Heterogeneity by Age in Sales Response to Market Tumult

Dependent variable: log 1099-B sales volume, USD
Reported coefficient: interaction between change in log VIX and age group indicator

	Sample Period			
	2008-2009		September - November 2008	
Number of 1-day lagged differences:	1	10	1	10
	(1)	(2)	(3)	(4)
60+	0.314***	1.839*	0.304***	2.062***
	(0.091)	(1.029)	(0.111)	(0.498)
50-59	0.063	0.243	0.053	0.91***
	(0.059)	(0.640)	(0.089)	(0.278)
40-49	0.010	0.148	-0.037	-0.530
	(0.066)	(0.709)	(0.094)	(0.413)
Group-day observations	1,992	1,992	248	248
R-squared	0.96	0.96	0.98	0.98

Notes: All regressions include day and income-group fixed effects. 1-day lagged difference is the difference between the lagged and twice lagged value (t-1 and t-2). Columns 2 and 4 report sums of 10 1-day lagged differences (for t-1 and t-2, t-2 and t-3,…, t-10 and t-11). Omitted category is taxpayers age 18-39. Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Heterogeneity by Social Security Income Receipt in Sales Response to Market Tumult

Dependent variable: log 1099-B sales volume, USD
Reported coefficient: interaction between change in log VIX and indicator for contemporaneous receipt of social security income

	Sample Period			
	2008-2009		September - November 2008	
Number of 1-day lagged differences:	1	10	1	10
	(1)	(2)	(3)	(4)
Receipt of Social Security Income	0.306***	1.206*	0.349***	1.755***
	(0.074)	(0.696)	(0.110)	(0.581)
Group-day observations	996	996	124	124
R-squared	0.99	0.99	0.99	0.99

Notes: All regressions include day and income-group fixed effects. 1-day lagged difference is the difference between the lagged and twice lagged value (t-1 and t-2). Columns 2 and 4 report sums of 10 1-day lagged differences (for t-1 and t-2, t-2 and t-3,…, t-10 and t-11). The omitted category consists of taxpayers not receiving social security income. Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Heterogeneity by Average Dividend Receipt in Sales Response to Market Tumult

Dependent variable: log 1099-B sales volume, USD
Reported coefficient: interaction between change in log VIX and dummy for average dividend percentile

	Sample Period			
	2008-2009		September - November 2008	
Number of 1-day lagged differences:	1	10	1	10
	(1)	(2)	(3)	(4)
[99, 100]	0.567***	6.076***	0.482***	5.524***
	(0.163)	(1.920)	(0.136)	(0.958)
[95, 99)	0.458***	5.077***	0.421***	4.921***
	(0.137)	(1.547)	(0.106)	(0.821)
[75, 95)	0.222*	3.399**	0.204*	2.758***
	(0.134)	(1.545)	(0.115)	(0.781)
Group-day observations	1,992	1,992	248	248
R-squared	0.91	0.92	0.97	0.98

Notes: All regressions include day and income-group fixed effects. 1-day lagged difference is the difference between the lagged and twice lagged value (t-1 and t-2). Columns 2 and 4 report sums of 10 1-day lagged differences (for t-1 and t-2, t-2 and t-3,…, t-10 and t-11). Dividends refer to the average of qualifying taxable dividends. Omitted category is taxpayers with average dividends in [0, 75). Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7. Heterogeneity by Receipt of Partnership/S-Corp Income in Response to Market Tumult

Dependent variable: log 1099-B sales volume, USD Reported coefficient: interaction between change in log VIX and dummy for receipt of positive partnership or S-corporation income				
	Sample Period			
	2008-2009		September - November 2008	
Number of 1-day lagged differences:	1	10	1	10
	(1)	(2)	(3)	(4)
Receipt of Partnership/S-corp Income	0.170***	1.547***	0.054	0.444
	(0.041)	(0.582)	(0.044)	(0.282)
Group-day observations	996	996	124	124
R-squared	0.97	0.97	0.99	0.99

Notes: All regressions include day and income-group fixed effects. 1-day lagged difference is the difference between the lagged and twice lagged value (t-1 and t-2). Columns 2 and 4 report sums of 10 1-day lagged differences (for t-1 and t-2, t-2 and t-3,…, t-10 and t-11). Omitted category is taxpayers not receiving positive partnership or S-corporation income. Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8. Heterogeneity by Income and Age in Sales Response to Market Tumult

Dependent variable: log 1099-B sales volume, USD Reported coefficient: interaction between change in VIX and two-way group indicator						
A. 2008-2009, 1 day lagged difference of log VIX						
	Age: 80+	70-79	60-69	50-59	40-49	<40
Average AGI:						
[99.9, 100]	0.813***	0.800***	0.559***	0.382***	0.370**	0.270
	(0.285)	(0.158)	(0.153)	(0.139)	(0.146)	(0.203)
[99, 99.9)	0.781***	0.665***	0.505***	0.396***	0.312**	0.441***
	(0.166)	(0.137)	(0.125)	(0.117)	(0.129)	(0.137)
[95, 99)	0.624***	0.608***	0.418***	0.206*	0.223*	0.351**
	(0.145)	(0.126)	(0.120)	(0.118)	(0.130)	(0.151)
[85, 95)	0.580***	0.587***	0.357***	0.201	0.100	0.221*
	(0.136)	(0.127)	(0.115)	(0.130)	(0.136)	(0.133)
[75, 85)	0.537***	0.553***	0.320***	0.227*	0.152	0.109
	(0.141)	(0.125)	(0.123)	(0.132)	(0.142)	(0.150)
[0, 75)	0.615***	0.566***	0.337***	0.215	0.007	(omitted)
	(0.133)	(0.123)	(0.126)	(0.132)	(0.155)	
B. September-November 2008, 1 day lagged difference of log VIX						
Average AGI:						
[99.9, 100]	0.955*	0.570***	0.472***	0.308**	0.214	0.333*
	(0.575)	(0.189)	(0.157)	(0.137)	(0.161)	(0.174)
[99, 99.9)	0.760***	0.513***	0.388***	0.342***	0.202	0.305**
	(0.164)	(0.139)	(0.110)	(0.100)	(0.129)	(0.136)
[95, 99)	0.643***	0.677***	0.405***	0.223**	0.262*	0.335
	(0.153)	(0.120)	(0.102)	(0.109)	(0.158)	(0.212)
[85, 95)	0.629***	0.634***	0.458***	0.216**	0.086	0.256*
	(0.141)	(0.121)	(0.110)	(0.107)	(0.123)	(0.137)
[75, 85)	0.712***	0.678***	0.365***	0.285**	0.145	0.138
	(0.164)	(0.122)	(0.104)	(0.113)	(0.136)	(0.142)
[0, 75)	0.717***	0.669***	0.339***	0.249**	-0.017	(omitted)
	(0.136)	(0.128)	(0.117)	(0.108)	(0.150)	

Notes: Each panel reports the results of a separate regression. The reported coefficients are interactions between a change in VIX and an income-group-by-age fixed effect. All regressions include day and income-group-by-age fixed effects. 1 day lagged difference is the difference between the lagged and twice lagged value (t-1 and t-2). Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Gross and Net Sales in the Barber-Odean Discount Brokerage Data

	Dependent variable:					
	Log gross sales volume, taxable accounts	Net sales volume (% of portfolio value), taxable accounts	Gross sales volume (% of portfolio value), taxable accounts	Net sales volume (% of portfolio value), taxable accounts	Log gross sales volume, non-taxable accounts	Log gross sales volume, taxable accounts, large portfolios
	(1)	(2)	(3)	(4)	(5)	(6)
Contemp. 1 day diff. of log VIX	1.010***		0.526***	0.171***	1.140***	1.087***
	(0.176)		(0.086)	(0.058)	(0.239)	(0.226)
Lagged 1 day diff. of log VIX	0.414***		0.228**	0.116*	0.606**	0.531**
	(0.189)		(0.093)	(0.070)	(0.241)	(0.224)
Contemp. gross sales volume		0.342***				
(% of portfolio value)		(0.029)				
Adj. R^2	2.51%	26.85%	4.11%	1.10%	1.53%	1.93%
Observations	1496	1475	1474	1474	1496	1474

Notes: Large portfolios in the last column are those above the 80th percentile by the total value of all positions at the end of the previous month. Newey-West standard errors (10 day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Gross Sales and Changes in Dividend Income

Dependent Variable: Dividends in t+1 minus Dividends in t-1	t = 2008	t = 2009	t = 2008	t = 2009
	(1)	(2)	(3)	(4)
Gross Sales	-0.0065***	-0.0068***	-0.0049***	-0.043***
	(0.000041)	(0.000051)	(0.000086)	(0.000094)
Gross Sales x AGI percentile [75,95]			-0.0004***	-0.0008***
			(0.00011)	(0.00013)
Gross Sales x AGI percentile [95,99]			-0.0005***	-0.0012***
			(0.00012)	(0.00014)
Gross Sales x AGI percentile [99,99.9]			-0.0006***	-0.0017***
			(0.00013)	(0.00015)
Gross Sales x AGI percentile [99.9,100]			-0.0004***	-0.0017***
			(0.00022)	(0.00027)
AGI group fixed effects	NO	NO	YES	YES
R-square	9.41%	6.48%	11.47%	8.69%
Observations	1,888,174	1,885,874	1,888,174	1,885,874

Notes: For computational reasons, regressions are estimated on a random 10% sample of taxpayers who have positive dividends in year t-1. We winsorize all variables at the 1 and 99th percentile to eliminate the effect of outliers (many of which are obvious data errors) on the estimates. White standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Net Sales in Taxable Accounts and Total Net Sales, 2007-2009

Dependent Variable: Net Purchases (Negative Sales) from 2007 to 2009		
	(1)	(2)
Net Taxable Purchases (or Sales)	0.925***	0.908***
	(0.075)	(0.123)
Net Taxable Purchases x HH income percentile [75,95]		0.146
		(0.139)
Net Taxable Purchases x HH income percentile [95,99]		0.030
		(0.140)
Net Taxable Purchases x HH income percentile [99,100]		0.015
		(0.153)
AGI group fixed effects	NO	YES
R-square	0.772	0.728
Observations	3,857	3,857

Notes: Household (HH) income percentiles are based on the SCF. Heteroskedasticity-robust standard errors, adjusted for multiple imputations in the survey data, are reported in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 12. Which Stocks Were Sold? Heterogeneity by Fama-French 12-Industry Stock Classification

Dependent variable: log 1099-B sales volume by industry, USD
Reported coefficient: interaction between change in log VIX and asset type indicator

	Sample Period			
	2008-2009		September - November 2008	
Number of 1-day lagged differences	1	10	1	10
	(1)	(2)	(3)	(4)
Business Equipment	0.282	6.465***	0.240	0.949
	(0.237)	(2.334)	(0.340)	(2.380)
Chemicals	0.577**	7.203***	0.694	2.525
	(0.277)	(2.371)	(0.453)	(2.457)
Consumer Nondurables	0.329	7.118***	0.553	4.718**
	(0.230)	(1.910)	(0.354)	(2.346)
Energy	0.424*	6.943***	0.092	3.105
	(0.344)	(2.106)	(0.334)	(2.361)
Finance	0.345	7.222***	0.069	0.522
	(0.255)	(2.447)	(0.349)	(2.474)
Healthcare	0.299	3.152	0.486	1.974
	(0.233)	(2.041)	(0.328)	(2.419)
Manufacturing	0.188	3.837**	0.046	2.427
	(0.219)	(1.820)	(0.323)	(2.298)
Other	0.090	4.418**	0.209	0.422
	(0.222)	(1.971)	(0.357)	(2.489)
Shops	0.154	4.786**	0.292	1.047
	(0.227)	(1.856)	(0.342)	(2.428)
Telecommunications	0.293	4.854**	0.295	0.921
	(0.226)	(1.905)	(0.341)	(2.385)
Utilities	0.547**	7.879***	0.608	4.279*
	(0.242)	(2.021)	(0.344)	(2.333)
Sectors	12	12	12	12
Days	505	505	63	63
Sector-Days	6,060	6,060	756	756
R-squared	0.957	0.958	0.981	0.983

Notes: All regressions include day and sector fixed effects. 1-day lagged difference is the difference between the lagged and twice lagged value (t-1 and t-2). Columns 2 and 4 report sums of 10 1-day lagged differences (for t-1 and t-2, t-2 and t-3,…, t-10 and t-11). Sectors are defined using the Fama-French 12-industry classification system. The omitted category is consumer durables. Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 13: Sales of Stock versus Sales of Mutual Funds

Dependent variable: log 1099-B sales volume in either stocks or mutual funds, USD
Reported coefficient: interaction between change in log VIX and asset type indicator

	Sample Period			
	2008-2009		September - November 2008	
Number of 1-day lagged differences	1	10	1	10
	(1)	(2)	(3)	(4)
Stock	-0.374**	-2.275	-0.060	0.391
	(0.159)	(2.137)	(0.425)	(2.852)
Days	505	505	63	63
Asset-type-day observations	1,010	1,010	126	126
R-squared	0.961	0.960	0.814	0.895

Notes: All regressions include day and asset type fixed effects. 1-day lagged difference is the difference between the lagged and twice lagged value (t-1 and t-2). Columns 2 and 4 report sums of 10 1-day lagged differences (for t-1 and t-2, t-2 and t-3,…, t-10 and t-11). The omitted category is mutual funds. Assets are classified as stocks or mutual funds based on the reported CUSIP number. Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 14. Heterogeneity in Sales of Stock versus Sales of Mutual Funds, by Income and Age

	Dependent variable: log 1099-B sales volume of stocks only, USD Reported coefficient: interaction between measure of log VIX and group indicator			
	Asset Type			
	Stocks only		Mutual funds only	
Number of 1-day lagged differences	1	1	1	1
Sample Period	2008-2009	September - November 2008	2008-2009	September - November 2008
	(1)	(2)	(3)	(4)
	Average AGI groups			
AGI pctl [99.9, 100]	0.392***	0.415***	0.067	-0.386***
	(0.122)	(0.113)	(0.114)	(0.148)
AGI pctl [99, 99.9)	0.278***	0.239***	0.126	-0.167
	(0.073)	(0.080)	(0.091)	(0.115)
AGI pctl [95,99)	0.158**	0.185*	0.055	-0.015
	(0.074)	(0.098)	(0.090)	(0.104)
AGI pctl [75, 95)	0.081	0.120*	0.051	0.006
	(0.079)	(0.070)	(0.090)	(0.115)
Group-day observations	2,490	310	2,490	310
R-squared	0.922	0.949	0.906	0.958
	Age groups			
Age 60+	0.281***	0.360***	0.435***	0.126
	(0.086)	(0.115)	(0.131)	(0.131)
Age 50-59	0.034	0.063	0.174*	-0.015
	(0.056)	(0.087)	(0.103)	(0.121)
Age 40-49	-0.006	-0.013	0.049	-0.175
	(0.061)	(0.096)	(0.115)	(0.161)
Group-day observations	1,992	248	1,992	248
R-squared	0.96	0.97	0.931	0.980

Notes: All regressions include day and group fixed effects. 1-day lagged difference is the difference between the lagged and twice lagged value (t-1 and t-2). We omit estimates of 10-day effects for space. Average AGI and age groups are defined exactly as in Tables 3 and 4. The results for AGI and the results for age come from separately estimated regressions. Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Online Appendix – Not for Publication

Aggregate Measures of Sales Volume

To gain a sense of the usefulness and limitations of the data we examine in the main part of the analysis, Figure A2 compares the share of total sales volume reported on matched Form 1099-B's to total sales volume as measured by CRSP.[27] Panel A plots logged trading volume from these two sources over time, and Panel B depicts matched 1099-B sales as a fraction of CRSP sales volume. The total volume coverage rate does not vary substantially with market volatility.[28] This share increases modestly throughout 2009. We also see large increases in the matched 1099-B shares during the very last days of 2008 and 2009. This phenomenon is likely at least partly attributable to the well-known tendency of individual investors to rebalance their portfolio at year-ends, including their tendency to "harvest" capital losses for tax purposes (Hoopes et al. 2015; Poterba and Weisbenner 2001). Opportunities for loss harvesting were especially abundant at the end of 2008 and 2009 because of the crisis. When we later examine heterogeneity in the propensity to sell assets, we use day fixed effects to control for these types of behaviors.

Figure A3 examines the number of transactors and the sales volume per transactor. Panel A plots the total sales volume and the number of individual investors selling stocks (the number of transactors) from our Form 1099-B data. The number of transactors on a given day ranges

[27] The positive relationship between market sales volume and volatility is well documented in the literature; see the survey by Karpoff (1987) for references to classic studies on this topic. In our sample period, a one standard deviation increase in the log VIX difference is associated with a 3.7 percent increase in market sales volume, significant at the one-percent level. Sales volume from matched Form 1099-B's is slightly less strongly associated: a one standard deviation increase in the log VIX difference is associated with a 2.4 percent increase in 1099-B sales volume. Appendix Table A.1 provides summary statistics and Appendix Table A.2 provides details of these regressions.

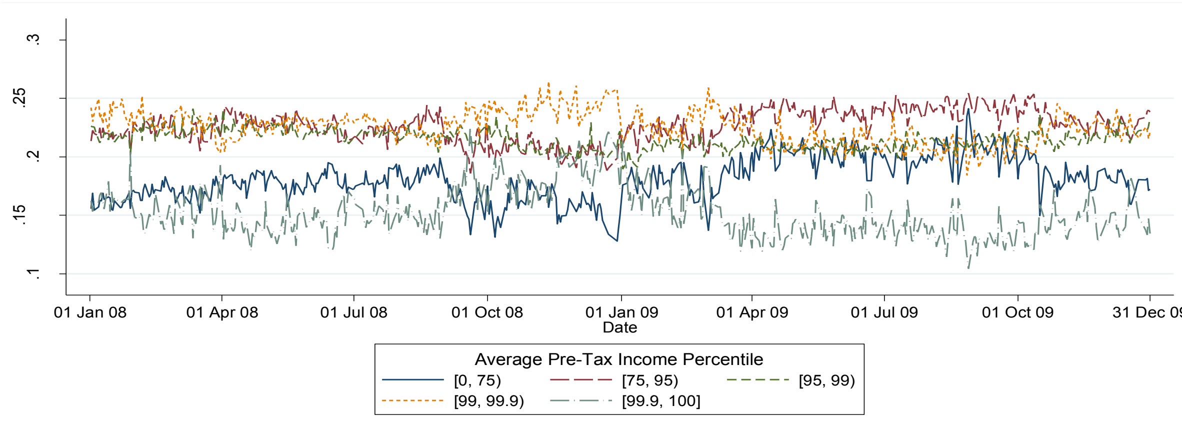
[28] A one standard deviation increase in the lagged difference of log VIX is associated with a 0.08 percentage point decrease in the total coverage rate. See column 3 of Appendix Table A.2.

from 294,000 to 773,000. The two series, total sales volume and number of transactors, exhibit a strong correlation (0.69) during our sample period. Panel B displays the average daily sales volume per transactor, which ranges from $16,000 to $46,000 dollars. The increase in sales volume after an increase in VIX appears to be driven mostly by an increase in sales volume per transactor, rather than by an increase in the number of transactors.[29]

[29] Column (5) of appendix Table A.2 shows that a one standard deviation increase in log VIX (of 0.068) corresponds to a 1.5 percent increase in the average volume per transactor, significant at the one-percent level. In column (4) the same increase in log VIX leads to a 0.9 percent increase in the number of transactors, although this is statistically indistinguishable from zero. Appendix Table A.3 provides the correlations of 1-day lagged log VIX differences, going back ten days; there is a significant negative correlation, of between -0.173 and -0.179, of the one-day-apart differences and, somewhat surprisingly, of from -0.106 to -0.108 of five-day-apart differences.

Figure A.1 Shares of 1099-B Sales Volume by Average Pre-Tax Income Percentiles

Panel A. Daily Shares, 2008-2009



Panel B. Daily Shares, 2008-2009, Normalized by Average Share of Trading Volume from 2008-2009

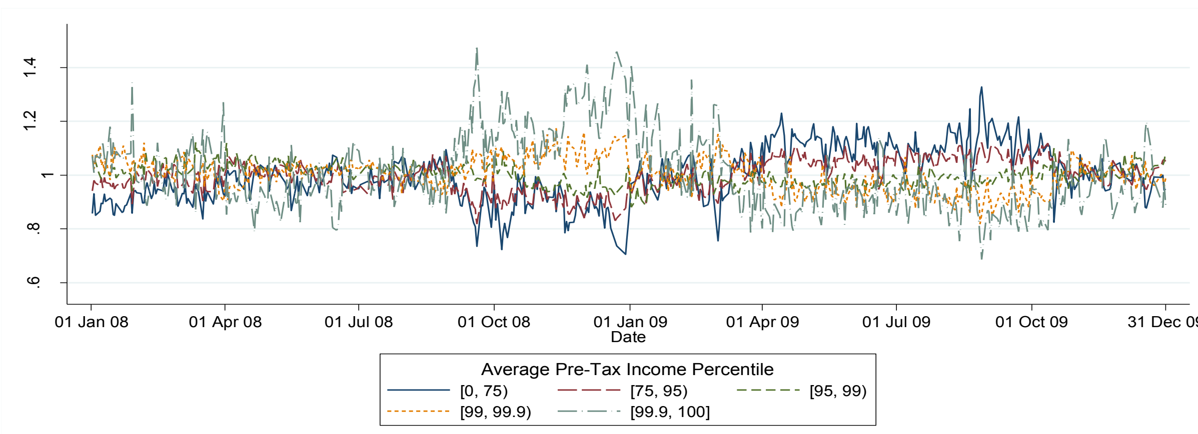
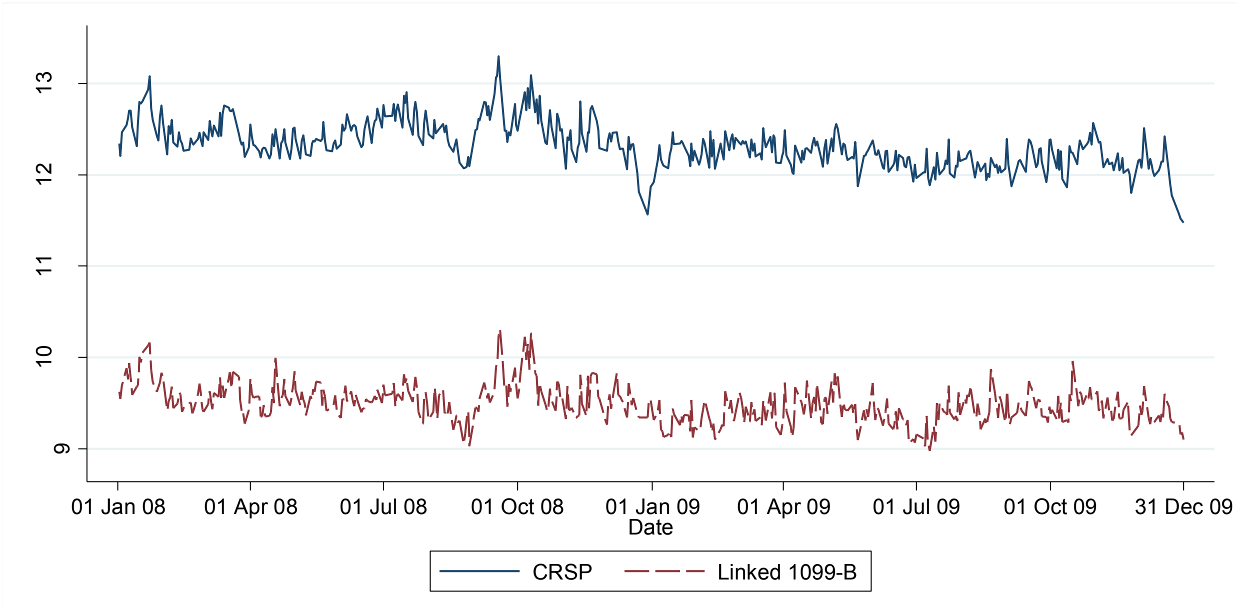
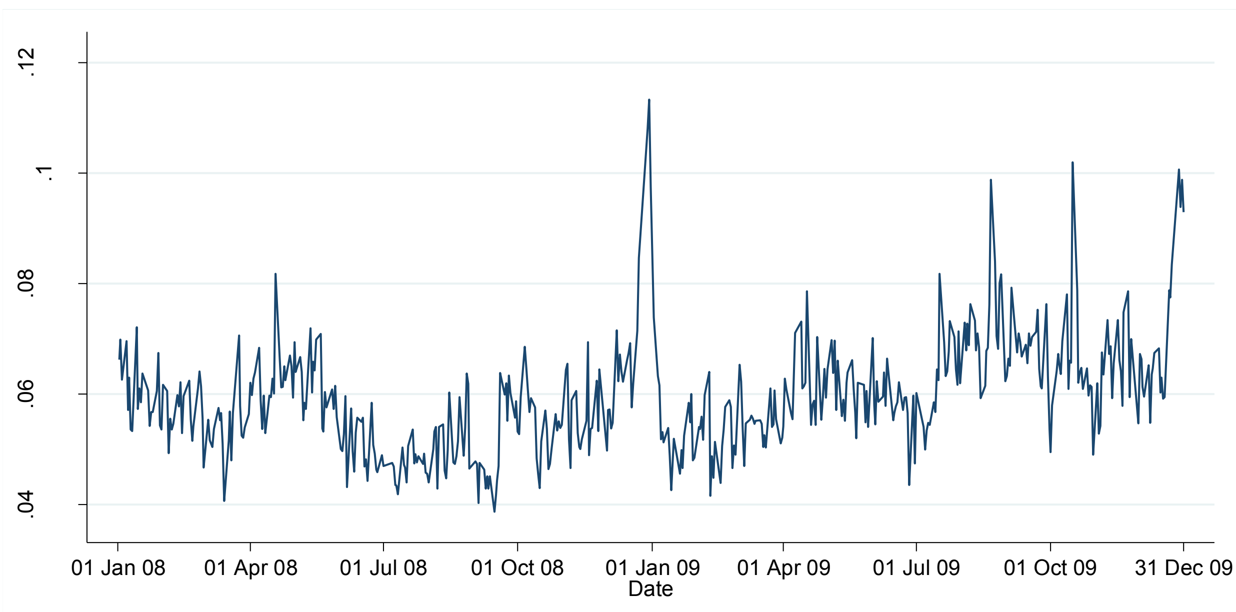


Figure A2. Sales and Trading Volume from Matched 1099-B's and CRSP

Panel A. Log Sales Volume, Matched 1099-B's and Universe of Stocks on CRSP



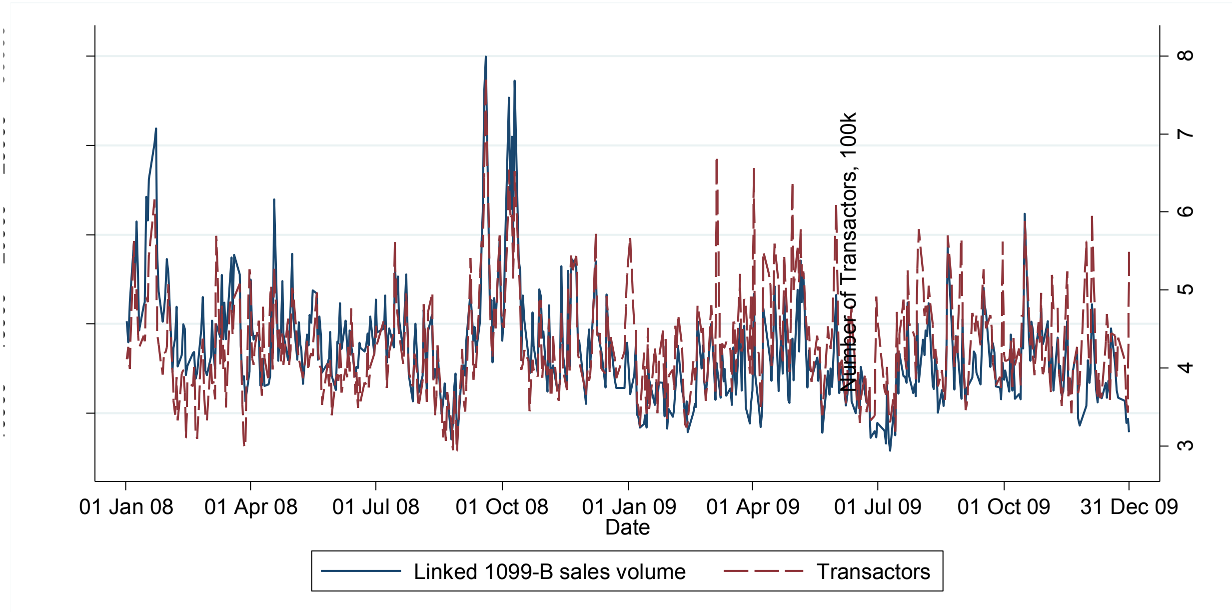
Panel B. Fraction of Total Sales Volume Represented by Matched 1099-B's



Notes: Total sales volume equals ending price per share times number of shares traded for the universe of stocks on CRSP. We divide the trading volume of NASDAQ stocks by two because it is a dealer market (see Anderson and Dyl 2007). The mean and median of the depicted share is 0.059.

Figure A3. Sales Volume and Number of Transactors

Panel A. Sales Volume and Number of Transactors, Matched Form 1099-B's



Panel B. Average Sales Volume per Transactor, Matched Form 1099-B's

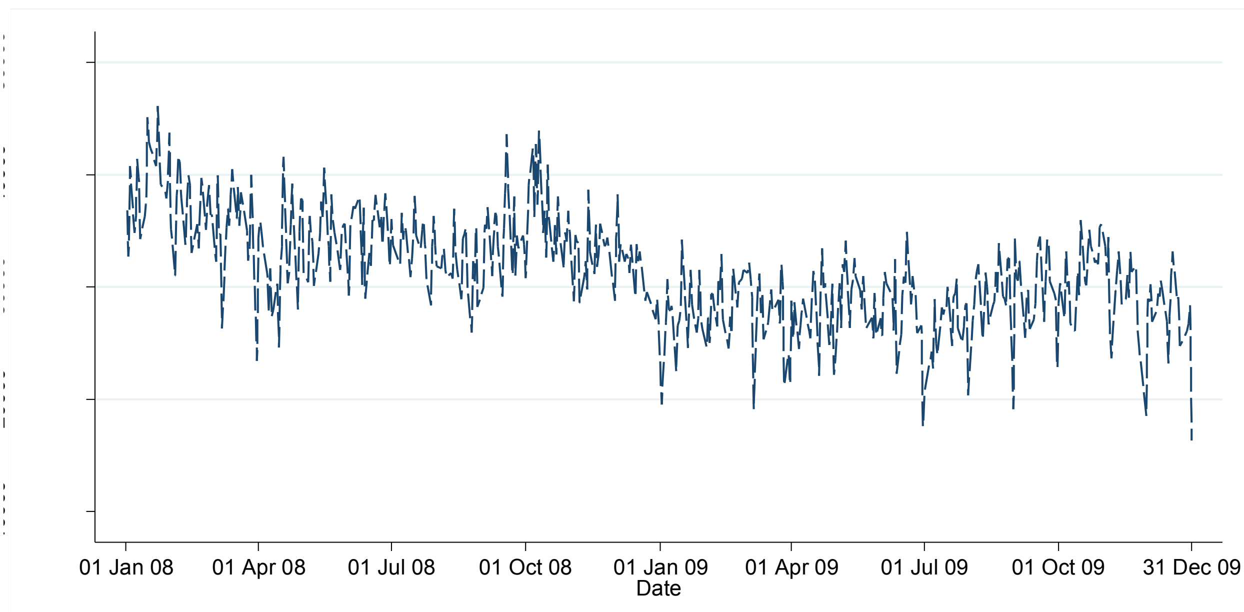


Table A.1. Summary Statistics

	2008-2009				September-November 2008			
	Mean	SD	Minimum	Maximum	Mean	SD	Minimum	Maximum
Log sales volume, CRSP, millions USD	12.330	0.250	11.477	13.300	12.598	0.245	12.069	13.300
Log sales volume, 1099-B, millions USD	9.491	0.206	8.976	10.308	9.661	0.240	9.326	10.308
Log number of transactors, 100k	1.444	0.151	1.078	2.045	1.511	0.181	1.236	2.045
Log average volume per transactor, USD	10.350	0.153	9.700	10.738	10.453	0.098	10.260	10.690
Log ratio, 1099-B to CRSP volume	-2.839	0.163	-3.253	-2.178	-2.937	0.139	-3.253	-2.667
Ratio, 1099-B to CRSP volume	0.059	0.010	0.039	0.113	0.054	0.007	0.039	0.069
Log sales volume, average AGI	21.678	0.285	20.676	22.701	21.854	0.284	21.308	22.701
Log sales volume, average income	21.679	0.282	20.725	22.706	21.853	0.289	21.290	22.706
Log sales volume, age	21.877	0.366	20.852	23.202	22.038	0.407	21.128	23.202
Log sales volume, social security	22.430	0.662	21.215	23.853	22.613	0.656	21.636	23.853
Log sales volume, average dividend receipt	21.840	0.470	20.474	23.243	21.979	0.562	20.749	23.243
Log sales volume, partnership and S-corporation income	22.610	0.216	22.072	23.544	22.776	0.263	22.332	23.544
1 day lagged difference, log VIX	0.000	0.068	-0.283	0.296	0.018	0.114	-0.283	0.296
1 day lagged difference, VIX	0.000	0.029	-0.174	0.165	0.007	0.063	-0.174	0.165
Log VIX	-1.208	0.359	-1.814	-0.212	-0.737	0.389	-1.540	-0.212
VIX	0.321	0.132	0.163	0.809	0.512	0.174	0.214	0.809

Table A.2. Total Sales Volume, Coverage Rates, Number of Transactors, and Market Tumult

	Dependent variable:				
	Log sales volume, CRSP, millions USD	Log sales volume, 1099-B, millions USD	Ratio of 1099-B to CRSP sales volume	Log number of transactors, 100k	Log average volume per transactor, USD
	(1)	(2)	(3)	(4)	(5)
1 day lagged difference of log VIX	0.541***	0.346**	-0.013**	0.132	0.214***
	(0.156)	(0.135)	(0.005)	(0.090)	(0.076)
Observations	498	498	498	498	498
R-squared	0.02	0.01	0.01	0.00	0.01

Notes: The regressand in column 4 is the natural log of the number of transactors divided by 100,000, i.e. log(N/100000). Newey-West standard errors with a maximum of 10-day lag orders of autocorrelation are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.3. Correlation of 1-day Lagged Log VIX Differences

	Correlation between 1-day lagged difference of log VIX									
	1	2	3	4	5	6	7	8	9	10
1	1.000									
2	-0.179*	1.000								
3	-0.070	-0.178*	1.000							
4	0.006	-0.070	-0.178*	1.000						
5	-0.054	0.006	-0.069	-0.178*	1.000					
6	0.108*	-0.055	0.002	-0.069	-0.178*	1.000				
7	-0.060	0.108*	-0.056	0.003	-0.069	-0.176*	1.000			
8	-0.032	-0.060	0.106*	-0.056	0.003	-0.068	-0.176*	1.000		
9	0.002	-0.033	-0.063	0.106*	-0.057	0.008	-0.064	-0.173*	1.000	
10	0.020	0.002	-0.031	-0.063	0.106*	-0.060	0.006	-0.066	-0.173*	1.000

Notes: The first column relates to the difference of days t-1 and t-2, the second column for days t-2 and t-3, and so on. Stars indicate significance at the 5-percent level or better.

Table A.4. Heterogeneity by Income in Sales Response to Market Tumult, Comparison of Log VIX and VIX

Dependent variable: log 1099-B sales volume, USD Reported coefficient: interaction between change in VIX and average AGI percentile indicator				
	Sample Period			
	2008-2009		September - November 2008	
1 day lagged difference of:	Log VIX	VIX	Log VIX	VIX
	(1)	(2)	(3)	(4)
[99.9, 100]	0.327***	0.707**	0.224**	0.509***
	(0.110)	(0.287)	(0.103)	(0.144)
[99, 99.9)	0.255***	0.536***	0.147**	0.328***
	(0.072)	(0.187)	(0.072)	(0.108)
[95,99)	0.146**	0.353*	0.152*	0.293**
	(0.071)	(0.182)	(0.080)	(0.128)
[75, 95)	0.076	0.201	0.100	0.199*
	(0.077)	(0.200)	(0.066)	(0.102)
Group-day observations	2,490	2,490	310	310
R-squared	0.91	0.91	0.96	0.96

Notes: All regressions include day and income-group fixed effects. The 1-day lagged difference is the difference between the lagged and twice lagged value (t-1 and t-2). Omitted category is taxpayers with an average income in [0, 75). Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.5. Heterogeneity by Income in Sales Response to Market Tumult, Comparison of 1 day lagged difference in Log VIX with Negative Market Return

	Dependent variable: log 1099-B sales volume, USD					
	Sample Period					
	2008-2009			September - November 2008		
	(1)	(2)	(3)	(4)	(5)	(6)
1 day lagged difference of log VIX (normalized)						
[99.9, 100]	0.022***		-0.023	0.015**		-0.008
	(0.008)		(0.014)	(0.007)		(0.014)
[99, 99.9)	0.017***		-0.009	0.010**		-0.001
	(0.005)		(0.010)	(0.005)		(0.012)
[95,99)	0.010**		-0.013	0.010*		-0.001
	(0.005)		(0.009)	(0.005)		(0.011)
[75, 95)	0.005		-0.006	0.007		-0.004
	(0.005)		(0.010)	(0.005)		(0.011)
Negative 1 day lagged market return (normalized)						
[99.9, 100]		0.038***	0.056***		0.017***	0.023*
		(0.008)	(0.016)		(0.006)	(0.012)
[99, 99.9)		0.026***	0.033***		0.010**	0.011
		(0.006)	(0.011)		(0.004)	(0.010)
[95,99)		0.018***	0.029***		0.010**	0.011
		(0.005)	(0.010)		(0.005)	(0.009)
[75, 95)		0.009	0.014		0.007*	0.010
		(0.006)	(0.012)		(0.004)	(0.009)
Group-day observations	2,490	2,490	2,490	310	310	310
R-squared	0.91	0.92	0.92	0.96	0.96	0.96

Notes: Both the 1-day lagged difference of log VIX and the negative 1-day lagged market return are normalized to have mean zero and standard deviation one over 2008-2009. All regressions include day and income-group fixed effects. Omitted category is taxpayers with average AGI in [0, 75). Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.6. Lag Structure of Heterogeneity by Income in Sales Response to Market Tumult, 2008-2009

Dependent variable: log 1099-B sales volume, USD Reported coefficient: interaction between lagged difference of log VIX and average AGI percentile indicator					
		[75, 95)	[95,99)	[99, 99.9)	[99.9, 100]
Leads	(t+5) - (t+4)	0.002	0.036	0.009	0.114
		(0.091)	(0.080)	(0.084)	(0.131)
	(t+4) - (t+3)	0.024	0.027	-0.013	0.109
		(0.102)	(0.090)	(0.093)	(0.151)
	(t+3) - (t+2)	0.002	0.006	-0.050	-0.046
		(0.109)	(0.096)	(0.101)	(0.157)
	(t+2) - (t+1)	-0.002	0.042	0.007	0.029
		(0.115)	(0.104)	(0.110)	(0.168)
	(t+1) - (t)	-0.001	0.017	-0.002	-0.047
		(0.120)	(0.109)	(0.114)	(0.173)
Lags	(t) - (t-1)	0.061	0.249**	0.395***	0.422**
		(0.115)	(0.106)	(0.111)	(0.164)
	(t-1) - (t-2)	0.098	0.222**	0.370***	0.448***
		(0.118)	(0.107)	(0.111)	(0.166)
	(t-2) - (t-3)	0.113	0.220*	0.289**	0.396**
		(0.129)	(0.114)	(0.118)	(0.190)
	(t-3) - (t-4)	0.057	0.192*	0.223*	0.329*
		(0.130)	(0.117)	(0.122)	(0.188)
	(t-4) - (t-5)	0.079	0.207*	0.257**	0.419**
		(0.136)	(0.122)	(0.125)	(0.205)
	(t-5) - (t-6)	0.060	0.169	0.255**	0.390**
		(0.124)	(0.112)	(0.117)	(0.178)
	(t-6) - (t-7)	0.072	0.150	0.174*	0.319*
		(0.111)	(0.103)	(0.104)	(0.169)
	(t-7) - (t-8)	0.030	0.138	0.153	0.304**
		(0.101)	(0.092)	(0.093)	(0.153)
	(t-8) - (t-9)	0.074	0.182*	0.196**	0.405***
		(0.103)	(0.094)	(0.097)	(0.156)
	(t-9) - (t-10)	0.054	0.170*	0.162*	0.288*
		(0.107)	(0.096)	(0.098)	(0.157)
	(t-10) - (t-11)	0.084	0.194**	0.197**	0.337**
		(0.093)	(0.086)	(0.089)	(0.136)
	(t-11) - (t-12)	0.071	0.213**	0.236**	0.376***
		(0.101)	(0.093)	(0.096)	(0.142)
	(t-12) - (t-13)	0.024	0.117	0.139	0.300**
		(0.092)	(0.086)	(0.089)	(0.132)

(t-13) - (t-14)	0.025	0.144	0.167*	0.362**
	(0.096)	(0.088)	(0.091)	(0.141)
(t-14) - (t-15)	0.047	0.165*	0.178*	0.391***
	(0.100)	(0.092)	(0.094)	(0.144)
(t-15) - (t-16)	0.041	0.179**	0.177**	0.371***
	(0.091)	(0.084)	(0.084)	(0.135)
(t-16) - (t-17)	0.055	0.186**	0.148*	0.287**
	(0.092)	(0.083)	(0.086)	(0.133)
(t-17) - (t-18)	0.043	0.148*	0.152*	0.255**
	(0.092)	(0.084)	(0.087)	(0.130)
(t-18) - (t-19)	0.052	0.102	0.081	0.171
	(0.097)	(0.087)	(0.088)	(0.144)
(t-19) - (t-20)	0.051	0.172*	0.155*	0.256*
	(0.101)	(0.089)	(0.091)	(0.149)
(t-20) - (t-21)	0.051	0.150*	0.153*	0.361***
	(0.095)	(0.087)	(0.091)	(0.131)
(t-21) - (t-22)	0.051	0.165**	0.206**	0.379***
	(0.091)	(0.082)	(0.082)	(0.131)
(t-22) - (t-23)	0.004	0.083	0.130	0.197
	(0.097)	(0.089)	(0.089)	(0.141)
(t-23) - (t-24)	0.011	0.140	0.190*	0.285*
	(0.107)	(0.097)	(0.100)	(0.150)
(t-24) - (t-25)	0.063	0.164*	0.218**	0.235
	(0.104)	(0.097)	(0.100)	(0.148)
(t-25) - (t-26)	0.061	0.166*	0.211**	0.302**
	(0.101)	(0.091)	(0.093)	(0.148)
(t-26) - (t-27)	0.033	0.136	0.177*	0.191
	(0.106)	(0.097)	(0.099)	(0.154)
(t-27) - (t-28)	0.051	0.152	0.163	0.204
	(0.107)	(0.099)	(0.103)	(0.153)
(t-28) - (t-29)	0.088	0.178*	0.174*	0.258*
	(0.103)	(0.095)	(0.097)	(0.148)
(t-29) - (t-30)	0.026	0.118	0.161*	0.218
	(0.092)	(0.085)	(0.085)	(0.138)
(t-30) - (t-31)	0.036	0.098	0.097	0.172
	(0.089)	(0.082)	(0.085)	(0.128)

Notes: Results come from a single regression, estimated on data from 2008-2009. The regression includes day and income-group fixed effects. The omitted category is taxpayers with average AGI in [0, 75). Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.7. Heterogeneity by Gender in Sales Response to Market Tumult

Dependent variable: log 1099-B sales volume, USD
Reported coefficient: interaction between change in log VIX and male gender dummy

	Sample Period			
	2008-2009		September - November 2008	
Number of 1-day lagged differences:	1	10	1	10
	(1)	(2)	(3)	(4)
	-0.010	-0.411	-0.060	-1.036**
	(0.063)	(0.742)	(0.064)	(0.465)
Group-day observations	996	996	124	124
R-squared	1.00	1.00	1.00	1.00

Notes: All regressions include day and gender fixed effects. Omitted category is female taxpayers. See note to Table 3 for more details. Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.8. Heterogeneity by Marital Status in Sales Response to Market Tumult

Dependent variable: log 1099-B sales volume, USD
Reported coefficient: interaction between change in log VIX and dummy for being married

	Sample Period			
	2008-2009		September - November 2008	
Number of 1-day lagged differences:	1	10	1	10
	(1)	(2)	(3)	(4)
Married	-0.016	0.235	0.005	0.105
	(0.024)	(0.149)	(0.040)	(0.258)
Group-day observations	996	996	124	124
R-squared	1.00	1.00	1.00	1.00

Notes: All regressions include day and marital status fixed effects. Omitted category is unmarried taxpayers. See note to Table 3 for more details. Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.9. Heterogeneity by Mortgage Interest Deduction Receipt in Sales Response to Market Tumult

Dependent variable: log 1099-B sales volume, USD
Reported coefficient: interaction between change in log VIX and dummy for claiming mortgage interest deduction in given year

	Sample Period			
	2008-2009		September - November 2008	
1 day lagged difference of:	Log VIX	VIX	Log VIX	VIX
	(1)	(2)	(3)	(4)
	-0.086**	0.008	-0.084	-0.289
	(0.036)	(0.384)	(0.072)	(0.340)
Group-day observations	996	996	124	124
R-squared	0.98	0.98	0.99	0.99

Notes: All regressions include day and mortgage interest receipt fixed effects. Omitted category is taxpayers not claiming a mortgage interest deduction. See note to Table 3 for more details. Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.10. Heterogeneity by Amount of Mortgage Interest Deduction Receipt in Sales Response to Market Tumult

Dependent variable: log 1099-B sales volume, USD
Reported coefficient: interaction between change in log VIX and dummy for decile of mortgage interest deduction amount in given year

	Sample Period			
	2008-2009		September - November 2008	
Number of 1-day lagged differences:	1	10	1	10
	(1)	(2)	(3)	(4)
[80, 100]	0.009	1.382**	-0.105**	0.107
	(0.053)	(0.632)	(0.052)	(0.306)
[50, 80)	0.011	0.479	0.022	1.004***
	(0.046)	(0.521)	(0.070)	(0.261)
[30, 50)	0.165***	1.740**	0.039	1.334***
	(0.060)	(0.754)	(0.088)	(0.332)
Group-day observations	1,992	1,992	248	248
R-squared	0.94	0.94	0.98	0.98

Notes: All regressions include day and mortgage interest receipt group fixed effects. The omitted category consists of taxpayers with a mortgage interest deduction amount in [0, 30). See note to Table 3 for more details. Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.11. Heterogeneity by Region in Sales Response to Market Tumult

Dependent variable: log 1099-B sales volume, USD
Reported coefficient: interaction between change in log VIX and dummy for Census region

	Sample Period			
	2008-2009		September - November 2008	
Number of 1-day lagged differences:	1	10	1	10
	(1)	(2)	(3)	(4)
Midwest	-0.025	-1.010**	-0.091**	-0.583
	(0.050)	(0.416)	(0.038)	(0.443)
South	0.022	-0.297	-0.094**	-0.569
	(0.042)	(0.292)	(0.045)	(0.379)
West	-0.008	-0.553*	-0.100**	-0.318
	(0.042)	(0.322)	(0.043)	(0.371)
Group-day observations	1,992	1,992	248	248
R-squared	0.99	0.99	0.99	0.99

Notes: All regressions include day and region fixed effects. Omitted category is the Northeast region. See note to Table 3 for more details. Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.12. Heterogeneity by State in Sales Response to Market Tumult

	Dependent variable: log 1099-B sales volume, USD Reported coefficient: interaction between change in log VIX and dummy for state			
	Sample Period			
	2008-2009		September - November 2008	
Number of 1-day lagged differences:	1	10	1	10
	(1)	(2)	(3)	(4)
AL	0.074	0.011	-0.057	0.127
	(0.100)	(0.741)	(0.071)	(1.055)
AK	0.119	-1.032	-0.081	-0.420
	(0.117)	(0.885)	(0.204)	(1.072)
AZ	-0.037	-0.330	-0.060	0.872
	(0.069)	(0.885)	(0.084)	(0.598)
AR	-0.154	-0.790	-0.214	0.070
	(0.102)	(0.765)	(0.138)	(0.801)
CO	-0.024	-0.108	-0.020	0.606*
	(0.062)	(0.675)	(0.062)	(0.347)
CT	0.034	0.808	-0.050	1.380***
	(0.062)	(0.681)	(0.071)	(0.447)
DE	-0.060	-0.701	0.235	0.932
	(0.111)	(0.848)	(0.225)	(0.886)
DC	0.123	1.945*	-0.061	0.646
	(0.148)	(1.135)	(0.190)	(1.244)
FL	0.127**	1.045*	-0.030	-0.490
	(0.057)	(0.611)	(0.078)	(0.354)
GA	-0.084	0.289	-0.158**	0.285
	(0.063)	(0.685)	(0.076)	(0.737)
HI	0.058	0.185	-0.271**	0.548
	(0.113)	(0.821)	(0.129)	(1.029)
ID	-0.002	-1.273	0.059	-1.005
	(0.114)	(1.117)	(0.158)	(1.287)
IL	0.045	-0.047	-0.007	-0.256
	(0.059)	(0.576)	(0.063)	(0.388)
IN	0.063	0.248	-0.043	-0.349
	(0.080)	(0.675)	(0.124)	(0.547)
IA	-0.114	-1.179	-0.029	2.299*
	(0.089)	(0.856)	(0.130)	(1.241)
KS	-0.133	-1.081	-0.059	0.700*
	(0.090)	(0.748)	(0.116)	(0.41)
KY	-0.025	-0.539	0.109	2.709***
	(0.068)	(0.62)	(0.094)	(0.742)

LA	-0.046	-1.528*	-0.103	1.469
	(0.084)	(0.859)	(0.105)	(1.371)
ME	0.193**	-1.142	0.276***	2.628***
	(0.095)	(0.849)	(0.106)	(0.971)
MD	-0.079	-0.389	-0.001	1.870***
	(0.061)	(0.644)	(0.062)	(0.46)
MA	-0.023	0.386	-0.012	-0.022
	(0.067)	(0.6)	(0.067)	(0.337)
MI	-0.012	-0.222	-0.010	0.118
	(0.065)	(0.587)	(0.095)	(0.457)
MN	-0.126**	-0.589	-0.108*	2.304***
	(0.063)	(0.628)	(0.062)	(0.466)
MS	0.130	1.943**	-0.147	1.040
	(0.117)	(0.971)	(0.154)	(0.915)
MO	0.012	-0.377	-0.028	0.937**
	(0.078)	(0.885)	(0.090)	(0.467)
MT	-0.004	0.679	0.000	1.843**
	(0.107)	(0.958)	(0.154)	(0.913)
NE	-0.077	-1.607**	-0.059	-1.321**
	(0.099)	(0.728)	(0.128)	(0.562)
NV	0.054	3.475***	-0.135	8.156***
	(0.153)	(1.325)	(0.260)	(1.198)
NH	-0.003	-0.894	0.063	1.153
	(0.101)	(1.011)	(0.099)	(1.405)
NJ	-0.017	0.593	-0.020	0.135
	(0.077)	(0.94)	(0.071)	(0.423)
NM	0.227*	1.320	0.189	1.077
	(0.122)	(0.932)	(0.243)	(1.287)
NY	0.026	1.035	0.116*	1.205
	(0.080)	(0.77)	(0.067)	(0.776)
NC	-0.006	-0.186	-0.062	0.637
	(0.059)	(0.577)	(0.056)	(0.415)
ND	-0.342**	-0.115	-0.151	0.006
	(0.172)	(0.996)	(0.250)	(1.42)
OH	-0.039	-0.710	-0.073	0.930
	(0.060)	(0.593)	(0.070)	(0.682)
OK	0.085	0.289	0.008	1.903
	(0.120)	(1.143)	(0.145)	(2.954)
OR	-0.017	-0.624	0.024	2.080***
	(0.067)	(0.717)	(0.060)	(0.707)
PA	-0.007	-0.364	0.092	2.091***
	(0.053)	(0.532)	(0.063)	(0.401)
RI	0.114	0.762	-0.078	3.222***

	(0.106)	(1.013)	(0.148)	(0.704)
SC	0.033	0.090	0.051	0.802*
	(0.067)	(0.575)	(0.057)	(0.485)
SD	-0.021	-0.149	0.148	3.983***
	(0.153)	(0.932)	(0.267)	(1.107)
TN	0.048	0.682	0.085	2.037*
	(0.077)	(0.713)	(0.098)	(1.132)
TX	-0.018	-0.134	-0.067	0.782
	(0.068)	(0.685)	(0.107)	(0.709)
UT	-0.101	-0.827	-0.224	-1.565*
	(0.095)	(0.789)	(0.143)	(0.817)
VT	0.087	1.587	0.324	7.252***
	(0.141)	(1.406)	(0.249)	(2.252)
VA	0.005	0.412	-0.058	0.203
	(0.062)	(0.664)	(0.065)	(0.577)
WA	0.034	-0.657	-0.132	1.188*
	(0.076)	(0.7)	(0.189)	(0.63)
WV	-0.249	-1.579	0.074	3.772***
	(0.167)	(1.022)	(0.329)	(1.419)
WI	-0.102	-0.810	-0.092	0.810
	(0.066)	(0.682)	(0.065)	(0.526)
WY	-0.289	-1.788	-0.793***	-0.198
	(0.191)	(1.572)	(0.291)	(1.437)
p-value, joint significance test	0.0742	0.000	0.0759	0.000
Group-year observations	25,398	25,398	3,162	3162.000
R-squared	0.99	0.99	0.99	0.99

Notes: All regressions include day and state fixed effects. The omitted category is California. See note to Table 3 for more details. Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.13. Heterogeneity by 2007 House Price Growth in Sales Response to Market Tumult

Dependent variable: log 1099-B sales volume, USD
Reported coefficient: interaction between change in log VIX and dummy for percentile of 2007 ZIP code level house price growth

	Sample Period			
	2008-2009		September - November 2008	
Number of 1-day lagged differences:	1	10	1	10
	(1)	(2)	(3)	(4)
[80, 100]	-0.053	-0.451	0.044	1.693***
	(0.044)	(0.410)	(0.072)	(0.285)
[60, 80)	-0.049	-0.381	0.098**	1.267***
	(0.037)	(0.294)	(0.049)	(0.251)
[40, 60)	-0.097***	-0.330	-0.015	1.266***
	(0.034)	(0.251)	(0.046)	(0.230)
[20, 40)	-0.043	0.119	0.037	1.791***
	(0.043)	(0.386)	(0.070)	(0.249)
Group-day observations	2,490	2,490	310	310
R-squared	0.97	0.97	0.98	0.98

Notes: All regressions include day and group fixed effects. Omitted category is [0, 20). See note to Table 3 for more details. Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.14. Heterogeneity by Prior Trading Frequency

Dependent variable: log 1099-B sales volume, USD
Reported coefficient: interaction between measure of log VIX and lagged trading frequency percentile indicator

	Sample Period			
	2008-2009		September - November 2008	
Number of 1-day lagged differences:	1	10	1	10
	(1)	(2)	(3)	(4)
[75, 100]	0.356	2.073	0.267*	1.706
	(0.217)	(2.872)	(0.155)	(1.229)
[50, 75)	0.335**	1.946	0.392***	3.284***
	(0.143)	(1.871)	(0.100)	(0.647)
[25, 50)	0.147	1.348	0.238*	2.906***
	(0.164)	(2.094)	(0.125)	(0.870)
Group-day observations	1,992	1,992	248	248
R-squared	0.955	0.955	0.987	0.989

Notes: Trading frequency is measured by the number of 1099-B transactions by a given individual in the previous year. All regressions include day and group fixed effects. Omitted category is [0,25). See note to Table 3 for more details. Newey-West standard errors (10-day lag) in parentheses. *** p<0.01, ** p<0.05, * p<0.1