The Retail Put

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Abstract

Retail investors are traditionally viewed as uninformed noise traders with little effect on aggregate prices. This paper shows that the substantial growth in retail participation has changed that view. Using high-frequency retail flow, I show that retail investors systematically buy following market declines. Their demand is highly asymmetric, increasing sharply after losses but little following comparable gains, resembling the payoff of a put option. To identify the causal effect of retail demand on prices, I exploit a regression discontinuity at the zero threshold in displayed returns. Crossing this threshold generates a discrete increase in retail buying while other market conditions vary smoothly. Instrumenting retail flow with this discontinuity, I estimate that a one-percentage-point increase in net retail purchases raises subsequent 30-minute market returns by 40 basis points, with no sign of reversal. The results suggest that households play a larger role in aggregate risk-bearing than is previously recognized, absorbing selling pressure and reducing short-term volatility.

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1 Introduction

> *"The claim that financial markets are efficient is backed by an implicit argument that misinformed 'noise traders' can have little influence on asset prices in equilibrium."*
>
> — De Long et al. (1990)

Who moves aggregate markets? For decades, the conventional view has been that aggregate market prices are determined primarily by institutional investors, while individual investors were too small, too dispersed, and too uninformed to matter for aggregate prices. De Long et al. (1990) challenged this view theoretically by showing that sufficiently large and correlated noise trader demand can influence equilibrium asset prices. Whether retail investors satisfy these conditions, however, has remained largely an empirical question. This paper revisits that question in today's financial markets.

Retail participation has increased steadily over the past two decades, with a record 58% of U.S. households now directly holding equities (Federal Reserve, Survey of Consumer Finances). Retail trading likewise accounts for roughly 17% to 20% of total U.S. equity market trading volume (JP Morgan), accounting for $5.4 trillion in trading activity across stocks and exchange-traded funds in 2025 (Fortune). Meanwhile, the growth of online brokerages and social media has made retail investors increasingly informed and coordinated. Together, these developments raise a natural question: do retail investors now have an impact on aggregate market dynamics? This paper shows that they do.

I begin by documenting three empirical facts about retail investors in aggregate equity markets. First, retail participation has increased steadily over the past decade, both in dollar trading volume and trading share. Second, retail investors behave systematically differently from the rest of the market. Rather than trading with market movements, they trade against them, increasing their purchases following market declines. Finally, periods of elevated retail buying are followed by market recoveries. Together, these new trends suggest that retail investors have become a quantitatively important and distinct source of aggregate demand with the potential to influence market-wide prices.

To characterize the timing of this trading behavior, I turn to high-frequency retail order flow in SPY, the largest and most actively traded ETF tracking the U.S. equity market. I document that retail investors respond rapidly to market declines. Net retail purchases increase immediately after prices fall, peak within the subsequent 30 to 60 minutes, and continue to accumulate over the next several hours. Importantly, these purchases are not subsequently reversed, indicating that retail investors retain rather than quickly unwind the positions acquired during market downturns. The speed and persistence of retail demand suggest that retail investors generate sustained buying pressure following negative

market shocks.

More importantly, retail trading exhibits a pronounced asymmetry. Retail investors buy aggressively following market losses but exhibit little corresponding tendency to reduce purchases following comparable market gains. Aggregate retail demand therefore resembles the payoff of a put option: a "retail put." A similar asymmetry appears in subsequent market returns. Market declines are followed by significantly higher cumulative future returns, whereas comparable market advances generate little subsequent price movement. The parallel asymmetry in retail demand and future returns is consistent with the hypothesis that stronger retail buying following market declines has short-run upward price pressure.

The reduced-form asymmetry, however, does not by itself identify the causal effect of retail demand on prices. Alternative mechanisms can generate the same nonlinear relation between current and future returns. One possibility is temporary fire sales. During market downturns, financially constrained investors may be forced to liquidate their positions, temporarily depressing prices below fundamentals. As selling pressure subsides, prices naturally recover, producing higher subsequent returns. More generally, any mechanism that generates stronger return reversals following market declines than market advances would produce the same reduced-form evidence. Therefore, rather than relying on the nonlinearity, I exploit a discontinuity in how retail investors *perceive* market returns.

When retail investors make trading decisions, prices and returns displayed by their brokerage platform are among the most frequently consulted pieces of information (Laarits and Wurgler, 2025). Brokerage platforms display returns relative to the previous day's close, so an economically negligible change in the underlying index around zero mechanically changes the displayed return from a gain to a loss, often accompanied by a change in color from green to red. Although this threshold is economically arbitrary, individuals often process continuous information categorically rather than continuously (Graeber et al., 2025). As a result, observations immediately on either side of the zero threshold in displayed return face nearly identical underlying market conditions but induce a discrete change in retail demand. I exploit this discontinuity in a regression discontinuity design to identify the causal effect of retail trading on subsequent aggregate market returns.

Consistent with this mechanism, crossing the zero displayed-return threshold generates a discrete increase of approximately 0.026% of lagged shares outstanding in subsequent retail flow. This discontinuity remains after controlling for underlying return, lagged retail flow, intraday trading patterns, and market open and close, yielding first-stage F-statistics above 400 across all specifications.

Using this plausibly exogenous variation, I estimate that a one-percentage-point in-

crease in retail order flow raises subsequent 30-minute returns by 40 basis points. The estimated price impact is remarkably similar in both the SPY ETF and the E-mini S&P 500 futures market, indicating that retail demand affects aggregate market prices rather than merely ETF-specific prices. Equivalently, a one-standard-deviation increase in retail order flow increases subsequent returns by 0.03 basis points. These estimates imply that retail investors do not merely respond to market downturns. They actively absorb selling pressure and support aggregate price.

The causal interpretation relies on the exclusion condition that crossing the zero displayed return threshold affects subsequent returns only through its effect on retail demand. I evaluate several competing explanations, including changes in aggregate market conditions, trading by other market participants, ETF-specific market microstructure, and temporary fire-sale dynamics. None exhibits the discontinuous behavior required to explain the estimated price effects.

I next examine the robustness of the main results to alternative sample constructions and estimation choices. First, I show that the findings extend beyond SPY to two additional broad-market ETFs, QQQ (Nasdaq 100) and IWM (Russell 2000). The estimated price impacts are economically and statistically similar across all three ETFs, indicating that the results are not unique to a single market index. Second, I demonstrate that the estimates are stable across a range of bandwidths around the zero displayed-return threshold. Third, I estimate the model separately over the 2011-2015, 2016-2020, and 2021-2025 subsamples. The estimated price impact remains positive and statistically significant throughout the sample period and becomes somewhat larger in the later years, consistent with the growing participation of retail investors in U.S. equity markets. Taken together, these results indicate that the estimated price impact of retail demand is robust to different broad-market ETFs, alternative bandwidth choices, and different sample periods.

More broadly, the results suggest that households play a larger role in aggregate risk-bearing than is historically recognized. Much of the intermediary asset pricing literature emphasizes financial intermediaries as the marginal suppliers of risk-bearing capacity. My results suggest that households increasingly perform a similar role during market downturns. As direct household participation continues to expand, understanding retail demand becomes increasingly important for understanding aggregate asset prices and short-run market dynamics.

This paper contributes to two strands of the literature. First, it contributes to the literature on household finance and retail trading by shifting the focus from individual securities to aggregate market risk. While existing work has primarily studied retail trading in individual stocks, I show that retail investors systematically buy aggregate market de-

clines and that this demand is strongly asymmetric, resembling the payoff of a put option. Second, I provide causal evidence that retail demand has economically meaningful effects on aggregate asset prices. Existing evidence on retail price impact is largely confined to the cross section of individual securities. I show that household demand also moves the aggregate market.

Outline of the Paper The remainder of the paper proceeds as follows. Section 2 reviews the related literature. Section 3 presents descriptive evidence on aggregate retail trading. Section 4 describes the data and measurements. Section 5 documents intraday patterns, and Section 6 presents the main identification. Section 7 examines the economic significance, and Section 8 concludes.

2 Related Literature

This paper contributes to the literature on household finance and retail investor trading behavior. A large body of work studies how retail investors trade individual securities. Early work documents the disposition effect (Odean, 1998), while more recent work suggests that retail investors actively trade against recent price movements Kaniel et al. (2008, 2012); Grinblatt and Keloharju (2000, 2001); Choe et al. (1999); Jackson (2003); Richards (2005); Welch (2022); Fedyk (2021); Luo et al. (2023); Gabaix et al. (2023). This paper differs from the existing literature in both scope and measurement. Rather than studying individual stocks or specific brokerage samples, I use transaction records covering the entire U.S. National Market System to characterize retail trading in the aggregate market. Focusing on retail flow in SPY shifts the question from stock selection to market timing and asks whether retail investors systematically buy aggregate market declines.

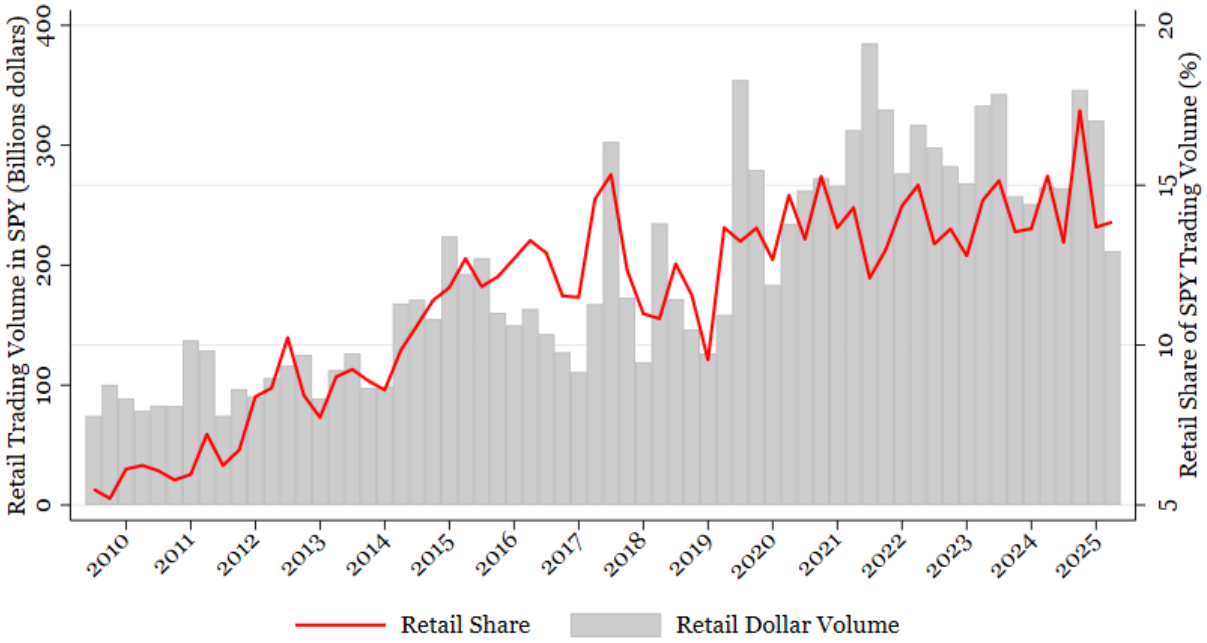
This paper also contributes to the literature on price impact of retail trading. Early theories model retail investors as noise traders whose demand can move prices away from fundamentals (Black, 1986; Shleifer and Summers, 1990; Foucault et al., 2011). More recent empirical evidence shows that retail trading predicts returns, generating short-run price pressure but longer-run reversals Odean (1998); Barber and Odean (2000); Barber et al. (2008); Hvidkjaer (2008); Kaniel et al. (2008); Barber et al. (2008); Kelley and Tetlock (2013); Barrot et al. (2016); Boehmer et al. (2021); Glossner et al. (2025). Existing evidence, however, is largely confined to the cross section of individual securities. This paper provides causal evidence that retail demand also affects aggregate asset prices. Because SPY represents ownership of the market portfolio, retail demand through the index fund changes aggregate demand for equity risk rather than simply reallocating capital across firms.

Third, and more broadly, this paper contributes to the literature on intermediary asset pricing by highlighting the role of households in absorbing aggregate market risk. A large literature argues that financial intermediaries are the marginal investors, whose balance sheet capacity determines asset prices and risk premia (Adrian et al., 2014; He et al., 2017). In these models, intermediaries absorb risk when other investors wish to reduce their exposures, and fluctuations in intermediary capital are central to asset pricing. I complement this literature by showing that households also supply aggregate risk-bearing capacity. Retail investors systematically increase their purchases following market declines, absorbing selling pressure precisely when intermediary balance sheets are likely to be most constrained.

3 Aggregate Patterns in Retail Trading

Retail participation in U.S. equity markets has increased substantially over the past decade. I begin by documenting this trend in SPY, the oldest, largest, and most actively traded exchange-traded fund tracking the U.S. equity market. Because SPY is widely used by both retail and institutional investors to obtain broad market exposure, retail order flow in SPY provides a natural measure of aggregate household demand for equity while abstracting from firm-specific trading driven by idiosyncratic news. Figure 1 plots quarterly retail trading volume and retail share from 2010 to 2025.

FIGURE 1: RETAIL PARTICIPATION OVER TIME



Note: The figure plots quarterly retail trading activity in SPY from 2010 to 2025. The bars show total retail trading volume in billions of dollars (left axis). The solid line shows retail trading volume as a share of total SPY trading volume (right axis). Retail trading volume is measured as the sum of marketable retail buy and sell volume identified using the algorithm of Barber et al. (2024).

Retail trading accounted for 5% of total SPY trading volume in 2010 but increased steadily over the following decade, reaching above 15% by the end of the sample. Over the same period, retail dollar trading volume increased by an order of magnitude. These trends motivate the central question of this paper: whether the growing participation of retail investors has affected aggregate market dynamics.

The growth of retail participation has been accompanied by changes in how they trade on aggregate. Rather than acting independently, retail investors increasingly receive information through common online channels. Recent evidence shows that online investment platforms facilitate the rapid dissemination of investment research (Farrell et al., 2022) and that retail investors respond strongly to common signals (Barber et al., 2022). As a result, retail trading has become increasingly coordinated, making retail investors a more important source of aggregate demand.

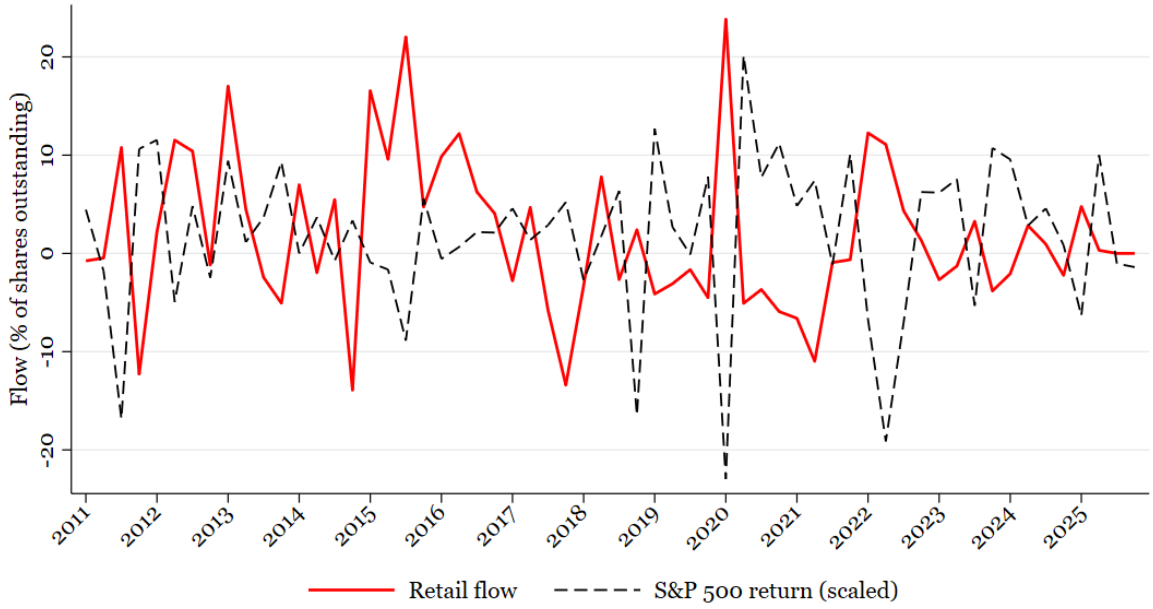
Having established that retail investors have become an important share of market activity, I next examine how they trade the aggregate market and how that differs from the rest of the market. Panel A and B of Figure 2 plot the quarterly retail and non-retail flow against aggregate market returns. Retail net purchases are strongly negatively correlated

with market returns, with a correlation of -59%, whereas non-retail net purchases display the opposite pattern, with a correlation of 50%. Thus, retail investors systematically increase their purchases following market declines, while the rest of the market reduces its net purchases.

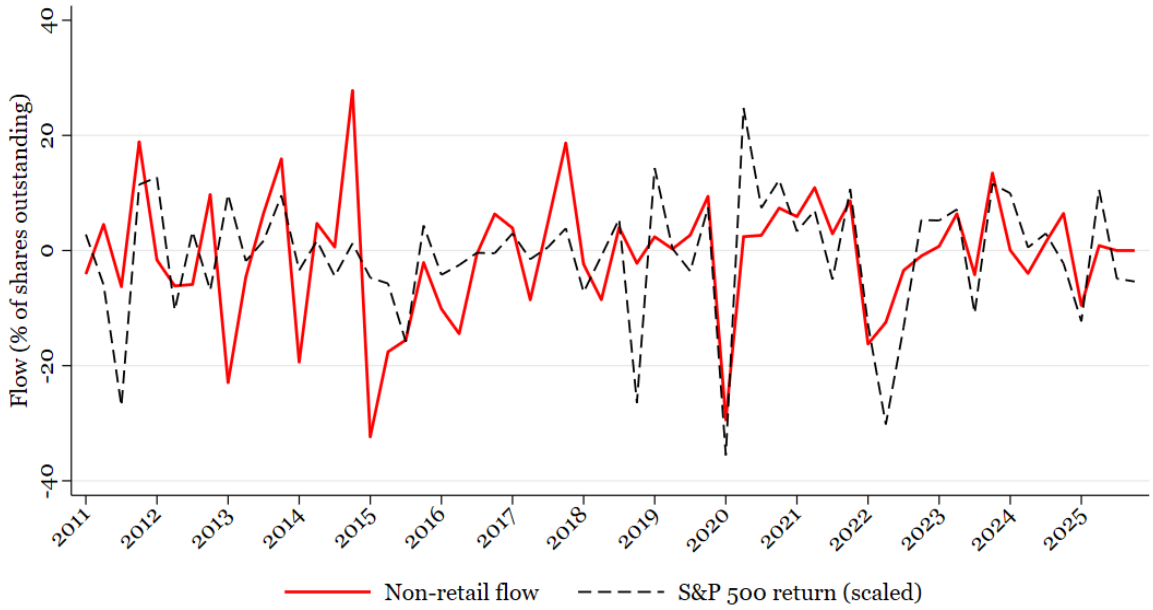
Panel C examines how the flow-return relationship evolves over time. It plots the annual flow-return coefficients for retail and aggregate flows, together with the retail share. Retail investors remain consistently contrarian through the sample, with a negative flow-return coefficient in every year. Over the same period, the aggregate flow-return coefficient declines steadily and becomes negative around 2020. Together with the growth in retail participation documented in Figure 1, these patterns suggest that the aggregate flow-return relationship increasingly reflects retail behavior.

FIGURE 2: FLOW-RETURN RELATIONSHIP

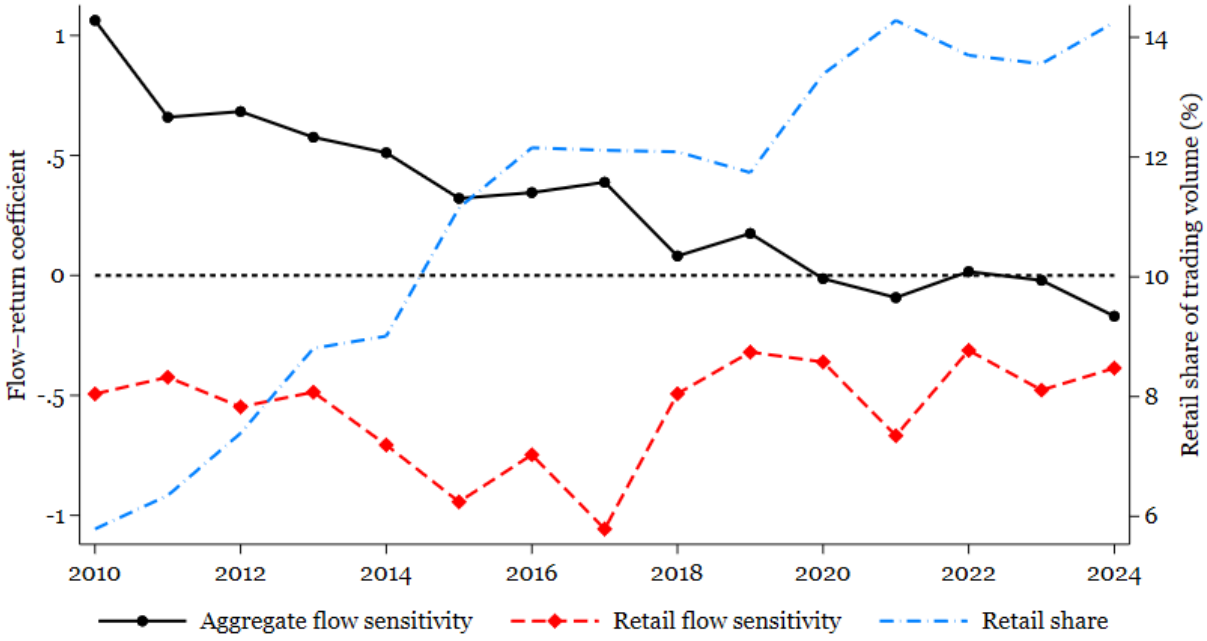
PANEL A: RETAIL FLOW



PANEL B: NON-RETAIL FLOW



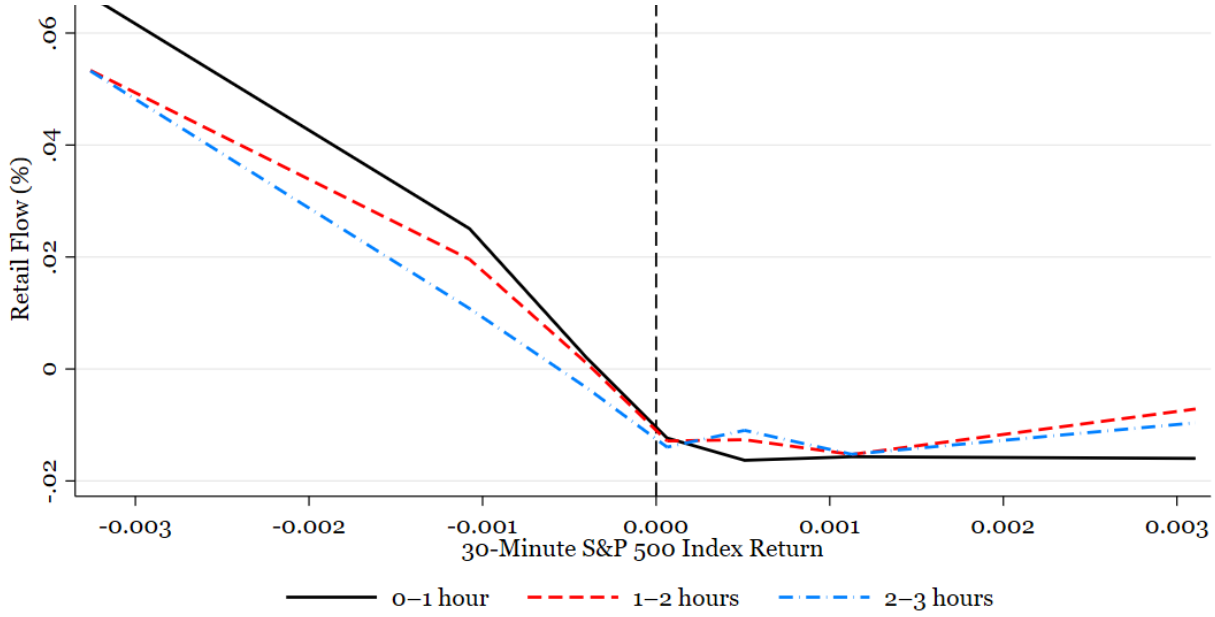
PANEL C: RETAIL PARTICIPATION AND FLOW-RETURN SENSITIVITY



Note: Panel A shows quarterly retail flow, measured as net retail purchases divided by lagged shares outstanding, and the quarterly S&P 500 return. Panel B shows quarterly non-retail flow, measured as the change in shares outstanding net of retail net purchases, divided by lagged shares outstanding, and the quarterly S&P 500 return. In both panels, the mean and standard deviation of S&P 500 returns are adjusted to match those of the corresponding flow series. Panel C plots the annual flow-return coefficients for retail and aggregate flows together with the retail share of trading volume. For each calendar year, the coefficients are estimated from regressions of daily retail or aggregate flow on contemporaneous S&P 500 returns. The sample period is 2011 to 2025.

The negative correlation in Figure 2 establishes that retail investors trade against aggregate market movements on average. It does not, however, reveal whether this behavior reflects symmetric contrarian trading, buying after market declines and selling after market increases, or whether retail investors respond primarily to downside market movements. Figure 3 shows that the relationship is highly asymmetric by relating subsequent retail purchases to contemporaneous 30-minute market returns.

FIGURE 3: RETAIL FLOW ACROSS RETURN



Note: The figure plots the relation between 30-minute S&P 500 index returns and subsequent retail flow. Returns are grouped into equal-width bins, and each point reports the average retail flow, measured as a percentage of lagged shares outstanding, during the indicated 30-minute interval after the return. The legend identifies the timing of each flow interval relative to the end of the return interval.

The relationship is strongly asymmetric. Figure 3 shows that retail investors purchase aggressively following market declines, with net buying increasing sharply as returns become more negative. By contrast, retail demand changes little following comparable market gains. Rather than trading symmetrically against market movements, retail investors primarily provide demand during market downturns. This pattern resembles the payoff of a put option.

Having documented that retail purchases are concentrated during market downturns, I next examine the dynamics of this trading behavior. Figure 4 plots the evolution of retail demand and market returns around large market declines. Market decline events are defined as the lowest-return month within episodes in the bottom decile of monthly market returns. Panel A shows cumulative retail net purchases around these events, while Panel B shows cumulative market returns relative to the event month.

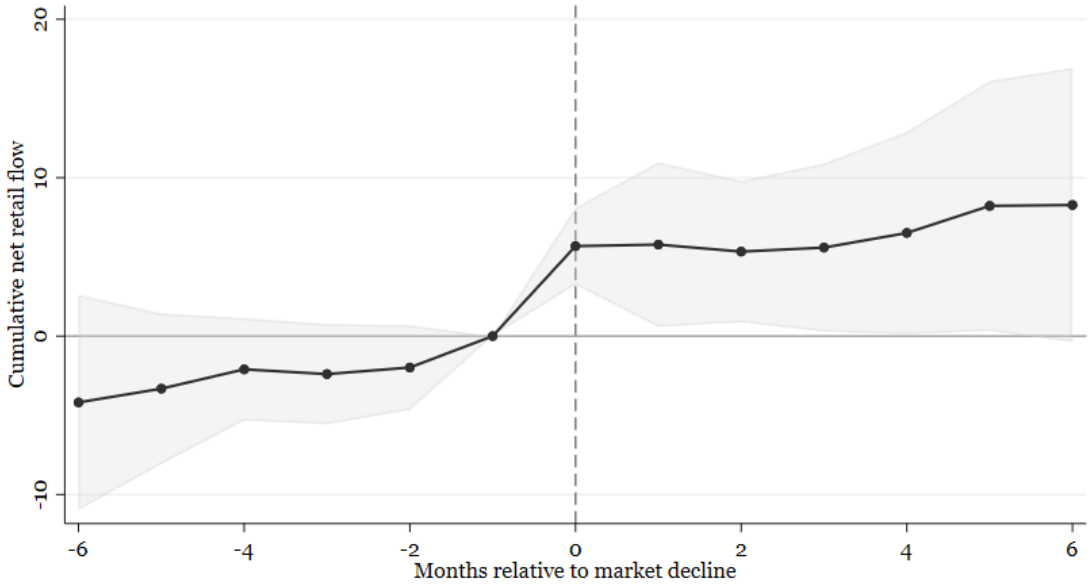
Retail investors increase their purchases sharply following large market declines. Net retail purchases rise by 6.3% during the event month and remain elevated. The persistence indicates that retail investors do not simply buy the initial decline and subsequently unwind their positions, but instead continue providing demand well after the market trough. Over the same period, market prices recover, with cumulative returns increasing

by roughly 10% over the following months.

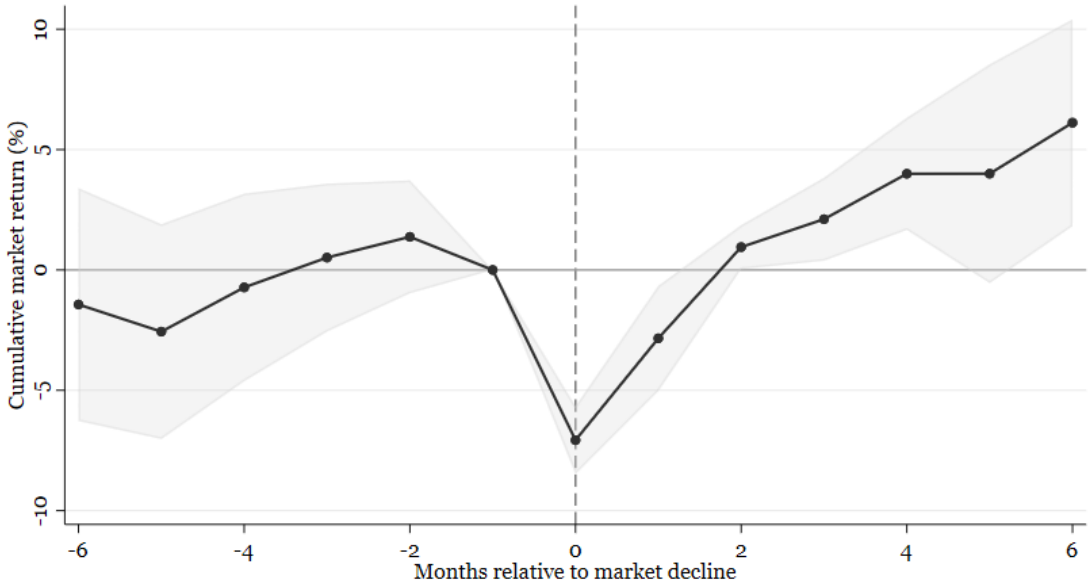
Overall, Figures 2-4 document a consistent pattern in aggregate household demand. Households systematically increase their purchases following market declines. These purchases are concentrated on the downside rather than offset by selling during market advances, and they persist well beyond the initial decline. The accompanying recovery in market prices is suggestive that retail demand may influence aggregate prices. However, these descriptive patterns alone cannot distinguish the price impact of retail demand from changes in underlying fundamentals. The following sections develop an empirical design to isolate the causal effect of retail demand on aggregate asset prices.

FIGURE 4: RETAIL TRADING AROUND LARGE MARKET DECLINES

PANEL A: CUMULATIVE RETAIL BUYING



PANEL B: CUMULATIVE MARKET RETURN



Note: This figure illustrates the evolution of retail trading and market prices around large market declines. Event months are defined as months in the bottom 10% of the distribution of monthly market returns over 2011-2025. Consecutive decline months occurring within the same market-decline episode are grouped together, and the month with the lowest market return is selected as the event month (11 event months in total). Panel A plots cumulative retail flow, measured as the sum of monthly retail flow (as a percentage of lagged shares outstanding) and normalized to zero in the month preceding the event. Panel B plots cumulative market returns relative to the event month, normalized to zero in the month preceding the event. Shaded areas denote 95% confidence intervals.

4 Data and Measurement

4.1 Data

Retail trading. The primary source of retail trading data is the NYSE Trade and Quote (TAQ) database. Retail trades are identified using the subpenny price-improvement methodology developed by Boehmer et al. (2021), which exploits the fact that retail market orders are frequently internalized by wholesalers and executed at prices that improve upon the National Best Bid and Offer by fractions of a cent. I implement the refinement proposed by Barber et al. (2024), which improves the accuracy of retail-trade identification by applying the midpoint quote method. Following the literature, the sample begins in 2010, when subpenny price improvement became widespread in U.S. equity markets after the rapid expansion of retail internalization. The TAQ database provides transaction-level information on execution prices, trade sizes, timestamps, and prevailing bid and ask quotes. I apply the Boehmer-Barber identification procedure to classify each transaction as retail or non-retail and, for retail trades, identify whether the trade is buyer- or seller-initiated.

Market data. Market data are obtained from several complementary sources. Daily SPY shares outstanding are obtained from Bloomberg over the 2010-2025 sample period. Daily SPY returns and trading volume are obtained from CRSP. Intraday SPY transaction prices are obtained from the TAQ database. To complement the ETF data, I also obtain intraday prices for E-mini S&P 500 futures from CME Group. The E-mini contract is the most actively traded futures contract on the S&P 500 Index and provides a high-frequency measure of aggregate U.S. equity market prices.

4.2 Measuring flows and returns

I construct measures of retail trading activity at both the daily and intraday frequencies. The daily measures provide evidence on the evolution of retail trading and its aggregate patterns over time. The intraday measures exploit the precise timing of trades to examine retail investors' response to market movements and to estimate the causal effect of retail demand on aggregate prices.

Daily measures I begin by aggregating classified retail purchases and retail sales across all transactions within each trading day. Retail trading volume is defined as the sum of retail purchases and retail sales. Retail share is then measured as retail trading volume divided by total SPY trading volume.

The primary measure of retail demand is retail net marketable order flow (retail flow), defined as retail purchases minus retail sales, scaled by lagged shares outstanding:

$$Flow_t^{Retail} = \frac{sb_t - ss_t}{sh_{t-1}}$$

where sb_t and ss_t denote the total shares of retail buys and sells on day t, respectively, and sh_{t-1} denotes lagged shares outstanding. Scaling by lagged shares outstanding expresses retail demand as a fraction of the ETF's size, allowing comparisons across time as SPY grows substantially over the sample period.

To compare retail demand with aggregate trading activity, I measure aggregate flow using changes in SPY shares outstanding,

$$Flow_t^{Total} = \frac{sh_t - sh_{t-1}}{sh_{t-1}}$$

Because aggregate flow reflects the combined trading of retail and non-retail investors, non-retail flow is defined as the residual:

$$Flow_t^{NonRetail} = Flow_t^{Total} - Flow_t^{Retail}$$

Panel A of Table 1 provides summary statistics for variables at the daily level. Retail investors purchase and sell more than five million SPY shares per day on average. Although purchases and sales are broadly balanced, retail investors are net buyers on average, purchasing approximately 0.03% of lagged shares outstanding per day. Retail demand also varies substantially over time. At the 10th percentile, retail investors are net sellers of 0.73% of shares outstanding, whereas at the 90th percentile they are net buyers of 0.84%.

Intraday measures For the intraday analysis, transactions are aggregated into non overlapping 30-minute intervals in order to reduce microstructure noise while preserving the dynamics of retail trading. Retail purchases and retail sales are aggregated within each interval, and intraday retail flow is constructed analogously to the daily measure as interval net retail purchases scaled by lagged shares outstanding.

Market returns are measured using both SPY transaction prices and E-mini S&P 500 futures prices. I construct two return measures. The interval return is the return over the current 30-minute interval and serves as the outcome variable in the price-impact analysis. The displayed return is the cumulative SPY return from the previous trading day's close through the end of the current interval. This is the return displayed to investors at the time of their trading decision, and it serves as the running variable in the regression discontinuity design.

Panel B of Table 1 reports summary statistics for the intraday variables. Average 30-minute returns are close to zero, while displayed returns exhibit greater dispersion because they accumulate over the course of the trading day. Retail investors purchase and sell approximately 0.4 million SPY shares during a typical 30-minute interval.

TABLE 1: SUMMARY STATISTICS

	Mean (1)	SD (2)	P10 (3)	Median (4)	P90 (5)
Panel A: Daily Data					
Market variables					
S&P 500 Return (%)	0.05	1.09	-1.10	0.07	1.16
Trading Volume (mill. shares)	111.90	69.13	51.25	91.92	197.02
Shares Outstanding (mill.)	878.82	100.78	708.78	901.33	989.08
Retail trading					
Retail Buy Shares (mill.)	5.81	5.68	1.67	4.08	11.53
Retail Sell Shares (mill.)	5.53	4.44	1.97	4.30	10.26
Retail Trading Volume (mill. shares)	11.34	7.27	4.95	9.58	19.08
Retail Share of Trading Volume (%)	11.05	4.82	5.41	10.57	17.04
Flow measures					
Retail Flow (%)	0.03	0.83	-0.73	-0.02	0.84
Aggregate Flow (%)	0.02	1.16	-1.14	0.01	1.12
Non-retail Flow (%)	-0.02	1.59	-1.61	0.01	1.52
Observations (days)			3,773		
Panel B: Intraday Data					
	Mean (1)	SD (2)	P10 (3)	Median (4)	P90 (5)
Retail trading					
Retail Buy Shares (mill.)	0.44	0.84	0.07	0.21	1.02
Retail Sell Shares (mill.)	0.42	0.67	0.07	0.21	0.96
Return and flow measures					
30-Minute Return (%)	0.00	0.22	-0.21	0.01	0.20
Displayed Return (%)	0.04	0.90	-0.91	0.06	0.98
E-mini S&P 500 Future Return (%)	0.04	0.90	-0.91	0.06	0.98
Retail Flow (%)	0.00	0.12	-0.07	0.00	0.08
Observations (30-minute intervals)			50,474		

Notes: This table provides summary statistics for variables used in the analysis. Panel A reports daily variables from 2010 to 2025. Panel B reports variables measured over 30-minute intervals over the same sample period. Retail buy and sell shares are identified from the TAQ database using the sub-penny price-improvement methodology of Boehmer et al. (2021) with the refinement of Barber et al. (2024). Retail flow is defined as net retail purchases divided by lagged SPY shares outstanding. Aggregate flow is measured as the percentage change in SPY shares outstanding, and non-retail flow is defined as aggregate flow minus retail flow. The displayed return is the cumulative SPY return from the previous day's market close to the end of the current 30-minute interval, while the 30-minute return is the contemporaneous SPY return over the interval.

5 Intraday Evidence

The aggregate evidence shows that retail investors trade against aggregate market movements. These patterns, however, mask the timing and dynamics of retail trading. In this section, I turn to high-frequency data to characterize the dynamics of retail demand following intraday market returns and then show that both retail demand and subsequent market returns exhibit a nonlinearity.

5.1 Retail trading dynamics

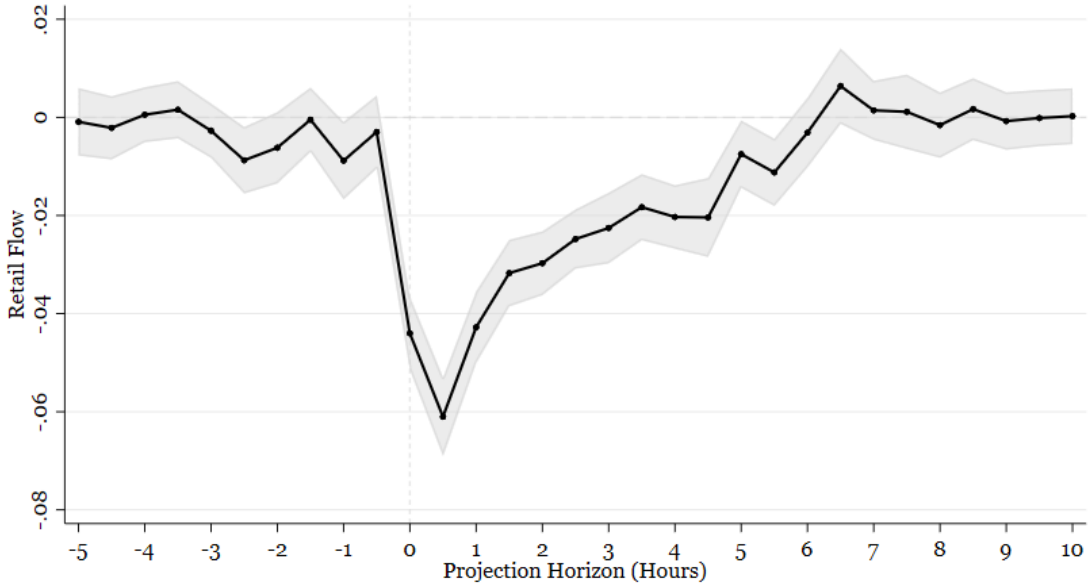
How quickly do retail investors respond to changes in market returns? Traditional views characterize retail investors as inattentive traders who adjust their portfolios infrequently (Agnew et al., 2003). If this characterization continues to hold, retail demand should respond only gradually to market movements and is therefore unlikely to have price pressure at intraday horizons. By contrast, if retail investors respond rapidly, their demand may become an important source of short-run buying and selling pressure. The growth of online brokerage platforms and real-time access to market information has substantially reduced the costs of monitoring markets and executing trades, making the speed of retail response ultimately an empirical question. I therefore begin by tracing the evolution of retail flow following intraday market returns using local projections. Specifically, I estimate the following specification:

$$Flow_{t+h} = \alpha_h + \beta_h R_t + \varepsilon_{t,h} \tag{1}$$

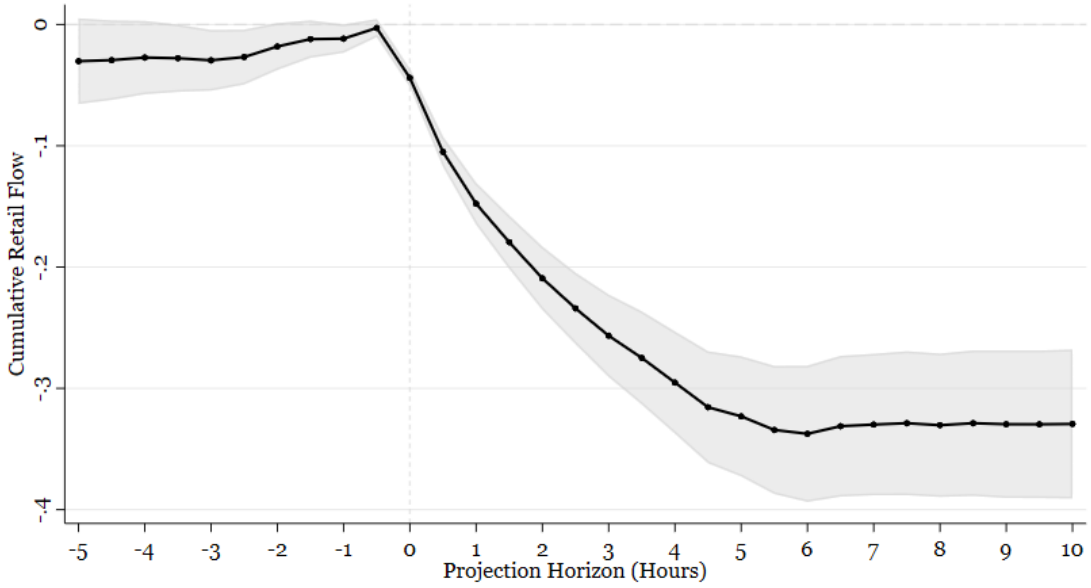
where $Flow_{t+h}$ denotes retail flow h 30-minute intervals after return R_t. Standard errors are clustered by trading day.

FIGURE 5: RETAIL FLOW AROUND INTRADAY RETURN

PANEL A: RETAIL FLOW RESPONSE



PANEL B: CUMULATIVE RETAIL FLOW RESPONSE



Note: This figure reports local projection estimates of the response of retail flow to 30-minute S&P 500 index returns. Panel A plots retail flow, and Panel B plots cumulative retail flow, at each 30-minute horizon relative to the return interval. Retail flow is measured as net retail purchases scaled by lagged shares outstanding. Horizon 0 denotes the contemporaneous return interval. Shaded areas represent 95% confidence intervals based on trading-day clustered standard errors.

Panel A of Figure 5 plots the coefficient β_h from the local projection. Retail investors respond immediately to market movements. A 1% decline in the market over a 30-minute

interval is associated with an increase in net retail purchases of 0.044% of lagged shares outstanding in the same interval. The response peaks over the subsequent 30 to 60 minutes before gradually dissipating over the following several hours.

The rapid adjustment of retail demand makes it plausible that retail investors can influence short-run price dynamics. This finding also complements the existing literature on retail investor inattention. While previous studies document limited attention to firm-specific information, aggregate market returns are simple and highly salient signals that are continuously displayed on trading platforms and financial media. Retail investors may therefore react much more quickly to broad market movements than to news about individual securities.

How persistent is the retail response? Panel A shows that retail investors react quickly to market movements, but initial reaction alone is not sufficient for retail demand to affect prices. If retail investors quickly unwind the positions they acquire following market declines, their trades are unlikely to generate sustained buying pressure. By contrast, if they continue to accumulate and hold these positions, retail demand may have more persistent pressure on prices. I therefore examine the cumulative response of retail flow following market declines to distinguish between these possibilities. Specifically, I estimate the following local projection:

$$CumFlow_{t+h} = \alpha_h + \gamma_h R_t + \varepsilon_{t,h} \tag{2}$$

and $CumFlow_{t+h}$ denotes cumulative retail order flow from period t through $t+h$.

Panel B of Figure 5 plots the cumulative response of retail flow. Retail purchases continue to accumulate over the first five hours following a market decline, with no evidence of an offsetting reversal. This pattern indicates that retail investors retain the positions they acquire after market downturns rather than quickly unwinding them. The persistence of retail demand strengthens the possibility that retail trading may generate sustained buying pressure.

5.2 Retail put

The previous evidence establishes that retail investors respond rapidly and persistently to intraday market movements. An equally important question is whether this response is symmetric between market gains and losses. If retail investors react similarly in both directions, they simply trade against short-run market fluctuations. By contrast, if retail demand is concentrated following market declines, retail investors provide risk-bearing capacity precisely when financial intermediaries are most likely to face balance sheet con-

straints. Such asymmetric demand would imply that retail investors play a disproportionately important role during market downturns.

The aggregate evidence presented earlier suggests such an asymmetry. Figure 3 provides a nonparametric illustration of the relationship between current market returns and subsequent retail trading. The horizontal axis reports the contemporaneous 30-minute market return, while each line plots average retail flow follwoing the return. Retail demand responds sharply to market declines but only weakly to comparable market advances. Following returns in the lowest quintile (averaging around -0.4%), retail investors become substantial net buyers during the next 30-minute interval (averaging around 0.05% of total shares outstanding), and elevated buying persists over the following several hours. In contrast, positive returns induce little corresponding selling. The resulting payoff resembles that of a put option: retail investors supply demand when the market falls but do not symmetrically withdraw demand when the market rises.

I now quantify this asymmetry using a simple piecewise-linear specification. Panel A of Table 2 formally quantifies this asymmetry. Across all horizons, the slope relating future retail flow to negative returns is large, negative, and statistically significant. Economically, a 1% decline in the market predicts an increase of 14.8 basis points of shares outstanding in retail purchases during the next 30-minute interval. By contrast, the estimated response to non-negative returns is economically small and statistically insignificant at most horizons. The asymmetry is persistent: the effect remains highly significant for retail flow measured up to four hours after the initial market movement. These results suggest that retail investors disproportionately supply liquidity during market downturns rather than responding symmetrically to gains and losses.

The retail put documented above raises a natural question: if retail investors buy after declines, are those episodes followed by higher returns? If so, retail demand may contribute to short-run price pressure by supporting prices after market declines. By contrast, if subsequent returns do not differ following positive and negative market movements, the asymmetric trading behavior documented above is less likely to have meaningful implications for price dynamics. To answer this, Panel B of Table 2 estimates the same piecewise-linear specifications as in Panel A, replacing subsequent retail flow with cumulative future market returns as the dependent variable.

Panel B shows a parallel asymmetry in subsequent market returns. Across all horizons, market declines are followed by significantly higher cumulative future returns, whereas market advances are followed by little or no subsequent price movement. Economically, a 1% decline in the market predicts a cumulative return reversal of 3.7 basis points over the next 30 minutes, increasing to 16.6 basis points over the subsequent three hours be-

TABLE 2: ASYMMETRIC DYNAMICS FOLLOWING MARKET RETURNS

	Panel A: 30-Minute Retail Flow (%)				
	(1) 30 Minutes	(2) 1 Hour	(3) 2 Hours	(4) 3 Hours	(5) 4 Hours
Return < 0	-14.820^{***}	-13.637^{***}	-11.939^{***}	-10.906^{***}	-11.439^{***}
	(0.940)	(0.868)	(0.927)	(0.922)	(1.136)
Return ≥ 0	-2.356^{***}	-0.547	-0.320	-0.296	-1.294
	(0.818)	(0.849)	(0.841)	(0.957)	(1.111)
Observations	45,130	41,367	33,825	26,202	18,578
	Panel B: Cumulative future return (%)				
	(1) 30 Minutes	(2) 1 Hour	(3) 2 Hours	(4) 3 Hours	(5) 4 Hours
Return < 0	-0.037^{***}	-0.058^{***}	-0.131^{***}	-0.166^{***}	-0.121^{***}
	(0.014)	(0.020)	(0.029)	(0.038)	(0.046)
Return ≥ 0	0.017	0.028	0.026	0.009	-0.047
	(0.015)	(0.022)	(0.029)	(0.039)	(0.046)
Observations	46,444	42,570	34,808	26,965	19,120

Notes: The table presents regressions of future retail flows and market returns on positive and negative market returns.

$$Flow_{t+h} = \alpha + \beta^{-} Ret_t^{-} + \beta^{+} Ret_t^{+} + \varepsilon_{t+h}, \tag{3}$$

$$CumRet_{t+h} = \alpha + \beta^{-} Ret_t^{-} + \beta^{+} Ret_t^{+} + \varepsilon_{t+h}, \tag{4}$$

Panel A reports regressions of subsequent retail flow on the current 30-minute market return, where $Flow_{t+h}$ denotes the retail flow during the 30-minute interval at horizon h intervals after the current returns. Thus, the columns correspond to retail flow over the intervals 0-30 minutes, 30-60 minutes, 90-120 minutes, 150-180 minutes, and 210-240 minutes after the current return. Panel B reports the analogous specification using cumulative future market returns as the dependent variable, where $CumRet_{t+h}$ is the cumulative market return from the next 30-minute interval through the horizon indicated by the column heading (30 minutes, 1 hour, 2 hours, 3 hours, and 4 hours). In both panels, Ret_t is the 30-minute interval return. Standard errors are clustered by trading day. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

fore gradually attenuating thereafter. In contrast, the estimated response following non-negative returns is small and statistically insignificant at every horizon. These reduced-form patterns are consistent with the view that stronger retail buying following market declines contributes to short-run price pressure.

However, this evidence remains only suggestive. The same asymmetry could also arise from other mechanisms unrelated to retail demand. Establishing a causal effect therefore requires exogenous variation in retail trading, which is the focus of the next section.

6 Identification

The evidence so far establishes that retail investors respond rapidly to market movements, their demand is persistent and highly asymmetric, and stronger retail buying is followed by higher subsequent returns. Together, these findings are consistent with retail demand exerting short-run price pressure but do not establish causality. This section develops an identification strategy that isolates exogenous variation in retail demand.

6.1 Identification challenge

The reduced-form evidence does not identify the causal effect of retail demand on prices because the same patterns can arise from alternative mechanisms. One possibility is temporary fire sales. During market downturns, financially constrained investors may be forced to liquidate their positions, temporarily depressing prices below fundamental values. As this selling pressure subsides, prices naturally rebound, generating positive subsequent returns. Because fire sales occur primarily after market declines, they generate the same asymmetric relation between current and future returns, even if retail demand has no price impact. More generally, any mechanism that produces stronger return reversals after market declines than after comparable market advances generates the same nonlinear relation between current and future returns. Documenting nonlinearity is therefore not sufficient to identify the price impact of retail demand.

Identification therefore requires a discontinuity, not merely a nonlinearity. Fire-sale intensity, market fundamentals, and other determinants of future returns should vary smoothly with the magnitude of market returns. There is no reason why these forces should change discretely when the market return moves from +0.01% to -0.01%, two observations that are economically nearly identical. A discontinuity at this threshold is therefore difficult to reconcile with these alternative explanations.

6.2 Identification strategy

I exploit a discontinuity in retail demand at the zero *displayed-return* threshold. Brokerage platforms report returns relative to the previous day's close, and displayed returns and prices are among the most frequently consulted pieces of information in retail investors' trading decisions (Laarits and Wurgler, 2025). If retail investors classify small gains and losses differently, retail demand changes discretely when the displayed return crosses zero, even though the underlying market return changes only marginally.

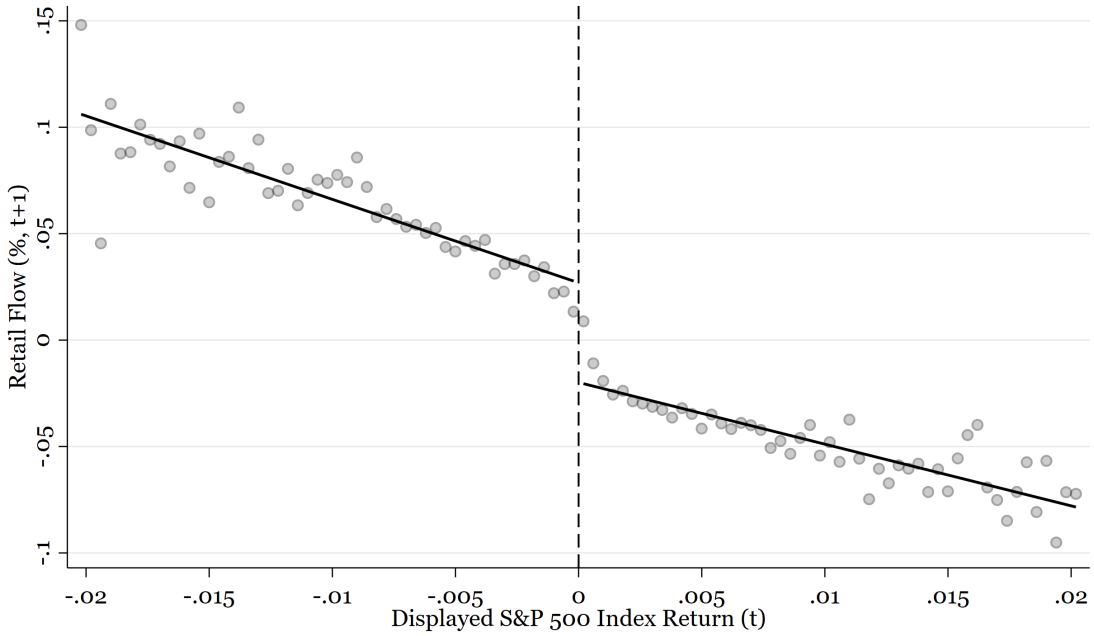
The empirical design compares observations immediately above and below the zero displayed-return threshold. Around this cutoff, market fundamentals, liquidity conditions, and fire-sale intensity should evolve smoothly. The only discrete change is that the displayed return switches from a gain to a loss, often accompanied by a change in color from green to red. Consequently, any discontinuous change in retail demand can be attributed to this change in presentation rather than underlying market conditions.

The identifying assumption is that all other determinants of future returns evolve smoothly around the zero displayed-return threshold, so retail demand is the only source of discontinuous variation at the cutoff. Under this assumption, any discontinuity in subsequent returns identifies the causal effect of retail demand. Section 6.5 provides evidence supporting this assumption.

6.3 First stage results: retail demand discontinuity

I first examine whether retail demand changes discontinuously around the zero displayed-return threshold. If retail investors treat small gains and losses differently, retail demand should increase discontinuously as the displayed return crosses from a small gain to a small loss. Figure 6 plots retail flow over the subsequent 30-minute interval against the displayed return observed immediately before trading takes place. Retail flow increases sharply at the cutoff, with substantially higher net retail purchases immediately below zero than immediately above zero.

FIGURE 6: DISCONTINUITY IN RETAIL FLOWS



Note: This figure plots retail flow in the next 30-minute interval against the displayed S&P 500 return in the current 30-minute interval. Retail flow is measured as net retail share purchases (shares bought minus shares sold) during the interval, scaled by SPY shares outstanding at the previous trading day's close, and expressed in percentage points.

The discontinuity in retail demand is consistent with evidence that investors simplify complex information using categorical heuristics and respond more strongly to salient information. Rather than responding continuously to small differences in returns, investors often classify outcomes as gains or losses, leading behavior to change discretely around psychologically meaningful thresholds (Graeber et al., 2025). In addition, brokerage platforms typically display gains and losses using different colors. Crossing the zero displayed-return threshold therefore changes the visual presentation of otherwise similar returns, potentially making the threshold particularly salient and increasing investors' responsiveness (Frydman and Wang, 2020). The empirical design does not distinguish between these behavioral mechanisms: both predict a discontinuous increase in retail demand when displayed returns cross zero.

As a placebo, Appendix Figure 1 repeats the same analysis using the contemporaneous 30-minute return as the running variable. Unlike the displayed return, the contemporaneous 30-minute return is not prominently displayed to investors on brokerage platforms. I find no discontinuity in retail order flow around this threshold. This evidence suggests that the discontinuity is driven by the salience of displayed gains and losses rather than by the underlying return process itself.

To quantify the discontinuity, I estimate the following local linear regression discontinuity specification:

$$Flow_{t,t+1} = \alpha + \pi D_t + \beta_1 R_t^D + \beta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + \varepsilon_t \tag{5}$$

where R_t^D is the displayed return from the previous trading day's close through the end of interval t, and D_t is an indicator equal to one when the displayed return is below zero. $Flow_{t,t+1}$ denotes net retail order flow during the subsequent 30-minute interval. The coefficient of interest, π, captures the discontinuous change in retail demand at the zero displayed-return threshold. Table 3 progressively introduces the running variable, additional controls, time-of-day fixed effects, and sample restrictions around the market open and close. The sample is restricted to observations with displayed returns within one standard deviation of zero ($\pm 0.89\%$). Standard errors are clustered by trading day.

Table 3 reports the first-stage estimates. Across all specifications, crossing the zero displayed-return threshold generates a positive and statistically significant increase in subsequent retail purchases. The estimated discontinuity remains stable as I progressively introduce local-linear controls, lagged return and retail-flow controls, time-of-day fixed effects, and the exclusion of the market open and close, indicating that the effect is not driven by any of them.

The preferred specification in column (3) implies that a displayed return just below zero increases subsequent net retail purchases by approximately 2.6 basis points of lagged shares outstanding over the following 30-minute interval. While smaller than the raw discontinuity of 6.5 basis points, the effect remains economically meaningful after accounting for smooth variation in returns and trading activity around the threshold. Moreover, the first-stage F-statistics exceed 400 in every specification, indicating that the discontinuity provides a highly informative source of exogenous variation in retail demand.

The estimates also reveal a strong negative relationship between displayed returns and retail order flow within the local neighborhood around the threshold. Retail investors purchase more aggressively following larger market declines, consistent with the contrarian trading pattern documented with lower frequency data. The discontinuity therefore captures a discrete increase in buying that arises when displayed returns switch from gains to losses, beyond the smooth tendency of retail investors to buy larger declines. This behavioral response forms the basis for the instrumental variables strategy used to estimate the causal price impact of retail demand in the next section.

TABLE 3: FIRST-STAGE EFFECT OF NEGATIVE DISPLAYED RETURNS ON RETAIL FLOW

	Retail Flow (t, t+1)				
	(1)	(2)	(3)	(4)	(5)
$\mathbf{1}\{\text{Displayed Return} < 0\}$	0.065***	0.030***	0.030***	0.030***	0.026***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Displayed Return		−0.050***	−0.048***	−0.048***	−0.043***
		(0.004)	(0.005)	(0.005)	(0.005)
Negative Displayed Return		−0.006	−0.001	−0.001	−0.002
		(0.007)	(0.007)	(0.007)	(0.007)
Return (t-1, t)			−0.032***	−0.032***	−0.028***
			(0.004)	(0.004)	(0.005)
Retail Flow (t-1, t)			0.083***	0.083***	0.072***
			(0.019)	(0.019)	(0.020)
Time-of-Day Fixed Effects	No	No	No	Yes	Yes
Exclude First and Last Hours	No	No	No	No	Yes
Observations	36,584	36,584	33,248	33,248	27,178
F-Statistic	2125.00	782.12	546.86	547.43	433.21

Notes: This table reports first-stage estimates from the regression discontinuity design.

$$Flow_{t,t+1} = \alpha + \pi D_t + \beta_1 R_t^D + \beta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + \varepsilon_t$$

The sample consists of 30-minute intervals for SPY from January 2010 to June 2025. The dependent variable is the next 30-minute retail flow, measured as net retail purchases during the 30-minute interval, scaled by lagged shares outstanding. The running variable is the displayed market return, and the instrument is an indicator for a negative displayed return. All specifications include the negative displayed-return indicator. Column (2) additionally controls for the displayed return and its interaction with the indicator, corresponding to a local linear regression discontinuity specification. Column (3) further controls for the 30-minute interval return and lagged retail flow. Column (4) additionally includes time-of-day fixed effects. Column (5) excludes the first and last trading hours. The sample is restricted to observations with displayed returns within one standard deviation of zero ($\pm 0.89\%$). Standard errors are clustered by trading day. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

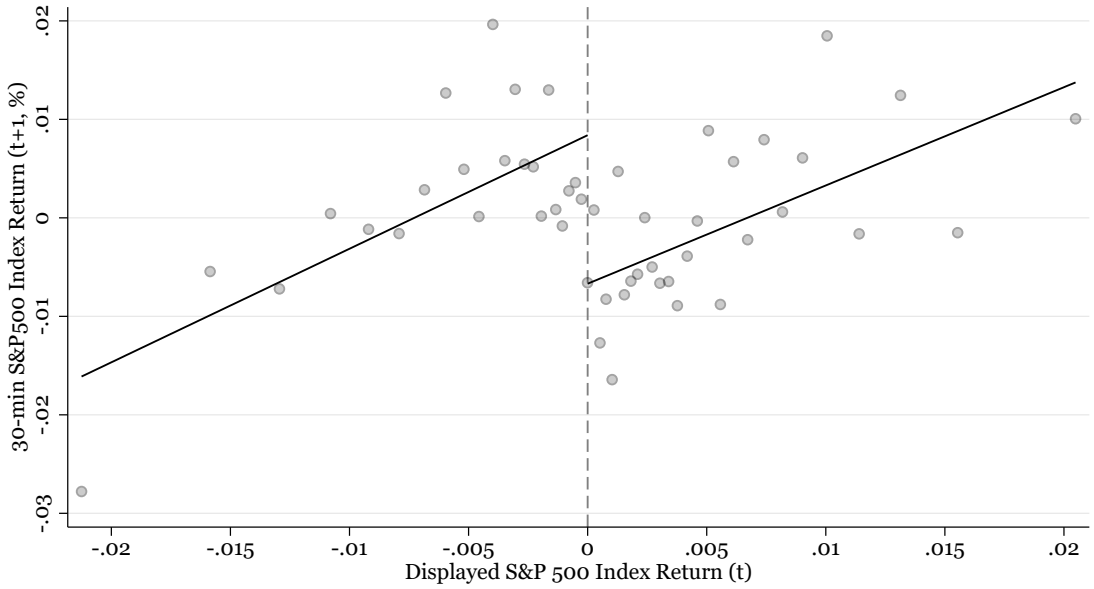
6.4 Second stage results: price impact of retail demand

Having established a discontinuity in retail demand around the zero displayed-return threshold, I next examine whether this discontinuity translates into subsequent market prices. If retail demand affects prices, observations immediately below the threshold should experience higher subsequent returns than observations immediately above the threshold.

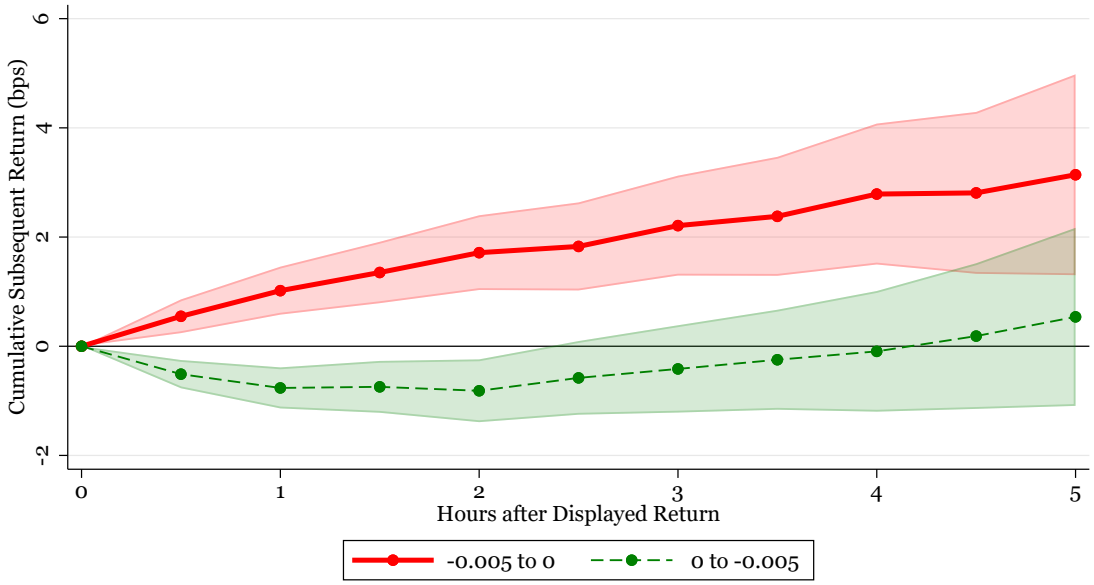
Panel A of Figure 7 plots the subsequent 30-minute market return against the displayed return around the cutoff. Future returns exhibit a positive discontinuity at the threshold, providing reduced-form evidence that the increase in retail demand is associated with higher subsequent returns. Panel B plots cumulative returns following the threshold crossing. The gap in cumulative returns widens over the subsequent several hours, with observations just below zero continuing to outperform those just above zero.

FIGURE 7: DISCONTINUITIES IN SUBSEQUENT RETURNS

PANEL A: SUBSEQUENT 30-MINUTE RETURN



PANEL B: CUMULATIVE SUBSEQUENT RETURN



Note: This figure examines subsequent market returns around the zero displayed-return threshold. Displayed return is measured as the SPY return relative to the previous trading day's closing price at the end of each 30-minute interval. Panel A shows the average market return over the subsequent 30-minute interval plotted against the contemporaneous displayed return. Panel B shows the average cumulative S&P 500 return from the subsequent 30-minute interval through each horizon, conditional on the contemporaneous displayed return. The horizontal axis measures 30-minute intervals relative to the displayed-return interval, where interval 0 denotes the contemporaneous interval used to define the displayed return and is excluded from the cumulative return calculation.

These reduced-form estimates imply that observations just below the threshold experience both higher retail demand and higher subsequent returns. I next combine these two discontinuities in a fuzzy regression discontinuity design to estimate the price impact of retail demand. I do so by running the following 2SLS regression:

$$Flow_{t,t+1} = \alpha + \pi D_t + \beta_1 R_t^D + \beta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + \varepsilon_t, \tag{6}$$

$$Ret_{t,t+1} = \alpha + \theta \widehat{Flow}_{t,t+1} + \delta_1 R_t^D + \delta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + u_t, \tag{7}$$

The first stage is identical to Equation 5. The difference is in the second stage. The displayed return is observed at the end of interval t, before retail investors trade. Retail order flow and the dependent subsequent return are then measured over the subsequent 30-minute trading interval $(t, t+1)$. The coefficient θ measures the local price impact of retail demand around the zero displayed-return threshold. Across columns, I progressively introduce the local-linear controls, lagged return and retail-flow controls, time-of-day fixed effects, and the exclusion of the first and last trading hours.

Table 4 reports the instrumental variables estimates of the price impact of retail demand. Across all specifications, the estimated effect of retail flow on subsequent returns is positive, economically large, and statistically significant. The estimates remain stable as I progressively introduce local-linear controls, lagged return and retail-flow controls, time-of-day fixed effects, and the exclusion of the market open and close, suggesting that the estimated price impact is not driven by any of them.

The preferred specification in column (3) implies that a one-percentage-point increase in net retail purchases raises subsequent SPY returns by approximately 43 basis points over the following 30-minute interval. Equivalently, a one-standard-deviation increase in retail order flow increases subsequent returns by roughly 0.03 basis points.

Panel B of Table 4 provides a validation of this interpretation by replacing SPY returns with E-mini S&P 500 futures returns. Unlike the ETF itself, E-mini futures are highly liquid index derivatives whose prices are less susceptible to ETF-specific trading frictions or temporary demand imbalances. Nevertheless, the estimated price impact is nearly identical across the two markets. This finding suggests that retail demand does not simply move the price of SPY. Instead, retail demand affects aggregate market prices more broadly.

To examine the persistence of the price impact, I estimate the dynamic response of cumulative market returns to retail order flow. Specifically, for each horizon h, I estimate

TABLE 4: PRICE IMPACT OF RETAIL FLOW

Panel A: SPY returns (t, t+1)					
	(1)	(2)	(3)	(4)	(5)
$\widehat{\text{Retail Flow}}$ (t, t+1)	0.167***	0.431***	0.433***	0.431***	0.416***
	(0.030)	(0.106)	(0.110)	(0.110)	(0.131)
Displayed Return		0.034***	0.035***	0.035***	0.031***
		(0.010)	(0.010)	(0.010)	(0.010)
Negative Displayed Return		−0.017*	−0.017*	−0.018*	−0.017*
		(0.009)	(0.009)	(0.009)	(0.010)
Return (t-1, t)			0.003	0.003	0.002
			(0.013)	(0.013)	(0.014)
Retail Flow (t-1, t)			−0.051***	−0.051***	−0.037**
			(0.017)	(0.017)	(0.016)
Time-of-Day Fixed Effects	No	No	No	Yes	Yes
Exclude First and Last Hours	No	No	No	No	Yes
Observations	36,584	36,584	33,248	33,248	27,178
Panel B: E-mini futures returns (t, t+1)					
	(1)	(2)	(3)	(4)	(5)
$\widehat{\text{Retail Flow}}$ (t, t+1)	0.104***	0.426***	0.434***	0.432***	0.443***
	(0.030)	(0.109)	(0.114)	(0.113)	(0.137)
Displayed Return		0.041***	0.037***	0.037***	0.034***
		(0.010)	(0.010)	(0.010)	(0.011)
Negative Displayed Return		−0.019**	−0.019**	−0.020**	−0.018*
		(0.009)	(0.010)	(0.010)	(0.010)
Return (t-1, t)			0.062***	0.062***	0.058***
			(0.014)	(0.014)	(0.015)
Retail Flow (t-1, t)			−0.050***	−0.050***	−0.038**
			(0.018)	(0.018)	(0.017)
Time-of-Day Fixed Effects	No	No	No	Yes	Yes
Exclude First and Last Hours	No	No	No	No	Yes
Observations	36,584	36,584	33,248	33,248	27,178

Notes: This table reports instrumental variables estimates of the price impact of retail flow. The estimates are obtained from the two-stage regression

$$Flow_{t,t+1} = \alpha + \pi D_t + \beta_1 R_t^D + \beta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + \varepsilon_t, \quad \text{(Stage 1)}$$

$$Ret_{t,t+1} = \alpha + \theta \widehat{Flow}_{t,t+1} + \delta_1 R_t^D + \delta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + u_t, \quad \text{(Stage 2)}$$

where R_t^D is the displayed return from the previous trading day's close through the end of 30-minute interval t, and D_t is an indicator equal to one when the displayed return is below zero. $Flow_{t,t+1}$ denotes net retail order flow during the subsequent 30-minute interval. In Panel A, $Ret_{t,t+1}$ denotes the SPY return over the same interval, while in Panel B it denotes the corresponding E-mini S&P 500 futures return. Retail flow is instrumented using the negative displayed-return indicator. Column (1) includes only the instrument. Column (2) adds the displayed return and its interaction with the negative displayed-return indicator, corresponding to a local-linear regression discontinuity specification. Column (3) further controls for the 30-minute interval return and lagged retail flow. Column (4) adds time-of-day fixed effects. Column (5) retains these controls and fixed effects while excluding the first and last trading hours. The sample consists of 30-minute intervals for SPY from January 2010 to June 2025 and is restricted to observations with displayed returns within one standard deviation of zero (-0.89% to 0.89%). Standard errors are clustered by trading day. Significance levels: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

the two-stage least squares specification:

$$Flow_{t,t+1} = \alpha + \pi D_t + \beta_1 R_t^D + \beta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + \varepsilon_t, \tag{8}$$

$$Ret_{t,t+h} = \alpha + \theta_h \widehat{Flow}_{t,t+1} + \delta_1 R_t^D + \delta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + u_t, \tag{9}$$

Figure 8 plots the estimated coefficient θ_h for cumulative returns over horizons ranging from 30 minutes to 5 hours. The estimated price impact is positive throughout the horizon. The cumulative return remains statistically significant for approximately the first three hours following the initial retail flow shock. At longer horizons, the point estimates remain positive but become weaker in terms of statistical power. Overall, the evidence suggests that retail-induced price movements are not immediately reversed. Instead, the initial price impact persists for several hours, indicating that retail flow has a persistent effect on market prices rather than generating only a transitory price fluctuation.

Taken together, the first-stage and second-stage results indicate that negative displayed returns induce a discrete increase in retail demand, which subsequently translates into higher aggregate market returns. The dynamic estimates further show that this price impact persists for several hours rather than being immediately reversed. Retail investors therefore do not merely buy after market declines. Their purchases exert causal price pressure on the aggregate market, implying that households are sufficiently large and coordinated to influence short-run aggregate price formation.

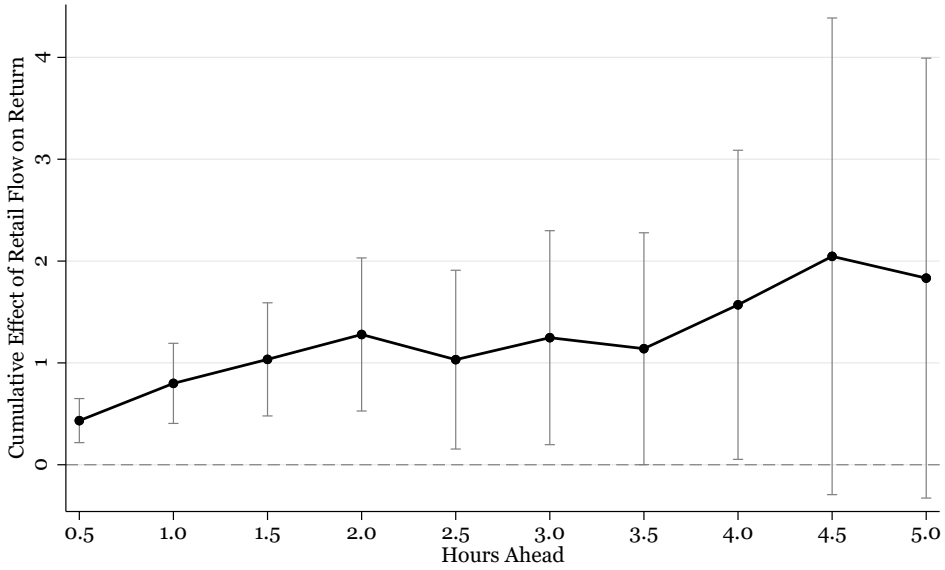
6.5 Identification Assumptions and Validity

The exclusion restriction requires that crossing the zero displayed-return threshold affects subsequent returns only through the induced change in retail flow. A violation would arise if some other determinant of future returns also changed discontinuously when the displayed return crossed zero. I consider four classes of alternative explanations.

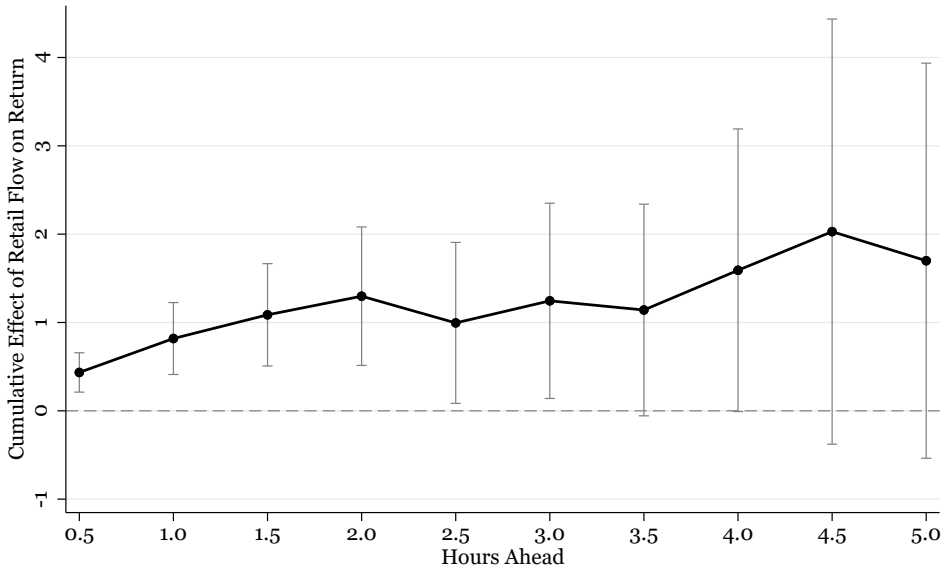
Continuity of market conditions The first requirement is that market conditions evolve smoothly around the threshold. Appendix Figure 2 examines changes in implied volatility (VIX) around zero. Market returns and volatility are strongly negatively related, so implied volatility rises as displayed returns decline. The key observation, however, is that this relationship does not change discretely at zero. Changes in the VIX remain continuous through the threshold, indicating that the discontinuity in retail order flow is not accompanied by a discontinuous change in aggregate uncertainty.

FIGURE 8: DYNAMIC PRICE IMPACT OF RETAIL FLOW

PANEL A: SPY RETURNS



PANEL B: E-MINI FUTURES RETURNS



Note: This figure plots the two-stage least squares estimates of the cumulative effect of retail order flow on market returns at horizons from 30 minutes to 3 hours. At each horizon h, the following regression system is estimated:

$$Flow_{t,t+1} = \alpha + \pi D_t + \beta_1 R_t^D + \beta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + \varepsilon_t, \tag{10}$$

$$Ret_{t,t+h} = \alpha + \theta_h \widehat{Flow}_{t,t+1} + \delta_1 R_t^D + \delta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + u_t, \tag{11}$$

$Ret_{t,t+h}$ denotes the cumulative market return from the end of interval t through the end of interval $t+h$, where $h = 1, \ldots, 6$. In Panel A, $Ret_{t,t+h}$ denotes the cumulative SPY return, while in Panel B it denotes the corresponding cumulative E-mini S&P 500 futures return. The sample consists of 30-minute intervals for SPY from January 2010 to June 2025 within a $\pm 0.89\%$ bandwidth around zero displayed returns. Error bars report 95% confidence intervals based on standard errors clustered by trading day.

Other market participants Another concern is that the estimated discontinuity reflects the trading behavior of market participants other than retail investors. One possibility is that the observed jump in retail flow simply reflects an aggregate discontinuous increase in demand for SPY, in which case retail investors would not be the source of the estimated price impact.

To examine this possibility, I first consider aggregate ETF flows. If overall demand for SPY changes discontinuously at the threshold, aggregate ETF flow should also exhibit a discontinuity. Appendix Figure 4 shows that total ETF flow evolves smoothly through the zero displayed-return threshold, indicating that the discontinuity is not driven by a market-wide shift in demand for SPY.

The discontinuity in retail flow is mechanically mirrored by an offsetting discontinuity in non-retail flow because the two series sum to aggregate ETF flow. This pattern, however, should not be interpreted as evidence that non-retail investors independently change their demand at the threshold. Retail trades are identified using the price-improvement algorithm, which classifies retail investors as trade initiators. Consequently, the corresponding change in non-retail flow reflects passive counterparties taking the opposite side of retail orders rather than an independent change in their trading behavior. The identifying variation therefore comes from retail trade initiation rather than aggregate or non-retail demand for the ETF.

A related concern is that the discontinuity is generated by sophisticated market participants, such as market makers, algorithmic traders, or option dealers dynamically hedging their positions, rather than by retail investors. Unlike retail investors, these participants base their trading decisions on continuously observed market prices and quantitative trading rules rather than the rounded returns displayed on brokerage platforms. In particular, dealer hedge adjustments are continuous functions of the underlying price and option Greeks, and therefore should not change discretely when the displayed return moves from a small gain to a small loss. Consequently, if sophisticated trading were responsible for the estimated discontinuity, a similar jump should appear when the running variable is defined using the underlying 30-minute market return. Appendix Figure 1 rejects this prediction. No discontinuity is observed when the running variable is the underlying market return, and the discontinuity appears only at the displayed-return threshold. This pattern is consistent with retail investors responding to the salience of gains and losses, rather than with trading by sophisticated market participants.

ETF market microstructure The third potential concern is that the estimated discontinuity reflects ETF-specific market microstructure rather than retail investor price impact.

One possibility is the bid-ask bounce. If a sequence of aggressive sell orders causes the last transaction in a 30-minute interval to occur at the bid, the measured ETF return may temporarily understate the efficient price. As trading activity normalizes, transaction prices naturally revert toward the midpoint of the bid-ask spread, generating a short-run return reversal. More broadly, temporary dislocations arising from ETF market making or arbitrage could also produce the discontinuous return dynamics unrelated to retail demand.

If such ETF-specific mechanisms drive the results, the discontinuity should be specific to SPY trading and therefore disappear when market returns are measured using the underlying S&P 500 index or E-mini S&P 500 futures, which trade in different market structures. To examine this possibility, I repeat the analysis using these alternative return measures (Panel B of Table 4 and Appendix Table 1). The estimated price impact remains quantitatively similar across all three return measures, suggesting that the estimated price impact reflects movements in the underlying market rather than ETF-specific microstructure.

A related concern is that crossing the zero displayed-return threshold may trigger ETF-specific arbitrage or temporary pricing inefficiencies. If so, the estimated discontinuity would reflect a temporary divergence between the ETF price and the value of the underlying market rather than genuine movements in aggregate prices. Such a mechanism has two observable implications. First, SPY should temporarily trade at a larger premium or discount relative to its net asset value. Second, SPY should temporarily diverge from other instruments tracking the same underlying index, such as E-mini S&P 500 futures. Appendix Figure 3 examines both predictions by plotting the SPY-NAV spread and the SPY-futures basis around the zero displayed-return threshold. Neither measure exhibits a discontinuity at the cutoff. If the estimated price impact were instead driven by ETF-specific arbitrage or temporary mispricing, one or both measures would be expected to jump discretely. Their smooth behavior therefore suggests that the discontinuity reflects movements in the underlying market rather than ETF-specific pricing distortions.

Firesales A remaining concern is that the estimated discontinuity reflects temporary fire sales rather than retail demand. Fire-sale pressure is expected to increase gradually as market declines become more severe, generating a nonlinear relationship between current and future returns. Under this mechanism, observations immediately below the threshold should exhibit a different local slope than observations immediately above the threshold. To examine this possibility, I allow the slope of the running variable to differ on either side of the cutoff. Table 3 shows that the estimated slope difference, β_2, is economically small and statistically insignificant. The data therefore favor a discontinuous shift in retail

demand rather than a change in the local relationship between current and future returns driven by fire sales.

Taken together, these tests support the identifying assumption that the zero displayed-return threshold affects subsequent market returns only through its effect on retail demand. Alternative explanations, including changes in market conditions, trading by other market participants, ETF-specific market microstructure, and temporary fire sales, are inconsistent with the observed discontinuity or are shown to evolve smoothly through the cutoff. The discontinuity in retail demand therefore provides plausibly exogenous variation for identifying its causal effect on short-run market returns.

6.6 Robustness to specification choices

In this section, I study the robustness of my results with respect to a variety of choices that affect the construction of the sample and implementation of analysis.

Alternative bandwidths. The baseline specification restricts the sample to observations within one standard deviation of the displayed return around the zero displayed-return threshold. To assess the sensitivity of the estimates to this choice, Table 5 reports the first and second stage results using a range of alternative bandwidths. The estimated price impact remains economically similar across all bandwidths. As expected, estimates obtained using narrower bandwidths are less precisely estimated because of the smaller number of observations, but the qualitative conclusions are unchanged.

TABLE 5: ROBUSTNESS TO ALTERNATIVE BANDWIDTH

	First Stage				Second Stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbf{1}\{\text{Displayed Return} < 0\}$	0.031***	0.030***	0.027***	0.020***				
	(0.002)	(0.002)	(0.002)	(0.003)				
$\widehat{\text{Retail Flow}}$ (t, t+1)					0.489***	0.442***	0.376***	0.352
					(0.106)	(0.115)	(0.136)	(0.216)
Displayed Return	−0.043***	−0.050***	−0.063***	−0.101***	0.038***	0.041***	0.036**	0.044
	(0.004)	(0.005)	(0.007)	(0.013)	(0.009)	(0.011)	(0.016)	(0.033)
Negative Displayed Return	−0.006	0.005	0.015*	0.039**	−0.013	−0.028***	−0.037***	−0.057**
	(0.006)	(0.007)	(0.009)	(0.017)	(0.009)	(0.010)	(0.013)	(0.022)
Return (t-1, t)	−0.029***	−0.031***	−0.035***	−0.034***	0.008	−0.001	0.002	−0.019
	(0.004)	(0.004)	(0.005)	(0.006)	(0.013)	(0.013)	(0.014)	(0.017)
Retail Flow (t-1, t)	0.084***	0.076***	0.068***	0.065***	−0.056***	−0.052***	−0.050***	−0.041*
	(0.019)	(0.019)	(0.020)	(0.023)	(0.018)	(0.018)	(0.018)	(0.021)
Window	(-1.0, 1.0)	(-0.8, 0.8)	(-0.6, 0.6)	(-0.4, 0.4)	(-1.0, 1.0)	(-0.8, 0.8)	(-0.6, 0.6)	(-0.4, 0.4)
Observations	34,790	31,709	27,506	21,450	34,790	31,709	27,506	21,450
First-Stage F-Statistic	590.80	537.29	412.56	265.95				

Notes: This table examines the robustness of the regression discontinuity estimates to the choice of bandwidth around the zero displayed-return threshold. The results are from the two-stage regression

$$Flow_{t,t+1} = \alpha + \pi D_t + \beta_1 R_t^D + \beta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + \varepsilon_t, \quad \text{(Stage 1)}$$

$$Ret_{t,t+1} = \alpha + \theta \widehat{Flow}_{t,t+1} + \delta_1 R_t^D + \delta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + u_t, \quad \text{(Stage 2)}$$

The sample consists of 30-minute intervals for SPY from January 2010 to June 2025. Each pair of columns reports the first-stage and second-stage estimates using observations within the indicated bandwidth of the displayed return. All specifications are identical to those in Table 4 except for the bandwidth. Standard errors are clustered by trading day. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Alternative market ETFs. The baseline analysis focuses on SPY, the ETF tracking the S&P 500 index. To examine whether the results generalize beyond a single market index, Table 6 repeats the analysis using the QQQ (Nasdaq 100) and IWM (Russell 2000) ETFs. The estimated price impacts are economically and statistically similar across all three ETFs, suggesting that the results reflect a broader feature of aggregate retail trading rather than an artifact of a particular ETF.

TABLE 6: ROBUSTNESS ACROSS MARKET ETFS

	First Stage			Second Stage		
	(1) SPY	(2) QQQ	(3) IWM	(4) SPY	(5) QQQ	(6) IWM
$\mathbf{1}\{\text{Displayed Return} < 0\}$	0.030***	0.023***	0.034***			
	(0.002)	(0.002)	(0.003)			
$\widehat{\text{Retail Flow}}$ (t, t+1)				0.433***	0.461**	0.362**
				(0.110)	(0.189)	(0.149)
Displayed Return	−0.048***	−0.017***	−0.031***	0.035***	0.013*	0.020**
	(0.005)	(0.003)	(0.004)	(0.010)	(0.007)	(0.009)
Negative Displayed Return	−0.001	−0.014***	−0.002	−0.017*	−0.000	0.005
	(0.007)	(0.004)	(0.006)	(0.009)	(0.010)	(0.009)
Return (t-1, t)	−0.032***	−0.014***	−0.020***	0.003	0.003	−0.004
	(0.004)	(0.003)	(0.004)	(0.013)	(0.011)	(0.011)
Retail Flow (t-1, t)	0.083***	0.104***	0.065***	−0.050***	−0.063**	−0.011
	(0.019)	(0.015)	(0.013)	(0.017)	(0.026)	(0.015)
Window	.89	1.09	1.20	.89	1.09	1.20
Observations	33,255	29,933	32,547	33,255	29,933	32,547
First-Stage F-Statistic	547.04	254.06	223.59			

Notes: This table reports the regression discontinuity estimates for three broad market ETFs. The results are from the two-stage regression

$$Flow_{t,t+1} = \alpha + \pi D_t + \beta_1 R_t^D + \beta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + \varepsilon_t, \quad \text{(Stage 1)}$$

$$Ret_{t,t+1} = \alpha + \theta \widehat{Flow}_{t,t+1} + \delta_1 R_t^D + \delta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + u_t, \quad \text{(Stage 2)}$$

The sample consists of 30-minute intervals for SPY from January 2010 to June 2025. For each ETF, the sample consists of 30-minute intervals from January 2010 to June 2025 and is restricted to observations within one standard deviation of the displayed return around the zero displayed-return threshold. All specifications are otherwise identical to those in Table 4. Standard errors are clustered by trading day. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Subsample analysis. Retail participation increased substantially over the sample period, raising the possibility that the baseline estimates are driven by a particular episode or market environment. To address this concern, Table 7 reports the estimates separately for the 2011-2015, 2016-2020, and 2021-2025 subsamples. The estimated price impact remains positive and statistically significant throughout the sample period. While the estimates of price impact become somewhat larger in the later subsamples, consistent with the growth in retail participation over time.

TABLE 7: ROBUSTNESS ACROSS SAMPLE PERIODS

	First Stage			Second Stage		
	(1) 2011–2015	(2) 2016–2020	(3) 2021–2025	(4) 2011–2015	(5) 2016–2020	(6) 2021–2025
$\mathbf{1}\{\text{Displayed Return} < 0\}$	0.027***	0.035***	0.027***			
	(0.005)	(0.003)	(0.003)			
$\widehat{\text{Retail Flow}}$ (t, t+1)				0.365*	0.298**	0.675**
				(0.212)	(0.135)	(0.272)
Displayed Return	−0.061***	−0.035***	−0.037***	0.038*	0.022**	0.049**
	(0.013)	(0.004)	(0.005)	(0.022)	(0.011)	(0.020)
Negative Displayed Return	0.010	−0.013	−0.001	−0.033**	0.001	−0.042**
	(0.016)	(0.009)	(0.008)	(0.016)	(0.016)	(0.018)
Return (t-1, t)	−0.041***	−0.033***	−0.030***	0.009	−0.022	0.015
	(0.011)	(0.007)	(0.005)	(0.023)	(0.026)	(0.023)
Retail Flow (t-1, t)	0.055*	0.113***	0.120***	−0.026	−0.048	−0.133**
	(0.028)	(0.014)	(0.023)	(0.019)	(0.030)	(0.058)
Window	0.78	0.98	0.92	0.78	0.98	0.92
Observations	10,396	11,427	9,284	10,396	11,427	9,284
First-Stage F-Statistic	166.97	267.05	207.84			

Notes: This table examines the robustness of the regression discontinuity estimates across sample periods. The results are from the two-stage regression

$$Flow_{t,t+1} = \alpha + \pi D_t + \beta_1 R_t^D + \beta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + \varepsilon_t, \quad \text{(Stage 1)}$$

$$Ret_{t,t+1} = \alpha + \theta \widehat{Flow}_{t,t+1} + \delta_1 R_t^D + \delta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + u_t, \quad \text{(Stage 2)}$$

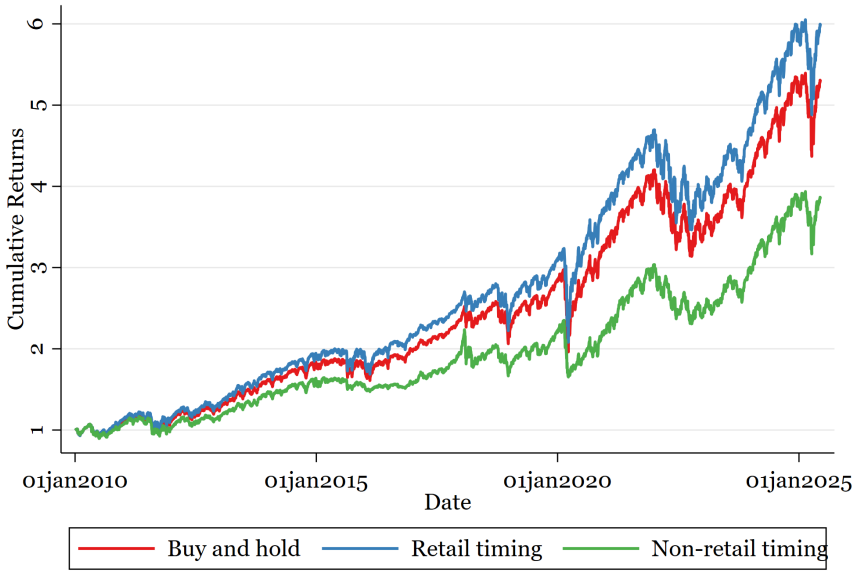
. Within each subsample, the sample is restricted to observations within one standard deviation of the displayed return around the zero displayed-return threshold. All specifications are otherwise identical to those in Table 4. Standard errors are clustered by trading day. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

7 Economic Significance

The previous section shows that retail investors systematically buy following market declines and that these purchases move prices. A natural question is whether this trading behavior is economically beneficial. To answer this question, I construct hypothetical trading strategies that adjust market exposure using observed retail and non-retail order flow. The two strategies differ only in the timing of their trades: both allocate wealth between SPY and the risk-free asset and normalize flows to have the same mean as SPY over the previous 30 trading days, ensuring that any performance differences reflect timing rather than differences in average exposure.

Figure 9 reports the cumulative returns of the retail, non-retail, and buy-and-hold strategies from 2010 to 2025. The retail strategy substantially outperforms the non-retail strategy over the sample period, generating roughly 1.5 times as much cumulative wealth. It also modestly outperforms the buy-and-hold benchmark. The difference is most pronounced during periods of market stress. During the COVID market decline, retail investors continue buying throughout the selloff and therefore participate more fully in the subsequent recovery, whereas non-retail investors reduce their exposure during the downturn and re-enter more gradually, resulting in a slower recovery.

FIGURE 9: RETAIL PERFORMANCE ACROSS INVESTMENT HORIZONS



Note: This figure plots the cumulative returns of a daily retail timing strategy and a daily buy-and-hold strategy. The retail timing strategy adjusts its daily SPY exposure based on retail dollar flows, where the portfolio weight is normalized by its trailing 252-day average, with the remaining wealth invested at the risk-free rate. All strategies are normalized to an initial value of one.

8 Conclusion

This paper asks whether retail investors affect aggregate market prices. Using high-frequency data on retail trading in the SPY ETF, I show that retail investors systematically buy aggregate market declines. Their demand is highly asymmetric, resembling the payoff of a put option: retail investors provide little additional demand during normal market conditions but purchase aggressively when markets fall. Exploiting a regression discontinuity generated by the zero-return threshold in displayed market returns, I show that these purchases have a causal impact on subsequent aggregate returns. A

one-percentage-point increase in net retail purchases raises subsequent 30-minute market returns by approximately 40 basis points. Retail investors therefore do not merely react to market movements: they move the market.

This finding has broader implications for aggregate asset pricing. The existing literature largely views retail investors as small, dispersed investors whose trades have little influence on aggregate outcomes, while emphasizing financial intermediaries and institutional investors as dominating the market and being the primary suppliers of aggregate risk-bearing capacity. The evidence in this paper suggests that this characterization has become incomplete. As retail participation has expanded, households increasingly absorb market-wide selling pressure during downturns and contribute to aggregate price formation. Understanding aggregate market dynamics therefore requires understanding not only the behavior of intermediaries, but also the behavior of households.

More broadly, the paper highlights how changes in market participants can alter the forces that determine aggregate prices. The rapid growth of direct household participation, commission-free trading, and digital investment platforms has fundamentally changed who trades the market. Whether these developments have also changed market efficiency, liquidity provision, the transmission of aggregate shocks, or the interaction between households and traditional intermediaries remains an open question. Similarly important is understanding why retail investors systematically buy market declines. Whether this behavior reflects changes in beliefs, preferences, risk tolerance, or the way investors process information is likely to be central to understanding the growing role of households in financial markets.

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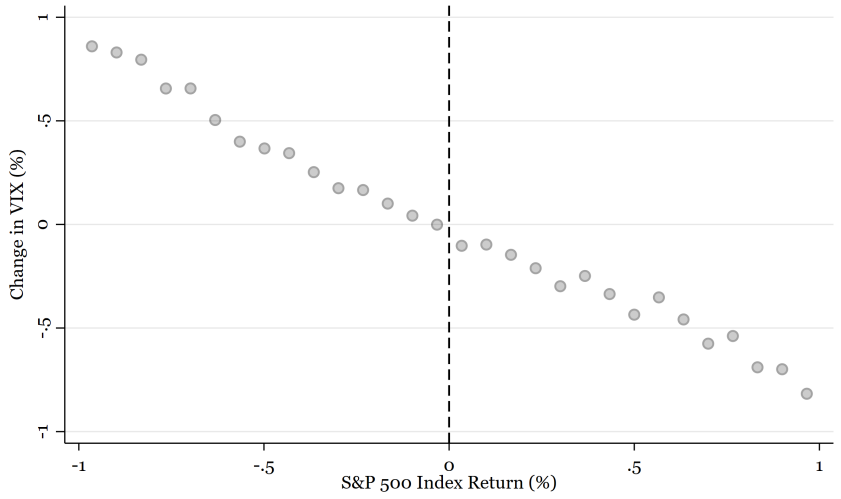
A Additional Tables and Figures

FIGURE 1: RETAIL FLOWS VS 30-MIN RETURN



Note: This figure plots retail flow in the next 30-minute interval against the S&P 500 return in the current 30-minute interval. Retail flow is measured as net retail share purchases (shares bought minus shares sold) during the interval, scaled by SPY shares outstanding at the previous trading day's close, and expressed in percentage points.

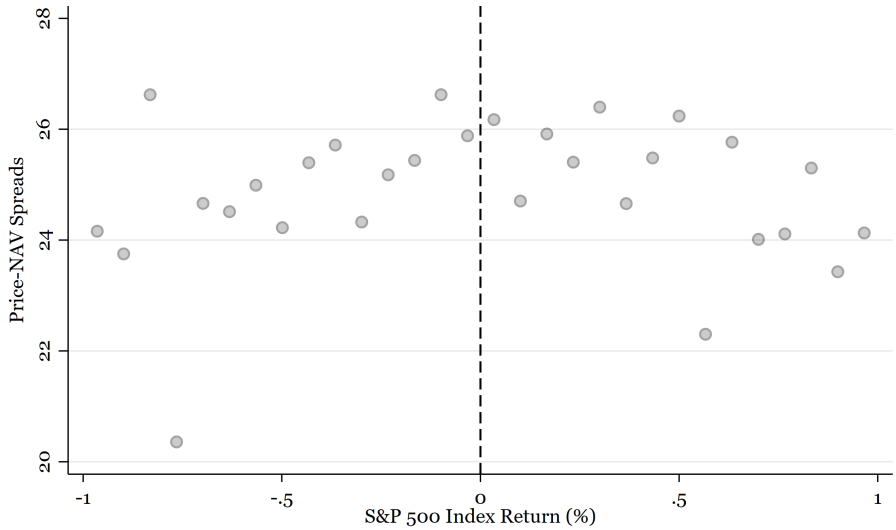
FIGURE 2: CHANGE IN VIX VS MARKET RETURN



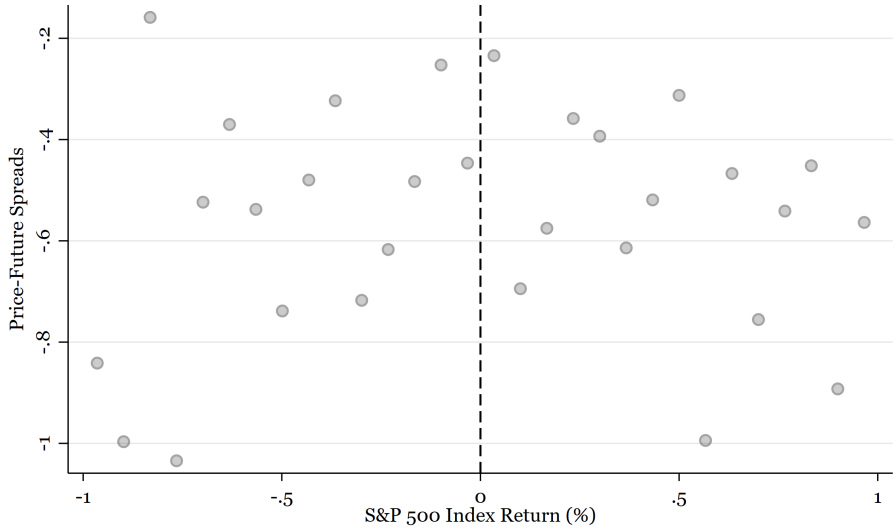
Note: This figure plots change in VIX against the S&P 500 return at the daily level.

FIGURE 3: ETF MISPRICING MEASURES VS MARKET RETURN

PANEL A: ETF PRICE - NAV



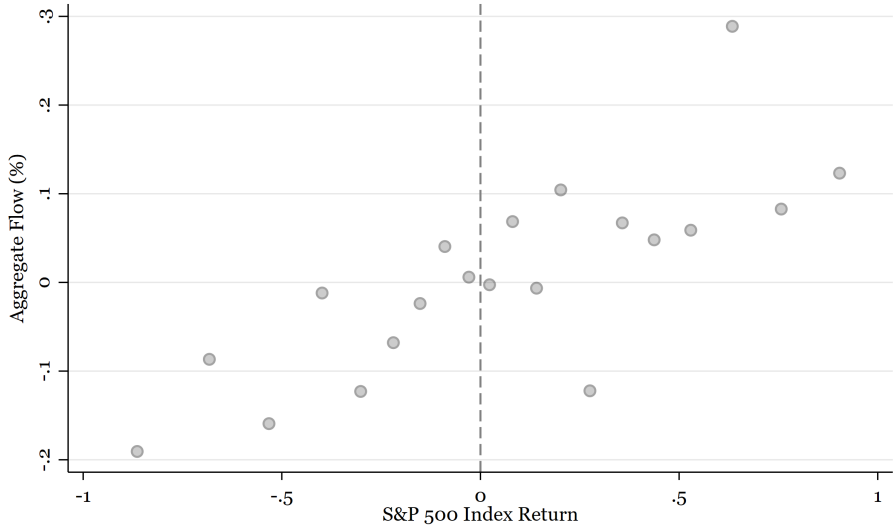
PANEL B: ETF PRICE - FUTURE PRICE



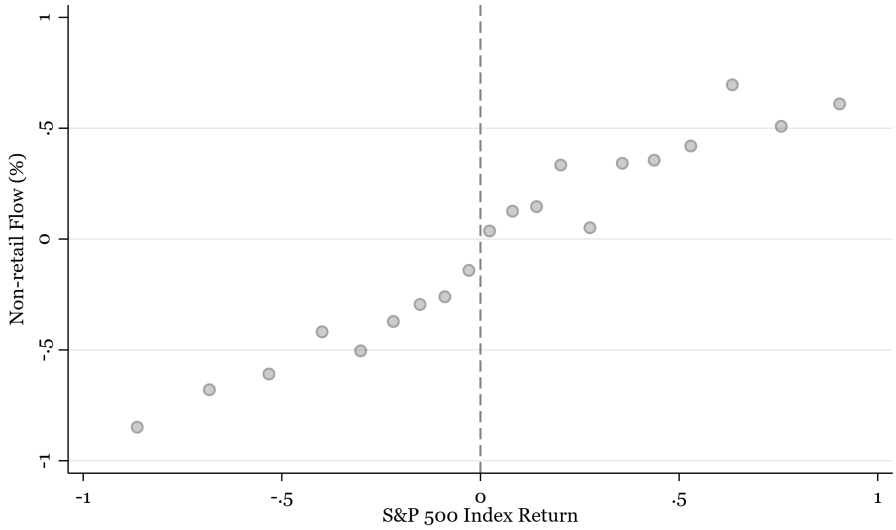
Note: Panel A plots ETF-NAV spreads against the S&P 500 return at the daily level. Panel B plots ETF-future spreads against the S&P 500 return at the daily level.

FIGURE 4: FLOWS VS MARKET RETURN

PANEL A: AGGREGATE FLOW



PANEL B: NON-RETAIL FLOW



Note: Panel A plots aggregate flow (measured with change in share outstandings) against the S&P 500 return at the daily level. Panel B plots non-retail flow (difference between aggregate and retail flows) against the S&P 500 return at the daily level.

TABLE 1: PRICE IMPACT OF RETAIL FLOW

S&P 500 index returns (t, t+1)					
	(1)	(2)	(3)	(4)	(5)
$\widehat{\text{Retail Flow}}$ (t, t+1)	0.105***	0.411***	0.417***	0.415***	0.440***
	(0.030)	(0.107)	(0.111)	(0.111)	(0.134)
Displayed Return		0.039***	0.036***	0.036***	0.035***
		(0.010)	(0.010)	(0.010)	(0.011)
Negative Displayed Return		−0.018**	−0.019*	−0.019**	−0.018*
		(0.009)	(0.010)	(0.010)	(0.010)
Return (t-1, t)			0.049***	0.048***	0.048***
			(0.013)	(0.013)	(0.014)
Retail Flow (t-1, t)			−0.051***	−0.052***	−0.041**
			(0.018)	(0.018)	(0.018)
Time-of-Day Fixed Effects	No	No	No	Yes	Yes
Exclude First and Last Hours	No	No	No	No	Yes
Observations	36,464	36,464	33,128	33,128	27,075

Notes: This table reports instrumental variables estimates of the price impact of retail flow. The estimates are obtained from the two-stage regression

$$Flow_{t,t+1} = \alpha + \pi D_t + \beta_1 R_t^D + \beta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + \varepsilon_t, \quad \text{(Stage 1)}$$

$$Ret_{t,t+1} = \alpha + \theta \widehat{Flow}_{t,t+1} + \delta_1 R_t^D + \delta_2 D_t \times R_t^D + Ret_{t-1,t} + Flow_{t-1,t} + u_t, \quad \text{(Stage 2)}$$

where R_t^D is the displayed return from the previous trading day's close through the end of 30-minute interval t, and D_t is an indicator equal to one when the displayed return is below zero. $Flow_{t,t+1}$ denotes net retail order flow during the subsequent 30-minute interval. $Ret_{t,t+1}$ denotes the S&P 500 index returns over the same interval. Column (1) includes only the instrument. Column (2) adds the displayed return and its interaction with the negative displayed-return indicator, corresponding to a local-linear regression discontinuity specification. Column (3) further controls for the contemporaneous 30-minute return and lagged retail flow. Column (4) adds time-of-day fixed effects. Column (5) retains these controls and fixed effects while excluding the first and last trading hours. The sample consists of 30-minute intervals for SPY from January 2010 to June 2025 and is restricted to observations with displayed returns within one standard deviation of zero (-0.89% to 0.89%). Standard errors are clustered by trading day. Significance levels: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.