Feedback, Flow-induced Fire Sales, and Option Returns

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Abstract

We identify a feedback loop between fire sales and equity option returns. The demand effect of fire sales induced by mutual fund extreme outflows decreases delta-hedged put option returns by 4–10% per year and increases the expensiveness by 2.5%. We address endogenous concerns using instrumental variable and difference-in-differences designs. The demand effect is more substantial under equity illiquidities than volatility, distress, sustainability risks, or short-sale constraints. Option returns also have anticipation effects on predicting fire sales, where information leakage in derivatives markets exacerbates extreme outflows.

Keywords: Fire sale, mutual funds, option, demand, feedback loop

JEL: G13, G14, G23

1 Introduction

Fire sales are so intense and widespread that they distort markets and elevate uncertainty to impair efficiency. Literature has documented a long-lasting negative effect of fire sales on financial asset prices in stock and bond markets (Coval and Stafford, 2007; Huang, Ringgenberg, and Zhang, 2019; Falato et al., 2021). Recent fire sales in financial institutions, tightly intertwined with tremendous derivatives trading, depict another perspective: Derivatives markets magnify fire sales, which induce subsequent turbulence.[1]

This paper identifies a feedback loop to illustrate the effect between fire sales and derivatives. We first provide new evidence connecting mutual fund fire-sale pressure to delta-hedged at-the-money put option returns (i.e., *demand effect*). We then show a negative relationship of option returns on subsequent levels and probabilities of fire sales (i.e., *anticipation effect*). Figure 1 illustrates the feedback loop of fire sale pressure through derivatives markets. Using the mutual fund fire-sale pressure measure *MFFlow* defined as total fractions of stock share value held by mutual funds experiencing extreme outflows (Edmans, Goldstein, and Jiang, 2012), we estimate the relationship between the *MFFlow* and puts returns from 1996 to 2018.

(Insert Figure 1 Here)

The importance of focusing on mutual fund fire sales is as follows. First, flow-induced fire sales are exogenous and uninformed. Second, most mutual funds, especially active domestic equity funds, have little exposure to derivatives (Koski and Pontiff, 2002); thus, we can ease the strategic allocation to derivatives markets which mechanically alter option returns. Third, mutual funds' leverage and margin requirements are less severe; hence, these restrictions do not directly affect the feedback

[1] The sudden implosion of Archegos Capital Management in late March 2021 and the subsequent fire sales are accompanied by options market fluctuation. For example, ViacomCBS, one of Archegos' heavily held stocks, its near-the-money put option returns decrease −32.73%. Moreover, meme stocks roared in January 2021 are fueled by colossal trading in the options market. This meme boom is followed by a heavy loss in Melvin Capital Management and the bankruptcy of White Square Capital. The bankruptcy of Long-Term Capital Management is another earlier example of hedge funds with the astronomical sum of derivative contracts and intertwining with other institutions, leading to the severe fluctuation in institutional holdings and financial markets.

loop. Derivatives markets provide a laboratory environment because first, it is debatable whether derivatives stabilize or exaggerate market fluctuation. Second, options trading is forward-looking; thus, its price reflects the arbitrageur reactions and inference on subsequent uncertainty. Lastly, using delta-hedged returns, we can alleviate the contamination of turbulent market conditions.

Options contracts are sorted into quintiles at the end of the month using univariate portfolio analysis based on the previous quarter *MFFlow*. The result reveals a negative cross-sectional relation between *MFFlow* and delta-hedged option returns using open-interest- and equal-weighted schemes. For open-interest-weighted portfolios, the average return spread between the high and low quintiles is -0.42% per month or 5.0% per year. Risk-adjusting returns with exposure to a conditional version of Carhart (1997), macroeconomic, and tail risk factors produce a spread between the extreme quintiles of -0.84% per month or -10.1% per year. Our multivariate regression method uses panel regressions with multiple fixed effects and double clusters. Coefficient estimates indicate that one standard deviation increase in *MFFlow* is associated with a reduction in weekly average option returns of two basis points, *ceteris paribus* (equivalently, -3.9% per year, and comparably, size has an annualized 0.8% effect). These results establish the demand effect that an increase in mutual fund fire-sale pressure corresponds to a lower expected option return.

To address the endogenous concerns of *MFFlow*, we employ the instrumental variable regression method by adopting two alternative fire-sale measures suggested by Wardlaw (2020). The second-stage results support our baseline evidence, suggesting that our empirical test is less biased by endogenous issues. We also investigate the mandatory portfolio disclosure as the natural experiment and apply difference-in-differences design in a three-year window around the event. Since more portfolio disclosures impose more frequent pressure from fund fire sales to the options market, we define a high-*MFFlow* dummy as those greater than the median *MFFlow*s and a post-period dummy if the month is after 2004. We find that the diff-in-diff term is negative, suggesting that higher fire-sale pressure after the policy would induce a larger demand effect on option prices, leading to even lower delta-hedged option returns.

To demonstrate alternative explanations to the demand effects of *MFFlow* on option returns, we examine risk-based and limit of arbitrage (friction-based) explanations. We take idiosyncratic volatility, credit downgrading, and sin stock dummy as the proxies for volatility, distress, and sustainability risks. The short interest rate, the Amihud illiquidity, and the option bid-ask spread measure short-sale constraints and illiquidity frictions. We find that the interaction of these alternative explanatory variables and *MFFlow* has no power to predict option returns, suggesting that fire-sale pressure affects option prices through the demand effect channel.

In addition to options returns, we investigate fund fire-sale pressure on option expensiveness. We define *expensiveness* as the spread between an at-the-month option's implied volatility and reference volatility. For simplicity, we take historical volatility, calculated using prior 365-day returns, as the reference volatility. Consistent with Garleanu, Pedersen, and Poteshman (2009), the demand effect due to fire sales significantly increases option expensiveness.

We further shed light on the anticipation effect of option returns on fund fire sales. Using OLS and logit regressions, one unit standard deviation increase in option returns is associated with 0.4% lower fire sale pressure and 0.02% less severe fire sale events. To identify the mechanism of the anticipation effect, we discuss the information leakage in derivatives and use introducing weekly options as a natural experiment. Investors have more prompt information sources when a stock has a new weekly options series in the derivatives market after 2010. The at-the-money put option contracts would have a lower anticipation effect. Due to the staggering feature of introducing weekly options, our first DID design focuses on a three-year window around 2010, when the introduction began. We define a weekly option dummy if a standard option series is accompanied by a weekly option and define a post-period dummy if the year is after 2010. Our second design constructs cohorts upon a new weekly option being introduced and select control groups using propensity score matching within the same 2-digit industry with similar βs, size, and book value-to-market value of equity ratios. Then we restrict the cohort DID specification to a

12-month window. Both DID designs support our OLS results, suggesting that the anticipation effect is essential to connect the options market to fund flows, as well as information leakage in exacerbating extreme outflow.

Lastly, we perform robustness tests of demand and anticipation effects of *MFFlow*. We verify that split sample into non-extreme market conditions based on the VIX index and market portfolio returns, high-low sentiment months, January and other months, and 5-year partitions. These subsamples do not change the main results. To address the concern that liquidity in the options market concentrates on only a few option series, we use options trading volume as a weight variable in all regressions and find that the coefficients are slightly lower but statistically indifferent and significant. We also consider mutual fund performance persistence and cash holdings. To argue that fire sale pressure does not inherit from fund performance, we focus on fire sale events in funds with persistent high abnormal returns. To identify if fire-sale pressure from cautious mutual funds with high cash holdings has little impact, we use average cash holdings from those mutual funds that hold a specific stock as a weight variable in all regressions. These alternatives do not change our main results.

The paper is related to several strands of literature. First, the recent financial crisis and collapse of financial institutions have highlighted the importance of understanding the impact of fund fire sales on the financial markets (Shleifer and Vishny, 2011).

In the equity market, Coval and Stafford (2007) show that U.S mutual funds redeem investments due to funding shocks originating from extreme outflows, and these forced redemptions significantly affect domestic equity prices. Greenwood and Thesmar (2011) argue that if a highly volatile fund holds a stock, then this stock is more fragile. The international return comovement in equity markets also inherits from flows to funds (Jotikasthira, Lundblad, and Ramadorai, 2012). In contrast to the fast-growing body of work in equity markets, relatively little empirical work measures fire-sale effects in the options market. We fill the gap in the literature by linking mutual fund fire sales to option prices. We further complement the literature by connecting fire sale and spillover effects with the anticipation effect through derivatives in a feedback loop (See, Duarte and Eisenbach (2021); Falato et al. (2021)).

Second, our paper is relevant to demand-based option pricing theory. Bollen and Whaley (2004) find that the downward sloping implied volatility depends on net public demand for a particular option series. Garleanu, Pedersen, and Poteshman (2009) demonstrate a positive relationship between net demand of dealers and option expensiveness and risk premium. Similarly, Muravyev (2016) shows demand for options and the resulting inventory risk significantly affects option prices. Chen, Joslin, and Ni (2018) also consider supply shocks to intermediary constraints. Unlike these seminal papers, we identify a demand effect on derivative prices due to fire-sale pressure in the equity market.

Third, regarding the anticipation effects of the derivative market, some studies have examined the role of derivatives markets on return prediction and corporate valuations. For example, Cao, Simin, and Xiao (2020) use the implied volatility spread between at-the-money calls and puts to predict up to six-month aggregate equity market returns. Pan and Poteshman (2006) show option volumes predict near future individual stock returns. There are also studies about the positive influence of options trading volume on Tobin's q (Roll, Schwartz, and Subrahmanyam, 2009) and corporate innovation (Blanco and Wehrheim, 2017). However, the direct implication of option returns on fire sales is rare, which is essential to understand the integration of financial markets and regulate alternative financial tools to maintain stability among financial intermediation.

Finally, our paper is related to option return predictability. Volatility significantly predicts option returns (Goyal and Saretto, 2009; Cao and Han, 2013). Cao et al. (2021) further examine the relation between option returns and a series of stock characteristics. Boyer and Vorkink (2014) find that the ex-ante skewness of an option has a significant effect on option returns. Ramachandran and Tayal (2021) connect short-sale constraints and find that option returns are higher with tighter restrictions on underlying mispriced stocks. Our paper complements this literature by addressing whether flow-induced pressure predicts option returns.

The rest of this paper is organized as follows. Section 2 describes the data and the econometric specification, Section 3 presents the main results, Section 4 reports robustness tests, and Section 5 concludes the paper.

2 Data and specification

To assess the effect of mutual fund flows on option returns, we compile data on the mutual fund holdings, option prices, and firm characteristics. This section presents the data and describes the econometric methods.

2.1 Delta-hedged option returns

The data on options are from the OptionMetrics database. The data contain information on the U.S. equity option market and includes daily closing bid and ask quotes on American options and their implied volatilities and Greeks (deltas, gammas, vegas) from January 1996 through December 2018. We use closing bid-ask midpoints as a proxy for option prices. The implied volatility and Greeks are calculated using a binomial tree model.

We filter out irregular individual put options to minimize the impact of recording errors. First, we eliminate illiquid options, including those with zero trading volumes, zero open interests, and zero implied volatilities on one particular day. Second, we restrict options with reasonable bid and ask prices. The filters include (1) the option bid price is higher than its ask price, (2) the option bid-ask spread is higher than $1/8, and (3) the option price does not violate the option valuation.[2] We retain firms listed on NYSE/AMEX/NASDAQ from 1996 to 2018 and drop financial (Standard Industry Classification (SIC) codes 6000–6999), utilities (4900–4999), and public administration firms (9000–9999). Lastly, we delete option contracts with dividend payments within a month to maturity to avoid look-ahead bias.

Following Goyal and Saretto (2009), we construct portfolios of options and their underlying stocks. Delta-hedged put positions are obtained by buying one put contract and short-selling delta shares of the underlying stock. Our delta-hedged port-

[2] We restrict put options such that strike prices are higher than option prices, and $P \geq \max(0, K - S, e^{-r_f \times T} K - S)$, where P is the put option price.

folios are held until expiration and not rebalanced during the holding period. These portfolios are formed based on information available on the first trading day (usually a Monday) immediately following the expiration Saturday or Friday of the month. To have a continuous-time series with constant maturity, we only consider options that expire next month. We then select the closest to at-the-money (ATM) contracts among these options with one month to maturity. Since it is not always possible to select options with moneyness, defined as the ratio of the strike price to the stock price, exactly equal to one, we keep options with moneyness between 0.7 and 1.3. Thus, for each stock and each month in the sample, we select the put contract closest to ATM and expire next month. After next month's expiration, we select a new put contract which is at that time closest to ATM and has one month to expiration. For each month, to get comparable delta-hedged returns, we divide monthly returns by the number of weeks before maturity. We use this weekly delta-hedged option returns (ret^{opt}) in most of our regression studies.

2.2 Mutual fund fire sale pressure

Coval and Stafford (2007) examine the return patterns of stocks sold by mutual funds with large outflows. They show that the selling behavior results in significant downward price pressure but is unrelated to firms' fundamentals and takes multiple months to reverse.

Edmans, Goldstein, and Jiang (2012) propose a measure of mutual fund fire-sale pressure to be constructed in such a way as to exclude any potential information effects implied by the act of selling by funds. They use the extreme outflows of a group of mutual funds scaled by the percentage of the mutual fund portfolio represented by each stock. They then sum the scaled flow measure over mutual funds that experience large outflows and scale the price pressure by the dollar volume of the stock over the quarter. This measure, denoted by *MFFlow*, captures the total dollar amount of each stock sold by these funds, scaled by its dollar volume if all the funds were to sell their stocks in proportion to their initial holdings.

The first component of this measure is the net dollar flow to each mutual fund in the quarter ($F_{j,q}$), which is defined as

$$F_{j,q} = TNA_{j,q} - (1 + ret_{j,q})TNA_{j,q-1}$$

Other components are the percentage of the holding value of fund j in each stock i to total net assets under management of fund j at the end of the previous quarter ($s_{i,j,q-1}$), the dollar volume of each stock over the quarter ($Dvol_{i,q}$), the shares held by each fund at the end of the last quarter ($Shares_{i,j,q-1}$), the price of the stock at the end of the last quarter ($prc_{i,q-1}$), and the total net asset under management of each fund at the end of the last quarter ($TNA_{j,q-1}$). The definition of *MFFlow* is

$$\begin{aligned} MFFlow_{i,q} &= \sum_{j=1}^{N} \frac{|F_{j,q}| \times s_{i,j,q-1}}{Dvol_{i,q}} \\ &= \sum_{j=1}^{N} \frac{|F_{j,q}| \times Shares_{i,j,q-1} \times prc_{i,q-1}}{TNA_{j,q-1} \times Dvol_{i,q}} \end{aligned} \tag{1}$$

where $s_{i,j,q-1} = \frac{Shares_{i,j,q-1} \times prc_{i,q-1}}{TNA_{j,q-1}}$ and conditional on the outflow of fund j being greater than 5% of total assets, $\frac{|F_{j,q}|}{TNA_{j,q-1}} > 5\%$. We take the summation over all mutual funds with stock i in their holding portfolios, $j = 1, \cdots, N$. $|\cdot|$ is the absolute value operator.

The measure calculates percentage holdings of each fund at the beginning of a quarter and multiplies by the flow over quarter q scaled by the dollar volume over quarter q. In the calculation, only extreme outflows ($\frac{|F|}{TNA} > 5\%$) are considered because these are the funds most likely to be forced into a "fire sale" of their holdings. Because fund flows are measured as a net change, flow $F_{j,q}$ is always negative. We take the absolute value of fund net flow; thus *MFFlow* is also consistently positive by construction. As a result, stocks with a higher value of *MFFlow* experience more significant outflow pressure and should see a more considerable fire-sale-pressure-induced decrease in stock returns over the quarter.

Figure 2 presents the cumulative abnormal stock returns around the fire-sale event window. Abnormal return is defined as the difference between stock returns and the market portfolio return. The event study window is selected following Coval and Stafford (2007); that is, 12 months before and 24 months after fire sales. The shadow area is the even period (0 to 2). It shows that abnormal returns fluctuate around zero before a fire sale and jump upon the event happens. It takes around two years for stocks to rise back to the zero level, and the returns hit bottom during the quarter after the event. The pattern is similar to Figure 2 in Edmans, Goldstein, and Jiang (2012).

(Insert Figure 2 Here)

Our mutual fund data comes from the CRSP Survivorship Bias-Free Mutual Fund Database and Thomson Reuters s12 holding files. CRSP Mutual Fund Database includes fund net returns, total net asset under management, annualized fees, investment objectives, and other fund characteristics. We merge the CRSP database with stock holdings in Thomson Reuters s12 files using MFLINKS. Our sample covers the time between 1995 and 2018. We focus on actively managed domestic equity mutual funds, for which the holdings data are complete and reliable. The sample is filtered using investment objective codes. We eliminate index funds, exchange-traded funds, balanced funds, bond funds, international funds, and sector funds. Mutual funds often have multiple share classes, which differ only in the fee structure and the target clientele. We aggregate all subclasses into a single fund using their lagged TNA. Elton, Gruber, and Blake (2001) show that the returns on small funds are biased in the CRSP database. We delete observations with end-of-month TNA smaller than $15 million. To reduce the effect of incubation bias (Evans, 2010), we also remove observations earlier than the initial offer date. We also exclude funds that hold fewer than ten stocks and delete held stocks with a price lower than $2. Lastly, we obtain stock prices, total shares outstanding, and trading volumes from CRSP monthly stock price data.

2.3 Control variables

The accounting and stock data are from Compustat and CRSP, and Cahart four factors and risk-free interest rates from Ken French's data library. We exclude firms located or incorporated outside the United States and observations with either negative or missing total assets, shareholder's equities, and the book value of equities. We further remove observations with an end-of-month stock price lower than $2.

Existing studies (see for example, Goyal and Saretto (2009); Cao and Han (2013); Cao et al. (2021)) have identified multiple stock and option characteristics that affect option returns. Following these studies, the first set of characteristics is related to the option's liquidity and volatility. *Volume/open interest* is the ratio of daily option trading volume of an option contract to total open interest for the same contract. *bid-ask spread* is computed as the difference between the closing ask and bid quotes scaled by the midpoint quote. $HV - IV$ is the difference between the option's historical volatility (HV) and implied volatility (IV). We compute HVs based on daily returns over a 365-day interval. OptionMetrics provide IVs. *Gamma* is the derivative of the option deltas to the stock price, which captures the exposure to realized volatilities, and *Vega* is the derivative of the option price to volatility, which captures the exposure to implied volatilities.

The second set includes underlying stock variables. β is estimated using the CAPM model with prior 36-month stock and market excess returns with at least 30 non-missing observations. *Size* is the natural logarithm of market capitalization of the underlying stock (in millions of dollars). *Book-to-market ratio* is the ratio of equity book value to equity market value. *12-month momentum* is the cumulative return over the past twelve months. *1/stock price* is the inverse of adjusted end-of-month stock prices. *Excess stock return* is defined as the end-of-month delisting adjusted returns minus the risk-free interest rate. *Idiosyncratic volatility* is the standard deviation of the residuals, calcuated from regressions of monthly stock returns on the Carhart (1997) four factors over the previous 36 months with non-missing 30 observations. *HHI* is the Herfindahl-Hirschman index, calculated as the 2-digit industry summation of squared firm-to-industry sales.

(Insert Table 1 Here)

Our final put option sample includes 4,506 stocks and is composed of 186,493 monthly delta-hedged put option portfolios with moneyness in range $[0.823, 1.189]$ and mean 0.995 (median 0.997). We present the mean, standard deviation, minimum, 25th percentile (P25), median (P50), 75th percentile (P75), maximum, skewness, and kurtosis for delta-hedged weekly average returns, *MFFLow* and other firm-specific attributes in Table 1.

MFFlow has a mean equal to 0.34%, implying that a hundred dollar traded in a stock contains \$0.34 fire-sale induced trading. The minimum value of is almost 0 and the maximum value is 4, indicating that there has been a sample stock for which the fire-sale induced trading consists of as much as 4% of its dollar trading volume and a stock whose induced trading is approximately zero due to its holding shares in mutual funds are low. Thus, *MFFlow* has a positively skewed and leptokurtic distribution with a skewness statistic of 4.22 and a kurtosis statistic of 24.29. The average weekly delta-hedged option return is -0.11% and its median is -0.37%. The average option has option trading volume-to-open interest of 0.62, gamma of 0.12, vega of 4.72, bid-ask spread of 0.18, and HV$-$IV being -0.66%. Underlying stock, on average, has β equal to 1.33, 4.06 billion dollars in size, book-to-market ratio being 0.39, price of \$4.76, 0.91% excess stock return, idiosyncratic volatility based on Carhart four factor model being 0.11, and Herfindahl-Hirschman index (HHI) being 0.06.

2.4 Specification

To estimate the relation between delta-hedged option returns and mutual fund flows, we consider the following baseline specification:

$$ret_{i,t}^{opt} = \alpha + \beta \text{MFFlow}_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + \xi_i + \xi_t + \varepsilon_{i,t} \tag{2}$$

where $ret_{i,t}^{opt}$ is the weekly average delta-hedged put option returns in month t, following Goyal and Saretto (2009) and defined on every third Friday with one month to maturity and moneyness close to at-the-money options. $MFFlow_{i,t-1}$ is defined as in Edmans, Goldstein, and Jiang (2012), where the extreme outflow is categorized as the absolute value of flow to the total net asset under management greater than 5%, and the selling pressure is the sum of fractions of holding values times flows to dollar value ratio of stock in all funds. Therefore, the coefficient, β, shows the impact of a mutual fund fire sale on subsequent delta-hedged option returns.

Under different specifications, $\boldsymbol{X}_{i,t-1}$ contains option and stock control variables of firm i at month $t-1$. ξ_i and ξ_t are firm and time (year-month) fixed effects. We include firm-specific dummy variables to control time-invariant, unobserved firm characteristics that impact option prices. We include time fixed effects to control for time-varying shocks that influence options. We estimate standard errors in Eq. (2) allowing for industry and time double clustering, that is, correlation in the error terms within an industry over time.

We scale all variables by their standard deviation. The advantage of this scaling is that the magnitude of the estimated coefficients is directly informative about the economic significance. By construction, a negative and significant β measures that a one standard deviation increase in outflows, because of mutual fund fire sales, negatively affect option returns.

3 Empirical results

This section estimates the effect of mutual fund fire-sale pressure on subsequent delta-hedged option returns using portfolio analysis and regressions. We apply the value of raw variables in the portfolio analysis, and we use standardized variables in regressions for each firm using a monthly window.

3.1 Demand effects: Fire-sale pressure on option returns

3.1.1 Portfolio analysis

At the end of each month, put options are sorted into quintiles based on mutual fund fire-sale pressure in the previous quarter. For each quintile-month, we calculate open interest-weighted and equal-weighted average portfolio delta-hedged returns in excess of the risk-free rate, $ret^{opt} - r_f$, as well as the difference in average returns between the extreme quintiles (H−L). Next, we calculate the time-series average return for each of the portfolios. In the portfolio analysis, we primarily use monthly option returns to match with monthly factors; the results are similar using weekly average returns in the subsequent month.

We also measure risk-adjusted returns for each portfolio as the alpha (α) from a time-series regression of portfolio excess returns on various factors. Since option payoffs inherit non-linear patterns, we include various stock and macroeconomic factors. The alternative factors include the Carhart four factors (Carhart, 1997), the conditional Carhart four factors (Ferson and Schadt, 1996), the macro-bond factors (Ludvigson and Ng, 2009), the Carhart plus left tail momentum factors (LTM, Atilgan et al. (2020)), the Carhart plus LTM and macroeconomic risk factors (Bali, Brown, and Caglayan, 2014), and the conditional version of all factors. In Appendix Table A.1, we describe definitions and sources of these factors. The Carhart four-factor model, for example, includes the market excess returns ($ret_m - r_f$), size (SMB), value (HML), and momentum (MOM) factors. We estimate time-series regressions for each quintile portfolio p and the H−L portfolio using the Carhart model, as well as the other five models listed above:

$$\begin{aligned} ret^{opt}_{p,t} - r_{f,t} \quad &= \quad \alpha_p + \beta_{mkt}(ret_{m,t} - r_{f,t}) + \beta_{smb}SMB_t + \beta_{hml}HML_t \\ &\quad + \beta_{mom}MOM_t + \varepsilon_{p,t},\ p = 1, \cdots, 5,\ \mathrm{H-L} \end{aligned} \tag{3}$$

Table 2 presents average excess returns and risk-adjusted returns for open interest-weighted (Panel A) and equal-weighted (Panel B) portfolios. We report the Newey and West (1987) t-statistics with a lag order of 12 months to account for potential autocorrelation and heteroskedasticity. In Panel A, the lowest fire-sale pressure quintile has an average excess return of -0.51% in the month following portfolio formation. The highest pressure quintile has an average excess monthly return of -0.93%. The difference in excess returns between these quintiles is -0.42% per month (-5.0% per year) and is significant at the 1% level. These results indicate that expected delta-hedged option returns are lower on average for firms experiencing high pressure than low pressure.

(Insert Table 2 Here)

The following six columns report risk-adjusted returns estimated using various factor models. After controlling for exposure to market, size, value, and momentum risk factors, the risk-adjusted return of the H$-$L spread portfolio remains economically and statistically significant: the monthly four-factor α spread is -0.33% with a t-statistic of -2.24 and the monthly conditional four-factor α spread is -0.37% with a t-statistic of -2.42. We find qualitatively similar adjusted returns in the Carhart model with the left tail momentum, and the macroeconomic risks factor. The spread is larger using the macro-bond factor model (-0.684% per month). Last, the conditional all-factors α spread between the high and low quintiles is -0.84% per month or -10.1% per year.

Table 2 Panel B reports equal-weighted portfolio results. The high quintile has an average excess return of -0.94%, and the low quintile has an average excess return of -0.50% per month. The average monthly return of the H$-$L portfolio is -0.43%. The average differences between the high and low quintiles of four-factor, conditional four-factor, and conditional all-factor αs are -0.36%, -0.41%, and -0.87% per month (-4.32%, -4.92%, and -10.4% per year). Thus, we find the results based on option interest-weighted portfolios, and those based on equal-weighted portfolios are qualitatively similar.

The results of portfolio sorting show that firms experiencing higher fire-sale pressure have lower future option returns relative to low pressure. These predictions imply that pressure is associated with lower expected returns and risk-adjusted returns. The H$-$L spreads in option interest-weighted and equal-weighted returns are economically and statistically significant, even after controlling for exposure to several sources of systematic risk. Any quintiles do not drive the return differences solely. Instead, average returns and alphas decrease almost monotonically as pressure increases across quintiles. These results suggest that demand effects due to fire-sale pressure predicts lower returns.

3.1.2 Baseline regression results

In this section, we examine the relationship between the fire-sale pressure and subsequent option returns using Eq. (2). We apply the panel regression with multiple fixed effects and double clusters (Petersen, 2009). This approach is appropriate for regression analysis because it accounts for firm-individual and time-varying effects and heteroscedasticity and autocorrelation in residuals in a given month across industries. To facilitate interpretation and comparison of estimated coefficients, we standardize all variables to a mean of zero and one standard deviation. Therefore, each coefficient can be interpreted as unit changes in option returns with one unit standard deviation of an independent variable change.

(Insert Table 3 Here)

Table 3 reports estimated coefficients, *t*-statistics (in brackets), and the adjusted R^2 for each specification. We begin with a univariate regression of option returns on *MFFlow* in Column (1). The coefficient from this regression is negative and significant at the 1% level ($\beta = -0.016$). The reported univariate coefficient estimate can be interpreted as the average return decreases associated with a one standard deviation increase in the fire-sale pressure. Columns (2) and (3) include different control variables. After controlling for option (in Column (2)) and stock (in Column (3)) characteristics, coefficients on the fire-sale pressure remain negative and statistically significant, -0.012 and -0.017 (t-statistic$= -2.29$ and -3.13). Lastly, in Column (4), we include all control variables, and the coefficient is economically and statistically significant (-0.019 with t-statistic$= -3.54$).[3]

[3] We use firm and time fixed effects with industry and time double clustering standard errors in

Concerning the control variables, the signs of the coefficient estimates generally follow past studies' findings (for example, Goyal and Saretto (2009)). Options with smaller bid-ask spread, higher gamma and vega, and higher HV$-$IV predict higher delta-hedged returns. The coefficient of volume-to-open interest ratio is insignificant. The significant coefficient estimates indicate that stocks with the lower β, larger size, higher book-to-market ratio, higher momentum, higher past stock price, lower past stock returns, and lower idiosyncratic volatility are associated with higher expected option returns. The coefficient estimates for HHI are negative but insignificant.

Because the explanatory variables are standardized, the coefficient estimates reported in Table 3 can be compared to get a sense of the relative economic importance of each of the variables in explaining next month returns. Based on the coefficient estimates in Column (4), the *Option gamma* carries the most substantial explanatory power for next month's returns. An increase of one standard deviation increases next month's return by 0.09% on average, all else equal. Increases of one standard deviation in *Option vega*, HV$-$IV, *1/stock price*, *idiosyncratic volatility*, *Size*, and *MFFlow* are associated with average cross-sectional differences in expected monthly return of 0.066%, 0.065%, -0.064%, -0.060%, 0.050%, and -0.019%, respectively, holding all other variables constant. Thus, even after controlling for several well-known return predictors, the explanatory power of the mutual fund fire-sale pressure for expected returns is still economically significant ($52 \times \left(\frac{-0.019\times 2.06}{0.57}\right) = -3.6\%$ per year), suggesting that the demand effect from fire-sale pressure is economically significant.

3.2 Endogeneity

Wardlaw (2020) argues that the standard Edmans, Goldstein, and Jiang (2012) approach to computing the outflow-induced fire-sale pressure produces a measure that is a direct function of a stock's actual realized return during the outflow quarter, which might include information on fundamentals. Thus, Wardlaw decomposes the

most of our regressions. The appendix confirms the results using (1) firm-time double clusters and (2) industry$\times$time fixed effects. We further report the Fama-MacBeth regression with Newey-West standard error adjustment results in Appendix Table A.1.

pressure variable and finds that it relates to subsequent stock returns and prices, potentially affecting option prices. We investigate the endogenous biases by two identification designs: the instrumental variable regression and the difference-in-differences design.

3.2.1 Modified mutual fund flows: Instrumental variables

To address endogeneity, we instrument the mutual fund fire-sale pressure by isolating fire sales from fundamental shocks. We apply two alternative measures proposed by Wardlaw (2020) as instruments for *MFFlow*:

$$\text{Instrument 1: Flow-to-Volume}_{i,t} = \sum_{j=1}^{N} \frac{|F_{j,t}|}{TNA_{j,t-1}} \times \frac{Shares_{i,j,t-1}}{Vol_{i,t}} \tag{4}$$

$$\text{Instrument 2: Flow-to-Shares}_{i,t} = \sum_{j=1}^{N} \frac{|F_{j,t}|}{TNA_{j,t-1}} \times \frac{Shares_{i,j,t-1}}{\text{Shares Outstanding}_{i,t}} \tag{5}$$

Empirical Design In the first-stage regression, we regress *MFFlow* on *Flow-to-volume* and *Flow-to-shares outstanding* plus control variables and fixed effects. We estimate

$$\begin{aligned} \text{MFFlow}_{i,t} &= a_0 + b_1\text{Flow-to-volume}_{i,t} + b_2\text{Flow-to-shares outstanding}_{i,t} \\ &\quad + c\boldsymbol{X}_{i,t} + \xi_i + \xi_t + \eta_{i,t} \end{aligned} \tag{6}$$

where *Flow-to-volume*$_{i,t}$ and *Flow-to-shares outstanding*$_{i,t}$ are defined in Eq. (4) and (5). $\boldsymbol{X}_{i,t}$ contains option and stock control variables of firm i at t. ξ_i and ξ_t are firm- and time-fixed effects. Standard errors are clustered at the industry and time levels. In Appendix Table A.8, we report the first-stage regression results using all specifications. There is no evidence of weak identification based on Stock-Yogo F-statistics ($p = 0.000$), and the t-statistics of instruments are larger than six (the t-statistics of Flow-to-volume is even greater than 105).

In the second-stage regression, we replace $MFFlow_{i,t-1}$ in Eq. (2) with the fitted value from the first-stage regression Eq. (6), $\widetilde{\text{MFFlow}}_{i,t-1}$, which gives us the specification:

$$ret_{i,t}^{opt} = \alpha + \beta \widetilde{\text{MFFlow}}_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + \xi_i + \xi_t + \varepsilon_{i,t} \tag{7}$$

where $\varepsilon_{i,t}$ and $\eta_{i,t}$ are assumed to be independent. The second-stage regression results are reported in Table 4 Panel A. The first column estimates the monthly instrumental variable regression of the delta-hedged puts return on the fitted *MFFlow* without any controls. In this specification, we find a negative and significant relation between the fire-sale pressure and option returns, and the coefficient is quantitatively larger than that in Column (1) of Table 3 (-0.024 and -0.016). The estimate is significant at 1% level (t-statistic $= -5.55$). Columns (2) to (4) of Table 4 contain results of specifications with different controls. The estimates are consistently negative and larger than those in OLS estimates. The coefficient for *MFFlow* with all controls in Column (4) is -0.028 (t-statistic $= -7.05$).

The IV estimates are consistently higher than those using OLS regressions. It implies that the original *MFFlow* includes current stock price and return information that leads to higher option returns. This measurement error in fire-sale pressure downward biases the OLS estimate of the treatment effect. OLS estimates are thus smaller than IV estimates. Moreover, omitted variables could be negatively correlated with the fire-sale pressure, which would also lead to a downward bias in the OLS estimate of the *MFFlow* coefficient.

Exclusion Restriction Condition The exclusion restriction requires that *Flow-to-volume* and *Flow-to shares outstanding* has no *direct* effect on subsequent delta-hedged option returns (i.e., other than through fire-sale pressures). While the exclusion restriction cannot be tested directly, its validity can be supported using out-of-sample evidence. If the exclusion restriction is violated, fire-sale pressures affect option returns through channels other than the demand channel. Such alternative channels should be apparent when exploring *Flow-to-volume* and *Flow-to-shares outstanding* outside the fire-sale pressure occasion where demand is less severe.

Therefore, we select stocks whose holding funds experience modest outflows (no less than -1%). To avoid the contamination of fire sale related stocks, we restrict " non-overlapping" stocks held only by funds with modest outflows. The assumption is that funds with near-zero outflows have little pressure on stock prices; thus, demand effects are insignificant. Using this setting as a placebo test and reporting results in Appendix Table A.9, we find that flow pressure due to the low negative fund flows do not predict significant negative put option returns.

Selection bias: Is fire-sale pressure mechanical? Mutual fund extreme outflows decrease stock prices significantly (Edmans, Goldstein, and Jiang, 2012). Stock returns plunge into negative regime upon the occurrence of fire sales (See Fig. 2). The fire-sale pressure on option returns thus might inherit selection bias from negative stock returns, rather than the demand effects as predicted by Garleanu, Pedersen, and Poteshman (2009), where end-users in derivatives demand more options and change the returns. The question is whether selection bias mechanically leads to the negative relation.

We use Heckman (1979)'s two-step correction method to address the issue, i.e., the selection step and the instrumental estimation step. The selection dummy is one if the underlying stock return is negative, and zero otherwise. Using the estimates from the selection step, we can compute the Inverse Mills Ratio, and we include it as an explanatory variable in our second-stage regression using Eq. (7). Suppose the coefficient β is negative and statistically significant, as well as quantitatively similar with estimates in Table 4. In that case, we conclude that selection bias does not drive the demand effect. In Appendix Table A.10, we document the evidence and show that the instrumental variable regression results are not influenced by selection bias. Furthermore, Appendix Table A.7 investigates the alternative that lower stock returns (or stock price) mechanically change the option returns. The insignificance of coefficients on the variable $\Psi = \{\text{stock returns, stock price}\}$ eliminate the possibility.

3.2.2 Natural experiment: Mandatory Portfolio Disclosure

In May 2004, the Investment Company Act of 1940 mandated that individual mutual funds complete and file portfolio disclosure forms (Form N-CSR and N-Q) at the end of each fiscal quarter. Mandatory disclosure of institutional investors' portfolio holdings is a crucial part of securities market regulation. SEC introduced the regulation to address concerns that lower frequent disclosures provided limited information because these disclosures were stale and could hide their investment strategies. More frequent disclosure allows investors to make informed asset allocation decisions. The regulation facilitated the monitoring of fund managers and their influence on the market by providing more information about stocks holdings. Therefore, the policy change provides a quasi-natural experiment.

Our identification design relies on the informational benefit of providing more frequent portfolio disclosures. Research has shown that portfolio disclosures contain valuable information and help infer market efficiency and corporate myopia (Agarwal, Vashishtha, and Venkatachalam, 2017). We argue that because of the elimination of opacity through more frequent portfolio disclosures, market participants can identify the stocks affected by mutual fund fire-sale pressures. They can promptly hedge against the shock by entering option contracts. Therefore, the demand for options would be higher, and the option returns would be lower.

Empirical Design The policy was introduced in May 2004. Since the SEC allows for less than 60-day delay to publish the disclosure files, we implement our regressions by skipping observations in 2004 and focusing on a three-year monthly window around 2004 (2001 to 2007). We design the difference-in-differences strategy as the interaction between higher than median *MFFlow* fund flow dummy $D(\text{MFFlow} > \text{Median})$ and the post-period dummy $D(\text{After 2004:5})$.

$$\begin{aligned} ret_{i,t}^{opt} &= \alpha + \delta D(\text{MFFlow} > \text{Median})_{i,t-1} \times D(\text{After 2004:5})_{t-1} \\ &\quad + \beta D(\text{MFFlow} > \text{Median})_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + \xi_i + \xi_t + \varepsilon_{i,t} \end{aligned} \tag{8}$$

(Insert Table 4 Here)

Results are reported in Table 4 Panel B. The fifth column estimates the difference-in-differences regression of the delta-hedged return on *MFFlow* without any controls. We identity a negative and significant relation between the option returns and the intersection of the dummy of *MFFlow* begin higher than its median and the post mandatory disclosure period dummy, which can be interpreted as 4.2 basis points lower in returns after the policy change (equivalently, $52 \times \left(\frac{-0.042 \times 2.06}{0.57}\right) = -7.9\%$ per year), more than doubled the effect using the OLS estimation in Table 3 (i.e., -0.019 or -3.6% per year). The coefficient on *MFFlow* is marginally similar to that in Column (1) of Table 3 (-0.018 and -0.016). The estimate is significant at 1% level (t-statistic$= -3.13$). Columns (2) to (4) of Table 4 contain results of specifications with different controls. The estimates are consistently negative and similar to those in OLS estimates. The results suggest that given a shock that provides more information and frequency about fire sales, derivatives react more severely.

Placebo test Agarwal, Vashishtha, and Venkatachalam (2017) investigate the 1985 inverse policy shock as a placebo test. However, due to the data restriction, we cannot trace back equity option returns beyond 1996. Instead, we randomly assign the mandatory portfolio disclosure policy shock to different years. The assumption is that other years than 2004 would have no shock on fire sales and there would be no result of the demand effect.

We select three pseudo policy years: (1) 1999, five years before 2004, (2) 2009, five after 2004, and (3) 2014, ten years after 2004. Then we report the difference-in-differences estimates within a 3-year window corresponding to each of the above three pseudo policy years. Table A.11 shows the results and implies that none of these placebo tests have significant coefficients on the diff-in-diff term. Thus, the disclosure frequency change is an exogenous quasi-natural experiment setting.

Falsification test: Parallel and reversal The investigation on parallel trend assumption and reversal effects after the pressure has three implications. First, it is essential for identification since diff-in-diff estimators attribute any differences in trends between treated and control firms that coincide with the fire-sale pressure to option return changes. So if treated and control groups started on different trends, our estimates could be biased. Second, a significantly persistent estimate suggests a robust demand effect in the treatment group which will not diminish or reverse shortly. Third, we need to verify if option returns significantly decrease after, not before, the fire-sale pressure. It provides evidence that this relation is not due to investors who can time the demand effect; thus, we can isolate the confounding effects by deteriorating firm, fund, or market conditions (omitted variables).

Appendix Figure A.1 illustrates the test results. First, the coefficients in the month before the mandatory portfolio disclosure are not statistically significant ($t = 0.59$, $t = -1.24$, and $t = 0.37$ for three months before the event month). It means that pre-trends do not differ significantly between treated and control groups. Second, additional leading dummies test for possible post-shock reversals. Over the next four months, coefficients are insignificantly positive at first (2004:6) and statistically significant and negative in the following months. Four months after the disclosure, option return is 0.26% lower relative to control firms, which is statistically significant ($p = 0.00$). It indicates that the diff-in-diff estimate is persistent.

3.3 Alternative explanations

In this subsection, we investigate two potential alternative explanations to the negative relationship between fire-sale pressures and option returns: risk-based and friction-based channels. We include an interaction term between mutual fund fire-sale pressure and an explanatory variable Φ. If the coefficient on this interaction term is significant, then the demand effect may coincide or undermine the alternative explanations.

3.3.1 Risks: Volatility, distress, and sustainability

The evidence that option returns are more sensitive to fire-sale pressure could arise if a stock has different risk exposures. This explanation is reminiscent of the empirical option returns literature that argues that the volatility and distress risk significantly affect option returns (Bakshi and Kapadia, 2003; Goyal and Saretto, 2009; Cao and Han, 2013; Vasquez and Xiao, 2020; Cao et al., 2021).

First, the story developed in our paper potentially generates return predictability in options due to the changes in risks or uncertainties, rather than experiencing fire-sale pressure. We try to isolate risks of volatilities or distresses. Volatility risk is the dummy that equals one if idiosyncratic volatility is higher than the cross-sectional median, $\Phi = D(IVOL \geq Med)$. We define the idiosyncratic volatility as the standard deviation of the residuals of the Carhart four-factor model using 36-month delisting adjusted stock returns with a minimum of 30 observations. Distress risk is the dummy that equals one if a firm's credit rating is downgraded, $\Phi = D(\text{Downgrade})$. We collect the firm's credit rating information from the S&P credit rating database. We identify the risk explanations by interacting mutual fund fire-sale pressure with risk measures. If the demand effect is inherited from risks, the estimated coefficient of the interaction term is significant; thus, the risk-based explanation dominates the demand effect of fire-sale pressures. The results are provided in the first two columns of Table 5; that is, the coefficients of $MFFlow \times \Phi$ are insignificant.[4] Notably, higher volatility risk hurts delta-hedged put option returns ($\beta_2 = -0.045$ with $t = -5.32$), implying that higher volatility would further boost prices but lower returns. The negative coefficients of *MFFlow* are consistent with the demand effect. Yet, the higher probability of credit downgrading has a marginally significant positive effect on returns ($\beta_2 = 0.015$ with $t = 1.74$).

Second, institutional investors seek to incorporate environmental, social, and governance (ESG) into their investment process. Sustainability considerations lower expected returns because investors enjoy holding ESG assets to hedge climate risk.

[4] The results are similar if we use the raw idiosyncratic volatility.

However, these assets outperform when positive shocks hit the ESG factor (Hong and Kacperczyk, 2009; Pástor, Stambaugh, and Taylor, 2020). Therefore, firms focusing on ESG could survive mutual fund fire sales, and the marginal effect on option prices could be limited. To isolate the ESG risk effect, we include the sin stock dummy, which equals one if a firm produces alcohol, tobacco, and gaming and zero otherwise. We concentrate on the interaction between mutual fund pressure and the sin stock dummy. The hypothesis is that if ESG risk explains the demand effect of fire-sale pressure on option returns, the interaction should yield a significantly positive coefficient, and the fire sale pressure should become insignificant. We report the results of the sin stock dummy in the third column of Table 5. The ESG risk does not change the mutual fund fire-sale pressure estimate, similar to the volatility and distress risks. The *MFFlow* has quantitatively the same coefficient as in Table 3, and the interaction is insignificant. Moreover, the sin stock dummy has almost no effect on option returns, suggesting either mutual funds hold little sin stocks in their portfolios, as documented in Hong and Kacperczyk (2009), or options of sin stocks seldom respond to unexpected shocks from mutual funds.

3.3.2 Frictions: Short-sale constraints and liquidity

Another potential reason that delta-hedged put option returns are responsive to mutual fund fire-sale pressure is relevant to market frictions. In this subsection, we discuss two possible frictions.

First, Ramachandran and Tayal (2021) find that delta-hedged put option returns are sensitive to the short-sale constraints in stocks; particularly, average put option returns are negative and monotonically decreasing in constraint measures. To isolate the effect of short-sale constraints, we define short interest rate (*SII*) as the ratio between the monthly short interest to the total shares outstanding, where a higher *SII* implies lower short constraints. We define a constraint indicator $D(SII \leq Med)$ that equals one if *SII* is smaller than the cross-sectional median and zero otherwise. If short friction is essential to explain the demand effect, the interaction between fire-sale pressure and the short constraint dummy would be significantly negative. The results are in the fourth column of Table 5; that is, $MFFlow \times \Phi$ are insignificant ($t = 0.05$). Consistent with Ramachandran and Tayal (2021), the short constraint dummy has a significantly negative estimate ($\beta_2 = -0.032$ with $t = -3.86$).

Second, liquidity is an important determinant of asset prices, especially in the options market, where liquidity concentrates in large-size stocks. Therefore, we consider two liquidity measures in both stocks and options markets. The first one is the Amihud illiquidity measure (Amihud, 2002), which captures how illiquid stock is based on its price impact:

$$illiq_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D_t} \frac{|ret^{stock}_{i,d,t}|}{DVol_{i,d,t}}$$

where $illiq_{i,t}$ is the Amihud illiquidity measure of stock i in the month t, $ret^{stock}_{i,d,t}$ is the daily delisting adjusted stock return of stock i on date d in the month t, $DVol_{i,d,t}$ is the dollar value of stock i on date d in the month t, and D_t is the total number of trading days in the month t. The second is the options market liquidity, defined as the bid-ask spread scaled by their midpoint using daily closing quote bid and ask prices of options contracts used to construct the delta-hedged portfolio:

$$Spread^{opt}_{i,t} = \frac{\text{Bid price}_{i,t} - \text{Ask price}_{i,t}}{\text{Midpoint of bid and ask prices}_{i,t}}$$

The last two columns of Table 5 document the estimated coefficients on the interaction of liquidity friction measures and the fire-sale pressure. Notably, only the Amihud illiquidity interaction has a significantly positive estimate, implying that given the fire-sale pressure, if the underlying stock is less liquidity, that is, higher Amihud illiquidity, investors will yield higher option returns. If we consider the partial effect of the pressure, which is captured by $\frac{\partial ret^{opt}}{\partial MFFlow} = \beta_1 + \delta \times \Phi$, then one percent standard deviation increase in the Amihud illiquidity would yield a net effect on option return of -0.016% ($= -0.031 + 0.015$). However, options market illiquidity does not have a significant effect on this interaction ($t = 0.67$).

(Insert Table 5 Here)

In a word, alternative explanations based on risks and frictions do not significantly explain the relationship between mutual fund fire-sale pressure and option returns.

3.4 Demand Effects: Fire-sale pressure on option expensiveness

Bollen and Whaley (2004) demonstrate that changes in implied volatility correlate with signed option volume. Garleanu, Pedersen, and Poteshman (2009) use unique option trading data to identify the net demand in index and equity stocks options from aggregate positions of dealers and end-users. They discuss whether option demand affects the overall level (i.e., expensiveness) of option prices.

We complement these studies by investigating the relationship between the demand induced by mutual fund fire-sale pressure and the implied volatility. Following Garleanu, Pedersen, and Poteshman (2009), we define the equity option expensiveness as the difference between the implied volatility and reference volatility, in which we use historical volatility.

$$expensive_{i,t}^{opt} \quad = \quad \alpha + \beta \text{MFFlow}_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + \xi_i + \xi_t + \varepsilon_{i,t} \tag{9}$$

where $expensive_{i,t}^{opt}$ is the difference between implied volatility and historical volatility during the past 365 days. $MFFlow$ and $\boldsymbol{X}$ are defined as in Eq. (2), except that we drop HV$-$IV from $\boldsymbol{X}$ because it is almost the same as *expensiveness* according to their definition. We include firm and time fixed effects and calculate standard errors clustering by industry and time levels.

Table 6 Columns (1) to (4) report the expensiveness results. We begin with a univariate regression of option expensiveness on *MFFlow* in Column (1). The coefficient of this regression is positive and significant at 1% level (t-statistic $= 6.30$). The estimate indicates that one standard deviation increase in *MFFlow* predict 0.03% higher expensiveness (equivalently, $12 \times \left(\frac{0.031 \times 13.69}{2.06}\right) = 2.47\%$ per year). Columns (2) and (3) include different control variables. After controlling for option (in Column (2)) and stock (in Column (3)) characteristics, the coefficients on the fire-sale pressure remains positive and statistically significant, 0.034 and 0.027 (t-statistic $= 6.67$ and 5.93).

The economic significance of fire-sale pressure in Columns (2) and (3) is similar to the univariate regression result.

Lastly, in Column (4), we include all control variables, and the coefficient is economically and statistically significant (0.041 with t-statistics 7.50). Based on the coefficient estimates in Column (4), *Option gamma* carries the most substantial explanatory power for the next month option expensiveness and is marginally larger than the coefficient of *MFFlow*. Thus, after controlling for several well-known return predictors, the explanatory power of the mutual fund fire-sale pressure on the expensiveness is still economically significant, suggesting that the demand effect from fire-sale pressure strongly influences the equity stock option expensiveness.

(Insert Table 6 Here)

Garleanu, Pedersen, and Poteshman (2009) further discuss that the net demand effect is more substantial among more actively traded options, measured by the options trading volume. Nevertheless, mutual fund-initiated pressure is orthogonal to derivatives by construction; thus, the marginal effect of the pressure on high trading volume options might be insignificant. We include an interaction of *MFFlow* and trading volume:

$$expensive_{i,t}^{opt} = \alpha + \beta \text{MFFlow}_{i,t-1} + \delta \text{MFFlow}_{i,t-1} \times Vol_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + \xi_i + \xi_t + \varepsilon_{i,t}$$

where $Vol_{i,t-1}$ is the individual option i's trading volume at time t. The coefficient of interest is δ on the interaction term between *MFFlow* and Vol, which measures the marginal effect of the activeness in options trading on the demand effect. We also include firm and time fixed effects and report the t-statistics calculated using the clustered standard errors at the industry and time levels.

Table 6 Columns (5) to (7) document the coefficients of trading volume. The estimate of the interaction term is consistently insignificant. This finding supports the hypothesis that the demand effect does not react to trading activeness. However, the coefficients of trading volume are positive and significant at 1% because greater option activity should positively correlate with more capital running to option marketmaking and a smaller price impact per unit of options demand.

In Appendix Table A.3, we document the robustness tests, including (1) firm-time double clustering, (2) time-varying industry fixed effects, (3) instrumental variable regression using *Flow-to-volume* and *Flow-to-shares outstanding*, and (4) Fama-MacBeth regression results.

3.5 Anticipation effects: From options to mutual fund fire-sales

This subsection attempts to estimate the anticipation effect – the impact of delta-hedged put option returns on the mutual fund fire-sale pressure.

3.5.1 OLS and logit results

We regress subsequent fire-sale pressure on delta-hedged put option returns, option, and firm-specific control variables, and a set of firm and time fixed effects to investigate the feedback effects. Therefore, we identify the effect of option returns on fire-sale pressure levels and probabilities. The specification is:

$$\begin{aligned} &\text{OLS: MFFlow}_{i,t} = \alpha + \beta ret^{opt}_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + \xi_i + \xi_t + \varepsilon_{i,t} \\ &\text{logit: } D(MFFlow \geq Median)_{i,t} = \delta_0 + \delta_1 ret^{opt}_{i,t-1} + \delta \mathbf{X}_{i,t-1} + \xi_t + \eta_{i,t} \end{aligned} \tag{10}$$

where $MFFlow_{i,t}$ is defined as in Edmans, Goldstein, and Jiang (2012), the selling pressure is categorized as the absolute value of flow to the total net asset under management greater than 5%. $ret^{opt}_{i,t-1}$ is the weekly average delta-hedged option returns, defined as Goyal and Saretto (2009) on every third Friday with one month to maturity and moneyness close to at-the-money options. Therefore, the coefficient, β, shows the impact of delta-hedged option returns on subsequent mutual fund fire sales. $\boldsymbol{X}_{i,t-1}$ contains all option and stock control variables of firm i at $t-1$. ξ_i and ξ_t are firm and time fixed effects, respectively. We include firm-specific dummy variables to control time-invariant, unobserved firm characteristics that impact options prices. Time-fixed effects control for time-varying shocks that influence options. We allow for industry and time double clustering of standard errors, allowing for correlation in the error terms within an industry over time.

We further define a dummy variable, where $D(MFFlow \geq Median)_{i,t} = 1$ if the fire sale is higher than the cross-sectional median in time t and zero otherwise. In the logit regression, we include time-fixed effects and cluster the standard error at the firm level. The marginal effects are evaluated at the median of independent variables, and we calculate standard errors using the delta method. Lastly, to account for multiple comparisons, we adjust p-values based on the upper limits of the Bonferroni inequality.

Since fire sale is of quarterly frequency and the option return is monthly, in addition to the monthly frequency regression as in previous sections, we also examine Eq. (10) at a quarterly frequency. We use the same fire sale each month within a quarter for the monthly regression, and we use average independent variables in the quarterly regression.

(Insert Table 7 Here)

Table 7 quantifies the extent to which option returns affect mutual fund fire sales, with the left panel being OLS regression evidence and the right panel reporting marginal effects of the logit regression. One unit increase in option returns will decrease the level of a flow-induced fire sale by 0.46% per month in Column (1) without controls (equivalently, $12 \times \frac{0.459 \times 0.57}{2.06} = 1.5\%$ per year). The effect is stronger with all stock and option control variables (i.e., 0.659% per month given one unit increase in option returns, or 2.2% per year). The probability of a stock confronted with higher than the median fire sale events is higher, i.e., 0.1%–0.3% higher. In Panel B, we report the quarterly frequency results, and they are like the monthly evidence.

Other untabulated variables generate signs consistent with the literature; for example, a firm with a higher β, larger market capitalization, lower book-to-market ratios, and lower idiosyncratic volatilities would suffer lower fire sale pressure. We conclude that worse option returns are associated with severe fund outflows and generate higher fire sales. Next, we discuss the source of this anticipation effect and provide a reasonable explanation to complete the feedback loop between derivatives markets and mutual fund flow-induced fire sales.

3.5.2 Connection to theories: Mechanism of anticipation effects

There has been a long history of discussion about what causes and amplifies fire sales. The literature identifies three main channels: limits of arbitrage (Shleifer and Vishny, 1997; Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2008), adverse selection (Malherbe, 2014; Dow and Han, 2018; Kuong, 2021), and information constraints. Krishnamurthy (2010) emphasizes information amplifiers through opacity, complexity, and uncertainty. New shocks imply market participants have a short time to formulate valuation, risk management, and hedging models, leading to information leakage in the market.

However, the information channel and the importance of derivatives in fire sales are less discussed. Barbon et al. (2019) find fire sales are exaggerated by information leakage through brokers who intermediate large portfolio liquidation trading. In terms of derivatives, Biais, Heider, and Hoerova (2021) find that the information constrained-efficiency works in risk-management subject to incentive constraints. The reason is that those who will be hurt in a fire sale can write an insurance contract with those who benefit in a fire sale. Therefore, derivatives provide information concerning fire sales.

Besides collateral and balance sheet information from firms and intermediaries, investors can directly gather market public and forward-looking information from derivatives markets. Whenever they identify potential negative signals to the market, they would precautiously reallocate their capital, such as redeeming mutual fund shares. Therefore, information leakage between derivatives and mutual fund investors contributes to the anticipation effects, which completes the feedback loop.

3.5.3 The source of anticipation effects: Information leakage

Derivatives market movement being associated with worse fire sales inherits from information leakage. We identify the causal relationship between options returns and fire sale pressures by exploiting the introduction of weekly options as a positive shock to a firm's information environment.

The Chicago Board Options Exchange (CBOE) introduced the weekly options for individual stocks in 2010.[5] These weekly options are distinguished from traditional options in terms of shorter maturities with more prompt information (Andersen, Fusari, and Todorov, 2017; Oikonomou et al., 2019). The introduction is a quasi-natural experiment because the exchange selects individual equities to issue weekly options, and the decisions on which firms to include were staggered over time. We expect that the introduction of weekly options improves the information environment; thus, the information leakage of derivatives would be limited.

We propose two continuous difference-in-differences designs. First, we define the treatment group as firms that introduced weekly options after 2010 within a three-year window (i.e., our identification strategy applies 2007–2013). We label this design as *DID*. The specification therefore is:

$$\begin{aligned}\text{MFFlow}_{i,t} &= \alpha + \delta ret^{opt}_{i,t-1} \times D(\text{Weekly options})_{i,t-1} + \beta_1 ret^{opt}_{i,t-1} \\ &\quad + \beta_2 D(\text{Weekly options})_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + \xi_i + \xi_t + \varepsilon_{i,t} \qquad (11)\end{aligned}$$

where $D(\text{Weekly options})_{i,t-1}$ is the dummy of firm introducing weekly options. $ret^{opt}_{i,t-1}$ is the weekly average delta-hedged option returns. The continuous diff-in-diff term is the interaction between the option return $ret^{opt}_{i,t-1}$ and the weekly option dummy $D(\text{Weekly options})_{i,t-1}$; thus, the coefficient of interest is δ, which captures the effect of changes in the information environment on derivatives and fire sale pressure. We expect $\delta > 0$ if introducing weekly options provides more forward-looking information to investors such that the information leakage is alleviated. $\boldsymbol{X}_{i,t-1}$ contains all option and stock control variables of firm i at $t-1$. ξ_i and ξ_t are firm and time-fixed

[5] CBOE first introduced weekly options based on indexes (SPX, XSP, OEX, and XEO) in October 2005, which are one-week options as opposed to traditional options that have a life of months or years before expiration. From June 25 to July 5, 2010, CBOE introduced weekly options based on individual equities (GLD, XLF, EEM, C, BAC, AAPL, BP, F, and GOOG). Since 2010, weekly options have grown sharply, with premium and risk strategies driving demand. Weekly expirations accounted for 28% of total volume in 2017, a 5-year compound average growth rate of nearly 18%. There are 526 stocks with weekly expirations (11% of the total) representing a range of index, ETF, and single stock instruments.

effects, respectively. We allow for industry and time double clustering of standard errors.

Table 8 Panel A reports the *DID* results. We find that, on average, firm-level fire sale pressure is higher after introducing weekly options. The estimates without controls, reported in column (1), indicate that, after the introduction, treated firms experience fire sale pressure by an average of 0.65% more than control firms, given one unit weekly average option returns (equivalently, $12 \times \frac{0.648 \times 0.57}{2.06} = 2.15\%$ per year). The treatment effect is robust under different specifications in Columns (2) to (4) with various control variables. It shows that after introducing weekly options, investors can gather more prompt information through derivatives markets by observing option returns. They can better predict whether they should redeem shares in funds or adjust their portfolio weights in equities. Hence, the natural experiment provides information leakage in the anticipation effect, which helps complete the feedback loop. We can also conclude that derivatives markets play an essential role in affecting fire sales in the financial market.

Delta-hedged returns have consistently adverse effects on subsequent fire sales. However, the introduction of weekly option dummy insignificantly affects fire sales, suggesting that the information in short-term options mainly diffuses through market trading rather than the financial instruments themselves.

(Insert Table 8 Here)

Second, due to the staggered introduction of weekly options, we apply a difference-in-differences design in cohorts. For each introduction event after 2010 (until 2018), we construct a cohort of treated and control firms using firm-time observations for the twelve months before and the twelve months after each introduction. That is, we construct the cohort in a twelve-month window for each event. Hence, firms within a cohort are relatively comparable. Firms are not required to be in the sample for the entire two years around each event. We match each of these firms with a control firm in the same 2-digit SIC industry using a propensity score matching approach that matches the β, market capitalization, and book-to-market ratio. The matching process yields a sample of 338 unique pairs of treated and control firms. We then pool the data across cohorts, i.e., across all new introductions, and estimate the average treatment effect. We label this design as *Cohort*. The specification is

$$\begin{aligned}
\text{MFFlow}_{i,c,t} &= \alpha + \delta ret^{opt}_{i,t-1} \times D(\text{Weekly options})_{i,t-1} + \beta_1 ret^{opt}_{i,t-1} \\
&\quad + \beta_2 D(\text{Weekly options})_{i,t-1} + \gamma \mathbf{X}_{i,t-1} \\
&\quad + \xi_i \times \xi_c + \xi_t \times \xi_c + \eta_{i,c,t} \qquad (12)
\end{aligned}$$

We include firm-cohort fixed effects, $\xi_i \times \xi_c$, and time-cohort fixed effects, $\xi_t \times \xi_c$. The firm- and time-fixed effects varying by cohort are more conservative than simple fixed effects. We further weight the regression using propensity matching scores. Finally, to account for potential covariance among outcomes within the same industry and over time, we cluster the standard errors at the industry and date level.

The estimates in Panel B of Table 8 show that the introduction of short-term options still has a positive effect on subsequent higher fire sale pressures. When we zoom in on comparable pairs of treated and control firms, the treatment effect is relatively immune to firm heterogeneity and industry confounding factors. The results are more substantial in Column (5), i.e., given one unit option return, the fire sale pressure would be 9.15% more severe after the introduction of weekly options. The results are robust if we add stock and option characteristics control variables in Columns (6) to (8). Like the DID design results, delta-hedged option returns predict significantly lower fire sales, and the introduction dummy has an insignificant effect. Lastly, the results imply conservative fixed effects have a marginal impact on our main results, suggesting that the information leakage contributes to the anticipation effect.

In conclusion, we complete the feedback loop by examining the introduction of weekly options to investigate the information leakage in the anticipation effect.

4 Robustness tests

This section analyzes the robustness of demand and anticipation effects under alternative sample conditions, trading liquidity, and mutual fund features.

4.1 Subsamples

Fire sales are typically related to the downside market (Shleifer and Vishny, 2011). Thus, we examine whether our results hold under normal economic conditions. We also consider the impact of investor sentiment and anomalies seasonality. Lastly, to address the time-varying concerns, we partition the sample into successive five-year subsamples. In all subsample tests, we include firm and industry$\times$month (time-varying industry) fixed effects and cluster standard errors at the firm and date levels such that our estimates are even more robust and conservative than main results.

Exclude extreme VIX change The first subsample excludes all months with significant changes in the VIX index, defined as differences in VIX of higher than 90 percentile over time. This filter removes about 10% of the sample.

We exclude extreme VIX change months to restrict significant market movement effect to investors' demand. The aim is to alleviate macroeconomic confounding factors that affect firm fundamentals (e.g., financing constraints) and mutual fund investment opportunities (e.g., funding liquidity).

We find that the demand effect in this restricted sample is -0.02%, comparable to the baseline results (-0.019%). The magnitude of instrumental variable regression coefficients on *MFFlow* is also not appreciably affected (-0.026 vs. -0.028). Similarly, the anticipation effect yields quantitatively indifferent results with those in non-restrictive sample estimates (-0.698 vs. -0.655). If anything, the coefficient of expensiveness test is lower after excluding the months of large changes in VIX (0.022 vs. 0.041).

Exclude extreme market moves We also restrict the sample in the months without extremely large or small market returns, i.e., top and bottom ten percentiles. Thus, we eliminate not only the downside market, which might coincide with fire sales, but also the extreme upside market when investors can actively reallocate their capital and place unexpected buying and selling pressures on mutual funds. The results are similar to baseline evidence and also the VIX subsample.

Investor sentiment Investors' behavioral bias towards options with low underlying prices is more substantial when the overall sentiment in the markets is high. Han (2007) finds that S&P 500 index option volatility smile is steeper, and the risk-neutral skewness of monthly index return is more negative when market sentiment becomes more bearish. We split the sample by higher and lower than the median of sentiment index, which is the aligned investor sentiment proposed by Huang et al. (2014). We find that both demand and anticipation effects are of similar estimated coefficients in the low sentiment sample. The demand effect on returns is lower in the high sentiment sample, yet the options are more expensive when confronted with fire-sale pressures in the high sentiment months. Nevertheless, the demand effect of option returns remains highly significant in times of high market sentiment as well. Moreover, the anticipation effect is not significant in the high sentiment sample, suggesting that mutual funds experience no fire sales directly related to option return changes.

(Insert Table 9 Here)

Turn-of-the-year effect Small stocks tend to outperform in January (Reinganum, 1983) and stock anomalies are more likely to concentrate in January rather than other months. Therefore, we separate the sample into January and the other months. The evidence in Table 9 Columns (5) and (6) reveal some differences in option returns in January versus non-January months. For example, OLS regressions in Panel A show that non-January observations on average have a lower demand effect than January observations. However, the difference is not statistically significant (F-statistics $=$ 1.16 with p-value $=$ 0.29). Similarly, the difference between January and non-January estimates in the anticipation effect is statistically indifferent (F-statistics $= 2.93$ with p-value $= 0.10$). The differences in instrumental variable regression and expensiveness regression are significant (F-statistics $= 3.17$ with p-value $= 0.09$ and F-statistics $= 8.86$ with p-value $= 0.01$), implying that option trading in January tends to more sensitive to demand effects.

Subperiods: Expansions and recessions Lastly, we arbitrarily split the entire sample into five-year stratifications. We find similar significant results across these subperiods and recessions in the sample 1996–2001 and 2007–2012.

4.2 Trading volumes in option market: Liquidity effects

The option market is less liquid than equity and Treasury bond markets; thus, whether fire-sale information could promptly spread among investors is unclear. Due to low liquidity, demand and anticipation effects might mechanically raise from delayed market movement, rather than a reaction to fire-sale pressure. Current analysis uses an equal-weighted scheme and assign more emphasis to non-liquid options, which biases the results by incorporating unobservable market frictions.

Therefore, we consider the trading volume as a weight variable in all regressions. The aim is to assign higher weights to liquid options and identify demand and anticipation effects using more liquid options with efficient information diffusion. We select trading volume as a weight variable for simplicity, and the results are similar and significant if we use open interest. If liquidity drives demand and anticipation effects, we expect the estimates in all analyses are lower, since these illiquid options have less importance; otherwise, our results are robust. We also include firm and industry$\times$month (time-varying industry) fixed effects and cluster standard errors at the firm and date levels, which are more conservative than our main specifications.

Panel A in Table 10 reports the weighted regression results. The estimates are relatively larger than baseline coefficients. For example, in Column (2), the OLS demand effect coefficient is -0.023, more prominent than that in the baseline regression (-0.019). The instrumental variable regression with trading volume as weight also yields higher coefficients (-0.034 vs. -0.028). Similarly, we find that the anticipation effect is more substantial (-0.956 vs. -0.655). The robustness tests illustrate stronger estimates, even though these differences are insignificant (F-statistics$\leq$ 1). Expensiveness has a lower demand effect (0.014 vs. 0.041). It suggests that liquid options are better at incorporating market information and adjusting their implied volatilities relative to the references. In a word, liquidity does not drive our main results.

(Insert Table 10 Here)

4.3 Mutual fund characteristics

4.3.1 Mutual fund persistence

High abnormal performance attracts subsequent fund inflows (for example, Coval and Stafford (2007)). Fire sales hence occur with lower probability and have less impact on the market. Therefore, demand and anticipation effects might be diminishing with persistent mutual fund performance.

We analyze whether persistent outperformed mutual fund fire-sale pressure has no demand and anticipation effects. We first calculate mutual fund monthly Carhart (1997) four-factor αs using prior 36-month excess returns with at least 30 non-missing observations. Then, we select funds whose αs are in the top two quintiles for successively three months (a quarter). Lastly, we calculate the fire-sale pressure measure using these outperformed mutual funds.

Panel B in Table 10 shows the results. We include firm and time-varying industry fixed effects and cluster standard errors at the firm and date levels. Demand effect and anticipation effect are still significant, though the magnitudes are smaller. For example, the OLS estimate of demand effect with all controls in Column (2) is -0.011 (t-statistics=-2.25), lower in economic and statistical levels than baseline results in Table 3 (-0.019, t-statistics=-3.54). This evidence suggests that fire-sale pressure has a more negligible demand effect on option prices when a mutual fund has persistent outperformance. Nevertheless, the results are statistically significant.

4.3.2 Fund cash holdings

Mutual funds can take actions to prevent the effect of fire-sale pressures by holding more cash in their portfolios. Cash holdings also allow managers to make quick investments in attractive stocks without costly fire sales. Cash holdings allow mutual funds to reduce the damage from fire sales by directly providing liquidity before redemption or portfolio rebalancing, especially with unexpected shock to non-fundamental firm values.

Mutual funds with higher cash holding exert better managerial skills (Simutin, 2013). We expect fire sales do not affect stocks if high-cash-holding funds hold them; thus, demand effects and anticipation effects are less significant. We analyze how average cash holding in mutual funds would affect their stock performance in the derivative market.

We first take an average of the percentage invested in cash for each mutual fund that holds a particular firm in our sample. If a fund does not report its cash holdings in its portfolio, we delete this observation directly, which reduces 21% observations. Then, we assign the average cash as a weight for each firm-option observation in the regression analysis, providing that firms held by higher cash holding funds weigh higher. Panel C in Table 10 shows the results. Firm and time-varying industry fixed effects are included and standard errors are clustered at the firm and date levels. We find that other things equal, the coefficient is very similar between the cash-weight estimation and baseline results. Therefore, cash holdings in mutual funds do not affect our results.

5 Conclusion

The paper identifies a feedback loop and studies the demand and anticipation effects of mutual fund fire-sale pressure and option prices. Using both portfolio analysis and regression methods, we identify a demand effect of mutual fund fire sale pressures on the equity option returns, which decreases delta-hedged put option returns by

4–10% per year. Demand effects due to extreme mutual fund flows also increase the expensiveness by 2.5% per year. We find that equity illiquidity contributes to the negative relation between mutual fund fire-sale pressure and option returns; yet, risks like stock idiosyncratic volatilities, distress risk due to the credit downgrading, and sustainability risks, i.e., whether a stock belongs to a sin stock category, cannot explain the effect. Moreover, short-sale constraints cannot explain the demand effect in fire sales.

To migrate the endogeneity issue, we apply the instrumental variable and difference-in-differences designs. Using two alternative exogenous fire-sale pressure measures suggested by Wardlaw (2020) as the instrumental variables, we find that the results are robust and the effect is quantitatively similar. We also employ the mandatory portfolio disclosure in May 2004 as a natural experiment and investigate the demand effect. We find that with more frequent informational disclosure, the demand effect of fire-sale pressure on delta-hedged put option returns is stronger.

Lastly, we investigate the anticipation effect from put option returns on the level of fire-sale pressure, i.e., 1 unit increase in delta-hedged put option returns is associated with 0.4% higher subsequent fire-sale pressure. Using the introduction of weekly options after 2010, which represents higher level of information flow in the market, the difference-in-differences results suggest information leakage in exacerbating extreme outflows.

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Figure 1

Amplified fire sales through derivatives markets in a feedback loop.

The figure illustrates that initial fire sale pressure (negatively) affects prices in derivatives markets. The changes in derivative prices further cast (negative) effects on subsequent fire sales, which finalizes a feedback loop. Demand and anticipation effects are presented by two anecdotal examples: (1) *Demand effect*: ViacomCBS held by Archegos Capital Management after its meltdown in March 2021, and (2) *Anticipation effect*: the bankruptcy of White Square Capital due to the turbulence of the option-fueled Gamestop in June 2021. The positive feedback loop is accomplished when both demand and anticipation effects have same impact directions.

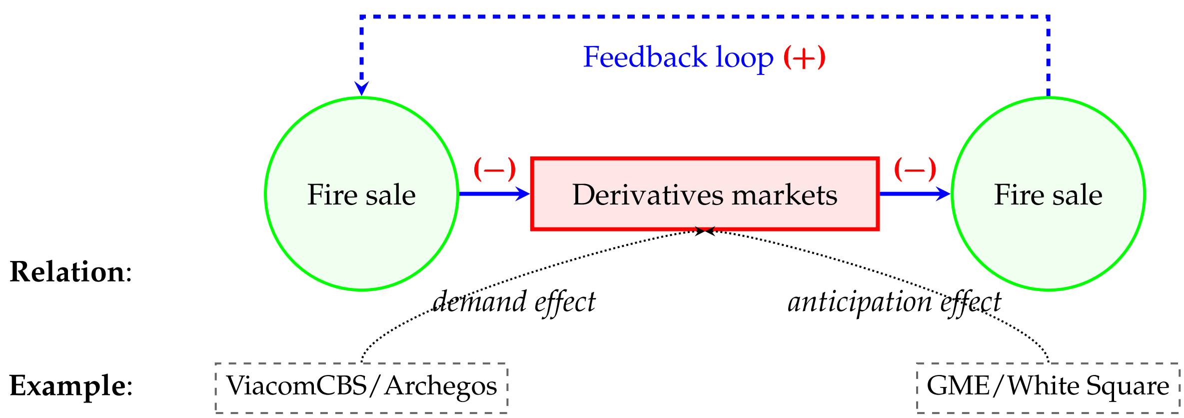

Figure 2
Cumulative stock returns around mutual fund fire-sale pressure.
The figure shows the monthly cumulative market adjusted stock returns around mutual fund fire-sale pressure. We construct the pressure following Edmans, Goldstein, and Jiang (2012) and the gray area represents the fire-sale window. The sample period is 1996:01 to 2018:12.

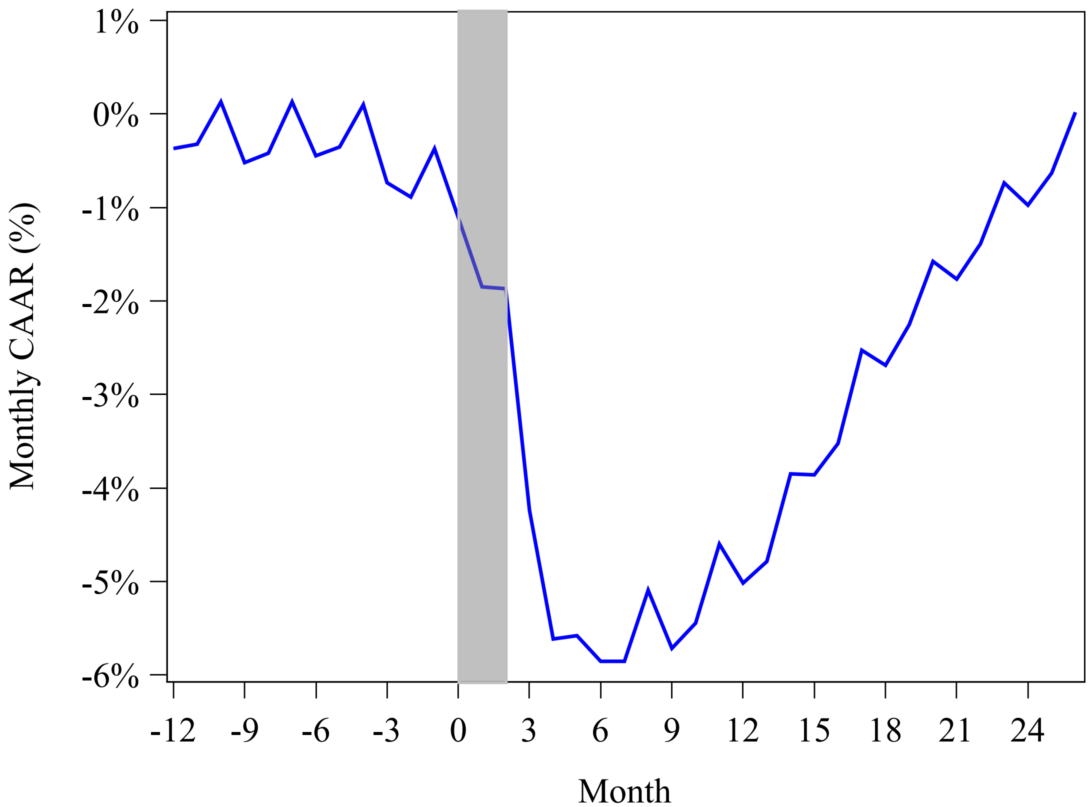

Table 1. Summary Statistics.

The table reports summary statistics of key variables in the paper, including means (Mean), standard deviations (Std), quartiles (P25, P50, and P75), minimum and maximum (Min and Max), skewness (Skew), and kurtosis (Kurt). The table summarizes the dependent variable, delta-hedged weekly returns (%), defined as Goyal and Saretto (2009) on every third Friday with one month to maturity and moneyness close to at-the-money put options, and then take the weekly average. The key independent variable is *MFFlow*, defined as in Edmans, Goldstein, and Jiang (2012), where the fire-sale pressure is categorized as the absolute value of flow to the total net asset under management greater than 5%. We include the following option characteristics: option moneyness (*Moneyness*) defined as the ratio between strike price and underlying stock prices, options trading volume-to-option interest ratio (*Volume/option interest*), gamma, vega, options bid-and-ask spread scaled by the midpoint of the closing quoted bid and ask prices (*Option bid-ask spread*), and historical volatility calculated using 365 days minus implied volatility ($HV-IV$). Underlying stock characteristics include market beta calculated using prior 36-month excess stock returns (β), natural logarithm of market capitalization ($ million, *Size*), firm book value of equity to market value of equity ratio (*Book-to-market ratio*), long-term momentum using cumulative stock returns from $t-1$ to $t-12$ (*12-month momentum*), inverse of stock price (*1/stock price*), *excess stock returns*, idiosyncratic volatility calculated as hte standard deviation of residuals using 36-month prior excess stock returns in the Carhart (1997) four-factor model (*idiosyncratic volatility*), and Herfindahl-Hirschman index (*HHI*) based on industry concentration based on sales. See Appendix Table A.2 for variable definitions. The sample consists of all NYSE/AMEX/NASDAQ common stocks with stock prices greater than $2 at the end of each month. We also require liquid options contracts with non-zero trading volume, open interest, and implied volatility, and option prices satisfy the pricing boundary. The sample period is 1996:1 through 2018:12.

	Mean	Std	Min	P25	P50	P75	Max	Skew	Kurt
Delta-hedged weekly returns (%)	-0.11	2.06	-4.81	-1.21	-0.37	0.60	9.87	1.63	8.59
MFFlow (%)	0.34	0.57	0.00	0.05	0.16	0.37	4.00	4.22	24.29
Moneyness	1.00	0.05	0.82	0.97	1.00	1.02	1.19	0.22	5.43
Volume/open interest	0.62	1.84	0.00	0.04	0.14	0.45	15.00	6.08	43.58
Option gamma	0.12	0.09	0.01	0.06	0.10	0.15	0.50	1.87	7.41
Option vega	4.72	4.27	0.36	2.01	3.61	5.98	29.41	2.68	13.19
Option bid-ask spread	0.18	0.19	0.01	0.07	0.12	0.21	1.20	2.88	13.17
HV−IV (%)	-0.66	13.69	-54.45	-6.61	-0.50	5.16	46.97	-0.16	6.33
β	1.33	0.84	-0.22	0.76	1.20	1.76	4.12	0.92	4.04
Size	8.31	1.73	3.71	7.11	8.24	9.50	12.38	0.03	2.83
Book-to-market ratio	0.39	0.32	-0.30	0.19	0.32	0.53	1.76	1.54	6.64
12-month momentum	0.21	0.61	-0.75	-0.14	0.11	0.39	3.43	2.25	11.07
Idiosyncratic volatility	0.11	0.06	0.03	0.06	0.09	0.13	0.31	1.24	4.50
1/stock price	0.04	0.04	0.00	0.02	0.03	0.05	0.25	2.60	11.26
Excess stock returns	0.01	0.13	-0.37	-0.06	0.01	0.07	0.48	0.33	4.89
HHI	0.06	0.06	0.02	0.03	0.04	0.07	0.37	2.88	12.30

Table 2. Univariate sorting on delta-hedged put returns by *MFFlow*.
The table presents the univariate sorting on delta-hedged put returns (% monthly) by mutual fund fire-sale pressure, constructed following Edmans, Goldstein, and Jiang (2012). Panel A reports open interest weighted portfolio excess returns and risk-adjusted returns, and equal-weighted results are in Panel B. Column (1) reports raw excess returns, defined as the difference between delta-hedged puts returns and risk-free interest rate. Columns (2) and (3) report unconditional and conditional Carhart (1997) four-factor model αs. Column (4) uses Ludvigson and Ng (2009) macro bond factors, including eight factors plus cubic in the first factor formed from a large macro dataset, estimated using the principal components analysis (PCA). Columns (5) and (6) add left tail momentum, LTM (Atilgan et al., 2020), and macroeconomic risk index, Macro (Bali, Brown, and Caglayan, 2014). Column (7) includes all conditional Carhart factors, macro bond factors, left tail momentum, and macroeconomic risk index. See Appendix Table A.1 for factor definitions and sources. "Low" and "High" contain underlying put options experiencing relatively low and high mutual fund pressures. "H−L" is the portfolio spread between high- and low-pressure groups. The standard errors are adjusted based on Newey and West (1987) with 12 lags, and we report t-statistics in the bracket under coefficients. *, **, *** represent 10%, 5%, and 1% significance levels, respectively. The sample is from 1996:01 to 2018:12.

	(1) Excess Return	(2) Carhart	(3) Conditional Carhart	(4) Bond Macro	(5) Carhart +LTM	(6) Carhart+LTM +Macro	(7) Conditional ALL
			Panel A: Open interest-weighted Portfolio				
Low	-0.508***	-0.531***	-0.562***	-0.360	-0.472**	-0.451**	-0.611***
	[-2.90]	[-3.14]	[-2.85]	[-1.60]	[-2.57]	[-2.43]	[-2.71]
2	-0.490***	-0.527***	-0.492***	-0.409**	-0.449***	-0.425**	-0.716***
	[-2.94]	[-3.22]	[-2.63]	[-1.97]	[-2.61]	[-2.54]	[-3.22]
3	-0.539***	-0.540***	-0.562***	-0.523***	-0.502***	-0.480***	-0.901***
	[-3.45]	[-3.39]	[-3.10]	[-3.06]	[-2.83]	[-2.72]	[-5.70]
4	-0.766***	-0.730***	-0.757***	-0.819***	-0.685***	-0.661***	-1.147***
	[-4.72]	[-4.41]	[-4.13]	[-3.79]	[-3.65]	[-3.52]	[-5.03]
High	-0.925***	-0.863***	-0.927***	-1.044***	-0.787***	-0.768***	-1.448***
	[-4.95]	[-4.53]	[-4.79]	[-4.74]	[-3.49]	[-3.35]	[-6.38]
H−L	-0.416***	-0.333**	-0.365**	-0.684***	-0.315*	-0.317*	-0.837***
	[-2.61]	[-2.24]	[-2.42]	[-3.52]	[-1.86]	[-1.90]	[-3.90]
			Panel B: Equal-weighted Portfolio				
Low	-0.504***	-0.524***	-0.546***	-0.336	-0.456**	-0.434**	-0.570***
	[-2.90]	[-3.16]	[-2.81]	[-1.55]	[-2.56]	[-2.40]	[-2.64]
2	-0.464***	-0.498***	-0.461**	-0.361*	-0.424**	-0.400**	-0.650***
	[-2.77]	[-3.06]	[-2.46]	[-1.75]	[-2.48]	[-2.42]	[-2.95]
3	-0.505***	-0.503***	-0.528***	-0.499***	-0.461**	-0.440**	-0.874***
	[-3.18]	[-3.11]	[-2.86]	[-2.81]	[-2.54]	[-2.41]	[-5.16]
4	-0.735***	-0.694***	-0.718***	-0.769***	-0.647***	-0.624***	-1.091***
	[-4.66]	[-4.34]	[-4.01]	[-3.63]	[-3.61]	[-3.46]	[-4.88]
High	-0.936***	-0.883***	-0.954***	-1.036***	-0.813***	-0.794***	-1.435***
	[-5.17]	[-4.76]	[-5.08]	[-4.84]	[-3.75]	[-3.61]	[-6.67]
H−L	-0.432***	-0.359**	-0.408***	-0.700***	-0.357**	-0.360**	-0.865***
	[-2.79]	[-2.48]	[-2.87]	[-3.73]	[-2.22]	[-2.27]	[-4.32]

Table 3. Mutual fund fire-sale pressure and put option delta-hedged returns: Demand effects.
The table presents the effects of the fire-sale pressure from mutual fund flows on the put option delta-hedged returns using the double-clustered panel regression:

$$ret_{i,t}^{opt} = \alpha + \beta MFFlow_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + \xi_i + \xi_t + \varepsilon_{i,t}$$

where $ret_{i,t}^{opt}$ is the weekly average delta-hedged put option returns, defined as Goyal and Saretto (2009) on every third Friday with one month to maturity and moneyness close to at-the-money put options. $MFFlow_{i,t-1}$ is defined as in Edmans, Goldstein, and Jiang (2012), where the fire-sale pressure is categorized as the absolute value of flow to total net asset under management greater than 5%. $\boldsymbol{X}$ includes option and stock characteristics. See Appendix Table A.2 for definitions. All variables are winsorized at 1% level and standardized to have mean zero and standard deviation one. All regressions include firm (ξ_i) and month (ξ_t) fixed effects and the standard errors are clustered at industry and date levels, and we report t-statistics in the bracket under coefficients. *, **, *** represent 10%, 5%, and 1% significance levels, respectively. The sample is from 1996:01 to 2018:12.

	(1)	(2)	(3)	(4)
MFFlow	-0.016***	-0.012**	-0.017***	-0.019***
	[-2.74]	[-2.29]	[-3.13]	[-3.54]
β			-0.015**	-0.014*
			[-2.11]	[-1.91]
Size			0.118***	0.050**
			[6.13]	[2.09]
Book-to-market ratio			0.012**	0.011**
			[2.40]	[2.24]
12-month momentum			0.016**	0.017**
			[2.08]	[2.16]
1/stock price			-0.006	-0.064***
			[-0.40]	[-3.45]
Excess stock returns			-0.007	-0.012**
			[-1.44]	[-2.45]
Idiosyncratic volatility			-0.049***	-0.060***
			[-5.27]	[-6.76]
HHI			-0.007	-0.009
			[-0.83]	[-0.93]
Volume/open interest		-0.001		-0.001
		[-0.31]		[-0.64]
Option bid-ask spread		-0.023***		-0.018***
		[-4.84]		[-3.83]
Option gamma		0.041***		0.091***
		[5.04]		[7.88]
Option vega		0.093***		0.066***
		[8.43]		[5.86]
HV−IV		0.065***		0.065***
		[7.05]		[7.33]
Constant	-0.006***	-0.005***	-0.011***	-0.009***
	[-497.44]	[-7.87]	[-10.15]	[-5.72]
N	186,127	186,127	186,127	186,127
Adj. R^2	0.099	0.105	0.102	0.108

Table 4. Mutual fund fire-sale pressure and put option delta-hedged returns: Endogeneity.

The table addresses the endogenenity concerns of the fire-sale pressure from mutual fund flows on the put option delta-hedged returns using the instrumental variable method and the difference-in-differences design with the double-clustered panel regressions. The instrumental variable method uses two instruments, *Flow-to-volume* and *Flow-to-Shares outstanding*, and the two-stage least square regressions are:

$$\text{2nd: } ret^{opt}_{i,t} = \alpha + \beta \widetilde{MFFlow}_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + \xi_i + \xi_t + \varepsilon_{i,t}$$

$$\begin{aligned}\text{1st: } MFFlow_{i,t-1} = a_0 + b_1 \text{Flow-to-volume}_{i,t-1} + b_2 \text{Flow-to-shares outstanding}_{i,t-1} \\ + c\mathbf{X}_{i,t-1} + \xi_i + \xi_t + \eta_{i,t}\end{aligned}$$

where $\widetilde{MFFlow}_{i,t-1}$ is the first-stage fitted value. The sample is from 1996:01 to 2018:12. The difference-in-differences design is based on a three-year window around the mandatory portfolio disclosure in May 2004:

$$\begin{aligned}ret^{opt}_{i,t} = \alpha + \delta D(MFFlow > \text{Median})_{i,t-1} \times D(\text{After 2004:5})_{t-1} + \beta D(MFFlow > \text{Median})_{i,t-1} \\ + \gamma \mathbf{X}_{i,t-1} + \xi_i + \xi_t + \varepsilon_{i,t}\end{aligned}$$

where the dummy $D(\text{After 2004:5})_{t-1}$ is one if the month is after May 2004 and is zero otherwise. Discrete treatment dummy $D(MFFlow > \text{Median})_{i,t-1}$ is one if *MFFlow* is higher than sample median and zero otherwise. The diff-in-diff term is $D(MFFlow > \text{Median}) \times D(\text{After 2004:5})$. The sample is from 2001:01 to 2007:12 without year 2004. $ret^{opt}_{i,t}$ is the monthly delta-hedged option returns, defined as Goyal and Saretto (2009) on every third Friday with one month to maturity and moneyness close to at-the-money put options. $MFFlow_{i,t-1}$ is defined as in Edmans, Goldstein, and Jiang (2012), where the fire-sale pressure is categorized as the absolute value of flow to total net asset under management greater than 5%. $\boldsymbol{X}$ includes option and stock characteristics. See Appendix Table A.2 for definitions. All variables are winsorized at 1% level and standardized to have mean zero and standard deviation one. The regression includes firm (ξ_i) and month (ξ_t) fixed effects and the standard errors are clustered at industry and date levels, and we report *t*-statistics in the bracket under coefficients. *, **, *** represent 10%, 5%, and 1% significance levels, respectively.

	Panel A Instrumental variables				Panel B Difference-in-differences			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MFFlow	-0.024***	-0.022***	-0.025***	-0.028***	-0.018***	-0.010*	-0.015**	-0.014**
	[-5.55]	[-5.43]	[-6.35]	[-7.05]	[-3.13]	[-1.70]	[-2.55]	[-2.15]
D(*MFFlow*>Median)					-0.042**	-0.030*	-0.031*	-0.030*
×D(After 2004:5)					[-2.51]	[-1.86]	[-1.92]	[-1.76]
D(*MFFlow*>Median)					-0.006	-0.002	-0.021	-0.018
					[-0.43]	[-0.13]	[-1.55]	[-1.24]
Stock controls	NO	NO	YES	YES	NO	NO	YES	YES
Option controls	NO	YES	NO	YES	NO	YES	NO	YES
N	186,127	186,127	186,127	186,127	53,147	53,147	53,147	53,147
Adj. R^2	0.000	0.007	0.004	0.011	0.083	0.096	0.092	0.102

Table 5. Mutual fund fire-sale pressure and put option delta-hedged returns: Alternative explanations.

The table presents alternative explanations to the effects of the fire-sale pressure from mutual fund flows on the put option delta-hedged returns using the double-clustered panel regression:

$$ret^{opt}_{i,t} = \alpha + \delta MFFlow_{i,t-1} \times \Phi_{i,t-1} + \beta_1 MFFlow_{i,t-1} + \beta_2 \Phi_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + \xi_i + \xi_t + \varepsilon_{i,t}$$

where the alternative explanatory channel variable $\Phi_{i,t-1}$ includes (1) risks, i.e., volatility risks (higher than the median idiosyncratic risk dummy $D(IVOL \geq Med)$), distress risks (credit downgrading dummy $D(Downgrade)$), and ESG risks (sin stock dummy *D(Sin stock)*), and (2) frictions, i.e., short-sale constraints (lower than the median short interest rate $D(SII \leq Med)$), stock illiquidity (higher than the median Amihud illiquidity $D(Liq \geq Med)$), and option illiquidity (higher than the median bid-ask spread $D(Spd \geq Med)$). $ret^{opt}_{i,t}$ is the monthly delta-hedged option returns, defined as Goyal and Saretto (2009) on every third Friday with one month to maturity and moneyness close to at-the-money put options. $MFFlow_{i,t-1}$ is defined as in Edmans, Goldstein, and Jiang (2012), where the fire-sale pressure is categorized as the absolute value of flow to total net asset under management greater than 5%. $\boldsymbol{X}$ includes all option and stock characteristics and all regressions contain these control variables. See Appendix Table A.2 for definitions. All variables are winsorized at 1% level and standardized to have mean zero and standard deviation one. All regressions include firm (ξ_i) and month (ξ_t) fixed effects and the standard errors are clustered at industry and date levels, and we report t-statistics in the bracket under coefficients. *, **, *** represent 10%, 5%, and 1% significance levels, respectively. The sample is from 1996:01 to 2018:12.

	(1)	(2)	(3)	(4)	(5)	(6)
$\Phi =$	D(IVOL≥Med)	D(Downgrade)	D(Sin stock)	D(SII≤Med)	D(Illiq≥Med)	D(Spd≥Med)
MFFlow	-0.019***	-0.019***	-0.019***	-0.018***	-0.031***	-0.022***
	[-3.35]	[-3.77]	[-3.56]	[-3.11]	[-5.74]	[-4.10]
$MFFlow \times \Phi$	0.003	0.006	0.007	0.000	0.015***	0.004
	[0.63]	[0.65]	[0.36]	[0.05]	[3.02]	[0.67]
Φ	-0.045***	0.015*	0.000	-0.032***	0.030***	-0.018**
	[-5.32]	[1.74]	[0.00]	[-3.86]	[3.06]	[-2.11]
N	186,127	186,127	186,127	186,127	186,127	186,127
Adj. R^2	0.108	0.108	0.108	0.109	0.108	0.108

Table 6. Mutual fund fire-sale pressure and put option expensiveness.
The table presents the effects of the fire-sale pressure from mutual fund flows on the put option excess-implied expensiveness using the double-clustered panel regression:

$$expensive^{opt}_{i,t} = \alpha + \beta MFFlow_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + \xi_i + \xi_t + \varepsilon_{i,t}$$

where $expensive^{opt}_{i,t}$ is the monthly difference between put option implied volatility and historical volatility, defined in Garleanu, Pedersen, and Poteshman (2009). $MFFlow_{i,t-1}$ is defined as in Edmans, Goldstein, and Jiang (2012), where the fire-sale pressure is categorized as the absolute value of flow to total net asset under management greater than 5%. $\boldsymbol{X}$ includes option and stock characteristics. See Appendix Table A.2 for definitions. Columns (1) to (4) investigates the demand effect on expensiveness, and Columns (5) to (7) include option trading volume and its interaction with *MFFlow*. All variables are winsorized at 1% level and standardized to have mean zero and standard deviation one. All regressions include firm (ξ_i) and month (ξ_t) fixed effects and the standard errors are clustered at industry and date levels, and we report t-statistics in the bracket under coefficients. *, **, *** represent 10%, 5%, and 1% significance levels, respectively. The sample is from 1996:01 to 2018:12.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MFFlow	0.031***	0.036***	0.007	0.019***	0.031***	0.006	0.016**
	[5.68]	[6.23]	[1.26]	[2.96]	[4.96]	[0.90]	[2.21]
MFFlow×Volume					0.003	0.001	0.002
					[1.18]	[0.45]	[0.93]
Volume					0.018***	0.024***	0.021***
					[5.22]	[8.86]	[8.49]
β			-0.032***	-0.049***		-0.033***	-0.050***
			[-3.25]	[-4.56]		[-3.29]	[-4.55]
Size			-0.098***	-0.160***		-0.104***	-0.171***
			[-3.82]	[-5.75]		[-3.87]	[-5.93]
Book-to-market ratio			-0.042***	-0.030**		-0.041***	-0.030**
			[-3.84]	[-2.34]		[-3.66]	[-2.23]
12-month momentum			0.058***	0.058***		0.060***	0.060***
			[3.26]	[3.21]		[3.40]	[3.32]
1/stock price			0.106***	0.414***		0.107***	0.411***
			[7.23]	[12.40]		[7.28]	[12.36]
Excess stock returns			-0.055***	-0.051***		-0.053***	-0.049***
			[-6.22]	[-5.69]		[-6.01]	[-5.51]
Idiosyncratic volatility			-0.283***	-0.337***		-0.289***	-0.342***
			[-21.37]	[-24.71]		[-21.34]	[-24.75]
HHI			0.009	-0.008		0.005	-0.011
			[0.51]	[-0.40]		[0.30]	[-0.61]
Volume/open interest		0.003		0.002	-0.006*		-0.010***
		[1.48]		[0.77]	[-1.84]		[-3.56]
Option bid-ask spread		0.049***		-0.005	0.053***		-0.001
		[6.28]		[-0.49]	[7.03]		[-0.11]
Option gamma		-0.215***		-0.468***	-0.213***		-0.465***
		[-9.19]		[-10.49]	[-9.15]		[-10.48]
Option vega		-0.135***		-0.112***	-0.132***		-0.107***
		[-8.53]		[-8.59]	[-8.65]		[-8.46]
Constant	0.017***	0.020***	0.033***	0.053***	-0.012*	-0.009*	0.015***
	[215.50]	[25.01]	[20.40]	[30.39]	[-1.89]	[-1.84]	[3.90]
N	187,022	187,022	187,022	187,022	187,022	187,022	187,022
Adj. R^2	0.444	0.466	0.473	0.526	0.466	0.475	0.528

Table 7. Mutual fund fire-sale pressure and put option delta-hedged returns: Anticipation Effects.

The table presents the anticipation effects of the put option delta-hedged returns on (1) the fire-sale pressure using the double-clustered panel regression:

$$\text{OLS: } MFFlow_{i,t} = \alpha + \beta ret^{opt}_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + \xi_i + \xi_t + \varepsilon_{i,t}$$

where $MFFlow_{i,t-1}$ (multiplied by 100) is defined as in Edmans, Goldstein, and Jiang (2012), where the fire-sale pressure is categorized as the absolute value of flow to total net asset under management greater than 5%, and (2) the probability of fire-sale pressure from mutual fund flows higher than the cross-sectional median using logit regression

$$\text{Logit: } D(MFFlow \geq Median)_{i,t} = \alpha + \delta ret^{opt}_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + \varepsilon_{i,t}$$

where $D(MFFlow \geq Median)_{i,t}$ is the dummy of fund i confronted with an extreme flow-induced fire sale event that is more severe than cross-sectional median at time t. $ret^{opt}_{i,t-1}$ is the monthly delta-hedged option returns, defined as Goyal and Saretto (2009) on every third Friday with one month to maturity and moneyness close to at-the-money put options. The data frequency includes monthly (matching quarterly *MFFlow* with monthly returns) and quarterly (aggregate returns and other variables to quarterly and match with fire sales). $\boldsymbol{X}$ includes option and stock characteristics. See Appendix Table A.2 for definitions. All variables are winsorized at 1% level. The OLS regression includes firm (ξ_i) and month (ξ_t) fixed effects, and standard errors are clustered at industry and date levels. The logit regression results report the marginal effect and the Bonferroni standard errors at the median of all independent variables. We report t-statistics in the bracket under coefficients. *, **, *** represent 10%, 5%, and 1% significance levels, respectively. The sample is from 1996:01 to 2018:12.

	Fire sale: OLS Levels				Prob(Fire sales): logit Marginal effects at median			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Monthly frequency				
ret^{opt}	-0.459*	-0.373	-0.484**	-0.655***	-0.026***	-0.009	-0.020***	-0.025***
	[-1.98]	[-1.60]	[-2.25]	[-2.91]	[-4.34]	[-1.56]	[-3.38]	[-4.27]
Controls	NO	Option	Stocks	ALL	NO	Option	Stocks	ALL
Firm FE	YES	YES	YES	YES				
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.521	0.521	0.528	0.528				
Pseudo R^2					0.009	0.017	0.074	0.076
				Panel B: Quarterly frequency				
ret^{opt}	-0.723*	-0.617	-0.633	-0.777*	-0.038***	-0.009	-0.017*	-0.021**
	[-1.67]	[-1.43]	[-1.53]	[-1.85]	[-3.89]	[-0.94]	[-1.79]	[-2.23]
Controls	NO	Option	Stocks	ALL	NO	Option	Stocks	ALL
Firm FE	YES	YES	YES	YES				
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.498	0.498	0.505	0.505				
Pseudo R^2					0.009	0.021	0.087	0.088

Table 8. Mutual fund fire-sale pressure and put option delta-hedged returns: Anticipation effects natural experiments.

The table presents the anticipation effects of fire-sale pressure from mutual fund flows on put option delta-hedged returns using (monthly) double-clustered panel regression:

$$\text{DID: } MFFlow_{i,t} = \alpha + \delta ret^{opt}_{i,t-1} \times \text{D(Weekly Option)}_{i,t-1} + \beta ret^{opt}_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + \xi_i + \xi_t + \varepsilon_{i,t}$$

$$\text{Cohort: } MFFlow_{i,c,t} = \alpha + \delta ret^{opt}_{i,t-1} \times \text{D(Weekly Option)}_{i,t-1} + \beta ret^{opt}_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + \xi_i \times \xi_c + \xi_t \times \xi_c + \varepsilon_{i,c,t}$$

where $MFFlow_{i,t-1}$ is defined as in Edmans, Goldstein, and Jiang (2012), where the fire-sale pressure is categorized as the absolute value of flow to total net asset under management greater than 5%. $ret^{opt}_{i,t-1}$ is the monthly delta-hedged option returns, defined as Goyal and Saretto (2009) on every third Friday with one month to maturity and moneyness close to at-the-money options. In difference-in-differences specification, $D(Weekly\ Option)_{i,t-1}$ is the dummy of introducing a weekly option for stock i at time $t-1$, and the DID term is the interaction between option returns and weekly option dummy with experiment window 2010:01–2015:12. The Cohort DID specification is similar where c represents each cohorts, which is defined as 12-month window before and after introducing weekly options. $\boldsymbol{X}$ includes option and stock characteristics. See Appendix Table A.2 for definitions. All variables are winsorized at 1% level. The DID regression includes firm (ξ_i) and month (ξ_t) fixed effects and the Cohort DID regression includes firm×cohort (ξ_c) and time×cohort (ξ_c) fixed effects. All standard errors are clustered at industry and date levels, and we report t-statistics in the bracket under coefficients. We multiple coefficients by 100. *, **, *** represent 10%, 5%, and 1% significance levels, respectively. The sample periods are listed in the table.

	Panel A: Difference-in-differences				Panel B: Cohort DID			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ret^{opt}	-0.648*	-0.644*	-0.789**	-0.991***	-4.567**	-4.005**	-5.578**	-5.902**
	[-1.71]	[-1.70]	[-2.20]	[-2.79]	[-2.47]	[-2.54]	[-2.45]	[-2.50]
ret^{opt}×D(Weekly Option)	7.405***	7.329***	7.493***	7.442***	9.151**	8.569**	10.314**	9.724**
	[3.04]	[3.00]	[3.12]	[3.22]	[2.33]	[2.60]	[2.27]	[2.38]
D(Weekly Option)	5.996	5.811	7.821	6.839	-1.969	-1.386	-2.406	-2.799
	[0.96]	[0.94]	[1.30]	[1.12]	[-0.32]	[-0.21]	[-0.34]	[-0.39]
Stock controls	NO	NO	YES	YES	NO	NO	YES	YES
Option controls	NO	YES	NO	YES	NO	YES	NO	YES
Firm FE	YES	YES	YES	YES	NO	NO	NO	NO
Time FE	YES	YES	YES	YES	NO	NO	NO	NO
Firm×Cohort FE	NO	NO	NO	NO	YES	YES	YES	YES
Time×Cohort FE	NO	NO	NO	NO	YES	YES	YES	YES
N	51,743	51,743	51,743	51,743	6,061	6,061	6,061	6,061
Adj. R^2	0.614	0.614	0.618	0.619	0.707	0.718	0.725	0.735

Table 9. Subsample tests

The table reports subsample test results. Panel A reports OLS results of the demand effect in Eq. (2), while Panel B is the second-stage results using the instrumental variable regression in Eq. (7). Panel C regresses *expensiveness* on *MFFlow* using Eq. (9). Panel D displays the anticipation effect results using Eq. (10) and multiples coefficients by 100. Column (1) restricts samples to months with non-extreme VIX index (lower than 90 percentile). Column (2) consists of months whose market returns are within top and bottom ten percentiles. Columns (3) and (4) are subsamples partitioned into higher and lower than the median of the investor sentiment defined in Huang et al. (2014). Columns (5) and (6) are samples of non-January and January observations. Columns (7) to (10) separate the sample every five years, where Columns (7) and (9) include the NBER recession periods. All regressions include firm and time-varying industry fixed effects. All standard errors are clustered at firm and date levels, and we report t-statistics in the bracket under coefficients. *, **, *** represent 10%, 5%, and 1% significance levels, respectively. The sample is from 1996:01 to 2018:12.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	VIX	MKT	HSent	LSent	Non-Jan	Jan	96–01	02–06	07–11	12–18
Panel A: OLS $ret^{opt}_{i,t} = \alpha + \beta MFFlow_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + \xi_i + \zeta_t + \varepsilon_{i,t}$										
MFFlow	-0.020***	-0.020***	-0.011	-0.022***	-0.016***	-0.030**	-0.023*	-0.016**	0.004	-0.024***
	[-4.52]	[-4.74]	[-1.38]	[-4.24]	[-3.10]	[-2.35]	[-1.97]	[-2.39]	[0.26]	[-3.17]
N	167,014	148,074	92,848	91,775	168,880	15,213	34,821	43,049	47,662	59,071
Adj. R^2	0.119	0.110	0.174	0.121	0.157	0.102	0.087	0.116	0.259	0.133
Panel B: Instrumental variable $ret^{opt}_{i,t} = \alpha + \beta \widetilde{MFFlow}_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + \xi_i + \zeta_t + \varepsilon_{i,t}$										
MFFlow	-0.026***	-0.028***	-0.023***	-0.028***	-0.025***	-0.046***	-0.035***	-0.024***	-0.015	-0.029***
	[-6.58]	[-6.94]	[-4.18]	[-5.96]	[-6.31]	[-3.98]	[-3.90]	[-3.75]	[-1.65]	[-4.06]
N	167,014	148,074	92,848	91,775	168,880	15,213	34,821	43,049	47,662	59,071
Adj. R^2	0.011	0.012	0.012	0.011	0.011	0.010	0.023	0.020	0.014	0.013
Panel C: OLS $expensivenes_{i,t} = \alpha + \beta MFFlow_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + \xi_i + \zeta_t + \varepsilon_{i,t}$										
MFFlow	0.022***	0.021***	0.028***	0.016**	0.024***	-0.001	0.030***	0.030***	0.021**	0.022***
	[4.64]	[4.39]	[5.02]	[2.55]	[5.38]	[-0.12]	[3.18]	[3.25]	[2.14]	[3.35]
N	167,014	148,074	92,848	91,775	168,880	15,213	34,821	43,049	47,662	59,071
Adj. R^2	0.559	0.522	0.636	0.472	0.570	0.531	0.478	0.475	0.760	0.475
Panel D: OLS $MFFlow_{i,t} = \alpha + \beta ret^{opt}_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + \xi_i + \zeta_t + \varepsilon_{i,t}$										
ret^{opt}	-0.698***	-0.619**	-0.246	-0.689**	-0.498**	-2.155**	0.371	0.312	-1.153***	-0.947***
	[-3.04]	[-2.28]	[-0.77]	[-2.36]	[-2.10]	[-2.23]	[0.89]	[0.85]	[-2.79]	[-2.67]
N	165,330	145,994	91,904	90,813	167,849	14,418	34,741	42,770	42,113	63,150
Adj. R^2	0.548	0.547	0.553	0.607	0.548	0.533	0.518	0.706	0.677	0.581

Table 10. Robustness tests.

The table reports robustness test results. Panel A uses option trading volumes as the weight variable in regressions to incorporate options trading liquidity effects. Panel B selects persistent outperformed mutual funds whose Carhart (1997) four-factor αs are in the top two quintiles in the past quarter, and we calculate fire-sale pressure using these funds. Panel C calculates the average percentage investment in cash holdings among mutual funds that hold a specific stock and uses the average cash holding as the weight variable in regressions. Columns (1) to (6) report demand effects using Eq. (2) and (9), where Columns (1) to (4) regress option returns and Columns (5) and (6) regress *expensiveness* on *MFFlow*. Columns (3) and (4) apply the instrumental variable regression method using Eq. (7). The last two columns report the anticipation effect and multiple coefficients by 100; regress *MFFlow* on option returns using Eq. (10). The odd columns have no controls, and the even columns include all control variables. All regressions include firm and time-varying industry fixed effects. All standard errors are clustered at firm and date levels, and we report *t*-statistics in the bracket under coefficients. *, **, *** represent 10%, 5%, and 1% significance levels, respectively. The sample is from 1996:01 to 2018:12.

	Demand						Anticipation	
	OLS		IV		Expensive		OLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: option trading volume as weights								
MFFlow	-0.014*	-0.023***	-0.026***	-0.034***	0.023***	0.014*		
	[-1.78]	[-2.91]	[-3.69]	[-5.06]	[3.01]	[1.78]		
ret^{opt}							-0.506*	-0.956***
							[-1.67]	[-3.10]
All controls	NO	YES	NO	YES	NO	YES	NO	YES
N	87,094	87,094	87,094	87,094	87,094	87,094	86,067	86,067
Adj. R^2	0.213	0.223	0.000	0.012	0.590	0.657	0.620	0.629
Panel B: Mutual funds with persistent outperformance								
MFFlow	-0.011**	-0.011**	-0.017***	-0.011**	0.018***	0.013***		
	[-2.25]	[-2.30]	[-4.81]	[-2.30]	[4.10]	[3.16]		
ret^{opt}							-0.877**	-0.900**
							[-2.23]	[-2.26]
All controls	NO	YES	NO	YES	NO	YES	NO	YES
N	151,032	151,032	151,032	151,032	151,032	151,032	151,032	151,032
Adj. R^2	0.155	0.163	0.000	0.010	0.530	0.598	0.430	0.435
Panel C: Mutual funds cash holding as weight								
MFFlow	-0.011*	-0.015**	-0.020***	-0.015**	0.032***	0.023***		
	[-1.77]	[-2.56]	[-4.09]	[-2.56]	[5.18]	[4.05]		
ret^{opt}							-0.707**	-0.902***
							[-2.31]	[-2.97]
All controls	NO	YES	NO	YES	NO	YES	NO	YES
N	147,902	147,902	147,902	147,902	147,902	147,902	147,902	147,902
Adj. R^2	0.183	0.190	0.000	0.009	0.565	0.634	0.608	0.617

Appendix

A Variable definitions and sources

Table A.1. Definitions and variable names of risk factors used in the portfolio analysis.

Factors	Definitions and variable names				
	(1)	(2)	(3)	(4)	(5)
Carhart[1]	$ret_m - r_f$	size	value	momentum	
(×4)	MKT	SMB	HML	MOM	
Conditional[2] Carhart	Carhart	r_f×MKT	dy×MKT	tms×MKT	dfs×MKT
(×8)		Treasury bill rate	dividend yield	term spread	default spread
Macro bond factors[3]	F_1 to F_8	Cubic of F_1			
(×9)		F_1^3			
Carhart + LTM[4]	Carhart	left tail momentum			
(×5)		LTM			
Carhart+ LTM	Carhart	LTM	PCA of GARCH residuals of macro variables		
+ macro risk[5] (×6)			macro risk		
All	Conditional	Macro bond	LTM	macro risk	
(×19)	Carhart				

Data sources:

[1] Ken French: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.
[2] Amit Goyal: `http://www.hec.unil.ch/agoyal/`.
[3] Sydney Ludvigson: `https://www.sydneyludvigson.com/data-and-appendixes`.
[4,5] Turan Bali: `https://sites.google.com/a/georgetown.edu/turan-bali/data-working-papers`.

Table A.2. Variable definitions and sources.

Variable name	Definition	Source
Delta-hedged returns	We select an option contract for each month with the closest moneyness to at-the-money and one month to expiration. Option contracts have non-zero trading volume, open interest, and implied volatility. We also require option prices to satisfy boundary conditions. All options are expired on the third Friday every month. Delta-hedged return is defined as the expiration payoff ($\max(S_T - K, 0)$) minus delta×stock price, scaled by option price, which is the midpoint of the closing quoted bid and ask prices.	OptionMetrics, CRSP
Expensiveness	Implied volatility provided by OptionMetrics minus a reference volatility, which is the historical volatility calculated using prior 365-day returns.	OptionMetrics
MFFlow	If a mutual fund experiences an extreme outflow, i.e., $\frac{\lvert F_{jt}\rvert}{TNA_{j,t-1}} > 5\%$, then we consider its fire-sale pressure. For each holding of this mutual fund, we calculate the stock holding value ($Shares_{i,j,t-1} \times prc_{i,t-1}$) to total asset under management ($TNA_{j,t-1}$) fraction at $t-1$ ($s_{i,j,t-1}$), and time this fraction with the fund's aboslute flow at t ($\lvert F_{j,t}\rvert$) and scale by stock dollar volume at t ($DVOL_{i,t}$). Then, for each stock, sum this ratio over all funds.	Thomson Reuters, CRSP
Flow	Total net assets under management minus current period fund returns times lagged TNA.	CRSP
Flow-to-volume	Similar with *MFFlow* but does not include stock prices.	Thomson Reuters, CRSP
Flow-to-shares outstanding	Similar with Flow-to-volume but replace volume in the denominator with shares outstanding.	Thomson Reuters, CRSP
Moneyness	Option strike price divided by stock price at expiration.	OptionMetrics
Volume/open interest	Option trading volume divided by option open interest.	OptionMetrics
Option gamma	Derivative of delta to stock price.	OptionMetrics
Option vega	Derivative of the option price to implied volatility.	OptionMetrics
Option bid-ask spread	Difference between bid and ask prices, divided by the midpoint of the closing quoted bid and ask prices.	OptionMetrics
HV−IV	Historical volatility calculated using previous 365 days stock returns minus implied volatility calculated using the binomial tree mode and provided by OptionMetrics.	OptionMetrics
β	The coefficient on market excess returns in the CAPM model using 36-month prior monthly stock excess returns with at least 30 non-missing observations.	CRSP, Ken French
Size	Natural logarithm of market capitalization (in million dollar), where market capitalization is calculated as stock price times its adjusted total shares outstanding.	CRSP
Book-to-market ratio	Stock book value of equity divided by market value of equity.	Compustat
12-month momentum	Stock cumulative returns over $t-12$ to $t-1$.	CRSP
1/stock price	The inverse of stock prices.	CRSP
Excess stock returns	Delisting adjusted monthly stock return minus risk-free interest rate.	CRSP, Ken French
Idiosyncratic volatility	The standard deviation of residual time series estimated from a Carhart four-factor model (MKT, SMB, HML, and MOM) using prior 36-month stock excess returns with 30 non-missing observations.	CRSP, Ken French
HHI	Square of the ratio between individual firm sale and 2-digit industry sum of sales, and sum over all firms within this 2-digit industry.	Compustat
Credit downgrading dummy	An indicator equal to one if a firm's S&P credit rating is lower than its previous available rating.	Capital IQ
Sin stock dummy	An indicator equal to one if a company's primary industry classification is in smoke or tobacco, beer or alcohol, or gaming.	Compustat
Short interest rate (*SII*)	Monthly short interest divided by total shares outstanding.	CRSP, Compustat
Amihud illiquidity	Monthly sum of daily absolute delisting adjusted returns divided by daily dollar volume, scaled by multiplying 10^6 and requiring monthly five non-missing returns and volumes for NYSE/AMEX stocks and at least 50 number of trades for NASDAQ stocks.	CRSP
Sentiment	Aggregate investor sentiment measure constructed using closed-end fund discount rate, share turnover, number of IPOs, first-day returns of IPOs, dividend premium, and equity share in new issues based on partial least square to eliminate a common noise component.	Guofu Zhou's website

Internet Appendix to

"Feedback, Flow-induced Fire Sales, and Option Returns"

Han Xiao

September 13, 2021

A Robustness tests

In this section, we provide robustness tests to the baseline model.

A.1 Demand effects: Delta-hedged put option returns

A.1.1 Additional fixed effect and cluster combinations

We estimate Equation (2), and we use firm fixed effects, time fixed effects, and/or industry$\times$time fixed effects and double clustered standard errors at the firm and time level. Explanatory variables are standardized to facilitate interpretation of the coefficient estimates.

A.1.2 Fama-MacBeth regression

We investigate the results of average coefficients estimated using Fama-MacBeth regressions. To be comparable to the portfolio analysis results, we use raw values of all variables, and use monthly delta-hedged put option returns as the explanatory variable. In the first stage, we estimate monthly cross-sectional regressions of excess option returns in month t on values of mutual fund fire-sale pressures and control variables measured in month $t-1$. The cross-sectional model estimated at the end of each month t is

$$ret_{i,t}^{opt} = \alpha + \beta MFFlow_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + \varepsilon_{i,t},\ \forall\, i,\ t = 1, \cdots, T$$

In the second stage, we calculate the time-series averages of the cross-sectional regression coefficient estimates. Table reports average slope coefficients, Newey and West (1987) t-statistics (in bracket), and the average adjusted R^2 for each specification.

(Insert Table A.1 Here)

A.1.3 Long-horizon prediction

(Insert Table A.2 Here)

A.2 Demand effects: Expensiveness

(Insert Table A.3 Here)

A.3 Anticipation effects: Robustness tests

(Insert Table A.4 Here)

A.4 Spillover effects: Fire-sale pressure on peer option returns

We define firms in the same 2-digit industry classification as peer firms. We then regress peer firms' option returns on the fire-sale pressure of a firm, which primarily evaluates the spillover effect of fire sales.

(Insert Table A.5 Here)

A.5 Alternative fire-sale pressure definitions

A.5.1 Bottom flow ranks

We sort and rank mutual funds into ten groups and select the bottom group.

A.5.2 Other flow thresholds

We select flow thresholds being 10% and 15%.

(Insert Table A.6 Here)

A.6 Do option price determinants dominate fire sales?

(Insert Table A.7 Here)

B Additional results for identification designs

B.1 Instrumental variable regressions

We present some additional empirical results along with instrumental variable regressions, including first-stage results, the exclusion restriction assumption placebo test, and the selection bias.

B.1.1 First-stage results

(Insert Table A.8 Here)

B.1.2 Placebo tests

(Insert Table A.9 Here)

B.1.3 Selection bias results

Mutual fund extreme outflows decrease stock prices significantly (Edmans, Goldstein, and Jiang, 2012). According to demand-based option pricing theory, fire-sale pressure effect on option returns might inherit selection bias due to negative stock returns. The question is whether selection bias mechanically leads to the negative relation.

To address the issue, we use Heckman (1979)'s two-step correction method. The first step involves estimating a selection equation.

$$\begin{aligned} \text{selection dummy}_{i,t} &= a_0 + b_1 \times \text{Flow-to-volume}_{i,t} + b_2 \times \text{Flow-to-shares outstanding}_{i,t} \\ &\quad + c\boldsymbol{X}_{i,t} + \xi_i + \xi_t + \phi_{i,t} \end{aligned} \tag{13}$$

where *selection dummy*$_{i,t}$ is a dummy that equals one if a stock return is negative and zero otherwise. Using the estimates from the *selection dummy*, we can compute the *Inverse Mills Ratio* and include it as an explanatory variable in our second-stage regression using Eq. (7). If the coefficient β is negative and statistically significant, as well as quantitatively similar with estimates in Table 4, we conclude that selection bias does not drive the demand effect.

(Insert Table A.10 Here)

B.2 Difference-in-differences placebo tests

(Insert Figure A.1 Here)

(Insert Table A.11 Here)

C Additional summary statistics

(Insert Table A.12 Here)

(Insert Table A.13 Here)

(Insert Figure A.2 Here)

D Buy pressures: Extreme inflows

(Insert Table A.14 Here)

D.1 Put options

(Insert Table A.15 Here)

D.2 Call options

(Insert Table A.16 Here)

Figure A.1

Falsification test of difference-in-differences estimation: Parallel trend and reversal.

The figure presents the estimated coefficients (δ_k) of the following regression:

$$ret^{opt}_{i,t} = \alpha + \sum_{k=-3}^{4} \delta_k \lambda_{i,t+k} \times D(MFFlow > \text{Median})_{i,t-1} + \beta D(MFFlow > \text{Median})_{i,t-1}$$

$$+\xi_i + \xi_{ind} \times \xi_t + \varepsilon_{i,t}$$

where $\lambda_{i,t+k}$ is an indicator that equals one if event time $= t$ and zero otherwise, where t is the period when treatment occurs (2004:5) and $t-1$, for example, is period before treatment (2004:4). Following the recommendations in Gormley and Matsa (2016), we do not include any control variables but add industry×time fixed effects ($\xi_{ind} \times \xi_t$) to address time-varying industry variations.

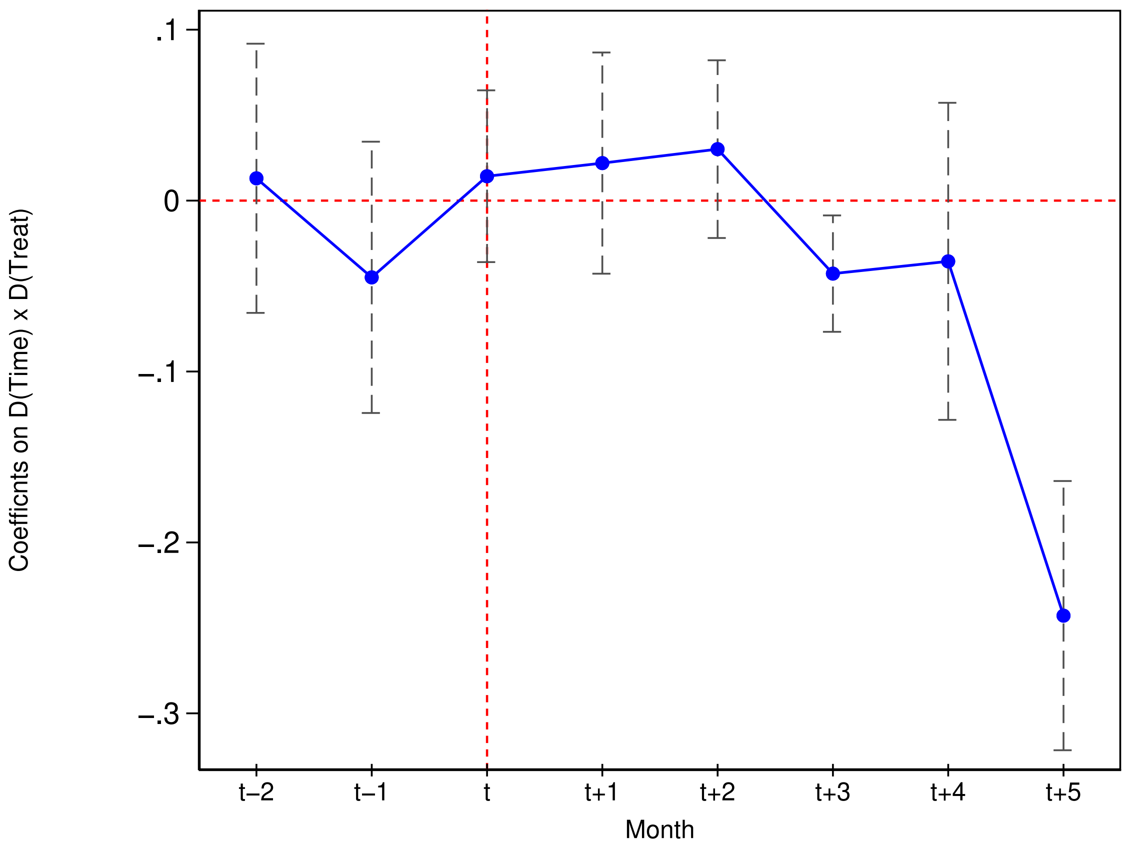

Figure A.2
Time series: Mutual fund flow and delta-hedged option returns.

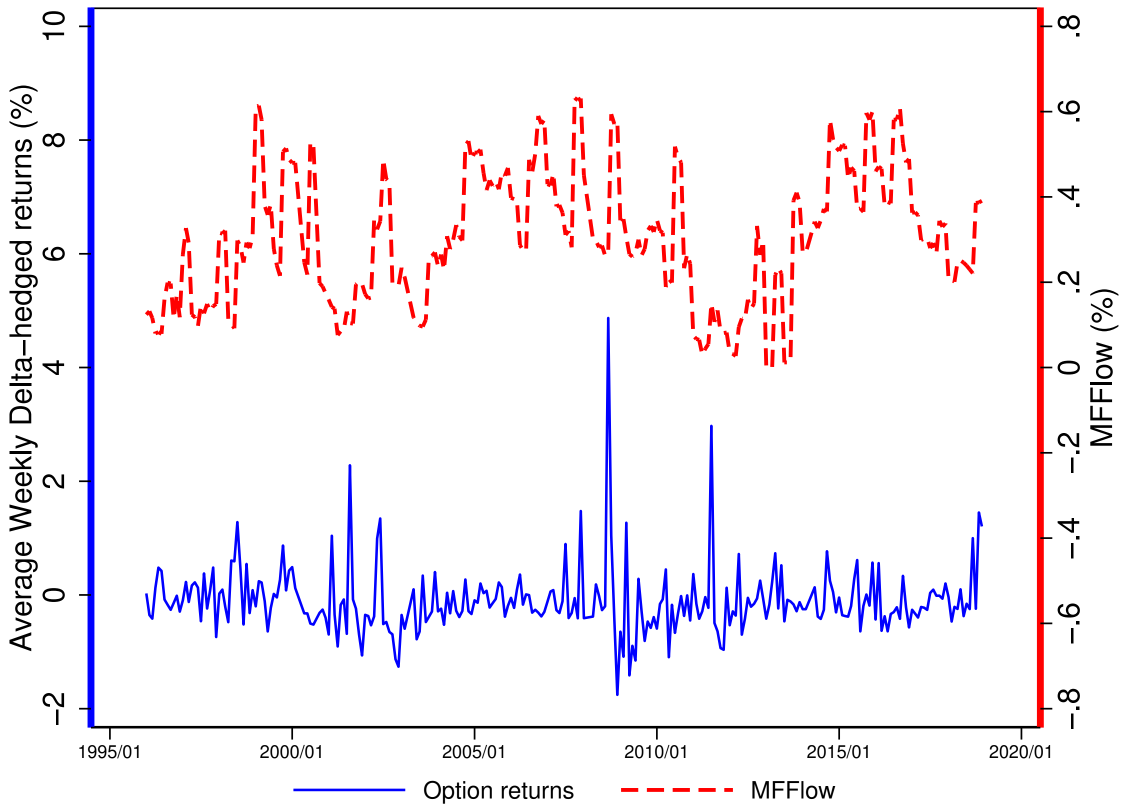

Table A.1. Robustness tests: Clusters, fixed effects, and Fama-MacBeth results.
The table presents the robustness test results of baseline regression using panel regressions:

$$\text{Panel: } ret_{i,t}^{opt} = \alpha + \beta MFFlow_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + FE_{i,t} + \varepsilon_{i,t}, \quad \forall\, i,\ t$$

in Columns (1) to (4), where $FE_{i,t}$ represents different combinations of fixed effects. Columns (1) and (2) include firm and time fixed effects and estimate standard errors using firm and time double clustering. Column (3) and (4) include firm and industry×time fixed effects and report industry and time double clustering. In Columns (5) and (6), we use Fama-MacBeth regression, where the first step is

$$\text{Fama-MacBeth: } ret_{i,t}^{opt} = a_t + b_t MFFlow_{i,t-1} + \boldsymbol{c}_t \boldsymbol{X}_{i,t-1} + e_{i,t}, \quad \forall\, i,\ t = 1, 2, \cdots, T$$

estimated for each cross-sectional observations in time $t = 1, 2, \cdots, T$. The second step is to take sample average of estimated coefficients in the first step and report standard errors corrected for heteroskedasticity and autocorrelation using Newey and West (1987) an optimal order of lags. $ret_{i,t}^{opt}$ is the monthly delta-hedged put option returns, defined as Goyal and Saretto (2009) on every third Friday with one month to maturity and moneyness close to at-the-money options. $MFFlow_{i,t-1}$ is defined as in Edmans, Goldstein, and Jiang (2012), where the fire-sale pressure is categorized as the absolute value of flow to total net asset under management greater than 5%. $\boldsymbol{X}$ includes option and stock characteristics. See Appendix Table A.2 for definitions. All variables are winsorized at 1% level and standardized to have mean zero and standard deviation one. We report t-statistics in the bracket under coefficients. *, **, *** represent 10%, 5%, and 1% significance levels, respectively. The sample is from 1996:01 to 2018:12.

	Firm and time clusters		Industry×time FE		Fama-MacBeth	
	(1)	(2)	(3)	(4)	(5)	(6)
MFFlow	-0.016***	-0.019***	-0.013**	-0.016***	-0.024***	-0.025***
	[-3.05]	[-3.68]	[-2.44]	[-3.06]	[-3.31]	[-3.17]
β		-0.014**		-0.014*		0.004
		[-2.06]		[-1.94]		[0.57]
Size		0.050**		0.054**		-0.025***
		[2.33]		[2.14]		[-3.16]
Book-to-market ratio		0.011**		0.011**		0.010*
		[2.04]		[2.52]		[1.94]
12-month momentum		0.017**		0.017**		0.001
		[2.47]		[2.54]		[0.13]
1/stock price		-0.064***		-0.066***		-0.118***
		[-4.58]		[-3.68]		[-7.18]
Excess stock returns		-0.012**		-0.013**		-0.014
		[-2.28]		[-2.60]		[-1.59]
Idiosyncratic volatility		-0.060***		-0.059***		-0.032**
		[-6.65]		[-7.56]		[-2.54]
HHI		-0.009		-0.003		0.009***
		[-1.00]		[-0.05]		[2.80]
Volume/open interest		-0.001		-0.001		0.011*
		[-0.59]		[-0.31]		[1.95]
Option bid-ask spread		-0.018***		-0.016***		-0.036***
		[-3.61]		[-3.18]		[-5.54]
Option gamma		0.091***		0.091***		0.117***
		[10.64]		[7.21]		[6.65]
Option vega		0.066***		0.070***		0.053***
		[8.08]		[5.98]		[3.74]
HV−IV		0.065***		0.067***		0.079***
		[7.55]		[8.61]		[12.50]
Constant	-0.006***	-0.009***	-0.006***	-0.009***	0.002	0.002
	[-185.37]	[-7.21]	[-54.61]	[-4.57]	[0.10]	[0.06]
Firm FE	YES	YES	YES	YES	–	–
Time FE	YES	YES	NO	NO	–	–
Industry×Time FE	NO	NO	YES	YES	–	–
N	186,127	186,127	184,174	184,174	186,493	186,493
Adj R^2	0.099	0.108	0.141	0.150	–	–
Average R^2	–	–	–	–	0.006	0.108

Table A.2. Long horizon demand effects.

	2 quarters			3 quarters			4 quarters		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	IV	Expense	OLS	IV	Expense	OLS	IV	Expense
MFFlow	-0.007*	-0.007*	0.021***	0.006	0.006	-0.008**	-0.003	-0.002	-0.005
	[-1.83]	[-1.87]	[4.28]	[0.71]	[0.62]	[-2.60]	[-0.48]	[-0.31]	[-1.46]
β	-0.012*	-0.012*	-0.053***	-0.009*	-0.009*	-0.045***	-0.011**	-0.011**	-0.043***
	[-1.77]	[-1.77]	[-5.04]	[-1.79]	[-1.79]	[-4.64]	[-2.02]	[-2.01]	[-4.32]
Size	0.063**	0.063**	-0.158***	0.153***	0.153***	-0.188***	0.149***	0.149***	-0.192***
	[2.64]	[2.64]	[-5.43]	[5.89]	[5.86]	[-4.13]	[6.00]	[6.05]	[-4.12]
Book-to-market ratio	0.010**	0.010**	-0.028**	0.006	0.006	-0.030**	0.009**	0.009**	-0.030**
	[2.24]	[2.24]	[-2.19]	[1.59]	[1.59]	[-2.33]	[2.62]	[2.61]	[-2.29]
12-month momentum	0.019**	0.019**	0.057***	0.020***	0.020***	0.026	0.018***	0.018***	0.029
	[2.41]	[2.41]	[3.28]	[3.23]	[3.23]	[1.18]	[2.96]	[2.96]	[1.29]
1/stock price	-0.058***	-0.058***	0.426***	-0.009	-0.009	0.357***	-0.010	-0.010	0.359***
	[-3.17]	[-3.18]	[11.97]	[-0.60]	[-0.60]	[11.10]	[-0.74]	[-0.74]	[11.49]
Excess stock returns	-0.010**	-0.010**	-0.052***	-0.005	-0.005	-0.057***	-0.008*	-0.008*	-0.057***
	[-2.06]	[-2.06]	[-6.22]	[-1.25]	[-1.25]	[-5.55]	[-1.90]	[-1.91]	[-5.17]
Idiosyncratic volatility	-0.056***	-0.056***	-0.331***	-0.044***	-0.044***	-0.286***	-0.041***	-0.041***	-0.277***
	[-6.61]	[-6.63]	[-24.77]	[-5.91]	[-5.89]	[-17.78]	[-4.79]	[-4.79]	[-17.49]
HHI	-0.005	-0.005	-0.011	-0.000	-0.000	-0.013	-0.002	-0.002	-0.012
	[-0.58]	[-0.58]	[-0.56]	[-0.04]	[-0.04]	[-0.82]	[-0.33]	[-0.33]	[-0.75]
Volume/open interest	-0.001	-0.001	0.002	-0.001	-0.001	0.003	-0.001	-0.001	0.003
	[-0.47]	[-0.47]	[0.84]	[-1.53]	[-1.53]	[1.59]	[-1.54]	[-1.54]	[1.63]
Option bid-ask spread	-0.017***	-0.017***	-0.006	-0.001	-0.001	0.005	-0.001	-0.001	0.007
	[-3.48]	[-3.48]	[-0.67]	[-0.11]	[-0.11]	[0.41]	[-0.11]	[-0.11]	[0.55]
Option gamma	0.093***	0.093***	-0.471***	0.054***	0.054***	-0.407***	0.056***	0.056***	-0.413***
	[7.70]	[7.71]	[-10.18]	[4.68]	[4.67]	[-6.89]	[4.64]	[4.64]	[-7.23]
OPtion vega	0.064***	0.064***	-0.111***	0.013	0.013	-0.035**	0.012	0.012	-0.035**
	[5.59]	[5.59]	[-7.55]	[1.37]	[1.37]	[-2.09]	[1.35]	[1.34]	[-2.14]
HV−IV	0.064***	0.064***		0.048***	0.048***		0.047***	0.047***	
	[7.34]	[7.33]		[5.17]	[5.17]		[5.03]	[5.03]	
Constant	-0.010***		0.048***	-0.017***		0.034***	-0.016***		0.028***
	[-6.19]		[27.38]	[-12.03]		[16.89]	[-12.37]		[16.29]
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	186,758	186,758	186,758	186,422	186,422	186,422	186,213	186,213	186,213
Adj. R^2	0.106	-0.012	0.527	0.079	-0.016	0.482	0.083	-0.016	0.485

Table A.3. Expensiveness robustness tests.

The table presents the robustness test results of baseline regression using panel regressions:

$$\text{Panel: } expensiveness_{i,t} = \alpha + \beta MFFlow_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + FE_{i,t} + \varepsilon_{i,t}, \quad \forall\, i,\ t$$

in Columns (1) to (6), where $FE_{i,t}$ represents different combinations of fixed effects. Columns (1) and (2) include firm and time fixed effects and estimate standard errors using firm and time double clustering. Columns (3) and (4) include firm and industry$\times$time fixed effects and report industry and time double clustering. Columns (5) and (6) report the second-stage estimation using instrumental variable regression using firm and time fixed effects and standard errors clustered at industry and time levels. In Columns (7) and (8), we use Fama-MacBeth regression, where the first step is

$$\text{Fama-MacBeth: } expensiveness_{i,t} = a_t + b_t MFFlow_{i,t-1} + \boldsymbol{c}_t \boldsymbol{X}_{i,t-1} + e_{i,t}, \quad \forall\, i,\ t = 1, 2, \cdots, T$$

estimated for each cross-sectional observations in time $t = 1, 2, \cdots, T$. The second step is to take sample average of estimated coefficients in the first step and report standard errors corrected for heteroskedasticity and autocorrelation using Newey and West (1987) an optimal order of lags. $expensiveness_{i,t}$ is the monthly option expensiveness measure, defined as the difference between at-the-money implied volatility and a reference volatility (historical volatility). $MFFlow_{i,t-1}$ is defined as in Edmans, Goldstein, and Jiang (2012), where the fire-sale pressure is categorized as the absolute value of flow to total net asset under management greater than 5%. $\boldsymbol{X}$ includes option and stock characteristics. See Appendix Table A.2 for definitions. All variables are winsorized at 1% level and standardized to have mean zero and standard deviation one. We report t-statistics in the bracket under coefficients. *, **, *** represent 10%, 5%, and 1% significance levels, respectively. The sample is from 1996:01 to 2018:12.

	Firm-time clusters		Industry$\times$time FE		IV		Fama-MacBeth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MFFlow	0.030***	0.041***	0.029***	0.040***	0.016***	0.006	0.038***	0.004
	[6.34]	[8.66]	[6.03]	[6.95]	[4.33]	[1.10]	[3.71]	[0.39]
β		-0.126***		-0.108***		-0.050***		-0.104***
		[-10.10]		[-8.93]		[-4.56]		[-6.41]
Size		-0.060*		-0.063**		-0.161***		-0.044***
		[-1.95]		[-2.17]		[-5.77]		[-3.07]
Book-to-market ratio		-0.035***		-0.017		-0.031**		0.000
		[-3.01]		[-1.22]		[-2.38]		[0.03]
12-month momentum		0.022**		0.008		0.058***		0.075***
		[2.07]		[0.47]		[3.15]		[6.55]
1/stock price		0.360***		0.378***		0.409***		0.539***
		[16.46]		[10.46]		[12.33]		[23.56]
Excess stock returns						-0.052***		-0.028***
						[-5.92]		[-3.97]
Idiosyncratic volatility						-0.340***		-0.316***
						[-24.11]		[-19.90]
HHI						-0.008		-0.001
						[-0.42]		[-0.22]
Volume/open interest		0.004*		0.003		0.002		0.002
		[1.87]		[1.29]		[0.83]		[0.57]
Option bid-ask spread		0.011**		0.002		-0.005		-0.017**
		[2.39]		[0.19]		[-0.49]		[-2.16]
Option gamma		-0.430***		-0.458***		-0.467***		-0.564***
		[-25.82]		[-10.02]		[-10.56]		[-22.48]
Option vega		-0.109***		-0.101***		-0.112***		-0.147***
		[-9.77]		[-11.04]		[-8.62]		[-15.03]
Constant	0.018***	0.039***	0.017***	0.039***			-0.022	-0.015
	[343.76]	[24.61]	[177.64]	[22.71]			[-0.31]	[-0.24]
Firm FE	YES	YES	YES	YES	YES	YES	–	–
Time FE	YES	YES	NO	NO	YES	YES	–	–
Industry$\times$Time FE	NO	NO	YES	YES	NO	NO	–	–
N	186,127	186,127	184,174	184,174	186,127	186,127	186,493	186,493
Adj. R^2	0.445	0.499	0.492	0.546	-0.022	0.130	–	–
Average R^2	–	–	–	–	–	–	0.008	0.281

Table A.4. Anticipation effect robustness test.
The table presents the robustness test results of baseline regression using panel regressions:

$$\text{Panel: } MFFlow_{i,t} = \alpha + \beta ret^{opt}_{i,t-1} + \gamma \boldsymbol{X}_{i,t-1} + FE_{i,t} + \varepsilon_{i,t}, \quad \forall\, i,\ t$$

in Columns (1) to (4), where $FE_{i,t}$ represents different combinations of fixed effects. Columns (1) and (2) include firm and time fixed effects and estimate standard errors using firm and time double clustering. Column (3) and (4) include firm and industry×time fixed effects and report industry and time double clustering. In Columns (5) and (6), we use Fama-MacBeth regression, where the first step is

$$\text{Fama-MacBeth: } MFFlow_{i,t} = a_t + b_t ret^{opt}_{i,t-1} + \boldsymbol{c}_t \boldsymbol{X}_{i,t-1} + e_{i,t}, \quad \forall\, i,\ t = 1, 2, \cdots, T$$

estimated for each cross-sectional observations in time $t = 1, 2, \cdots, T$. The second step is to take sample average of estimated coefficients in the first step and report standard errors corrected for heteroskedasticity and autocorrelation using Newey and West (1987) an optimal order of lags. $MFFlow_{i,t}$ is defined as in Edmans, Goldstein, and Jiang (2012), where the fire-sale pressure is categorized as the absolute value of flow to total net asset under management greater than 5%. $ret^{opt}_{i,t-1}$ is the weekly delta-hedged put option returns, defined as Goyal and Saretto (2009) on every third Friday with one month to maturity and moneyness close to at-the-money options. $\boldsymbol{X}$ includes option and stock characteristics. See Appendix Table A.2 for definitions. All variables are winsorized at 1% level and standardized to have mean zero and standard deviation one. We report t-statistics in the bracket under coefficients. *, **, *** represent 10%, 5%, and 1% significance levels, respectively. The sample is from 1996:01 to 2018:12.

	Firm and time clusters		Industry×time FE		Fama-MacBeth	
	(1)	(2)	(3)	(4)	(5)	(6)
ret^{opt}	-0.004*	-0.006***	-0.004*	-0.006***	-0.013***	-0.006*
	[-1.84]	[-2.60]	[-1.81]	[-2.72]	[-3.30]	[-1.66]
β		0.009		-0.001		0.010
		[1.10]		[-0.08]		[1.08]
Size		-0.364***		-0.384***		-0.399***
		[-3.50]		[-3.33]		[-16.61]
Book-to-market ratio		-0.008		-0.013		-0.030**
		[-0.51]		[-0.84]		[-2.40]
12-month momentum		-0.009		-0.004		0.025**
		[-1.45]		[-0.66]		[2.41]
1/stock price		-0.150***		-0.150***		-0.125***
		[-5.88]		[-4.95]		[-6.57]
Excess stock returns		-0.005		-0.003		0.006
		[-1.25]		[-0.69]		[1.31]
Idiosyncratic volatility		-0.129***		-0.119***		-0.240***
		[-7.76]		[-6.02]		[-15.20]
HHI		-0.035**		-0.009		0.006
		[-2.47]		[-0.12]		[0.80]
Volume/open interest		0.002		0.003		0.007**
		[0.76]		[1.33]		[2.50]
Option bid-ask spread		0.013***		0.013**		0.021***
		[3.10]		[2.50]		[2.75]
Option gamma		0.042***		0.035**		0.105***
		[3.03]		[2.44]		[7.58]
Option vega		0.048*		0.056**		0.032***
		[1.90]		[2.23]		[3.74]
HV−IV		-0.001		-0.004		0.003
		[-0.11]		[-0.62]		[0.37]
Constant	0.009***	0.024***	0.006***	0.023***	-0.089*	-0.094**
	[2,564.43]	[5.09]	[331.93]	[4.00]	[-1.69]	[-1.98]
Firm FE	YES	YES	YES	YES	–	–
Time FE	YES	YES	NO	NO	–	–
Industry×Time FE	NO	NO	YES	YES	–	–
N	184,289	184,289	182,303	182,303	184,623	184,623
Adj. R^2	0.509	0.517	0.527	0.534	–	–
Average R^2	–	–	–	–	0.005	0.199

Table A.5. Spillover effects.

	OLS		IV		Expensive	
	(1)	(2)	(3)	(4)	(5)	(6)
MFFlow	0.008**	0.006**	0.007*	0.005*	0.007***	0.010**
	[2.25]	[2.07]	[1.95]	[1.68]	[2.84]	[2.55]
Volume/open interest		0.011		0.011		-0.012
		[1.15]		[0.80]		[-1.36]
Option bid-ask spread		-0.045***		-0.045**		-0.094***
		[-4.50]		[-1.99]		[-5.28]
Option gamma		0.121		0.121***		-0.899***
		[1.49]		[3.07]		[-7.00]
OPtion vega		0.019		0.019		-0.263***
		[0.34]		[0.71]		[-2.77]
HV-IV		0.052***		0.052***		
		[3.23]		[2.66]		
beta		-0.025**		-0.025		-0.104***
		[-2.10]		[-1.61]		[-6.61]
Size		0.014		0.014		-0.112***
		[0.46]		[0.50]		[-3.58]
Book-to-market ratio		-0.012		-0.012		0.005
		[-0.50]		[-0.64]		[0.17]
12-month momentum		0.009		0.009		0.024
		[0.36]		[0.40]		[0.99]
1/stock price		-0.123**		-0.123***		0.865***
		[-2.64]		[-2.85]		[15.38]
Excess stock returns		0.022		0.022		0.021
		[1.33]		[1.43]		[1.19]
Idiosyncratic volatility		-0.022*		-0.022		-0.269***
		[-1.72]		[-0.92]		[-8.56]
HHI		-0.135*		-0.135**		-0.116
		[-1.86]		[-2.21]		[-1.54]
Constant	-0.072***	-0.057			0.231***	0.097***
	[-1,195.42]	[-1.55]			[7,463.08]	[2.88]
N	505,070	505,070	505,070	505,070	505,070	505,070
Adj. R^2	0.100	0.115	-0.008	0.008	0.202	0.391

Table A.6. Alternative fire-sale pressure definitions: Flow ranking and different flow thresholds.

	Demand						Anticipation	
	OLS		IV		Expensive		OLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Bottom flow decile				
MFFlow	-0.013***	-0.014***	-0.020***	-0.022***	0.026***	0.016***		
	[-2.69]	[-3.37]	[-5.73]	[-7.43]	[6.80]	[3.23]		
ret^{opt}							-0.003	-0.004*
							[-1.27]	[-1.79]
All controls	NO	YES	NO	YES	NO	NO	NO	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
N	176,519	176,519	176,519	176,519	176,519	176,519	174,867	174,867
Adj. R^2	0.101	0.110	-0.023	-0.013	0.458	0.537	0.424	0.432
				Panel B: Flow threshold -10%				
MFFlow	-0.011**	-0.013**	-0.018***	-0.019***	0.024***	0.014***		
	[-2.15]	[-2.63]	[-4.67]	[-5.89]	[6.23]	[2.87]		
ret^{opt}							-0.001	-0.002
							[-0.48]	[-0.78]
All controls	NO	YES	NO	YES	NO	NO	NO	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
N	169,118	169,118	169,118	169,118	169,118	169,118	168,327	168,327
Adj. R^2	0.103	0.112	-0.024	-0.013	0.467	0.544	0.412	0.420
				Panel C: Flow threshold -15%				
MFFlow	-0.014***	-0.015***	-0.018***	-0.018***	0.019***	0.010**		
	[-3.58]	[-4.25]	[-5.31]	[-6.26]	[4.70]	[2.31]		
ret^{opt}							0.001	0.000
							[0.34]	[0.10]
All controls	NO	YES	NO	YES	NO	NO	NO	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
N	146,812	146,812	146,812	146,812	146,812	146,812	146,554	146,554
Adj. R^2	0.108	0.117	-0.026	-0.016	0.493	0.568	0.357	0.362

Table A.7. Delta-hedged put option returns and underlying stock returns and prices during fire sale pressure.

$\Psi =$	Stock returns				Stock prices			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ψ	-0.002	-0.009	-0.003	-0.010*	-0.000	-0.000	-0.000	-0.000
	[-0.36]	[-1.60]	[-0.57]	[-1.79]	[-0.96]	[-0.86]	[-1.08]	[-0.95]
MFFlow$\times\Psi$			-0.003	-0.003			0.000	0.000
			[-1.06]	[-1.27]			[1.34]	[1.15]
MFFlow			-0.017***	-0.015***			-0.017***	-0.014**
			[-3.32]	[-2.99]			[-3.05]	[-2.63]
β		-0.026***		-0.027***		-0.027***		-0.027***
		[-3.88]		[-3.95]		[-3.96]		[-4.01]
Size		0.151***		0.150***		0.146***		0.145***
		[7.65]		[7.56]		[7.15]		[7.07]
Book-to-market ratio		0.012**		0.012**		0.011**		0.011**
		[2.54]		[2.49]		[2.33]		[2.27]
12-month momentum		0.011		0.010		0.012		0.011
		[1.48]		[1.43]		[1.64]		[1.60]
Constant	-0.006***	-0.014***	-0.006***	-0.014***	-0.006***	-0.014***	-0.006***	-0.013***
	[-68.88]	[-13.11]	[-41.45]	[-13.15]	[-2,545.05]	[-12.77]	[-228.94]	[-12.58]
N	187,022	187,022	187,022	187,022	187,022	187,022	187,022	187,022
Adj. R^2	0.098	0.101	0.098	0.101	0.098	0.101	0.098	0.101

Table A.8. First-stage regression results.

The table presents the first-stage regression results of instrumental variable method of fire-sale pressure from mutual fund flows on put option delta-hedged returns. The instrumental variable method is based on two instruments, *Flow-to-volume* and *Flow-to-Shares outstanding*, and the first-stage least square regressions are:

$$MFFlow_{i,t-1} = a_0 + b_1\text{Flow-to-volume}_{i,t-1} + b_2\text{Flow-to-shares outstanding}_{i,t-1}$$

$$+c\boldsymbol{X}_{i,t-1} + \xi_i + \xi_t + \eta_{i,t}$$

$MFFlow_{i,t-1}$ is defined as in Edmans, Goldstein, and Jiang (2012), where the extreme outflow is categorized as the absolute value of flow to total net asset under management greater than 5%. $\boldsymbol{X}$ includes option and stock characteristics. See Appendix Table A.2 for variable definitions. All variables are winsorized at 1% level and standardized to have mean zero and standard deviation one. The regression includes firm (ξ_i) and month (ξ_t) fixed effects and the standard errors are clustered at industry and date levels, and we report t-statistics in the bracket under coefficients. *, **, *** represent 10%, 5%, and 1% significance levels, respectively. We also report p-values of the weak identification test (Stock-Yogo) and the overidentification test (Hansen J) statistics.

	(1)	(2)	(3)	(4)
Flow-to-volume	0.920***	0.919***	0.921***	0.920***
	[114.25]	[114.12]	[116.46]	[116.42]
Flow-to-shares outstanding	0.075***	0.075***	0.073***	0.073***
	[6.60]	[6.61]	[6.44]	[6.52]
β			-0.001	-0.000
			[-0.74]	[-0.07]
Size			0.003	0.016***
			[0.61]	[2.77]
Book-to-market ratio			-0.001	-0.001
			[-0.93]	[-1.20]
12-month momentum			-0.004***	-0.005***
			[-3.59]	[-4.04]
1/stock price			0.003	-0.010***
			[1.22]	[-2.82]
Excess stock returns			-0.035***	-0.034***
			[-13.18]	[-13.19]
Idiosyncratic volatility			-0.003	0.003*
			[-1.62]	[1.85]
HHI			0.000	0.001
			[0.08]	[0.70]
Volume/open interest		-0.002***		-0.001***
		[-4.25]		[-3.29]
Option bid-ask spread		-0.005***		-0.003***
		[-5.48]		[-3.62]
Option gamma		0.016***		0.020***
		[9.16]		[7.81]
Option vega		-0.001		-0.002
		[-1.01]		[-1.10]
HV-IV		-0.018***		-0.016***
		[-8.95]		[-10.22]
N	186,127	186,127	186,127	186,127
Stock-Yogo	0.000	0.000	0.000	0.000
Hansen J test	0.000	0.000	0.000	0.000

Table A.9. IV placebo tests.

	(1)		(2)		(3)		(4)	
	1^{st}	2^{nd}	1^{st}	2^{nd}	1^{st}	2^{nd}	1^{st}	2^{nd}
MFFlow		0.048		0.037		0.051		0.041
		[1.22]		[1.02]		[1.26]		[1.07]
Flow-to-volume	0.994***		0.993***		0.994***		0.997***	
	[19.85]		[19.57]		[20.01]		[19.91]	
Flow-to-shares outstanding	0.034		0.035		0.033		0.032	
	[0.59]		[0.60]		[0.59]		[0.55]	
β					-0.005	0.092***	-0.006	0.079**
					[-0.59]	[2.88]	[-0.78]	[2.45]
Size					0.012	0.207	0.087	0.226*
					[0.37]	[1.52]	[1.62]	[1.88]
Book-to-market ratio					0.001	-0.090	-0.003	-0.077
					[0.15]	[-1.56]	[-0.40]	[-1.50]
12-month momentum					-0.001	-0.049	0.001	-0.040
					[-0.05]	[-0.95]	[0.13]	[-0.79]
1/stock price					0.002	-0.078	0.000	-0.171***
					[0.17]	[-1.55]	[0.04]	[-3.86]
Excess stock returns					-0.009***	-0.036	-0.009***	-0.034
					[-2.79]	[-1.30]	[-3.08]	[-1.30]
Idiosyncratic volatility					-0.011	-0.129	-0.012*	-0.143
					[-1.41]	[-1.25]	[-1.71]	[-1.40]
HHI					0.025	0.121	0.020	0.116
					[1.12]	[1.00]	[1.22]	[0.99]
Volume/open interest			0.001	-0.004			0.001	-0.005
			[0.61]	[-0.14]			[0.65]	[-0.18]
Option bid-ask spread			0.000	0.021			0.000	0.027
			[0.09]	[0.73]			[0.06]	[0.98]
Option gamma			0.008*	0.074			0.018***	0.185**
			[1.70]	[1.12]			[3.64]	[2.45]
Option vega			-0.026**	0.119*			-0.049**	0.051
			[-2.16]	[1.96]			[-2.46]	[0.97]
HV−IV			-0.002	0.155***			-0.004	0.122***
			[-0.48]	[3.40]			[-0.79]	[2.86]
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
N		3152		3152		3152		3152
Adj. R^2		0.000		0.017		0.008		0.026

Table A.10. Selection bias

	(1) Probit	(2) OLS	(3) IV
MFFlow	1.433***	-0.021***	-0.025***
	[24.54]	[-4.42]	[-6.36]
Flow-to-volume	-1.366***	–	–
	[-24.94]		
Flow-to-shares outstanding	-0.044***	–	–
	[-3.97]		
β	-0.011*	-0.013*	-0.013*
	[-1.91]	[-1.70]	[-1.69]
Size	-0.076***	0.055**	0.053**
	[-16.45]	[2.26]	[2.21]
Book-to-market ratio	-0.024***	0.013***	0.013***
	[-3.64]	[2.67]	[2.67]
12-month momentum	-0.008**	0.018**	0.018**
	[-2.01]	[2.33]	[2.31]
1/stock price		-0.063***	-0.064***
		[-3.40]	[-3.43]
Excess stock returns		-0.008	-0.008
		[-1.58]	[-1.61]
Idiosyncratic volatility		-0.061***	-0.062***
		[-6.92]	[-7.00]
HHI		-0.009	-0.009
		[-1.00]	[-1.01]
Volume/open interest		-0.001	-0.001
		[-0.53]	[-0.53]
Option bid-ask spread		-0.017***	-0.017***
		[-3.72]	[-3.71]
Option gamma		0.089***	0.089***
		[7.74]	[7.76]
Option vega		0.066***	0.067***
		[5.88]	[5.91]
HV−IV		0.067***	0.066***
		[7.52]	[7.51]
Inverse Mills Ratio		-0.058***	-0.059***
		[-2.73]	[-2.74]
Constant	-0.232***	-0.009***	
	[-3.26]	[-5.71]	
Observations	186,493	186,127	186,127
Industry FE	YES	–	–
Firm FE	–	YES	YES
Time FE	YES	YES	YES
Pseudo R-squared	0.136	–	–
Adjusted R-squared	–	0.109	-0.011

Table A.11. DID placebo event time.

$T =$	1999:05		2009:05		2014:05	
	(1)	(2)	(3)	(4)	(5)	(6)
D(*MFFlow*>Median)	0.015	-0.002	-0.002	0.003	-0.002	-0.001
×D(After *T*)	[0.50]	[-0.08]	[-0.07]	[0.11]	[-0.08]	[-0.04]
D(*MFFlow*>Median)	-0.028	-0.003	-0.018	-0.027	-0.018	-0.028
	[-1.06]	[-0.13]	[-0.86]	[-1.41]	[-1.06]	[-1.64]
MFFlow	-0.021*	-0.017	0.012	0.008	-0.009	-0.015
	[-1.92]	[-1.59]	[0.81]	[0.54]	[-0.95]	[-1.57]
β		-0.041*		-0.019		-0.028
		[-1.81]		[-1.34]		[-1.66]
Size		0.252**		-0.028		0.039
		[2.00]		[-0.49]		[0.54]
Book-to-market ratio		0.063***		0.014		0.027***
		[2.95]		[1.24]		[3.14]
12-month momentum		-0.027*		-0.007		-0.010
		[-1.94]		[-0.56]		[-0.80]
1/stock price		-0.052		-0.111***		-0.092**
		[-1.03]		[-6.24]		[-2.12]
Excess stock returns		-0.023**		-0.032***		-0.004
		[-2.08]		[-2.99]		[-0.57]
Idiosyncratic volatility		-0.115***		-0.094***		-0.116***
		[-3.97]		[-4.65]		[-5.00]
HHI		-0.011		0.005		-0.027
		[-0.33]		[0.20]		[-0.49]
Volume/open interest		-0.002		-0.004		-0.003
		[-0.25]		[-0.95]		[-0.75]
Option bid-ask spread		0.012		-0.008		-0.017*
		[0.83]		[-0.61]		[-1.95]
Option gamma		0.176***		0.100***		0.125***
		[4.76]		[4.63]		[6.23]
Option vega		0.264***		0.110***		0.039**
		[7.02]		[3.33]		[2.61]
HV−IV		0.088***		0.065***		0.017
		[4.93]		[3.11]		[0.97]
Constant	-0.004	0.143***	0.021***	0.034***	-0.021***	-0.092***
	[-1.01]	[8.02]	[3.00]	[2.72]	[-5.61]	[-7.57]
N	36,028	36,028	48,929	48,929	42,274	42,274
Adj. R^2	0.068	0.089	0.175	0.185	0.064	0.075
Firm FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES

Table A.12. Delta-hedged option return summary statistics by year.

Year	Mean	Std	P50	Year	Mean	Std	P50
1996	-0.057	2.20	-0.385	2008	0.237	3.01	-0.333
1997	-0.005	2.27	-0.352	2009	-0.526	2.12	-0.759
1998	0.191	2.52	-0.235	2010	-0.302	1.62	-0.444
1999	0.088	2.72	-0.366	2011	-0.302	1.79	-0.506
2000	-0.215	2.88	-0.632	2012	-0.173	1.25	-0.309
2001	-0.166	2.64	-0.535	2013	-0.188	1.43	-0.345
2002	-0.330	2.39	-0.653	2014	-0.060	1.62	-0.254
2003	-0.270	1.85	-0.463	2015	-0.079	1.75	-0.305
2004	-0.213	1.74	-0.380	2016	-0.264	1.67	-0.436
2005	-0.048	1.73	-0.262	2017	-0.114	1.64	-0.292
2006	-0.129	1.68	-0.325	2018	0.153	1.91	-0.150
2007	0.052	1.96	-0.232				

Table A.13. Pearson correlation of returns, fire-sale pressure, and controls.

	ret^{opt}	$MFFlow$	Vol/OI	Spread	Gamma	Vega	HV−IV	β	Size	BM	mom_{12}	$1/p$	$ret - r_f$	IVOL	HHI
ret^{opt}	1.000														
$MFFlow$	-0.009	1.000													
	(0.000)														
Vol/OI	-0.007	0.015	1.000												
	(0.001)	(0.000)													
Spread	-0.040	0.104	0.047	1.000											
	(0.000)	(0.000)	(0.000)												
Gamma	-0.017	0.090	-0.013	0.153	1.000										
	(0.000)	(0.000)	(0.000)	(0.000)											
Vega	0.063	-0.074	0.001	-0.230	-0.501	1.000									
	(0.000)	(0.000)	(0.681)	(0.000)	(0.000)										
HV−IV	0.029	-0.072	-0.010	-0.077	0.117	0.029	1.000								
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)									
β	-0.016	0.010	-0.006	0.008	0.123	-0.201	0.094	1.000							
	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)								
Size	0.050	-0.275	-0.053	-0.329	-0.279	0.506	0.043	-0.292	1.000						
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)							
BM	-0.007	0.031	0.011	0.080	0.223	-0.206	0.079	0.060	-0.166	1.000					
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
mom_{12}	0.035	-0.068	0.004	-0.055	-0.190	0.151	0.002	0.081	0.035	0.019	1.000				
	(0.000)	(0.000)	(0.099)	(0.000)	(0.000)	(0.000)	(0.348)	(0.000)	(0.000)	(0.000)					
$1/p$	-0.066	0.082	-0.001	0.243	0.745	-0.539	-0.026	0.291	-0.540	0.206	-0.196	1.000			
	(0.000)	(0.000)	(0.674)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
$ret - r_f$	-0.013	-0.066	0.007	0.002	-0.055	0.073	0.180	0.016	0.049	0.024	-0.006	-0.090	1.000		
	(0.000)	(0.000)	(0.003)	(0.435)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)	(0.000)			
IVOL	-0.048	-0.046	0.014	0.052	0.101	-0.341	0.142	0.447	-0.545	0.004	0.203	0.431	0.033	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.073)	(0.000)	(0.000)	(0.000)		
HHI	0.009	0.014	-0.011	-0.034	-0.036	0.046	-0.006	-0.085	0.018	0.053	-0.028	-0.059	-0.003	-0.101	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.182)	(0.000)	

Table A.14. Summary statistics: Buy pressure.

	Mean	Std	P25	P50	P75	N
Panel A: Call options under buy pressure						
Delta-hedged weekly returns (%)	-0.18	2.37	-1.38	-0.43	0.61	226,787
MFFlow (%)	0.39	0.74	0.06	0.16	0.40	226,787
Moneyness	1.01	0.05	0.98	1.00	1.03	226,787
Volume/open interest	0.49	1.34	0.04	0.13	0.37	226,787
Option gamma	0.13	0.09	0.07	0.10	0.16	226,787
Option vega	4.46	4.01	1.90	3.34	5.64	226,787
Option bid-ask spread	0.19	0.20	0.08	0.13	0.22	226,787
HV−IV (%)	0.49	13.46	-5.63	0.29	6.19	226,787
β	1.34	0.84	0.77	1.20	1.77	226,787
Size	8.09	1.75	6.87	8.02	9.29	226,787
Book-to-market ratio	0.40	0.32	0.19	0.33	0.54	226,787
12-month momentum	0.21	0.61	-0.14	0.11	0.40	226,787
1/stock price	0.05	0.04	0.02	0.03	0.06	226,787
Excess stock returns	0.01	0.13	-0.06	0.01	0.08	226,787
Idiosyncratic volatility	0.11	0.06	0.07	0.09	0.14	226,787
Herfindahl-Hirschman index	0.06	0.06	0.03	0.04	0.07	226,787
Panel A: Call options under buy pressure						
Delta-hedged weekly returns (%)	-0.11	2.07	-1.21	-0.37	0.60	188,025
MFFlow (%)	0.34	0.63	0.05	0.15	0.36	188,025
Moneyness	1.00	0.05	0.97	1.00	1.02	188,025
Volume/open interest	0.62	1.82	0.04	0.14	0.45	188,025
Option gamma	0.12	0.08	0.06	0.10	0.15	188,025
Option vega	4.68	4.23	1.99	3.58	5.95	188,025
Option bid-ask spread	0.18	0.19	0.07	0.12	0.21	188,025
HV−IV (%)	-0.64	13.71	-6.61	-0.49	5.20	188,025
β	1.34	0.84	0.76	1.20	1.76	188,025
Size	8.29	1.74	7.08	8.23	9.49	188,025
Book-to-market ratio	0.39	0.32	0.19	0.32	0.53	188,025
12-month momentum	0.21	0.62	-0.14	0.11	0.39	188,025
1/stock price	0.04	0.04	0.02	0.03	0.05	188,025
Excess stock returns	0.01	0.13	-0.06	0.01	0.07	188,025
Idiosyncratic volatility	0.11	0.06	0.06	0.09	0.13	188,025
Herfindahl-Hirschman index	0.06	0.06	0.03	0.04	0.07	188,025

Table A.15. Buy pressure and put option delta-hedged returns: Demand and anticipation effects.

	Demand						Anticipation	
	OLS		IV		Expensive		OLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MFFlow	-0.017***	-0.028***	-0.024***	-0.035***	0.016**	0.011**		
	[-4.74]	[-8.41]	[-5.87]	[-9.31]	[2.40]	[2.63]		
ret^{opt}							-0.005	-0.009***
							[-1.64]	[-3.33]
β		-0.015**		-0.016**		-0.052***		-0.035***
		[-2.17]		[-2.21]		[-4.99]		[-4.80]
Size		0.043*		0.040		-0.176***		-0.428***
		[1.76]		[1.65]		[-6.29]		[-4.09]
Book-to-market ratio		0.012**		0.012**		-0.027**		-0.003
		[2.47]		[2.46]		[-2.02]		[-0.20]
12-month momentum		0.019**		0.019**		0.060***		0.020**
		[2.24]		[2.27]		[3.35]		[2.08]
1/stock price		-0.071***		-0.072***		0.405***		-0.169***
		[-3.87]		[-3.95]		[12.56]		[-4.45]
Excess stock returns		-0.011**		-0.011**		-0.050***		0.023***
		[-2.12]		[-2.13]		[-5.70]		[5.55]
Idiosyncratic volatility		-0.059***		-0.059***		-0.344***		-0.117***
		[-6.73]		[-6.81]		[-25.43]		[-7.33]
HHI		-0.007		-0.007		-0.010		-0.026*
		[-0.83]		[-0.84]		[-0.55]		[-1.76]
Volume/open interest		-0.002		-0.002		0.002		-0.000
		[-1.00]		[-1.01]		[0.69]		[-0.18]
Option bid-ask spread		-0.017***		-0.017***		-0.008		0.021***
		[-3.51]		[-3.47]		[-0.78]		[5.37]
Option gamma		0.090***		0.090***		-0.468***		0.056***
		[8.09]		[8.16]		[-10.33]		[4.70]
Option vega		0.067***		0.068***		-0.110***		0.098***
		[5.91]		[5.95]		[-8.82]		[3.91]
HV−IV		0.066***		0.066***				-0.000
		[7.79]		[7.79]				[-0.04]
Constant	-0.006***	-0.008***			0.019***	0.054***	0.014***	0.033***
	[-66.00]	[-4.96]			[852.48]	[30.05]	[548.07]	[7.72]
N	187,675	187,675	187,675	187,675	187,675	187,675	184,796	184,796
Adj. R^2	0.098	0.109	-0.023	-0.011	0.441	0.524	0.491	0.501

Table A.16. Buy pressure and call option delta-hedged returns: Demand and anticipation effects.

	Demand						Anticipation	
	OLS		IV		Expensive		OLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MFFlow	-0.020***	-0.029***	-0.028***	-0.038***	0.019***	0.011**		
	[-5.60]	[-8.05]	[-6.91]	[-9.37]	[2.84]	[2.53]		
ret^{opt}							-0.007**	-0.011***
							[-2.26]	[-3.73]
β		-0.014**		-0.015**		-0.056***		-0.035***
		[-2.24]		[-2.30]		[-5.61]		[-4.68]
Size		0.021		0.018		-0.153***		-0.447***
		[0.83]		[0.69]		[-6.15]		[-4.57]
Book-to-market ratio		0.013***		0.013***		-0.025*		-0.004
		[2.87]		[2.85]		[-1.82]		[-0.27]
12-month momentum		0.017**		0.017**		0.060***		0.018**
		[2.19]		[2.23]		[3.42]		[2.36]
1/stock price		-0.072***		-0.074***		0.398***		-0.171***
		[-4.76]		[-4.88]		[12.77]		[-4.87]
Excess stock returns		-0.006		-0.006		-0.056***		0.022***
		[-1.10]		[-1.12]		[-6.85]		[5.86]
Idiosyncratic volatility		-0.061***		-0.062***		-0.357***		-0.112***
		[-7.35]		[-7.48]		[-27.28]		[-7.77]
HHI		-0.005		-0.005		-0.014		-0.034**
		[-0.49]		[-0.50]		[-0.86]		[-2.53]
Volume/open interest		0.001		0.001		0.018***		-0.001
		[0.30]		[0.29]		[8.63]		[-0.50]
Option bid-ask spread		-0.034***		-0.034***		-0.046***		0.013***
		[-8.43]		[-8.37]		[-11.34]		[3.09]
Option gamma		0.073***		0.074***		-0.436***		0.054***
		[6.65]		[6.72]		[-11.00]		[6.11]
Option vega		0.060***		0.061***		-0.104***		0.099***
		[5.68]		[5.73]		[-8.24]		[4.34]
HV$-$IV		0.072***		0.072***				-0.001
		[10.81]		[10.79]				[-0.13]
Constant	-0.003***	-0.005***			0.022***	0.053***	0.012***	0.030***
	[-27.56]	[-2.92]			[950.38]	[34.53]	[268.64]	[8.20]
N	226,521	226,521	226,521	226,521	226,521	226,521	223,076	223,076
Adj. R^2	0.093	0.103	-0.020	-0.009	0.413	0.497	0.489	0.500