Quantitative Investing and Market Instability

William Beggs

Jonathan Brogaard

Austin Hill-Kleespie

Abstract

The May 2010 Flash Crash and August 2007 Quant Meltdown raised concerns about the impact of quantitative investment strategies on market instability. We examine whether quantitative investing dampens or exacerbates market instability by focusing on mutual fund fire sales. We find that quantitative fund fire sales have a much larger impact on market instability than fire sales by traditional mutual funds. For the same magnitude fire sale, quantitative funds' impact is over eight times as large. The larger impact is due to quantitative funds' reliance on similar trading strategies and their strategies' sensitivity to the time-series of returns.

JEL classification: G11, G23, G40

Keywords: Investment management, security selection, quantitative funds, mutual funds, fire sales, herding, market stability

William Beggs is at the University of San Diego School of Business, San Diego, CA 92110. Email address: wbeggs@sandiego.edu. Jonathan Brogaard is at the David Eccles School of Business, University of Utah, Salt Lake City, UT, 84112. Email address: brogaardj@eccles.utah.edu. Austin Hill-Kleespie is at the G. Brint Ryan College of Business, University of North Texas, Denton, TX, 76201. Email address: austin.hill-kleespie@unt.edu.

1. Introduction

Quantitative investing is the process of making investment decisions based on systematic, rule-based criteria. Until recently quantitative investing had been contained to a subset of hedge funds. In recent years it has become increasingly mainstream and is now accessible to retail investors through quantitative mutual funds. Among the largest quantitative mutual fund managers is AQR, with over $140 billion in assets under management. While mutual funds are a well-studied segment of financial markets, little attention has been given to the rise of quantitative mutual funds. In particular, the effect that the rise in popularity of quantitative investing has on market stability remains an open question. This paper examines whether quantitative funds have a differential effect on market stability compared to traditional mutual funds.

Theory is split on how quantitative investing may impact market instability. It may benefit financial markets because quantitative managers take a calculated and emotionless approach to investing. This could suppress managers' behavioral biases and help to reduce inefficiencies and therefore reduce idiosyncratic periods of market instability (Kirilenko and Lo (2013)). Alternatively, quantitative investors may exacerbate instability due to their reliance on similar strategies. If quantitative managers analyze past data in a similar fashion and come to similar conclusions about what are the optimal signals to forecast future returns they are likely to make similar trading decisions. Too many quantitative investors trading on the same signals may induce greater price pressure on securities as they enter and exit trades which ultimately decreases stability (Falato et al. (2016), Chaderina et al. (2018), and Cai et al. (2019)).

We test whether quantitative and non-quantitative mutual funds undergoing fire sales, as defined by Coval and Stafford (2007), have a differential impact on market stability. We find that flow-induced selling by quantitative funds generates transitory price declines over eight times as large as non-quantitative funds for the positions sold in their portfolios. In addition, it takes at least one month longer for these stocks to recover to fundamental value. The result leads naturally to the question of why is the quantitative fire sale so much more impactful. We document that quantitative mutual funds tend to have higher levels of portfolio and trading overlap, likely due to their following similar signals. Digging further into fund trading behavior, we find that quantitative funds' selling decisions are more heavily influenced by peer fire sales and that recent returns appear to be more influential for selling decisions. It is likely that these behaviors lead to a stronger negative feedback loop for quantitative funds whereby selling begets more selling across an increasing segment of quantitative funds.

We identify funds that use a quantitative investment process by performing textual analysis of mutual fund prospectuses.[1] To understand how funds typically describe their investing process we begin by reviewing the "Principal Investment Strategies" section of mutual fund prospectuses for a subset of equity funds. For example, the T. Rowe Price Blue Chip Growth Fund (TRBCX) explains *"It focuses on companies with leading market positions, seasoned management, and strong financial fundamentals."* Whereas the Leuthold Select Industries fund (LSLTX) states *"In investing in equity securities, the fund uses a disciplined, unemotional, quantitative investment approach that is based on the belief investors can achieve superior investment performance through group selection (Select Industries Strategy)."*

Using our methodology, the latter fund would be identified as a quantitative fund and the former as a non-quantitative fund. We generate a phrase list reflective of a quantitative investment process and use this to flag quantitative mutual fund prospectuses. We consider prospectuses on

[1] As described in Section 2.1 the identification methodology is similar to Harvey et al. (2017) and Abis (2020) both of whom examine differences in quantitative versus fundamental investment management. As a robustness check, in Section 5.2 we repeat the main analysis using Harvey et al. (2017)'s identification strategy and find similar results.

the EDGAR database for funds available to investors from 2006 to 2015.[2] The label "Quantitative funds" refers to those funds that the textual analysis has identified as using a quantitative investing strategy. "Non-quantitative" (or fundamental) funds are those who do not refer to the use of a quantitative investing process in their prospectus. Over the course of the sample period, we find that the total number of quantitative funds in our sample increases steadily. In 2008 we identify 95 (7%) quantitative funds in the sample and in 2015 we find 116 (8.5%) quantitative funds out of 1,372 total mutual funds within our sample.

To test for differential effects on market stability, we focus the analysis on mutual funds that experience large outflows and inflows, referred to colloquially as "fire sales," and follow Coval and Stafford (2007) in identifying these events. We bifurcate the fire sale events based on the classification of quantitative and non-quantitative funds. Both types of funds outflows are associated with short-term negative abnormal returns. However, the price impact on underlying securities resulting from outflows from quantitative funds is over eight times as large as that for similarly sized outflows from non-quantitative funds.

Why is the price pressure from quantitative fund fire sales so much larger? We test three possible mechanisms: overlapping positions, momentum exposure, and cash holdings.

We first explore overlapping portfolio holdings. Greater portfolio overlap among quantitative funds would increase the likelihood that multiple funds liquidate the same securities in a fire sale. While a single fund liquidating positions may be able to adequately coordinate securities transactions in a manner that minimizes market impact, multiple funds liquidating the same stocks are likely to be unaware of each other's trading intentions and the liquidation of overlapping positions would occur in a less coordinated fashion. We find evidence in support of

[2] Though we identify funds throughout this sample period we find that the lower number of funds identified prior to 2009 combined with the necessary filters limits our ability to consider the entire sample period in our analysis.

this hypothesis. Specifically, we document that quantitative funds exhibit significantly greater portfolio overlap and selling overlap (more than double) relative to non-quantitative funds.

Next, we test the momentum exposure mechanism. If quantitative funds rely more heavily on past price momentum in their selling decisions, this could generate a negative feedback loop in the returns of stocks widely sold by quantitative funds undergoing fire sales. Downward price pressure generated by a single quantitative fund fire sale may generate enough negative momentum to induce other quantitative funds with the same positions to sell these securities. This downward momentum could be a further catalyst for fire sales by other funds and eventually lead to market destabilization (Stein (2012), Falato et al. (2016), Cai et al. (2019)). Consistent with the momentum exposure hypothesis, we find that quantitative funds are much more sensitive to recent poor returns than non-quantitative funds when deciding which stocks to sell upon suffering extreme outflows.

Finally, we examine the cash holdings channel. Funds that hold lower levels of cash may need to sell more securities more aggressively to meet the same level of investor redemptions, potentially generating a larger effect on prices. While we find that quantitative funds tend to hold less cash than their non-quantitative counterparts, the level of cash holdings do not correlate with the magnitude of the fire sale returns. Thus, cash is not likely to play a role in contributing to the larger distortion from quantitative funds.

Together, the overlapping positions and momentum exposure hypotheses help explain why quantitative funds' price pressure from fire sales is larger than non-quantitative funds' price pressure.

This study makes two core contributions to the literature. First, it builds on the fire sale literature generally. Coval and Stafford (2007) note that selling by mutual funds receiving large outflows can cause stock prices to become distressed. Furthermore, the fire sale stock pressure can lead to market distortions and can have a destabilizing effect in capital markets (Cai et al. (2019); Duarte and Eisenbach (2018)). We show that the level of distortion differs between quantitative and fundamental mutual funds. Our study also complements recent work on the use of price pressure from fire sales as an instrument to shock asset prices (e.g., Edmans, Goldstein, and Jiang (2012)). Two recent papers argue that mutual fund fire sales do not satisfy the necessary conditions for a valid instrument. Berger (2018) argues that fire sales are not a valid instrument because they are correlated with firm fundamentals and Wardlaw (2020) shows that scaling by dollar volume induces a mechanical correlation with returns. Our study does not examine fire sales as an instrument. We instead explore how funds' investment processes impact the magnitude of securities mispricings from fire sales.

Second, we document an externality of quantitative investing on the broader financial markets. While the last decade has seen a growing literature on algorithmic trading (e.g. Hendershott, Jones, and Menkveld (2011), Hendershott and Riordan (2013), and Weller (2017)) the literature on quantitative investing is still nascent. Birru, Gokkaya, and Liu (2018) study how quantitative sell-side research analysts and find that quantitative research increases market efficiency. D'Acunto, Prabhala, and Rossi (2019) study the effects of robo-advising and find that it results in increased diversification and reduced volatility. Kirilenko and Lo (2013) theorize about quantitative investing and its' ability to destabilize markets.

2. Data

This section details the investment strategy identification methodology and data sources used for the analyses.

2.1. Identifying quantitative mutual funds

To the best of our knowledge, no conventional datasets identify mutual funds following quantitative investment processes. To identify quantitative funds in the cross section, we rely on hand collected text from the "Principal Investment Strategies" section mutual fund prospectuses. Since every fund is required to file a prospectus containing information on their investment strategy each year, we are able to retrieve this information from the SEC's EDGAR archives. We use a multi-step approach which combines both automated and manual hand collection methods.

We first develop a list of common keywords and phrases used to describe the investment strategies of quantitative funds in SEC filings. We review the "Principal Investment Strategies" section for a subset of prospectuses by hand to generate a list of phrases (Appendix B) we believe to be indicative of a quantitative investing process.[3] To identify potential quantitative funds, we first automate a review of summary prospectuses (Form 497K) on the SEC's EDGAR database to determine if funds appear to incorporate quantitative aspects into their portfolio management process. Summary prospectuses are filed in EDGAR beginning in 2009 and are filed at the fund level and are searchable by ticker and CIK.[4] To identify potential quantitative funds in the pre-2009 period, we search a synopsis of the "Principal Investment Strategies" section available from the Morningstar Principia CDs (e.g., Kostovetsky and Warner 2019) for quantitative keywords.[5] We find that these steps alone are not sufficient for two different reasons. First summary

[3] For robustness, we reidentify quantitative funds using an alternate list of keywords following Harvey et al. (2017) and our findings are statistically and economically similar.

[4] We start by searching the full summary prospectus text. We focus on summary prospectuses as opposed to the full prospectuses because summary prospectuses are filed at the fund level. Funds' complete prospectuses are filed at the series level (typically with other funds launched during the same time period) and are contained in Form 485 filings. There is no standard format for Form 485 filings which makes parsing investment strategy text for individual funds and an automated review not possible.

[5] We thank Leonard Kostovetsky for sharing this data. The data begin in 2000. Morningstar may only provide partial text from this section if the strategy description is overly lengthy. Consistent with this notion, we find that quantitative fund identification is spotty and incomplete as Morningstar may pull different parts of a fund's investment strategy text from year to year.

prospectuses appear to over identify quantitative funds since we search the entire text as opposed to the just the “Principal Investment Strategies” section. Second the Morningstar Principia synopses of fund strategies under identify quantitative funds since the text provided is incomplete.

To address these shortcomings we perform targeted hand collection of the “Principal Investment Strategies” section for all quantitative fund candidates. Specifically, if a fund’s strategy is identified as quantitative using text from the above sources we hand collect the “Principal Investment Strategies” section for the fund for all years 2000 to 2015.[6] We primarily focus on the post-2006 period since Form 485 filings, where the prospectus is contained, are not searchable by ticker on EDGAR prior to February of 2006.[7] Finally, we use the hand collected text from the “Principal Investment Strategies” section for each fund-year and our phrase list from Appendix B to create a dynamic quantitative fund indicator variable.

We then re-examine this time series of investment strategy sections using the most popular word stems from our original phrase list. We do so on a filing year basis to allow for the possibility that funds may have changed or altered their investment process across time. Additionally, as in Abis (2020) for this final round of identification we choose to use word stems to allow maximal flexibility in identifying funds employing a quantitative investment process.

Our methodology is similar to those employed by Harvey et al. (2017) and Abis (2020) with a few small differences. We choose to use phrases in the initial step rather than individual words to mitigate the possibility of misidentifying funds as quantitative on the basis of commonly used words in the prospectus. In particular key words of interest can have ambiguous meaning in

[6] Where multiple filings are available within a single year the earliest filing for that year is used. In total this targeted hand collection procedure produced more than 4,000 investment strategy sections across our time frame. An equivalent procedure for non-quantitative funds would have required us to manually collect in excess of 50,000 investment strategies. Given this substantial difference in magnitude and our ability to use a binary indicator in our analysis we chose to focus on collecting this investment strategy information for quantitative funds only.

[7] See https://www.sec.gov/edgar/search-and-access.

the context of investment management (i.e. "quantitative") and thus relying on phrases decreases the probability of committing a Type I error.[8] Like Abis (2020) the bulk of the phrases utilize "quantitative"[9] and thus its root is a primary means of identification. Our inclusion of "quantitative" generally agrees with results from the random forest algorithm utilized in her setting which finds the "quantit-" word root to be the most important for the identification of quantitative funds. Abis (2020) also relies on identification performed by examining prospectuses hosted on the EDGAR database. We also examine fund names on CRSP and look for those containing "quantitative" in the name and categorize those as quantitative funds which Abis (2020) also uses as a complimentary means of identification. In comparison to her sample we have identified fewer funds but are also confident that the methodology is robust to misidentification as any remaining bias attributable to misidentification is due to quantitative funds being misidentified as non-quantitative. Such misidentification would generate a bias against our ability to identify results that are different between the fund types.

2.2. Mutual fund and holdings data

Once quantitative funds have been identified, we match this identifier to both the Thomson Reuters and CRSP Survivor-Bias-Free US Mutual Fund Databases. We restrict the sample to actively managed domestic equity mutual funds operating between 2008 and 2015 using CRSP objective codes.[10] Mutual fund holdings data are obtained from both Thomson Reuters and CRSP.[11] We focus specifically on the post-2008 period since CRSP holdings data are reliable after

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[8] If non-quantitative funds are falsely identified as quantitative funds in the sample differences between the fund types would be expected to be minimal meaning that we are more likely to accept a null hypothesis of no differences between fund types.
[9] For example: "quantitative model," "quantitative approach," "quantitatively driven," etc.
[10] ETFs, variable annuities, and index funds are dropped from the sample using CRSP flags and name searches.
[11] Holdings data from Thomson Reuters are linked to the CRSP data using the MFLINKS table.

this date. Potter and Schwarz (2016) find that both of these databases contain many voluntarily disclosed portfolios, and that researchers can gain up to a 35% increase in observed manager trading by combining data sources. Another benefit of using holdings reports from CRSP in addition to Thomson is that Zhu (2020) finds 58% of the newly founded funds (post-2008) cannot be matched from Thomson Reuters to the CRSP database. We follow Coval and Stafford (2007) in examining fire sales at the quarterly frequency. Specifically, we keep portfolios reported on calendar quarter ends to ensure a sufficient number of quantitative funds are available to sort in the computation of the pressure variables.

Figure 1 shows that at the beginning of our sample period in 2008 there were 95 quantitative funds out of 1,299 total active domestic equity funds (about 7%). Throughout the sample period we observe that quantitative funds make up an average of just over 8% of all the funds.

Insert Figure 1 About Here

Additionally, we examine the characteristics of quantitative and non-quantitative funds. Fund characteristics and returns from CRSP are aggregated across share classes on an asset-weighted basis using the crsp_cl_grp variable. The oldest available share class is used to compute fund age. CRSP returns are net of fees, expenses and brokerage commissions but before any front-end or back-end loading fees. Net fund returns are converted to excess returns by subtracting the corresponding risk-free rate. Monthly return data for the market (MKT_RF), size (SMB), value (HML), momentum (MOM), investment (CMA), and profitability (RMW) factors were retrieved from Kenneth French's website.[12] We include information on fund factor exposures generated by a 6-factor model which includes factors from both Carhart (1997) and Fama and French (2015).[13] The coefficients are estimated using fund returns and factor data from the prior 24 months. Following Sirri and Tufano (1998), we calculate monthly net fund flows using net asset and return data. Flows consist of the monthly growth in net assets not attributable to returns and are calculated as:

$$Flow_{j,t} = \frac{TNA_{j,t} - (1 + r_{j,t})TNA_{j,t-1}}{TNA_{j,t-1}} \tag{1}$$

Table 1 presents descriptive statistics of fund characteristics for the sample of quantitative and non-quantitative mutual funds.

Insert Table 1 About Here

The summary statistics indicate that quantitative funds generally have greater exposure to known risk factors in the 6-factor model than non-quantitative funds. For instance, the mean momentum coefficient for quantitative funds is 0.05 which is more than four times as large as the 0.01 coefficient for non-quantitative funds. Similar differences are observed for the other five factors with quantitative funds generally having larger coefficients on Fama and French (2015) factors.

[12] To access Kenneth French's website see http://mba.tuck.dartmouth. edu/pages/faculty/ken.french/. We thank Kenneth French for making these data available.
[13] Specifically, the six factors we consider include excess market return (MKT_RF), value (HML), size (SMB), profitability (CMA), and investment (RMW) from Fama and French (2015) and momentum (MOM) from Carhart (1997).

The higher reliance on known anomalies and lower standard deviation of coefficients implies quantitative funds are more homogenous compared to their non-quantitative counterparts.

Differences between the two types of funds are found in other fund level characteristics as well. Specifically, we find that on average, quantitative funds tend to have experienced lower net flows, and exhibit both greater turnover and lower expense ratios than non-quantitative funds. Of particular note we find that quantitative funds tend to be smaller than their non-quantitative peers. This suggests that the larger distortion we document is not merely a mechanical byproduct of large funds selling off a sizeable portion of their assets. We also note that quantitative funds hold more positions relative to non-quantitative funds which is consistent with the findings of Abis (2020). This finding also runs counter to our results since portfolios with a greater breadth of holdings are thought to be more liquid (e.g., Pastor, Stambaugh, and Taylor (2020)).

Later in the paper we use a number of additional stock-level variables as controls. We follow Gompers and Metrick (2001) and consider the following stock level variables: natural log of market capitalization, natural log of firm age, dividend yield, book-to-market ratio, natural log of share price, turnover, volatility, the stock's return over the previous three months, and the stock's return over the nine months preceding the prior quarter. We also add investment and profitability as calculated in Fama and French (2015). See Appendix A for further detail on variable construction.

3. Do Quantitative and Non-Quantitative Mutual Fund Fire Sales Differ?

In this section we test whether quantitative fire sales have a differential impact on stock prices than non-quantitative fire sales. We begin by measuring the difference in the performance of securities sold (bought) by quantitative and non-quantitative funds during a fire sale (purchase).

We follow Coval and Stafford (2007) and identify funds with the largest net flows, and their associated stocks, as experiencing a fire sale. We find that fire sale stocks sold by quantitative funds experience an approximately 50 basis point greater decline relative to those sold by non-quantitative funds over the course of the entire quarter. Additionally, we find that the amount of time it takes these stocks to recover to their fundamental value is significantly longer than non-quantitative funds.

3.1 Identifying fire sale stocks

We use quarterly mutual fund flows to identify stocks with significant transactional pressure due to liquidity based trading by mutual funds.[14] To identify "pressure stocks," we follow Coval and Stafford (2007)'s methodology. To start, we split the sample into quantitative and non-quantitative mutual funds every quarter. We begin by examining stocks undergoing pressure from quantitative funds. Quantitative fund flow induced sales (purchases) are identified as reductions (increases) in the number of shares owned by quantitative funds experiencing severe outflows (inflows). Severe flows are defined as those below (above) the 10th (90th) percentile of quarterly flows. *QuantPressure* is the flow-motivated trading by quantitative funds in a given stock scaled by shares outstanding

$$QuantPressure_{i,t} = \frac{\begin{array}{l}\sum_j \left(\max(0, \Delta Holdings_{j,i,t}) \mid flow_{j,t} > Quantpctl(90th)\right) - \\ \sum_j \left(\max(0, -\Delta Holdings_{j,i,t}) \mid flow_{j,t} < Quantpctl(10th)\right)\end{array}}{Shrout_{i,t-1}} \qquad (2)$$

[14] Calculated as the sum of the interim monthly flows.

To achieve a ‘matched’ comparison of pressure from the trading of non-quantitative funds, we calculate non-quantitative pressure using the flow induced sales (purchases) made by non-quantitative funds undergoing flows within the same range experienced by the quantitative fire sale funds during the quarter.

$$NonQuantPressure_{i,t} = \frac{\begin{array}{l}\sum_j \left(\max(0, \Delta Holdings_{j,i,t}) \mid Quantpctl(100th) > flow_{j,t} > Quantpctl(90th) \right) - \\ \sum_j \left(\max(0, -\Delta Holdings_{j,i,t}) \mid Quantpctl(0th) < flow_{j,t} < Quantpctl(10th) \right)\end{array}}{Shrout_{i,t-1}} \tag{3}$$

We observe much more variation in the *NonQuantpressure* variable than *QuantPressure* in our sample. Greater variation for *NonQuantPressure* is not surprising given there are significantly more non-quantitative funds than quantitative funds. However, despite fewer shares sold or purchased by quantitative funds we still find that their effect is larger. This unexplained larger effect implies that something besides the total dollar amount traded leads to the larger distortions generated by quantitative funds.

3.2 Quantitative fire sales: portfolio sorts

We examine the abnormal returns of stocks sold by each fund type during fire sales. To do so we again follow Coval and Stafford (2007) and in each of the event quarters, we sort stocks by *QuantPressure* and *NonQuantPressure.* In particular, we identify stocks in the top and bottom deciles for each pressure measure and label stocks in these top and bottom deciles “pressure stocks.” Stocks in the top decile have upward price pressure meaning that they are being purchased by the funds receiving net inflows. Conversely those in the lowest decile are those that are being most heavily sold due to outflows. Table 2 presents summary statistics information on pressure stocks held by both quantitative and non-quantitative funds.

Insert Table 2 About Here

We consider a combination of variables associated with firm level stock returns including age, size, trailing returns, return volatility, investment and profitability. In general, the information in Table 2 indicates that quantitative pressure stocks tend to have similar characteristics when compared to non-quantitative pressure stocks. This suggests that any differences in the effects of fire sale trading for each type of fund would likely stem from something besides stock level considerations. There are some modest differences between the groups. For example, stocks undergoing quantitative fund selling pressure tend to be more growth-oriented relative to stocks undergoing selling pressure from non-quantitative funds. To ensure that the results are not driven by firm level characteristics, we later conduct a set of multivariate regressions on abnormal returns which control for these stock level characteristics.

To perform a preliminary analysis of the effect flow induced selling pressure has on stock returns, we form equally weighted portfolios consisting of stocks in the lowest pressure deciles (both quantitative and non-quantitative) in each event quarter. Daily abnormal portfolio returns are computed using a 6-factor model which includes the Fama and French (2015) five factors plus momentum. We choose to include the momentum factor from Carhart (1997) due to findings from Lou (2012) that flow based trading induces momentum in stock returns. Additionally, we use daily returns rather than monthly returns to more accurately estimate factor loadings for individual securities at the time the fire sale occurs.[15]

Portfolio betas are estimated using a window from minus 250 days to minus 22 days and daily portfolio abnormal returns are computed using the following model:

$$AR_{l,t} = r_{i,t}^{e} - \left(\hat{\beta}_{1,l}RMRF_{t} + \hat{\beta}_{2,l}SMB_{t} + \hat{\beta}_{3,l}HML_{t} + \hat{\beta}_{4,l}CMA_{t} + \hat{\beta}_{5,l}RMW_{t} + \hat{\beta}_{6,l}MOM_{t}\right). \quad (4)$$

Where $r_{i,t}^{e}$ is portfolio *l*'s return in excess of the risk-free rate on day *t*. The model's benchmark returns for each portfolio are calculated using beta coefficient estimates from the estimation window and time *t* factor realizations. These are then subtracted from the portfolio's realized excess returns to form the daily abnormal returns. To reduce the impact of idiosyncratic market days we further average the daily abnormal portfolio returns over each event quarter. Our calculation methodology generates daily average abnormal returns. Finally, we sum the daily average abnormal portfolio returns over the event quarter and subsequent quarters to obtain cumulative average abnormal returns (CARs) for the portfolios of quantitative and non-quantitative fire sales stocks. By removing return variation driven by factor exposure we isolate the effect of the fire sale on the stock return.

Figure 2 illustrates how the CARs for quantitative and non-quantitative fire sale stock portfolios develop over the course of both the fire sale quarter and subsequent quarters.

Insert Figure 2 About Here

[15] In Section 5, we recalculate these results using a monthly data as a robustness check and find no difference.

We find that the magnitude of abnormal returns for a portfolio of stocks that are heavily sold by quantitative mutual funds is noticeably more negative than the abnormal returns realized by the portfolio of stocks heavily sold by non-quantitative funds. Further, we observe that the difference between the security types is not trivial. Over the course of the entire quarter, the quantitative fire sale stock portfolio CAR is nearly 50 basis points less than the non-quantitative fire sale stock portfolio. Moreover, we find that time it takes for the portfolio of quantitative fund stocks to return to fundamental value is more delayed, taking approximately 80 more trading days on average. Simply put not only do securities sold by quantitative funds experience a large deviation from fundamental value, it takes these securities significantly longer to recover.

It is not obvious why the size of the distortion and delay is so much larger for quantitative stocks. However, these large differences provide initial compelling evidence that quantitative funds have a greater impact on market stability. To confirm that stock level characteristics are not driving the difference we employ a multivariate regression framework.

3.3 Quantitative fire sales: multivariate regression analyses

The findings in the previous section indicate that, on average, quantitative fund fire sales generate larger and longer lasting market distortions. However, Table 2 suggests that this may be driven by minor differences in firm level characteristics of the stocks sold by each fund type. To account for these differences, we use a panel OLS regression framework with stock level controls and thus mitigate any confounding effect.

Table 3 reports the coefficient estimates from regressions of cumulative abnormal stock returns observed over the course of the fire sale event quarter on both contemporaneous quantitative pressure and non-quantitative pressure. The cumulative abnormal returns for individual stocks are computed using the same estimation procedure used for the portfolio analyses described in Section 3.2. Each regression includes quarter fixed effects to account for variation attributable to macroeconomic and market environment and column (4) includes stock fixed effects to examine the time varying within stock effects pressure has on abnormal returns. We also follow guidance from Peterson (2009) and cluster standard errors at the stock and quarter level. Finally, we use t-tests to determine if the coefficient estimates on quantitative and non-quantitative pressure in each column are statistically different from one another. Our testing methodology allows us to evaluate how significant the pressure from each fund type is in driving abnormal returns.

Insert Table 3 About Here

We begin by estimating coefficients for *QuantPressure* and *NonQuantPressure* in column (1) prior to adding covariates to the model. In column (2) we add each stock's total ownership (as a percentage of shares outstanding) by quantitative and non-quantitative funds as possible explanatory variables. Columns (3) and (4) include a vector of stock characteristic control variables following both Gompers and Metrick (2001) and Fama and French (2015). Doing so ensures that the observed effect is not driven by any differences in firm level characteristics as observed in Table 2.

The results in all four columns show that quantitative fund pressure has an economically larger impact on stock returns during the fire sale quarter compared to non-quantitative fund pressure. The coefficient for quantitative fund pressure is positive and statistically significant at the 1% level while the coefficient for non-quantitative fund pressure is positive and statistically significant at the 10% level. We also note the magnitude of the coefficient on quantitative fund pressure is much larger. A t-test of the coefficients yields that the difference is statistically significant at the 1% level in all four models.

In column (3), the magnitude of the pressure coefficient quantitative funds is approximately eight times larger (0.441) than the coefficient for non-quantitative funds (0.053). The economic interpretation of these coefficients is straightforward, a 1% decrease in stock ownership from quantitative funds undergoing a fire sales is associated with a 4.41% decrease in abnormal stock returns over the event quarter while a 1% decrease in stock ownership from a non-quantitative funds undergoing a fire sales is associated with a 0.53% decrease in abnormal returns during the quarter.[16] Given the economically large difference in magnitudes between the quantitative and non-quantitative funds the natural next question is why does there exist such a large effect for quantitative funds relative to non-quantitative funds?

4. What Drives Quant Funds' Larger Impact?

The results in Section 3 show that quantitative funds undergoing fire sales generate larger distortions than fire sales by non-quantitative funds. In this section we test three potential mechanisms that could explain the result. First, if quantitative funds approach the investment process in a similar manner, they are more likely to hold and trade the same securities and exert

[16] A recent working paper by Huang, Ringgenberg, and Zhang (2019) finds that fund managers do not uniformly scale down their portfolio following a flow shock, but tend to sell a subset of low quality stocks whose prices remain depressed for a period of time after the fire sale event. Their results suggest that information, in addition to price pressure, may play a role in price declines of fire sale stocks. Following their methodology, we decompose selling pressure from quantitative funds into its discretionary and expected components, and note that our results are driven by discretionary pressure, i.e. the sale of fund positions in excess of scaling down the portfolio. However, inconsistent with an information based explanation for our results, we observe a reversal in prices for discretionary quantitative pressure stocks following the event period.

more pressure as they exit these positions. Second, quantitative funds may be more likely to consider similar stock characteristics when choosing which securities to liquidate in their portfolios. In particular, we focus on negative security price momentum since momentum is a common quantitative fund strategy and it may be that a fire sale by one fund generates negative momentum leading other quantitative funds to liquidate their positions. Third, quantitative funds may systematically hold different levels of cash than non-quantitative funds. All else being equal, funds that hold less cash would have to sell a greater quantity of securities to meet investor redemptions for the same level of fund flows during a fire sale. This could potentially generate greater downward pressure on prices. The result support the overlapping positions and momentum hypothesis but not the cash level mechanism.

4.1 Portfolio and trading overlap

We start by exploring overlapping portfolio holdings and trading activities of funds undergoing fire sales during the sample period. Table 1 provides evidence that quantitative funds tend to pursue significantly greater exposure to risk factors suggesting that they respond to similar signals in their investment processes. This may result in the choice sets of stocks for quantitative funds being more correlated than those for non-quantitative funds.

Greater portfolio overlap among quantitative funds would increase the likelihood that multiple funds liquidate the same securities in a fire sale. While a single fund liquidating positions may be able to adequately coordinate securities transactions in a manner to minimize market impact, multiple funds liquidating the same stocks are likely unaware of each other's trading intentions and overall liquidations would occur in a less coordinated fashion. This would result in greater price impact for the liquidated securities. Consistent with this idea, early drafts of Coval and Stafford (2007) use the number of funds selling or buying a stock in a fire sale as opposed to actual shares sold to gauge the magnitude of the fire sale. Furthermore, recent work by Chaderina et al. (2018) shows that multiple insurance companies liquidate the same or similar bonds (more liquid bonds) when undergoing simultaneous fire sales causing greater price impact for those securities.

To test if this explanation contributes to our results we examine the portfolio overlap and selling overlap of quantitative and non-quantitative funds undergoing fire sales. In particular, we test if quantitative funds exhibit greater portfolio overlap and greater selling overlap relative to their non-quantitative counterparts. To calculate portfolio overlap we generate unique fund pairs for all fire sale funds (both quant and non-quant) for all quarter in the sample period. The measures of portfolio and sale overlap for each fund pair (h, j) in quarter t are computed as:

$$Portfolio\,Overlap(h_t, j_t) = 1 - \frac{1}{2}\sum_{k=1}^{K}\left|w_{h,k,t} - w_{j,k,t}\right| \tag{5}$$

and

$$Sale\,Overlap(h_t, j_t) = \frac{\sum_{k=1}^{K}\min\left\{I^{-}_{h,k,t}, I^{-}_{j,k,t}\right\}}{\min\left\{\sum_{k=1}^{K}I^{-}_{h,k,t}, \sum_{k=1}^{K}I^{-}_{j,k,t}\right\}}\quad. \tag{6}$$

Our measure of portfolio overlap is computed as one minus the active share measure of Cremers and Petajisto (2009), where $w_{h,k,t}$ is fund h's weight (as a fraction total portfolio market value) in stock k in quarter t. It can be thought of as the fraction of the funds' portfolios held in common as measured by market value of each position in the portfolio. The sale overlap measure follows Pool et al. (2015) and is the fraction of stocks commonly sold by the two funds. Specifically, I^- is a dummy variable equal to one if funds *h* and/or *j* reduce the number of shares held in stock *k* during the quarter. In addition to the portfolio and sale overlap measures, we also examine the raw number of stocks commonly held or sold by the funds in each pair.

Table 4 presents the sample means for the overlap measures and the number of securities in held or sold in common between fund pair portfolios. To investigate whether quantitative funds have greater portfolio and trading similarity relative to non-quantitative funds, we partition the sample of fire sale fund pairs into (quant, quant), (quant, non-quant), and (non-quant, non-quant) pairs. Panel A reports means on holdings overlap for these fund pair types while Panel B reports means for sale overlap.

Insert Table 4 About Here

In column (1) of Panel A, we find that quantitative fund pairs have average portfolio overlap of 7.70%. This is significantly larger than non-quantitative funds whose average portfolio overlap is shown to be 4.58% in column (2). We use a t-test to determine whether these means are statistically significantly different from one another, and the difference is statistically significant at the 1% level. In Columns (3) and (4), we find that results are more pronounced when measuring portfolio overlap using the number of stocks held in common. The results show that quantitative fund pairs hold more than twice as many common positions relative to non-quantitative fund pairs (15.16 versus 6.43).

Panel B examines sell overlap between all three types of fund pairs. Columns (1) and (2) show that fire sale quantitative fund pairs have significantly greater overlap in their selling activity relative to their non-quantitative fund counterparts. We find that quantitative funds have nearly 50% greater overlap (10.58% versus 7.15%) in their selling activity on average. As in Panel A, we find that the results are most pronounced when examining selling activity as the number of stocks commonly sold. Columns (3) and (4) show that quantitative fund pairs have more than twice as many common sales (6.61 versus 3.11) as compared to their non-quantitative fund counterparts. T-tests show that the differences in selling and portfolio overlap are significant at better than the 1% level.

Taken together, the results in Table 4 confirm that quantitative funds undergoing fire sales are more likely to hold and transact in the same securities as other quantitative funds. Combined with results from Table 1 on the coefficients from the 6-factor model these findings suggest quantitative funds have significantly more overlap in their underlying investment processes compared to non-quantitative funds. The significant overlap in selling activity among quantitative funds suggests that their crowded liquidations contribute to a larger distortion from their fire sales.

4.2 The role of security returns and characteristics in the liquidation decision

Prior tests document quantitative funds' reliance on factor exposures. This suggests they may undertake similar processes when choosing which securities to liquidate in their portfolios. Among other factors, momentum is a common trading strategy for quantitative funds. A potential contributing explanation for our results is that the larger distortion is caused by negative price momentum. Prior literature shows that mutual fund flows induce subsequent price momentum in stocks (Warther (1995) and Lou (2012)). If quantitative funds rely heavily on past price momentum in their selling decisions, this could commence a negative feedback loop in the returns of stocks widely sold by quantitative funds undergoing fire sales. Specifically, it is possible that downward price pressure generated by a single quantitative fund fire sale may generate enough negative momentum to induce other quantitative funds with the same positions to sell these securities (Warther (1995), Geanakoplos (2009), Lou (2012)). This downward momentum could be a further catalyst for fire sales by other funds and eventually lead to market destabilization (Stein (2012), Falato et al. (2016), Cai et al. (2019)).

We test if quantitative funds are more sensitive to past returns and other stock characteristics in their selling decisions in Table 5.

Insert Table 5 About Here

This table presents the coefficient estimates from a linear probability model. We model each fire sale fund's decision to sell a position in their portfolio on the lagged stock characteristics. Observations are at the holdings level and represent all individual positions held by funds at the beginning of the fire sale quarter. The dependent variable is an indicator variable equal to one if the fund reduces the number of shares held for that position over the course of the quarter and zero otherwise (*Sell Dummy*). Independent variables consist of the stock characteristic control variables used in Table 3, and include stock returns over the prior quarter (Ret_{t-1}) and stock returns over the three quarters preceding the prior quarter ($Ret_{t-2,t-4}$). For the negative momentum feedback loop hypothesis, we would expect that quantitative funds would be particularly sensitive to recent returns (e.g., over the past quarter) and not necessarily as sensitive to returns realized over time periods further in the past.

Columns (1) and (2) tabulate results separately for the samples of quantitative and non-quantitative funds and columns (3) and (4) pool the samples to test for differences in the coefficients on the stock characteristics of interest for quantitative and non-quantitative funds. The results of these *t*-tests are tabulated in column (5). Each regression includes fund-by-quarter fixed effects so that sell decisions are compared amongst stocks held in the same portfolio in the same quarter, and standard errors are clustered at the stock level.

Table 5 presents evidence consistent with the negative momentum hypothesis. Specifically, the coefficient on prior quarter returns for quantitative funds is significantly more negative than the coefficient on past quarter returns for non-quantitative funds (-0.084 versus 0.001). Column (5) shows that this difference is statistically significant at the 1% level. In contrast, we find no clear relationship between quantitative and non-quantitative funds' decisions to sell securities based on returns that are realized further in the past (i.e., the coefficients on $Ret_{t-2,t-4}$).

Overall, the results in Table 5 demonstrate that quantitative funds sell criteria during fire sales differ materially from non-quantitative funds, and provide evidence that the negative momentum hypothesis contributes the larger distortion from quantitative funds. We find that quantitative funds are significantly more sensitive to past recent returns. This heightened sensitivity to recent past returns opens the possibility that the securities they liquidate enter a negative feedback loop whereby other quantitative funds undergoing liquidity-based sales choose to sell the same securities.

4.3 Differences in cash holdings

We next consider the hypothesis that if quantitative funds systematically hold different levels of cash in their portfolios which could make them particularly vulnerable in fire sales. Funds with lower levels of cash generally have to sell more securities to meet investor redemptions and may generate more downward pressure in security prices. To test if cash contributes to the larger distortion from quantitative funds, we match our sample of quantitative funds with non-quantitative funds that have disadvantaged levels of cash and examine the resulting price impact during a fire sale.

We first calculate cash levels for quantitative and non-quantitative funds undergoing extreme flows. Fund level cash is calculated by asset-weighting the *per_cash* variable in CRSP across fund share classes. We find that, on average, quantitative funds tend to hold significantly less cash (2.2%) in their portfolios than non-quantitative funds (3.9%) prior to experiencing flow-based transactional pressure. The difference in means for these cash levels is statistically significant at the 1% level.

This substantial difference in cash may put quantitative funds at a disadvantage when having to meet flow based redemptions. To examine if cash is contributor to the larger distortion from quantitative funds, we retabulate the baseline multivariate results using a sample of non-quantitative fire sale funds that is cash 'disadvantaged.' To do so we examine the impact of flow-based transactional pressure for non-quantitative funds with the lowest levels of cash undergoing extreme outflows and the highest levels of cash undergoing extreme inflows.[17] Specifically, for each calendar quarter we identify the number of quantitative funds in the top and bottom deciles of quantitative fund flows. Then we retain an identical number of non-quantitative funds in these top and bottom decile ranges. For the bottom decile of flows we retain the non-quantitative funds with the lowest non-negative levels of cash. For the top decile of flows, we retain the non-quantitative funds with the highest levels of cash. We then calculate the non-quantitative pressure variable for each stock under consideration using this 'matched' sample of cash disadvantaged non-quantitative funds. If cash plays a significant role in the observed distortion from quantitative

[17] Funds undergoing extreme inflows that have high levels of cash arguably have more urgency to put cash to use.

funds, we would expect to see the differences in price distortions observed in our main results be substantially mitigated when focusing on non-quantitative funds with adverse cash positions.

Table 6 retabulates the results keeping the quantitative pressure variable as before but now considering pressure from non-quantitative funds with the least favorable cash positions as the comparison group.

Insert Table 6 About Here

We find the results remain economically and statistically similar to the baseline results. Interestingly, we find that the coefficient on *NonQuantPressure* is slightly weaker as compared to the baseline specification even when focusing on funds with relatively disadvantaged levels of cash. This suggests that the findings are likely not driven by systematic differences in the levels of cash between the two types of funds.

5. Robustness Checks

This section presents robustness checks of the main results. First, we consider if crisis periods drive our results. Crisis periods are often marked with significant withdrawals from mutual funds and negative returns in broader capital markets. In particular, it is possible that the financial crisis of 2008 and 2009 is responsible for our results. We also consider a robustness test of our identification methodology and the specifications of our main results in Table 3. We find that the magnitudes of coefficients are larger in crisis periods but results are not driven by these time periods. We also find the results are robust to our decisions in the categorization of funds and to tweaks in specification.

5.1. The financial crisis

We first consider how the financial crisis years may the findings. Specifically, we test if the baseline results are primarily driven by crisis periods in the sample. The financial crisis was marked by significant redemptions and liquidity concerns for clients of asset managers. For example, net domestic equity mutual fund outflows in 2008 and 2009 amounted to approximately $243 billion.[18] This put an exorbitant amount of pressure on fund managers to raise cash by selling securities to meet redemptions during this particular time period. To the extent that quantitative funds behave differently in crisis periods than non-quantitative funds, carving out these periods can help for us to determine if the results are driven by quantitative funds operating across all types of market conditions versus quantitative funds operating in crisis periods.

Columns (1) and (2) of Table 7 retabulate the baseline multivariate results using crisis and non-crisis subsample periods.

Insert Table 7 About Here

Column (1) tabulates results for 2008 and 2009, and Column (2) tabulate results for 2010 to 2015. In column (1), during the crisis years, we find that the magnitudes of the coefficients on both *QuantPressure* and *NonQuantPressure* increase more than twofold. Specifically, we note that the coefficient on *QuantPressure* increases to 1.058 and the coefficient on *NonQuantPressure* increases to 0.251. In column (2) when excluding the crisis years, we find that the results are still economically important. Economically, the magnitude of the coefficients on *QuantPressure* and

[18] See the 2010 ICI Factbook.

NonQuantPressure are smaller in magnitude relative to the baseline results but the inferences remain similar. The coefficient on *QuantPressure* (0.251) remains more than eight times larger than the coefficient on *NonQuantPressure* (0.012 and is statistically different at better than the 1% level. Overall, the findings are consistent with quantitative funds' greater impact on markets being realized across different types of market conditions.

5.2. Harvey et al. (2017) quantitative classifications, Fama-MacBeth specification, and alternate abnormal return calculations

Next, we test the robustness of our identification of quantitative funds by following Harvey et al. (2017)'s identification methodology in our setting. Importantly, though there is minor overlap in the language used in both our and Harvey et al. (2017)'s identifying phrase lists they are sufficiently orthogonal to each other. This is unsurprising given that the documentation requirements and audience is sufficiently different in their setting compared to ours. However, these differences are merely cosmetic and Harvey et al (2017)'s phrase list provides a natural means of robustness testing our identification and findings.

To do so we re-examine the hand collected investment strategy data. However, this time we use the much more narrow word list from Harvey et al. (2017)[19] to identify quantitative mutual funds. As with our main sample we once again use word stemmed versions of the prospectus language which is in line with the methodology used by Abis (2020). We use this alternative means of identification as a robustness tests of our results.

Column (3) of Table 7 retabulates the baseline results using the Harvey et al. (2017) classifications of quantitative and non-quantitative funds. Specifically, we rerun the multivariate

[19] "Algorithm," "approx," "computer," "model," "statistical," and "system," respectively.

panel regression in column (3) of Table 3. We document a similar effect from quantitative funds fire sales relative to non-quantitative fire sales when using the Harvey et al. (2017) classification. Specifically, we find that the coefficient on *QuantPressure* in column (3) of Table 7 is more than eight times larger then the coefficient on *NonQuantPressure* and these coefficients are different at the 5% level. These results speak to the robustness of the findings with respect to decisions made in the classification process.

Finally, for robustness, we also tabulate the base line regression in Table 3 using Fama-MacBeth regression in column (4) of Table 7. We also use alternate methods for computing abnormal returns. In column (5), we estimate abnormal returns using the market model as opposed to a 6-factor model. In column (6), we use monthly returns instead of daily returns to estimate betas and compute quarterly CARs. Specifically, in column (6) we use a (-36, -2) month window to estimate betas and cumulate the monthly abnormal returns over the quarterly event window.[20] We find that our inferences remained unchanged with these changes in methodologies.

6. Conclusion

This paper examines the role of quantitative investing on financial stability by examining stock returns around quantitative mutual funds fire sales. Relative to non-quantitative funds, securities sold by quantitative funds undergoing fire sales experience greater price pressure and take longer to return to their previous value. The greater effect of quantitative fire sales is due to their relatively homogeneous investment approach resulting in overlapping holdings and their heightened sensitivity to certain stock characteristics when choosing which position to sell.

[20] The number of observations is fewer in column (7), since we require three years of past returns to be available to compute stock level alphas.

That quantitative investing may destabilize markets is not obvious as each individual quantitative investor is attempting to profit from mispricings. However, we show that the emphasis on momentum trading specifically and the homogeneity in strategies resulting in overlapping positions across funds results in more potent fire sale price pressure. The results suggest that quantitative investing can result in a less stable market environment.

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Appendix A: Definitions and Data Sources of Variables

Variable Name	Data Source	Variable Definition and Construction
1. Key Independent and Dependent Variables		
Quant	Prospectuses	An indicator variable which is equal to one if the fund follows a quantitative investment process and zero otherwise. See Appendix B for further detail on quantitative fund identification.
Portfolio and stock abnormal returns	CRSP Stock Database and Ken French's website.	Daily abnormal returns are estimated using a 6-factor model which includes the market (Mkt-Rf) factor, size (SMB), value (HML), momentum (MOM) investment (CMA) and profitability (RMW) factors. Coefficients are estimated over a (-250, -22) window, and abnormal returns are computed as excess returns minus model benchmark return at time *t*. $$AR_{i,t} = r^{e}_{i,t} - \left(\hat{\beta}_{1,i} RMRF_t + \hat{\beta}_{2,i} SMB_t + \hat{\beta}_{3,i} HML_t + \hat{\beta}_{4,i} CMA_t + \hat{\beta}_{5,i} RMW_t + \hat{\beta}_{6,i} MOM_t\right)$$
QuantPressure	CRSP Mutual Fund and Stock Databases	$$Quantpressure_{i,t} = \frac{\sum_j \left(\max(0, \Delta Holdings_{j,i,t}) \mid flow_{j,t} > Quantpctl(90th)\right) - \sum_j \left(\max(0, -\Delta Holdings_{j,i,t}) \mid flow_{j,t} < Quantpctl(10th)\right)}{Shrout_{i,t-1}}$$ Aggregate fraction of shares outstanding sold (purchased) by quantitative funds in the bottom (top) decile of flows for during the quarter. Quarterly flows are calculated by summing monthly flows.
NonQuantPressure	CRSP Mutual Fund and Stock Databases	$$NonQuantpressure_{i,t} = \frac{\sum_j \left(\max(0, \Delta Holdings_{j,i,t}) \mid Quantpctl(100th) > flow_{j,t} > Quantpctl(90th)\right) - \sum_j \left(\max(0, -\Delta Holdings_{j,i,t}) \mid Quantpctl(0th) < flow_{j,t} < Quantpctl(10th)\right)}{Shrout_{i,t-1}}$$ Aggregate fraction of shares outstanding sold (purchased) by non-quantitative funds in the bottom (top) decile range of flows for quantitative funds for during the quarter.
Pressure stocks	CRSP Mutual Fund and Stock Databases	Stocks in the bottom/top deciles of the above pressure measures in a given calendar quarter.
Portfolio overlap	Thomson Reuters Mutual Fund Holdings	The percentage overlap of two funds' portfolio holdings computed as: $$Portfolio\ Overlap(h_t, j_t) = 1 - \frac{1}{2}\sum_{k=1}^{K}\left\lvert w_{h,k,t} - w_{j,k,t}\right\rvert$$ where $w_{h,k,t}$ is fund *h*'s weight (as a fraction total portfolio market value) in stock *k* in quarter *t*.
Sale overlap	Thomson Reuters Mutual Fund Holdings	The percentage of overlapping trades (measured in stock names) made by two funds in a given quarter, computed as:

		$$Sale\,Overlap(h_t, j_t) = \frac{\sum_{k=1}^{K} \min\left\{I^-_{h,k,t}, I^-_{j,k,t}\right\}}{\min\left\{\sum_{k=1}^{K} I^-_{h,k,t}, \sum_{k=1}^{K} I^-_{j,k,t}\right\}}$$ Where I^- is an indicator variable equal to 1 if fund *h* or *j* reduces its number of shares in stock *k* during the quarter.
Sell	Thomson Reuters Mutual Fund Holdings	Indicator variable equal to one if the number shares the fund holds for a given stock has declined since the prior report date and zero otherwise.
2. Stock Characteristic Controls		
QuantOwnership	CRSP Stock Database	Aggregate percentage of shares outstanding owned by quantitative mutual funds
NonQuantOwnership	CRSP Stock Database	Aggregate percentage of share outstanding owned by non-quantitative mutual funds.
Log(Mkt cap) or Size	CRSP Stock Database	Natural log of the company's market capitalization. Market capitalization is in thousands of dollars and is computed as price times shares outstanding (Shrout) in CRSP.
BM	COMPUSTAT, CRSP Stock Database	Book value of equity for the fiscal year ended before the most recent June 30, divided by market capitalization of December 31 during that fiscal year.
Div yield	COMPUSTAT, CRSP Stock Database	Cash dividend for the fiscal year ended before the most recent 30, divided by market capitalization as of December 31 in that fiscal year.
Volatility	CRSP Stock Database	The variance of monthly returns over the previous two years.
Age (months)	CRSP Stock Database	Number of months since the first return appears in CRSP.
Price	CRSP Stock Database	Price per share.
Ret_{t-1}	CRSP Stock Database	Past three-month gross return. This is the percentage return earned in the current quarter (i.e., June 30—September 30 return for a September 30th filing).
$Ret_{t-2,t-4}$	CRSP Stock Database	nine-month gross return preceding the quarter of filing (i.e., September 30—June 30 return for a September 30th filing).
Stock turnover	CRSP Stock Database	Volume divided by shares outstanding, measured for the month prior to the beginning of the quarter.
Investment	COMPUSTAT	Asset growth for the fiscal year ended before the most recent June 30. Measured as the difference between total book assets and lagged total book assets scaled by total book assets.
Profitability	COMPUSTAT	Profitability for the fiscal year ended before the most recent June 30. Measured as revenues less cost of goods sold, interest expense and SG&A scaled by total assets. Firms are required to have available data on firm revenues

		as well as one of the following: cost of goods sold, interest expense or SG&A.
3. Mutual Fund Variables		
Monthly/Quarterly Fund Flows	CRSP Mutual Fund Database	We calculate flows at the fund level using asset-weighted returns and aggregate TNA for all of the funds' share classes. Share classes are aggregated using the WFICN identifier in the MFLINKS table. Monthly flows are calculated as $[TNA_t - (1+r_t)*TNA_{t-1}]/ TNA_{t-1}$. Quarterly flows are the sum of the relevant monthly flows.
6-factor Model Coefficients: Market, Size, Value, Momentum, Investment, and Profitability	CRSP Mutual Fund Database and Ken French's website	The 6-factor model consists of the market (Mkt-Rf) factor, size (SMB), value (HML), momentum (MOM) investment (CMA) and profitability (RMW) factors. Factor loadings are estimated using fund and factor returns over the previous 24 months.
Fund Family TNA	CRSP Mutual Fund Database	Aggregate fund family total net assets. Fund families are identified in CRSP using the MGMT_CD variable.
Fund age	CRSP Mutual Fund Database	Number of years (months/12) between the current month and the month the fund's oldest share class was first offered in CRSP (first_offer_dt).
Fund TNA	CRSP Mutual Fund Database	Aggregate TNA of each of a fund's share classes in CRSP. Share classes are aggregated using the WFICN identifier in the MFLINKS table.
Net flows	CRSP Mutual Fund Database	Sum of the net monthly fund flows (as a percent of TNA) over the past 12 months. Monthly flows are calculated as $[TNA_t - (1+r_t)*TNA_{t-1}]/ TNA_{t-1}$.
Stdev flows	CRSP Mutual Fund Database	Standard deviation of net monthly fund flows (as a percent of TNA) over the past 12 months. Monthly flows are calculated as $[TNA_t - (1+r_t)*TNA_{t-1}]/ TNA_{t-1}$.
Fund turnover	CRSP Mutual Fund Database	The fund's lagged annual portfolio turnover. Turnover is TNA weighted across share classes in CRSP using the WFICN variable.
Expense	CRSP Mutual Fund Database	The fund's lagged annual expense ratio. The fund's expense ratio is TNA weighted across share classes in CRSP using the WFICN variable.

Appendix B: Quantitative Phrase List

quantitative investment, quantitative model, quantitative analysis, quantitative process, quantitative tools, quantitative formula, quantitative computer, statistically driven, statistical methods, quantitative methodology, quantitative management, quantitative method, quantitative models, quantitative analytics, quantitatively-driven, quantitatively-derived, quantitative approach, quantitative value, quantitative statistics, quantitatively investing, quantitative measures, quantitative techniques, quantitative research, quantitative methods, quantitative, factor-based, quantitative three factor, quantitative approaches, quantitative computer valuation, quantitative optimization, quantitatively driven, quantitative studies, quantitative computer valuation, quantitatively assess, quantitative assessment, quantitative research, quantitatively-oriented, multi-factor, multifactor, multi factor

Figure 1: Quantitative Domestic Equity Mutual Funds in the Sample
This figure presents time series information on the number of quantitative funds and families operating quantitative funds for each year of the sample. The solid line indicates the number of quantitative funds identified each year and the dashed line shows this number as a percentage of all active equity funds.

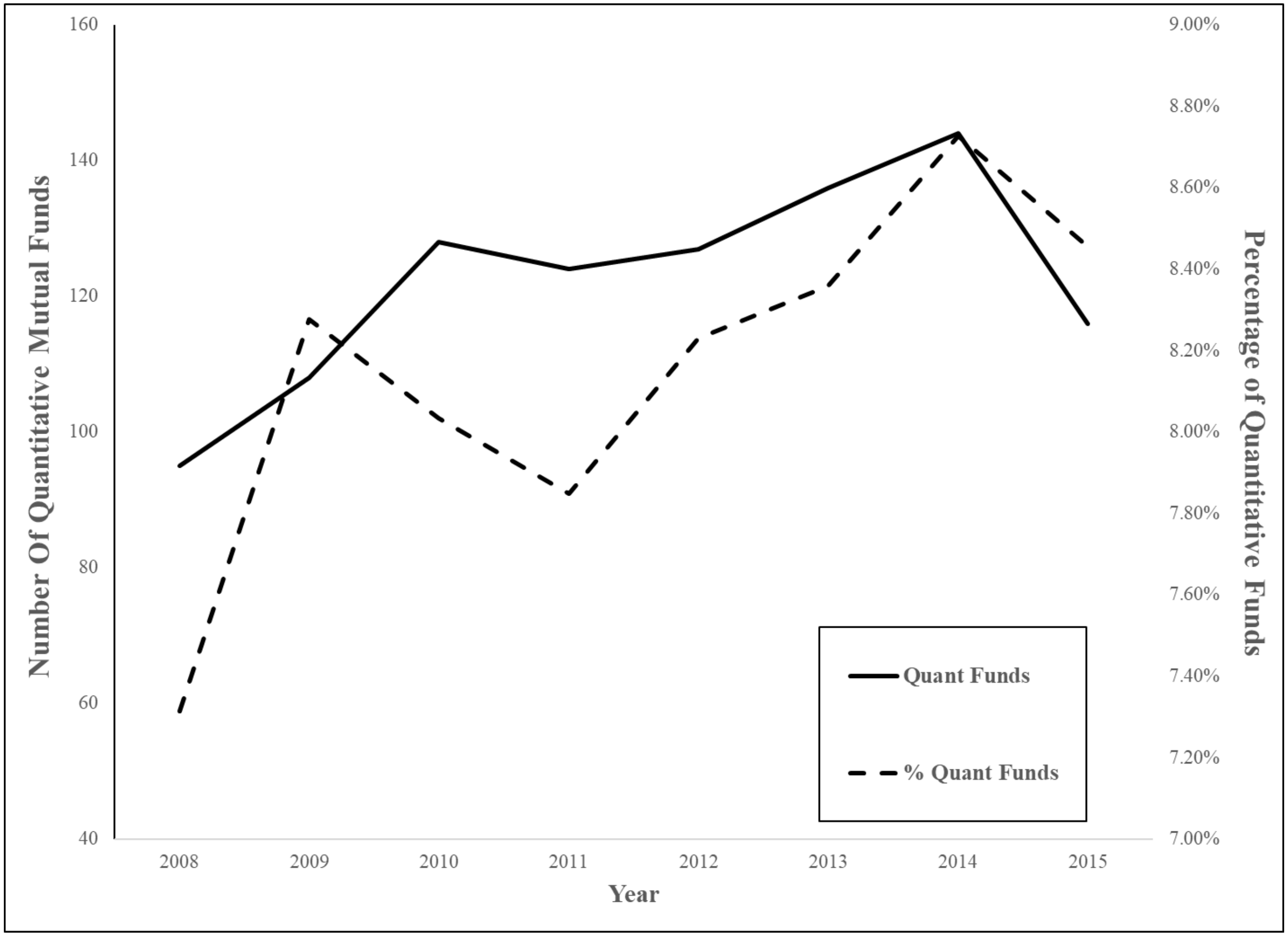

Figure 2: Cumulative Average Abnormal Returns for Bottom Decile Pressure Stocks
This figure shows the daily cumulative average abnormal returns experienced by securities heavily sold by quantitative (solid) and non-quantitative (dashed) funds undergoing significant investor redemptions. These are the securities in the bottom decile of pressure as calculated following Coval and Stafford (2007). The shaded portion of the graph represents the fire sale event quarter.

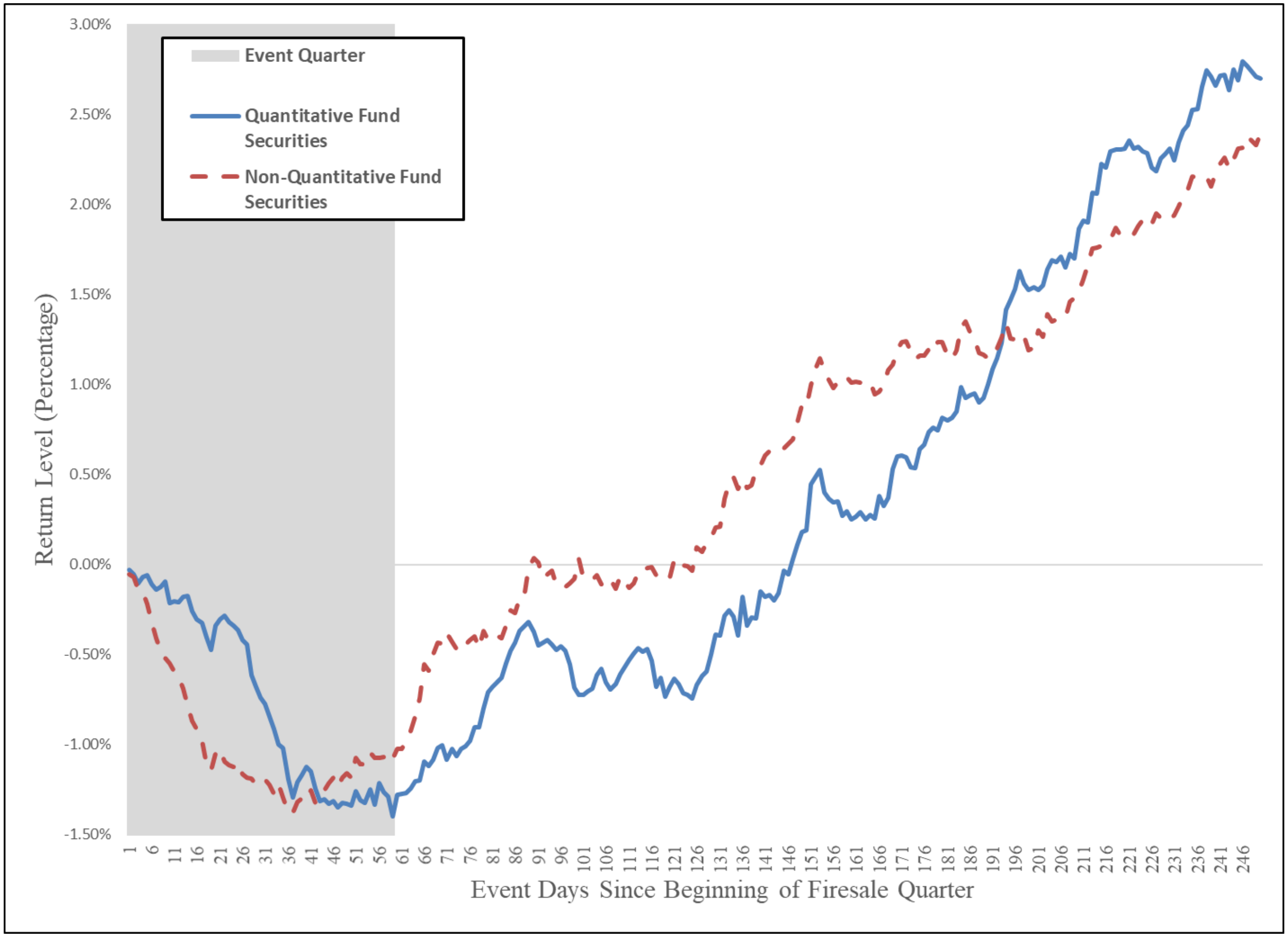

Table 1: Mutual Fund Summary Statistics

This table reports fund-quarter summary statistics for non-specialty actively managed domestic equity funds operating between 2008 and 2015. Columns 1 to 6 report summary statistics for funds following a quantitative investment process and columns 7 to 12 report summary statistics for non-quantitative funds. Differences in means for these variables are shown in Column 13 and t-statistics for the difference are shown in Column 14. Standard errors are from univariate regressions and are clustered at the fund level. Definitions and data sources can be found in Appendix A. Quarterly observations are restricted to funds which report a calendar quarter-ends in Thomson. For results in columns 13 and 14 t-statistics are shown in parentheses and standard errors are clustered on fund. ***, ** and * indicate significance at the 1%, 5% or 10% levels.

	Quantitative Mutual Funds						Non-Quantitative Mutual Funds						Difference in Means	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
6 Factor Model Coefficients	N	mean	median	Stdev	p10	p90	N	mean	median	Stdev	p10	p90	Difference (2) – (8)	t-statistic
Market	3,016	0.98	0.99	0.11	0.86	1.09	33,843	0.94	0.96	0.15	0.78	1.09	0.0354***	(5.70)
Size	3,016	0.22	0.13	0.37	-0.18	0.77	33,843	0.20	0.09	0.36	-0.17	0.76	0.0176	(0.60)
Value	3,016	0.05	0.04	0.23	-0.24	0.35	33,843	0.02	0.01	0.26	-0.29	0.46	0.0230	(1.63)
Momentum	3,016	0.05	0.04	0.13	-0.09	0.20	33,843	0.01	0.01	0.14	-0.15	0.16	0.0397***	(5.71)
Investment	3,016	-0.09	-0.07	0.33	-0.52	0.29	33,843	-0.14	-0.12	0.37	-0.60	0.28	0.0558***	(3.19)
Profitability	3,016	-0.01	0.03	0.29	-0.36	0.30	33,843	-0.04	-0.02	0.31	-0.40	0.29	0.0340**	(2.40)
Fund Characteristics														
Family TNA ($MM)	3,016	173,442	49,988	450,408	905	259,562	33,843	170,192	26,219	404,493	201	401,068	3,250	(0.08)
Fund TNA ($MM)	3,016	705	193	1,416	28	1,755	33,843	1,760	294	6,790	17	6,935	-1,056***	(-4.80)
Fund age (years)	3,016	13.93	12.33	9.11	4.33	25.00	33,843	13.95	12.75	9.19	3.33	25.75	-0.02	(-0.03)
Net flows (%)	3,016	0.96	-6.00	38.50	-33.00	41.35	33,843	5.43	-3.36	40.61	-28.48	49.07	-4.47**	(-2.47)
Stdev flows (%)	3,016	3.90	2.22	4.52	0.60	9.20	33,843	3.81	2.20	4.58	0.59	8.67	0.07	(0.35)
# Holdings	3,016	163.23	99.00	199.39	40	346	33,843	104.19	68.00	140.27	29.00	195.00	59.05***	(4.16)
Fund turnover	3,016	0.89	0.72	0.73	0.24	1.64	33,843	0.75	0.55	1.47	0.16	1.42	0.14**	(2.49)
Expense (%)	3,016	1.10	1.10	0.38	0.63	1.56	33,843	1.12	1.14	0.43	0.74	1.57	-0.09***	(-2.80)

Table 2: Pressure Stock Summary Statistics

This table reports stock-quarter summary statistics for stocks undergoing significant transactional pressure from quantitative and non-quantitative funds experiencing extreme inflows/outflows during the quarter. *High Pressure Stocks* are defined as stocks undergoing transactional pressure from funds who have received high levels of inflows. *Low Pressure* Stocks are stocks undergoing selling pressure from fund undergoing outflows. Columns 1 through 6 contain summary statistics for stocks of both types held by funds utilizing a quantitative investment strategy. Columns 7 through 12 contain summary statistics on stocks of both types for mutual funds that do not use a quantitative investment process. Definitions and data sources can be found in Appendix A. Quarterly stock observations are restricted to the 61 quarters in Thomson where at least 75 quantitative funds are operating. The symbol † denotes average values which are significantly different between high and low pressure stocks held by funds of the same type. The significance level of these differences is denoted as: † p<0.10, †† p<0.05, and ††† p<0.01 respectively.

	Quantitative Mutual Funds						**Non-Quantitative Mutual Funds**					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
High Pressure Stocks:	*N*	*mean*	*median*	*Stdev*	*p10*	*p90*	*N*	*mean*	*median*	*Stdev*	*p10*	*p90*
Log(Mkt Cap)	3,979	14.02†††	13.91	1.43	12.26	15.95	6,391	13.73†††	13.47	1.32	12.14	15.42
Dividend yield (%)	3,979	0.0016†††	0.0005	0.0030	0.0000	0.0044	6,391	0.0013	0.0001	0.0025	0.0000	0.0035
B/M	3,979	0.0007†††	0.0005	0.0005	0.0002	0.0012	6,391	0.0006†††	0.0005	0.0005	0.0002	0.0011
Turnover	3,979	1.8483†††	1.4886	1.4532	0.6254	3.3691	6,391	1.6556†††	1.3462	1.3232	0.5118	3.0853
Price	3,979	38.47	25.22	113.61	7.99	68.03	6,391	89.96	23.90	2,606.80	7.56	61.91
Ret_{t-1} (%)	3,979	7.72†††	5.98	26.24	-17.19	32.04	6,391	4.34	2.75	23.14	-19.69	28.12
$Ret_{t-2,t-4}$ (%)	3,979	15.77†††	10.51	50.70	-30.87	60.28	6,391	16.58††	10.44	54.43	-26.67	58.72
Volatility (%)	3,979	11.07†††	9.39	7.48	4.84	18.55	6,391	10.62†††	9.29	6.48	5.17	17.17
Firm age (months)	3,979	256†††	208	172	60	537	6,391	239†††	199	162	54	501
Investment	3,979	0.0630	0.0574	0.01595	-0.9420	0.2367	6,391	0.0707††	0.0597	0.1569	-0.0813	0.2497
Profitability	3,979	0.1014†††	0.0963	0.1017	0.0141	0.2171	6,391	0.1001	0.1002	0.1042	0.0113	0.2138
Low Pressure Stocks:	*N*	*mean*	*median*	*Stdev*	*p10*	*p90*	*N*	*mean*	*median*	*Stdev*	*p10*	*p90*
Log(Mkt Cap)	4,076	14.13	13.95	1.50	12.43	16.16	6,871	13.96	13.83	1.42	12.22	15.86
Dividend yield (%)	4,076	0.0013	0.0000	0.0030	0.0000	0.0033	6,871	0.0013	0.0000	0.0028	0.0000	0.0035
B/M	4,076	0.0006	0.0005	0.0006	0.0002	0.0011	6,871	0.0007	0.0005	0.0006	0.0002	0.0012
Turnover	4,076	2.1315	1.7041	1.6302	0.7287	3.9044	6,871	2.0372	1.5514	1.7735	0.6143	3.9396
Price	4,076	36.82	26.82	65.88	7.86	67.17	6,871	103.47	23.44	1,919.23	6.72	64.32
Ret_{t-1} (%)	4,076	3.88	3.23	22.36	-21.49	27.83	6,871	4.08	3.31	26.91	-22.85	28.85
$Ret_{t-2,t-4}$ (%)	4,076	21.52	13.35	70.86	-26.76	69.46	6,871	14.41	8.12	57.47	-35.35	62.52
Volatility (%)	4,076	11.60	10.00	7.11	5.10	19.56	6,871	11.54	9.86	8.41	5.30	19.09
Firm age (months)	4,076	244	199	169	56	511	6,871	249	208	165	60	511
Investment	4,076	0.0663	0.0578	0.1729	-10.90	26.67	6,871	0.0647	0.0580	0.1698	-0.1015	0.2533
Profitability	4,076	0.1145	0.1088	0.1039	0.0183	0.2312	6,871	0.0987	0.0976	0.1042	0.0125	0.2129

Table 3: The Effect of Fire Sales on Stock Prices: Quantitative versus Non-Quantitative

This table presents coefficient estimates from panel regressions of quarterly abnormal stock returns on measures of price pressure resulting from fire sales (purchases) by quantitative and non-quantitative mutual funds undergoing similar levels of flows. Coefficients are estimated from the following the OLS model:

$$CAR_{i,t} = \beta_0 + \beta_1 Quantpressure_{i,t} + \beta_2 NonQuantpressure_{i,t} + \beta X_{i,t-1} + QuarterFE + \varepsilon_{i,t}\ .$$

$QuantPressure_{i,t}$, and $NonQuantPressure_{i,t}$ are measures of flow induced transactional pressure from quantitative and non-quantitative mutual funds undergoing fire sales (purchases) for stock *i* in quarter *t*. Cumulative abnormal returns are calculated using the Fama-French (2015) five-factor model plus momentum. This six factor model is estimated using daily returns and a (-250,-22) window. As controls, we also include measures of lagged ownership for both fund types (*QuantOwnership* and *NonQuantOwnership*). See Appendix A for further detail on variable construction. All columns use quarter fixed effects. Columns 3 and 4 add lagged stock level controls following Gompers and Metrick (2001) and Fama and French (2015). Column (4) adds stock fixed effects. Standard errors are clustered on both stock and quarter. T-statistics are shown in parentheses and ***, ** and * indicate significance at the 1%, 5% or 10% levels.

VARIABLES	(1) CAR	(2) CAR	(3) CAR	(4) CAR
QuantPressure	0.470***	0.442***	0.441***	0.433***
	(3.38)	(3.25)	(3.32)	(3.66)
NonQuantPressure	0.052*	0.050*	0.053*	0.041
	(1.87)	(1.72)	(1.80)	(1.45)
QuantOwnership		-0.052***	-0.058***	-0.086***
		(-3.06)	(-3.11)	(-4.14)
NonQuantOwnership		-0.003	-0.001	-0.010***
		(-1.58)	(-0.64)	(-3.18)
Stock Controls	No	No	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes
Stock FEs	No	No	No	Yes
N	78,901	78,901	78,901	78,901
Adj. R^2	0.002	0.003	0.005	0.077
H_0: *QuantPressure – NonQuantPressure = 0*	0.418*** (3.30)	0.392*** (3.16)	0.388*** (3.21)	0.392*** (3.91)

Table 4: Fire Sale Fund-Pairs' Portfolio and Sale Overlap

This table reports mean fund-pair holdings and sale overlap for quantitative and non-quantitative mutual funds undergoing fire sales due to extreme outflows during the sample period 2008 to 2015. The key variables of interest are measures of portfolio and sale overlap. We compute mean portfolio and sale overlap for (quant, quant), (quant, non-quant), and (non-quant, non-quant) fund pairs separately. Holdings overlap is computed as one minus the measure of portfolio independence used in calculating active share (i.e., Cremers and Petajisto (2009)). Sale overlap follows Pool et al. (2015).

$$Portfolio\,Overlap(h_t, j_t) = 1 - \frac{1}{2}\sum_{k=1}^{K}\left|w_{h,k,t} - w_{j,k,t}\right|$$

$$Sale\,Overlap(h_t, j_t) = \frac{\sum_{k=1}^{K}\min\left\{I^{-}_{h,k,t}, I^{-}_{j,k,t}\right\}}{\min\left\{\sum_{k=1}^{K} I^{-}_{h,k,t}, \sum_{k=1}^{K} I^{-}_{j,k,t}\right\}}$$

Where $w_{h,k,t}$ is fund h's weight (as a fraction total portfolio market value) in stock k in quarter t and I^{-} is an indicator variable equal to 1 if fund h or j reduces its number of shares in stock k during the quarter. Additionally, we compute the average number of stocks held and sold in common during the fire sale event quarter. Standard errors are doubled clustered on each fund in the pair. ***, ** and * indicate significance at the 1%, 5% or 10% levels.

Panel A: Holdings Overlap

	Mean Portfolio Overlap		Mean Number of Common Holdings	
	(1)	(2)	(3)	(4)
Fund Types	Quant	Non-Quant	Quant	Non-Quant
Quant	7.70%	5.35%	15.16	8.35
Non-Quant		4.58%		6.43
H_0: Quant Pairs – Non-Quant Pairs = 0	3.12%*** (3.27)		8.73*** (3.71)	

Panel B: Sale Overlap

	Mean Sale Overlap		Mean Number of Sales in Common	
	(1)	(2)	(4)	(5)
Fund Types	Quant	Non-Quant	Quant	Non-Quant
Quant	10.58%	7.99%	6.61	3.77
Non-Quant		7.15%		3.11
H_0: Quant Pairs – Non-Quant Pairs = 0	3.43%*** (3.19)		3.50*** (3.38)	

Table 5: Selling Activity of Fire Sale Funds

This table reports coefficient estimates from OLS regressions of fund *i*'s decision to sell stock *j* in its portfolio on stock characteristics. Quarterly holdings observations are restricted to quantitative and non-quantitative funds undergoing fire sales from 2008 to 2015. The dependent variable in all columns is a Sell indicator variable which takes a value of one if the fund is a net seller (reduces shares) of the stock during the fire sale quarter and zero otherwise. The explanatory variables are stock level characteristics. Definitions and data sources for all variables can be found in Appendix A. Column (1) restrict the sample to quantitative fund holdings. Column (2) restricts the sample to non-quantitative fund holdings. Columns (4) and (5) present results from a single regression allowing for different coefficients on quantitative and non-quantitative funds for ease of comparison. Column (5) presents the results of t-tests to examine if the coefficients for quantitative and non-quantitative funds are statistically different. Each regression includes fund-by-quarter fixed effects. Standard errors are clustered on stock and quarter. ***, ** and * indicate significance at the 1%, 5% or 10% levels.

	Sell Dummy		Sell Dummy		
VARIABLES	(1) Quant Funds	(2) Non-Quant Funds	(4) Quant Funds	(5) Non-Quant Funds	(6) Diff (4) – (5)
Ret_{t-1}	-0.084***	0.001	-0.085***	0.001	-0.085***
	(-3.83)	(0.06)	(-3.97)	(0.06)	(-3.97)
$Ret_{t-2,t-4}$	0.012	-0.006	0.012	-0.006	0.018
	(1.09)	(-1.14)	(1.11)	(-1.17)	(1.38)
Log(Mkt cap)	0.027***	0.018***	0.026***	0.018***	0.008
	(4.64)	(8.71)	(4.74)	(8.75)	(1.45)
B/M	0.034	0.004	0.034	0.004	0.030
	(0.72)	(1.61)	(0.71)	(1.57)	(1.57)
Div yield	-0.288**	0.036**	-0.285**	0.036**	-0.322**
	(-2.09)	(2.33)	(-2.08)	(2.31)	(2.31)
Log(Price)	0.009	0.001	0.009	0.001	0.009
	(1.20)	(0.51)	(1.22)	(0.51)	(1.09)
Volatility	0.009	-0.032	0.009	-0.030	0.039
	(0.13)	(-0.59)	(0.13)	(-0.59)	(0.43)
Log(Age)	-0.007	0.004*	-0.007	0.004*	-0.011
	(-1.05)	(1.91)	(-1.06)	(1.91)	(-1.62)
Investment	-0.028	-0.003	-0.028	-0.003	-0.025
	(-1.35)	(-0.71)	(-1.34)	(-0.72)	(-1.18)
Profitability	0.087***	0.008	0.089***	0.008	0.081***
	(2.89)	(0.84)	(2.95)	(0.81)	(2.70)
Fund x Quarter FE	Yes	Yes	Yes		
N	60,954	352,172	413,126		
Adj. R^2	0.183	0.210	0.207		

Table 6: Comparison to High and Low Cash Non-Quantitative Funds

This table presents coefficient estimates from panel regressions of quarterly abnormal stock returns on measures of price pressure resulting from fire sales (purchases) by quantitative and non-quantitative mutual funds as in Table 3. $QuantPressure_{i,t,}$ and $NonQuantPressure_{i,t}$ are measures of flow induced transactional pressure from quantitative and non-quantitative mutual funds undergoing fire sales (purchases) for stock *i* in quarter *t*. This table uses a matched sample of non-quantitative funds that have 'disadvantaged' cash positions, i.e., low cash funds experiencing extreme outflows and high cash funds experiencing extreme inflows. The sample only includes stock observations beginning in 2003 when fund cash became widely populated the CRSP mutual fund database. Cumulative abnormal returns are calculated using the Fama-French (2015) five-factor model plus momentum. This six factor model is estimated using daily returns and a (-250,-22) window. As controls, we also include measures of lagged ownership for both fund types (*QuantOwnership* and *NonQuantOwnership*). See Appendix A for further detail on variable construction. All columns use quarter fixed effects. Column 3 adds lagged stock level controls following Gompers and Metrick (2001) and Fama and French (2015). Each regression includes event quarter fixed effects and standard errors are clustered on stock and quarter. T-statistics are shown in parentheses and ***, ** and * indicate significance at the 1%, 5% or 10% levels.

VARIABLES	(1) CAR	(2) CAR	(3) CAR	(4) CAR
QuantPressure	0.480***	0.452***	0.451***	0.442***
	(3.32)	(3.20)	(3.27)	(3.58)
NonQuantPressure	0.025*	0.018	0.019	0.009
	(1.81)	(1.27)	(1.40)	(0.57)
QuantOwnership		-0.052***	-0.034***	-0.086***
		(-3.05)	(-3.11)	(-4.14)
NonQuantOwnership		-0.003	-0.001	-0.010***
		(-1.59)	(-0.70)	(-3.22)
Stock Controls	No	No	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes
Stock FEs	No	No	No	Yes
N	78,901	78,901	78,901	78,901
Adj. R^2	0.002	0.003	0.005	0.076
H_0: *QuantPressure – NonQuantPressure = 0*	0.455*** (3.09)	0.434*** (2.99)	0.432*** (3.05)	0.461*** (3.03)

Table 7: Alternate Explanations and Robustness Checks

This table presents coefficient estimates from panel regressions of quarterly abnormal stock returns on measures of price pressure resulting from fire sales (purchases) by quantitative and non-quantitative mutual funds. *QuantPressure* and *NonQuantPressure* are measures of flow induced transactional pressure from quantitative and non-quantitative mutual funds undergoing fire sales (purchases). Cumulative abnormal returns are calculated using the Fama-French (2015) five-factor model plus momentum. This six factor model is estimated using daily returns and a (-250,-22) window. Column (1) restricts the sample to crisis years i.e., 2008 – 2009. Column (2) restricts the sample to non-crisis years by excluding 2007 – 2009. Column (3) tabulates baseline results using the Harvey et al. (2017) phrase list to identify quantitative funds. Column (4) uses Fama-MacBeth regression as opposed to panel regression to estimate coefficients. Column (5) uses abnormal returns from the market model as the dependent variable in the panel regression. Column (6) computes abnormal returns using monthly returns as opposed to daily returns and a (-36, -2) window. Control variables in all columns are identical to those used in column (3) of Table 3. Each regression includes event quarter fixed effects and standard errors are double clustered on stock and quarter. T-statistics are shown in parentheses and ***, ** and * indicate significance at the 1%, 5% or 10% levels.

	CAR					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	2008- 2009	Excluding 2008-2009	Harvey Quant IDs	Fama-MacBeth	CAR Market Model	Monthly CARs
QuantPressure	1.058*	0.250***	0.430***	0.722***	0.604***	0.613***
	(1.88)	(3.24)	(2.63)	(2.73)	(2.73)	(3.28)
NonQuantPressure	0.251***	0.012	0.052*	0.068*	0.058*	0.060
	(2.72)	(0.89)	(1.82)	(1.80)	(1.90)	(1.57)
Stock Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	N/A	Yes	Yes
N	20,661	58,240	78,901	78,901	78,901	68,140
Adj. R-squared	0.016	0.005	0.006	0.041	0.040	0.044
H_0 *QuantPressure – NonQuantPressure = 0*	0.807	0.238***	0.378***	0.654**	0.545***	0.554***
	(1.67)	(3.07)	(2.36)	(2.45)	(2.55)	(3.22)