Quantitative Investing and Market Instability*

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Abstract

The May 2010 Flash Crash and August 2007 Quant Meltdown raised concerns about the impact of quantitative investment strategies on market stability. Theory is split on whether quantitative investing dampens or exacerbates market instability. To test the theory we focus 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 five times as large. The evidence suggests this is due to quantitative funds' reliance on similar trading signals and sensitivity to the time-series of returns.

JEL classification: G11, G23, G40

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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 $200 billion in assets under management.[2] 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 firms 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 aim to take a calculated and emotionless approach to investing, which could help to reduce inefficiencies, and therefore reduce idiosyncratic periods of market instability (Kirilenko and Lo (2013)). Alternatively, quantitative investors may decrease market stability due to following 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. As a result of too many quantitative investors trading on the same information the exhibit greater price pressures 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 mutual fund fire sales, as defined by Coval and Stafford (2007), behave differently for quantitative funds versus non-quantitative funds. We find that flow-induced selling by quantitative funds generate transitory price declines over five times as large as non-quantitative

[2] www.aqr.com.

funds for the positions sold in their portfolios. In addition, it takes three months 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 the signal generation algorithm, we find that quantitative firms' selling decisions are more heavily influenced by peer fire sales and that recent returns are more influential for selling decisions. These behaviors may lead to a stronger negative feedback loop for quantitative firms.

We identify funds that use a quantitative investment process by performing textual analysis of mutual fund prospectuses.[3] To understand how funds typically describe their investing process we begin by reviewing the Morningstar "Investment Strategy" field 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 fundamental fund. We generate a phrase list reflective of a quantitative investment process and use this to analyze mutual fund prospectuses. We consider prospectuses on the EDGAR database for funds available to investors from 1999 to 2015. The label "Quantitative

[3] As described in Section 1.1 the identification methodology is similar to Harvey et al. (2017) and Albina (2017) both of whom examine differences in quantitative versus fundamental investment management. As a robustness check, in Section 4.3 we repeat the main analysis using Harvey et al. (2017)'s identification strategy and find qualitatively similar results.

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 increases steadily. In 2000 we identify 109 (7%) quantitative funds in the sample and in 2015 we find 168 (13%) quantitative funds out of 1,283 total mutual funds.

We focus the analysis on mutual funds that experience large outflows and inflows, referred to colloquially as "fire sales," and we 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 five times as large as that for similarly sized outflows from fundamental 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 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. We find that quantitative funds exhibit significantly greater portfolio overlap and selling overlap (more than double) relative to non-quantitative funds which supports the overlapping positions hypothesis.

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 in order 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 strains other funds and the largest 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.

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 (2018) study the effects of robo-advising and find that it results in increased diversification and reduced volatility. Kirilenko and Lo (2013) theorize that quantitative investing and its' ability to destabilize markets.

1. Data

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

1.1. Identifying quantitative mutual funds

To identify quantitative funds within the sample we rely on hand collected data as well as public data sources. We first examine descriptions of mutual funds' investment strategies taken from the *Investment Strategy* field on the Morningstar Direct database. The *Investment Management* field holds partial descriptions of the methods and investment strategies employed by the mutual fund and is collected from the fund's most recent SEC filing.[4] The SEC mandates

[4] Morningstar Direct describes the Investment Strategy field in the following manner: "The first sentence will always be the fund's investment objective. From there, the rest of the description will be a summary of that fund's principal investment strategies as written in the prospectus – this should include first of all what a fund "normally" or "primarily" invests in, followed by what the fund "may" invest in. Additionally, it includes information about what the fund does not invest in, if applicable. Finally, if the fund is non-diversified, it will include a non-diversification

that all mutual funds disclose the principle investment strategy to investors. This data field is also used by Kostovetsky and Warner (2019) when evaluating innovation in the mutual fund industry. We review the *Investment Strategy* by hand for a subset of domestic equity funds to generate a list of phrases (Appendix B) indicative of a quantitative investing process.

Once we established our list of identifying phrases, we deploy an algorithm to scan summary prospectuses on the SEC's EDGAR database to determine if funds incorporate quantitative aspects into their portfolio management process. The algorithm examines the full text of the prospectus for the presence of one or more of the phrases on our list. We scan the entire prospectus because the Morningstar data field contains only partial information from the prospectus. This lack of information necessitates our collecting of information from the EDGAR database. We search all prospectuses on the EDGAR database from 1999 until 2015

For the period from 2009 until 2015 we use the summary prospectus filed as form 497K with the SEC. Prior to 2009, funds used several forms so we perform the search on forms 497K1, 497K2, 497K3A, and 497K3B. We generate an indicator variable equal to one if a fund uses the quantitative investing terms in its prospectus and zero otherwise (*Quant*). We also collect information on the ticker(s) from the prospectus as well as the company name, CIK number, and the filing date. We categorize funds that are not identified as quantitative by the methodology as "fundamental" or "non-quantitative" funds.

Our method of categorizing funds is most similar to Harvey et al. (2017) Harvey et al. (2017) uses information from the Hedge Fund Research (HFR) database to examine hedge funds.

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statement. This is written for every OE, CE, and VA fund in the Morningstar universe and is pulled from the most recent SEC filing (prospectus or supplement)."

We focus on the Investment Strategy from the fund's prospectus and reported by Morningstar Direct to generate our phrase list.

One major difference is that our methodology generates more identifying language than Harvey et al. (2017) and focuses on the use of phrases instead of individual words. We also utilize documentation provided directly by the fund rather than data hosted by secondary providers. The reasoning for these decisions is two-fold, first by using a larger list of identifying language we are better able to identify funds as quantitative and decrease the risk of misidentifying funds as non-quantitative which would lead to Type II errors[5].

We also choose to use phrases 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 the context of investment management (i.e. "quantitative") and thus relying on phrases decreases the probability of committing a Type I error.[6] Also, unlike Harvey et al. (2017) we consider the entirety of the documentation provided directly from the fund rather than relying on the data provided by an intermediary. Our belief is that it is unclear if the *Investment Strategy* section on Morningstar adequately and regularly captures pertinent information even for the portion of the prospectus detailing how the fund invests. By considering the entirety of the document we do not omit any information from consideration which decreases the likelihood of committing a Type I error.

[5] Over identification resulting from the use of the word "quantitative" may cause funds that use simple value screens to be identified as quantitative funds. Often these screens are described as a "quantitative screen" and it is possible that fundamental funds of that type exhibit behavior more reflective of their fundamental investing style than a quantitative methodology. Results from these falsely identified funds may be significant but would be incorrectly attributed to a quantitative investing style thereby committing a Type II error of falsely rejecting the null hypothesis.

[6] 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.

Like Albina (2017) the bulk of the phrases utilize “quantitative”[7] 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. Albina (2017) 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 Albina (2017) 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 in either direction as it requires one of the phrases in the list to be used precisely and will not identify simply for the use of the word “quantitative.”

1.2. Mutual fund and holdings data

Once we have identified quantitative funds we match the funds to the CRSP Survivor-Bias-Free US Mutual Fund Database sample of actively managed domestic equity mutual funds operating between 2000 and 2015. CRSP provides data on fund net assets, returns, and other characteristics. We focus our analysis on funds with designated CRSP investment objectives of mid-cap, small-cap, micro-cap, growth, growth and income, and equity income. ETFs, variable annuities, and index funds are dropped from the sample using CRSP flags and name searches. Mutual fund holdings data comes from Thomson Reuters and is merged to the CRSP database via the MFLINKS table. These holdings are then merged with the CRSP stock database to obtain returns and other relevant characteristics. To be included in the tests, a mutual fund must hold at least twenty CRSP-merged stocks on a report date. We apply the filters used in Frazzini (2006) to

[7] For example: “quantitative model,” “quantitative approach,” “quantitatively driven,” etc.

the Thomson Reuters data to exclude observations that appear to be errors. Additionally, holdings are set to "missing" when the number of shares a fund holds is greater than the number of shares outstanding for that stock or the value of the position is greater than the fund's total asset value.

Figure 1 shows that at the beginning of our sample period in 2000 there were 109 quantitative funds out of 1,471 total active domestic equity funds (about 7%).

Insert Figure 1 About Here

In 2015, there are 168 quantitative funds out of 1,283 total funds (about 13%). This indicates that not only are the total number of quantitative funds increasing but they now also make up a substantial amount of all active equity funds.

Fund characteristics and returns from CRSP are aggregated across share classes on an asset-weighted basis using the WFICN variable from the MFLINKS table. 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.[8] 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).[9] The coefficients are estimated using fund returns and factor data

[8] 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.
[9] 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).

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:

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

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 twice as large as the 0.02 coefficient for non-quantitative funds. Similar differences are also found for the other five factors. Additionally quantitative funds tend to have a lower standard deviation of these coefficients indicating that these funds are operating using similar signals. The higher reliance on known anomalies and lower standard deviation of coefficients implies quantitative funds are more homogenous compared to their non-quantitative counterparts. Greater differences between the two types are found in other fund level characteristics. 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, given our findings on the larger distortions created by quantitative funds, we find that quantitative funds are smaller than their non-quantitative peers. The difference is size alone indicates that the larger distortion is not merely a mechanical byproduct of a large fund selling off a sizeable portion of its assets.

Later in the paper we use a number of additional variables as controls. We follow Gompers and Metrick (2001) and consider the following stock level variables: natural log of market capitalization, firm age, dividend yield, book-to-market ratio, 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.

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

In this section we examine 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 by quantitative and non-quantitative funds during a fire sale. We follow Coval and Stafford (2007) and label funds with the largest net outflows, and their associated stocks, as experiencing a fire sale. We find that fire sale stocks sold by quantitative funds experience a 100 basis point greater decline than those from a non-quantitative funds. 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.

2.1 Identifying fire sale stocks

We use quarterly mutual fund flows to identify stocks with significant downward pressure due to liquidity based trading by mutual funds.[10] To perform this identification of "pressure

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

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 downward 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 10^{th} (90^{th}) percentile of quarterly flows. *QuantPressure* is the flow-motivated trading by quantitative funds in a given stock scaled by shares outstanding

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

Additionally, we restrict the analyses to the 56 calendar quarters in the sample period where at least 75 quantitative funds report their holdings at the beginning and end of the quarter. As in Coval and Stafford (2007) we additionally require that at least 10 mutual funds of either type hold a stock before the pressure variable is calculated. 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. The increased variation for *NonQuantPressure* is not surprising given there are more non-quantitative funds than quantitative funds. However, despite fewer shares sold or purchased by quantitative funds we still find that their effect is much larger. This unexplained larger effect implies that something besides the total dollar amount traded leads to the larger distortions generated by quantitative funds.

2.2 Quantitative fire sales: portfolio sorts

We examine the outcomes for stocks sold by each fund type during fire sales. To do so we again follow Coval and Stafford (2007) and in each of the 56 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 fund types.

Insert Table 2 About Here

Panel A presents the characteristics of stocks undergoing high and low levels of pressure from quantitative funds' trades. While Panel B presents characteristics of high and low pressure stocks for non-quantitative funds. 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 the low pressure stocks (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.[11]

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:

$$AR_{l,t} = r_{i,t}^{e} - \left(\hat{\beta}_{1,l} RMRF_t + \hat{\beta}_{2,l} SMB_t + \hat{\beta}_{3,l} HML_t + \hat{\beta}_{4,l} CMA_t + \hat{\beta}_{5,l} RMW_t + \hat{\beta}_{6,l} MOM_t \right). \tag{4}$$

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

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 the 56 quarters. 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

We find that the magnitude of abnormal returns for a portfolio of stocks that are heavily sold by quantitative mutual funds is substantially 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. During the event quarter, the quantitative fire sale stock portfolio CARs are nearly 100 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 in Section 2.3

2.3 Quantitative fire sales: multivariate regression analyses

The findings in Section 2.2 indicate that on average quantitative fund fire sales generate larger market distortions and these distortions take longer to recover from. However, Table 2 indicates 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 2.2. As before stocks must be held by at least 10 mutual funds to enter the sample. Each regression includes quarter fixed effects to account for variation attributable to macroeconomic and market environment. 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 a possible explanatory variable. Column (3) includes 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 the slight differences in firm level characteristics as observed in Table 2.

The results in all three columns provide show that quantitative fund pressure has an economically larger impact on stock returns during the fire sale event window compared to non-quantitative fund pressure. The coefficients for both quantitative and non-quantitative fund pressure are positive and statistically significant at the 1% level. However, the magnitude of the coefficient on quantitative fund pressure is larger. A t-test of the coefficients yields that the difference is statistically significant at the 1% level in all three models.

In column (3), the magnitude of the pressure coefficient quantitative funds is over five times larger (0.497) than the coefficient for non-quantitative funds (0.091). The economic interpretation of these coefficients is straightforward, a 1% decrease in stock ownership from a quantitative fund undergoing a fire sale is associated with a 4.97% decrease in abnormal stock returns over the event quarter while a 1% decrease in stock ownership from a non-quantitative fund undergoing a fire sale is associated with a 0.91% decrease in abnormal returns during the quarter. 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?

3. What Drives Quant Funds' Larger Impact?

The results in Section 2 demonstrate that fire sales from quantitative funds generate larger distortions than fire sales by non-quantitative funds. In this section we test three potential mechanisms that could drive 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 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.

3.1 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) in the 56 quarters 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

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

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 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 8.12%. This is significantly larger than non-quantitative funds whose average portfolio overlap is shown to be 5.56% in column (2). We use a t-test to determine whether these means are statistically significantly different from each other. Quantitative fund overlap is found to be larger and the difference between like fund overlap for each fund type 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 (14.84 versus 6.13).

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 than their non-quantitative fund counterparts. We find that quantitative funds have nearly 50% greater overlap (10.17% versus 6.92%) 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 common stocks sold. Columns (3) and (4) show that quantitative fund pairs have more than twice as many common sales (6.07 versus 2.74) 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 Fama and French (2015) 6-factor model these findings suggest quantitative funds have significantly more overlap in their underlying investment process compared to non-quantitative funds. The greater overlap in selling activity among quantitative funds suggests that their crowded liquidations contribute to a larger distortion from their fire sales.

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

Prior tests on the heightened factor exposures and common trades/holdings for quantitative funds suggest that 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 results of regressions of 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 the 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 from 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 quarter fixed effects and standard errors are clustered at the stock level.

Consistent with the idea that quantitative funds rely heavily on stock characteristics in their selling decisions, we find that the adjusted R^2 from the sell regression for quantitative funds in column (1) is more than three times larger (7.5%) than the adjusted R^2 from the sell regression for non-quantitative funds (1.9%) in column (2). We find significant differences in many of the coefficients for quantitative and non-quantitative funds in column (5). For example, quantitative funds are more likely to sell the larger and arguably more liquid stocks in their portfolios relative to non-quantitative funds. Moreover, we find evidence consistent with our 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 -0.039). 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 operate differently during fire sales than non-quantitative funds and provide evidence that the negative momentum hypothesis contributes the larger distortion from quantitative funds. We find that quantitative funds are more significantly more sensitive to past recent returns. This heightened sensitivity to recent past returns opens the possibility that the securities they liquidate are more likely to enter a negative feedback loop whereby other quantitative funds undergoing liquidity-based sales choose to sell the same securities.

3.3 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 impacts 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. Since the *per_cash* variable is only widely populated starting in January of 2003, the cash analyses are restricted to the portion of the sample period starting in 2003. We find that, on average, quantitative funds tend to hold significantly less cash (2.8%) in their portfolios than non-quantitative funds (3.9%) when experiencing flow-based transactional pressure. The difference in these mean 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.[12] Specifically, for each calendar quarter we identify 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 levels 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 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 non-quantitative funds with the least favorable cash positions as the comparison group.

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

Insert Table 6 About Here

We find that the results remain economically and statistically similar to the baseline results. Interestingly, we find that the coefficient on *NonQuantPressure* is relatively unchanged from 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.

4. Robustness Checks

This section focuses on robustness checks of the main results. First, we consider whether crisis periods either for quantitative managers or for the broader financial market are driving our results. Crisis periods are often marked with significant withdrawals from mutual funds and negative returns in broader capital markets. In particular, quantitative funds experienced a crisis in 2007 known as the "Quant Crisis" (or "Quant Quake") that was marked with losses for a number of major quantitative hedge funds (Kirilenko and Lo (2013)). It is possible that this and the financial crisis of 2008 and 2009 drive 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 results are stronger in crisis periods but 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.

4.1. The "quant meltdown" and financial crisis

We first consider how crisis periods may impact the findings. Specifically, we test if the baseline results are primarily driven by crisis periods in the sample. We consider calendar years which include both the quant crisis and the financial crisis. The "Quant Meltdown" (or "Quant Crisis") occurred during the summer of 2007 and as explained in Kirilenko and Lo (2013) was the result of deleveraging by quantitative funds driving security prices away from fundamental value and causing other funds with similar holdings to experience significant losses. The Quant Meltdown was a fire sale event that led to a rapid unwinding by numerous funds and generated market instability and funds rushed to simultaneously exit their positions.

The financial crisis is also 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.[13] 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) excludes the crisis years of 2007, 2008, and 2009 and Column (2) restricts the sample to the crisis years of 2007 to 2009. In column (1) when excluding the crisis years, we find that the

[13] See the 2010 ICI Factbook.

results remain largely unchanged. Economically, the magnitude of the coefficients on *QuantPressure* and *NonQuantPressure* are slightly smaller in magnitude relative to the baseline results but the inferences remain similar. The coefficient on *QuantPressure* (0.403) remains more than five times larger than the coefficient on *NonQuantPressure* (0.068). Both coefficients maintain their significance at the 1% and are statistically different at better than the 1% level.

In column (2), 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 0.952 and the coefficient on *NonQuantPressure* increases to 0.206. While the coefficients are larger for both types of funds we curiously note that the coefficient on *QuantPressure* retains a similar relative magnitude compared to *NonQuantPressure* as it is more than four times larger. Overall, the findings are consistent with quantitative funds' greater impact on markets being realized across all types of market conditions.

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

We first consider a test of the quantitative fund identification by approximating 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.

We first perform a search on the Morningstar Direct database for all funds categorized as "Equity" using the *Global Broad Category Group* filter while also requiring that the fund is not an index fund, is the oldest share class of the fund, and that the base currency is the U.S. Dollar. This produces a list of 12,823 funds for review. We collect information on the *Investment Strategy, Ticker,* and *FundID*. Next we scrape the *Investment Strategy* field using the word list from Harvey et al. (2017)[14] to identify quantitative mutual funds. We use this alternative means of identification as a final robustness tests of our results.

Column (4) 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 panel regression in column (3) of Table 3. Given that Harvey et al (2017)'s phrase list includes fewer words it is not surprising that we identify fewer quantitative funds in the sample. Moreover, since we require at least 75 quant funds report in a given quarter to calculate the pressure variables, this analysis only uses 52 calendar quarters as opposed to the 56 calendar quarters in the baseline tests. This explains the lower number observations in this specification relative to the baseline analyses.

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 (4) of Table 7 is nearly four times as large as the coefficient on *NonQuantPressure* and these coefficients are different at the 10% level. These results speak to the robustness of the findings with respect to decisions made in the classification process.

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

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

5. 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.

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*. $AR_{l,t} = r^{e}_{i,t} - \left(\hat{\beta}_{1,l}RMRF_t + \hat{\beta}_{2,l}SMB_t + \hat{\beta}_{3,l}HML_t + \hat{\beta}_{4,l}CMA_t + \hat{\beta}_{5,l}RMW_t + \hat{\beta}_{6,l}MOM_t\right)$
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: $Portfolio\ Overlap(h_t, j_t) = 1 - \frac{1}{2}\sum_{k=1}^{K} \left\| w_{h,k,t} - w_{j,k,t} \right\|$ where $w_{h,k,t}$ is fund *h*'s weight (as a fraction total portfolio market value) in stock *k* in quarter *t*.
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 CRSP 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 dashed line line indicates the number of quantitative funds identified each year since 2000 and the solid line shows this number as a percentage of all active equity funds.

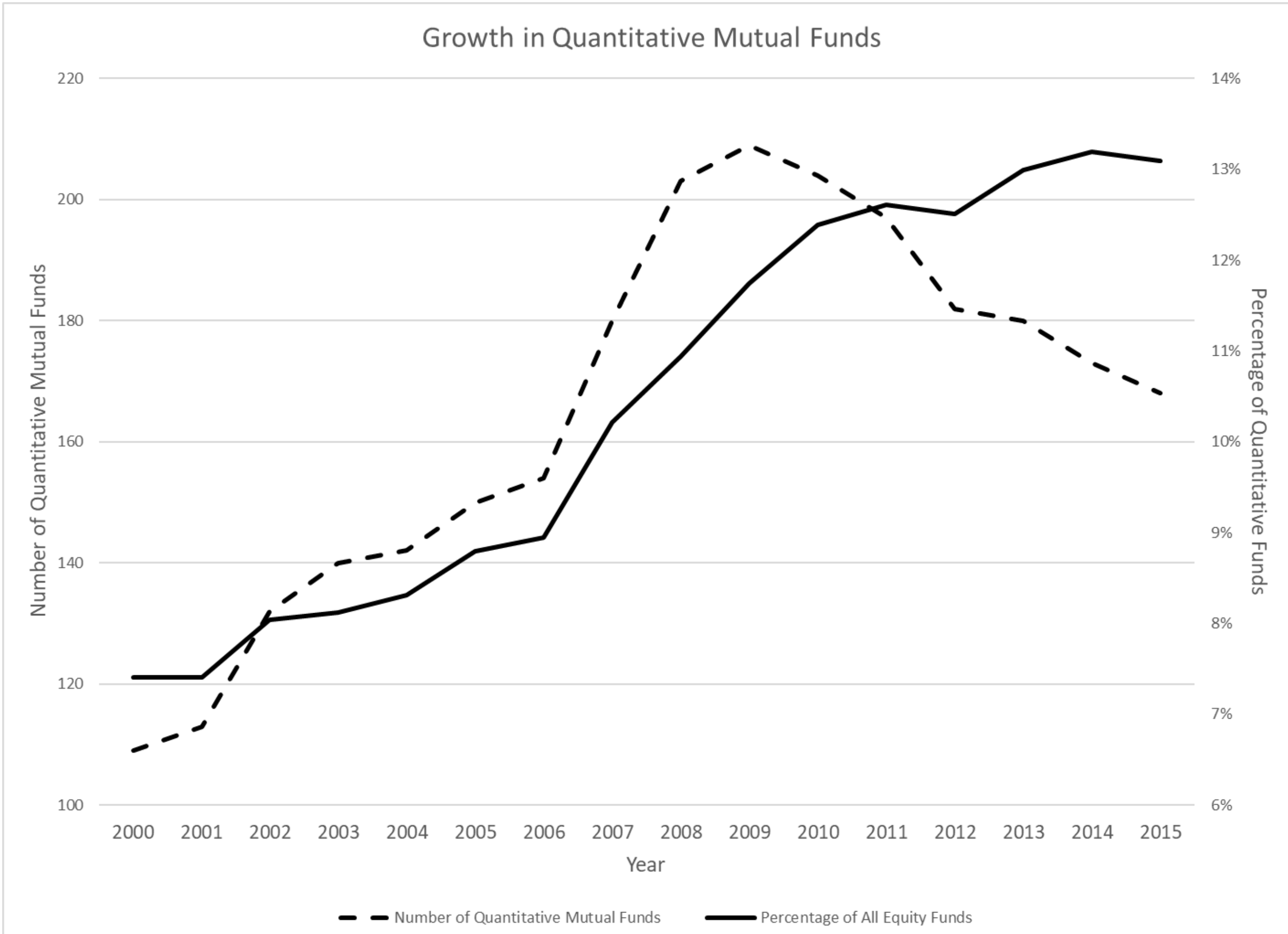

Figure 2: Cumulative Average Abnormal Returns for Bottom Decile Pressure Stocks

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.

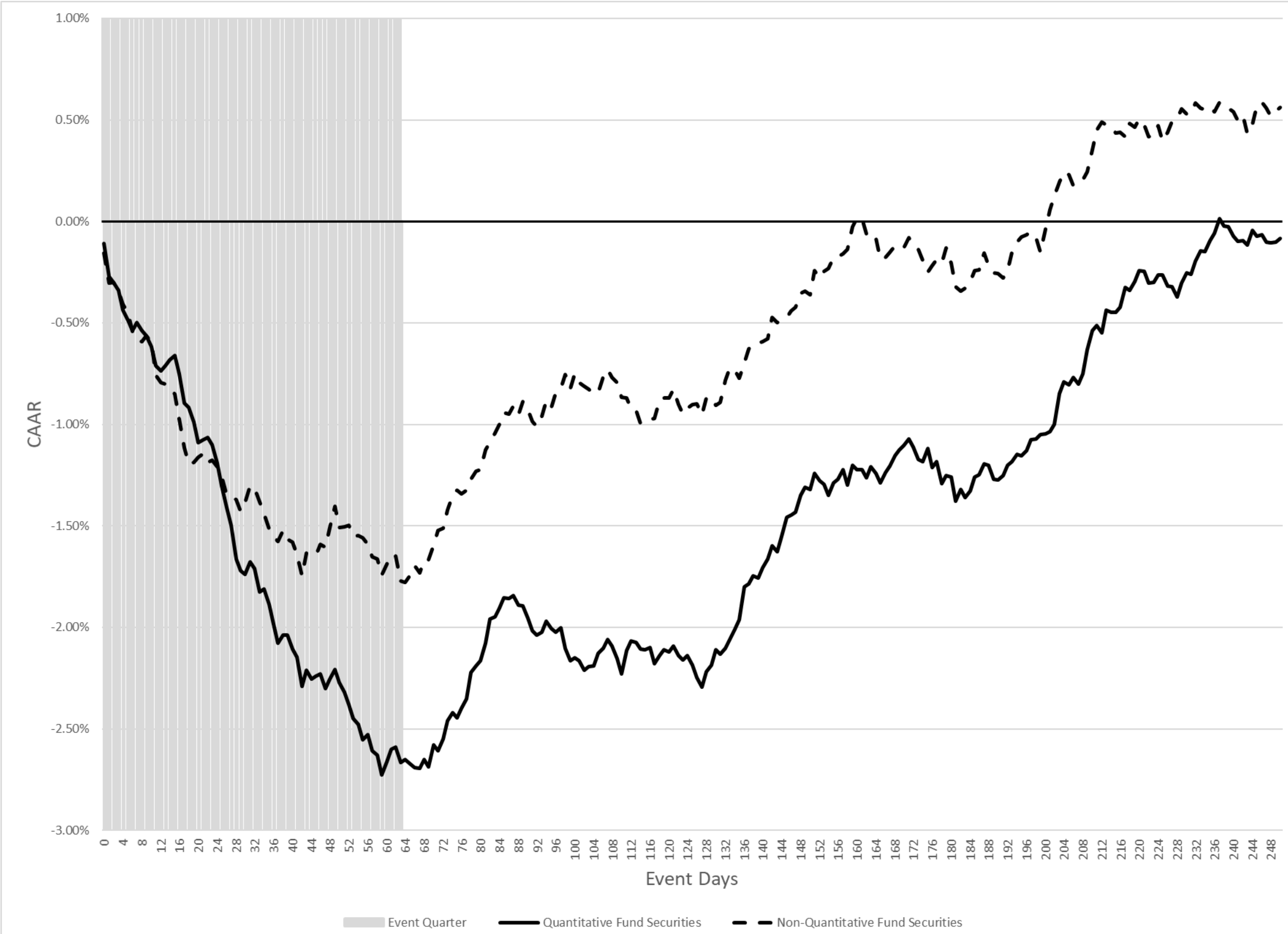

Table 1: Mutual Fund Summary Statistics

This table reports fund-quarter summary statistics for non-specialty actively managed domestic equity funds operating between January 2000 and December 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 fund observations are restricted to the 56 quarters in Thomson where at least 75 quantitative funds report holdings. For results in columns 13 and 14 t-statistics are shown in parentheses and ***, ** 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	6,162	0.99	0.99	0.12	0.85	1.12	54,613	0.96	0.97	0.17	0.79	1.13	0.024***	(4.03)
Size	6,162	0.23	0.10	0.39	-0.18	0.80	54,613	0.22	0.13	0.37	-0.18	0.76	0.012	(0.42)
Value	6,162	0.04	0.03	0.26	-0.28	0.37	54,613	0.02	0.02	0.30	-0.34	0.38	0.013	(0.87)
Momentum	6,162	0.05	0.04	0.14	-0.09	0.22	54,613	0.02	0.01	0.17	-0.15	0.22	0.026***	(4.47)
Investment	6,162	-0.09	-0.07	0.32	-0.50	0.26	54,613	-0.12	-0.10	0.38	-0.58	0.31	0.026*	(1.90)
Profitability	6,162	0.01	0.02	0.28	-0.34	0.30	54,613	-0.04	-0.01	0.33	-0.43	0.32	0.034***	(2.73)
Fund Characteristics														
Fund family TNA ($MM)	6,162	79,780	22,654	247,235	1,307	94,386	54,613	72,968	9,827	202,291	168	143,666	6,813	(0.40)
Fund TNA ($MM)	6,162	890	263	1,729	40	2,159	54,613	1,575	262	6,265	20	3,173	-705.1***	(-3.51)
Fund age (years)	6,162	13.36	11.33	9.23	3.92	25.33	54,613	12.75	10.83	8.70	3.67	24	0.61***	(0.88)
Net flows (%)	6,162	3.91%	-4.29%	39.53%	-29.05%	47.00%	54,613	6.21%	-3.17%	41.57%	-38.07%	51.30%	-2.30%*	(-1.85)
Stdev flows (%)	6,162	3.54%	2.03%	4.09%	0.59%	7.85%	54,613	3.49%	2.05%	4.07%	0.58%	7.89%	0.05%	(0.36)
Fund turnover	6,162	0.93	0.75	0.78	0.26	1.68	54,613	0.82	0.59	1.23	0.17	1.63	0.11**	(2.32)
Expense (%)	6,162	1.12%	1.09%	0.38%	0.70%	1.62%	54,613	1.28%	1.21%	0.60%	0.81%	1.80%	-0.16%***	(-5.78)

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. Panel A reports summary statistics for stocks undergoing transactional pressure from funds following a quantitative investment process and Panel B reports summary statistics for stocks undergoing pressure from non-quantitative funds. High pressure stocks are stocks undergoing purchasing pressure from funds receiving inflows and low pressure stocks are the stocks undergoing selling pressure from fund undergoing outflows. Definitions and data sources can be found in Appendix A. Quarterly stock observations are restricted to the 56 quarters in Thomson where at least 75 quantitative funds are operating.

Panel A: Quantitative Pressure Stocks

VARIABLES	(1) n	(2) mean	(3) median	(4) stdev	(5) p(10)	(6) p(90)
High Pressure Stocks:						
Log(Mkt Cap)	7,642	14.2	14.1	1.4	12.6	16.0
Dividend yield	7,642	0.00	0.00	0.09	0.00	0.05
B/M	7,642	0.63	0.49	1.13	0.17	1.07
Turnover	7,642	1.83	1.46	1.41	0.61	3.44
Price	7,642	61.3	27.4	1551.5	10.0	63.3
Ret_{t-1}	7,642	0.07	0.05	0.27	-0.17	0.29
$Ret_{t-2,t-4}$	7,642	0.17	0.11	0.51	-0.25	0.60
Volatility	7,642	0.10	0.09	0.07	0.05	0.18
Firm age (months)	7,642	243	196	166	59	507
Investment	7,642	0.08	0.07	0.19	-0.08	0.27
Profitability	7,642	0.10	0.10	0.12	0.02	0.22
Low Pressure Stocks:						
Log(Mkt Cap)	7,638	14.1	13.9	1.4	12.6	16.1
Dividend yield	7,638	0.01	0.00	0.03	0.00	0.03
B/M	7,638	0.57	0.44	0.72	0.14	1.04
Turnover	7,638	2.04	1.61	1.92	0.69	3.75
Price	7,638	43.5	26.6	858.9	8.7	61.8
Ret_{t-1}	7,638	0.04	0.03	0.23	-0.22	0.28
$Ret_{t-2,t-4}$	7,638	0.25	0.14	0.76	-0.26	0.75
Volatility	7,638	0.11	0.10	0.07	0.05	0.19
Firm age (months)	7,638	217	169	159	51	484
Investment	7,638	0.09	0.07	0.20	-0.08	0.30
Profitability	7,638	0.11	0.10	0.11	0.02	0.22

Panel B: Non-Quantitative Pressure Stocks

VARIABLES	(1) n	(2) mean	(3) median	(4) Stdev	(5) p(10)	(6) p(90)
High Pressure Stocks:						
Log(Mkt Cap)	12,208	13.9	13.8	1.3	12.3	15.6
Dividend yield	12,208	0.00	0.00	0.06	0.00	0.04
B/M	12,208	0.62	0.47	1.06	0.16	1.07
Turnover	12,208	1.65	1.32	1.40	0.50	3.09
Price	12,208	79.5	25.3	2167.3	9.1	60.6
Ret_{t-1}	12,208	0.06	0.03	0.25	-0.19	0.31
$Ret_{t-2,t-4}$	12,208	0.22	0.13	0.64	-0.23	0.67
Volatility	12,208	0.11	0.09	0.07	0.05	0.18
Firm age (months)	12,208	223	178	158	52	532
Investment	12,208	0.08	0.07	0.21	-0.08	0.28
Profitability	12,208	0.10	0.10	0.12	0.01	0.22
Low Pressure Stocks:						
Log(Mkt Cap)	12,438	13.9	13.8	1.3	12.4	15.7
Dividend yield	12,438	0.01	0.00	0.08	0.00	0.03
B/M	12,438	0.64	0.45	1.76	0.16	1.07
Turnover	12,438	1.95	1.50	2.13	0.61	3.69
Price	12,438	81.4	24.2	2224.6	8.1	58.5
Ret_{t-1}	12,438	0.04	0.02	0.25	-0.23	0.29
$Ret_{t-2,t-4}$	12,438	0.20	0.11	0.63	-0.30	0.68
Volatility	12,438	0.11	0.10	0.08	0.05	0.19
Firm age (months)	12,438	219	175	156	52	477
Investment	12,438	0.09	0.07	0.21	-0.09	0.30
Profitability	12,438	0.10	0.10	0.12	0.01	0.22

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. 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. 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 double 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
QuantPressure	0.572***	0.535***	0.497***
	(6.81)	(6.49)	(6.75)
NonQuantPressure	0.104***	0.117***	0.091***
	(3.48)	(4.03)	(3.28)
QuantOwnership		-0.033***	-0.054***
		(-3.20)	(-5.04)
NonQuantOwnership		-0.001***	-0.004***
		(-0.66)	(-2.74)
Stock Controls	No	No	Yes
Quarter FEs	Yes	Yes	Yes
N	151,876	151,876	132,337
Adj. R^2	0.004	0.006	0.011
H_0: *QuantPressure – NonQuantPressure = 0*	0.469*** (5.61)	0.419*** (5.27)	0.406*** (5.65)

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 2000 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 estimated from univariate regressions and 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	8.12%	6.05%	14.84	8.05
Non-Quant		5.56%		6.13
H_0: Quant Pairs – Non-Quant Pairs = 0	2.56%*** (2.79)		8.71*** (4.02)	

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	10.17%	7.81%	6.07	3.52
Non-Quant		6.92%		2.74
H_0: Quant Pairs – Non-Quant Pairs = 0	3.24%*** (3.19)		3.32*** (3.90)	

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 funds undergoing fire sales in the 56 quarters in Thomson where at least 75 quantitative funds are operating. 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 since the prior holdings report and zero otherwise. The key independent 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 quarter fixed effects. Standard errors are clustered on stock. ***, ** 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}	-0.080***	-0.038***	-0.084***	-0.039***	-0.045***
	(-9.15)	(-10.00)	(-11.21)	(-10.38)	(-5.65)
$Ret_{t-2,t-4}$	0.019***	-0.001***	-0.012***	0.005***	-0.017***
	(5.77)	(-0.39)	(-3.18)	(3.33)	(-4.12)
Log(Mkt cap)	0.029***	0.017***	0.032***	0.017***	0.014***
	(26.44)	(32.47)	(29.11)	(32.39)	(12.85)
B/M	-0.102***	-0.003	-0.095***	-0.000	-0.095***
	(-4.96)	(-0.02)	(-4.69)	(-0.03)	(-4.68)
Div yield	-0.378	-0.025	-0.488**	-0.029	-0.459**
	(-1.58)	(-0.40)	(-2.24)	(-0.45)	(-2.08)
Price	-0.000***	0.000*	-0.000***	-0.000*	-0.000***
	(-16.51)	(-1.86)	(-11.59)	(-1.83)	(-10.51)
Volatility	-0.001	-0.007	0.290***	-0.062***	0.351***
	(-0.02)	(-0.46)	(10.60)	(-4.12)	(11.75)
Firm age	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(-3.04)	(-3.94)	(-5.57)	(-3.79)	(-3.34)
Investment	0.004	0.013**	0.002	0.015***	-0.013
	(0.54)	(3.98)	(0.30)	(4.35)	(-1.52)
Profitability	0.026*	0.006	0.084***	0.000	0.084***
	(1.82)	(0.92)	(5.59)	(0.01)	(5.28)
Quarter FE	Yes	Yes	Yes		
N	90,686	526,429	617,115		
Adj. R^2	0.075	0.019	0.022		

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
QuantPressure	0.469***	0.413***	0.418***
	(5.47)	(5.01)	(5.08)
NonQuantPressure	0.112**	0.094**	0.100**
	(2.52)	(2.17)	(2.36)
QuantOwnership		-0.052***	-0.054***
		(-4.74)	(-4.79)
NonQuantOwnership		-0.005***	-0.003*
		(-3.25)	(-1.87)
Stock Controls	No	No	Yes
Quarter FEs	Yes	Yes	Yes
N	130,063	130,063	114,768
Adj. R^2	0.004	0.006	0.007
H_0: *QuantPressure – NonQuantPressure = 0*	0.357*** (3.93)	0.319*** (3.61)	0.319*** (3.55)

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 non-crisis years by excluding 2007 – 2009. Column (2) restricts the sample to crisis years i.e., 2007 – 2009. Column (3) reruns 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					
VARIABLES	(1) Excluding 2007- 2009	(2) 2007-2009	(3) Harvey Quant IDs	(4) Fama-MacBeth	(5) CAR Market Model	(6) Monthly CARs
QuantPressure	0.403***	0.952***	0.309***	0.422***	0.509***	0.436***
	(5.32)	(4.09)	(2.94)	(2.97)	(6.97)	(6.56)
NonQuantPressure	0.068**	0.206***	0.098***	0.112***	0.109	0.095***
	(2.46)	(3.32)	(3.63)	(3.43)	(3.57)	(3.11)
Stock Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	N/A	Yes	Yes
N	102,051	30,286	115,274	132,337	132,337	132,337
Adj. R-squared	0.011	0.015	0.010	0.043	0.046	0.046
H_0 *QuantPressure – NonQuantPressure = 0*	0.335*** (4.57)	0.746*** (3.17)	0.211* (1.85)	0.310** (2.13)	0.400*** (5.48)	0.341*** (5.50)