Stock Price Fragility*

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Abstract

We study the relation between the ownership structure of financial assets and non-fundamental risk. We define an asset to be fragile if it is susceptible to non-fundamental shifts in demand. An asset can be fragile because of concentrated ownership, or because its owners face correlated or volatile liquidity shocks, i.e., they must buy or sell at the same time. We formalize this idea and apply it to mutual fund ownership of US stocks. Consistent with our predictions, fragility strongly predicts price volatility. We then extend the logic of fragility to investigate two natural extensions: (1) the forecast of stock return comovement and (2) the potentially destabilizing impact of arbitrageurs on stock prices.

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1. Introduction

In traditional asset pricing theory, the composition of ownership of a financial asset does not influence future returns or risk. If the current holders of the asset buy or sell for reasons unrelated to fundamentals, new owners immediately take their place, with no impact on price. Underlying the conventional theory is the assumption that arbitrageurs are willing to trade aggressively against the liquidity shocks of other investors, thus ensuring that demand curves for individual financial assets are flat. However, a vast empirical literature in finance challenges this assumption, finding that investor demand unrelated to fundamentals can impact prices.[1] A natural implication of these findings is that knowing whether the owners of a financial asset will collectively face liquidity shocks should be useful for forecasting non-fundamental risk. While it is challenging to forecast liquidity shocks, it may be simpler to forecast the *volatility* of these shocks based on the prior behavior of the owners.

In this paper, we show how to compute the expected volatility of non-fundamental demand given an asset's ownership structure. We call this variable "fragility." We then calculate fragility for US stocks using mutual fund ownership data, and show that fragility strongly predicts stock return volatility. We explore extensions of this approach to stock return comovement, and to the potentially stabilizing role of arbitrage in dampening non-fundamental risk.

To illustrate the basic reasoning, consider an asset with few owners who each hold large percentage stakes. If the volatility of their liquidity needs is low (i.e., they never have to buy or

[1] For example, Shleifer (1986) and Harris and Gurel (1986) show that stock prices rise when stocks are added to a stock index. More recent work has extended these findings to document price effects of investor demand in numerous settings, including retail demand for stocks (Barber, Odean, and Zhu, 2009; Foucault, Sraer, and Thesmar, 2009), retail demand for options (Garleanu, Pedersen, and Poteshman, 2009), hedge fund demand for convertible bonds (Mitchell, Pederse,n and Pulvino, 2007), investor demand for bonds (Greenwood and Vayanos, 2009), and mutual funds' flow-driven demand for stocks (Coval and Stafford, 2007; Frazzini and Lamont, 2008; Lou, 2010).

sell for reasons unrelated to the fundamentals of the asset), then the asset is not exposed to much non-fundamental risk. However, if one of the owners were to experience volatile liquidity shocks, his trading is unlikely to be "cancelled" by the trades of the other owners, resulting in price impact. In this case, non-fundamental volatility will be high.

On the opposite extreme, consider a financial asset with diversified ownership—the typical blue chip stock trading on the NYSE, for example. The owners may individually experience liquidity shocks which require them to buy more shares or to scale their position down. Yet, the net effect on price is mitigated by the effective cancelling of their trades. There are limits to such ownership diversification, however: an asset with diversified ownership will still be fragile if its owners' liquidity shocks are highly correlated. Overall, fragility depends on ownership concentration and the volatilities and correlations of owners' expected liquidity trades.

While the intuition underlying fragility is straightforward, whether it is useful empirically depends on whether we can measure (a) the composition of ownership and (b) the ex ante variance-covariance structure of the liquidity needs faced by its owners. For many assets, even if we can observe ownership, estimating the volatility or correlation of the owners' liquidity needs presents a challenge. Fortunately, mutual fund ownership of US-listed equities satisfies both criteria above, because the correlation structure of mutual funds' liquidity-driven trades can be inferred from investor flows into and out of these funds, and because mutual funds regularly report their positions. We thus implement our suggested measures of fragility on US stocks between 1990 and 2007.

Our findings are as follows. First, fragility is a statistically strong and economically significant predictor of future total and idiosyncratic volatility (the univariate R^2 is approximately 8%). This predictive power remains once we control for the determinants of volatility suggested by the existing literature. The strength of these results is particularly surprising given that mutual funds own only about 15% of the shares outstanding for the median stock in our sample, meaning that we measure true fragility (i.e., the non-fundamental demand volatility of *all* owners, not just mutual funds) with quite a lot of noise.

We next study two natural extensions of our fragility measure. First, the logic of fragility can be extended to forecast comovement: We define two assets to be "co-fragile" if they are held by investors who have correlated trading needs. The notion of co-fragility can be used to derive a "fragility beta," which measures the extent to which an asset's owners have flows which are correlated with the flows into a given portfolio—e.g., a stock has a high fragility beta if it tends to experience inflows at the same time as the market portfolio experiences inflows. Empirically, co-fragility and fragility betas both predict comovement quite well. For instance, 25% of the cross-sectional variation in the beta with respect to the Fama and French (1993) HML factor can be explained by the ownership of these securities: i.e., many stocks comove with HML simply because they are held by funds which have flows that are correlated with flows into value funds.

In our second extension, we try to understand under which circumstances fragility will be a better forecaster of non-fundamental risk. In principle, fragility will be less useful for forecasting non-fundamental risk if the flow-driven trades of mutual funds are aggressively accommodated by other investors. We investigate this idea, focusing on hedge funds as potential liquidity providers, but also considering whether mutual funds may play a role through their non-flow-driven active trades. Consistent with the intuition outlined above, we find that fragility exerts a more modest effect on volatility among stocks in which arbitrageurs are willing to trade against liquidity shocks. Conversely, for some stocks where arbitrageurs tend to trade in the *same direction* as mutual funds' liquidity trades, fragility has a stronger effect on volatility. Our results here are linked to a number of recent papers that investigate the price destabilizing behavior of arbitrageurs.[2]

Taken together, our results establish a connection between ownership structure and risk, thus shedding light on earlier work which correlates institutional ownership with stock price volatility (Sias, 1996; Bushee and Noe, 2000; Koch, Ruenzi, and Starks, 2009). We note that it is not so much the fraction of mutual fund ownership per se, but rather the composition of ownership that matters for predicting volatility.

An important concern in interpreting our results is that ownership structure is potentially endogenous. For example, the relationship between fragility and volatility could partly reflect the selection of funds with volatile flows into stocks with volatile fundamentals. We partially address this concern by controlling for a host of time-varying determinants of volatility, as well as using firm fixed effects in several specifications. Concerns about endogeneity loom larger, however, when interpreting the evidence that links ownership structure with stock return comovement. Here it is easy to see reasons why funds with correlated flows might rush into similar stocks, constituting a form of omitted variable bias. Although we again seek to control for as many fundamental determinants of return comovement as possible, we view these results as more suggestive.

Our findings build on a series of papers on the price impact of mutual fund flow-driven trades. Frazzini and Lamont (2008) show that stocks bought by funds that receive disproportionate inflows underperform in the long run. Coval and Stafford (2007) show that stocks heavily sold by distressed mutual funds have positive long-run returns. These two papers

[2] Brunnermeier and Nagel (2004) and Griffin, Harri,s and Topaloglu (2009) study the role of hedge funds in the technology bubble. Both studies find that hedge funds have amplified mispricing. Fishman, Hong, and Kubik (2009) study positive earnings announcements for heavily shorted stocks. Chen, Hanson, Hong, and Stein (2008) study hedge fund responses to mutual fund liquidity trades.

provide evidence that flow-driven trading by mutual funds has price impact. We build more directly on Lou (2010), who also explores the relationship between flow-driven trading and returns. After establishing the relationship between flow-driven trading and returns, Lou uses it to provide a joint explanation of stock return momentum and mutual fund performance persistence: when a stock performs well, funds that hold it perform well, leading to future inflows which generate additional buying pressure and positive returns.

Our co-fragility results contribute to the literature on the excess comovement of stock returns (Barberis and Shleifer, 2003; Barberis, Shleifer, and Wurgler, 2005). Our comovement results are closest to two recent papers. Kumar, Page, and Spalt (2009) predict comovement by looking at aggregate retail investor trading: we focus instead on mutual funds, which allows us to identify trades that are less likely to be connected with information. Anton and Polk (2010) show that stocks with common owners have more correlated returns: our co-fragility measure complements their approach by showing that stocks also comove because different owners have correlated trading needs. In contrast to us, however, Anton and Polk look at different asset pricing implications of their comovement measure: they find that stocks held by common owners that temporarily diverge can be predicted to eventually reconverge, leading to a profitable trading strategy.

We proceed as follows. The next section formalizes a definition of fragility. Section 3 describes how we calculate fragility for common stocks using mutual fund ownership data. Section 4 analyzes the relationship between fragility and volatility. Section 5 turns to our first extension: co-fragility and fragility betas. In Section 6, we look at the impact of arbitrageur trading in volatility. The last section concludes.

2. Asset fragility

In this section, we develop our fragility measure and use it to explore the link between ownership structure and non-fundamental risk. We first assume (Section 2.1) that we can observe the portfolios of the complete universe of investors and their holdings in all securities. Section 2.2 illustrates the intuition with a simple example. Section 2.3 discusses the issues that arise when we try to compute fragility empirically using data on an incomplete subset of investors.

2.1. Definition

For a given investor *k*, the dollar weight w_{ikt} of security *i* in the investor's portfolio at date *t* is:

$$w_{ikt} = \frac{n_{ikt} P_{it}}{a_{kt}}, \tag{1}$$

where n_{ikt} is the number of securities *i* held by *k* at *t*, a_{kt} is the total portfolio value of that investor, and P_{it} is the price per security. By log-linearizing Eq. (1), net dollar purchases of *i* by *k* can be decomposed into two parts:

$$P_{it} \Delta n_{ikt} = n_{ikt} P_{it} \left(\frac{\Delta w_{ikt}}{w_{ikt}} - \frac{\Delta P_{it}}{P_{it}} \right) + w_{ikt} \Delta a_{kt}, \tag{2}$$

where $\Delta x_t \equiv x_{t+1} - x_t$, i.e., the period-ahead change in *x*. The change in portfolio assets Δa_{kt} is the sum of two effects: net inflows into *k*'s portfolio, and changes in the (dividend-adjusted) prices of its constituents:

$$\Delta a_{kt} = f_{kt} + \sum_j n_{jkt} \Delta P_{it}. \tag{3}$$

Net inflows f_{kt} can have several interpretations. They may literally be inflows into a mutual fund, hedge fund, or pension plan. Or, more broadly, flows can represent inflows into an individual's financial wealth through savings, inheritance, job loss, or shocks to human capital.

Substituting (3) into (2) and rearranging yields:

$$\begin{aligned} P_{it}\Delta n_{ikt} &= n_{ikt}P_{it}\left(\frac{\Delta w_{ikt}}{w_{ikt}} - \frac{\Delta P_{it}}{P_{it}}\right) + w_{ikt}\left(f_{kt} + \sum_j \left(n_{jkt}\Delta P_{jt}\right)\right) \\ &= \underbrace{n_{ikt}P_{it}\left(\frac{\Delta w_{ikt}}{w_{ikt}} - \left(\frac{\Delta P_{it}}{P_{it}} - \sum_j \left(w_{jkt}\frac{\Delta P_{jt}}{P_{jt}}\right)\right)\right)}_{\text{Active rebalancing}} + \underbrace{w_{ikt}f_{kt}}_{\text{Flow-driven trading}}. \end{aligned} \tag{4}$$

where the j subscript denotes other securities held by investor k. The first term in the decomposition in Eq. (4) is the contribution of active portfolio rebalancing, i.e., the trading that results from a willingness to change the weight of security i beyond the mechanical effect of relative price changes and flows. The last term in Eq. (4) is the contribution of flows, holding fixed the composition of the portfolio.

We assume that there is a stable relationship between aggregate flow-driven buys into security i (the sum of all flow-driven buys into i) and its contemporaneous return:

$$r_{it+1} = \alpha + \lambda \frac{\sum_k \left(w_{ikt}f_{kt}\right)}{\theta_{it}} + \varepsilon_{it+1}, \tag{5}$$

where r_{it+1} is the return of security i, taken between t and t+1, and θ_{it} is a scaling factor (we use market capitalization, as is common in the literature). ε_{it+1} is an error term with conditional mean of zero, which may reflect other sources of variation of returns, and which can be interpreted naturally as reflecting news about fundamentals.

In writing Eq. (5), we assume that flow-driven trading is not motivated by fundamentals, but rather by investors' demand for liquidity. For instance, a mutual fund experiencing a 10%

withdrawal may sell 10% of each security it owns. Or, an individual who loses her job may liquidate her equity portfolio pro-rata to pay future expenses. If flow-driven demands do not cancel out across owners, this will exert some temporary pressure on prices, as long as there is limited market-making capital. Under this interpretation, the λ term in (5) measures the price impact of liquidity trades: a high value of λ means that prices react strongly to uninformed demand.[3]

Is it reasonable to assume that flows do not predict future fundamentals, i.e., that f_{ikt} and ε_{it+1} are uncorrelated? For example, if investors are informed, then it is possible that a fund's outflows could predict deteriorating fundamentals of the stocks held by that fund. While theoretically possible, empirical evidence runs counter to this idea. Frazzini and Lamont (2008) show that mutual fund inflows are "dumb money," meaning that net inflows tend to forecast *low* long-run returns. Coval and Stafford (2007) study fire sales by mutual funds which experience large outflows, and which thus have to sell quickly. Khan, Kogan, and Serafeim (2009) and Lou (2010) also study flow-induced trading. These papers all find that the price changes accompanying flow-induced trading are temporary, reverting in about a year. In contrast, if flow-driven trading were driven by information, then contemporaneous price changes would be permanent. In summary, consistent with the empirical evidence, we assume that ε_{t+1} and f_t are conditionally independent.

To get to the volatility of returns, we need to take the variance of (5). Before doing this, we first rewrite the right-hand terms in Eq. (5) using vector notation:

$$r_{it+1} = \alpha + \frac{\lambda}{\theta_{it}} W_{it}' F_t + \varepsilon_{it+1}, \tag{6}$$

[3] Hence, $1/\lambda$ is the price elasticity of demand (Wurgler and Zhuravskaya, 2002; and Chacko, Jurek, and Stafford, 2008). We generally assume a constant λ across assets, but relax this assumption in Section 6.

where $W'_{it} = \left(w_{i1t}, ..., w_{iKt}\right)$ is the vector of weights of each investor in security i and $F_t = \left(f_{1t}, ..., f_{Kt}\right)$ is the vector of net dollar inflows. K denotes the number of investors.

Given independence between the error term and flow-driven trading, we can compute the conditional variance of the t+1 return:

$$\text{var}_t\, r_{it+1} = \lambda^2 \left(\frac{1}{\theta_{it}}\right)^2 W'_{it}\Omega_t W_{it} + \sigma_{it}{}^2, \tag{7}$$

where Ω_t is the conditional variance-covariance matrix of dollar flows F_t between t and t+1, and σ_{it} is the conditional volatility of ε_{it+1}. We define the fragility G as:

$$G_{it} \equiv \frac{1}{\theta_{it}^2} W'_{it}\Omega_t W_{it}. \tag{8}$$

Fragility measures the effective concentration of ownership of a financial asset, weighted by the volatility and correlation of the trading needs of its investors. Eq. (7) tells us that, if we regress returns volatility on fragility, the regression coefficient should recover the (squared) price impact of flow-driven trading, λ.

2.2 Ownership concentration and non-fundamental risk: An example

We can illustrate the intuition behind fragility using a simple example. Let θ_{it} be the market capitalization of security i: $\theta_{it} = n_{it}P_{it}$. Suppose that i is held by a small number of concentrated investors and a large number of dispersed investors. K_C concentrated investors each own a fraction x/K_C of shares outstanding, thus collectively they own fraction x of the shares outstanding. They receive inflows and outflows of identical variance σ^2, as well as having constant flow covariance across investor pairs of $\rho\sigma^2$. Dispersed investors have infinitely small positions and experience independent and identically distributed inflows and outflows, which are also independent from those of the concentrated investors. In this case, we can substitute into Eq. (8) to get:

$$G_{it} = \frac{1}{K_C}\sigma^2 x^2 + \left(1 - \frac{1}{K_C}\right)\rho\sigma^2 x^2. \tag{9}$$

The first term in brackets comes from the diagonal terms of Ω_t, while the second term comes from Ω_t's off-diagonal elements. Dispersed investors do not contribute to fragility because their trades are uncorrelated and their number infinite.

Suppose that flows between the concentrated investors are perfectly uncorrelated (ρ=0). Then, for a given ownership composition, fragility decreases with the number of concentrated investors, reflecting a form of ownership diversification. If there are many owners with uncorrelated liquidity needs, fragility tends to zero. In the opposite extreme, if flows are perfectly correlated (ρ=1), then the right-hand-side of (9) simplifies to $\sigma^2 x^2$ which is the same as if the asset was held by one single owner.

Eq. (9) also makes clear the role of flow volatility σ. With highly concentrated ownership within the group of concentrated investors (low K_C), flow volatility has a larger effect on return volatility. However, as the number of concentrated investors increases, flow volatility exerts a smaller effect on returns. Again, this reflects the benefits of ownership diversification.

2.3 Discussion: empirical vs. theoretical fragility

In practice, it may be difficult to calculate fragility precisely because of incomplete ownership data. In our empirical analysis, for example, we only use mutual fund ownership, thereby ignoring the potential contributions of other owners. This section discusses the implications of incomplete data on our estimates.

We can split the weight vector W from Eq. (8) into two parts: W_o, weights of O observed investors and $W_{U,}$ the weights of U unobserved ones. We sort investors by putting observed ones in the first O lines and unobserved ones in the last U lines. Similarly, we partition the Ω matrix into four parts:

$$\Omega = \begin{pmatrix} \Omega_{OO} & \Omega'_{UO} \\ \Omega_{UO} & \Omega_{UU} \end{pmatrix}. \tag{10}$$

Ω_O is the OxO matrix of variance-covariance of flows into observed investors, Ω_U is the UxU variance matrix of flows into unobserved investors, and Ω_{UO} is the off-diagonal UxO matrix of covariance between flows into observed and unobserved investors. Using this decomposition, we can rewrite fragility as:

$$G = \frac{1}{\theta_{it}^2}\left(\underbrace{W_O'\Omega_O W_O}_{\text{observed fragility}} + \underbrace{W_U'\Omega_U W_U + 2W_U'\Omega_{UO} W_O}_{\text{unobserved fragility}} \right), \tag{11}$$

which decomposes fragility into three terms: the fragility of observed investors (for which we can actually compute the flow variance matrix and holdings), the fragility of unobserved investors (whose trading needs may be correlated or volatile), and the holdings-weighted covariance between the flows of observed and unobserved investors.

Eq. (11) illustrates the biases that may arise when we calculate fragility using the available data instead of the whole universe of investors. First, observed fragility may be high when unobserved fragility is high too. For instance, suppose that growth stocks are fragile because they are held by mutual funds with similar inflow patterns, but also because they are owned by retail investors whose stock market investment depends on the economy. Second, flows into unobserved and observed investors may be correlated: for instance when speculative retail investors become wealthier, they invest more in growth stocks and invest in funds that own growth stocks. For either of these two reasons, regressing volatility on observed fragility may lead to an overestimate of the impact of fragility. However, counterbalancing these effects, the usual errors-in-variables introduced by unobserved investors works in the opposite direction.

Because mutual funds are the only investors for which we have detailed holding and flow data, there is no easy way to figure out how much our partial observation may bias our results. Keeping in mind these possible biases, when we turn to the data, we implicitly assume that unobserved investors are dispersed and have uncorrelated flows, much like in the example in Section 2.2. Notwithstanding these concerns, we take some steps to alleviate the omitted variable bias by also showing some weighted regressions, in which stocks with high mutual fund ownership get larger weight. For these stocks, estimated fragility is a better proxy for the true fragility *G*. And, as we will show, the fit in the weighted regressions tends to be a bit stronger.

3 The fragility of US stocks 1990–2007

In this section we describe the calculation of fragility for US-listed common stocks using quarterly mutual fund ownership data.

3.1 Constructing fragility

We extract quarterly mutual fund holdings from Thomson Financial between December 1989 and December 2007. We start in 1989 because data on monthly flows begin for most funds in 1990. Every quarter, we obtain the dollar positions of all funds in stocks of NYSE decile 5 or greater. We limit the sample to these large stocks to keep the matrix computations manageable, but this has the additional advantage of focusing on stocks of greater dollar importance. In addition, liquidity-driven trades will be more likely to affect prices when we capture a large share of a stock's ownership, which tends to be the case among larger stocks.

We aggregate fund classes to the portfolio level and rely on reported holdings as of the filing date (Thomson Financial FDATE). Early in the sample period, there is some staleness in holdings due to infrequent reporting. To get the weight vector W_{it} used in Eq. (8), we divide the dollar holdings $n_{ijt}P_{it}$ of each fund *j* at the end of each quarter by total assets under management (AUM) a_{jt}. We only include mutual funds for which we can also identify total net assets and returns. For the median stock in our sample, we are able to match 83% of mutual funds on a dollar-weighted basis.

Monthly mutual fund flows are drawn from the Center for Research in Security Prices (CRSP) and are calculated according to standard practice in the literature. For fund *j* between *t* and *t*+1, flows are changes in total fund assets adjusted for returns:

$$f_{jt} = TNA_{jt} - TNA_{jt-1}(1 + R_{jt}), \tag{12}$$

where TNA_{jt} is the total net assets of the fund at the end of quarter *t*, and R_{jt} is the total return of the fund between *t*-1 and *t*. We note that upper-case *R* denotes fund-level returns, while lower-case *r* denotes stock returns.

We then estimate Ω_t, the conditional variance-covariance matrix of *dollar* flows. We do not compute the covariance directly because of a heteroskedasticity problem: the sample covariance of dollar flows overestimates the future variance of flows into funds that have declined in size, and underestimates the future variance of flows into funds that have grown. To get around this issue, we first compute quarterly *percentage* flows, by normalizing dollar flows by beginning-of-quarter fund assets, i.e., f_{jt} / TNA_{jt-1}. For each quarter *t*, we then compute the rolling variance-covariance of percentage flows $\Omega_t^{\%}$ taking all observations from the last quarter of 1989 to quarter t. To obtain our estimate of Ω_t, the matrix of dollar flows, we then rescale $\Omega_t^{\%}$ by fund assets at date t:

$$\hat{\Omega}_t = diag\left(TNA_t\right)\Omega_t^{\%} diag(TNA_t), \tag{13}$$

where $diag(TNA_t)$ is the K-by-K diagonal matrix whose kth term is TNA_{kt}. Using $\hat{\Omega}_t$ and the ownership vector W_{it}, we calculate stock-level fragility according to Eq. (8).

Our remaining data are from CRSP and Compustat. We compute the quarterly variance and standard deviation of daily stock returns and excess stock returns for each stock from one-, three-, and four-factor models (including the market risk factor, the Fama and French (1993) SMB and HML factors, and momentum). We focus primarily on volatilities and covariances based on daily stock returns, but also weekly, bi-weekly, and monthly volatilities and covariances.

3.2 Components of fragility

Before relating fragility to volatility, here we look at fragility's components and their variation in the sample. For the purpose of exposition, we can decompose fragility by breaking the Ω matrix in Eq. (8) into its on- and off-diagonal elements:

$$G = \underbrace{\frac{1}{\theta_{it}^2} W_{it}'(\Omega_t - D_t)W_{it}}_{\text{Off-diagonal terms}} + \underbrace{\frac{1}{\omega_{it}^2} W_{it}'(D_t - \omega_t I)W_{it} + \omega_t (mf_{it}^2)H_{it}}_{\text{On-diagonal terms}}, \tag{14}$$

where D_t is the matrix of the diagonal elements of Ω_t, ω_t is the mean of these diagonal elements, and I is the identity matrix. mf_{it} is the share of stocks held by mutual funds and H the sum of the squared shares held by each mutual fund. H is thus a pure measure of ownership concentration: it is the equivalent of a Herfindahl index, equal to one if there is just one mutual fund owner; and zero if there is a large number of very small ones.

The first term on the right-hand-side of (14) is the contribution to fragility coming from the off-diagonal terms of Ω_t: if flows are uncorrelated across funds, this term is equal to zero. The next terms comprise the contributions from the on-diagonal terms of the Ω_t matrix: it contains the effects of both ownership concentration and flow volatility. The effect of ownership concentration appears clearly if we further break the diagonal matrix D_t into $D_t - \omega_t I$ and $\omega_t I$.

The last term in Eq. (14) shows that the on-diagonal part is mechanically linked with mutual fund ownership mf_t. We thus include mf_t as a control in many regressifon specifications.[4] The last term of Eq. (14) also highlights the key role played by ownership concentration.

Fig. 1. shows the evolution over time of median fragility, along with changes in mutual fund ownership and concentration. Fragility has a clear upward trend over the past two decades, which reflects the increasing share of mutual fund ownership. The simultaneous trend toward less concentration of ownership suggests that the new, smaller funds, have flows that are correlated and variable enough to compensate for the effect of ownership dispersion.

Table 1 describes the sample variation of two measures of ownership concentration: *H*, as it appears in Eq. (14), and the number of owners. There is significant variation in ownership concentration, with the number of owners going from 31 (25th percentile) to 102 (75th percentile). The median stock has 53 mutual fund owners and H=0.127.

The bottom two panels of Table 1 describe the sample variation of the on- and off-diagonal terms of Ω_t. The table shows that the volatility of flows has been increasing from about 10% of AUM per quarter to about 14% of AUM per quarter by 2003. Because Ω_t is

[4] Another issue in our data is that mutual fund ownership has increased steadily from about 8% in 1989 to 30% in late 2007 (see Fig. 1A and Rydqvist, Spizman, and Strebulaev, 2009). This makes fragility increase steadily over the 1990s. At the same time, it is well known that stock price volatility has had medium-term fluctuations (Campbell, Lettau, Malkiel, and Xu, 2001; Brandt, Brav, Graham, and Kumar, 2010). To avoid spuriousness from common trends, we mostly report Fama and MacBeth (1973) estimates.

estimated on a rolling basis, this understates the growth in flow volatility. We summarize the off-diagonal terms by showing mean correlation ρ and mean absolute correlation $|\rho|$. The table shows a rich correlation structure: the median correlation term is close to zero, but the 25% to 75% range lies between -0.18 and 0.24.[5]

3.3 Correlates of fragility

We next provide a descriptive analysis of the main correlates of fragility. Table 2 shows stock-level summary statistics sorted by fragility quintiles, based on quarterly breakpoints. As can be seen, fragility is quite persistent: this is partly a mechanical outcome from the calculation of Ω_t, which is done on a rolling basis. But ownership structure is highly persistent too: for instance, the one-quarter-autocorrelation coefficient of the number of owners is 0.98. It is interesting to note that fragility can be much more persistent than the identity of the owners. This is because, if one owner sells, she may well be replaced by another owner with similar flow volatility and correlation.

More surprisingly perhaps, fragility is not monotonically correlated with the number of owners. This reflects that fragility depends both on ownership dispersion and the correlation of owners' trading needs. Smaller firms are more fragile, which is not surprising given that smaller firms have more concentrated ownership: firms in the sixth decile of market capitalization have about 70 owners on average, while firms in the top decile have more than 320. Table 2 also shows that firms which have been actively purchased by mutual funds, past winners and growth stocks, all have higher fragility.[6]

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[5] We have also investigated the factor structure of the $\Omega^{\%}$ matrix. Cross flow correlation is complex and cannot easily be summarized by a few factors: For the typical fund, aggregate flows explain less than 10% of the total variation in percentage flows. Among the 500 largest mutual funds, 47% of the variation in flows can be explained by a set of five principal components.

[6] In untabulated results, we have also checked whether fragility correlates with common measures of liquidity. Using data from Joel Hasbrouck's Web site, we find a weak negative correlation between fragility and the Amivest

3.4 Validating fragility as a measure of non-fundamental risk

For fragility to be a useful instrument for non-fundamental risk, it must be that fragility forecasts mutual fund flow-induced trading volatility in the next quarter.[7] This is not guaranteed, because fragility is based on the *past* volatility of inflows experienced by a security's *current* owners. For fragility to be a good forecaster of future volatility in security-level flows, the mutual flow variance-covariance matrix needs to be stable over time, and ownership cannot be too volatile from one quarter to the next.[8]

We estimate a first-stage forecasting regression of the absolute value of flow-induced trading on fragility, i.e.,

$$\left| W_{it+1} F_{it+1} \right| = a + bG_{it} + cZ_{it} + u_{it}. \tag{15}$$

We run this regression using the Fama-MacBeth procedure. We find that *b* is positive and statistically significant (*b*=0.169 with a *t*-statistic of 4.5, *R*-squared of 0.17). *b* is economically significant too: a one-standard-deviation increase in fragility predicts an increase of approximately 17% of a standard deviation in absolute flow-induced trading. Both statistical and economic significance are robust to inclusion of controls such as size, share of mutual fund holdings, and stock and year fixed effects.

4. Fragility and non-fundamental risk

liquidity measure. Lou's (2010) measure of flow-motivated trading takes into account differences in liquidity in the first stage of his analysis.

[7] It is interesting to ask under what circumstances would our fragility measure *not* be a useful instrument for the volatility of future flow-driven demand. This might be the case if, for example, the covariance matrix of flows was not forecastable using the prior covariance matrix. While it is true that our estimation of the flow covariance matrix is subject to considerable noise, the noisiness is attenuated by the aggregation procedure used to compute fragility. In any case, to the extent that our right-hand-side variable is noisy, it may cause some attenuation bias in our regression results.

[8] Intuitively, we require that if we observe a fund's ownership of a stock at the end of quarter *t*, that this stock is still in their portfolio (on average) when the fund experiences flows in quarter *t*+1.

We start by looking at the relationship between fragility and return volatility in graphical form. For each decile of fragility (breakpoints set quarterly), we draw the average volatility of total returns in Fig. 2, Panel A. There is a clear positive correlation between fragility and subsequent volatility, although this relationship starts at the second decile of fragility. For the first five deciles, daily volatility is about 2%; it then steadily increases to about 3% for the top fragility decile. Fig. 2, Panel B repeats the exercise, but here we restrict the sample to stocks for which mutual fund ownership is above 20%. For these stocks, the relationship between fragility and volatility is more linear and increasing, although its economic significance appears similar to Panel A. We obtain very similar results if, instead of restricting ourselves to stocks with more than 20% of mutual fund ownership, we shift our focus to the 2000s only—a period during which aggregate mutual fund ownership was higher. Stronger results for these subsamples is consistent with less measurement error in our fragility variable when we can observe a greater fraction of the stock's total ownership.

Table 3 shows the corresponding statistical tests. In all regressions, we use one-quarter-ahead daily volatility σ_{it+1} as the dependent variable, and regress it on the square root of fragility $\sqrt{G_{it}}$, together with various controls Z_{it}:

$$\sigma_{it+1} = a + b\sqrt{G_{it}} + Z_{it}C + u_{it+1}. \qquad (16)$$

We use the square root of fragility because, as can be seen in Eq. (7), fragility is proportional to variance. All regressions are estimated following Fama and MacBeth (1973) to account for trends. The exception is column 6, in which we report panel fixed effect estimates. Notice that, if Eq. (7) holds, b should in principle be equal to λ, which measures price impact.

In the first column, we predict future volatility using mutual fund ownership and the number of owners. As expected, daily volatility is positively correlated with mutual fund ownership: an increase in mutual fund ownership by 10% leads to an increase in daily volatility of about 0.2 %, which is approximately 10% of the sample mean. This finding is reminiscent of Sias (1996) and Bushee and Noe (2000) who find that increases in institutional ownership are accompanied by a rise in stock volatility. Controlling for mutual fund ownership, the coefficient on the number of mutual funds is negative, however. This suggests that ownership dispersion is accompanied by a reduction in volatility: if, for a given mutual fund ownership, the number of funds goes up from 100 (first quartile) to 300 (third quartile), daily volatility is reduced by about 0.1%. In summary, not only total fund ownership, but also ownership concentration, seems to matter for forecasting volatility.

Starting in the second column, we replace mutual fund ownership and the number of owners with fragility. Fragility captures some of the effects of the mutual fund share and the number of owners, but is theoretically a better predictor of volatility because it looks at actual dispersion (i.e., whether we have one large owner and 199 tiny ones; or 200 equal-sized owners), as well as taking into account the correlation of trading needs of the different owners. As shown in column 2, fragility is a strong predictor of future volatility. A 0.008 increase in fragility (from the 25th to the 75th percentile) leads to an increase in daily volatility by 0.5%, about one-quarter of the mean volatility. In this specification, *b* is 0.70, and the *t*-statistic is approximately 15.[9] We can compare this coefficient to estimates of price impact from other papers. For instance, Wurgler and Zhuravskaya (2002) use index addition to estimate the demand to price elasticity:

[9] We follow standard practice and report *t*-statistics based on Fama MacBeth standard errors. One can do a further correction for the persistence of coefficient estimates between subsequent cross-sections, by calculating Newey- West (1987) standard errors on the time-series of slope coefficients. Applying this adjustment to the baseline estimates in column 2, the *t*-statistic on fragility drops to 8.39.

they themselves obtain a price impact coefficient between 0.1 and 0.2, and do not report any study with an impact above 10.. In a more comparable setting, Lou (2010) has a price impact coefficient of about 0.2.[10] To recover a comparable elasticity, we need to adjust for the fact that our volatility variable is based on daily returns—this yields $0.70\times\sqrt{63}=5.5$. Thus, the results from the univariate estimation suggests that price impact is quite high compared to previous research, possibly due to omitted variable bias.[11]

In column 3 we repeat the regression from column 2, except that we weight observations in each cross-section by their mutual fund ownership share. Weighting by mutual fund ownership is essentially equivalent to downweighting observations with high measurement error. As can be seen, and consistent with graphical evidence shown in Figs. 2A and 2B, this strengthens the results slightly. As it turns out, all other estimates are much stronger under the weighted regression approach: for instance, the fixed effect estimate in column 7 more than doubles if one weights observation by mutual fund ownership (not reported).

In column 4 we break fragility into two parts: the first component ($\sqrt{G}$ (Diag)) corresponds to the (square root of the) on-diagonal terms in Eq. (14). It uses only diagonal terms of the flow covariance matrix Ω_t . The second component ($\sqrt{G}$ (Diag)), corresponds to the (square root of the) off-diagonal terms in Eq. (14)). Recall that the first component measures the conditional volatility of flow-driven trading, under the assumption that fund flows are uncorrelated. On-diagonal fragility should still generate volatility if ownership is not dispersed enough, or if fund flows are very volatile. Off-diagonal fragility measures the extent to which

[10] In Table III, Lou sorts stocks by decile of flow-induced trading. The difference in flow trading between stocks in the top and bottom deciles is 22.27% of shares outstanding. Differences in contemporary return is 1.73% monthly, hence, 5.2% quarterly. This leads to a price impact of 5.2/22.27=0.23.

[11] Once we include past volatility and other controls, the price impact estimates are more in line with existing research.

funds have correlated flows: if their flows are perfectly uncorrelated, it is equal to zero. The results in column 4 show that both parts of fragility contribute equally to volatility.

Column 5 checks that fragility has explanatory power beyond pure ownership concentration. To test this, we include the ownership Herfindahl index *H* as a control, as well as the fraction of shares held by mutual funds. Compared to the univariate estimates in column 2, the coefficient on fragility is unaffected by the two controls, increasing only slightly. This suggests that fragility contains more information (mutual fund flow volatility as well as correlation) than simply ownership concentration and mutual fund holdings.[12] Interestingly, compared to column 1, the sign of mutual fund ownership is reversed and becomes economically less significant. One plausible interpretation is that the direct effect of mutual fund ownership on volatility found in earlier work is channelled through fragility: what matters is not mutual fund ownership per se, but the volatility and correlation of mutual funds' inflows and outflows.

In the next three columns, we check that the predictive power of fragility is robust to various controls and specification adjustments. In column 6, we control for log share price, the book-to-market ratio, the stock return during the past year, age, lagged skewness, and lagged turnover. All these variables have been found to be correlated with volatility in previous literature.[13] With the full suite of controls, the coefficient on fragility drops by about two thirds to 0.23 (*t*-stat of 6.27). In column 7, we estimate a fixed effect panel regression with a firm fixed effect. The fragility coefficient returns to its initial estimated value of 0.70 and is highly

[12] Eq. (14) makes clear that ownership concentration *H* in isolation may not have much ability to forecast volatility: what is relevant is ownership concentration scaled by total mutual fund ownership *mf*. In untabulated regressions, we have used the interaction of *H* and *mf* to forecast volatility. This interaction term attracts a coefficient of 0.3 (*t*-stat =12.6). Once we introduce fragility, however, this variable is wiped out.

[13] Brandt, Brav, Graham, and Kumar (2010) show that low-priced stocks attract retail investors, causing volatility. Stocks with high past returns may be attention grabbing (Barber and Odean, 2008). Volume may signal the presence of retail traders which in turn may lead to volatility (Odean, 1998). The book-to-market ratio proxies for distance to default, which is accompanied with more equity volatility (Merton, 1974). Younger firms may be more volatile because of a poor information environment. Stock skewness may attract gamblers which in turn cause further volatility (Bali, Cakici, and Whitelaw, 2011).

significant.[14] However, this estimate is not directly comparable with column 6 since the panel estimation does not remove common trends in volatility and fragility. Column 7 does suggest, however, that stocks which have experienced the biggest increase in fragility are also the ones which have experienced the largest increase in volatility.

In column 8, we include the lagged volatility as a control, since volatility is highly persistent over time. Compared to column 6 estimates, the fragility coefficient decreases slightly from 0.23 to 0.15 but remains highly significant (*t*-stat of 4.81). Including a full set of controls as we do in column 8 brings our estimate of price impact more in line with existing studies. Adjusting for daily returns, the price impact estimate from column 8 is $0.152\times\sqrt{63}=1.2$, which is in the upper range of the comparable estimates reported by Wurgler and Zhuravskaya (2002, p. 603).

The results in columns 7 and 8 help alleviate concerns about the endogeneity of ownership. The general concern here is whether fragility *causes* volatility, or whether the relationship runs in the other direction. For example, young funds with volatile inflows might herd into volatile stocks, while more established funds with stable assets under management may prefer less volatile stocks. There is no panacea for ownership endogeneity in our tests, because we cannot identify exogenous changes in ownership.[15] However, our results hold with both firm fixed effects, and controls for lagged volatility. These results provide some comfort, because it seems unlikely that owners select particular stocks because they forecast *changes* in future volatility.

[14] For the panel regression in column 6, we have also computed Thompson (2011) standard errors. The *t*-statistic is barely affected: it goes down from 7.4 to 6.9. This is not surprising as our data set features many more firms than time periods. See Petersen (2009) for a discussion.

[15] A large literature uses inclusion in the S&P 500 stock index as an exogenous change in ownership (e.g., Shleifer, 1986, Harris and Gurel, 1986). We have considered this, but in the data we do not find any systematic change in fragility surrounding index additions. We suspect that this is because fragility is based not only on total mutual fund ownership—which increases following inclusion—but also on the correlation structure of inflows and outflows.

In the last three columns of Table 3, we replace the dependent variable with the volatility of returns in excess of a one-, three-, and four-factor model and re-estimate our baseline specification.[16] A priori, we expect to get somewhat weaker results when forecasting excess volatility, since aggregated versions of fragility may predict the volatility of risk factors themselves. For example, if funds holding smaller stocks experience higher flow volatility than funds holding larger stocks, we would expect the volatility of the Fama and French (1993) SMB factor to be high. As can be seen, the coefficients on fragility fall slightly when we adjust for factor exposure.

5. Co-fragility and comovement

We now explore a straightforward extension of our approach to the prediction of asset return comovement. We first show how the approach followed in Section 2 can be extended to a multi-asset context: this leads us to define two measures: co-fragility and fragility-beta. We then explain how these measures can be computed using our data and provide evidence of their predictive power for returns correlation and factor loadings.

5.1 Defining co-fragility and fragility beta

From Eq. (6), we can write the covariance of returns between assets *i* and *j*:

$$\mathrm{cov}_t(r_{it+1}, r_{jt+1}) = \frac{\lambda^2}{\theta_{it}\theta_{jt}} W_{it}'\Omega_t W_{jt} + \mathrm{cov}(\varepsilon_{it+1}, \varepsilon_{jt+1}). \tag{17}$$

If owners have correlated trading needs or if large owners of the two assets are the same, as in Anton and Polk (2010), then returns will comove. We define the co-fragility of assets *i* and *j* as:

[16] In the case of the single-factor model, the dependent variable is the volatility of market-adjusted returns, where market beta is allowed to vary by stock and by quarter. The three-factor model includes the HML and SMB factors, and the four-factor model adds momentum as well.

$$G_{ijt} \equiv \frac{W_{it}'\Omega_t W_{jt}}{\theta_{it}\theta_{jt}}. \tag{18}$$

Given Eq. (17), co-fragility should predict covariance of returns. To predict correlations of returns instead, we normalize co-fragility by the square roots of fragilities of assets *i* and *j* and compute $G_{ijt}/\sqrt{G_{it}G_{jt}}$.

There is no reason to limit the exercise to pairwise correlations: we can use co-fragility to investigate the sources of a stock's comovement with a given portfolio (value firms, small firms etc.). Specifically, consider a portfolio *p*, defined by the weights $s^p{}_{jt}$ for each asset *j*.[17] The conditional return beta of stock *i* with respect to portfolio *p* is:

$$\beta_{it}^{p} = \frac{\mathrm{cov}_t\left(r_{it+1}, \sum_j s_{jt}^{p} r_{jt+1}\right)}{\mathrm{var}_t\left(\sum_j s_{jt}^{p} r_{jt+1}\right)}. \tag{19}$$

Given the relationship between flow trading and returns (5), it is therefore natural to define the fragility beta of asset *i* with respect to portfolio *p*:

$$\begin{aligned} G^{p}{}_{it} &= \frac{\mathrm{cov}_t\left(W_{it}F_t, \sum_j s_{jt}^{p} W_{jt} F_t\right)}{\mathrm{var}_t\left(\sum_j s_{jt}^{p} W_{jt} F_t\right)} \\ &= \frac{\sum_j \left[s_{jt}^{p} G_{ijt}\right]}{\sum_{j,j'} \left[s_{jt}^{p} s_{j't}^{p} G_{jj't}\right]}. \end{aligned} \tag{20}$$

[17] To avoid confusion, recall that s_{jt}^{p} denotes the weights of the portfolio in question, while w_{jkt} denotes the weight of security *j* in investor *k*'s portfolio.

Eq. (20) is the regression coefficient of flow-driven net buys of asset *i* onto flow-driven buys into portfolio *p*. We call this term the "fragility beta." The fragility beta should be positively related to the returns beta.

Eq. (20) captures the idea that, for instance, a stock will comove with growth stocks when its owners have the same liquidity needs as growth stock-investors. As shown above, the fragility beta can be written as a weighted average of co-fragilities. If an asset has positive co-fragilities with other assets in portfolio *p*, its fragility beta with respect to *p* will be high.[18]

Fragility beta is related to, but slightly different from, the concept of investor habitat described in Barberis, Shleifer, and Wurgler (2005). Barberis, Shleifer, and Wurgler suggest that a stock may comove with other securities in a portfolio because investors who own the stock also own the other securities in the portfolio. The difference between this and our notion of fragility beta is subtle: stocks comove even when they are not traded by the *same* investors. We only require that stocks are traded by investors who experience correlated liquidity needs. For example, a stock could have a high growth-stock beta if its owners experience flows which correlate with those of growth-stock owners. Yet, this stock might not be a growth stock in the usual sense of having growth-related characteristics such as high sales growth or a low book-to-market ratio.

To implement Eqs. (18) and (20) empirically, we substitute the same inputs as before into (18) to calculate co-fragility between any pair of stocks. Because the number of co-fragility observations grows with the square of the number of stocks, we limit our sample here to the largest 500 stocks with positive mutual fund ownership in each quarter (thus, yielding 500x500/2 = 125,000 unique stock pairs each quarter, although our regressions have fewer observations

[18] This approach differs from Kumar, Page, and Spalt (2009), who compute similar betas but use historical trades, instead of looking at historical liquidity needs of individual owners.

because of missing control variables). Thus, compared to our fragility-volatility estimates, our co-fragility results draw more heavily on larger stocks.

5.2 Explaining correlations

Fig. 3 provides graphical evidence on the relationship between co-fragility and return comovement. In Panel A, we sort all stock pairs into co-fragility deciles, and then compute for each decile the mean covariance of daily returns across stock pairs in the next quarter. The figure suggests that there is a monotonic relationship between co-fragility and covariance. Mean covariance goes up from 0.004% to 0.016%—a fourfold increase—from the bottom to the top decile. Similar conclusions can be drawn from Panel B, where we look at the relationship between co-fragility and correlation. From the second to the ninth decile of co-fragility, the correlation of daily returns increases from 16% to 23%.

In Table 4 we estimate the relationship between the co-fragility of two stocks and the comovement of their daily returns computed over the following quarter. Including each pair of stock pairs (*i*,*j*) in quarter *t*, we run the following cross-sectional forecasting regressions:

$$\sigma_{ijt+1} = a + bG_{ijt} + Z_{ijt}C + u_{ijt+1}, \tag{21}$$

and

$$\rho_{ijt+1} = a + b\frac{G_{ijt}}{\sqrt{G_{it}G_{jt}}} + Z_{ijt}C + u_{ijt+1}. \tag{22}$$

where the dependent variable is the covariance or correlation of *i* and *j* computed on daily returns over all trading days in quarter *t*+1. G_{ijt} is the co-fragility of *i* and *j* computed at the end-of-quarter *t*. In (22), we rescale co-fragility by the product of the stock-level fragilities. Z_{ijt} stands for the suite of stock-pair-level fundamental controls, as follows: Pindyck and Rotemberg (1993), Chen, Chen, and Li (2010), and Anton and Polk (2010) show that firms in the same industries have correlated earnings and therefore returns. We define industry similarity dummy variables as equal to one when both stocks belong to the same two-, three-, or four-digit industry. We also expect firms with similar size or book-to-market ratios to potentially share exposure to the same fundamental shocks. Hence, we include a variable that measures the difference in NYSE size deciles between *i* and *j*, and a variable measuring the difference in book-to-market (BE/ME) deciles. Last, we also introduce the (log of one plus the) number of common owners as a control, as Anton and Polk (2010) show that stocks with many common owners co-move.[19]

In the first panel of Table 4, the dependent variable is the covariance of returns; in the second panel, the dependent variable is the correlation. We first show the results from a regression which uses only the control variables. In both panels, the signs of the coefficients on the control variables go in the expected direction: stocks belonging to the same industry or having similar book-to-market ratios have higher comovement. The number of common owners is significant only in the correlation regression: when the stock pair moves from one to two common owners, the return correlation increases by 3%.

The second column in each panel shows the univariate relationship between comovement and co-fragility. Co-fragility is a statistically strong and economically sizeable determinant of covariance. A two-standard-deviation increase in co-fragility (i.e., an increase by 0.006%) leads to an increase by 0.005% of future returns covariance, which is about one-third of the sample standard deviation. A two-standard deviation increase in co-fragility (scaled by single-stock fragilities) forecasts a 5% increase in correlation, about one-third of its standard deviation.

[19] While common ownership certainly explains part of comovement, our fragility measure captures at least two additional dimensions of returns comovement: (1) the volatility of the outflows/inflows these owners are expected to face, and (2) owners can be different, but have highly correlated flows—this should in principle have exactly the same effect as having common owners.

The last two columns in each panel test the robustness of the univariate results by adding controls. As can be seen from columns 3 and 7, the relationship between covariance and co-fragility is almost unchanged. The relationship between correlation and scaled co-fragility is more attenuated. In this case, the regression coefficient is still highly statistically significant, but reduced by about 40% in magnitude. In columns 4 and 8, we additionally control for *current* quarter covariance/correlation; these controls make the coefficients slightly smaller, but are still highly significant.

In untabulated robustness tests, we have checked whether the relationship between co-fragility and comovement still holds after purging returns of their market, SMB, and HML exposures. To do this, we compute pairwise correlations and covariance of three-factor excess returns. The coefficient on co-fragility falls to 0.29 (*t*-stat of 4.82) in the covariance regressions, and to 0.11 in the correlation regressions (*t*-stat of 20.88). The weaker results here are driven by the fact that co-fragility explains a good deal of the variation in the factor loadings themselves, which we address in Section 5.4.

5.3 Explaining longer-horizon volatilities and comovement

In our analysis so far, we have used fragility and co-fragility to forecast the volatility and comovement of *daily* stock returns. But, if the price pressure posited in Eq. (5) is temporary—i.e., if flow-driven trades exert only a temporary effect on prices—then our results should be attenuated when returns are measured at longer horizons. This is because we can expect fundamentals to dominate in the long run. Consistent with this, papers on excess comovement such as Barberis, Shleifer, and Wurgler (2005) have shown stronger results when returns are measured at higher frequencies (i.e., daily betas vs. weekly or monthly betas).

Pointing in the other direction, however, flows into mutual funds are persistent, leading to potentially stronger effects at longer horizons. For example, Frazzini and Lamont (2008) show that when sorting stocks based on their inflow in quarter *t*, the high inflow stocks continue to receive flows several years later. And the price effects of mutual fund "fire sales" found by Coval and Stafford (2007) take a few months to revert, perhaps because mutual funds try to smooth their liquidity trades out over time. If flows are sufficiently persistent, then even with temporary price impact, the effect of fragility on volatility may strengthen as volatility is measured using longer-horizon returns.

Which of these effects dominates is an empirical question addressed in Table 5. Here we repeat the main specifications from Table 3 and Table 4, but instead measure volatility and comovements using weekly, bi-weekly (10-day), and monthly returns. Panel A of the table repeats the baseline regression from Table 3. As can be seen, the coefficient on fragility does not change much when we measure returns weekly, but drops more noticeably as we move to bi-weekly or monthly returns. The drop in R^2s is more impressive: from an average of 0.08 in the case of daily returns to 0.04 in the case of monthly returns. The remaining panels of the table repeat the general pattern from Panel A for predicting covariances and correlations. To summarize, there is some evidence that the effects of fragility dampen at longer horizons, but they continue to be statistically and economically significant even when returns are measured monthly.

5.4 Explaining factor comovements with fragility betas

Fig. 4 suggests that fragility betas are related to returns-based betas. Each quarter, we sort stocks by their fragility betas, and then compute the mean return beta in each decile with respect to various portfolios (market, SMB, and HML). In Panel A, we compute fragility betas with respect to the equal-weighted market portfolio. Leaving aside the first decile, the figure shows that stocks held by owners whose net inflows are correlated with *all* inflows tend to have a higher market beta. Stocks in the second decile of fragility beta have a market beta of approximately 0.8, while firms in the tenth decile have a market beta of 1.2.

Panel B shows fragility betas with respect to the HML portfolio. For instance, stocks in the top decile are stocks which receive inflows when owners of high book-to-market (value) stocks receive inflows, or when owners of low book-to-market (growth) stocks face outflows. As can be seen, the univariate relationship between HML fragility and return betas is very strong: moving from the first to the tenth decile of HML fragility beta, HML return beta increases from-.60 to +0.60.

Panel C shows fragility betas with respect to SMB. The relationship is not monotonic: univariate SMB returns beta is decreasing for the first two deciles of SMB fragility beta, and then increasing. One possible reason for the weaker relation is that our SMB fragility beta is imperfect: we restrict ourselves to stocks in the NYSE size decile 6 or above. The fragility beta thus classifies stocks in decile 6 of stock market capitalization as "small stocks," which differs from the definition Fama and French (1993) use in calculating SMB.[20]

Table 6 shows the statistical tests corresponding to Fig. 4. We estimate:

$$\beta_{it+1}^{p} = a + bG_{it}^{p} + Z_{it}C + u_{it+1}. \tag{23}$$

[20] This is because smaller stocks are left out of the study. As a result, high SMB *fragility* beta stocks are stocks whose owners receive inflows when owners of stocks in size decile number 6 receive inflows, while high SMB *returns* beta stocks correspond to firms whose returns comove with stocks in the first, second, and third deciles of stock market capitalizations. Our sample selection procedure therefore creates a mechanical discrepancy between the two variables.

The dependent variable is the one-quarter-ahead beta of stock *i*'s daily returns with respect to the returns of any portfolio *p* (here: the market portfolio, HML, or SMB). G_{it}^{p} is stock *i*'s fragility beta with respect to portfolio *p*, and Z_{it} denotes controls. If mutual fund flow-driven trading were the *only* source of volatility, then *b* should equal one.

The first two columns of Table 6 look at the determinants of the market beta. As can be seen, fragility market beta is strongly related to the market beta. A two-standard-deviation increase in the fragility beta (i.e., an increase of 1.5) leads to an increase of 0.40 standard deviations of market beta. In column 2, we introduce several controls: betas are higher for growth firms (Franzoni, 2002; Campbell and Vuolteenaho, 2004; Campbell, Polk, and Vuolteenaho, 2010), but betas are unrelated to size. The other two controls are the share of stocks held by mutual funds and the (log) number of mutual funds owning the stock. Including these controls reduces the effect of fragility beta by about 40%, but the coefficient remains highly statistically significant. In summary, a significant part of observed market betas could be explained by stocks' exposures to common fund flows.

The next two columns show regressions forecasting HML beta. Consistent with the graphical evidence from Fig. 4, this is where our methodology proves the most successful. Using the HML fragility beta as the sole explanatory variable, the mean R^2 is as high as 25%. Including additional controls increases the R^2 only marginally. The regression coefficient is economically significant: a two-standard-deviation increase in fragility beta leads to an increase equal to 80% of one sample standard deviation of the returns HML beta. The estimate of this coefficient is equal to 0.47, while its "theoretical value" (i.e., assuming flow-driven mutual fund trades are the *only* source of price variation) should equal one.

Columns 5 and 6 study determinants of SMB beta. The SMB fragility beta explains about 13% of the variance of the univariate SMB return betas. Including controls nearly doubles the explanatory power of our regression, but leaves the coefficient virtually unchanged. A two-standard-deviation increase in SMB fragility beta increases SMB return betas by about 0.70 standard deviations. The size of the coefficient is, however, smaller than for HML betas: 0.04 compared to 0.5.

6. Fragility and arbitrage

This section exploits the relationship between fragility and volatility found in Section 4, in order to shed some light on the impact of speculative trading and arbitrage capital on stock volatility. The idea is that the impact of fragility on non-fundamental volatility will be muted if there are many arbitrageurs who accommodate mutual funds' liquidity shocks.

We slightly amend the equation framework of Section 2.1 by taking the trading of some investors as being determined by factors other than net inflows from mutual funds. We adjust Eq. (6) to become:

$$r_{it+1} = \alpha + \lambda D^{MF}{}_{it} + \lambda D^{X}{}_{it} + \varepsilon_{it+1} \tag{24}$$

where, as in Eq. (6), $D_{it}^{MF} = W_{it}{}' F_t / \theta_{it}$ measures flow-induced trading by mutual funds between t and t+1. D_{it}^{X} is a new term representing the order imbalance (as a percentage of market capitalization) from other groups of investors such as hedge funds. D_{it}^{X} could also represent imbalances driven by the *active* trades of mutual funds.[21] D_{it}^{X} may accommodate, or exacerbate, flow-driven demand shocks by mutual funds.

We estimate the correlation between D_{it}^{X} and D_{it}^{MF} by running the following regression for each stock:

$$D^{X}{}_{it} = \delta_{it} + \gamma_{it} D_{it}^{MF} + \nu_{it} \quad . \tag{25}$$

The extent to which other trades accommodate or exacerbate flow-induced trading is captured by the stock-level parameter γ_{it}. For instance, if $\gamma_{it} < 0$ then other trades tend to dampen the price movements induced by flow-induced trading. Alternatively, if $\gamma_{i} > 0$, other trades tend to amplify flow-induced trading, as in Brunnermeier and Nagel (2004), Griffin, Harris, Shu, and Topaloglu (forthcoming), or Chen, Hanson, Hong, and Stein (2008). Why would γ vary across stocks? One simple reason is that the cost of supplying liquidity varies from stock to stock. Another one is specialization: Merton (1987) proposes that financial assets are often specialized and thus may have asset-specific amounts of arbitrage capital associated with them (see also Duffie and Strulovici, 2009).

Substituting (25) into (24) leads to:

$$\mathrm{var}_t\, r_{it+1} = \lambda^2 (1+\gamma_i)^2 G_{it}^2 + \mathrm{var}_t \left(\varepsilon_{it+1} + \frac{\lambda}{\theta_{it}} \zeta_{it} \right). \tag{26}$$

From (26) we can see that the sensitivity of volatility to fragility depends on $\left|1+\gamma_{it}\right|$. To the extent that other trades accommodate flow-driven trading, then $\left|1+\gamma_{it}\right|$ will be small and fragility can be expected to have a smaller impact on volatility.

[21] Fragility captures only the correlation structure of mutual funds' forced trades, but mutual funds also do considerable active trading. It is conceivable that mutual funds trade actively to counteract part of the flow-driven trades, and we do find this for some stocks.

As mentioned above, we consider two types of "other trades." First, we look at hedge fund order imbalances, i.e., quarter-to-quarter changes in aggregate hedge fund holdings using 13F data. Second, we look at active buys by mutual funds. Active buys are equal to total mutual funds imbalances (computed, like for hedge funds, as the change in total mutual funds holdings as available from their reported holdings) *net of* flow-induced trading, and correspond to the first term on the right-hand-side of Eq. (4). We also consider specifications which sum together hedge fund trades with the active trades of mutual funds.

Our analysis is done in two stages. First, for each stock-quarter, we estimate γ_{it} from Eq. (25) over the past 24 quarters, by regressing past D_{it}^{X} on past flow-induced trading. We thus have a stock-level time-varying measure of the extent to which other trades provide liquidity to flow-motivated traders. The median regression coefficient of hedge fund buys on *FIT* is approximately zero, meaning that hedge funds do not amplify or dampen mutual fund flow trading-induced volatility for the typical stock. There is, however, considerable heterogeneity across stocks: the 25th and 75th percentiles of the distribution are -0.35 and 0.33, respectively. The data also show that, on average, mutual funds accommodate their own flow-driven trades through active rebalancing. The median coefficient is equal to -0.6. As with the behavior of hedge fund trading, however, there is heterogeneity across stocks: the 25th and 75th percentiles of the distribution are equal to -1.12 and -0.06.

The second step of the analysis is to use the estimated γ_{it} terms as an input into the following cross-sectional regression:

$$\sigma_{it+1} = a + b\left|1+\hat{\gamma}_{it}\right| + c\sqrt{G_{it}} + d\left|1+\hat{\gamma}_{it}\right| \cdot \sqrt{G_{it}} + u_{it+1}. \tag{27}$$

Based on our discussion, *d* should be positive, i.e., stocks for which "other trades" go in the same direction as mutual fund liquidity trades should have a stronger volatility-fragility relationship.

Estimates of Eq. (27) are reported Table 7. The interaction coefficient *d* is positive and significant for hedge fund imbalances only, but not for active mutual fund buys. This means that, across stocks, the difference between hedge fund strategies (accommodate, or exacerbate) explains some of the effect of fragility on volatility. All in all, the data support the view that, while hedge funds do not front-run mutual fund trading on average, they consistently do so for some stocks, and this front-running exacerbates the impact of fragility on non-fundamental risk. Alternatively, for other stocks, hedge funds seem to act as providers of liquidity, by trading in the opposite direction to mutual fund flow-driven trades. In the latter case, when the correlation of trading patterns is negative, the results in Table 7 suggest that the effect of fragility on volatility is smaller.

7. Conclusions

This paper develops a simple definition of financial fragility which is based on an asset's ownership structure. An asset is fragile if it is exposed to high non-fundamental risk. We show that assets are fragile when ownership is concentrated, but also when ownership is dispersed but the owners experience correlated liquidity shocks. We implement measures of fragility on US stocks between 1990 and 2007, drawing on quarterly mutual fund ownership data.

The main attraction of our fragility variable is its empirical tractability. As we show, our measure of fragility is useful for forecasting volatility. Partly, this empirical success is driven by the fact that forecasting the volatility and comovement of investors' flows is much easier than predicting how any individual investor will trade in any given period. A simple extension of fragility to "co-fragility" is also useful for forecasting cross-stock return comovements and factor betas.

Although data availability constrains our analysis to the ownership of common stocks, we expect our fragility measure to be conceptually more useful among specialized assets for which ownership is more concentrated, or trading needs of its owners more correlated.

Our framework may be extended to consider circumstances in which the correlation structure of investors' liquidity trades is endogenous. In a richer model, it is not hard to see how the flow-driven trades by one investor may cause contagion: because flows result in price pressure, they affect the value of other investors' portfolios. These investors may subsequently experience inflows and outflows as a direct result. In this case, our measures of fragility may also be useful for forecasting the possibility of a crash.

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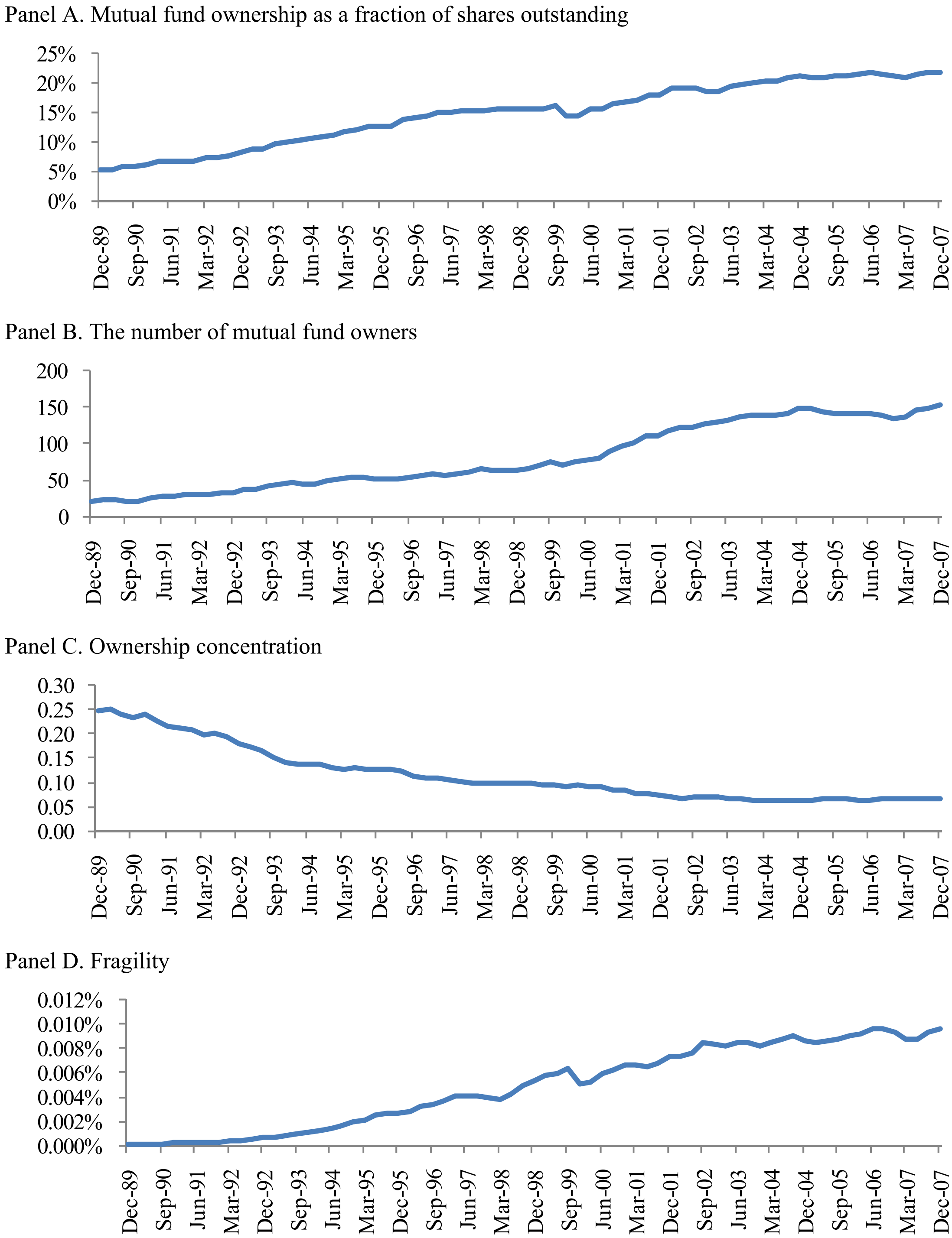
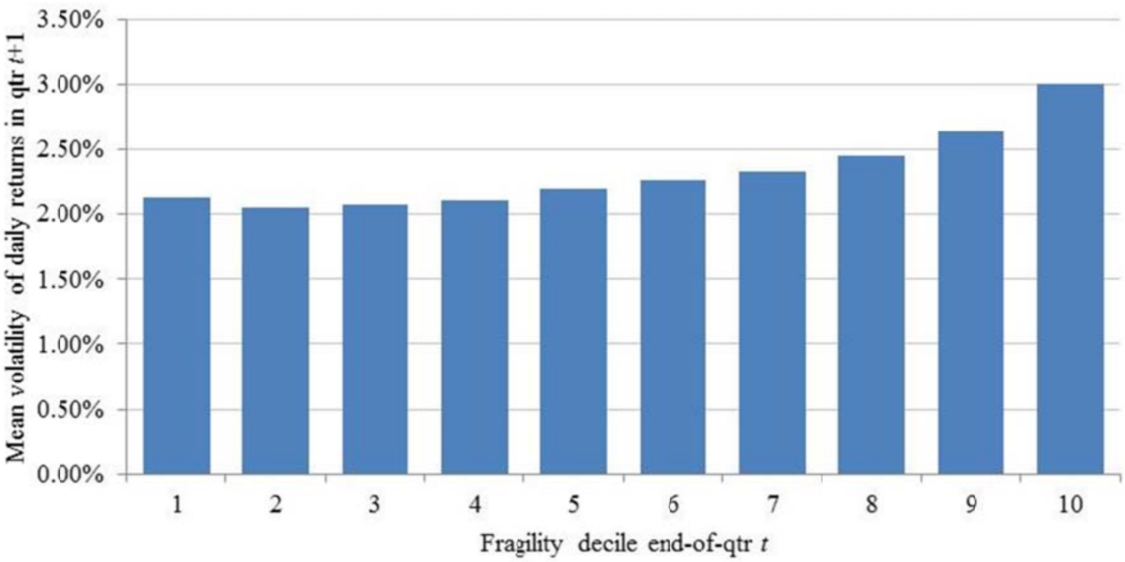


Fig. 1. Mutual fund ownership, concentration and fragility. For each characteristic, we plot the time-series of values for the median firm in each cross-section, drawn quarterly. The sample includes all stocks with market capitalization greater than the NYSE median between December 1989 and December 2007. Mutual fund ownership (Panel A) is the sum of shares owned by mutual funds, divided by shares outstanding. The number of mutual funds (Panel B) is the number of CRSP-listed funds owning a given stock. Ownership concentration (Panel C) is the sum of the squared shares held by mutual funds. Fragility (Panel D) is defined as the conditional expected variance of flow-driven net buys into a stock, and calculated according to Eq. (8) in the text. It is high when ownership is concentrated, or when mutual fund owners have volatile or correlated flows.

Panel A: Full sample



Panel B: Stocks whose mutual fund ownership exceeds 20% of shares outstanding

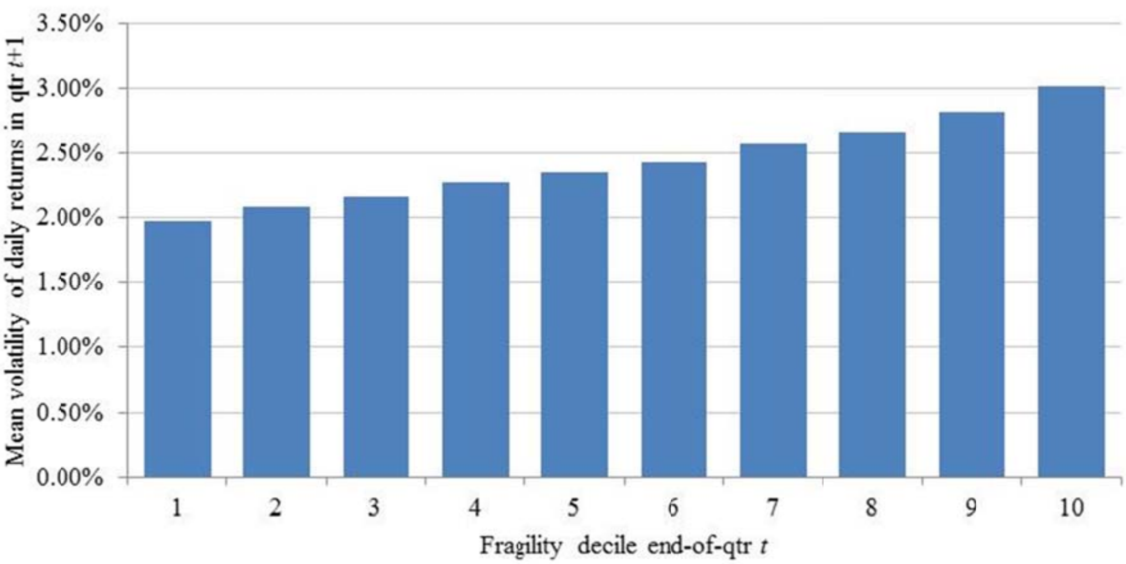
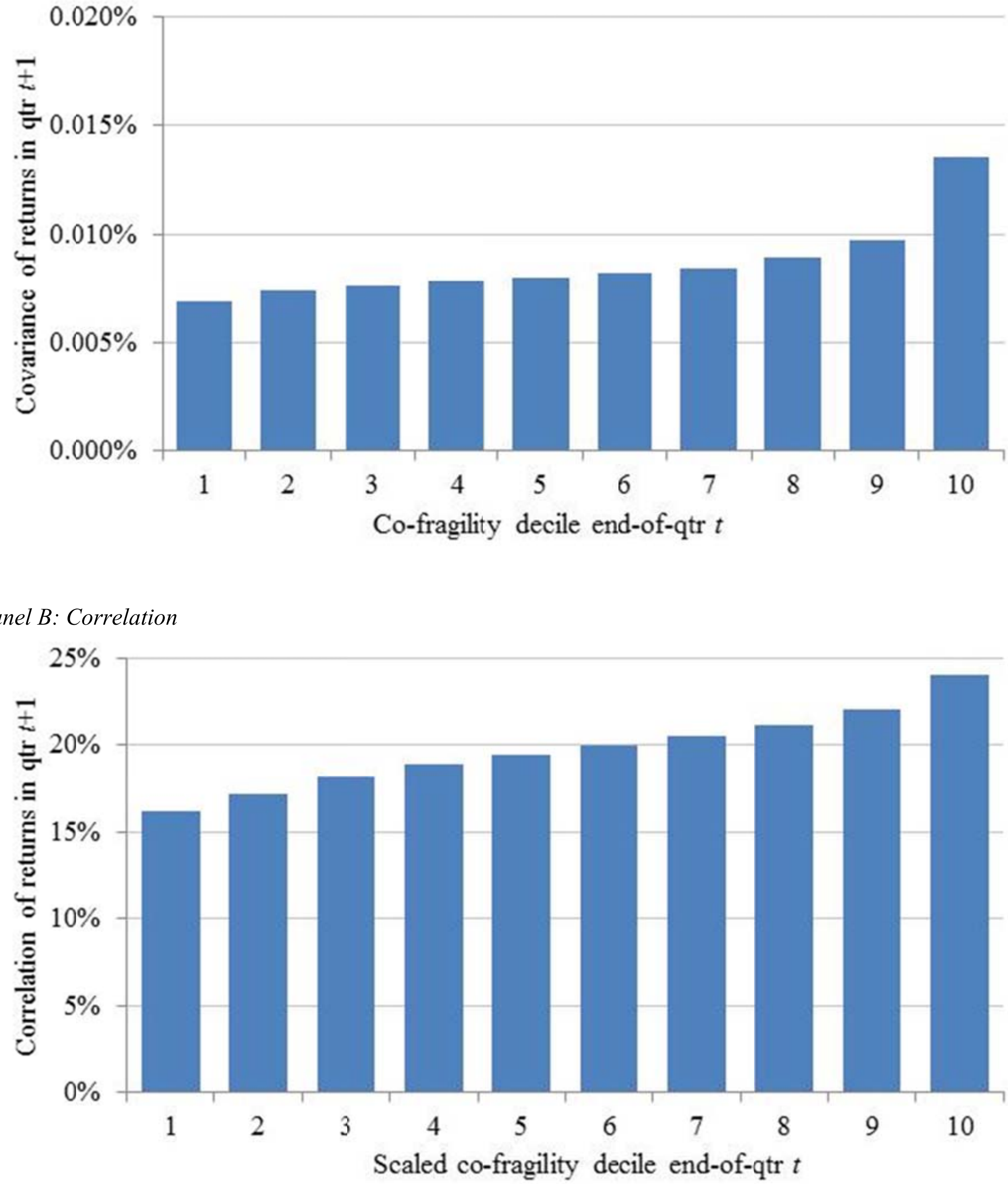


Fig. 2. Fragility and volatility. Each quarter, stocks are sorted into deciles according to their fragility. For each decile of fragility, we first compute, each quarter between 1989Q4 and 2007Q3, the mean volatility (standard deviation) of daily stock returns in the next quarter. The figures show the time series averages of these means, by decile of fragility. In Panel A, we draw on the full sample. In Panel B, we restrict the sample to firms with at least 20% of mutual fund ownership.

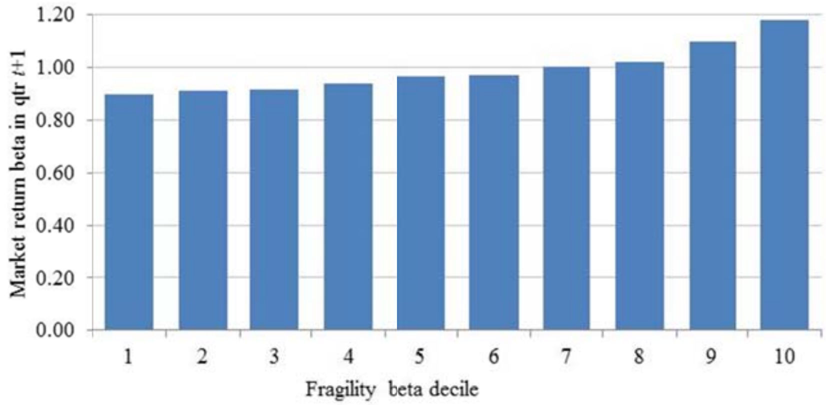
Panel A: Covariance



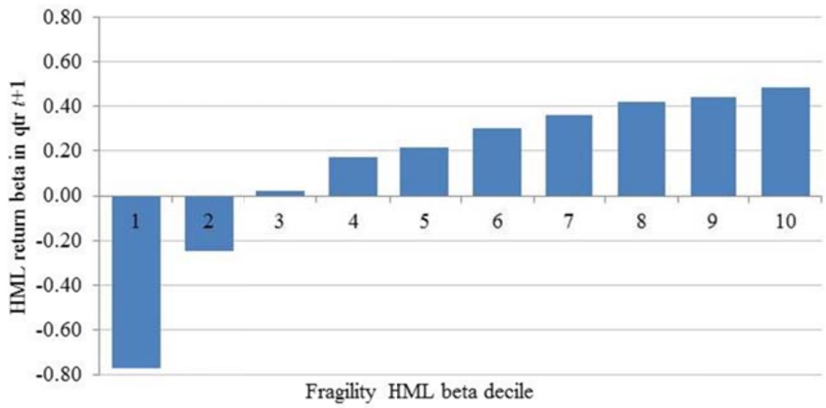
Panel B: Correlation

Fig. 3. Co-fragility and comovement of stock returns. Co-fragility is defined in Eq. (18) and measures the covariance of mutual fund flow-driven net buys into any pair of stocks i and j. Each stock pair in the sample is sorted into co-fragility deciles. For each decile of fragility, we compute, each quarter between 1989Q4 and 2007Q3, the mean covariance (Panel A), and the mean correlation (Panel B) of daily stock returns in the next quarter. The figures show the time-series average of these means.

Panel A: Market return beta



Panel B: HML return beta



Panel C: SMB return beta

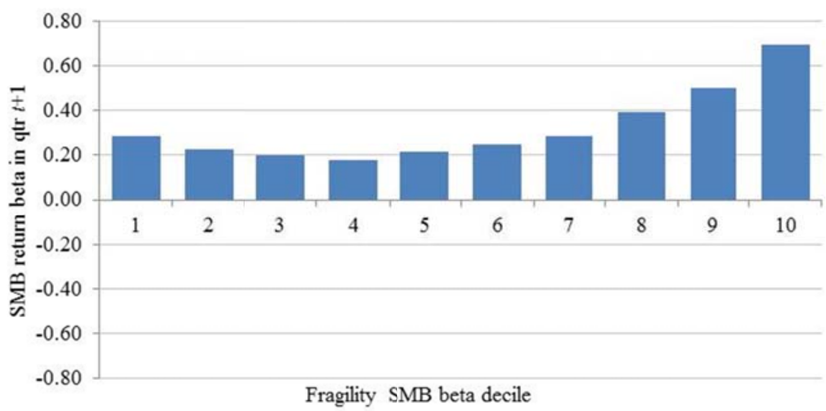


Fig. 4. Fragility betas and return betas. Fragility beta with respect to a portfolio *p* measures the correlation between flows received by a stock's mutual fund owners and flows into portfolio *p*. Each quarter from 1989Q4 to 2007Q3, stocks are sorted into deciles of fragility beta with respect to *p*. Then, for each decile of fragility beta, we first compute the average of the next quarter's return beta with portfolio *p*. The figure shows the mean future return beta, across dates, by decile of fragility beta. In Panel A, *p* is the market portfolio. In Panel B, *p* is the Fama and French (1993) HML portfolio. In Panel C, *p* is the Fama and French (1993) SMB portfolio.

Table 1
Constructing fragility.

The fragility of stock i in period t is given by:

$$G_{it} = \frac{1}{\theta_{it}^2} W_{it}{}' \Omega_t W_{it},$$

where W_{it} is the $K\times 1$vector of mutual fund ownership of stock i; Ω_t is the $K\times K$ variance-covariance matrix of fund flows; θ_{it} is stock i's stock market capitalization. K denotes the number of funds. The table reports summary statistics for the components of fragility. H_{it} is the sum of the squared fund positions, scaled by total mutual fund ownership of stock i at date t (for instance, H_{it}=1 if only one mutual fund owns the stock). The next rows show the number of mutual funds that hold a position in that stock for which we also have flow information. The bottom panels summarize the elements of the Ω_t matrix. For the standard deviation of fund flows σ_{kt}, the unit of observation is at the fund k level, each quarter. For the correlation between flows $\rho_{kk't}$ and its absolute value $|\rho_{kk't}|$, the unit of observation is at the fund pair *(k,k')* level, each quarter. Summary statistics are shown in 1995Q4, 1999Q4, and 2003Q4. Variances and covariances in Ω_t are computed using all observations from 1989Q4 to t. Fragility is winsorized at 0.5% and 99.5% levels.

	Mean	Min	25%	Median	75%	Max
Ownership:						
Concentration H_{it}:						
Dec-1995	0.173	0.017	0.078	0.127	0.203	1.000
Dec-1999	0.132	0.015	0.059	0.092	0.153	1.000
Dec-2003	0.110	0.012	0.042	0.063	0.106	1.000
Number of Owners:						
Dec-1995	78.716	1.000	31.000	53.000	102.000	571.000
Dec-1999	109.456	1.000	40.000	72.000	134.000	1001.000
Dec-2003	186.366	1.000	89.000	138.000	241.000	1278.000
Fund flows:						
Flow volatility σ_{kt}:						
Dec-1995	0.103	0.000	0.042	0.094	0.158	0.337
Dec-1999	0.121	0.000	0.061	0.126	0.174	0.375
Dec-2003	0.140	0.000	0.088	0.145	0.186	0.375
Flow correlation $\rho_{kk't}$:						
Dec-1995	0.026	-0.990	-0.183	0.022	0.236	0.990
Dec-1999	0.037	-0.990	-0.130	0.026	0.205	0.990
Dec-2003	0.041	-0.990	-0.112	0.030	0.196	0.990
Flow correlation $\|\rho_{kk't}\|$:						
Dec-1995	0.265	0.000	0.094	0.210	0.386	0.990
Dec-1999	0.229	0.000	0.071	0.168	0.329	0.990
Dec-2003	0.214	0.000	0.065	0.155	0.306	0.990
Fragility:						
Fragility G_{it}: (x10e-4)						
Dec-1995	0.651	0.000	0.075	0.270	0.761	6.865
Dec-1999	1.061	0.000	0.157	0.505	1.368	6.865
Dec-2003	1.274	0.000	0.324	0.813	1.811	6.875

Table 2
Characteristics of fragile stocks.

The sample includes all stocks that are owned by one or more mutual funds and which have end-of-quarter market capitalization above the NYSE median. The sample period is from December 1989 to December 2007. The table shows summary statistics for fragility-sorted portfolios, where fragility is the conditional expected variance of flow-driven net buys and computed according to Eq. (8) in the text. Stocks are sorted into portfolios based on end-of-quarter fragility. Active weight is the sum of the changes in weights adjusted for portfolio growth and adjusted for stock price appreciation; active weights are aggregated across funds to the individual stock level. BE/ME denotes the book-to-market ratio. The bottom rows of the table report statistics on the number of stocks in the portfolio at different points in time.

	Fragility Quintile:				
	Low	2^{nd} Quintile	Middle	4^{th} Quintile	High
Fragility *G* %	0.210	0.460	0.675	0.959	1.562
Fragility *G* (t-1) %	0.227	0.471	0.681	0.951	1.496
N Owners	92	168	150	132	118
MF Ownership %	5.331	12.349	16.767	21.074	28.657
Active weight %	0.026	0.028	0.064	0.148	0.445
NYSE decile	7.915	8.234	7.960	7.630	7.228
BE/ME	0.512	0.515	0.521	0.483	0.405
MOM decile	5.320	5.376	5.483	5.628	5.675
Returns: (%)					
Past quarter	3.325	3.431	3.672	4.446	4.394
Past 2 quarters	6.406	6.687	7.537	9.101	9.628
T (in quarters)	73	73	73	73	73
N (Dec 1989)	120	120	120	120	119
N (Dec 1995)	217	217	217	217	216
N (Dec 2000)	281	281	280	281	280
N (Dec 2005)	256	256	256	256	255
N (All)	16,423	16,386	16,387	16,387	16,360

Table 3
Fragility and stock return volatility.

The dependent variable is the one-quarter-ahead standard deviation of daily stock returns or excess returns in that quarter:

$$\sigma_{it+1} = a + b\sqrt{G_{it}} + Z_{it}C + u_{it+1}.$$

G_{it} denotes fragility, and Z_{it} is a list of control variables. The sample period is 1990-2007. Except for columns 3 and 7, we report Fama-MacBeth estimates, which are equal-weighted quarter-by-quarter, and t-statistics in brackets. In column 3, observations are weighted by mutual fund ownership at the end of the quarter. Column 7 shows a panel regression which includes a stock-level fixed effect, with standard errors clustered by period. The regressions in columns 5-7 further include a set of unreported controls: the log of unadjusted stock price, the log of market capitalization, the ratio of book equity to market equity, the past 12 month stock return, lagged skewness of stock returns, the log of age and share turnover. The remaining independent variables, whose coefficients are reported in the table, are: fragility, fragility calculated as if liquidity shocks of the different owners were uncorrelated (i.e. setting all off-diagonal terms of Ω_t to 0 in Eq. (8)), fragility calculated using only the correlation terms of liquidity shocks (i.e. setting all on-diagonal terms of Ω_t to 0 in Eq. (8)), the log of the number of mutual funds owning the stock, the fraction of stocks held by mutual funds, the ownership Herfindahl index H, the log of firm size, and the quarter-t volatility of returns. In the last three columns, the dependent variable is the standard deviation of excess returns, where excess returns are alternately based on the single-factor market model, the three-factor Fama and French (1993) model, or the three-factor Fama and French model plus momentum. FM denotes Fama-MacBeth estimation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Total return volatility σ:								Excess return volatility : 1-Factor σ	3-Factor σ	4-Factor σ
√G		0.696	0.711		0.793	0.226	0.699	0.152	0.583	0.564	0.556
		[15.17]	[16.67]		[12.60]	[6.27]	[7.43]	[4.81]	[16.97]	[17.27]	[17.29]
√*G* (Diag)				0.489							
				[11.75]							
√*G* (Off-diagonal)				0.524							
				[9.46]							
Log (# owners)	-0.001										
	[-6.57]										
MF share	0.022				-0.006	0.000	-0.030	0.000			
	[18.12]				[-3.89]	[0.03]	[-5.57]	[0.16]			
Ownership Herfindahl					-0.002	-0.001	-0.004	-0.002			
					[-2.86]	[-1.16]	[-1.41]	[-1.88]			
$\sigma(t)$								0.524			
								[36.38]			
Constant	0.024	0.018	0.018	0.018	0.019	0.029	-0.020	0.014	0.016	.016	.016
	[15.80]	[23.68]	[26.74]	[23.88]	[21.94]	[20.07]	[-1.21]	[9.05]	24.07	24.89	24.86
Observations	81,962	81,962	81,962	81,962	81,962	48,906	48,906	48,906	75,495	75,495	75,495
R-squared	0.06	0.08	0.11	0.09	0.09	0.48	0.57	0.58	0.08	0.08	0.08
Additional controls	No	No	No	No	No	Yes	Yes	Yes	No	No	No
Estimation	FM	FM	FM	FM	FM	FM	Panel+FE	FM	FM	FM	FM
Weighting	EW	EW	MF-weight	EW	EW	EW	EW	EW	EW	EW	EW

Table 4
Co-fragility, covariance, and correlation.

In panel A, the dependent variable is alternately the one-quarter-ahead covariance between daily returns of pairs of stocks *i* and *j*:

$$\sigma_{ijt+1} = a + bG_{ijt} + Z_{ijt}C + u_{ijt+1},$$

where G_{ijt} denotes co-fragility of stocks *i* and *j*, and *Z* is a list of pair-level control variables. In Panel B, the dependent variable is the one-quarter-ahead correlation between daily returns of stocks *i* and *j*:

$$\rho_{ijt+1} = a + b\frac{G_{ijt}}{\sqrt{G_{it}G_{jt}}} + Z_{ijt}C + u_{ijt+1}.$$

In Panel B, we rescale co-fragility G_{ijt} between stocks *i* and *j* by the square root of the product of their individual fragilities G_{it} and G_{jt}. The control variables include dummy variables for whether stocks *i* and *j* are in the same two-digit, three-digit, or four-digit SIC code, the absolute difference in log size between *i* and *j*, the absolute difference in log BE/ME between *i* and *j*, and one-quarter lagged correlation and covariance of stock returns between *i* and *j*. Regressions are estimated quarterly between December 1989 and December 2007 and include all stock pairs drawn from the largest 500 stocks each quarter. The table reports average regression coefficients and the associated Fama and MacBeth *t*-statistics.

	Panel A: Dependent variable = σ_{ijt+1}				Panel B: Dependent variable = ρ_{ijt+1}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
G_{ijt}		1.690	1.497	1.135				
		[4.06]	[4.10]	[3.94]				
$G_{ijt}/\sqrt{G_{it}}\sqrt{G_{jt}}$						0.088	0.057	0.047
						[17.38]	[8.32]	[7.48]
$SIC2_{it}=SIC2_{jt}$	0.344		0.329	0.243	0.057		0.055	0.048
	[4.94]		[4.90]	[5.68]	[9.65]		[9.70]	[9.39]
$SIC3_{it}=SIC3_{jt}$	0.386		0.348	0.272	0.045		0.047	0.039
	[3.20]		[3.06]	[3.62]	[4.88]		[5.29]	[4.66]
$SIC4_{it}=SIC4_{jt}$	0.113		0.141	0.125	0.055		0.053	0.048
	[1.45]		[1.88]	[2.20]	[7.90]		[7.87]	[7.33]
Common owners (log)	0.027		0.012	0.012	0.028		0.021	0.018
	[0.95]		[0.39]	[0.47]	[11.50]		[10.58]	[9.45]
Similar size	-0.011		-0.014	-0.010	-0.003		-0.004	-0.003
	[-1.21]		[-1.53]	[-1.60]	[-3.32]		[-4.24]	[-3.61]
Similar BE/ME	-0.021		-0.016	-0.013	-0.004		-0.003	-0.003
	[-5.44]		[-4.64]	[-4.41]	[-10.07]		[-8.39]	[-7.85]
σ_{ijt}				0.295				
				[13.36]				
ρ_{ijt}								0.194
								[17.22]
Observations	2,916,545	3,911,280	2,916,545	2,796,062	2,916,545	3,907,003	2,913,266	2,792,768
R-squared	0.04	0.04	0.08	0.17	0.06	0.02	0.07	0.11

Table 5
Forecasting volatility and comovement at longer horizons.

Univariate regressions forecasting the standard deviation of returns in the next quarter, the covariance of returns in the next quarter, or the correlation of returns in the next quarter, based on daily, weekly, bi-weekly, and monthly returns. G_{it} denotes fragility of stock *i*, and G_{ijt} denotes the cross-fragility between stocks *i* and *j*. The first column of each panel repeats the results from Table 3 and Table 4. The remaining columns re-estimate the regressions, with volatility and comovements based on weekly, bi-weekly, and monthly sampling of returns. In Panel A and Panel B, the regression coefficients are adjusted so that long-horizon results are directly comparable with the results from the daily regressions. Regressions are estimated quarterly between December 1989 and December 2007; the table reports average coefficients from the 73 quarterly regressions and the associated Fama and Macbeth t-statistics. The constant term is omitted.

	Panel A : Total return volatility $=\sigma_{it+1}$				Panel B : Covariance $=\sigma_{ijt+1}$				Panel C: Correlation $=\rho_{ijt+1}$			
Measurement interval :	Daily	Weekly	Bi-weekly	Monthly	Daily	Weekly	Bi-weekly	Monthly	Daily	Weekly	Bi-weekly	Monthly
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\sqrt{G_{it}}$	0.696	0.715	0.657	0.569								
	[15.17]	[14.13]	[14.40]	[13.90]								
G_{ijt}					1.690	2.134	1.814	1.141				
					[4.06]	[3.92]	[3.85]	[2.52]				
$G_{ijt}/\sqrt{G_{it}}\sqrt{G_{jt}}$									0.088	0.085	0.073	0.070
									[17.38]	[10.23]	[7.70]	[5.57]
Observations	81,962	81,962	81,962	81,962	3.9M	3.9M	3.9M	3.9M	3.9M	3.9M	3.9M	3.9M
R-squared	0.08	0.08	0.06	0.04	0.04	0.02	0.01	0.01	0.02	0.01	0.00	0.00

Table 6
Co-fragility and three-factor comovement.

Regressions of return betas with respect to portfolio p on fragility betas with respect to the same portfolio p:

$$\beta_{it+1}^{p} = a + bG_{it+1}^{p} + Z_{it}C + u_{it+1}.$$

In columns 1-2, *p* is the market portfolio. In columns 3-4, *p* is the Fama and French (1993) HML portfolio. In columns 5-6, *p* is the Fama and French (1993) SMB portfolio. Return beta β_{it+1}^{p} is the regression coefficient of stock *i*'s return on the return of portfolio *p*. Fragility beta G_{it+1}^{p} is the regression coefficient of flow-driven trades into stock *i* on flow driven trades into portfolio *p*. For example, G^{HML} is the regression coefficient of mutual fund flows into stock *i* on the flows into the portfolio that buys high BE/ME stocks and sells low BE/ME stocks, with similar constructions used for the market and SMB portfolios. The control variables include the fraction of shares outstanding held by mutual funds (MF Share), the number of mutual fund owners, the log of firm size, and the most recently recorded BE/ME ratio. Regressions are estimated quarterly between December 1989 and December 2007; the table reports average coefficients from the 73 quarterly regressions and the associated Fama and Macbeth t-statistics.

	β		β^{HML}		β^{SMB}	
	(1)	(2)	(3)	(4)	(5)	(6)
G^{β}	0.194	0.125				
	[11.78]	[7.40]				
G^{HML}			0.482	0.471		
			[21.15]	[18.52]		
G^{SMB}					0.043	0.042
					[9.17]	[9.61]
MF Share		0.880		1.451		-0.551
		[3.31]		[6.28]		[-3.36]
N Owners (log)		0.094		-0.106		-0.016
		[1.39]		[-1.85]		[-0.30]
Size (log)		-1.010		131.210		250.160
		[-0.02]		[4.07]		[9.03]
BE/ME		-0.243		0.289		0.313
		[-6.97]		[6.99]		[8.44]
Constant	0.778	0.369	-0.205	-3.001	-0.659	-6.085
	[34.62]	[0.59]	[-5.26]	[-6.09]	[-14.49]	[-15.52]
Observations	41,759	30,877	41,155	30,519	41,155	30,519
R-squared	0.06	0.15	0.25	0.29	0.13	0.25
Fama MacBeth	Yes	Yes	Yes	Yes	Yes	Yes

Table 7
Liquidity providers and the impact of fragility on volatility: two-stage regressions.

For each stock in each quarter, we first estimate the sensitivity of demand D_{it}^{X} of type X on total flow-driven buys from mutual funds D_{it}^{MF}:

$$D^{X}{}_{it} = \delta + \gamma D_{it}{}^{MF} + \nu_{it}$$

We consider active net buys by mutual funds (X=mutual funds' active purchases), net buys by hedge funds (X=hedge funds), and the sum of these (X=mutual funds active purchases + hedge funds). We estimate these regressions on a rolling basis, so that the estimate of γ_{it} is based on flows during the past 24 quarters. $|1+\gamma_{it}|$ serves as an estimate of the extent to which demand of type X accommodates flow-driven trades by mutual funds. When $|1+\gamma_{it}|$ is large, demand of type X acts as a destabilizing force. The table below reports results from second-stage regressions of one-quarter-ahead volatility of daily returns σ_{it+1} on fragility $\sqrt{G_{it}}$, $|1+\gamma_{it}|$, and the interaction of $|1+\gamma_{it}|$ and fragility $\sqrt{G_{it}}$.

$$\sigma_{it+1} = a + b\left|1+\hat{\gamma}_{it}\right| + c\sqrt{G_{it}} + d\left|1+\hat{\gamma}_{it}\right| \cdot \sqrt{G_{it}} + u_{it+1}.$$

Regressions are estimated quarterly between December 1989 and December 2007; the table reports average coefficients from the 73 quarterly regressions and the associated Fama and Macbeth t-statistics.

	Dependent variable = σ_{ijt+1}		
	(1)	(2)	(3)
$\|1+\gamma_1\|\cdot\sqrt{G}$ (Active MF buys + HF buys)	0.060		
	[2.95]		
$\|1+\gamma_2\|\cdot\sqrt{G}$ (HF buys)		0.138	
		[3.89]	
$\|1+\gamma_3\|\cdot\sqrt{G}$ (Active MF buys)			0.047
			[1.79]
$\|1+\gamma_1\|$ (Active MF buys + HF buys)	0.000		
	[2.71]		
$\|1+\gamma_2\|$ (HF buys)		-0.000	
		[-0.49]	
$\|1+\gamma_3\|$ (Active MF buys)			0.001
			[3.57]
$\sqrt{G}$	0.438	0.432	0.507
	[10.13]	[10.61]	[12.95]
Constant	0.016	0.017	0.016
	[25.79]	[26.18]	[28.80]
Mean estimates:	Mean(1+γ) = 1.033	Mean(1+γ) = 1.245	Mean(1+γ) = 0.781
Observations	32,046	48,143	43,534
R-squared	0.07	0.09	0.08