Stock Price Fragility*

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Abstract

We study the relationship 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 its demand. An asset can be fragile because of concentrated ownership, or because its owners face correlated or volatile liquidity shocks, ie., they must buy or sell at the same time. We formalize this idea and apply it to mutual fund ownership of US stocks between 1990 and 2007. Consistent with our predictions, fragility strongly predicts price volatility. We then extend the logic of fragility to investigate two natural issues: (1) the forecast of stock return comovement and (2) the potentially destabilizing impact of arbitrageurs on stock prices.

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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 have large effects on prices.[1]

If investor demand unrelated to fundamentals does influence security prices, then the composition of ownership of a financial asset should be useful for forecasting non-fundamental risk. In this paper, we propose a method to compute the expected volatility of the demand for an asset given its current owners, which we call "fragility". The fragility formula highlights the key role of ownership structure, both through ownership concentration but also through the correlation of its owners' trading needs. We then calculate fragility for US stocks, using mutual fund ownership data. We find that fragility strongly predicts stock returns volatility. Last, we explore two natural extensions of our approach. First, we extend the fragility approach to explain how stocks returns commove. Second, we use the fragility – volatility relationship to ask whether arbitrageurs destabilize stock prices.

To illustrate our 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, Pedersen and Pulvino, 2007), investor demand for bonds (Greenwood and Vayanos, 2009), and mutual funds' flow-driven demand for stocks (Coval and Stafford 2007; Lamont and Frazzini 2007; Lou 2009).

sell), 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 large blue chip stock trading on the NYSE, for example. The owners may individually experience liquidity shocks which require them to scale their positions up or 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 asset fragility is straightforward, whether it is useful empirically depends on whether we can measure (a) the composition of ownership and (b) the ex ante covariance structure of the liquidity needs faced by its owners. For many assets, even if we can observe the ownership, estimating the covariance of liquidity needs presents a challenge. Fortunately, mutual fund ownership of U.S. listed equities satisfies both criteria above, because the correlation structure of their liquidity-driven trades can be inferred from their inflows and outflows. 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. We find that fragility is not just picking up the positive correlation between ownership concentration and volatility: hence, the historical variance-covariance of trading needs across mutual funds also matters. We also propose tests to control for the fact that ownership structure of a stock may be endogenous with respect to future volatility. Beyond the array of controls that we look at, we include stock specific fixed effects to control for fixed unobserved heterogeneity. In addition, for each stock, we isolate a set of funds that have owned the stock for at least a year, and calculate fragility using these owners only. For these funds, the decision to own shares in year *t* is unlikely to reflect their anticipation of future volatility, and more likely to reflect inertia in their holdings in year *t-1*. We obtain similar results for these stocks.

We next study two natural applications of our fragility measure. First, we extend the logic to predict comovement. We provide a formal definition of "co-fragility", whereby two assets are co-fragile if they are held by investors (in our application, mutual funds) who have correlated trading needs. We also use the notion of co-fragility 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., the market portfolio). Empirically, we find that these two measures are successful at predicting co-movement: co-fragility is a statistically robust predictor of correlations between stock returns, but more impressively, fragility betas predict the risk factor loadings themselves. For instance, our ownership measure can explain 25% of the cross-sectional variation in HML beta: put differently, many stocks load on HML because they are held by funds whose flows are correlated with the flows of value investors. Because it is, however, easy to see why similar investors would rush into stocks that are similar, the co-fragility/fragility-beta results are more difficult to interpret than the fragility-volatility relationship. Although we take steps to minimize ownership endogeneity in these regressions through the use of controls, we view the co-fragility results as more suggestive.

In our second application, we use the relationship between fragility and volatility to shed some light on the effect of hedge fund trading on stock price stability. We start by measuring, at the stock level, the historical willingness of hedge funds to provide liquidity to mutual funds' liquidity needs. We find that such willingness varies greatly from stock to stock, perhaps driven by arbitrageurs' tendency to specialize. We find that fragility exerts a more modest effect on volatility among stocks in which arbitrageurs were willing to provide liquidity historically. 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 are linked to a number of recent papers that investigate the price destabilizing behaviour of arbitrageurs.[2]

Taken together, our results establish a connection between ownership structure and volatility, thus shedding light on earlier work which correlates institutional ownership with stock price volatility (Sias, 1996 and 2000; Bushee and Noe 2000; Koch, Ruenzi and Starks 2009). We find that it is not so much the fraction of mutual fund ownership per se, but rather the structure and behaviour of the individual owners that matters for predicting volatility. Looking at this, we also view our paper as also naturally related to the broader literature on the determinants of volatility (e.g., Brandt, Brav, Graham and Kumar, 2009).

Our co-fragility extension contributes to the literature on the excess comovement of stock returns (Barberis and Shleifer, 2003, Barberis, Shleifer and Wurgler, 2005). Our comovement

[2] Brunnermeier and Nagel (2004) and Griffin, Harris and Topaloglu (2009) look at the role of hedge funds in the tech bubble. Both studies find that hedge funds have amplified the price movement, instead of dampened it. Fishman, Hong and Kubik (2009) look at positive announcements when stocks are heavily shorted: they find that speculators' deleveraging tends to exacerbate stock price reaction to news. Chen, Hanson, Hong and Stein (2008) and Anton and Polk (2010) are more closely related to this paper. Chen et al (2008) focus on mutual fund liquidity trades, but do not use stock level hedge funds trading information as we do. Anton and Polk (2010) look at hedge funds response to liquidity induced comovement, while we focus on more traditional front running.

results are closest to two recent papers. Kumar, Page and Spalt (2009) predict comovement by looking at aggregate retail investor trading: our focus on mutual funds allows us to identify trades that are less likely to be connected with information. Anton and Polk (2010) were the first to show that stocks with common owners have more correlated returns: computing co-fragility complements their approach by showing that stocks also comove because different owners have correlated trading needs.

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

I. Asset fragility

In this section, we develop our fragility measure and use it to explore the link between ownership structure and non-fundamental risk.

a. Definition

The weight w_{ikt} of asset *i* in the portfolio of investor *k* at date *t* is:

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

where n_{ikt} is the number of shares of *i* held by investor *k* at date *t*, a_{kt} is the total assets managed by that investor, and P_{it} is the asset price. Net dollar purchases of *i* by *k* can be decomposed into active changes in weights and changes driven by asset growth:

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

where $\Delta x_t \equiv x_{t+1} - x_t$, i.e., the period-ahead change in *x*. We denote net inflows in to fund *k* as the change in portfolio assets adjusted for changes in the prices of its constituents:

$$f_{kt} \equiv \Delta a_{kt} - \sum_j n_{jkt} \Delta P_{jt} \tag{3}$$

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

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

where the *j* subscript denotes the other assets in fund k's portfolio. The first term in the decomposition is the contribution of portfolio rebalancing: it calculates the trading that results from a willingness to change the weight of a stock, beyond the mechanical effect of relative price changes. The second term is the contribution of flows, holding fixed the composition of the portfolio. We focus on the second term of the decomposition, which is exogenous to any given firm in the portfolio, and yet has been shown by several authors to trigger price impact. Specifically, Coval and Stafford (2007), Kahn et al (2009) and Lou (2009) show that mutual funds typically scale up and down their existing positions in response to inflows and outflows and that these "passive" trades have price impact.

Under the assumption that flow-driven liquidity trades are associated with some price pressure, we posit the following relationship between total liquidity trades and returns:

$$r_{it+1} = \alpha + \lambda \frac{\sum_k w_{ikt} f_{kt}}{\theta_{it}} \tag{5}$$

Equation (5) says that price impact is proportional to total flow-driven demand across all investors *k*, scaled by θ_{it}. In writing (5) we omit risk-based determinants of returns; this is done for simplicity only. We also temporarily omit residual returns driven by shocks to fundamentals (which would form the error term in (5)).

In our empirical work, we scale all trades by market capitalization (i.e., θ=MV), as is common practice in the literature. The coefficient λ measure the "illiquidity" of the asset: when the market can absorb net imbalances with little price impact, then λ is small. $1/\lambda$ 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 V, where we argue that it may depend on the presence of arbitrageurs who can lean against non-fundamental shocks.

The right-hand terms in equation (5) can be written in vector form:

$$r_{it+1} = \alpha + \frac{\lambda}{\theta_{it}} W'_{it} F_t \tag{6}$$

where $W'_{it} = \left(w_{i1t}, ..., w_{iKt} \right)$ is the vector of weights of each fund in asset *i* and $F_t = \left(f_{1t}, ..., f_{Kt} \right)$ is the vector of net dollar inflows experienced by each investor.

The conditional variance of the *t*+1 return of asset *i* is given by:

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

where Ω_t is the conditional variance-covariance matrix of dollar fund flows F_t between *t* and *t*+1. We define the fragility *G* of asset *i* 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 owners. By virtue of equation (7), the square root of fragility $\sqrt{G_{it+1}}$ is proportional to the standard deviation of returns $\sqrt{\text{var}_t\, r_{it+1}}$, and the proportionality coefficient is λ, the inverse price elasticity of demand.

b. Ownership concentration and non-fundamental risk: An example

Here we illustrate the intuition behind our fragility measure using a simple example. Consider a stock held by *K* investors who each own a fraction *x*/*K* of shares outstanding. Other dispersed investors own the remaining 1-*x*. Let $\theta_{it}=MV_{it}$ i.e., price impact is proportional to the inverse of market capitalization. Suppose that the investors' net flows have the same variance σ^2 and covariance $\rho.\sigma^2$, where $\rho<1$. In this case, we can substitute terms into equation (8) and see that:

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

The first term in brackets comes from the diagonal terms of Ω_t, while the second term comes from the off-diagonal elements.

Suppose that flows between investors are perfectly uncorrelated (ρ=0). Then, for a given ownership composition, fragility decreases with the number of owners, 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 $\lambda^2\sigma^2x^2$ which is the same as if the asset were held by one single owner.

Equation (9) also makes clear the role of asset growth volatility σ. With concentrated ownership (*K* is low), asset growth volatility has a large effect on return volatility. However, as the number of owners increases, asset growth volatility exerts a smaller effect on returns because of diversification. In the limit, for $|\rho|<1$, perfectly dispersed ownership (i.e., $K \rightarrow \infty$) is associated with zero price volatility.

II. 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. Mutual fund ownership of listed equities provides a good setting to test the link between fragility and non-fundamental risk because their holdings are readily available and because we can estimate the historical covariance of their inflows and outflows. A drawback of the mutual fund data is that for most stocks, we only capture a fraction of total ownership. Thus, our fragility measures will be more comprehensive for stocks with high total mutual fund ownership.

a. 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 begins 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. (6), we divide the dollar holdings $n_{ijt}P_{it}$ of each fund j at the end of each quarter by total assets under management 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 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:

$$f_{jt} = TNA_{jt} - TNA_{jt-1}(1 + R_{jt}) \qquad (10)$$

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.[3]

We then estimate Ω_t, the conditional variance-covariance matrix of *dollar* flows. We do not compute the covariance directly because of heteroskedasticity of \$ flows: 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 problem, 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:

$$\hat{\Omega}_t = diag\left(TNA_t\right)\Omega_t^{\%} diag(TNA_t) \qquad (11)$$

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

[3] We use upper-case R to denote fund returns; lower-case r denotes stock returns.

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, SMB, HML, and in the case of the 4-factor model, UMD).

b. Components of Fragility

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

$$G_{it} = \underbrace{\frac{1}{\theta_{it}^2} W'_{it}\left(\Omega_t - D_t\right) W_{it}}_{\text{Off-diagonal terms}} + \underbrace{\frac{1}{\theta_{it}^2} W'_{it}\left(D_t - \omega_t I\right) W_{it} + \omega_t m f_t^2 H_t}_{\text{On-diagonal terms}} \tag{12}$$

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_t 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 1 if there is just one mutual fund owner; and 0 if there is a large number of very small ones.

The first term on the right-hand-side of (12) (off-diagonal terms) is the contribution to fragility of the off-diagonal terms of Ω_t: if flows are uncorrelated across funds, this term is equal to zero. The second term (on-diagonal terms) is the contribution of the 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 equation (12) 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 regression specifications.[4] The last term of equation (12) also highlights the key role played by ownership concentration. In Table 1, we describe the sample variation of two measures of ownership concentration: *H*, as it appears in equation (12), and the number of owners. There is significant variation in ownership concentration, with a number of owners going from 1 (25^{th} percentile) to 102 (75^{th} percentile). The median stock has 53 mutual fund owners and *H*=0.127.[5]

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 2005. Because Ω_t is 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 |ρ|. 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.[6]

c. 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 quintile based on quarterly breakpoints. As can be seen, fragility is quite persistent: this is partly a mechanical outcome from the calculation of

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[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 Figure 1A, and Rydqvist, Spitzman 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, 2009). To avoid the spuriousness that may arise from common trends, we report Fama Mc Beth estimates in most of our specifications.

[5] To get a sense of this number, take, for instance, First Security Corporation, a stock which is close to the median *H* in December 1995. Together, mutual funds control approximately 11% of shares outstanding. The seven funds with the largest positions collectively control about 7%, with the remaining 44 controlling only 4%.

[6] We have also investigated the factor structure of the $\Omega^{\%}$ matrix. 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 5 principal components. Hence, cross fund flow correlation is complex and cannot be summarized by a few factors.

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.

More surprisingly perhaps, fragility is not monotonically correlated with the number of owners. This serves as a reminder 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. Last, Table 2 shows that firms which have been actively purchased by mutual funds, past winners, growth stocks, all exhibit higher fragility.

III. Fragility and non-fundamental risk

a. Predicting volatility

Figure 2 shows the relationship between fragility and future return fragility in graphical form. For each decile of fragility (breakpoints set quarterly), we compute the average volatility of total returns. 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. 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.

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 X_{it}:

$$\sigma_{it+1} = a + b\sqrt{G_{it}} + X_{it}C + u_{it+1} \tag{13}$$

We use the square root of fragility because, as can be seen in Equation (6), fragility is proportional to variance. All regressions are estimated following Fama MacBeth (1973) to account for trends. The exception is the last column, in which we report panel fixed effect estimates. Notice that, if equation (7) holds, b should in principle be equal to λ, a measure of 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 ten percentage points leads to an increase in daily volatility of about 0.2 percentage points, 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 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 percentage points, about one quarter of the mean volatility. In this specification, *b* is 0.7, and the t-statistic is approximately 15.[7] We can compare this coefficient to estimates of price impact from other papers. For instance, Wurgler and Zhuruskaya (2000)) use index addition to estimate the demand to price elasticity. To recover a comparable elasticity, we need to adjust for the fact that our volatility variable is based on daily returns, not quarterly ones—this yields $1/\left(0.7\times\sqrt{60}\right)$=0.2. In short, our results suggest that price impact is quite high compared to previous research.

Column 3 breaks fragility into two parts: the first component ("√G (Diag)") corresponds to the (square root of the) on-diagonal terms in equation (12). It uses only diagonal terms of the flow covariance matrix Ω_t. The second component ("√G (Diag)", corresponds to the (square root of the) off-diagonal terms in equation (12)). Recall that the first component measure the conditional volatility of flow driven trading, assuming that fund flows are uncorrelated. This "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 funds have correlated flows: if their flows are perfectly uncorrelated, it is equal to zero. The results in column 3 show that both parts of fragility contribute equally to volatility.

Column (4) 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

[7] 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 and 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.

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—it increases only a little. This suggests that fragility contains much more information (mutual fund flow volatility as well as correlation) than simply ownership concentration and mutual fund holdings.[8] 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 documented in earlier work is channelled through fragility: what matters is not so much ownership by mutual funds, but the volatility of their trading needs.

In the next three columns, we check that the predictive power of fragility is robust to various controls and specification adjustments. In column (5), we control for log share price, the book-to-market ratio, past annual stock return, age, lagged skewness, and lagged turnover. All these variables have been found to be correlated with volatility in previous literature.[9] 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 (6), we estimate a fixed effect panel regression with a firm fixed effect. The fragility coefficient returns to its initial estimated value of 0.7 and is highly significant.[10] However, this estimate is not directly comparable with column (5) since the panel estimation does not remove common trends in volatility and fragility. Column (6) does suggest, however, that stocks that

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[8] Equation (12) 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 entirely wiped out.

[9] Brandt, Brav, Graham, and Kumar (2009) 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 volatility in the value of equity (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, Kakici and Whitelaw, 2009).

[10] For the panel regression in column (5), we have also computed Thomson standard errors. The t statistic is barely affected: it goes down from 7.4 to 6.9. This is not really surprising as our dataset features much more firms than time periods.

have experienced the biggest increase in fragility are also the ones that have experienced the largest increase in volatility.

In column (7), we include the controls from column (5) but add lagged volatility, since volatility is highly persistent over time. Compared to column (5) estimates, the fragility coefficient decreases slightly from 0.23 to 0.15 but remains highly significant (t-stat of 4.81). We note that the persistence of both fragility and volatility make it difficult to identify the pure fragility effect on volatility in either column (6) or column (7).

Our analysis so far has been limited to forecasting total return volatility. In the last three columns, 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.[11] 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. 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 SMB to be high. On the other hand, because the Fama MacBeth technique removes quarter-specific variation, we might not expect there to be much of a change in the results. As can be seen, the coefficients on fragility fall only slightly when we adjust for factor exposure.

b. Endogeneity concerns

One concern in interpreting these results is that ownership structure may be endogenous with respect to future volatility. For example young, inexperienced, funds with volatile inflows might rush 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

[11] 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 Fama and French HML and SMB factors, and the four-factor model adds momentum as well.

our tests, because we cannot identify exogenous changes in ownership.[12] However, we note that our results appear to hold with (a) firm fixed effects, and (b) controlling for lagged volatility. Both of these results provide some comfort, because it seems unlikely that owners select particular stocks because they forecast changes in future volatility.

Another potential cure for endogeneity is to focus on stocks for which the ownership structure was established long ago. In this case, it is more difficult to claim that the current ownership is endogenous with respect to *future* volatility. On the other hand, focusing on these stocks is likely to weaken our results because we will throw out ownership information that is not endogenous with respect to changes in volatility.

For each stock we isolate a set of funds that have owned the stock for at least a year, and calculate fragility using only these owners, denoted G^{Stale}. We then estimate a forecasting regression of the form:

$$\sigma_{it+1} = a + b\sqrt{G_{it}^{Stale}} + c(\sqrt{G_{it}} - \sqrt{G_{it}^{Stale}}) + X_{it}D + u_{it} \tag{14}$$

Table 4 shows these results. The coefficient *b* enters significantly positive and strongly significant, even when we control for lagged volatility in the third column. As expected, it is smaller than estimates of Table 3, Panel A. In the second column, stale fragility has a coefficient of 0.3, compared to 0.7 when we just use lagged fragility. In column (3), where we also control for lagged volatility, the coefficient drops to 0.13, compared to 0.15 in our specification .

IV. Co-fragility and Comovement

[12] 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, but also on the correlation structure of inflows and outflows.

This section explores one straightforward extension of our approach to the prediction of stock return comovement. We first show how the approach followed in Section I 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 respective predictive power for returns correlation and factor loadings.

a. Defining co-fragility and fragility beta

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

$$\operatorname{cov}_t\left(r_{it+1}, r_{jt+1}\right) = \frac{\lambda^2}{\theta_{it}\theta_{jt}} W_{it}' \Omega_t W_{jt} . \tag{15}$$

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 co-move. We thus define the co-fragility of assets *i* and *j*:

$$G_{ijt} \equiv \frac{W_{it}' \Omega_t W_{jt}}{\theta_i \theta_j} . \tag{16}$$

Co-fragility should predict covariance. To predict correlation instead, we just need to combine equations (8) and (16) and obtain:

$$corr_t\left(r_{it+1}, r_{jt+1}\right) = \frac{G_{ijt}}{\sqrt{G_{it} G_{jt}}} . \tag{17}$$

Note that equation (17) suggests that the regression coefficient of returns correlation on $G_{ijt} / \sqrt{G_{it} G_{jt}}$ should be equal to 1, provided equation there is no other source of common variation in stock returns

We can use co-fragility to define the "demand beta" of an asset with respect to a given portfolio. Consider a portfolio *p*, defined by the weights μ_{jt}^{p} for each asset *j*.[13] The conditional return beta of stock *i* with respect to portfolio *p* is:

$$\beta_{it}^{p} = \frac{\operatorname{cov}_t\left(r_{it+1}, R^{p}{}_{t+1}\right)}{\operatorname{var}_t R^{p}{}_{t+1}}. \tag{18}$$

Using equation (6), which relates returns to flows, we obtain:

$$\beta_{it}^{p} = \frac{\operatorname{cov}_t\left(\frac{1}{\theta_{it}} W_{it}' F_t, \sum_j \frac{1}{\theta_{jt}} \mu_{jt} W_{it}' F_t\right)}{\operatorname{var}_t\left(\sum_j \frac{1}{\theta_{jt}} \mu_{jt} W_{it}' F_t\right)}. \tag{19}$$

Equation (19) 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". According to (19), the fragility beta should be equal to the corresponding return beta of the asset. For instance, a stock will comove with growth stocks when its owners have the same liquidity needs as other funds who invest in growth stocks. Straightforward algebra shows that the fragility beta can easily be expressed as a function of co-fragilities:

$$\beta_{it}{}^{p} = \frac{\sum_j \mu_{jt}{}^{p} . G_{ijt}}{\sum_{j,j'} \mu_{jt}{}^{p} . \mu_{j't}{}^{p} . G_{jj't}}, \tag{20}$$

If an asset has positive co-fragilities with other assets in portfolio *p*, its fragility beta with *p* will be high.[14]

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[13] To avoid confusion, recall that μ denotes the weights of the portfolio in question, while we use *w* to denote the weights of investors in their portfolios.

[14] 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.

Implementing (16) and (19) empirically is straightforward using our data. We use the same inputs as before, except that we now substitute into (16) 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 because of missing control variables). Thus, it is important to keep in mind that, compared to our fragility-volatility estimates, our co-fragility results draw heavily on the largest stocks.

b. Explaining correlations

Figure 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 5 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 (*i*,*j*) in quarter *t*, we run the following cross-sectional forecasting regressions:

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

and

$$\rho_{ij,t+1} = a + b\frac{G_{ijt}}{\sqrt{G_{it}G_{jt}}} + Z_{ijt}C + u_{ijt} \quad (22)$$

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. $Z_{ij,t}$ stands the suite of stock-pair-level controls, as follows: Pindyck and Rotemberg (1993) and Chen, Chen and Li (2009) show that firms in the same industries have correlated earnings and therefore returns. We define industry similarity dummy variables equal to one when both stocks belong to the same two-, three- or four-digit industry. We also expect firms with similar market capitalization and similar book-to-market to be purchased by similar funds. Hence, we include a variable that measures the difference in NYSE size deciles between *i* and *j*, and a variable measuring the difference in 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) have shown that stocks with common owners co-move. While common ownership certainly explains part of co-movement, our fragility measure captures at least two additional dimensions of returns co-movement: first, what also matters is the volatility of the outflows/inflows these owners are expected to face. Second, owners can be different, but have highly correlated flows, which should, in principle, have exactly the same effect as having common owners.

In the first panel of Table 5, the dependent variable is the covariance of returns; in the second panel, the dependent variable is correlation. We start by showing the results from a regression using only the control variables.[15] In both panels, the signs of the coefficient on the control variables go in the expected direction: when stocks belong to the same industry or have

[15] The specification seems more relevant for correlation than covariance, because the controls are meant to capture co-movement rather than volatility (a stock pair may have high covariance but low comovement)

similar book-to-market ratios, their covariance and correlation is likely to be higher. The number of common owners is significant only in the correlation regression: when the stock pair moves from one to two common owners—a 100% increase—the return correlation increases by 3 percentage points, confirming Anton and Polk's (2010) results in our sample.

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 percentage points) leads to an increase by 0.005 percentage points 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 percentage point increase in correlation, also about a third of its standard deviation.

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, however. 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. We compute pairwise correlations and covariance of 3-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. We turn to this below.

c. Explaining factor comovements with fragility betas

Equation (24) shows that the fragility beta with respect to portfolio *p* is large when the stock and portfolio *p* are subject to flow-driven trades at the same time. Consistent with equation (24), Figure 4 suggests that fragility betas are related to returns-based betas. Each quarter, we sort stocks by their fragility betas, and then compute within deciles, the mean return beta 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 whose owners 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 returns betas is very strong: moving from the first to the tenth decile of HML fragility beta, HML return beta increases from -0.60 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”. Put differently, 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 commove with stocks in the first, second, and third deciles of stock market capitalizations. Our sample selection procedure is therefore going to create a mechanical discrepancy between the two variables.

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

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

The dependent variable is the one quarter ahead beta of stock *i*'s daily returns with respect to the returns of any portfolio *p* (either the market portfolio, HML or SMB). $G_{it}^{\beta,p}$ is stock *i*'s fragility beta with respect to portfolio *p*, and X_{it} are controls. Given equation (20), if mutual fund flow driven trading was the *only* source of volatility, then *b* should equal one.

Fama-MacBeth estimates are reported in Table 6. In Panel A, the dependent variable is the univariate betas from a regression of returns on the factor. The first two columns 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 forthcoming), 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.[16]

[16] In one interpretation, including the control variables is overly cautious, because, e.g, stocks with a lot of mutual fund ownership could be the held primarily by index funds, whose inflows co-move with aggregate inflows into the

The next two columns show regressions forecasting HML beta. Consistent with the graphical evidence from Figure 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, such as the book-to-market ratio 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 0.5, while its "theoretical value" (i.e. assuming flow driven mutual fund trades are the *only* source of price variation as in equation (20)) should be 1.

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 returns beta by about 0.70 standard deviations. The size of the coefficient is smaller than for HML betas: 0.04 compared to 0.5.

The last six columns of the table repeat the regressions described above, except that here we look at the multivariate market, HML and SMB betas as dependent variables. These betas are computed for each stock-quarter, by fitting a Fama and French (1992) three-factor model on daily stock returns. While looking at these betas is not well motivated by our conceptual framework, they are closer to the factor exposures that researchers conventionally study in asset pricing. For HML and SMB betas (columns (3)-(6), panel B), the explanatory power and coefficient estimates are similar to those in the left-panel. For the Fama-French market beta

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fund management industry. In summary, a significant part of observed market betas could be explained by whether stocks experience inflows at the same time as other stocks.

(columns 1 and 2), the explanatory power of the fragility beta disappears completely. This appears to be driven by the fact that CAPM beta is strongly correlated with the SMB beta, as noted by Fama and French (1992).

V. Fragility and Arbitrage

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

We slightly extend the framework of Section I to the case in which there is more than one type of investor. In this case, equation (6) becomes:

$$r_{it+1} = \alpha + \lambda \underbrace{\frac{W_{it}' F_t}{\theta_{it}}}_{FIT_{it}} + \lambda OT_{it} \tag{24}$$

where OT_{it} stands for "other trades" and FIT_{it} is shorthand for flow-induced trading, both taking place between *t* and *t+1*. Other trades may be executed by other groups of investors such as hedge funds, or by mutual funds which trade for informational reasons (the first term in equation (4))[17].

Trades OT_{it} may accommodate, or exacerbate, flow-driven demand shocks by mutual funds. To account for this, we assume that OT_{it} can be written as a linear function of flow induced trading FIT_{it} :

[17] Fragility captures only the correlation structure in 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, although the results in Coval and Stafford (2007) and Lou (2009) suggest this not to be true on average.

$$OT_{it} = \theta + \gamma_{it} FIT_{it} + \xi_{it} \tag{25}$$

where $E(\zeta_{it} | FIT_{it}) = 0$ and the extent to which other trades accommodate or exacerbate flow-induced trading is assumed to vary from stock to stock. For instance, if $-1 < \gamma_{it} < 0$, other trades for stock *i* tend to dampen the price movements induced by flow induced trading. Alternatively, if $\gamma_{it} > 0$, other trades tend to amplify flow induced trading, as in Brunnermeier and Nagel (2004), Griffin et al (2006), or Chen, Hanson, Hong, and Stein (2008).

Substituting (25) into (24) and taking the variance, we have:

$$\begin{aligned} &\text{var}_t\, r_{it+1} = \lambda^2 (1 + \gamma_{it})^2 G_{it} \\ &\Rightarrow \sigma_{it+1} = \lambda |1 + \gamma_{it}| \sqrt{G_{it}} \end{aligned} \tag{26}$$

Equation (26) says that the sensitivity of volatility to fragility depends on γ_{it}, which measures the extent to which other trades tend to accommodate flow-driven trading. If they accommodate, then fragility should be expected to have a smaller impact on volatility. Why would γ vary across stocks? One simple reason is that risk, and therefore 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. Duffie and Strulovici (2009) provide a model describing the allocation of capital across assets.

To take equation (26) to our data, we consider two types of *OT*. First, we look at hedge fund order imbalances, i.e. quarter to quarter changes in aggregate hedge funds 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. Such active buys correspond to the first term on the right-hand-side of equation (4).

Our analysis proceeds in two stages. First, for each stock-quarter, we estimate γ_{it} from Eq. (25) over the past 24 quarters, by regressing past OT_{it} 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. In a second step, we estimate the following cross-sectional regression:

$$\sigma_{i,t+1} = a + b\left|1+\hat{\gamma}_{it}\right| + c\sqrt{G_{it}} + d\left|1+\hat{\gamma}_{it}\right|\sqrt{G_{it}} + fZ_{ij,t} + e_{ijt} \qquad (27)$$

Based on our discussion above, *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. We consider three potential models of OT_{it}: (1) Hedge fund imbalances + Mutual fund active trades, (2) Hedge fund imbalances only, and (3) Mutual fund active trades only.

Before turning to estimates of (27), we first examine the sample distribution of first stage estimates γ. The median regression coefficient of hedge fund buys on FIT is 0.004. Hence, the distribution is symmetric around zero: for the median firm, hedge funds do not amplify or dampen mutual fund flow trading induced volatility. 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 behaviour of hedge fund trading, however, there is also a lot of heterogeneity across stocks: the 25th and 75th percentiles of the distribution are equal to -1.12 and -0.06.

Estimates of equation (27) are reported Table 7. The interaction coefficient *d* is positive and significant for hedge funds imbalances only, but not for active mutual fund buys. It means that, across stocks, the difference between hedge fund strategies (accommodate, or exacerbate) explains the effect of fragility on volatility. Depending on the stock, hedge funds act as liquidity providers from some stocks, and front runners for others. We find no such evidence for non flow driven mutual fund trading. All in all, the data supports the view that, while hedge funds do not front run mutual fund trading on average, they consistently do so for some stocks.

VI. 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 U.S. 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 co-movements and factor betas.

Although data availability constrains our analysis to the ownership of common stocks, we expect our fragility measure to be potentially more useful among specialized assets for which ownership is more concentrated, or trading needs more correlated. It could help, for instance, to predict the probability of crash of certain asset prices. Our framework may also be extended to consider circumstances in which the correlation structure of investors' liquidity trades is endogenous.[18] In this case, it would be interesting to understand the determinants of fragility better.

[18] For example, Pedersen (2010) compares investors' rush to sell a financial asset to moviegoers exiting a burning theatre. Allen, Babus, and Carletti (2009) and Adrian and Brunnermeier (2009) point out that connections between firms and banks may contribute to systemic risk.

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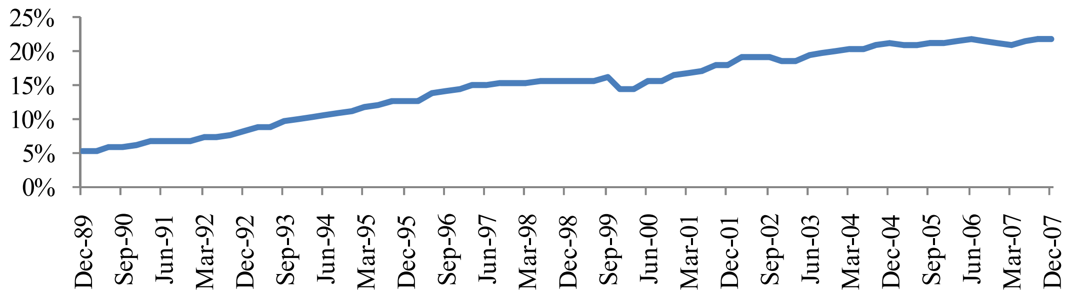
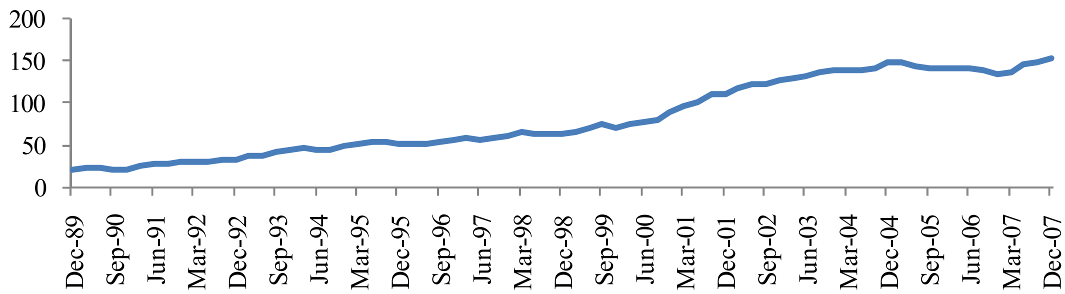
Figure 1
Mutual fund ownership, ownership dispersion, and fragility

For each characteristic, we plot the time-series of median values. Panel A shows total mutual fund ownership, expressed as a fraction of shares outstanding. Panel B shows the number of mutual fund owners. Panel C shows ownership dispersion. Panel D shows fragility.

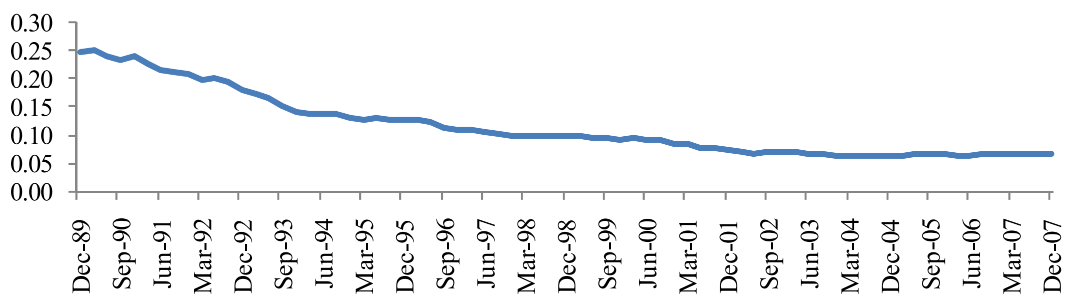
Panel A. Mutual fund ownership as a fraction of shares outstanding



Panel B. The number of mutual fund owners



Panel C. Ownership Dispersion



Panel D. Fragility

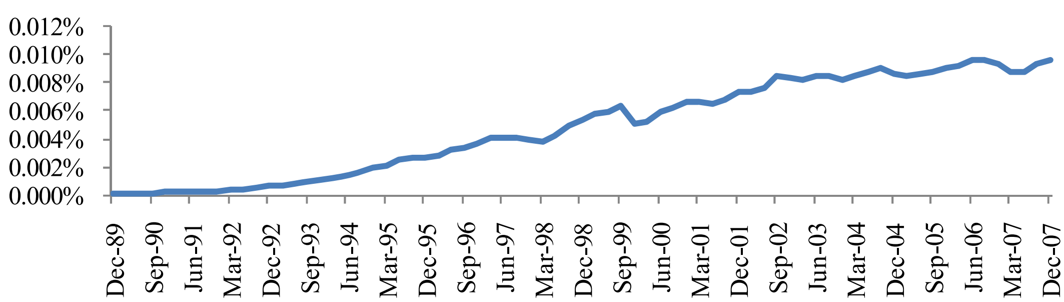
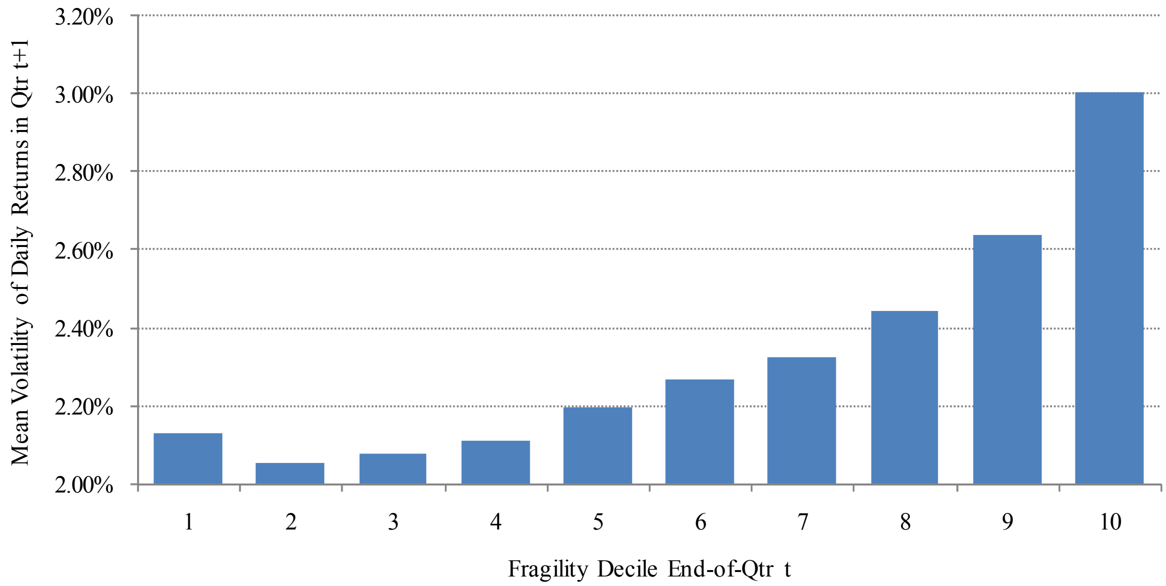


Figure 2
Fragility and volatility

Each quarter, stocks are sorted into deciles according to their estimated fragility. For each decile, we compute the mean volatility (standard deviation) of daily stock returns in the next quarter. The figures show the time series average of these volatilities, by decile. In Panel A, we draw on the full sample. In Panel B, we subset firms at least 20% owned by mutual funds.

Panel A: Full Sample



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

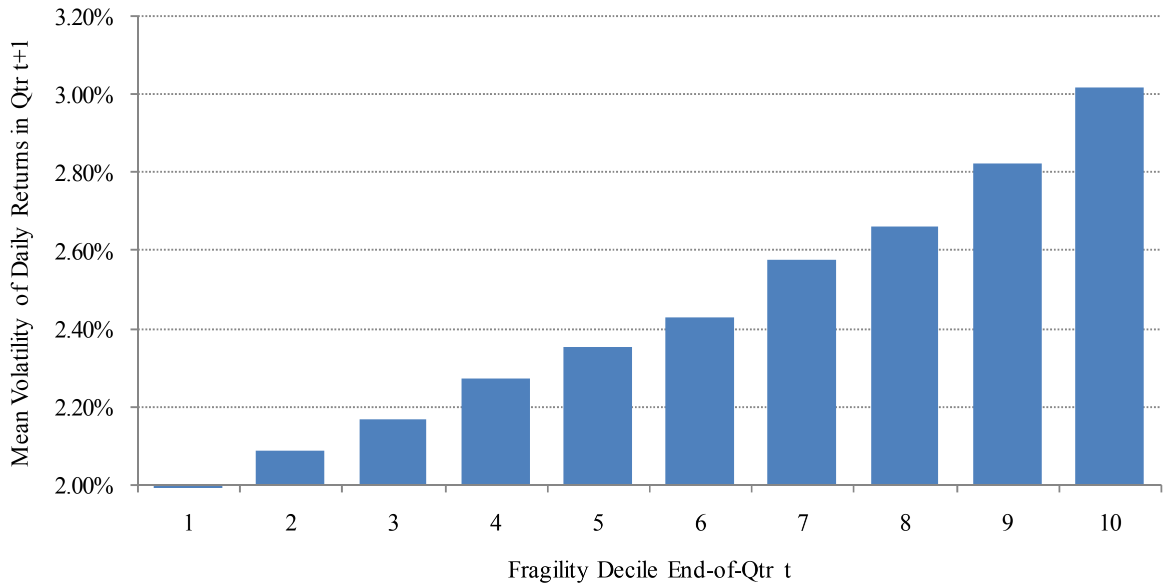
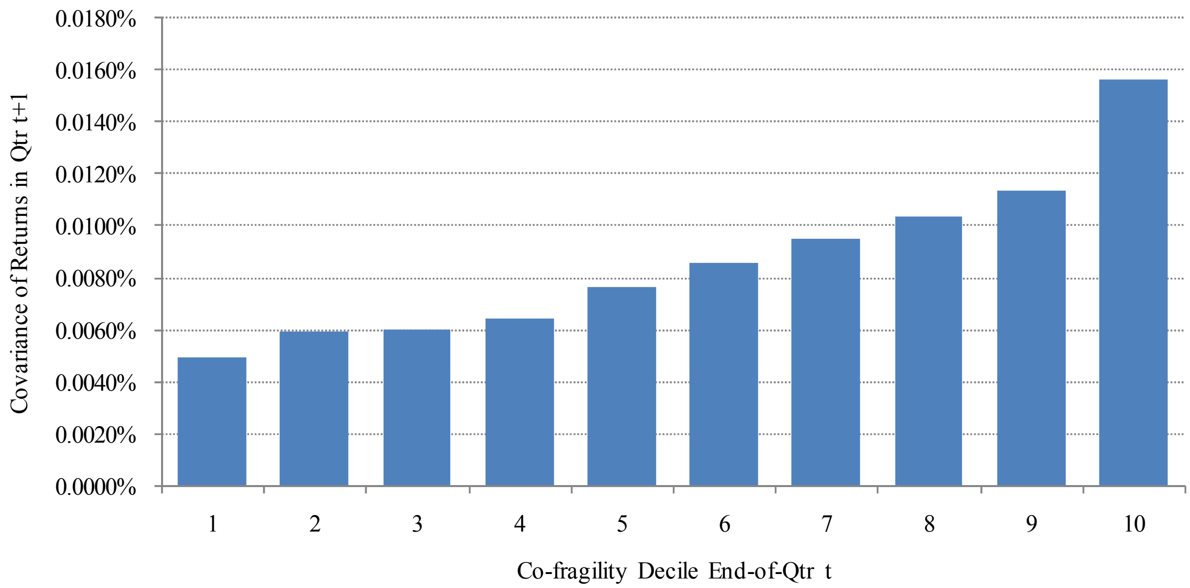


Figure 3
Co-Fragility and comovement of stock returns

Each quarter, we consider the correlation and covariance of every unique pair of stocks I and j. Each pair is sorted into deciles according to their estimated co-fragility. For each decile, we compute 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 sorts.

Panel A. Covariance



Panel B. Correlation

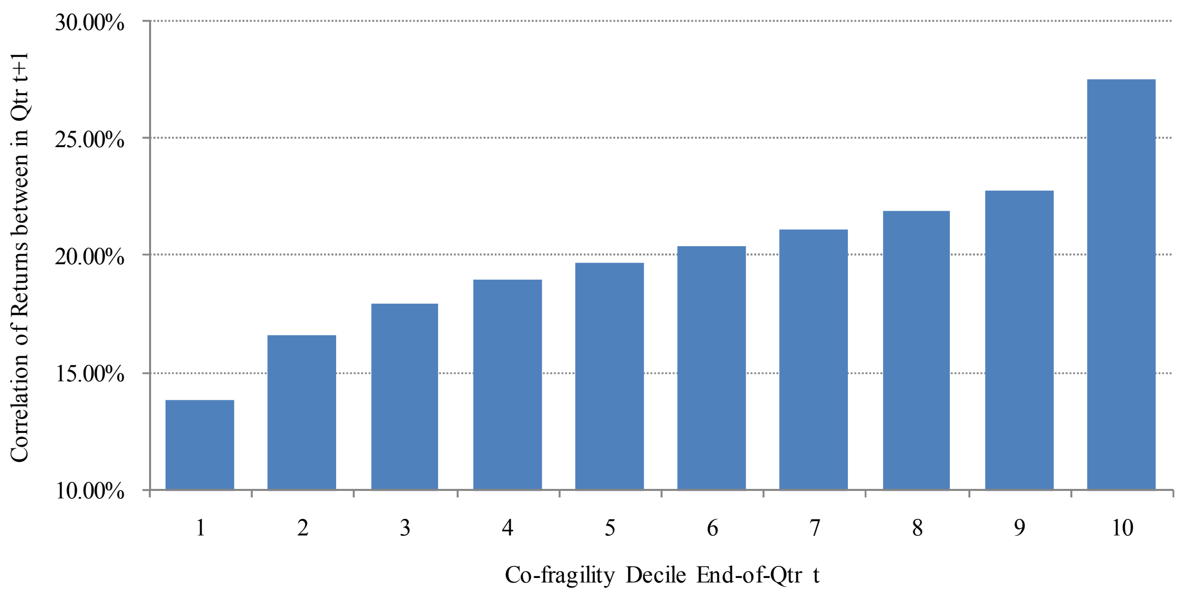
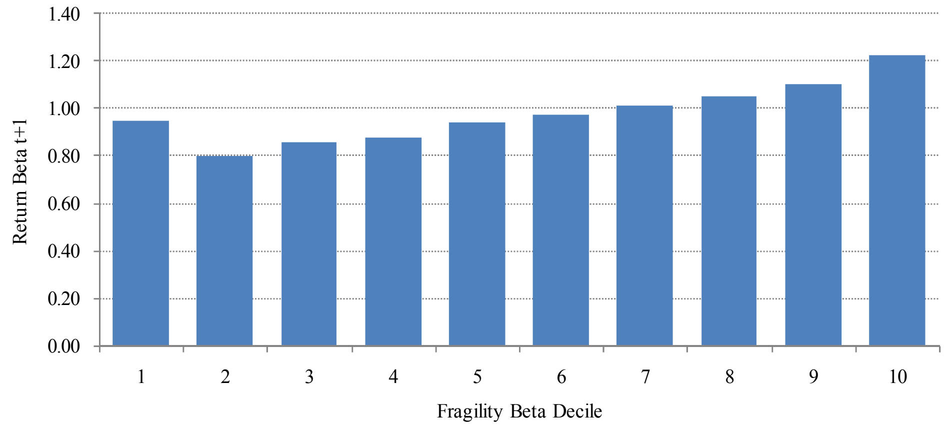


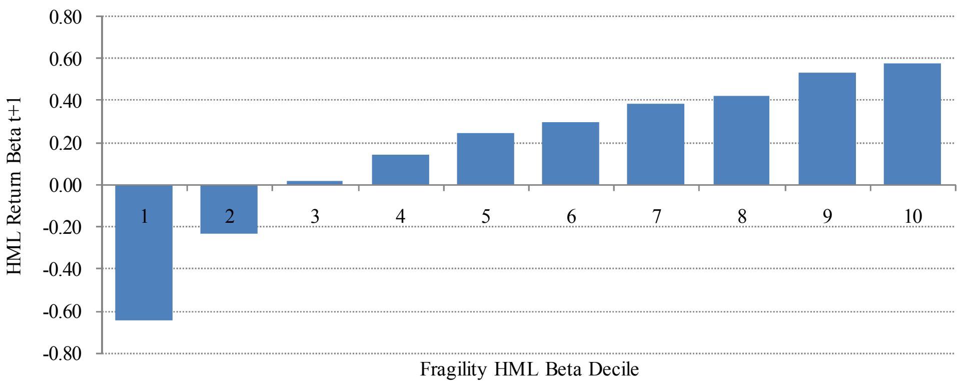
Figure 4
Fragility betas and return betas

Each quarter, we consider the correlation and covariance of every unique pair of stocks I and j. Each pair is sorted into deciles according to their estimated co-fragility. For each decile, we compute 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 sorts.

Panel A. Market Return Beta



Panel B. HML Return Beta



Panel C. SMB Return Beta

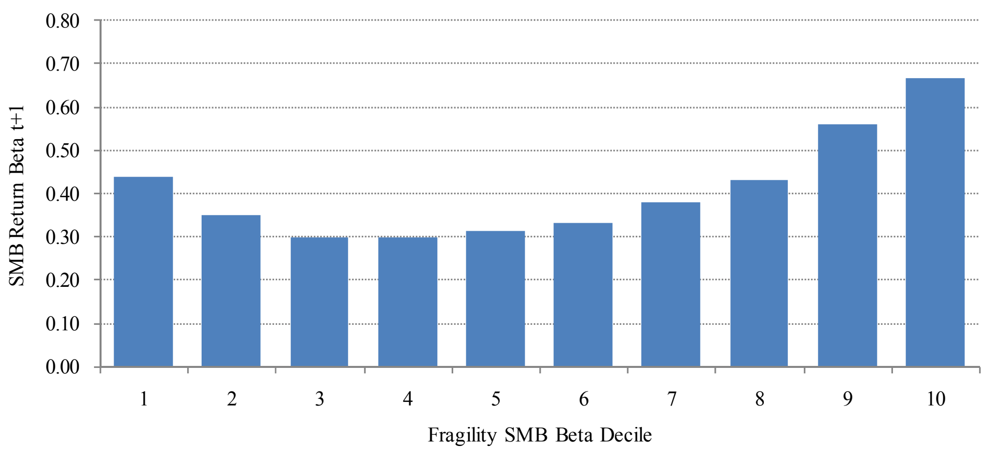


Table 1
Constructing Fragility

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

$$G = W_{it}'\Omega_t W_{it}$$

where *W* denotes the Kx1 vector of fund ownership in stock *i* and Ω is the KxK variance-covariance matrix of fund flows. K denotes the number of funds (5236 unique funds over the course of the sample). The table summarizes the inputs from the fragility calculation. H1 is the sum of the squared fund positions, scaled by total mutual fund ownership of that stock (for instance, H1=1 is there is only one fund). N Owners is 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 Ω by showing the standard deviation of fund flows, the correlation between flows ρ, and the absolute value of the correlation between flows |ρ|. Summary statistics are shown at December 1995, December 1999, and December 2003. Fragility is winsorized at the 0.5% and 99.5%.

	Mean	Min	25%	Median	75%	Max
Ownership:						
Concentration H1:						
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
N 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
Trading Needs:						
Flow volatility σ:						
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 ρ:						
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 |ρ|:						
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 F: (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 mutual fund or more and which have end-of-quarter market capitalization above the NYSE median. The table shows summary statistics for fragility-sorted portfolios, where fragility is the conditional expected variance of imbalances. Stocks are sorted into portfolios based on end-of-quarter fragility. Mutual fund share classes are aggregated to the portfolio level. 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. SUP 500 denotes index membership. M/B denotes the market-to-book 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	2nd Quintile	Middle	4th 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:

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

G denotes fragility, and *X* is a list of control variables. Fragility is the ex ante variance of imbalances and is summarized in Tables 1 and 2. Except for column (6), regressions are estimated quarter-by-quarter; we show average coefficients and t-statistics in brackets. Column (6) shows panel regressions which include a stock-level fixed effect, clustering standard errors by period. In columns (5)-(7), we further include a set of unreported controls, including: the log of unadjusted stock price, the log of market capitalization, the ratio of book equity to market equity, the past 12 months returns, the past skewness of returns, the log of the stock's age and 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 ("on diag" in equation (7)), fragility calculated using only the correlation terms of liquidity shocks ("off diag" in equation (7)), 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. Excess returns are alternately based on the single-factor market model, the 3-factor Fama and French model, or the 3-factor Fama and French model plus momentum.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Total return volatility :							1-Factor σ	3-Factor σ	4-Factor σ
√G		0.696		0.793	0.226	0.699	0.152	0.583	0.564	0.556
		[15.17]		[12.60]	[6.27]	[7.43]	[4.81]	[16.97]	[17.27]	[17.29]
√*G* (Diag)			0.489							
			[11.75]							
√*G* (Off Diag)			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 *H*				-0.002	-0.001	-0.004	-0.002			
				[-2.86]	[-1.16]	[-1.41]	[-1.88]			
σ(t)							0.524			
							[36.38]			
Constant	0.024	0.018	0.018	0.019	0.029	-0.020	0.014	0.016	.016	.016
	[15.80]	[23.68]	[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	48,906	48,906	48,906	75,495	75,495	75,495
R-squared	0.06	0.08	0.09	0.09	0.48	0.57	0.58	0.08	0.08	0.08
Additional Controls	No	No	No	No	Yes	Yes	Yes	No	No	No
Estimation	FM	FM	FM	FM	FM	Panel+FE	FM	FM	FM	FM

Table 4
Volatility and fragility based on stale holdings

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

$$\sigma_{it+1} = a + b\sqrt{G_{it}^{Stale}} + c(\sqrt{G_{it}} - \sqrt{G_{it}^{Stale}}) + X_{it}D + u_{it}$$

where G^{Scale} denotes our fragility based solely on mutual funds that have held the stock for the past year. G without the superscript denotes fragility, calculated using all available funds. In the last specification, volatility in the past quarter is used as a control. Regressions are estimated quarterly; Fama and MacBeth (1973) type mean coefficients and t-statistics are reported.

$\sqrt{G_{it}^{Stale}}$	0.236	0.29	0.134
	[4.53]	[7.49]	[6.76]
$\sqrt{G_{it}} - \sqrt{G_{it}^{Stale}}$		1.117	0.346
		[22.57]	[14.58]
σ_{it}			0.732
			[42.24]
Constant	0.023	0.02	0.005
	[22.59]	[23.77]	[14.45]
Observations	102,510	102,510	95,218
R-squared	0.02	0.10	0.51

Table 5
Co-fragility

The dependent variable is alternately the one-quarter-ahead covariance between daily returns of stocks *i* and *j*, or the one-quarter-ahead correlation between daily returns *i* and *j*:

$$\sigma_{ijt+1} = a + bG_{ijt} + X_{ijt}C + u_{ijt} \qquad \text{or} \qquad \rho_{ijt+1} = a + b\frac{G_{ijt}}{\sqrt{G_{it}G_{jt}}} + X_{it}C + u_{it}$$

where *G* denotes fragility, and *X* is a list of control variables. For the regressions in Panel B, we rescale the fragility between stocks *i* and *j* by dividing by the square root of the product of their individual fragilities. The control variables include dummy variables for whether stocks *i* and *j* are in the same 2-digit, 3-digit, or 4-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; 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: Dependent Variable = σ_{ijt+1}				Panel B: Dependent Variable = ρ_{ijt+1}			
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]
N	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 6
Co-fragility and 3-factor comovement

Regressions of market beta, HML loading, and SMB loadings on fragility betas:

$$\beta_{it+1} = a + bG^{\beta}_{it} + X_{it}C + u_{it}$$

For example, $G^{\beta HML}$ denotes the ex ante covariance between flows into stock *i* and 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. In Panel A, the dependent variable is the estimated beta of daily returns on the market, on the HML portfolio, and on the SMB portfolio. In Panel B, the dependent variables are the estimated betas from a multivariate regression of daily stock returns on the market, the HML portfolio, and then SMB portfolio.

	Panel A: Univariate Return βs						Panel B: Return βs from a Multivariate Regression					
	β		β^{HML}		β^{SMB}		β		β^{HML}		β^{SMB}	
G^{β}	0.194	0.125					0.050	-0.007				
	[11.78]	[7.40]					[5.13]	[-0.42]				
$G^{\beta HML}$			0.482	0.471					0.396	0.388		
			[21.15]	[18.52]					[18.97]	[17.78]		
$G^{\beta SMB}$					0.043	0.042					0.021	0.018
					[9.17]	[9.61]					[8.47]	[8.29]
MF Share		0.880		1.451		-0.551		0.275		1.062		-0.258
		[3.31]		[6.28]		[-3.36]		[1.87]		[5.54]		[-1.95]
N Owners (Log)		0.094		-0.106		-0.016		0.250		0.035		0.068
		[1.39]		[-1.85]		[-0.30]		[5.62]		[0.66]		[1.38]
Size (Log)		-1.010		131.210		250.160		-135.955		-46.062		208.242
		[-0.02]		[4.07]		[9.03]		[-5.33]		[-1.52]		[8.14]
BE/ME		-0.243		0.289		0.313		0.121		0.342		0.214
		[-6.97]		[6.99]		[8.44]		[4.71]		[8.27]		[7.89]
Constant	0.778	0.369	-0.205	-3.001	-0.659	-6.085	1.098	2.785	0.491	0.937	-0.363	-5.302
	[34.62]	[0.59]	[-5.26]	[-6.09]	[-14.49]	[-15.52]	[95.93]	[7.74]	[17.48]	[1.99]	[-16.98]	[-14.83]
Observations	41,759	30,877	41,155	30,519	41,155	30,519	41,155	30,519	41,155	30,519	41,155	30,519
R-squared	0.06	0.15	0.25	0.29	0.13	0.25	0.01	0.05	0.17	0.21	0.05	0.16
Fama Macbeth	Yes	Yes	Yes	Yes	Yes	Yes	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 estimate the sensitivity of order imbalance by traders of type X on total liquidity demand from mutual funds:

$$D_{Xit} = \alpha_i + \gamma_{Xit} D_{MFit} + \varepsilon_{it}$$

We consider active buys by mutual funds (X=1), buys by hedge funds (X=2), and the sum of these (X=3). We estimate these regressions on a rolling basis, so that each γ estimate is based on flows during the past 24 quarters. γ serves as an estimate of the extent to which each group X accommodates liquidity trades by mutual funds. The table reports results from second stage regressions of one-quarter-ahead volatility on fragility *G*, γ, and the interaction of γ and fragility *G*.

$$\sigma_{it+1} = a + b\,|1+\gamma_{Xit}| + c\sqrt{G_{it}} + d\,|1+\gamma_{Xit}|\sqrt{G_{it}} + u_{it}$$

These estimations are run quarterly. Average coefficients and Fama and MacBeth t-statistics are shown in brackets.

	Dependent Variable = σ_{ijt+1}		
	(1)	(2)	(3)
$\sqrt{G}$.$\|1+\gamma_1\|$ (Active MF buys + HF buys)	0.060		
	[2.95]		
$\sqrt{G}$ x $\|1+\gamma_2\|$ (HF buys)		0.138	
		[3.89]	
$\sqrt{G}$ x $\|1+\gamma_3\|$ (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($1+\gamma_1$) =	Mean($1+\gamma_2$) =	Mean($1+\gamma_3$) =
	1.033	1.245	0.781
N	32,046	48,143	43,534
R-squared	0.07	0.09	0.08