Abstract:
A securities transaction (or Tobin) tax, as usually described, is designed to slightly increase the cost of trading an asset such that informed traders are largely unaffected while uninformed noise traders find it too expensive to participate in the market. By excluding noise traders yet keeping informed traders in the market, the volatility of the asset should decrease. There should then be an inverse relationship between asset price volatility and the proportion of informed traders as a share of total traders. We test this using a well-known measure of the share of informed traders – the PIN measure of Easley et al (1997) – for a sample of U.S. equities. We find evidence supportive of the hypothesised relationship, suggesting that, all other things equal, a properly-designed and implemented transactions tax might be effective in reducing asset price volatility by a meaningful amount. Unfortunately, all other things are not equal and the overall impact of the tax on volatility is likely to be much smaller, while at the same time depressing share prices and reducing trading volume. These costs, together with uncertainties over the magnitude of the benefits, are sufficient to question the merits of policy intervention.
A securities transaction tax (STT or Tobin tax) is usually motivated by a desire to reduce the volatility of financial asset prices. As typically proposed, an STT is designed to make trading by uninformed investors sufficiently expensive that they are driven out of the market (Tobin, 1978; Stiglitz, 1989; Summers and Summers, 1989). Uninformed investors are assumed to have such short-term investment horizons that a small transaction tax would wipe out their expected trading profit and hence they would not trade (Hakkio, 1994; Tobin, 1996). Conversely, informed traders are assumed to trade over longer investment horizons such that the transaction tax has little impact on their trading behaviour. Asset prices are then set by informed traders only and so better reflect fundamental value. Similarly, the tax should reduce the variability of asset prices by removing excess (non-fundamental) volatility caused by uninformed noise traders, leaving any volatility to be of the fundamental variety.

The relatively simple logic behind Tobin’s proposal has been attacked in the literature in many ways. First, it is not clear that uninformed traders really do have a shorter investment horizon that informed traders and so it does not follow that an STT will raise the proportion of trading performed by informed investors (Schwert and Seguin, 1993). Second, some authors debate the claim that there is excess volatility in asset prices (Grundfest and Shoven, 1991). Third, on theoretical grounds, there is not an unambiguously negative effect of an STT on returns volatility. In a model where destabilising noise traders are present, Kupiec (1995) shows that the positive effect of an STT on price volatility is dominated by the reduction in the price of the traded asset for a range of plausible tax rates, leading to higher returns volatility.

Some papers address the impact of an STT on volatility directly by examining the impact of the introduction of an explicit STT either in an actual financial market (Umlauf, 1993) or in an experimental setting (Bloomfield, O’Hara and Saar, 2005). Others do so indirectly by looking at the impact of changes in non-STT transactions costs (Aliber, Chowdhry and Yan, 2003; Hau and Chevallier, 2000; Jones and Seguin, 1997). This empirical evidence has proved mixed at best. Umlauf (1993) finds that the imposition of

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1 Although the more recent surge in interest in them has been driven more by the desire to raise tax revenues for third world aid (see www.attac.org). This is a by-product of Tobin’s original proposal and not its principal purpose (Tobin, 1996)
an STT in Sweden slightly increases volatility. Jones and Seguin (1997) find that a reduction in commission costs on the NYSE raises trading volume and decreases volatility, also suggesting an STT would increase volatility. Saporta and Kan (1997) look at three changes in U.K. transactions costs and find no impact on volatility. Roll (1989) focuses on the 1987 global stock market crash and notes a small but statistically insignificant negative relationship between transactions costs and volatility across 23 stock markets. Finally, Hau and Chevallier (2000) consider an implicit increase in transactions costs in the French stock market and demonstrate a small but statistically significant decrease in volatility.

There are also many papers questioning the feasibility of transactions taxes. The most common argument is that traders will likely by-pass the tax by trading in un-taxed jurisdictions, or in related but un-taxed assets (Garber and Taylor, 1995; Kenen, 1986). Several historical examples can be produced to confirm the ingenuity of traders to avoid paying a tax that is less than universal in its application. Umlauf (1993) documents the substantial off-shore migration of stock trading following the introduction and subsequent increase in STT in Sweden. The emergence of the Eurodollar markets and migration of Nikkei put options trading are also cited.

In this paper we offer some empirical evidence that sheds light on the likely effect of a well-designed and well-imposed transactions tax. We sidestep discussion of the exact nature of this transactions tax and hence all the feasibility issues noted above. Instead, we examine one of the essential relationships in the proposal, namely the link between the relative amount of trading in an asset by informed traders relative to uninformed traders and the asset’s volatility. Proponents of the STT argue that an increase in the relative share of trading by informed traders, brought about by the tax, should decrease volatility. In this paper we examine the relationship between the volatility of U.S. common stock returns and the probability that trading in the stock is by informed investors. We measure the probability of information-based trading in a stock using the PIN measure of Easley, Kiefer and O’Hara (1996, 1997). This measure has proved useful in addressing several information-related asset pricing issues (Easley, Kiefer, O’Hara and Paperman, 1996; Easley, Hvidkjaer and O’Hara, 2002; Brown, Hildegeist and Lo, 2003). Evidence of a negative relationship would suggest that a transactions tax that
could not be avoided and which succeeded in reducing the trades of uninformed traders relative to those of informed traders might have the desired effect.

We feel that our approach has some advantages over previous research. Unlike many previous empirical studies such as Aliber, Chowdhry and Yan (2004), we are not limited to the use of just time-series methodologies. The method can both be applied cross-sectionally across stocks as well as on time-series giving it more explanatory power. A second advantage is that the method is not dependent on some particular conditions in time. This is the case with papers that perform either cross-sectional or event-study tests that examine permanent increases in tick sizes and transaction costs on stock exchanges such as Umlauf (1993). These methodologies are conditioned on the particular economic environment at a particular point in time in which the change in tick size or transaction cost happened, and their findings might not be representative. For example, when volatility is naturally time-varying, a drop in volatility around a market-wide change in transactions costs could be due to the transactions cost change or to the natural evolution of volatility (or both). It is hard for event studies to disentangle these effects. However, our panel-based approach can.

It is important to note again what this paper is not about. We will not discuss the nature of the policy change which brings about the increase in PINs. While couching the discussion in terms of STTs, it is not presupposed that an STT would necessarily increase PINs. Instead it is simply assumed that there is a policy measure – possibly radically different to an STT – that is capable of doing that. Should the evidence suggest that increasing PINs reduces volatility then the search for that policy measure has some extra impetus.

The paper is organized as follows. The next section details the derivation and estimation of the PIN measure. Section 2 details our econometric approach together with our data sources and definitions. Section 3 discusses the findings from our regressions and section 4 draws conclusions.
1. Probability of Information-Based Trading

In this section we briefly outline the model of Easley, Kiefer and O’Hara (1997) and show how the probability of information-based trading can be determined. The model is based on the trading game played by a market-maker and customers, repeated over independent and identically distributed trading intervals \( i = 1, \ldots, I \). At the start of each trading interval nature decides whether there is new information available. New information is available with probability \( \alpha \). This new information is a signal regarding the underlying asset value, and can be good news for the asset, suggesting a high price, or bad news, suggesting a low price. Conditional on new information occurring, good news happens with probability \((1-\delta)\) and bad news with probability \(\delta\). Customers arrive according to Poisson processes throughout the trading interval. The market maker sets buy and sell prices at each point in time and executes orders as they arrive. Some customers are able to observe the new information, and are termed informed. Informed customers arrive at a rate \( \mu \) (in information periods) and buy if they have observed good news and sell if they have observed bad news. Other customers and, crucially, the market maker are not able to observe the new information. Uninformed customers arrive and buy at rate \( \varepsilon_b \) and arrive and sell at rate \( \varepsilon_s \). If an order arrives at time \( t \), the market maker observes the trade and uses this information to update his beliefs about the underlying value of the asset, setting new prices accordingly. But at the start of the trading day, the probability of informed trade is given by:

\[
PIN = \frac{\alpha \mu}{\alpha \mu + \varepsilon_b + \varepsilon_s}
\]

The numerator is the expected number of trades from informed investors and the denominator is the expected total number of trades. The ratio of the two is the \textit{ex ante} probability that the first trade of the day is based on private information. This probability is decreasing in the willingness of the uninformed to trade the stock (\( \varepsilon_b \) and \( \varepsilon_s \)) and increasing when private information events are more frequent (\( \alpha \)) and when there is more informed trading (\( \mu \)).
Gross and net order flows allow the econometrician to estimate the key parameters of this model. The total number of trades made per interval ($TT = \text{buys} + \text{sells}$) equals the sum of the Poisson arrival rates of informed and uninformed customers.

$$TT = \alpha(1-\delta)(\varepsilon_b + \mu + \varepsilon_s) + \alpha\delta(\mu + \varepsilon_b + \varepsilon_s) + (1-\alpha)(\varepsilon_b + \varepsilon_s) = \alpha \mu + \varepsilon_b + \varepsilon_s$$

The trade imbalance ($K = \text{sells} - \text{buys}$) is such that

$$K = \alpha \mu (2\delta - 1)$$

More informatively, the absolute value of the net order flow, $|K|$ approximates to $\alpha \mu$ for large enough levels of $\mu$. Easley, Kiefer and O’Hara show that in trading interval $j$, conditional on the parameter vector $\Theta = [\alpha, \delta, \mu, \varepsilon_b, \varepsilon_s]^T$, the probability of observing $B$ buys and $S$ sells is given by:

$$\Pr[y_j = (B, S)|\Theta] = \alpha(1-\delta)\frac{(\mu + \varepsilon_b)^B}{B!} e^{-\varepsilon_s} \frac{\varepsilon_s^S}{S!} + \alpha\delta \frac{(\mu + \varepsilon_b)^B}{B!} e^{-\varepsilon_s} \frac{\varepsilon_s^S}{S!} + (1-\alpha)\frac{(\varepsilon_b)^B}{B!} e^{-\varepsilon_s} \frac{\varepsilon_s^S}{S!}$$

Because of the assumption of identically-distributed and independent trading intervals, the likelihood function is the product of this probability density over trading intervals.

Though a relatively simplistic model, the PIN estimates have proved useful in several applications. For example, the opening spread has been shown to be empirically related to PIN as suggested by the standard microstructure model with competitive, risk-neutral market makers. PIN estimates have been used to assess differential information contents of order flows across markets, to ascertain whether local or foreign investors trade more on private information, and to examine the information content of foreign exchange trading. Of particular importance for our study, PIN has recently been shown to matter for asset pricing.
We use the set of calendar year PINs between 1984 and 2001, kindly supplied by Soeren Hvidkjaer via his website. The sample covers all NYSE/Amex common stocks for which estimates could be obtained (see Easley, Hvidkjaer and O’Hara, 2004, for full details). The cross section dimension of the data set varies between 2,062 and 2,414 firms and the total number of observations is 41,637. We will use the time-series and cross-section variation in these PINs to estimate the impact that different levels of the probability of informed trading has on the volatility of individual stock returns. Based on this we make inference on the effect that a policy-induced exogenous change in the probability of informed trading might be expected to have on equity volatility.

2. **Estimation methods and data**

We use the natural logarithm of the standard deviation of a firm’s daily returns for each calendar year from the CRSP data files as our measure of volatility (denoted LSD).

Evidence that a higher PIN is associated with lower volatility would be supportive of a securities transaction tax.

Uncovering the nature of this relationship is, however, more complicated than a simple correlation statistic. First, several factors determine equity returns volatility besides PIN. There is, for example, a large literature on the volatility-volume relationship that suggests high trading volume is associated with high volatility. Furthermore, small firms are often thought to be more volatile than larger one, perhaps because of the portfolio nature of an investment in a large diversified firm. Volatility should then be related to both volume and size in addition to PIN.

The second complication is that all of these variables are potentially endogenous. This issue is magnified by our use of annual data, a choice determined by the computation of the PIN variable. In particular, at this frequency it is implausible that trading volume could be asserted to be exogenous. Further, the total impact of a change in PIN on volatility can only be examined if we study all the key variables simultaneously. For example, an increase in PIN may simultaneously affect trading volume and market

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2 In almost any utility framework, returns volatility is a better measure of welfare than price volatility.
capitalization in addition to volatility. If volume and market capitalization affect volatility (or PIN), then the indirect effects of the change in PIN on volatility also need to be taken into account.

To control for these factors we use a simultaneous equation framework. The system contains four equations determining volatility, volume, size and PIN of firm $i$ at time $t$:

$$
\begin{align*}
\text{volatility}_i &= a_1 + a_2 \times \text{volume}_i + a_3 \times \text{size}_i + a_4 \times \text{PIN}_i + \mu_1 C_{i1} + \epsilon_{i1} \\
\text{volume}_i &= b_1 + b_2 \times \text{volatility}_i + b_3 \times \text{size}_i + b_4 \times \text{PIN}_i + \mu_2 C_{i2} + \epsilon_{i2} \\
\text{size}_i &= c_1 + c_2 \times \text{volatility}_i + c_3 \times \text{volume}_i + c_4 \times \text{PIN}_i + \mu_3 C_{i3} + \epsilon_{i3} \\
\text{PIN}_i &= d_1 + d_2 \times \text{volatility}_i + d_3 \times \text{volume}_i + d_4 \times \text{size}_i + \mu_4 C_{i4} + \epsilon_{i4}
\end{align*}
$$

(1)

where $C_i$ is the vector of control variables included in equation $x$. The sets of control variables are specific to each regression in order to identify the system, and we discuss them in detail below.

In order to measure the direct and indirect effects of an exogenous change in PIN we express the system in (1) in matrix form (with firm and time identifiers suppressed):

$$
\begin{bmatrix}
\text{volatility} \\
\text{volume} \\
\text{size} \\
\text{PIN}
\end{bmatrix}
= \begin{bmatrix} a_1 \\ b_1 \\ c_1 \\ d_1 \end{bmatrix} + \begin{bmatrix} 0 \\ b_2 \\ c_2 \\ d_2 \end{bmatrix} \begin{bmatrix} a_2 \\ 0 \\ c_3 \\ d_3 \end{bmatrix} \begin{bmatrix} a_3 \\ b_3 \\ 0 \\ d_3 \end{bmatrix} \begin{bmatrix} a_4 \\ b_4 \\ c_4 \\ 0 \end{bmatrix} \begin{bmatrix} \text{volatility} \\
\text{volume} \\
\text{size} \\
\text{PIN}
\end{bmatrix}
+ \begin{bmatrix} \mu_1 C_{i1} \\ \mu_2 C_{i2} \\ \mu_3 C_{i3} \\ \mu_4 C_{i4} \end{bmatrix}
+ \begin{bmatrix} \epsilon_{i1} \\ \epsilon_{i2} \\ \epsilon_{i3} \\ \epsilon_{i4} \end{bmatrix}
$$

(2)

The direct effect of a change in PIN on volatility is given by the coefficient $a_4$. Denoting the $4 \times 4$ coefficient matrix by $\beta$ and the identity matrix by $I$, we can rewrite the system as:

$$
\begin{bmatrix}
\text{volatility} \\
\text{volume} \\
\text{size} \\
\text{PIN}
\end{bmatrix} = (I - \beta)^{-1} \begin{bmatrix} a_1 \\ b_1 \\ c_1 \\ d_1 \end{bmatrix} + (I - \beta)^{-1} \begin{bmatrix} \mu_1 C_{i1} \\ \mu_2 C_{i2} \\ \mu_3 C_{i3} \\ \mu_4 C_{i4} \end{bmatrix} + (I - \beta)^{-1} \begin{bmatrix} \epsilon_{i1} \\ \epsilon_{i2} \\ \epsilon_{i3} \\ \epsilon_{i4} \end{bmatrix}
$$

(3)

The total impact of an exogenous change in PIN is given by the $(1, 4)$ element of the matrix $(I - \beta)^{-1}$.

The third equation in the system is empirically difficult to model. Modelling the value of individual firms is beyond our analytical abilities. In the estimations below we will take two approaches to this equation. First, for simplicity, we assume that the coefficients $c_2$,
\( c_3 \) and \( c_4 \) are all equal to zero. This implies that there is no stock price reaction to changes in volatility, volume, or \( PIN \). Instead, the value of the firm is assumed determined by wholly exogenous factors. Second, using estimates already in the literature we relax these assumptions and parameterize this equation of the system. It turns out that the policy recommendations are not particularly sensitive to the exact nature of the relationship between size and \( PIN \).

However, since firm size enters the other three equations, we still need to model it. We measure size by the logarithm of the market capitalization value of the firms at the start of the year (denoted \( LCAP \)). \( LCAP \) is treated as an endogenous variable in the estimations below, even though we treat it as fully exogenous when imposing the zero restriction just discussed. We use the lagged logarithm of the book value of assets (\( LASSETS \)) as an instrument.

### 2.1 Identification

**Volatility equation**

We include the firm’s lagged leverage (denoted \( LEVER \)) and the logarithm of the lagged share price level (denoted \( LPRICE \)) in \( C_1 \). Leverage should be positively correlated with the share’s return volatility since for higher proportions of debt in the capital structure, more risk is being concentrated in the equity (Copeland, 2000). We measure leverage as the total book value of debt (Compustat items 9 + 34) divided by the book value of total assets (item 6). We constrain leverage to a maximum of 100% for the few cases where the calculated leverage lies above this level.

The level of the share price should be negatively related to volatility if effective or mandated minimum tick sizes are significant. For a low share price, the minimum tick requirement may mean that even the smallest share price movement is large as a proportion of the share price leading to high return volatility. \( LPRICE \) is winsorised at the top and bottom one percent of its distribution to remove the influence of penny stocks (where the logarithm of the stock price is otherwise a very large negative number) and outliers stocks with very high prices.
**Volume equation**

We define trading volume as the logarithm of the average daily ratio of total number of shares traded to total number of shares outstanding (denoted $LTO$). To identify the volume equation in the system we include $LPRICE$, the share’s lagged beta ($BETA$) and the lagged equity return partitioned into positive and negative components ($RETPOS$ and $RETNEG$) in $C_2$.³

We include $LPRICE$ in this regression because it would influence the minimum transaction value – a high share price combined with a minimum trade size specified in terms of the number of shares would lead to an expensive minimum transaction value. Thus a high share price might be expected to reduce transactions. Conversely, however, a high share price may attract attention to a stock, increasing transactions. We remain agnostic about the sign of the coefficient on this variable.

As noted by Chordia, Huh and Subrahmanyam (2005), Coles and Loewenstein (1988) and Coles, Loewenstein, and Suay (1995) argue that securities with high estimation uncertainty would tend to have high equilibrium betas. Since greater estimation uncertainty leads to greater error corrections and hence higher trading activity, beta should be positively related to turnover. We measure the variable $BETA$ from a regression of individual stock returns on the market return, over a four-year window. We impose the requirement that at least 24 monthly observations are available for estimation.

The disposition effect is the tendency of investors to lock in gains but to ride losses. Odean (1998) and Frazzini (2004) provide evidence that both individual and institutional investors appear influenced by the disposition effect. Since investors tend to sell winners to realize gains, we expect trading volume to be positively influenced by the firm’s lagged stock return if that return was positive. Since investors tend to hold onto losers, stocks with small negative returns are less likely to be traded but as losses grow, even loser stocks are traded. We expect trading volume to be positively related to the

³ That is, we include two variables characterizing the returns history for a stock. $RETPOS$ contains the share’s lagged return if that return is positive and a zero otherwise. Conversely, $RETNEG$ contains the absolute value of the lagged return if that return is negative and a zero otherwise.
magnitude of the return if that return is negative, and we also expect the coefficient on positive returns to be greater than that on negative returns.

PIN equation

We include the firm’s lagged return on assets (ROA) and lagged Tobin’s Q in $C_4$. Return on assets is measured as operating income after depreciation but before extraordinary items (Compustat item 178) divided by the book value of total assets (item 6). Following Aslan, Easley, Hvidkjaer and O’Hara (2006), we expect firms with a higher return on assets to attract informed traders since the potential for returns to information is presumably greater for such stocks.

Similarly, Aslan et al (2006) identify a negative relationship between Tobin’s $Q$ and PIN. $Q$ is constructed as the ratio of the market value to book value of assets. The market value of assets is defined as the book value of assets (item 6) plus the market value of equity (item 24 times item 25) minus the book value of common stock (item 60) and minus deferred taxes (item 74).

To avoid spurious inference, $Q$ and ROA are winsorized at the top and bottom one percent of their distributions respectively since these variables take extreme values for some firms.

In addition to these control variables, each equation in the system contains fixed effects to control for constant unobserved firm-specific characteristics, and year dummies to control for time-varying but common effects. The final sample consists of 29,122 year-firm observations from a total of 3,205 different firms.

2.2 Summary statistics and correlations

Table 1 provides summary statistics on the variables detailed above for the observations retained in the final sample. Our volatility measure, LSD, has a mean of -3.753 and a standard deviation of 0.53. The mean figure implies an average standard deviation of daily returns of around 2.3%, but the maximum and minimum figures indicate that the
standard deviations range between 0.3% and 44.9%. Nevertheless, Panel A of Figure 1 shows that the distribution of LSD is suitable for econometric analysis.

The PIN measure has a mean value of a little over 20% and a standard deviation of just over 8%. Although the maximum and minimum figures are again very wide, the distribution is well behaved (Panel B of Figure 1). Panels C and D of Figure 1 give the distributions of the other key endogenous variables LTO and LCAP, respectively.

The exogenous variables all have sensible means and standard deviations once outliers have been treated as detailed above.

The simple correlations in Table 2 suggest a positive relationship between volatility and PIN. Volatility and trading volume are positively correlated, as expected, and size is strongly negatively correlated with both volatility and PIN. Trading volume and PIN are also strongly negatively correlated.

Looking at some of the identifying relationships, we observe the expected positive correlation between volatility and lagged leverage, and the expected negative correlation between volatility and the lagged price level. Beta and trading volume are positively correlated and the expected asymmetry between the correlations of positive and negative lagged returns and volume is marked. Finally, both Q and ROA are negatively correlated with PIN. While we were expecting the latter pair to be positively related, we note that Aslan et al (2006) also find a negative simple correlation but a positive relationship in a multivariate framework.

3. Results

We estimate the three-equation version of the system in (1) using three-stage least squares. This procedure is consistent and asymptotically efficient for normally distributed disturbance terms. Further, it has the advantage of estimating the full covariance matrix and so accounts for the correlations in error terms across the equations in the system. This is particularly important in our application as all three equations refer to the same firm and year. The results are reported in Table 3.
We first focus on the regression results for the volatility equation. As expected, leverage is positively related to volatility while the level of the share price is negatively related to volatility. Both are highly statistically significant and we conclude that our identifying variables seem to do a good job in this equation. Trading volume is positively related to volatility as found in countless other studies, but firm size does not appear to be related to volatility (although both the unreported fixed effects terms and \( LPRICE \) may be capturing this relationship). The year dummies, while not reported in the table, are important in explaining common movements in equity volatilities. They appear to follow a sensible pattern, reaching peaks in the volatile years (1987, 1990 and 2000) and falling below average in the stable mid-1990s.

Turning to the relationship central to our analysis, we note that \( PIN \) is significantly negatively related to volatility. The coefficient suggests that if \( PIN \) increases by one percentage point, \( LSD \) falls by 1.68 percent. Put differently, a one standard deviation increase in \( PIN \) (8.1%) results in a 13.7 percent fall in volatility. The direct impact of an increase in \( PIN \) is therefore an economically and statistically important fall in volatility, supportive of the basic hypothesis behind securities transaction taxes. It appears that all other things equal, a policy that could increase \( PIN \) would be successful in reducing stock return volatilities.

As stressed above, however, this is only the direct impact of \( PIN \) on volatility and all other things are not equal. Determining the full impact entails also looking at the indirect effects resulting from the behaviour of the other endogenous variables.

The volume regression results indicate no impact of \( PIN \) on trading volumes, although the point estimate is very large. Similarly, at this stage, there is also no relationship leading from firm size to volume. However, volume and the four identifying and conditioning variables are all statistically significant. Firms with a higher dollar stock price turn over more frequently than lower priced firms, as do stocks with a higher beta. Trading volume is increasing with the magnitude of lagged equity returns. Surprisingly, the impact of gains is less than that of losses, inconsistent with the disposition effect.

The \( PIN \) equation suggests that increased volatility reduces \( PIN \), as does increased trading volume. Larger firms are associated with lower values of \( PIN \), consistent with
private information being a more important property of smaller firms as suggested by Easley et al (2002). While a higher $Q$ is associated with a higher $PIN$ this is not statistically significant. Reflecting the correlations noted above, a higher $ROA$ is associated with a significantly lower $PIN$. Neither of these is consistent with the findings of Aslan et al (2006) and the difference appears to be driven by the inclusion of firm fixed effects in our study.

Computing the total impact of an exogenous increase in $PIN$ on volatility also needs a measure of the impact of the other endogenous variables on market capitalization. As a first step, we assume that there is no impact from $PIN$, volume or volatility on market capitalization. The full impact of an exogenous increase of one percentage point in the value of $PIN$ is then a 0.68% decrease in $LSD$. Even taking into account the indirect influences on volatility, these results suggest that a policy-induced exogenous increase in the proportion of informed traders trading stocks would reduce volatility. However the magnitude of the impact appears limited. Based on these estimates, including the assumption of no effect from the increase in $PIN$ on market capitalization, a one standard deviation increase in $PIN$ would only reduce volatility by 5.5%. Given the difficulty in devising a policy measure capable of raising $PIN$ so far, together with the implementation problems discussed above, this is probably insufficient to attract the attention of policy-makers.

The full impact of a change in $PIN$ is noticeably down from the direct impact. The main reason is that an increase in $PIN$ raises trading volume which in turn raises volatility. However, while the coefficient on $PIN$ in the volume equation is positive, it is well below standard statistical significance levels. In Table 4, we re-estimate the system with different combinations of variables excluded from the regressions. We run different permutations because the two insignificant variables in the trading volume equation (size and $PIN$) are highly negatively correlated. Excluding either one from the volume equation makes the other significant.

Column (1) of Table 4 excludes $PIN$ from the volume equation. This restriction cannot be statistically rejected. They have little effect on the variance and $PIN$ equations but the coefficient on volatility (size) falls (rises) in the volume equation. We also note that the
disposition effect now appears in the volume equation since the coefficient on $RETPOS$ is three times the size of the coefficient on $RETNEG$.

More importantly, an exogenous one percentage point increase in $PIN$ now translates into a 3.17% fall in volatility. This change is driven by the restriction that a change in $PIN$ does not directly affect trading volume. Instead, the increase in $PIN$ reduces volatility directly, which reduces volume, which in turn reduces volatility. This reinforcing spiral magnifies the direct impact. This set of estimates implies that a policy measure capable of raising the $PIN$ by one standard deviation would reduce volatility by almost 26%. This is likely large enough to be attractive to policy-makers.

The other columns in Table 4, while restricting the system in alternative statistically reasonable ways reach broadly similar conclusions. The direct effect of an increase in $PIN$ is amplified by the indirect effects and the total magnitude is economically significant.

All of these estimates, however, are based on the assumption that there is no effect from $PIN$, volatility or volume onto firm size. While there is little strong evidence that either trading volume or volatility are relevant in asset pricing models (except insofar as total volatility is reflected in beta), Easley and O’Hara (2004) demonstrate theoretically why information risk should affect asset returns and Easley, Hvidkjaer and O’Hara (2004) provide empirical evidence that information risk as proxied by $PIN$ is a priced factor. The latter paper finds that a one percentage point increase in $PIN$ leads to a 0.25% increase in expected returns. It should be expected then, that an increase in $PIN$ would reduce market capitalization.

A back of the envelope Gordon growth model calculation gives a rough approximation of the magnitude of this effect. We suppose that the dividend, $D$, is arbitrarily set to 6. The steady-state growth rate of dividends, $g$, is given by the long-run average growth rate of US GDP of 4%. The risk-free rate, $rf$, is given by the long-run average 3-month Treasury bill rate of 2%, and the equity risk premium, $rp$, is given by its long run average, 8%. Initially we set the risk premium due to information differences, $rp^{PIN}$ equal to zero (i.e. we assume it is already subsumed in $rp$). The formula $P = D/(rf + rp + rp^{PIN} - g)$ indicates that the price level of the US equity market is 100. The one percentage point
increase in $PIN$ increases $rP^{PIN}$ to 0.0025, which reduces the price level by 4% to 96. This simple calculation suggests a coefficient value for $c_4$ of -4.0. Obviously we also apply a very wide confidence interval around this estimate. Small variations in the interest rate, growth rate or risk premiums can dramatically affect the estimated price level effect. However, 4% seems a reasonable benchmark.

If we set $c_4$ equal to 4.0 and recalculate the total effect of a one percentage point rise in $PIN$ we now find that volatility increases by 0.35% if we use the parameter values given in Table 2 (including the large but insignificant coefficient on $PIN$ in the volume equation). Using the restricted parameters in column (1) of Table 4 volatility still falls but by just 1.33%, down from the 3.17% computed under the assumption of no effect on market capitalization.

This change in the total effect happens because the increase in $PIN$ reduces stock prices, which in turn increases volatility. Note that this is not through market capitalization, which is insignificant in the volatility equation, but through the $LPRICE$ variable. The fall in $LPRICE$ also serves to reduce volume which in turn reduces volatility. However, this effect is relatively small. Further work is needed to understand the role played by $LPRICE$ in the regressions.

The total effect on volatility is negative as long as the coefficient value for $c_4$ remains above -6.6. This would appear to be at the upper end of any estimate of the sensitivity of stock prices to changes in $PIN$, implying that it is likely that a policy-induced increase in $PIN$ would be successful in reducing volatility. However, the size of the reduction would be relatively small and uncertain, especially given the parameter uncertainty associated with these estimations.

4. **Conclusions**

A securities transaction tax as usually proposed is designed to make short-term trading by uninformed investors sufficiently expensive that they are driven out of the market. Since uninformed traders are pushed out of the market, asset prices should be determined by informed investors and hence should reflect fair value. Any asset price volatility should
be of the “good” fundamental type since the “bad” excess volatility caused by uninformed speculators has been removed.

Empirical evidence on the effectiveness of securities transaction taxes is mixed at best and a neutral reader would probably conclude they do not serve their intended purpose. This is true whether explicit securities transaction taxes or a pseudo-STT such as mandated transactions costs are examined.

This failure could be for any number of reasons. One argument prominent in the literature questions whether the short-term traders most adversely affected by increased trading costs are necessarily uninformed. It is not clear a priori that the imposition of a securities transaction tax (or an increase in transaction costs more generally) raises the proportion of trades performed by informed investors.

However, if a policy measure could be devised that is capable of raising the proportion of trades performed by informed investors, would this reduce volatility as hoped? This is the key question addressed in the paper. We do so by looking at the effect of naturally occurring variations in the widely-used probability of information-based trading introduced by Easley, Kiefer, and O’Hara (1997) on returns volatility for a panel of U.S. stocks. Evidence that a higher PIN is associated with lower volatility would be, in principle, supportive of such a policy.

The general tenor of our results suggests that the impact of a policy-induced increase in PIN is likely to be successful in reducing volatility. However, the difficulty of designing and implementing such a policy is high, the benefits in terms of reduced volatility are both small and uncertain, and possible costs in terms of the wealth effects of lower stock prices would also need to be taken into account. We conclude that while we have found evidence supporting one of the links in the chain of reasoning behind imposing a securities transaction tax, the evidence is not strong enough to justify introducing an STT or to justify searching for an alternative policy capable of raising the proportion of transactions performed by informed investors.
References


Table 1

Summary Statistics

This table presents basic descriptive statistics about the variables analysed. *LSD* is the logarithm of the standard deviation of daily equity return. *LTO* is the logarithm of the average daily ratio of the number of shares traded to total number of shares outstanding. *LCAP* is the logarithm of the market capitalization of the firm at the end of the previous year. *PIN* is the probability of information-based trading as calculated by Easley, Hvidkjaer and O’Hara (2002). *LEVER* is the leverage of the firm at the end of the previous year, defined as the ratio of total debt to the book value of total assets (COMPUSTAT items [9+34]/6). *LPRICE* is the logarithm of the share price at the end of the previous year. *BETA* is the coefficient from a regression of the firm’s equity returns on the market equity return over the previous four years. *RETPOS* is the share return over the previous year if positive, zero otherwise. *RETNEG* is the absolute value of the share return over the previous year if negative, zero otherwise. *ROA* is the return on assets in the previous year, defined as operating income after depreciation but before extraordinary items divided by the book value of total assets (COMPUSTAT items 178/6). *Q* is a measure of Tobin’s Q at the end of the previous year, defined as the market value of assets divided by the book value of assets (COMPUSTAT items [6+24×25-60-74]/6). Some of the variables have been winsorised or had outliers removed as described in the text. The sample consists of 29,122 year-firm observations between 1984 and 2001. There are a total of 3,205 different firms in the sample.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSD</td>
<td>-3.753</td>
<td>0.530</td>
<td>-5.700</td>
<td>-0.800</td>
</tr>
<tr>
<td>LTO</td>
<td>0.663</td>
<td>0.871</td>
<td>-4.371</td>
<td>4.562</td>
</tr>
<tr>
<td>LCAP</td>
<td>-1.205</td>
<td>2.125</td>
<td>-8.791</td>
<td>7.447</td>
</tr>
<tr>
<td>PIN</td>
<td>0.205</td>
<td>0.082</td>
<td>0.000</td>
<td>0.910</td>
</tr>
<tr>
<td>LEVER</td>
<td>0.274</td>
<td>0.198</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>LPRICE</td>
<td>2.762</td>
<td>1.038</td>
<td>-0.575</td>
<td>4.589</td>
</tr>
<tr>
<td>BETA</td>
<td>1.002</td>
<td>0.591</td>
<td>-3.487</td>
<td>11.883</td>
</tr>
<tr>
<td>RETPOS</td>
<td>0.155</td>
<td>0.264</td>
<td>0.000</td>
<td>5.539</td>
</tr>
<tr>
<td>RETNEG</td>
<td>0.176</td>
<td>0.308</td>
<td>0.000</td>
<td>4.159</td>
</tr>
<tr>
<td>ROA</td>
<td>0.077</td>
<td>0.096</td>
<td>-0.326</td>
<td>0.930</td>
</tr>
<tr>
<td><em>Q</em></td>
<td>1.484</td>
<td>0.920</td>
<td>0.379</td>
<td>6.492</td>
</tr>
</tbody>
</table>
Table 2

Correlations

This table presents basic simple correlations between the variables analysed. \(LSD\) is the logarithm of the standard deviation of daily equity return. \(LTO\) is the logarithm of the average daily ratio of the number of shares traded to total number of shares outstanding. \(LCAP\) is the logarithm of the market capitalization of the firm at the end of the previous year. \(PIN\) is the probability of information-based trading as calculated by Easley, Hvidkjaer and O’Hara (2002). \(LEVER\) is the leverage of the firm at the end of the previous year, defined as the ratio of total debt to the book value of total assets (COMPUSTAT items \([9+34]/6\)). \(LPRICE\) is the logarithm of the share price at the end of the previous year. \(BETA\) is the coefficient from a regression of the firm’s equity returns on the market equity return over the previous four years. \(RETPOS\) is the share return over the previous year if positive, zero otherwise. \(RETNeg\) is the absolute value of the share return over the previous year if negative, zero otherwise. \(ROA\) is the return on assets in the previous year, defined as operating income after depreciation but before extraordinary items divided by the book value of total assets (COMPUSTAT items \([178/6]\)). \(Q\) is a measure of Tobin’s Q at the end of the previous year, defined as the market value of assets divided by the book value of assets (COMPUSTAT items \([6+24{\times}25-60-74]/6\)). Some of the variables have been winsorised or had outliers removed as described in the text. The sample consists of 29,122 year-firm observations between 1984 and 2001. There are a total of 3,205 different firms in the sample.

<table>
<thead>
<tr>
<th></th>
<th>(LSD)</th>
<th>(LTO)</th>
<th>(LCAP)</th>
<th>(PIN)</th>
<th>(LEVER)</th>
<th>(LPRICE)</th>
<th>(BETA)</th>
<th>(RETPOS)</th>
<th>(RETNeg)</th>
<th>(ROA)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(LTO)</td>
<td>0.179</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(LCAP)</td>
<td>-0.447</td>
<td>0.359</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>(PIN)</td>
<td>0.194</td>
<td>-0.464</td>
<td>-0.650</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>(LEVER)</td>
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<td>0.021</td>
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<td>0.023</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>(LPRICE)</td>
<td>-0.706</td>
<td>0.232</td>
<td>0.746</td>
<td>-0.439</td>
<td>-0.220</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(BETA)</td>
<td>0.215</td>
<td>0.244</td>
<td>0.001</td>
<td>-0.072</td>
<td>-0.005</td>
<td>-0.061</td>
<td></td>
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<td></td>
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<tr>
<td>(RETNeg)</td>
<td>0.050</td>
<td>0.133</td>
<td>-0.008</td>
<td>0.012</td>
<td>-0.006</td>
<td>0.078</td>
<td>0.070</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(ROA)</td>
<td>0.395</td>
<td>-0.004</td>
<td>-0.204</td>
<td>0.083</td>
<td>0.132</td>
<td>-0.405</td>
<td>0.068</td>
<td>-0.335</td>
<td></td>
<td>0.218</td>
</tr>
<tr>
<td>(Q)</td>
<td>-0.328</td>
<td>0.081</td>
<td>0.326</td>
<td>-0.200</td>
<td>-0.158</td>
<td>0.426</td>
<td>-0.020</td>
<td>0.045</td>
<td>0.218</td>
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<tr>
<td></td>
<td>0.071</td>
<td>0.174</td>
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<td>-0.181</td>
<td>-0.163</td>
<td>0.193</td>
<td>0.095</td>
<td>-0.164</td>
<td>0.085</td>
<td>0.272</td>
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</table>
Table 3

Three-Stage Least Squares Regression Results

The results of the three-stage least squares regression. The system has three equations with dependent variables $LSD$, $LTO$ and $PIN$. $LCAP$ is also treated as endogenous. In addition to the reported exogenous variables the logarithm of the previous year’s book value of assets (COMPSTAT item 6), $LASSETS$, and year dummies for each year 1984 through 2000 are used as instruments. The sample consists of 29,122 year-firm observations between 1984 and 2001. There are a total of 3,205 different firms in the sample. All regressions contain firm-specific fixed effects. The figures in parentheses are estimated standard errors. The row headed “First stage $R^2$” gives the goodness of fit statistic from the first-stage regression of the relevant dependent variable on all the exogenous variables in the system. The row headed “Pseudo- $R^2$” gives the final-stage goodness of fit statistic.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>$LSD$</th>
<th>$LTO$</th>
<th>$PIN$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$LSD$</td>
<td>0.2946</td>
<td>-0.0378</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.1393)</td>
<td>(0.0030)</td>
<td></td>
</tr>
<tr>
<td>$LTO$</td>
<td>0.4389</td>
<td>-0.0091</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0258)</td>
<td>(0.0039)</td>
<td></td>
</tr>
<tr>
<td>$LCAP$</td>
<td>-0.0083</td>
<td>0.0998</td>
<td>-0.0283</td>
</tr>
<tr>
<td></td>
<td>(0.0170)</td>
<td>(0.1983)</td>
<td>(0.0010)</td>
</tr>
<tr>
<td>$PIN$</td>
<td>-1.6808</td>
<td>2.4950</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.5599)</td>
<td>(6.7952)</td>
<td></td>
</tr>
<tr>
<td>$LPRICE$</td>
<td>-0.3666</td>
<td>0.2602</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0095)</td>
<td>(0.0563)</td>
<td></td>
</tr>
<tr>
<td>$LEVER$</td>
<td>0.1119</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0146)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$RETPOS$</td>
<td></td>
<td>0.1629</td>
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<tr>
<td></td>
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<td>(0.0238)</td>
<td></td>
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<tr>
<td>$RETNEG$</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>(0.0422)</td>
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</tr>
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<td>$BETA$</td>
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<tr>
<td></td>
<td></td>
<td>(0.0364)</td>
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</tr>
<tr>
<td>$ROA$</td>
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<td>-0.0068</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>(0.0030)</td>
<td></td>
</tr>
<tr>
<td>$Q$</td>
<td></td>
<td>0.0008</td>
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<tr>
<td></td>
<td></td>
<td>(0.0007)</td>
<td></td>
</tr>
<tr>
<td>First-stage $R^2$</td>
<td>0.460</td>
<td>0.191</td>
<td>0.138</td>
</tr>
<tr>
<td>Pseudo- $R^2$</td>
<td>0.294</td>
<td>0.126</td>
<td>0.118</td>
</tr>
</tbody>
</table>

Note: The first-stage goodness of fit statistic for the $LCAP$ regression is 0.6943.
### Table 4

Constrained Three-Stage Least Squares Regression Results

The results of three-stage least squares regressions with some coefficients constrained to zero. In column (1) PIN is set to zero in the LTO equation. In column (2) LCAP is set to zero in the LTO equation. The system has three equations with dependent variables LSD, LTO and PIN. LCAP is also treated as endogenous. In addition to the reported exogenous variables the logarithm of the previous year’s book value of assets (COMPSTAT item 6), LASSETS, and year dummies for each year 1984 through 2000 are used as instruments. The sample consists of 29,122 year-firm observations between 1984 and 2001. There are a total of 3,205 different firms in the sample. All regressions contain firm-specific fixed effects. The figures in parentheses are estimated standard errors.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>LSD</strong></td>
<td>0.9544</td>
<td>0.8759</td>
</tr>
<tr>
<td></td>
<td>(0.0532)</td>
<td>(0.0544)</td>
</tr>
<tr>
<td><strong>LTO</strong></td>
<td>0.4470</td>
<td>0.4463</td>
</tr>
<tr>
<td></td>
<td>(0.0257)</td>
<td>(0.0257)</td>
</tr>
<tr>
<td><strong>LCAP</strong></td>
<td>-0.0063</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.0170)</td>
<td>(NA)</td>
</tr>
<tr>
<td><strong>PIN</strong></td>
<td>-1.5846</td>
<td>-1.6026</td>
</tr>
<tr>
<td></td>
<td>(0.5591)</td>
<td>(0.5594)</td>
</tr>
<tr>
<td><strong>LPRICE</strong></td>
<td>-0.3688</td>
<td>-0.3687</td>
</tr>
<tr>
<td></td>
<td>(0.0095)</td>
<td>(0.0095)</td>
</tr>
<tr>
<td><strong>LEVER</strong></td>
<td>0.1013</td>
<td>0.1001</td>
</tr>
<tr>
<td></td>
<td>(0.0124)</td>
<td>(0.0120)</td>
</tr>
<tr>
<td><strong>RETPOS</strong></td>
<td>0.1520</td>
<td>0.1494</td>
</tr>
<tr>
<td></td>
<td>(0.0132)</td>
<td>(0.0129)</td>
</tr>
<tr>
<td><strong>RETNEG</strong></td>
<td>0.0488</td>
<td>0.0630</td>
</tr>
<tr>
<td></td>
<td>(0.0122)</td>
<td>(0.0114)</td>
</tr>
<tr>
<td><strong>BETA</strong></td>
<td>0.0258</td>
<td>0.0365</td>
</tr>
<tr>
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<td>(0.0057)</td>
<td>(0.0058)</td>
</tr>
<tr>
<td><strong>ROA</strong></td>
<td>-0.0016</td>
<td>-0.0064</td>
</tr>
<tr>
<td></td>
<td>(0.0052)</td>
<td>(0.0046)</td>
</tr>
<tr>
<td><strong>Q</strong></td>
<td>0.0011</td>
<td>0.0007</td>
</tr>
<tr>
<td></td>
<td>(0.0007)</td>
<td>(0.0007)</td>
</tr>
</tbody>
</table>
Figure 1
Distributions of the Endogenous Variables

Panel A: $LSD$

Panel B: $PIN$

Panel C: $LTO$

Panel D: $LCAP$