SOME EVIDENCE ON THE EFFECTIVENESS OF A SECURITIES TRANSACTION TAX FROM THE U.S. EQUITY MARKET

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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.

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A securities transaction tax (STT or Tobin tax) is usually motivated by a desire to reduce the volatility of financial asset prices.[1] 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

[1] Some of the recent surge in interest in STTs or Tobin taxes 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, Hillegeist 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 *PIN*s. While couching the discussion in terms of STTs, it is not presupposed that an STT would necessarily increase *PIN*s. 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 *PIN*s 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 reports the findings from our regressions and section 4 discusses the implications and robustness of the findings. The paper closes with a concluding section.

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 α. 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 δ. 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 μ (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 ε_b and arrive and sell at rate ε_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 *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 (ε_b and ε_s) and increasing when private information events are more frequent (α) and when there is more informed trading (μ).

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* = buys plus sells) equals the sum of the Poisson arrival rates of informed and uninformed customers.

$$TT = \underbrace{\alpha(1-\delta)(\varepsilon_b + \mu + \varepsilon_s)}_{\text{good news interval}} + \underbrace{\alpha\delta(\mu + \varepsilon_b + \varepsilon_s)}_{\text{bad news interval}} + \underbrace{(1-\alpha)(\varepsilon_b + \varepsilon_s)}_{\text{no news interval}} = \alpha\mu + \varepsilon_b + \varepsilon_s$$

The trade imbalance (*K* = sells – 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 μ. Easley, Kiefer and O'Hara show that in trading interval *j*, conditional on the parameter vector $\Theta = [\alpha, \delta, \mu, \varepsilon_b, \varepsilon_s]^{\mathrm{T}}$, the probability of observing *B* buys and *S* sells is given by:

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

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.[2]

[2] We appreciate that *PIN* is not a universally accepted concept. There is a literature that questions whether *PIN* proxies for asymmetric information (Benos and Jochec, 2007), and more specifically there are papers that question the pricing relevance of *PIN* (Duarte and Young, 2007; Mohanram and Rajgopal, 2006). We discuss the pricing of *PIN* further below.

We use the set of calendar year *PIN*s 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. We will use the time-series and cross-section variation in these *PIN*s 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*). [3] 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

[3] 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*:

$$\begin{aligned} volatility_{it} &= a_1 + a_2 \times volume_{it} + a_3 \times size_{it} + a_4 \times PIN_{it} + \mu_1 C_{1i} + \varepsilon_{i1} \\ volume_{it} &= b_1 + b_2 \times volatility_{it} + b_3 \times size_{it} + b_4 \times PIN_{it} + \mu_2 C_{2i} + \varepsilon_{i2} \\ size_{it} &= c_1 + c_2 \times volatility_{it} + c_3 \times volume_{it} + c_4 \times PIN_{it} + \mu_3 C_{3i} + \varepsilon_{i3} \\ PIN_{it} &= d_1 + d_2 \times volatility_{it} + d_3 \times volume_{it} + d_4 \times size_{it} + \mu_4 C_{4i} + \varepsilon_{i4} \end{aligned} \qquad \textbf{(1)}$$

where C_x 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):

$$\begin{bmatrix} volatility \\ volume \\ size \\ PIN \end{bmatrix} = \begin{bmatrix} a_1 \\ b_1 \\ c_1 \\ d_1 \end{bmatrix} + \begin{bmatrix} 0 & a_2 & a_3 & a_4 \\ b_2 & 0 & b_3 & b_4 \\ c_2 & c_3 & 0 & c_4 \\ d_1 & d_2 & d_3 & 0 \end{bmatrix} \begin{bmatrix} volatility \\ volume \\ size \\ PIN \end{bmatrix} + \begin{bmatrix} \mu_1 C_1 \\ \mu_2 C_2 \\ \mu_3 C_3 \\ \mu_4 C_4 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \end{bmatrix} \qquad \textbf{(2)}$$

The direct effect of a change in *PIN* on volatility is given by the coefficient a_4. Denoting the 4×4 coefficient matrix by β and the identity matrix by I we can rewrite the system as:

$$\begin{bmatrix} volatility \\ volume \\ size \\ PIN \end{bmatrix} = (I-\beta)^{-1} \begin{bmatrix} a_1 \\ b_1 \\ c_1 \\ d_1 \end{bmatrix} + (I-\beta)^{-1} \begin{bmatrix} \mu_1 C_1 \\ \mu_2 C_2 \\ \mu_3 C_3 \\ \mu_4 C_4 \end{bmatrix} + (I-\beta)^{-1} \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \end{bmatrix} \qquad \textbf{(3)}$$

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 size 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 end of the previous year (denoted *LCAP*). This value is calculated as the sum of the logarithm of the number of shares outstanding at the end of the previous year (*LSHARES*) and the logarithm of the share price at the end of the previous year (*LPRICE*). In some of the results below, *LCAP* is separated into these two components as this seems to better capture the relevant dependent variables.

2.1 Identification

Volatility equation

We include the firm's lagged leverage (denoted *LEVER*) and the logarithm of the lagged share price level (*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. Since *LPRICE* is included in the equation as an identifying variable, we also include *LSHARES* to capture the effect of company size.[4]

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 the share's lagged beta (*BETA*) and the lagged equity return partitioned into positive and negative components (*RETPOS* and *RETNEG*) in C_2.[5]

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 magnitude of the return if that return is negative, but we expect the coefficient on positive returns to be greater than that on negative returns.

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[4] To the extent that a firm's stock returns are related to its beta, the volatility of its returns should be related to its beta squared. However, beta squared is far from significant when included in the regressions. The poor performance of beta as a priced factor during the sample period perhaps accounts for this.

[5] 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.

PIN equation

We include lagged analyst coverage (*ANALYST*) and lagged number of analyst forecasts (*FCAST*) in C_4. We obtain these data from the I/B/E/S database. For each firm *i* year *t* observation in our sample, we count the number of different analysts providing fiscal-year-1-ahead earnings forecasts for company *i* within year *t*-1. We use the logarithm of 1+the number of analysts (denoted *ANALYSTS*) in the analysis below. We would expect *ANALYSTS* to be negatively correlated with *PIN* since Aslan et al (2006) argue that analyst coverage is viewed as a proxy for private information. Since many analysts make multiple one year ahead earnings forecasts for a company during a calendar year, we denote the logarithm of 1+the total number of fiscal-year-1-ahead forecasts made for company *i* in year *t*-1 as *FCAST*.

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.

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 variables *LTO* and *LCAP*, respectively.

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.

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.

Three stage least squares holds an additional advantage over, say, two stage least squares since it is quite possible that there is an omitted variable that influences all the equations in the system. This will induce covariances between the residuals of the various equations and all systems estimators will be biased and inconsistent. However the bias in 3SLS is likely to be smaller than 2SLS because it minimises the weight given to the observations where the covariances (and the impact of the omitted factor) are high.[6]

The results are reported in Table 3. Consider first the regression results for the volatility equation given in column 1. As expected, leverage is positively related to volatility and highly statistically significant. We conclude that our main identifying variable, leverage, seems to do a good job in this equation. The coefficient on *LPRICE* is negative, significant and very large in magnitude. It is unlikely that either of our two arguments for using the level of stock prices as an identifying variable could account for such a large coefficient. Neither is it a simple size effect since the coefficient on *LSHARES* is both

[6] We are grateful to Ron Smith for pointing this out to us.

small and insignificant. Relationships between share price level and several important firm characteristics, including ownership structure, default probability, and marketability[7] remain something of a puzzle in the literature and we are forced to conclude simply that the share price level appears to contain information relevant for volatility but not captured by the other explanatory variables (including the firm fixed effects).

Trading volume is positively related to volatility as found in countless other studies. 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 central relationship in 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 1.29 percent. Put differently, a one standard deviation increase in *PIN* (8.1%) results in a ten 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. We first review the other equations in the system before computing the full impact of a change in *PIN* on volatility.

The volume regression results indicate a significantly negative impact of *PIN* on trading volumes. There is also a negative relationship leading from firm size to volume, driven in this equation by the number of shares outstanding rather than the share price. All three identifying variables are statistically significant. As hypothesised, trading volume is increasing with the magnitude of lagged equity returns, and the impact of gains is almost

[7] See, among many others, Gompers and Metrick (2001), Seguin and Smoller (1997) and Fernando, Krishnamurthy and Spindt (2004).

twice as high as the impact of losses, consistent with the disposition effect. A test of equal coefficients on positive and negative returns is strongly rejected (*pval* = 0.000). Similarly, firms with a higher beta turn over more frequently than lower beta firms consistent with our expectations.

The *PIN* equation suggests that increased volatility reduces *PIN*. Trading volume is statistically insignificant. 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). The coefficients on the number of shares and the share price are very similar, suggesting that there is no need to separate market capitalization into its components in this equation. The coefficients on the number of forecasts and number of analysts are also of very similar magnitudes, but the signs differ. This suggests that an increased frequency of forecasting earnings reduces *PIN*.

To reduce the interrelatedness of our system, we estimate a more parsimonious version where we exclude the few insignificant relationships between our dependent variables noted above. Results are reported in Table 4. No parameter estimate alters significantly in this specification compared with those in Table 3, but estimated standard errors are noticeably lower. The coefficient on *PIN* in the volatility equation is slightly smaller in absolute value (-1.04) but remains significantly negative, suggesting a negative direct impact of *PIN* on volatility.

We now have three estimated equations explaining volatility, volume and *PIN*. As already noted, computing the total impact of an exogenous increase in *PIN* on volatility also needs a measure of the impact of the three modelled endogenous variables on market capitalization. This is not easy, and we will take two simple approaches to the issue.

First, we simply assume that there no impact from *PIN*, volume or volatility on market capitalization. That is, we assume there is no effect on either the price level or the number of shares outstanding from changes in *PIN*, *LSD* or *LTO*. The full impact of an exogenous increase of one percentage point in the value of *PIN* under this (strong) assumption is a 6.61% decrease in *LSD*.[8] This full impact of a change in *PIN* is

[8] This is based on the estimated coefficients from the parsimonious model. Coefficients from the full model would suggest a 6.67% drop.

noticeably larger than the direct impact. This substantial increase is mainly because an increase in *PIN* reduces trading volume substantially, which in turn also reduces volatility. The direct and the indirect channel both work to reduce volatility.

These results suggest that a policy-induced exogenous increase in the proportion of informed traders trading stocks would reduce substantially volatility. Based on the point estimates in Table 4, and including the assumption of no effect from the increase in *PIN* on market capitalization, a one standard deviation increase in *PIN* would reduce volatility by over 50%.

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 though a fall in stock prices.[9]

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 $P = D/\left(rf + rp + rp^{PIN} - g\right)$ 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

[9] Mohanram and Rajgopal (2006) cast doubt on whether *PIN* is a priced risk factor. Duarte and Young (2007) claim that liquidity effects unrelated to information asymmetry explain the relation between *PIN* and expected returns.

interest rate, growth rate or risk premiums can dramatically affect the estimated price level effect. However, 4% seems a reasonable benchmark. Our second approach to incorporating the effect of volume, volatility and *PIN* on market capitalization is therefore to assume that a one percentage point increase in *PIN* reduces *LPRICE* (but not *LSHARES*) by four percent. All other impacts remain set at zero.

Under this assumption, we now find that volatility decreases by 4.08% if we use the parameter values given in Table 4, somewhat less than the value of 6.61% computed under the assumption of no effect on market capitalization. The negative coefficient on share prices (*LPRICE*) in the volatility equation is behind this change since the falling share price has the direct effect of raising volatility, partially offsetting the effect of higher *PIN*.

Since our calculation for the impact of *PIN* on *LPRICE* is imprecise, it is important to see how sensitive our conclusions are to alternative values. We find that the total effect on volatility is negative as long as the coefficient value remains above -13.25. That is, a 1% increase in *PIN* would need to lead to stock price falls in excess of 13.25% for the overall effect on volatility to be positive. This would appear to be towards 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.

4. Discussion

Our point estimates suggest that an increase in the proportion of trades in an asset carried out by informed investors reduces the volatility of that asset. The direct impact of a one percentage point increase in *PIN* is a 1% fall in volatility. However an increase in *PIN* also reduces trading volume and, probably, stock prices. Taking these indirect effects into account magnifies the impact such that the total effect is a 5% fall in volatility.

Why are our findings so much at odds with the literature on the effect of securities transaction taxes which typically finds no impact (or even a rise in volatility) following increased costs of trading? We think the answer lies in one of the key assumption of the STT proposal. It is clear that the burden of a transactions tax falls mainly on short-term traders. These traders are assumed to be less informed than more long-term investors. Other things equal, an STT (or general increase in trading costs) increases the proportion of long-term investors trading an asset at the expense of short-term traders. It is *assumed* that this also increases the proportion of informed investors trading the asset. Our approach bypasses this leap of faith and instead directly tests the effect of altering the proportion of informed traders. We feel that our results differ from those in the literature primarily because that leap of faith is not justified – while an STT alters the investment horizon of market participants, it is not the case that it alters the informedness of traders in the desired way.[10]

How robust are our findings? We consider robustness across two dimensions. First, given that high values of *PIN* are primarily found for smaller companies (and the generalisation that many equity market phenomena are driven by small cap stocks) we consider whether the negative effect of *PIN* on volatility is driven by smaller stocks. Second, we examine whether the results are consistent through time.

Panel A of Table 5 reports the results of splitting the sample into quintiles based on market capitalisation. The first column of figures reports the direct effect of an increase in *PIN* on volatility, and columns 2 and 3 report the total effect assuming zero and four percent drops in equity prices following a one percentage point increase in *PIN* on asset prices respectively. The results show that the effect of *PIN* on volatility is not driven by small (or large) cap stocks. The magnitude of the direct effect of an increase in *PIN* on volatility is larger in each quintile than in the pooled results above, but the total effect is, if anything, larger for the mid-cap stocks in quintiles 2-4 than for either extremely small or extremely large stocks. Nevertheless, even the extreme quintiles show a negative relationship.

Panel B of Table 5 reports the results of examining sub-periods of the full sample. The point estimates of the direct impact show some instability, being low at the start and end of the sample, but are nevertheless always negative. However, the total effects are both

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[10] In addition, we have no doubt that in some cases resourceful investors simply bypassed the tax rendering it ineffective.

more stable and more in line with the full sample results, and again show a negative relationship between *PIN* and volatility.

We note that robustness tests of this nature make identification of our system more difficult. Splitting the sample into sub-periods makes the estimations of the important firm fixed effects harder and reduces the variability of some of our identifying variables. Analyst coverage, for example, is loss extensive in the early part of our sample meaning the *PIN* equation is less well determined. Similarly, splitting the sample into quintiles by market cap reduces the power of leverage to identify the volatility equation for larger quintiles. Experiments with additional identifying factors (such as beta squared in the volatility equation) or less dramatic partitioning of the data helped to improve the statistical performance of the models but did not change the main inference reached – in all specifications both the direct and total effects of an increase in *PIN* reduce the volatility of equity returns.

5. 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 but may be sufficient to justify searching for an alternative policy capable of raising the proportion of transactions performed by informed investors.

References

Aliber, Robert, Bhagwan Chowdhry, and Shu Yan (2003) "Some evidence that a Tobin tax on foreign exchange transactions may increase volatility" *European Finance Review* 7.

Aslan, Hadiye, David Easley, Soeren Hvidkjaer and Maureen O'Hara (2006) "The determinants of informed trading: Implications for assets pricing" *mimeo*.

Benos, Evangelos and Marek Jochec (2007) "Testing the PIN variable" *mimeo*.

Bloomfield, Robert, Maureen O'Hara, and Gideon Saar (2005) "The limits of noise trading: An experimental analysis" *mimeo*.

Brown, Stephen, S. Hillegeist and K. Lo (2004) "Conference calls and information asymmetry" *Journal of Accounting and Economics* 37, 343-366.

Coles, J. and U. Loewenstein (1988) "Equilibrium pricing and portfolio composition in the presence of uncertain parameters" *Journal of Financial Economics* 22, 279-303.

Coles, J., U. Loewenstein, and J. Suay (1995) "On equilibrium pricing under parameter uncertainty" *Journal of Financial and Quantitative Analysis* 30, 347-376.

Copeland, Laurence (2000) "The determinants of implied volatility: A test using LIFFE option prices" *Journal of Business Finance and Accounting* 27, 859-885.

Duarte, Jefferson and Lance Young (2007) "Why is PIN priced?" *Journal of Financial Economics*, forthcoming.

Easley, David, Nicholas Kiefer, and Maureen O'Hara (1996) "Cream-skimming or profit-sharing? The curious role of purchased orders" *Journal of Finance* 51, 811-833.

Easley, David, Nicholas Kiefer, and Maureen O'Hara (1997) "One day in the life of a very common stock", *Review of Financial Studies* 10, 805-835.

Easley, David, Nicholas Kiefer, Maureen O'Hara, and Joseph Paperman (1996) "Liquidity, information and infrequently traded stocks" *Journal of Finance* 51, 1405-1436.

Easley, David, Soeren Hvidkjaer, and Maureen O'Hara (2002) "Is information risk a determinant of asset returns?" *Journal of Finance* 57, 2185-2221.

Easley, David and Maureen O'Hara (2004) "Information and the cost of capital" *Journal of Finance* 59, 1553-1583.

Fernando, Chitru S., Srinivasan Krishnamurthy, and Paul A. Spindt (2004) "Are share price levels informative? Evidence from the ownership, pricing, turnover and performance of IPO firms" *Journal of Financial Markets* 7, 377-403.

Frazzini, Andrea (2006) "The disposition effect and under-reaction to news" *Journal of Finance* 61, 2017-2046.

Garber, Peter and Mark P. Taylor (1995) "Sand in the wheels of foreign exchange markets: A sceptical note" *Economic Journal* 105, 173-180.

Gompers, Paul A., and Andrew Metrick (2001) "Institutional investors and equity prices" *Quarterly Journal of Economics* 116, 229-259.

Grundfest, Joseph A., and John B. Shoven (1991) "Adverse implications of a securities transactions exercise tax" *Journal of Accounting, Auditing and Finance* 6, 409-442.

Hakkio, Craig (1994) "Should we throw sand in the gears of financial markets?" Economic Review Federal Reserve Bank of Kansas City, 17-30.

Hau, H. and Chevallier, A. (2000), "Estimating the volatility effect of a security transaction tax" *mimeo* ESSEC Graduate Business School

Jones, C.M. and P.J. Seguin (1997) "Transactions costs and price volatility: Evidence from commission deregulation" *American Economic Review* 87, 728-737.

Kenen Peter B. (1996) "The feasibility of taxing foreign exchange transactions" in Mahbub ul Haq, Ige Kaul and Isabelle Grunberg (eds.) *The Tobin Tax*, Oxford University Press, Oxford

Kupiec, Paul (1995) "A securities transactions tax and capital market efficiency" *Contemporary Economic Policy* 13, 101-112.

Odean, Terrence (1998) "Are investors reluctant to realize their losses?" *Journal of Finance* 53, 1775-1798.

Mohanram, Partha and Shiva Rajgopal (2006) "Is information risk (PIN) priced?" *mimeo*.

Roll, Richard (1989) "Price volatility, international market links, and their implications for regulatory policies" *Journal of Financial Services Research* 3.

Saporta, Victoria and K. Kan (1997) "The effects of stamp duty on the level and volatility of UK equity prices" *mimeo* Bank of England.

Schwert, G.W. and P.J. Seguin (1993) "Securities transaction taxes: An overview of costs, benefits and unresolved questions" *Financial Analysts Journal* 49, 27-35.

Seguin, Paul J., and Margaret Monroe Smoller (1997) "Share price and mortality: An empirical evaluation of newly listed Nasdaq stocks" *Journal of Financial Economics* 45, 333-363.

Stiglitz, Joseph (1989) "Using tax policy to curb speculative short-term trading" *Journal of Financial Services Research* 2, 101-116.

Summers, Lawrence, and Victoria Summers (1989) "When financial markets work too well: A cautious case for a securities transaction tax" *Journal of Financial Services Research* 2, 163-188.

Tobin, James (1978) "A proposal for international monetary reform" *Eastern Economic Journal* 4, 153-159.

Tobin James (1996) "Prologue" in Mahbub ul Haq, Ige Kaul and Isabelle Grunberg (eds.) *The Tobin Tax*, Oxford University Press, Oxford.

Umlauf, S.R. (1993) "Transaction taxes and the behavior of the Swedish stock market" *Journal of Financial Economics* 33, 227-240.

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 ration 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. There are a total of 3,205 different firms in the sample.

Variable	Mean	Std Dev.	Min	Max
LSD	-3.753	0.530	-5.700	-0.800
LTO	0.663	0.871	-4.371	4.562
LCAP	-1.205	2.125	-8.791	7.447
PIN	0.205	0.081	0.000	0.910
LEVER	0.274	0.198	0.000	1.000
LPRICE	2.762	1.038	-0.575	4.589
BETA	1.002	0.591	-3.487	11.883
RETPOS	0.155	0.264	0.000	5.539
RETNEG	0.176	0.308	0.000	4.159

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 ration 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. 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.

	LSD	*LTO*	*LCAP*	*PIN*	*LEVER*	*LPRICE*	*BETA*	*RETPOS*
LTO	0.179							
LCAP	-0.447	0.359						
PIN	0.194	-0.464	-0.650					
LEVER	0.184	0.021	-0.083	0.023				
LPRICE	-0.706	0.232	0.746	-0.439	-0.220			
BETA	0.215	0.244	0.001	-0.072	-0.005	-0.061		
RETPOS	0.050	0.133	-0.008	0.012	-0.006	0.078	0.070	
RETNEG	0.395	-0.004	-0.204	0.083	0.132	-0.405	0.068	-0.335

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*. In addition to the reported exogenous variables the logarithm of the previous year's book value of assets (COMPUSTAT item 6), *LASSETS*, and year dummies for each year 1984 through 2000 are used as instruments. The sample consists of 28,424 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. Significance at the 1%, 5% and 10% level are denoted ***, **, and * respectively.

	Dependent variable		
	LSD	*LTO*	*PIN*
LSD		-0.0171	-0.0459***
		(0.1698)	(0.0106)
LTO	0.3785***		-0.0043
	(0.0258)		(0.0066)
LSHARES	-0.0092	-0.2828***	-0.0305***
	(0.0192)	(0.0917)	(0.0008)
PIN	-1.2880**	-9.6345***	
	(0.5850)	(2.8699)	
LPRICE	-0.3519***	-0.0075	-0.0292***
	(0.0089)	(0.0820)	(0.0038)
LEVER	0.1072***		
	(0.0125)		
RETPOS		0.2137***	
		(0.0258)	
RETNEG		0.1100***	
		(0.0179)	
BETA		0.0586***	
		(0.0160)	
FCAST			-0.0043***
			(0.0012)
ANALYST			0.0040***
			(0.0013)

Table 4

Three-Stage Least Squares Regression Results, Parsimonious System

The results of the three-stage least squares regression. The system has three equations with dependent variables *LSD*, *LTO* and *PIN*. In addition to the reported exogenous variables the logarithm of the previous year's book value of assets (COMPUSTAT item 6), *LASSETS*, and year dummies for each year 1984 through 2000 are used as instruments. The sample consists of 28,424 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. Significance at the 1%, 5% and 10% level are denoted ***, **, and * respectively.

	Dependent variable		
	LSD	*LTO*	*PIN*
LSD			-0.0661***
			(0.0062)
LTO	0.3813***		
	(0.0198)		
LSHARES		-0.2700***	-0.0297***
		(0.0146)	(0.0008)
PIN	-1.0423***	-9.3485***	
	(0.1148)	(0.3816)	
LPRICE	-0.3481***		-0.0353***
	(0.0044)		(0.0018)
LEVER	0.1017***		
	(0.0106)		
RETPOS		0.2170***	
		(0.0127)	
RETNEG		0.0942***	
		(0.0114)	
BETA		0.0346***	
		(0.0056)	
FCAST			-0.0040***
			(0.0007)
ANALYST			0.0037***
			(0.0010)

Table 5

Robustness Tests

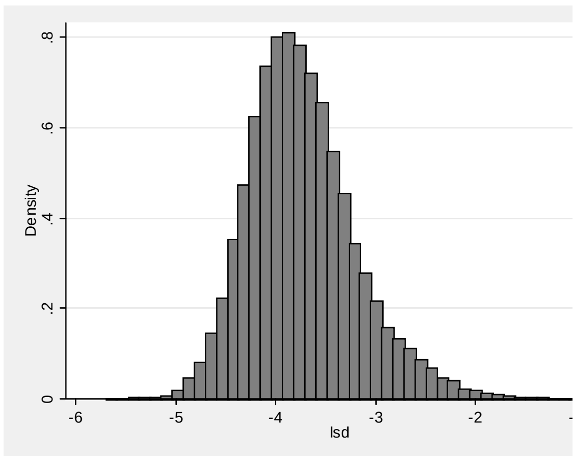
Results from estimating the parsimonious model of Table 4 on various subsets of the data. Panel A splits the sample into quintiles according to market capitalisation. Panel B splits the data sample into three sub-periods. The first column reports the direct effect of *PIN* on *LSD*, the second column reports the total impact of a one percentage point increase in *PIN* on *LSD* assuming no change in stock prices, and the third column reports the total impact of a one percentage point increase in *PIN* on *LSD* assuming a four percent drop in stock prices.

	Direct	Total (0%)	Total (-4%)
Panel A:			
Full Sample	-1.042	-6.613	-4.956
MktCap Smallest	-2.035	-3.159	-1.738
MktCap 2	-3.332	-8.354	-6.801
MktCap 3	-3.281	-8.108	-6.845
MktCap 4	-2.920	-10.668	-9.943
MktCap Largest	-7.258	-5.442	-4.813
Panel B:			
1984-1989	-0.381	-4.951	-3.784
1990-1995	-2.955	-8.236	-6.199
1996-2001	-0.588	-8.792	-7.590

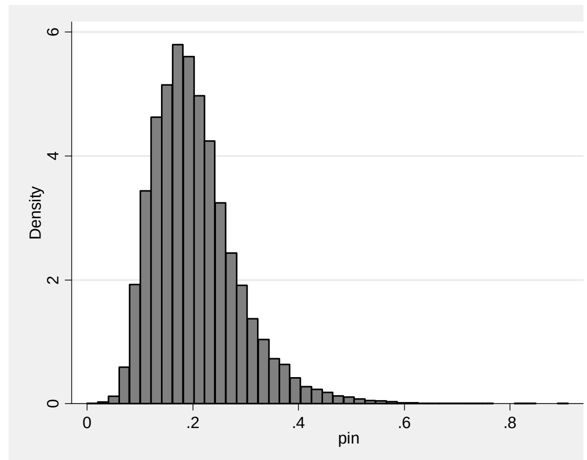
Figure 1

Distributions of the Endogenous Variables

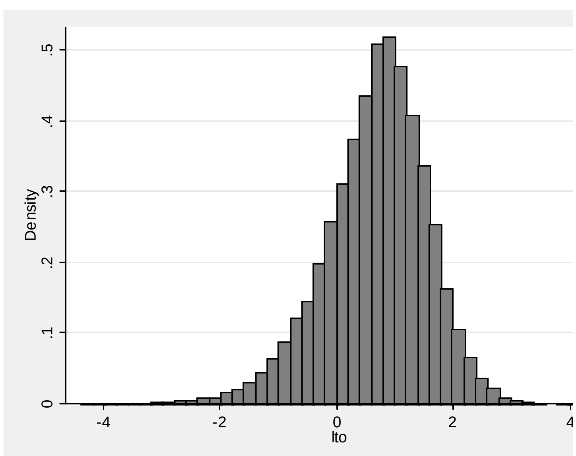
Panel A: *LSD*



Panel B: *PIN*



Panel C: *LTO*



Panel D: *LCAP*