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# DOES INFORMATION ASYMMETRY MATTER IN EMERGING MARKETS? EVIDENCE FROM SIX LATIN AMERICAN STOCK MARKETS

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**Abstract**

Does informed trading affect emerging stock markets? Market microstructure literature establishes that information asymmetry reduces liquidity and moves prices in the direction of the trade. We test for this theoretical implication by running the dynamic PIN model of Easley, Engle, O'Hara y Wu (2008), for stocks of Argentina, Brazil, Chile, Colombia, Mexico and Peru. We use panel data models to test for the relation between PIN, as a measure of information asymmetry, bid-ask spreads, as a measure of liquidity, and returns. The reported results confirm the mentioned theoretical implications, the empirical validity dynamic PIN model, and contribute to a better understanding of price formation in emerging markets.



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## Introduction

Classical microstructure models are based on the assumption that information asymmetry across the agents that trade in a financial market move asset prices and are an important determinant of liquidity. The liquidity provider faces adverse selection by trading with unidentified informed traders among many uninformed traders. The higher the probability of informed trading, the larger the transaction costs and the lower the liquidity in the market (Kyle 1985; Glosten y Milgrom 1985 and O´Hara 1998). In contrast, Samuelson (1958) and Grossman y Stiglitz (1983) remark that informed traders improve market efficiency by making the prices better reflect their fundamental values, earning extra returns in the process. In the real markets, informed agents trade according to estimations of the fundamental value of the stock, betting on macro or firm specific announcements, exploting predictable patterns in prices, or using insider trading (Harris 2003).

Whereas the efficient market hypothesis assumes that prices reflect all the available information, this clearly depends on the cost of acquiring that information, and the transaction costs required in using it ( Harris 2003). One important part of those transaction costs comes from information asymmetry, already mentioned (Hasbrouck, 2007). Information asymmetry allows informed trader to earn extra returns in the markets at the expense of uninformed markets, and induce liquidity providers to increase the cost of trading in the market (Kyle 1985)

An empirical study of the effects of informed trading depends critically on a valid measure of that variable. Easley, Kiefer, O´Hara and Paperman (1996), and Easley, Kiefer and O´Hara (1997) put forward the probability of informed trading (PIN) as a good proxy of information asymmetry reflected in the trades, based on the assumption that informed traders cause an important part of the observed order imbalance. A theoretical support for the PIN model can be found on models on Copeland and Galai (1983), Kyle (1985) and Glosten and Milgrom 1985), based on the assumption that informed traders are always on the right side of the trade. This might be explained by their ability to use private information or by their higher ability to process public information. Using the data on directional individual trades, the PIN model estimates the probabilities of informed and uninformed trading based on the order imbalance and the total number of transactions. Easley, Kiefer, O´Hara and Paperman (1996), and Easley, Kiefer and O´Hara (1997) originally offer a "static" version of the PIN model, with constant arrival rates of informed and uninformed trades. However, Easley, Engle, O'Hara y Wu (2008) (henceforth EEOW) propose a more general and realistic dynamic model that provides for the dynamic arrival of informed and uninformed trades with auto and cross correlations among them. Those correlations can be explained by herding effects (Lee, Liu, Roll y Subrahmanyan 2004; Scharfstein and Stein, 1990), or by the splitting of large orders to reduce the price impact (Kyle, 1985; Harris, 2003 ).

This paper presents evidence that informed trading moves prices and reduces liquidity in the six largest Latin-American stock markets, in agreement with the market microstructure theoretical models of information asymmetry. To estimate the degree of information asymmetry we use the dynamic PIN model of EEOW (2008), which, to the extent of our knowledge, has only been used in US stocks. EEOW (2008) presents a direct relation between PIN and liquidity for a sample of 16 US stocks, and Easley, Hvidkjaer y O'Hara (2002) find evidence of PIN predicting returns in 1843 NYSE stocks. Specifically, we test whether the dynamic PIN is related to a decrease in liquidity and returns for most of the stock of the six larger Latin American markets. As a contribution to the market microstructure literature, this study serves as validation of theoretical and empirical models of the role of information asymmetry in emerging markets. Besides, finding evidence of this relationship can help agents to optimize trading strategies, reducing transaction costs, and improving market efficiency.

The group of six Latin American emerging markets is an interesting object for market microstructure studies, almost not explored in similar studies, for their wide variety of size, liquidity and stage of development. The market liberalization of emerging markets in the late 80's and early 90's, as well as their impressive performance in the 2000's, including the aftermath of the 2008 crisis, have marked the increasing role of emerging markets in the world financial system, including those of Latin America. Concerns still linger about the liquidity, institutional design, transparency and efficiency of emerging markets. Thus, this study contributes to the literature in international finance by measuring and comparing both the liquidity and the informed trading intensity in a set of six emerging markets from the same region for a better understanding of those markets.

To the extent of our knowledge, this is the first study that uses the dynamic PIN in an extensive selection of stocks in a group of stock markets. Market microstructure studies have been mostly conducted in US and other G7's markets, without comparing across markets, including studies estimating the PIN model. A direct precedent of the current study is Cruces and Kawamura (2005) who estimate the static PIN for seven Latin-American stock markets, finding a cross-sectional relation between the quality of corporate governance and the average PIN across countries. In contrast, this study estimates the dynamic PIN model, which allows to be used in time series and panel data studies, reporting evidence of their effect on liquidity and returns, and comparing those effects across countries. Two other precedents are Lesmond (2005) who conducts a comprehensive study of liquidity in 31 emerging markets, in quarterly frequency and using liquidity proxies, and Beakert, Harvey and Lundblad (2005), who use monthly proxies of liquidity to test whether liquidity is a priced factor in a set of 19 emerging markets.

The rest of this paper is organized as follows: Section I summarizes the most relevant features of the dynamic PIN model and the theoretical relation between information asymmetry and asset liquidity and returns. Section II describes the data and defines the variables. Section III presents and discusses the results found for the six Latin-American stock markets. Finally, section IV presents the conclusions.

## I. Background

Model of Dynamic Probability of informed trading

The static PIN model describes the arrival of informed and uninformed trades to a market where a designated market maker trades a risky asset with informed and uninformed traders. A description of the model in presented in the Appendix. The dynamic PIN models extend the static PIN one, by allowing for the rate of arrival of informed trading, and uninformed trading varying over time. Lei and Wu (2005) develop a model with a variable arrival of informed and uninformed transactions, concluding that informed traders can observe the level of uninformed trading , adjusting their trading strategies in consequence to maximizing their utilities, as implied by the model of Kyle (1985). With the results of their model, they estimate a dynamic PIN measure that turns out to be good forecast for several liquidity measures.

EEOW (2008) develop a PIN model with dynamic rates of arrival of informed and uninformed traders conditional on the last values of those rates. This way, the probability of informed trading varies over time, but can be estimated to some extent from the previous history of trades, as described in the Appendix. Using this dynamic PIN, they found an increase (reduction) of informed trading before (after) earnings announcements.

Finally, Tay, Ting, Tse, and Warachka. (2009) propose a dynamic PIN model based on asymmetric autoregressive Conditional Duration" (AACD), first proposed by Bawens and Giot (2003), that allows for a joint modeling of the duration and direction of trades. This results in a PIN estimation not only daily but also on an intraday basis.

Information asymmetry and its relation with Liquidity and returns

Market microstructure theory poses that informed trading should reduce liquidity, as the market maker widens the spread between quotes and increases the cost of large trades, recognizing the higher adverse selection she faces on trading with informed traders (Kyle, 1985; Hasbrouk, 1991). While Easley, Hvidkjaer y O'Hara (2010) derive a theoretical relationship between PIN and margins, Easley, Kiefer y O´Hara (1997) provide evidence of this relation in US stocks. Hasbrouck (1988, 1991a y 1991b) establishes from a theoretical point of view and provides evidence that trades cause revisions in market quotes. Chung, Li y McInish (2005), using the PIN measure, provide evidence that larger information asymmetry increases the spread between quotes. EEOW(2008) goes further, by using the dynamic PIN to predict the opening of quotes on the next day.

On the other hand, Market microstructure theory also implies that informed trades should move prices in the direction of the trade (Kyle, 1985; Glosten and Milgrom 1985, Easley and O'Hara 1992). Easley, Hvidkjaer y O'Hara (2010) find that asymmetric information, as measured by PIN, exhibits a significant relation with the asset returns,  explained by the extra returns required to buy assets with larger information asymmetry. Finally, several studies have linked PIN with an excess return in stocks (Duarte y Young, 2009; Easley y O'Hara, 2004).

## II Data

Intraday data to estimate the dynamic PIN model and the liquidity measures is obtained from Bloomberg for the largest six Latin American stock markets: Argentina, Brazil, Chile, Colombia, Mexico and Perú, for the period August 2 2010 to March 4 2011. We used several filters to select the stocks. Starting from a total of 1,073 stocks traded in the period, we chose the 582 ones with an average daily trading value over US$ 10,000. For that group we obtained from Bloomberg the tick-by-tick data on quotes (bid and ask prices), and transaction prices and volumes for the sampled period.  Furthermore, we had to restrict the sample to the 343 stocks traded in more that 90% of the trading days to be able to estimate the dynamic PIN model. This selection still includes more than 85% of the total trading value for each country.

Following the standard procedure in the literature, Lee and Ready (1991), each transaction is classified as a buy or a sell, depending on the trade price and the current quotes. In a stock-day basis, we calculated as input data for the PIN estimation, the balanced trades (total number of buys plus sells) and the trade imbalance ( absolute value of buys minus sells).  The dynamic PIN is estimated, in a individual stock basis, with the model of EEOW(2008), based on a bivariate generalized autoregressive intensity process for the arrival rates of informed and uninformed trades. For each stock, the parameters of the model were estimated by Maximum Likelihood using MATLAB, starting with 120,000 seeds to make sure of obtaining the global maximum inside the feasible optimization region (Yan y Zhang, 2010).

As for liquidity measures, we estimate the quoted bid-ask spread as well as the effective bid-ask spread (Goyenko, Holden y Trzcinca, 2009; Chordia, Roll y Subrahmanyam, 2001). The quoted spread is estimated on a stock-day basis as the average of the logarithmic difference between the bid and ask prices at the end of each 5-min interval *t*:

$$Quoted\ spread_t = ln(Bid_t) - ln(Ask_t) \qquad [1]$$

The effective spread is averaged for each stock day, based on the transaction price $P_k$ for the $k$-th preade and the midpoint price $M_k$, namely the average between the prevailing bid and ask, as follows:

$$Effective\ spread_{\ k} = 2\left|ln(P_k) - ln(M_k)\right| \qquad [2]$$

## III Results

Summary statistics

Table 1 summarizes per country the results of the estimation of the dynamic PIN and the liquidity measures. It's remarkable the difference between the average PIN and liquidity among the studied countries, according to their trading activity and size. With a *t*-test we find that the largest and more active stock markets, Brazil and Mexico, exhibit a lower degree of asymmetric information, i.e. a lower average PIN than the others. In contrast, Argentina and Peru, the smaller markets, exhibit the highest degree of asymmetric information. This inverse relation between information asymmetry and market development is also evident on the average bid-ask spread that tends to be smaller for the largest markets. The inverse relation between asymmetric information and liquidity is consistent with the theoretical models and empirical evidence on the market microstructure literature mentioned above.

We also explored the behavior of the information asymmetry through the week (Table 2 ). We find evidence of the same U-pattern on the quoted bid-ask reported by Chordia, Roll y Subrahmanyam (2001) in US. Table 2 also shows a U-pattern on the information asymmetry.

Information asymmetry and Liquidity

Table 3 presents several specifications for the panel data model used, by daily frequency, to test for the relation between information asymmetry, as given by the PIN, and liquidity, as given by the quoted and effective bid-ask spreads. All of the alternative specifications include fixed effects, and were estimated with linear regression using PCSE ( panel-corrected standard error) and corrections for auto and cross-correlation and heterocedasticity. The dependent variables are the natural logs of quoted and effective spreads. Models 1.1, 1.2, 2.1 and 2.2 explore the contemporaneous relation between the spreads and the PIN. Models 1.3 and 2.3 explore this relation across countries by using country-specific dummies and interactive variables. Model 2.4 tests for a persistence effect of the asymmetric information on the effective spread, by including the lagged value of the PIN. Finally model 2.5 searches for day-of-the-week effects on the information asymmetry and liquidity relation.

Following previous cross-sectional and panel data models on liquidity (Stoll 2004, Grullon, Kanatas y Weston 2004, AUTHOR 2010), we include daily returns, volatility and trading activity as control variables. From that literature a positive sign for volatility is expected, whereas a negative sign for returns and trading activity should be obtained[1]. To establish the proper model specification Breusch and Pagan, Hausman, Wooldridge, modified Wald and Breusch and Pagan LM tests were used to test the models for random effects, fixed effects, autocorrelation, heterocedasticiy and cross correlation, respectively.

Table 4 reports the results for the models 1.1 to 2.4. As expected, we found a negative effect of daily returns and trading activity on spreads, and a positive effect from volatility, all of them significant statistically. Most importantly, in all the models is evident a positive and highly significant effect of information asymmetry (PIN) on the quoted and effective spreads, consistent with the hypothesis that a higher probability of informed trading should reduce liquidity. Economic significance is also substantial. From the results in models 1.1 and 1.2 (2.1 and 2.2) on Table 4, PIN has a 0.189 coefficient (0.229), meaning that for each 1% additional probability of informed trading quoted spreads increase 0.189% (0.229%) on average.

As for the differential effect of PIN on liquidity per country, the corresponding effect model 2.3 goes from 0.10 in Peru to 0.28 in Mexico. Figure 1 and Figure 2 plot the coefficients of dynamic PIN on the quoted and effective spreads as given by models 1.3 and 2.3, respectively. Information asymmetry effect on quoted spreads is the highest in Argentina and Colombia, intermediate for Chile, Brazil and México, and the lowest for Perú. In turn, the effect on effective spreads is again lower on Peru, and similar in all the five remaining countries.

The results of model 2.4 present a significant positive coefficient for the lagged PIN on the liquidity measures for all countries except Peru. This lagging effect of PIN, with the opposite sign, is consistent with the ability of PIN to predict next day liquidity reported in EEOW.

[1] Daily and intraday returns are calculated as the logarithmic difference between the closing price in a day and the former closing price, and between the closing and the opening prices, respectively. Daily volatility is taken as the absolute value of the daily return. As a trading activity measure we take the number of tradings. ( $NT_t$)

Information asymmetry and returns

The PIN measures the level of informed trading activity in a market as a function of the order imbalance and the trading activity in a given day, but says nothing about the direction of the information. Consequently, we define a derived measure, the signed dynamic PIN variable, giving to PIN the sign of the order imbalance of the day. This way, if in a given day buys were higher (lower) than sells, signed PIN will be positive (negative), meaning that probably the information in the day is predominantly positive (negative). This can be supported on Chordia, Roll and Subrahmainam (2002) who report evidence of a positive relation between order imbalance and return. From the informed trading models it follows that positive (negative) signed PIN should, in expectation,  increase (reduce) prices in a given day.

Table 6 shows alternative specifications of panel data models with fixed effects to test for the relation between the information asymmetry and returns. These models include corrections for heterocedasticity and cross-correlation in the residuals.  Models 1.1 and 2.1 test the relation between signed PIN and daily and intraday returns, respectively. Models 1.2 and 2.2 explore differential effects at country level. Finally, models 1.3 and 2.3 include lagged signed PINs to test for persistence of the effect of information asymmetry on returns. We run the same tests indicated above to assure proper specification of the panel data model.

As control variables for the stock returns, we include the return of each main market index, and the logarithmic change of the foreign exchange rate with the Dollars. These two variables deliver significant positive and negative signs, respectively, as can be seen in Table 7. The positive relation with the market index return captures, to some extent, the systematic component in the return of each stock. In turn, the negative sign with the foreign exchange rate is consistent with the portfolio rebalancing effect cited in the international finance literature (see references in AUTHOR, 2011).

Results in the models 1.1. and 2.1 in Table 7 present consistently a positive relation between information asymmetry and both daily and intraday returns of individual stocks, as predicted by the theory of market microstructure. Models 1.2 and 2.2., using interactive variables show the specific effect of the signed dynamic PIN on returns for each country, which is represented in figures 3 and 4.  This effect is significant for all the countries at the 1% level with the only exception being Chile. Figures 3 and 4, taken together, suggest that Argentina exhibits the larger effect of informed trading on returns; Brazil, Colombia, Mexico and Peru present an intermediate effect, whereas Chile exhibits almost no effect.

Economic significance can be illustrated with the individual country effects estimated in Model 1.2. A 1% increase on the signed PIN in Argentina represents an additional daily return of 0.021%, equivalent to a logarithmic annual return of

5.4%. The corresponding effects are 3.9% annual return for Brazil, 0.55% for Chile, 2.83% for Colombia, 2.9% for Mexico, and 1.8% for Peru.

As for the persistence of the signed PIN effect on returns, models 1.3 and 2.3 of Table 7 show a negative coefficient of the lagged signed PIN in Chile and Brazil, Peru and Mexico, statistically significant in most cases, implying some reversion of the PIN effect on the next day. In Colombia that effect is not significant, whereas in Argentina the sign is positive, suggesting some continuation in the next day. The reversion detected in four countries can be explained for liquidity, rather than information. Indeed, Duarte y Young (2009) suggest that PIN effect on returns can be twofold: a temporal effect due to liquidity restrictions, and a permanent effect associated to the information. The sum between the coefficients of the current and lagged signed PIN can be taken as a measure of the permanent effect of the information asymmetry on prices, and it's summarized in Table 8. On the other hand, the continuation detected in Argentina, is evidence against the weak-form-evidence. Specifically, in Argentina, if some agents observe a large number of buys than sells in a given day, suggesting a higher probability of positive information, they'll buy stocks the next day to obtain extra returns in expectation.

## IV. Conclusions.

The evidence presented in this study strongly supports the implications of the market microstructure theoretical models of information asymmetry (Kyle 1985; Glosten y Milgrom 1985 and O´Hara 1998), by testing their two more important implications: namely, that information asymmetry should reduce liquidity and move prices in the direction of the information. These implications were tested by using the dynamic PIN model of EEOW, which allows for a more rich dynamic structure of the arrival of informed and uninformed trading than the static PIN models of Easley, Kiefer, O´Hara and Paperman (1996), and Easley, Kiefer and O´Hara (1997). While tests of those models have been done using samples of US stocks, this study contributes to the literature by providing evidence in six emerging stock markets. The results presented here not only provide support for the asymmetric information models, but to the methodology of dynamic PIN ( EEOW).

On the other hand, the results portray a variation on the results across the six stock markets. There is some evidence suggesting that average PIN is related to the size and trading activity of the market, relation already established for liquidity (Lesmond 2005). Furthermore, Argentina stock market, the smallest by trading activity, presents, a high sensitivity to asymmetric information effects, both in liquidity and in returns, aside from the second highest average PIN and the highest quoted bid ask spreads. Peru, the second smallest market by trading activity, shows the highest average PIN and average effective spread and exhibits low sensitivities to asymmetric information both on liquidity and returns. Chile, an intermediate market by size, presents no sensitivity to asymmetric information in returns, but it does in liquidity. We leave for future research to test whether these differences can be explained by market design, institutions, information availability or different types of trades across markets.

Finally, for future research, we leave to study the dynamic PIN behavior on macro or company-specific announcements in Latin America, as a further test of the dynamic PIN model. It is expected that PINs are higher and their effect on liquidity and returns be larger in announcement days. Also, using Tay, Ting, Tse y Warachka (2009), PINs and their relationship with returns and liquidity, can be studied at intraday level.

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**Fig. 1 Average effect of PIN on quoted spreads and 95% IC**

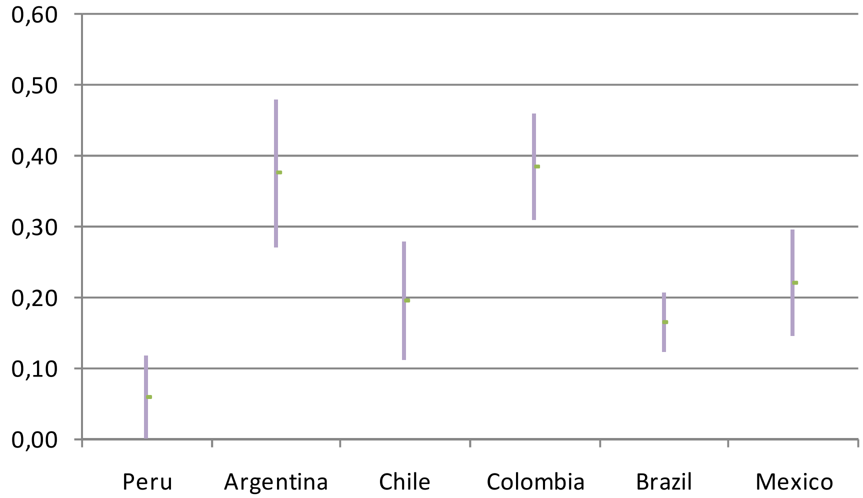



**Fig. 2 Average effect of PIN on effective spreads and 95% IC**

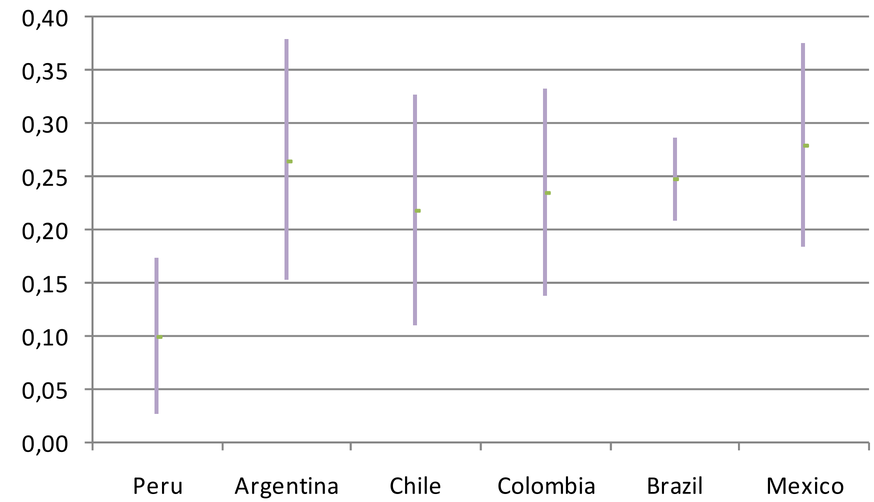



**Fig. 3 Average effect of PIN on daily returns and 95% IC**

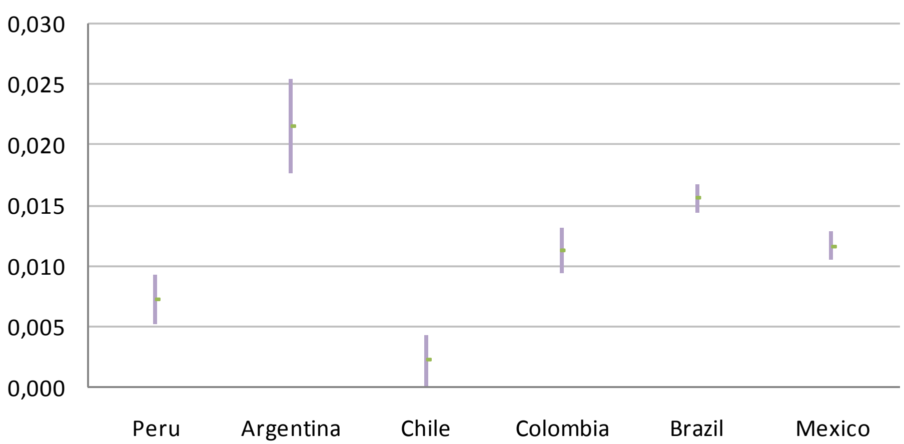
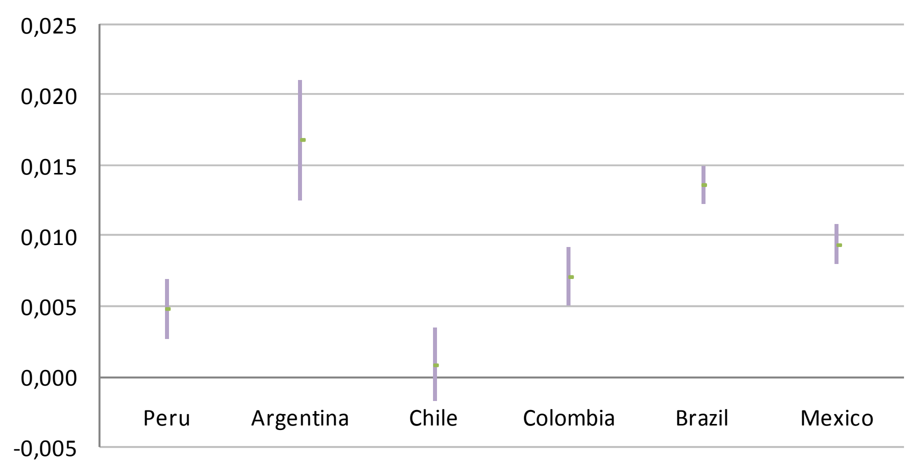



**Fig. 4 Average effect of PIN daily on intraday returns and 95% IC**



## Table 1. Summary statistics of the dynamic PIN model and liquidity measures

| Country | PIN | | | Quoted bid-ask spread | | | Effective bid-ask spread | | | VST** | DMC*** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Average | Confid. Interval 95%* | | Average | Confid. Interval 95%* | | Average | Confid. Interval 95%* | | | |
| Peru | 0,3387 | 0,3297 | 0,3478 | 1,55% | 1,50% | 1,60% | 2,08% | 2,02% | 2,14% | 5.009,61 | 103.347,48 |
| Argentina | 0,3251 | 0,3145 | 0,3356 | 1,48% | 1,40% | 1,57% | 2,72% | 2,56% | 2,88% | 3.815,20 | 63.909,79 |
| Chile | 0,2804 | 0,2755 | 0,2852 | 0,97% | 0,92% | 1,03% | 1,30% | 1,27% | 1,33% | 53.307,63 | 341.798,88 |
| Colombia | 0,2654 | 0,2583 | 0,2725 | 0,66% | 0,65% | 0,68% | 1,31% | 1,28% | 1,35% | 28.127,46 | 208.501,74 |
| Brazil | 0,2535 | 0,2507 | 0,2564 | 0,98% | 0,95% | 1,00% | 0,85% | 0,83% | 0,87% | 868.093,85 | 1.171.625,01 |
| Mexico | 0,2423 | 0,2374 | 0,2472 | 0,60% | 0,54% | 0,66% | 0,76% | 0,74% | 0,79% | 120.064,19 | 454.345,26 |

* Lower and Upper Bounds for a 95% Confidence interval for the average PIN for stock

** Value of Share Trading US$ Million - Federación Iberoamerica de Bolsas, Anuario Estadístico 2011

*** Domestic Market Capitalization US$ Million - Federación Iberoamerica de Bolsas, Anuario Estadístico 2011

## Table 2. Summary statistics of the dynamic PIN and liquidity and quoted spread by day of the week

| Day | PIN | | Average | Quoted bid-ask spread | | |
|---|---|---|---|---|---|---|
| | | Confid. Interval 95%* | | Average | Confid. Interval 95%* | |
| Monday | 0,2760 | 0,2713 | 0,2806 | 1,13% | 1,10% | 1,15% |
| Tuesday | 0,2702 | 0,2655 | 0,2749 | 1,07% | 1,05% | 1,09% |
| Wednesday | 0,2557 | 0,2514 | 0,2600 | 1,07% | 1,04% | 1,09% |
| Thursday | 0,2609 | 0,2566 | 0,2652 | 1,09% | 1,07% | 1,11% |
| Friday | 0,2655 | 0,2609 | 0,2700 | 1,11% | 1,09% | 1,14% |

* Lower and Upper Bounds for a 95% Confidence interval for the average for stock

**Table 3 Panel data specifications for modeling the liquidity measures**

| Model | Specification |
|---|---|
| 1.1 | $\ln(Quoted\ bid\_ask\ spread) = \beta_{i0} + \beta_1 r_t + \beta_2 v_t + \beta_3 PIN_t + \beta_4 \ln(NT_t) + \mu_{it}$ |
| 1.2 | $\ln(Quoted\ bid\_ask\ spread) = \beta_{i0} + \beta_1 r_i + \beta_2 v_t + \beta_3 PIN_t + \beta_4 \ln(NT_t) + \mu_{it}$ |
| 1.3 | $\ln(Quoted\ bid\_ask\ spread) = \beta_{i0} + \beta_1 r_t + \beta_2 v_t + \sum_{j=1}^{6} D_{3j} PIN_t + \beta_4 \ln(NT_t) + \mu_{it}$ |
| 2.1 | $\ln(Effective\ bid\_ask\ spread) = \beta_{i0} + \beta_1 r_t + \beta_2 v_t + \beta_3 PIN_t + \beta_4 \ln(NT_t) + \mu_{it}$ |
| 2.2 | $\ln(Effective\ bid\_ask\ spread) = \beta_{i0} + \beta_1 r_i + \beta_2 v_t + \beta_3 PIN_t + \beta_4 \ln(NT_t) + \mu_{it}$ |
| 2.3 | $\ln(Effective\ bid\_ask\ spread) = \beta_{i0} + \beta_1 r_t + \beta_2 v_t + \sum_{j=1}^{6} D_{3j} PIN_t + \beta_4 \ln(NT_t) + \mu_{it}$ |
| 2.4 | $\ln(Effective\ bid\_ask\ spread) = \beta_{i0} + \beta_1 r_t + \beta_2 v_t + \sum_{j=1}^{6} D_{3j} PIN_t + \sum_{j=1}^{6} D_{4j} PIN_{t-1} + \beta_5 \ln(NT_t) + \mu_{it}$ |
| 2.5 | $\ln(Effective\ bid\_ask\ spread) = \beta_i + \beta_1 r_t + \beta_2 v_t + \sum_{j=1}^{6} D_{3j} PIN_t + \beta_4 \ln(NT_t) + \sum_{k=1}^{4} D_{5k} + \mu_{it},$ |

$i$ : stock, $j$: country, $k$ : day-of-the week, $t$ = day, $r_t$: daily return, $v_t$: daily volatility, $NT_t$: number of transactions,.
$D_{3j}$, $D_{4j}$ : Country specific dummies. $D_{5k}$: Day of the week dummy

**Table 4. Results for Panel data regressions of liquidity measures on PIN**

| | Quoted bid-ask spread | | | Effective Bid-Ask Spread | | | |
|---|---|---|---|---|---|---|---|
| Parametro | model 1.1 | model 1.2 | model 1.3 | model 2.1 | model 2.2 | model 2.3 | model 2.4 |
| Daily return | -0.340 ** | | | -0.623*** | | | |
| Intradaily return | | -0.235 ** | -0.244 ** | | -0.511 *** | -0.515 *** | -0.435 *** |
| Daily volatility | 1.484*** | 1.437 *** | 1.428 *** | 2.674*** | 2.615 *** | 2.609 *** | 2.235 *** |
| pin | 0.189 *** | 0.190 *** | | 0.229 *** | 0.229 *** | | |
| Log Number of trades | -0.141 *** | -0.141 *** | -0.141 *** | -0.129 *** | -0.1299 *** | -0.129 *** | -0.158 *** |
| pinColombia | | | 0.384 *** | | | 0.235 *** | 0.449 *** |
| pinPeru | | | 0,059 | | | 0.100 * | 0.038 *** |
| pinChile | | | 0.195 *** | | | 0.219 *** | 0.207 *** |
| pinMexico | | | 0.221 *** | | | 0.279 *** | 0.266 *** |
| pinBrazil | | | 0.164 *** | | | 0.248 *** | 0.146 *** |
| pinArgentina | | | 0.375 *** | | | 0.265 *** | 0.442 *** |
| L.pinColombia | | | | | | | 0.076 * |
| L.pinPeru | | | | | | | -0.067 |
| L.pinChile | | | | | | | 0.166 *** |
| L.pinMexico | | | | | | | 0.172 *** |
| L.pinBrazil | | | | | | | 0.034 * |
| L.pinArgentina | | | | | | | 0.135 * |

* Statistically significant at the 10%, 5% and 1%, respectively

**Table 5 Panel data specifications for modeling the daily and intraday returns**

| Model | Specification |
|---|---|
| 1.1 | $r_t = \beta_{i0} + \beta_1 Signed\_PIN_t + \beta_2 index\_return_t + \beta_3 FEX\_return_t + \mu_{it}$ |
| 1.2 | $r_t = \beta_{i0} + \sum_{j=1}^{6} D_{1j} Signed\_PIN_t + \beta_2 index\_return_t + \beta_3 FEX\_return_t + \mu_{it}$ |
| 1.3 | $r_t = \beta_{i0} + \sum_{j=1}^{6} D_{1j} Signed\_PIN_t + \sum_{j=1}^{6} D_{2j} Signed\_PIN_{t-1} + \beta_2 index\_return_t + \beta_3 FEX\_return_t + \mu_{it}$ |
| 2.1 | $r\_intra_t = \beta_{i0} + \beta_1 Signed\_PIN_t + \beta_2 index\_return_t + \beta_3 FEX\_return_t + \mu_{it}$ |
| 2.2 | $r\_intra_t = \beta_{i0} + \sum_{j=1}^{6} D_{1j} Signed\_PIN_t + \beta_2 index\_return_t + \beta_3 FEX\_return_t + \mu_{it}$ |
| 2.3 | $r\_intra_t = \beta_{i0} + \sum_{j=1}^{6} D_{1j} Signed\_PIN_t + \sum_{j=1}^{6} D_{2j} Signed\_PIN_{t-1} + \beta_2 index\_return_t + \beta_3 FEX\_return_t + \mu_{it}$ |

$i$ : stock, $j$: country, $k$ : day-of-the week, $t$ = day, $r_t$: daily return, $r\_intra_t$: intraday return , $D_{1j}, D_{2j}$ : Country specific dummies.

**Table 6. Results for Panel data regressions of return on PIN**

| | Daily Return | | | Intradaily Return | | |
|---|---|---|---|---|---|---|
| Parametro | Modelo 1.1 | Modelo 1.2 | Modelo 1.3 | Modelo 2.1 | Modelo 2.2 | Modelo 2.3 |
| signed_pin | 0.0122 *** | | | 0.0098 *** | | |
| index_return | 0.1233 *** | 0.1274 *** | 0.1357 *** | 0.0846 *** | 0.08998 *** | 0.0954 *** |
| fex_return | -0.4121*** | -0.4023 *** | -0.4008 *** | -0.2305 *** | -0.2191 *** | -0.2239 *** |
| signed_pinColombia | | 0.0113 *** | 0.0120 *** | | 0.0071 *** | 0.0073 *** |
| signed_pinPeru | | 0.0072 *** | 0.0083*** | | 0.0048 *** | 0.0056 *** |
| signed_pinChile | | 0.0022 * | 0.0028 * | | 0.0009 | 0.0018 |
| signed_pinMexico | | 0.0116*** | 0.0133*** | | 0.0094 *** | 0.01051 *** |
| signed_pinBrazil | | 0.0156 *** | 0.0165 *** | | 0.0136 *** | 0.0142 *** |
| signed_pinArgentina | | 0.0215*** | 0.0203*** | | 0.0168 *** | 0.0158 *** |
| L.signed_pinColombia | | | -0.001 | | | 0,0002 |
| L.signed_pinPeru | | | -0.0039 ** | | | -0.0020 ** |
| L.signed_pinChile | | | -0.0018 | | | -0.0021 * |
| L.signed_pinMexico | | | -0.0047 *** | | | -0.0027 *** |
| L.signed_pinBrazil | | | -0.0044*** | | | -.0019 *** |
| L.signed_pinArgentina | | | 0.0049 *** | | | 0.0053*** |

* Statistically significant at the 10%, 5% and 1%, respectively

**Table 7. Estimation of the effects of a 1% increase on PIN on returns**

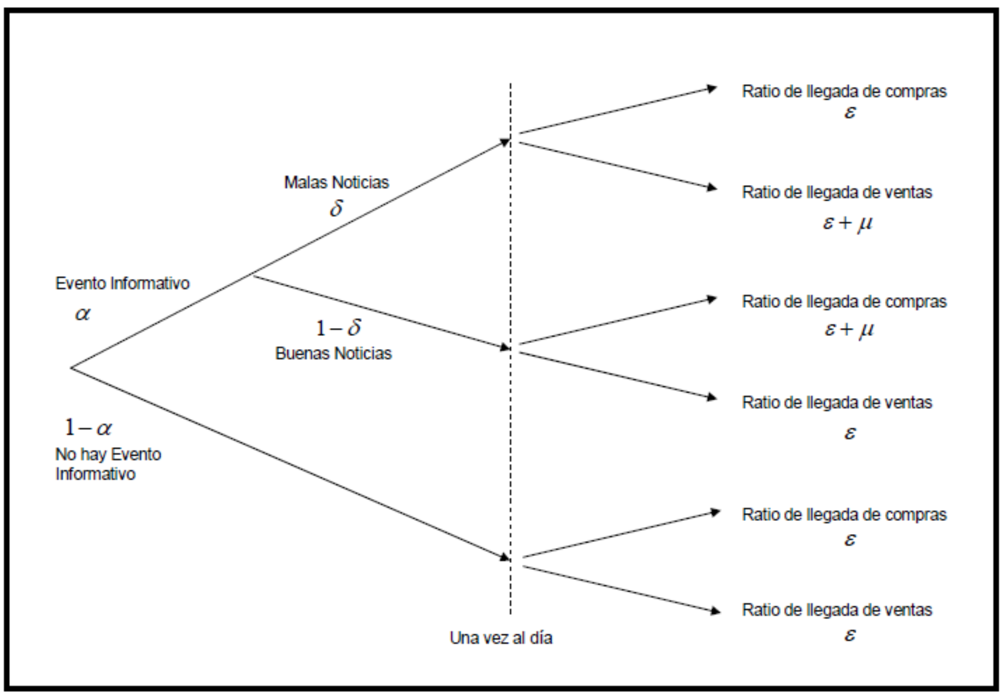
| | Effect on Daily return | | | Effect on Intraday return | | |
|---|---|---|---|---|---|---|
| Contry | Total | Temporal | Permanent | Total | Temporal | Permanent |
| Peru | 0,84% | -0,32% | 0,52% | 0,56% | -0,20% | 0,76% |
| Argentina | 2,04% | 0,50% | 2,53% | 1,58% | 0,53% | 1,05% |
| Chile | 0,29% | -0,18% | 0,11% | 0,18% | -0,21% | 0,39% |
| Colombia | 1,20% | -0,10% | 1,10% | 0,74% | 0,02% | 0,71% |
| Brasil | 1,65% | -0,45% | 1,21% | 1,43% | -0,19% | 1,62% |
| Mexico | 1,33% | -0,47% | 0,86% | 1,05% | -0,28% | 1,33% |

**APPENDIX.**

**Description of the Static and Dynamic PIN models**

Easley and O'Hara (1992) and Easley, Kiefer  O'Hara (1996, 1997) static PIN models start with a market that includes a competitive market maker who trades a risky asset with both informed and uninformed traders. Information events happen in trading days with a probability $\alpha$.  If an information event occurs, it is negative with a probability $\delta$, and a positive one with probability (1- $\delta$).   Informed traders' orders enter the market following a Poisson process with arrival rate $\mu$, only in days with information, and always on the "right"side of the market. It is, any informed trade is a sell in an negative information day, and a buy in a positive one.  In turn, uninformed traders' orders are placed in the market following a Poisson process with an arrival rate $\varepsilon$, independent on the day information, and they are equally likely to be a buy or a sale. The following figure summarizes the described information and trade arrival.

**Figura A1.  PIN arrival process  Source : Easley, Kiefer, O´Hara and Paperman, 1996.**




In such a model, the probability of observing a number of B buys and S sells on a certain day is given by the following expression ,where $y_t$ is the vector of observations ( number of buys and sales) in day $t$:

$$Pr[y_t = (B,S)] = \alpha(1-\delta)e^{-(\mu+2\varepsilon)}\frac{(\mu+\varepsilon)^B(\varepsilon)^S}{B!S!} + \propto \delta e^{-(\mu+2\varepsilon)}\frac{(\mu+\varepsilon)^S(\varepsilon)^B}{B!S!} + (1-\alpha)e^{-2\varepsilon}\frac{(\varepsilon)^{B+S}}{B!S!} \qquad [A.1]$$

[A.1] is a function of three Poisson process probabilities, weighted by the probability of being in a positive information day $\alpha(1-\delta)$,  a negative one ($\alpha\delta$ ) and a no information day $(1-\alpha)$. This is a static model in the sense that every day the arrival of informed and uninformed traders, conditional to the information events, don't change day to day. (EEOW, 2008).

Whereas the static PIN model assumes constant arrival rates for informed and uninformed traders, conditional to the information in the day, in a more general approach, agents continuously update their estimations on the arrival rates, based on the observed trading activity. Consequently, EEWO (1998) offers a methodology to estimate those dynamic rates, allowing the probabilities of buys and sells to vary over time, conditional to the predictions in the arrival rates.

According to EEWO (2008), defining the total number of trades TT = S + B, the expected number of trades in a day is the weighting of the informed and uninformed trading arrival rates, as follows

$$E[TT] = \alpha(1-\delta)(2\varepsilon+\mu) + \alpha\delta(2\varepsilon+\mu) + (1-\alpha)(2\varepsilon) = \alpha\mu + 2\varepsilon \qquad \text{[A.2]}$$

In turn, the expected value of the daily order imbalance $K = S - B$ is given by $E[K] = \alpha\mu(2\delta - 1)$ . Thus, the average of the order imbalance is related to the informed trading arrival. However, a more informative signal is the absolute value of the order imbalance, which is given by a first-order approximation of the difference between two Poisson process as $E[|K|] \doteq \alpha\mu$. Hence, agents can use those relations to estimate the arrival rates of the two types of traders.

Using the vector $\psi = [\alpha\mu\, , 2\varepsilon\,]^T$ to symbolize the two arrival rates, the deterministic trend is eliminated as $\tilde{\psi}_{it} = \psi_{it} * e^{-g_i t}$, *i*= 1, 2, where the vector $g = [g_1\, , g_2]^T$ is the rate of growth of the two components of $\psi$ Then, the untrended arrival rate vector is specified to follow a bivariate autorregressive process, similar to a GARCH model:

$$\widetilde{\psi_t} = \omega + \sum_{K=1}^{p} \Phi_k\, \tilde{\psi}_{t-k} + \sum_{j=0}^{q-1} \Gamma_j\, \tilde{Z}_{t-j} \qquad \text{[A.3]}$$

Where: $\tilde{\psi}_t$ is the predicted arrival vector in *t+1* (detrended) as predicted in *t*. $\tilde{Z}_{it} = Z_{it} * e^{-g_i t}$ , i=1, 2 , similarly detrended as above from $Z_t = [\![ |K|, TT_t - |K| ]\!]^T$

To estimate the model we set *p*=*q*=1, in the original trended variables.

$$\psi_t = \omega \odot e^{gt} + \Phi[\psi_{t-1} \odot e^{g}] + \Gamma Z_t$$

Where $\odot$ denotes the Adamant product. $\alpha$ is assumed to be constant over time, to be able to extract $u_t$ from the estimated $\alpha\mu_t$. Finally, the estimated variables are incorporated in the following modified function of transactions, which enables the Maximum Likelihood estimation of the parameters of the model:

$$Pr[y_t = (B_t, S_t)|\mathcal{F}_{t-1}] = \alpha(1-\delta)e^{-(\mu_{t-1}+2\varepsilon_{t-1})}\frac{(\mu_{t-1}+\varepsilon_{t-1})^{B_t}(\varepsilon_{t-1})^{S_t}}{B_t!\,S_t!} +$$

$$\propto \delta e^{-(\mu_{t-1}+2\varepsilon_{t-1})}\frac{(\mu_{t-1}+\varepsilon_{t-1})^{S_t}(\varepsilon_{t-1})^{B_t}}{B_t!\,S_t!} + (1-\alpha)e^{-2\varepsilon_{t-1}}\frac{(\varepsilon_{t-1})^{B_t+S_t}}{B_t!\,S_t!}$$