Does the Firm’s Business Geographical Distribution affect Stock Return Intraday Volatility?

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ABSTRACT: This paper analyzes the effect that the firm’s business geographical distribution has on stock return intraday volatility. We use data on the Spanish Stock Exchange, where most of its firms’ international activity is concentrated in South America. We find evidence that Spanish firms with a higher proportion of business in the Americas have a higher proportion of their intraday volatility concentrated in two periods: around the SSE opening, and during the SSE trading interval overlapped with the American business day. We interpret this evidence as the business geographical distribution affecting the intraday pattern of relevant information flow for stock pricing.

JEL classification: G10; G14

Keywords: Information; intraday volatility patterns; business geographical location.

INTRODUCTION

One of the aspects of financial globalization is the increasing number of stocks quoted in foreign markets. In the New York Stock Exchange, the relevance of foreign firms has increased during the last years (see Pulatkonak and Sofianos, 1999). This phenomenon has encouraged a growing interest in the price behavior of these stocks. Many papers study the contribution of the foreign market to the price discovery process (e.g., Howe and Ragan, 2002, Eun and Jang, 1997, Lieberman

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et al., 1999, Hupperets and Menkveld, 2002, Lau and Diltz, 1994, Pascual et al., 2006) and the usual finding is that the foreign market does contribute to some extent. This contribution may be based on new information flow during the foreign trading period or on trading activity by foreign investors.

Regarding the foreign investors trading activity, Chan et al. (1996) provide empirical evidence supporting that foreign traders mainly trade on public information previously released in the domestic market. Furthermore, related research supports the idea that the contribution to the price discovery in different markets is related to the trading activity of the investors operating in these markets. Froot and Dabora (1999) study “Siamese twin” companies traded in different stock markets that have different ownerships habitats, and find a significant price relation between the stocks and the stock market where trading is concentrated. Chan et al. (2003) study Hong Kong companies traded on the Hong Kong stock market with all their business activity concentrated in Hong Kong and Mainland China that moved their stocks from this market to the Singapore stock market. The geographical distributions of these firms did not change, however, after delisting in Hong Kong, these stocks’ prices where more related to the Singapore stock market index. Therefore, they conclude that price fluctuations are affected by country-specific investors sentiment. Jayaraman et al. (1993) find an increase in volatility for foreign stocks cross-listed on the US after the US listing, and explain this increase by more informed trading instead of new relevant information releases or noise. Finally, Kadapakkam et al. (2003), and Lieberman et al. (1999) find that the foreign market contribution to the price discovery process is higher for firms with a high foreign ownership.

Regarding the new information flow for cross-listed stocks, the usual claim in the literature is that the most of the information is released during the local market business day (e.g., Chan et al., 1996, Menkveld et al., 2003, Eun and Jang, 1997, Ely and Salehizadeh 2001). Little is known about the information that may be released during the foreign trading period when the local market business day is off. For example, when the foreign market is the US the usual claim is that US macro-economic announcements reveal new information
relevant for foreign firms (e.g., Hupperets and Menkveld, 2002).

However, for firms with significant business activity in the foreign market time zone geographical area there is a natural potential source of new information; there may be new information related to the firm’s business activity in the foreign market geographical area. The theoretical foundation for this source of information is based on Ross (1976) Arbitrage Pricing Theory. With two countries (local and foreign), it could be that the foreign firms’ country-specific factors affect the stock prices of local firms with business activity in the foreign country. Furthermore, there could be innovations in each stock not related to any common factor (idiosyncratic innovations), generated during the foreign country business day due to the firm’s business activity there. If this is the case, the firms’ business geographical distribution will affect the intraday pattern of relevant information flow. There will be new information being released during the foreign trading period, even if the local market is closed, for firms with business activity in the foreign market geographical time zone.

This paper is designed to provide empirical evidence on whether the firm’s geographical distribution affects the intraday pattern of relevant information flow. That is, whether it affects the patterns of arrival of information regarding the systematic factors and the idiosyncratic factor of the return generating process. Therefore, the contribution of this paper is to shed some light on the intraday pattern of the relevant information flow for stock pricing. Furthermore, this study complements the evidence on Chan et al. (2003). They concentrate their study on the effect of changing the trading location without changing the business geographical distribution, and this paper is centered on the effect of the business geographical distribution.

We approximate the intraday pattern of information flow by the intraday volatility pattern of stock returns. Therefore we measure the effect of the business geographical distribution of each firm on its stock return’s intraday volatility pattern. For this, we compare stock return’s intraday volatility patterns across firms with a different geographical distribution of business. Spanish firms on the Spanish Stock Exchange (SSE) form our sample. The international activity of Spanish multinational firms is mainly concentrated in the same
geographical time zone area, South America. Hence, the effect of business activity abroad on the intraday volatility pattern should be concentrated, for all stocks, on the same time interval of the SSE trading period. This facilitates the implementation of statistical tests in order to study whether this is a significant effect. We may isolate the effect of business activity in the Americas by testing whether differences in intraday volatility patterns across stocks are explained by differences in the proportion of business in the Americas. Furthermore, we may also isolate the American business activity effect from other potential effects distorting this relation. For example, American investors trading activity may cause a concentration of volatility during the last trading interval of the SSE. We may control for this effect using ownership data.

The empirical evidence presented in this paper suggests that the Spanish firms with a high proportion of business in the Americas have a concentration of volatility during the SSE trading interval that overlaps with the American business day (the last hours of the SSE trading time) and around the SSE opening. We interpret that this higher volatility is due to information generated during the American business day, which only affects the stock prices of firms with business in the Americas. Therefore, we report evidence suggesting that the firms’ geographical distribution of business affects the intraday volatility patterns, presumably because of influences on the pattern of arrival of relevant information. Furthermore this evidence complements the evidence on Chan et al. (2003) since it suggest that the business geographical distribution is relevant for the price fluctuations in addition to the location of trade.

The paper proceeds as follows. In section 2 we describe the effect of the business activity in the Americas on the intraday volatility patterns, and how we isolate it from other potential effects. Section 3 describes the data. Section 4 presents the statistical methodology. Section 5 presents the results, and section 6 concludes.

THE EFFECT OF THE BUSINESS ACTIVITY IN THE AMERICAS

Since we use the SSE data the following discussion centers on this market. We can differentiate two types of Spanish firms: firms with
business in Europe and in the Americas, and firms with business just in Europe. Under the Arbitrage Pricing Theory benchmark, if the country-specific factors that affect American firms also affect the Spanish firms with business in the Americas we should expect the patterns of information arrival for these firms to be different than that of Spanish firms without business there. The Spanish business day begins before the American business day and both are overlapped during the last hours of the Spanish business day (see Figure 1). We assume that the rate of arrival of information concerning innovations on the country-specific factors that affect American firms (Spanish firms) is higher during the American business day (Spanish business day).

**Figure 1: The Overlapping Period between the Spanish and American Business Days**

This figure describes the overlapping period between the American business day and the Spanish business day. The arrows represent new information regarding country-specific factors that affect American firms (Spanish firms) that are supposed to be active during the American business day (Spanish business day). In the middle of the figure it is shown the SSE trading period in relation to the American and the Spanish business days. There is the opening and the closing time of the SSE, in Spanish time and in New York time. The dotted area represents the SSE trading interval that it is supposed to have the highest rate of information arrival for Spanish firm with business in the Americas, if country-specific factors affecting American firms also affect these firms. The idiosyncratic factor of Spanish firms with business activity in the Americas could reinforce the concentration of information arrival during the dotted interval.
Furthermore, we also assume that information is incorporated into stock prices via volatility (see, Ross, 1989). Therefore, we expect stock prices of Spanish firms with business in the Americas to have a concentration of volatility during the last hours of the SSE trading period (overlapped with the American business day). In addition, the innovations on the American firms’ country-specific factors released after the SSE closing on a given day, will be introduced into the stock prices the following day, during the first periods of the SSE trading (see, Amihud and Mendelson, 1991, or Lin et al., 1994, for empirical evidence on the incorporation of overnight information into stock prices). In consequence, these firms will have a concentration of volatility during the first periods of the SSE trading. Moreover, the possible existence of idiosyncratic innovations on these firms’ stock prices due to their business in the Americas, generated during the American business day, would reinforce this volatility pattern.5

In consequence the statistical methodology of this study will be designed to test whether firms with business in the Americas have, proportionally, more volatility than firms without business there, during two intervals: around the SSE opening, and the SSE trading interval overlapped with the American business day.

There may be several circumstances that distort the effect of the business activity in the Americas on the intraday volatility patterns (American business activity effect). The rest of this section describes these circumstances and how we isolate the American business activity effect.

POTENTIAL DISTORTIONS ON THE AMERICAN BUSINESS ACTIVITY EFFECT

Trading Frequency
There is empirical evidence suggesting that the price of the more frequently traded stocks incorporates information faster (e.g., Low and Muthuswamy, 1996, or Lo and MacKinlay, 1988). Therefore, for the most traded stocks we may not find a concentration of volatility during the first periods of the SSE trading, since overnight information probably will be incorporated during the SSE pre-opening period.6
In addition, for the less traded stocks, we may find the concentration of volatility during the SSE trading interval overlapped with the American business day, to appear latter than for the most traded stocks.

**Dually-listing**

There are several Spanish firms cross-listed on the NYSE as American Depository Receipts. For these firms, most of the information generated during the American business day may be incorporated into its prices on the NYSE. Hence, there is less overnight information to be incorporated into stock prices at the SSE opening, and we should not expect to find a concentration of volatility at this opening as high as for other similar stocks.

In addition, Werner and Kleidon (1996) found British stocks dually listed in the US to have a concentration of their volatility and volume during the overlapping period of trading in the UK and the US stock markets (dual listing effect). This may appear in the Spanish firms dually listed on the NYSE. We found weak evidence suggesting that these firms have a higher proportion of volatility than the other firms during the overlapping period of trading in the NYSE and the SSE. Furthermore, as suggested by Chan et al. (1996) there may be trading activity based on previously released information causing some of this concentration of volatility.

**The Market Index**

It is well known that index funds trading causes some effects on the stocks that are added or removed from the market index. See for example Harris and Gurel (1986) or Lynch and Mendenhall (1997) for studies detecting an effect on stock prices. Regarding intraday volatility patterns, Harford and Kaul (1998) found empirical evidence of a shift in the intraday volatility pattern for the stocks added or removed from the market index (Index effect). Concretely, they study the US stock market and the changes in the S&P-500 composition. They find that stocks listed in the index have an increase in intraday volatility during the last hours of trading, and to a lesser extent, during
the beginning of the trading day. They explain these findings by the behavior of index funds. They argue that these funds have a clear preference for trading near the market close. In this way they are able to minimize the tracking error in their returns relative to their benchmark, whose value is computed using closing prices. In addition, by waiting until the end of trading they are able to offset individual inflows and outflows occurring during the day and minimize their transaction costs. This behavior may also cause some residual trading during the next day initial trading intervals. Index funds trading may be characterized as liquidity trading, therefore the inclusion of a given stock in the index causes a concentration of liquidity trading at the end of the trading session, and to a lesser extent, at the beginning of it. Informed traders attempt to trade when liquidity traders are active (Admati and Pfleiderer, 1988), therefore these traders should cause a concentration of volatility in these periods for stocks listed in the market index.

In addition, Harford and Kaul (1998) find that this index effect is inversely related to the stock’s size (Index-size effect). Their explanation is that larger stocks have higher proportions of information incorporated into their prices (e.g., Bhushan, 1989, Zeghal, 1984, Seyhun, 1986), thus informed traders activity is more profitable and, therefore, pronounced in small firms. Therefore, this concentration of volatility at the end and at the beginning of the trading session is more pronounced for the smaller stocks listed in the index.

We have not found previous studies documenting these effects for the SSE. However, since there is index fund trading based on the SSE main index (IBEX-35), we take into account both effects in order to isolate the American business activity effect.

**Foreign Investors**

American investors trading activity may affect the intraday volatility patterns of the Spanish firms they trade (e.g., trading on public information previously released in Spain). Furthermore, for non-dually listed stocks these traders cannot execute their trading decisions
during all their business day. During the first hours of their business day, overlapped with the last trading hours of the SSE, they can execute their trading decisions instantaneously. However, after this period they have to wait until the next day in order to execute their decisions. This may cause an effect on intraday volatility patterns of Spanish firms traded by these investors. For example, this may cause a concentration of foreign trading during the last trading hours of the SSE, and during the firsts trading intervals. This concentration of trading may also cause a concentration of volatility (Admati and Pfleiderer, 1988). In this case, foreign investors trading would cause a similar effect on intraday volatility patterns than the American business activity effect.

Foreigners invest in firms that they are better informed about (e.g., Kang and Stulz, 1997, or Dahlquist and Robertsson, 2001), and the Spanish firms with business in the Americas, the larger Spanish firms, and the Spanish firms quoted in an American stock market (e.g., NYSE) are more familiar to American investors than other Spanish firms. Therefore, we should take into account the foreign investors effect (henceforth American investors activity effect) in order isolate the American business activity effect.

**The Isolation of the American Business Activity Effect**

In this study we obtain, for each stock, a measure of intraday volatility for each intraday interval considered (intraday volatility pattern). In order to isolate the American business activity effect from the American investors activity effect we implement a cross-sectional multiple regression model for each intraday interval with the American business activity and the American investors activity measures as explanatory variables, and the measure of intraday volatility as the dependent variable. Then, the American business activity effect is isolated from the other potential effects implementing this multiple regression analysis on different samples of similar stocks.9

The first criteria to construct these different samples, is to take into account the different effect that the American business activity
could have on intraday volatility patterns depending on the stock frequency of trading. In consequence, we construct different samples of stocks that meet different requirements on the frequency of trading.

All the Spanish cross-listed stocks on the NYSE are also included on the IBEX-35 and are among the most traded stocks on the SSE. Thus, we construct a sample with just these stocks, where the differences in intraday volatility patterns must be due to the American business activity effect and, if it is relevant, to the Index-size effect.

Finally, in order to isolate the American business activity effect from all the other potential effects, even the Index-size effect, we analyze samples of stocks that are not dually listed and are not included in the IBEX-35. With these stocks we form different samples according the frequency of trading. Therefore, differences in intraday volatility patterns must be due to the American business activity effect.

THE DATA

Related papers on cross-listing stocks use to study the case of European and Japanese firms cross-listed on the US market (e.g., Chan et al., 1996 or Eun and Jang, 1997). It could be tested whether the proportion of these firms’ business in the US affects its stock return intraday volatility pattern there. However, this is not an appropriated sample to implement our approach, since we cannot distinguish whether we detect the effect of new information released during the US business day, or the effect of US investors trading on public information previously released in the domestic country, as suggested by Chan et al. (1996). For example, it may be that US investors have a better knowledge of these firms’ business in the US than domestic investors, and do a better judgment of the impact of public information. Consequently, causing a higher effect on these firms’ stock return intraday volatility pattern in the US market. Therefore, the potential differences on intraday volatility patterns of Japanese and European firms with significant business activity in the US may be due to new information or to trading on previously released information. The Spanish sample has a similar problem; the potentially higher volatility during the American business day may be due to
new information related to the business activity in the Americas or to the trading activity by American investors. The advantage of the Spanish sample is that using Americans ownership data it can be disentangled, to some extent, the American business activity effect from the American investors effect. In the US sample of European and Japanese stocks, there is US trading for all stocks and therefore its effect may not be disentangled form the American business activity effect.

Thus, our sample comprises all the stocks quoted on the “electronic trading system” of the SEE market for 1997-1998. The Sociedad de Bolsas of the Spanish Stock Exchange provided us with tick-by-tick transaction data on the SSE for all these stocks. We drop from the sample all the stocks not quoted on at least 95% of the trading days or that go un-traded for 5 consecutive days. We take the last price of each fifteen-minute interval as the price at the end of the interval and then compute fifteen-minute returns through differences in logarithms on these prices. We take the fist price of the day as the opening price whenever the transaction takes place during the first fifteen-minute period. Whenever there is no trading in one fifteen-minute period we replace the missing last price of the interval by the previous transaction price. Returns are adjusted for dividends, increases in capital, and splits. We also calculate the percentage of fifteen-minute periods with trading, and drop from the sample all the stocks for which this percentage is lower than 50 percent. This percentage is used as the measure of the frequency of trading mentioned in the previous section.

On 27 October 1997 there was a crisis in the Hong Kong financial market that was transmitted to the NYSE on the same day, and affected the SSE several times during the week. As is shown in the literature (for example King and Wadwani, 1990) there is usually a contagion effect between markets during crisis periods (transmission of stock price movements that reflects transmission of information with a high noise component). Since our aim is to detect the effect of information on stock prices, we eliminate the crisis week from the sample.

In order to obtain a measure of the percentage of business in the Americas for each firm (American business activity), we use the firms’
annual financial reports provided by the Information Services of the Madrid Stock Exchange. We measure each firm’s American business activity as the mean of the percentage of net sales in the Americas in 1997 and 1998. Whenever this information is not accessible we used the percentage of gross profits in the Americas (this happened for two firms: Iberdrola and Tabacalera). We end up with 42 firms for which we can calculate this percentage.12

Finally, to obtain a measure of American investors activity we use an ownership structure database provided by the Comisión Nacional del Mercado de Valores (CNMV). This is the Spanish financial markets regulator equivalent to the Securities and Exchange Commission in the US. This database is up-to-date (the maximum legal delay to communicate a significant ownership shift to the CNMV is seven business days after the transaction day) and identifies all the owners with a significant ownership (equal or larger than 5%). This is the most precise data on foreign investors activity available in the SSE, since the SSE do not provide data on foreign trading. This is clearly a limitation of this study, since a better measure of foreign investors activity is the percentage of foreign trading. Therefore, the conclusions have to be interpreted under the assumption of our foreign investor activity proxy. From this database we calculate the measure of American investors activity for every firm as the mean of the percentage of American investors ownership at the end of 1996, 1997, and 1998.

In the appendix we present all the stocks included in this study, and several of its characteristics (e.g., the measure of American business activity).

STATISTICAL METHODOLOGY

It is well known that there is a U-shaped intraday pattern in the stock return volatility (e.g., Harris, 1986, or Wood et al., 1985). We check whether differences in American business activity may explain differences in the U-shaped patterns. Our hypothesis is that differences in American business activity should affect the intraday pattern of information flow, and therefore, should affect the intraday volatility pattern.13
We estimate the intraday volatility patterns with the methodology proposed by Andersen and Bollerslev (1997). In a later paper Andersen et al. (2001) show that this methodology is specially appropriated to estimate intraday volatility patterns. Intraday return data use to have severe non-normality and present strong serial correlation in volatility. This renders sample volatility measures very noisy. The Andersen and Bollerslev (1997) methodology takes into account these characteristics of the data and represents a robust methodology to estimate intraday volatility patterns. Furthermore, this technique obtains the proportion of intraday volatility concentrated in each intraday interval, which is comparable among different stocks. Since the effect of the American business activity described in section 2 is in terms of the proportion of intraday volatility concentrated in different intraday intervals, this technique is especially appropriate for this study. Nonetheless, we introduce some minor changes in order to adapt it to the characteristics of this study.

Previous related studies on intraday volatility patterns such as Chan et al. (1996), or Werner and Kleidon (1996) do not use this technique. They compute a measure of volatility for each intraday interval, such as the sum of squared returns in Chan et al. (1996), and then estimate a system of equations on this volatility measures in order to statistically compare the proportion of volatility concentrated in a given intraday interval for one group of stocks with the proportion in the same interval for a second group of stocks. For example, Chan et al. (1996) use this technique in order to test whether cross-listed stocks have a different intraday volatility pattern than non-cross-listed stocks. This technique is not suitable for our study since it does not allow us to isolate the American business activity effect from the American investors activity effect on intraday volatility patterns. Furthermore, as shown in Andersen et al. (2001), these measures of volatility do not provide robust estimates of intraday volatility patterns. In a related study Martens et al. (2002) compare different methods to forecast intraday volatility and found that the Andersen and Bollerslev (1997) method, based on logs of squared returns, have a better forecasting performance than methods based on simple squared returns.
Intraday Volatility Patterns

The methodology of Andersen and Bollerslev (1997) supposes that intraday returns can be decomposed in the following way:

\[ R_{t,n} = E(R_{t,n}) + \frac{\sigma_{t,s_{t,n}}Z_{t,n}}{N^{1/2}} \]  

(1)

where \( R_{t,n} \) denotes the return on day \( t \) at the intraday period \( n \), \( E(R_{t,n}) \) denotes the unconditional mean, \( N \) refers to the number of return intervals per day, \( s_{t,n} \) is the intraday seasonal factor, \( \sigma_t \) the return volatility on day \( t \), and \( Z_{t,n} \) is a random variable with zero mean and variance equal one. Therefore, the conditional variance may be decomposed as:

\[ \sigma(R_{t,n})^2 = \frac{\sigma_t^2 s_{t,n}^2}{N} \]

In this expression it can be observed two variance processes, a daily process (\( \sigma_t^2 \)), and an intraday process (\( s_{t,n}^2 \)). The intraday process determines the intraday volatility pattern, that a priori may change every day.\(^{14}\) From equation 1, taking absolute values, squares, and logs, obtain:

\[ 2 \log \left[ R_{t,n} - E(R_{t,n}) \right] - \log \sigma_t^2 + \log N = \log s_{t,n}^2 + \log Z_{t,n}^2 \]

The intraday volatility factors are almost isolated on the right-hand side of the previous expression. Now the methodology defines a new variable \( x_{t,n} \) as:

\[ x_{t,n} \equiv 2 \log \left[ R_{t,n} - E(R_{t,n}) \right] - \log \sigma_t^2 + \log N \]  

(2)

This variable is observable from the data and contains the intraday volatility pattern with some noise that the methodology tries to eliminate. Furthermore, this variable is a robust measure of dispersion that allows the robust estimation of the intraday volatility pattern. The intraday pattern is assumed to depend non-linearly on the intraday time interval, \( n \) (U-shape), and on the daily volatility level, \( \sigma_t^2 \).
In order to obtain the intraday volatility factors the non-linear dependence is approximated by a flexible Fourier functional form like the one proposed by Gallant (1981, 1982). They allow this functional form to vary with the daily volatility level. We also allow a regression of dummy variables, one for each intraday time period, which can also vary with the daily volatility level. The dummy variable regressions are used as a benchmark with the best fit, which has the disadvantage of having more parameters to be estimated. The flexible Fourier functional form models we use are:

\[
\begin{align*}
    f(\theta; \sigma_t, n) &= \sum_{j=0}^{I} \sigma_j \left[ \mu_{0j} + \mu_{1j} \frac{n}{N} + \mu_{2j} \frac{n^2}{N^2} + \sum_{k=1}^{d} \gamma_k I_{n-k} + \sum_{p=1}^{P} \delta_{pj} \cos \frac{pn\pi}{N} + \delta_{pj} \sin \frac{pn\pi}{N} \right] \\
    &= \sum_{j=0}^{I} \sigma_j \left[ \sum_{n=1}^{N} \lambda_{nj} I_n \right]
\end{align*}
\]

where we allow \( j \) to be 0 or 1, and \( p \) to be from 1 to 6. \( I_n \) are dummy variables that may be included for any intraday interval that do not fit well within the overall regular periodic pattern. In the dummy variable regressions \( f(\theta; \sigma_t, n) \) takes the following form; 

\[
    f(\theta; \sigma_t, n) = \sum_{j=0}^{I} \sigma_j \left[ \sum_{n=1}^{N} \lambda_{nj} I_n \right]
\]

where we allow \( j \) to be 0 or 1. Finally, we use the Akaike selection criterion to choose the regression model between the twelve regression models implied in equation 4 and the two implied in equation 5. The Akaike model selection criterion penalizes the number of variables to be estimated, but not so much as other model selection criteria such as the Schwarz. Thus, we use the Akaike criterion in order to keep models with a good fit.

Finally, let \( \tilde{f}_{t,n} = f(\bar{\theta}; \bar{\sigma}_t, n) \) denote the resulting estimate of the non-linear function, by the flexible Fourier functional form regression or by the dummy variable regression. Let \( T \) denote the total number of fifteen-minute periods, so that \( \lfloor T/N \rfloor \) is the number of days. Andersen and Bollerslev (1997) suggest the following estimator of the intraday seasonal factor for interval \( n \) on day \( t \):
For each fifteen-minute intraday period, we take the mean of the intraday seasonal factors estimated in equation 6 as an estimation of each of the 28 intraday seasonal factors we have in our sample. The sum of these 28 factors equals 28. Therefore, each factor may be interpreted as the proportion of volatility of each fifteen-minute intraday period. This allows direct comparisons between different stocks.

For the practical estimation of these factors, it is necessary to calculate a variable equal to the right-hand side of equation 2 \( x_{t,n} \). For this, Andersen and Bollerlev (1997) assume that \( E(R_{t,n}) \) is the unconditional mean. A first modification we make of their methodology is to take into account that we are using transaction prices to calculate stock returns, and transaction prices are subject to fluctuations between the bid and the ask. As shown in the literature, this behavior induces spurious negative autocorrelation in the return time series (see for example, Roll, 1984, Lin et al., 1994, or Low and Muthuswamy, 1996). In order to take this behavior into account we use a moving average of order one (MA(1)) to calculate the expected return. We use a MA(1) in all cases for the following reasons: First, the spurious negative autocorrelation induced by bid-ask bouncing is a short memory process. For example, Roll (1984) just uses first order serial covariance of price changes to construct his measure of the Spread, which implies an MA(1) process. Second, as shown in Diebold (1987), the existence of autoregressive heteroskedasticity produces an upward bias in the usual statistics for determining the order of autocorrelation. Thus, before the elimination of the intraday and daily volatility processes it is difficult to evaluate the autocorrelation order. It is even difficult to isolate the spurious autocorrelation induced by bid-ask bouncing from any other autocorrelation in the data. If there is bouncing between the bid and the ask, the moving average term is expected to be negative, and this is what we obtained for all stocks.
Another difference with Andersen and Bollerlev (1997) is that they use GARCH models with daily series to estimate the daily volatility level, and we take the return’s standard deviation of every day in the sample. As Kofman and Martens (1997) argue, for a descriptive analysis that is not going to be used for forecasting, it seems better to calculate the daily volatility level from the series. However, some stocks have days without trading. On those days we have zero daily volatility and we get missing observations in $x_{t,n}$. In order to avoid these missing observations, we calculate the minimum value in the daily volatility series when it is larger than zero and replace the zero daily volatility values by this minimum. We carried out trials with and without this replacement and got close results.

In order to detect whether there are intraday periods for which the dummy variables ($I_{i,n}$) of equation 4 are needed, we estimate an empirical intraday volatility pattern for the IBEX-35, as the mean of $x_{t,n}$ in each intraday period. We observe an abnormal behavior that breaks the nice U-shaped pattern around the NYSE opening and in the last trading periods of the SSE. Therefore, we use dummy variables for those periods when we use equation 4 to estimate the intraday volatility factors of each stock in our sample.

**The Effect of American Business Activity on Intraday Stock Return Volatility Patterns**

We use the previous methodology to estimate the 28 intraday seasonal factors for each stock in our sample. In Figure 2 we graph these factors to observe the intraday volatility patterns of each stock. It can be seen that all stocks have the expected U-shaped pattern.

Define $\text{Fact}_i^n$ as the intraday volatility factor of the stock $i$ for the intraday interval $n$. For a sample composed of $K$ stocks we have a database composed by this factors with $n = 1,2,\ldots,28$, and $i = 1,2,\ldots,K$. Now define $\text{Fact}_n$ as a cross-sectional variable composed by the intraday volatility factors of all the $K$ stocks in the sample for the intraday interval $n$. Therefore, containing the following $K$ numbers: $\text{Fact}_1^n, \text{Fact}_2^n, \ldots, \text{Fact}_K^n$. Since we estimated 28 intraday volatility factors for each stock (one for each fifteen-minute interval), we have
Figure 2: Intraday Volatility Patterns

This figure represents the intraday volatility patterns of each stock in the sample. Each pattern is the graphical representation of the 28 intraday seasonal factors obtained using the methodology described in section 4.1. Each continuous line represents the intraday volatility pattern of one stock.

28 variables $\text{Fact}_n$ ($\text{Fact}_1, \text{Fact}_2, \ldots, \text{Fact}_{28}$). Define $\text{AME}_i$ as the American business activity measure of stock $i$, and define $\text{AME}$ as a variable containing this measure for all the stocks in the sample. Finally, define $\text{FOREIGN}_i$ as the American investors activity measure of stock $i$, and define $\text{FOREIGN}$ as a variable containing this measure for all the stocks in the sample.

Our aim is to study whether differences in American business activity explain differences in intraday volatility patterns once we take into account differences in American investors activity. For this we estimate the following multiple regressions:
For each intraday seasonal factor we estimate a cross-section regression with the seasonal factor as the dependent variable and AME and FOREIGN as the explanatory variables. To calculate the statistical significance of the coefficients we use the White (1980) standard errors, robust to heteroskedasticity.

For example, a statistically significant coefficient for AME in the regression with Fact as the dependent variable means that differences among stocks in the first intraday volatility factor are explained, to some degree, by differences in the American business activity. Moreover, if this coefficient is positive, it means that among the stocks with the same American investors activity, those stocks with higher American business activity tend to have a higher proportion of intraday volatility during the first fifteen-minute interval.

With this method we are comparing the intraday volatility patterns of each stock with the intraday volatility pattern of all the other stocks in the sample, and testing whether the differences are explained by differences in American business activity. Furthermore, we may know whether the American business activity is a relevant variable for some intervals and not for others, and whether firms with American business activity tend to have a higher proportion of intraday volatility for some intervals and lower for some other intervals.

To study the effect of the American business activity on the intraday volatility patterns, we repeat this analysis on ten samples constructed as described in section 2 in order to isolate the American business activity effect from all the other potential effects. In Table 1 we show some statistics on these samples (e.g., number of stocks in each sample). Five samples include dually listed stocks on the NYSE and the stocks included in the IBEX-35, and differ in the frequency of trading requirement. There we take into account just the frequency of trading distortion on the American business activity effect. One sample includes just dually listed stocks (all are highly traded and included in the IBEX-35). This sample is subject to the American
business activity effect and to the Index-size effect. Finally three samples that do not include dually listed stocks or stocks included in the IBEX-35, and differ in the frequency of trading requirement. Therefore there is juts the American business activity effect.

Table 1
Summary Statistics

This table presents summary statistics for each of the samples analyzed in this study. AME is a cross-sectional variable with the measure of business activity in the Americas of each firm. FOREIGN is a cross-sectional variable with the measure of American investors trading activity on the SSE of each firm. Both measures are described in section 3. The construction of the cross-sectional variables is described in section 4.2.

<table>
<thead>
<tr>
<th>Percentiles 7</th>
<th>Sample</th>
<th>Variable</th>
<th>Number of firms 4</th>
<th>Numb &gt; 0 5</th>
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<tr>
<td></td>
<td>19</td>
<td>8</td>
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<tr>
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<tr>
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<tr>
<td></td>
<td>17</td>
<td>7.9</td>
<td>47.3</td>
<td>24.6</td>
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<tr>
<td></td>
<td>19</td>
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<td>9.73</td>
<td>8.34</td>
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<td>8.91</td>
<td>5.27</td>
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<td>46.3</td>
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<td></td>
<td>14</td>
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<td>5.43</td>
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<tr>
<td>90%</td>
<td>23</td>
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<td>15</td>
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<td>5.03</td>
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RESULTS

In this section we show the results of applying the statistical methodology described in the previous section on each of the samples presented in Table 1. For each sample the results are presented graphically. For example, Figure 3(a) represents the results obtained on a sample containing all the stocks with a percentage of fifteen-minute intervals with trading higher than 50%. The horizontal axis represents the 28 fifteen-minute intervals of the SSE trading period. The vertical axis represents the coefficients of AME and FOREING in each of the cross-sectional multiple regressions described in the previous section, one for each intraday period with its seasonal factor as the dependent variable. The statistically significant coefficients at the 5% level are plotted on the continuous line with triangles for AME

<table>
<thead>
<tr>
<th>Nd-Ni 50-70°</th>
<th></th>
<th></th>
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<th></th>
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<td>3.4</td>
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<td>0</td>
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<td></td>
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<td></td>
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<td>9.8</td>
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<td>6</td>
<td>2.44</td>
<td>15.23</td>
<td>9.73</td>
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<td>Nd-Ni 50-90</td>
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<td></td>
</tr>
<tr>
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<td>4</td>
<td>3</td>
<td>42.5</td>
<td>9.8</td>
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<td>9.73</td>
<td>1.66</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

1. Sample with the stocks that have a percentage of fifteen-minute periods with trading higher than 50%.
2. Sample with just dually listed stocks, on the SSE and on the NYSE.
3. Sample without dually listed stocks and without stocks included in the IBEX-35, that have a percentage of fifteen-minute periods with trading higher than 50% and lower that 70%.
4. Number of firms in each sample.
5. Number of firms with the measure of American business activity higher than zero in each sample for AME. Number of firms with the measure of American investors activity higher than zero in each sample for FOREIGN.
6. Mean of AME in each sample. Mean of FOREIGN in each sample.
7. Percentile distribution of AME in each sample. Percentile distribution of FOREIGN in each sample.
8. Maximum of AME in each sample. Maximum of FOREIGN in each sample.
and on the discontinuous line with squares for FOREIGN. Circles represent non-significant coefficients for AME and crosses for FOREIGN. Therefore, interpreting the non-significant coefficients as being zero, from this graph we interpret that the American investors activity measure do not explain differences in intraday volatility patterns among stocks. The variable FOREIGN is not significant in every regression. The American business activity measure (AME) explains differences in intraday volatility patterns. Furthermore, stocks with higher American business activity tend to have a higher proportion of intraday volatility on the first fifteen-minute period and on the last intervals of the SSE trading period than other stocks (the coefficients of AME are positive and statistically significant for the regressions on the seasonal factors of these intervals). In addition, these firms tend to have a lower proportion of intraday volatility during the fifteen-minute intervals 4 to 18 than other firms.

The results obtained on all those samples presented in Table 1, that include the dually listed stocks and all the stocks included in the IBEX-35 are presented in Figure 3. We have five graphs, one for each sample of stocks. These samples differ in the frequency of trading requirement. For the first one it is just a 50% of intervals with trading, for the second a 60%, until the last sample with a 90%. In this way, we may study the effect of including firms with a lower frequency of trading on the results while maintaining a high number of stocks in each sample (see the appendix, and Table 1). In these samples we may study the American Business activity effect taking into account frequency of trading effect. The last samples, with the highest frequency of trading requirement, are more homogeneous samples with respect to this frequency.

In Figure 3 we find the two trading periods we expected to find in the SEE. Around the SSE opening and during the last hours of the SSE trading time, the firms with higher American business activity tend to have a higher proportion of intraday volatility than other firms. This last-hours period begin around the nineteenth fifteen-minute interval, that is 14:45 hours in Madrid time, 8:45 hours in New York time, or 9:45 hours in Buenos Aires time (Argentina). Therefore, we may interpret this period as the SSE trading interval overlapped with
Figure 3: Results for samples containing Dually Listed stocks on the NYSE and stocks included in the IBEX-35

This figure contains five graphs with the results of the statistical analysis presented in section 4, applied on five samples of stocks that include dually listed stocks on the NYSE and stocks included in the IBEX-35. The graph (a) contains the results on the sample that contains all the stocks with a percentage of periods with trading higher than 50%. In each graph the horizontal axis represents each intraday period. The vertical axis represents the coefficients of AME and FOREIGN in each of the cross-sectional multiple regressions presented in section 4.2, one for each intraday period with its seasonal factor as the dependent variable. Small circles represent the non-significant coefficients of AME, small crosses represent the non-significant coefficients of FOREIGN. Significant coefficients at the 5% level are on the continuous line with triangles for AME, and on the discontinuous line with squares for FOREIGN. Inference is based on White (1980) standard errors, robust to heteroskedasticity. A positive coefficient of AME for an intraday interval means that firms with a higher American business activity tend to have a higher concentration of intraday volatility in this interval than other firms. It is the opposite for a negative coefficient. The vertical line at the intraday period 22, is the beginning of the SSE trading interval overlapped with the NYSE trading time.
the American business day. During the rest of the trading period, after the opening and before the beginning of the American business day, the firms with higher American business activity tend to have a lower proportion of volatility than the firms with lower American business activity.

Comparing the results obtained in the different samples of Figure 3, we see that the concentration of volatility around the SSE opening for firms with higher American business activity just appears for the sample containing the less traded stocks. This may be because the less traded firms need a longer time period than the SSE pre-opening in order to incorporate the overnight information. In addition, the number of statistically significant coefficients declines for the samples with the most traded stocks. These samples contain a higher proportion of firms listed on the IBEX-35. The index effect is supposed to induce a concentration of volatility during the last trading interval and, to a lesser extent, during the first trading intervals. The stocks with higher American business activity tend to be listed in the Index. Thus, for the samples containing the less traded stocks the index effect may reinforce the concentration of volatility during the last period of trading and the first trading intervals for firms with American business activity. In addition the index-size effect implies that the index effect is higher for the smaller stocks. The firms with higher American business activity tend to be among the larger firms. Therefore, for the samples with the most traded stocks, the index-size effect and the American business activity effect have an opposite effect on the volatility patterns. The smaller firms may have a higher concentration of volatility during the last periods of trading due to the index-size effect. These firms are among the firms with less American business activity and, therefore, may have a lower concentration of volatility during the last periods of trading due to the American business activity effect. This may justify the lower number of statistically significant coefficients for the samples with the most traded stocks.

Regarding the American investors activity, it appears to be statistically significant just for the beginning of the trading day. This may be due to the trading activity of American investors with short-lived private information acquired after the SSE closing the day before.
In order to isolate the American business activity effect from the dually listing effect and the Index effect, in addition to the frequency of trading effect, we present in Figure 4 the results on a sample composed by just the dually listed stocks. All of them are between the most frequently traded stocks and pertain to the IBEX-35.

**Figure 4: Results of the sample containing just Spanish stocks Dually Listed on the NYSE**

This figure contains the results of the statistical analysis presented in section 4, applied on the sample of Spanish stocks cross-listed on the NYSE. All these stocks are included in the IBEX-35. The horizontal axis represents each intraday period. The vertical axis represents the coefficients of AME and FOREIGN in each of the cross-sectional multiple regressions presented in section 4.2, one for each intraday period with its seasonal factor as the dependent variable. Small circles represent the non-significant coefficients of AME, small crosses represent the non-significant coefficients of FOREIGN. Significant coefficients at the 5% level are on the continuous line with triangles for AME, and on the discontinuous line with squares for FOREIGN. Inference is based on White (1980) standard errors, robust to heteroskedasticity. A positive coefficient of AME for an intraday interval means that firms with a higher American business activity tend to have a higher concentration of intraday volatility in this interval than other firms. It is the opposite for a negative coefficient. The vertical line at the intraday period 22, is the beginning of the SSE trading interval overlapped with the NYSE trading time.
In Figure 4 we observe that the American business activity hardly affects the intraday volatility patterns. It is statistically significant for just four intraday intervals, although the effect is the expected one. In this sample the Index-size effect is mixed with the American business activity effect. One explanation for the few statistically significant coefficients may be the same than for the samples with the most traded stocks in Figure 3 previously discussed. However, in this case there is a relevant difference, the American investors activity effect seems to be the predominant effect. This is consistent with related research such as Chan et al. (1996), Froot and Dabora (1999) or Chan et al. (2003). For cross-listed stocks the foreign investors trading activity seems to be relevant.

In order to isolate the American business activity effect from the all other potential effects, we repeat the analysis with samples of stocks that are not included in the IBEX-35. These stocks are not dually listed, therefore these samples do not have the index related effects (index and index-size) neither the dually listing effect. Our total sample contains 18 stocks not included in the IBEX-35. Four of them have American business activity. These 18 stocks tend to have a low frequency of trading; none has a percentage of periods with trading higher that 90%. All these stocks with this percentage higher that 70% have zero American business activity. Therefore, we cannot utilize the sampling criteria used previously in order to take into account the frequency of trading effect. In this case we take one sample with the stocks that have a percentage of periods with trading higher that 50% and lower than 70%. A second one for those stocks with this percentage higher that 50% and lower than 80%, and a third one for the stocks with this percentage between 50% and 90%. The description of these samples can be found in Table 1. The results of this analysis are presented in Figure 5.

In Figure 5, we see again a significant American business activity effect. Furthermore, we find the expected effect, a higher proportion of volatility for stocks with higher American business activity around the SSE opening and during the SSE trading time overlapped with the American business day. However, in this case the pattern found in the graphs of Figure 3 seems to be pushed toward the right. This may be a low frequency of trading effect. Since information needs
Figure 5: Results for samples of stocks that do not include Dually Listed stocks on the NYSE Neither stocks included in the IBEX-35

This figure contains three graphs with the results of the statistical analysis presented in section 4, applied on three samples of stocks that are not cross-listed on the NYSE, and are not included in the IBEX-35. The graph (a) represent the results on the sample that contains all these stocks with a percentage of periods with trading higher than 50% and lower that 70%. In each graph the horizontal axis represents each intraday period. The vertical axis represents the coefficients of AME and FOREIGN in each of the cross-sectional multiple regressions presented in section 4.2, one for each intraday period with its seasonal factor as the dependent variable. Small circles represent the non-significant coefficients of AME, small crosses represent the non-significant coefficients of FOREIGN. Significant coefficients at the 5% level are on the continuous line with triangles for AME, and on the discontinuous line with squares for FOREIGN. Inference is based on White (1980) standard errors, robust to heteroskedasticity. A positive coefficient of AME for an intraday interval means that firms with a higher American business activity tend to have a higher concentration of intraday volatility in this interval than other firms. It is the opposite for a negative coefficient. The vertical line at the intraday period 22 is the beginning of the SSE trading interval overlapped with the NYSE trading time.
more time to be introduced into stock prices, overnight information needs more time after the SSE opening to be incorporated into stock prices, and information generated during the American business day starts to be incorporated later into stock prices.

The results presented in this section suggest that the American business activity affects intraday volatility patterns. Therefore, the business geographical distribution of firms affects intraday volatility patterns, presumably because affects the pattern of arrival of relevant information for the stock prices. However, this conclusion is subject to the assumption that all the relevant effects are considered in order to isolate the American business activity effect. Furthermore, it is subject to the assumption that the measures of American business activity and of American investors activity are good proxies for the business activity of each firm in the Americas and for the Americans trading activity on the SSE of those firms respectively.

CONCLUSION

In this paper we have studied whether the business geographical distribution of firms affects the intraday volatility pattern of stock returns. Our hypothesis is that the pattern of arrival of relevant information depends on this distribution. In order to obtain empirical evidence of this effect we have analyzed the SSE stocks’ intraday volatility pattern. The Spanish multinational firms have their business activity abroad concentrated in South America. Therefore, if new information generated during the American business day affects these firms’ stock prices, we would expect them to have a higher concentration of intraday volatility than other firms during two periods: around the SSE opening, and the SSE trading interval overlapped with the American business day. This paper reports empirical evidence supporting the effect of the business geographical distribution on intraday volatility patterns.

Our evidence relates the intraday pattern of relevant information flow to the firms’ business geographical distributions. Furthermore, complements the evidence on Chan et al. (2003) since it suggests that the business geographical distribution is relevant for stock price fluctuations in addition to the location of trade.
# Appendix

## Sample of Stocks

<table>
<thead>
<tr>
<th>Company Name</th>
<th>% Trading</th>
<th>America² A. Investors³</th>
<th>IBEX-35⁴</th>
<th>Dually⁵</th>
</tr>
</thead>
<tbody>
<tr>
<td>TELEFÓNICA</td>
<td>99.91%</td>
<td>24.61</td>
<td>5.06</td>
<td>Index 1</td>
</tr>
<tr>
<td>BANCO BILBAO VIZCAYA</td>
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<td>46.34</td>
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<td>10.65</td>
<td>4.97</td>
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</tr>
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<td>ARGENTARIA</td>
<td>99.75%</td>
<td>4.15</td>
<td>5.08</td>
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<tr>
<td>IBERDROLA</td>
<td>99.74%</td>
<td>4.0*</td>
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<td>Index 0</td>
</tr>
<tr>
<td>BANCO CENTRAL HISPANO</td>
<td>99.67%</td>
<td>19.39</td>
<td>0</td>
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</tr>
<tr>
<td>BANCO DE SANTANDER</td>
<td>99.63%</td>
<td>47.32</td>
<td>5.05</td>
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</tr>
<tr>
<td>BANCO POPULAR</td>
<td>99.17%</td>
<td>0</td>
<td>0</td>
<td>Index 0</td>
</tr>
<tr>
<td>DRAGADOS Y CONSTRUCCIONES</td>
<td>98.56%</td>
<td>12.87</td>
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<tr>
<td>GAS NATURAL SDG</td>
<td>98.39%</td>
<td>15.96</td>
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</tr>
<tr>
<td>ACERINOX</td>
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<td>AUTOPISTAS CONCESIONARIA ESPAÑOLA</td>
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<td>0.97*</td>
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<tr>
<td>PRYCA</td>
<td>96.05%</td>
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<tr>
<td>AUTOPISTAS DEL MARE NOSTRUM</td>
<td>94.72%</td>
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<tr>
<td>CORPORACION MAPFRE</td>
<td>94.69%</td>
<td>51.45</td>
<td>8.91</td>
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<tr>
<td>BANCO ESPAÑOL DE CREDITO (BANESTO)</td>
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<tr>
<td>VALLEHERMOSO</td>
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<td>SEVILLANA DE ELECTRICIDAD</td>
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<tr>
<td>FUERZAS ELECTRICAS DE CATALUÑA</td>
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<td>C.C. CONTINENTE</td>
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<tr>
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<tr>
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<td>0</td>
<td>No index 0</td>
</tr>
<tr>
<td>SOTOGRAUDE</td>
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<td>0</td>
<td>No index 0</td>
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<tr>
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<td>75.21%</td>
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<tr>
<td>METROVACESA</td>
<td>74.45%</td>
<td>0</td>
<td>0</td>
<td>No index 0</td>
</tr>
<tr>
<td>FILO</td>
<td>71.57%</td>
<td>0</td>
<td>9.73</td>
<td>No index 0</td>
</tr>
<tr>
<td>PROSEGUR</td>
<td>69.31%</td>
<td>9.84</td>
<td>8.34</td>
<td>No index 0</td>
</tr>
<tr>
<td>EL AGUILA</td>
<td>68.62%</td>
<td>0</td>
<td>5.27</td>
<td>No index 0</td>
</tr>
</tbody>
</table>

*contd. appendix*
### Notes

1. This explanation is inspired by the trading models of Varian (1989) and Harris and Raviv (1993).
2. Siamese twin companies are companies that pool their cash flows, such as Unilever N.V and Unilever PLC, or Royal Dutch Petroleum and Shell Transport and Trading.
3. Jayaraman et al. (1993) and Patro (2000) find that the US stock market index is not relevant for the returns generating process of foreign stocks traded in the US. This evidence seems to be against the relevance of the APT model with regional factors. However, these papers do not take into account the business activity of foreign firms in the US.
4. Ross (1989) show that information is incorporated into prices via volatility, and Kalev et al. (2004) show that the intraday public information flow has a similar pattern than the pattern of intraday volatility.
5. It could be studied whether American country-specific factors affect Spanish firms with business in the Americas. However for this we need to identify the relevant factors for each of the countries where the Spanish firms have business and the proportion of business in each of these countries for each firm. We do not have this detail on the information regarding business activity in the Americas. Furthermore, we want to study the intraday pattern of all the relevant information flow, not just information on common factors.

6. During this period traders just can submit orders, and indicative prices are released to show what the opening price would be given the submitted orders.


8. Index funds are those funds that simply hold the stocks listed in the market index used as their benchmark. Their object is to minimize the tracking error between the index return and their return, minimizing the transaction costs.

9. We could implement the cross-sectional multiple regression model in order to isolate the American business activity effect from all the potential effects. However, in our database, this approach has severe multicollinearity problems. For example, the stocks of firms with a higher proportion of business in the Americas are among the most frequently traded stocks, all the dually listed stocks pertain to this group of firms, and the higher the size of the index listed stocks the higher the percentage of business in the Americas. However, in our sample there are just seven firms with no American owners that have business activity in the Americas. Thus, it is not possible to find sensible samples of similar stocks in order to isolate the American business activity effect from the American investors activity effect, and a multiple regression analysis is required to isolate them. This analysis does not have the multicollinearity problem since there is low correlation between the American investors activity and the American business activity measures.

10. Therefore we have a zero return whenever there is no trading in a given interval.

11. In the case of splits there should be no effect on returns once we take into account the number of new shares assigned to each old share. However, some studies have found abnormal behavior in stock prices
whenever a split is effected; see for example Grinblatt et al. (1984), or Gómez-Salas (2001) in the case of Spain. We therefore eliminate from the sample, for each stock, all days when a split is effected.

12. Most of the firms are the matrix of a group, and in these cases we analyzed the annual report of the consolidated group. Under Spanish law, when the matrix has a low interest in the subsidiary firm, it does not have to include the subsidiary’s sales in the note to the annual accounts in which the matrix has to report the net sales’ geographical distribution. For this reason, whenever a company has expanded its business through low interest in American and other firms, the percentage of American business activity we have calculated is not exact. However, we think that for the purposes of this paper it is accurate enough.

13. Kalev et al. (2004) find the number of public information releases to have a U-shaped intraday pattern.


15. These Fourier flexible functional forms were introduced by Gallant (1981, 1982), and have also been applied in finance by Pagan and Schwert (1990). Kofman and Martens (1997) also used these functional forms for estimating intraday volatility patterns, but do not differentiate the daily process in variance from the intraday process in variance as assumed in equation 1. They filter the return time series with an AR(n) model and then use the absolute value of that error term as the dependent variable in equation 3 instead of $x_{t,n}$. 

16. Andersen and Bollerslev (1997) use $(N+1)/2$ instead of $N$ for the first variable of the polynomial, and $(N+1)(N+2)/6$ instead of $N^2$ for the second variable of the polynomial. We use the polynomial as do Kofman and Martens (1997). There should be no difference in the intraday patterns due to estimation with one polynomial rather than the other. With the appropriated parameters $\mu_1$ and $\mu_2$, both polynomials can reproduce the same functional forms.

17. During our sample time period, the trading period of the electronic trading system of the SSE was from 10:00 am to 17:00 pm.

18. For a related reason Kofman and Martens (1997) use an AR(n) filter.

19. These are models that modelize the autoregressive process in variance. Engel (1982) introduced the ARCH models and Bollerslev (1986) generalized the ARCH models with the GARCH models.
References


American Depository Receipts, *Journal of Banking and Finance* 17, 91-103.


