THREE PAPERS ON GEOGRAPHICAL DISTRIBUTION OF FIRMS' REAL ACTIVITY AND STRUCTURES IN STOCK RETURNS

Tesis doctoral presentada por

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Mayo 2000

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Aquesta tesi la dedico a la meva dona, Loli, i al meu futur fill/a

AGRADECIMIENTOS

En primer lugar quiero agradecer a Gonzalo Lozano toda la ayuda intelectual y tiempo dedicado a esta tesis. Su constante estímulo y orientación en la investigación, las constantes revisiones de versiones previas y muchos otros detalles que han contribuido a la elaboración final de este trabajo.

Agradecer también la ayuda recibida de los miembros del Departamento de Economía y Empresa de la UIB, en especial, el estímulo y orientación en la investigación recibido de Rafael Crespí, los comentarios de Joaquín Alegre en temas econométricos, y los comentarios de Joan Rosselló y Amedeo Spadaro.

Además quiero dedicar un especial agradecimiento al Departamento de Economía de la Empresa de la Universidad Carlos III de Madrid por todo el apoyo recibido para la elaboración de este trabajo durante mis estancias en ese departamento. Y en especial a Mikel Tapia por sus comentarios en la concepción y elaboración de algunos capítulos de esta tesis.

Algunos capítulos de la tesis se han beneficiado de los comentarios efectuados en diversos seminarios, workshops y congresos. Agradezco especialmente a los organizadores y participantes de los seminarios en la Universidad Carlos III de Madrid, en la Universidad de Castilla la Mancha, y en la Universidad de las Islas Baleares, así como a los organizadores y participantes en el Euro Working Group on Financial Modelling 24th Meeting (Valencia), Financial Management Association International European Meeting (Barcelona), European Financial Management Association (París, Francia), y en el 7th International Workshop PASE 2000 (Leuven, Bélgica).

RESUMEN

TRES TRABAJOS SOBRE LA DISTRIBUCIÓN GEOGRÁFICA DE LA ACTIVIDAD REAL DE LAS EMPRESAS Y ESTRUCTURAS EN LA RENTABILIDAD DE SUS ACCIONES

La creciente integración internacional de los mercados financieros ha propiciado la realización de una serie de trabajos empíricos cuyo objeto es analizar los mecanismos a través de los cuales los movimientos de precios se transmiten de un mercado financiero a otro. Además, esos trabajos estudian las implicaciones de esa transmisión para la valoración de activos financieros, de cara a la aplicación de estrategias de cobertura y de inversión. Desde que Grubel (1969) resaltó los beneficios de la diversificación internacional se tiene un mayor interés en aplicar estrategias de cobertura y de inversión utilizando activos financieros cotizados en diferentes mercados financieros.

Por otra parte, esos estudios también analizan las implicaciones de esa transmisión en las políticas reguladoras de cada mercado financiero. En Octubre de 1987 hubo una gran crisis financiera que se propagó a una gran parte de los mercados financieros del mundo. A raíz de esa crisis se aplicaron varias regulaciones y reglas institucionales con el objeto frenar el impacto de los *shocks* financieros internacionales[1]. Aun así, se siguen produciendo *shocks* financieros internacionales que se propagan de mercado en mercado. Por ejemplo, la crisis asiática de 1998 tuvo un gran impacto negativo en los mercados financieros Latino Americanos.

Por lo tanto, parece clara la importancia de detectar la existencia de transmisión de movimientos entre mercados financieros, lo cual está bien documentado en la literatura[2]. Pero, dando un paso más, también es importante analizar las causas de esa transmisión de movimientos. Un ejemplo documentado, que pone de manifiesto esa importancia, es el caso de la bolsa de Toronto. En 1988 la bolsa de Nueva York puso límites a las caídas de precios que puede haber en un día, implantó los llamados *circuit breakers*. Seguidamente la bolsa de Toronto implantó estos límites, de forma tal que siempre que el índice Dow Jones bajaba

[1] En Roll (1989) se describen esas políticas reguladoras.
[2] Ver, por ejemplo, Hamao, Masulis y Ng (1990), Francis y Leachman (1996), Booth, Martikainen y Tse (1997), o Peiró, Quesada y Uriel (1998).

en una cierta cantidad se suspendía la negociación en una serie de activos cotizados en la bolsa de Toronto. Esta medida se basaba en la creencia de que había una fuerte transmisión de movimientos entre Toronto y Nueva York. Más adelante Karolyi (1995) estudia la transmisión entre Toronto y Nueva York utilizando técnicas econométricas más sofisticadas que las utilizadas anteriormente, y llega a la conclusión de que la transmisión es menor de lo que se creía, y que ha ido disminuyendo con el tiempo, con lo cual lo más racional es ligar los *circuit breakers* de la bolsa de Toronto a un índice que recoja la evolución del mercado de Toronto y no al Dow Jones. En este caso, si se hubieran conocido los fundamentos económicos que hay detrás de la transmisión de movimientos entre Nueva York y Toronto, se habría podido detectar antes esa menor transmisión y se habría podido aplicar una regulación más adecuada.

En la literatura hay varias contribuciones sobre las causas de esa transmisión de movimientos entre mercados financieros. Una primera explicación está basada en el modelo APT de Ross (1976), donde se supone que hay factores que influyen en la valoración de activos de varios mercados y que son los que provocan la transmisión de movimientos entre esos mercados. En esta línea está el trabajo de King, Sentana y Wadhwani (1994) en el que suponen que hay factores observables y factores no observables: encuentran que la mayor parte de la transmisión de movimientos está explicada por los factores no observables. Otra explicación, mencionada por Engle, Ito y Lin (1990), es que podrían existir técnicas de análisis chartista que causaran transmisión de movimientos de un mercado a otro. Sin embargo, esta explicación contradice la hipótesis de eficiencia del mercado y por esa razón no analizan su relevancia. Finalmente, se ha argumentado que la coordinación estocástica de políticas económicas de diferentes países podría causar transmisión de movimientos entre los mercados financieros de esos países. Ito Engle y Lin (1992) estudian la relevancia de esta explicación en el mercado de divisas y llegan a la conclusión de que esta razón no es muy importante. En el mercado de acciones, Francis y Leachman (1996) plantean la posibilidad de que la competencia entre políticas económicas también cause transmisión de movimientos entre mercados, pero no estudian la relevancia de esta posibilidad.

A la primera de las explicaciones anteriores, la de los factores comunes, le falta la completa identificación de esos factores comunes que explicarían la transmisión de movimientos, y aun así parece ser la explicación más aceptada. Por ejemplo, King y

Wadhwani (1990) presentan un modelo de contagio basado en esta teoría de los factores comunes. En ese modelo suponen dos mercados en los que el precio de las acciones viene determinado por dos factores, uno común y otro específico de cada mercado. Los agentes de un mercado solamente pueden observar los movimientos en el precio del mercado extranjero, y al tratar de inferir que parte de ese movimiento se debe al factor común pueden incurrir en una sobrevaloración del movimiento de ese factor, y este es el origen de contagio.

Toda esta literatura sobre transmisión de movimientos entre mercados financieros solamente tiene en cuenta una parte de la globalización, la globalización financiera. Efectivamente, cada vez hay mas empresas cotizadas en diferentes mercados, con la tecnología de la información actual se pueden realizar movimientos de capitales entre mercados financieros de forma casi instantánea, etc... Sin embargo, no se ha prestado atención a la otra parte de la globalización, la que hace referencia a aspectos más reales de la economía. Hay un número creciente de empresas multinacionales que tienen sus mercados distribuidos en todo el mundo. Por ejemplo, la mayoría de empresas Japonesas que cotizan en Nueva York también realizan mucha actividad real en Estados Unidos. En 1998, Honada Motors realizó el 46,6% de sus ventas en Estados Unidos, Sony el 29,9%, Kyrocera el 21,3%, etc... Además las empresas multinacionales tienden a localizar sus centros de producción allí donde haya más ventajas en costes. Nuestra intuición es que para comprender la globalización financiera se debe tener en cuenta la otra cara de la globalización, la globalización real.

Esta tesis intenta ser el primer paso de una investigación sobre la relación entre la globalización de la economía real y la globalización de la economía financiera. Todavía no se entienden bien los mecanismos a través de los cuales las fluctuaciones en los precios se transmiten de mercado financiero en mercado financiero. Nuestra investigación intenta estudiar si teniendo en cuenta la globalización en la economía real podemos entender mejor la globalización financiera. En esta tesis presentamos tres trabajos empíricos que estudian la importancia de la distribución geográfica de los negocios de las empresas para explicar algunas estructuras en la rentabilidad de las acciones.

Esta tesis está organizada de la siguiente forma. En el capitulo 2 estudiamos el efecto de la actividad de las empresas multinacionales en la persistencia que suele detectarse en la volatilidad de la rentabilidad de las acciones. Utilizamos series de rentabilidades de acciones de empresas multinacionales cotizadas en los dos mercados financieros mas importantes del mundo: La bolsa de Nueva York y la bolsa de Tokio. Con estas acciones construimos dos carteras: i) Una con acciones de empresas que tienen una proporción significativa de negocios en las zonas horarias de Nueva York y de Tokio (empresas globales), y ii) otra con acciones de empresas que solamente tienen una proporción significativa de negocios en una de las zonas horarias (empresas no globales). Y encontramos que la transmisión de volatilidad de un mercado financiero al otro, o lo que es lo mismo, persistencia en la volatilidad lo suficientemente grande como para causar esa transmisión, es significativamente mayor en las empresas globales que en las no globales. Las principales causas para explicar esta persistencia en la volatilidad son: a) Dinámica de mercado[3] o b) procesos generadores de información. Nuestros resultados sugieren que la principal causa de la persistencia en la volatilidad encontrada son los procesos generadores de información relacionados con la actividad comercial que realizan las empresas globales alrededor del mundo.

Para interpretar los resultados del capitulo 2 suponemos que en el muy corto plazo hay información relacionada con la actividad del día a día de cada empresa que se introduce en el precio de su acción. Sin embargo, por lo que nosotros conocemos, la literatura no proporciona explicación teórica ni evidencia empírica que justifique nuestra suposición. Por lo tanto, la segunda parte de nuestra investigación, presentada en el capitulo 3, se centra en estudiar la validez de esta suposición. Para realizar esta investigación, la bolsa española constituye una buena muestra. La mayoría de las empresas multinacionales cotizadas en la bolsa española tiene concentrada su actividad multinacional extraeuropea en Sudamérica. Podemos, entonces, dividir el período de negociación en Madrid en dos subperíodos, uno cuando todavía es de noche en América (por la mañana en Madrid), y otro cuando ya es de día en América (por la tarde en Madrid). En este estudio, si en el muy corto plazo hay información relacionada con la actividad del día a día de las empresas que se introduce en los precios de las acciones, esperamos encontrar que las empresas con una proporción significativa de negocios en América tengan una mayor parte de su volatilidad diaria

[3]En Kyle (1985) o en Admati y Pfleiderer (1988), por ejemplo, se presentan modelos teóricos que explican dinámicas de mercado que pueden causar persistencia en la volatilidad.

concentrada en el período en que todos sus negocios están en funcionamiento, es decir cuando es de día en América. Y esos son los resultados que encontramos.

Si en el muy corto plazo hay información relacionada con la actividad del día a día de una empresa que se introduce en el precio de su acción, podemos esperar que todas las acciones de empresas con negocios en una región económica se muevan por informaciones genéricas que afectan a esa región. Podríamos pensar en factores regionales que incorporaran esa información. Esos factores serian comunes a todas las empresas con actividad en esa región y podrían provocar transmisión de movimientos entre mercados financieros con empresas que realizan actividades en esa región. En el capitulo 4 trabajamos con esta posibilidad. Intentamos contribuir en la identificación de esos factores comunes que podrían causar la transmisión de movimientos entre mercados financieros. En este trabajo estudiamos los comovimientos entre la bolsa española y el mercado de acciones estadounidense. Para la realización de este estudio, esos dos mercados constituyen una buena muestra porque: i) Las multinacionales españolas tienen concentrada su actividad internacional (fuera de Europa) en Sudamérica. ii) Hay grandes empresas estadounidenses con actividad en Sudamérica (muchas de las cuales están incluidas en índices del mercado de acciones estadounidense, como el S&P 500). iii) La mayoría de las exportaciones sudamericanas se dirige a Estados Unidos.

Por una parte, esperamos que las acciones de todas las empresas con actividad en Sudamérica estén movidas por factores que reflejen información relevante para Sudamérica, de manera que deberíamos encontrar un mayor comovimiento del mercado estadounidense con las empresas españolas con actividad en Sudamérica que con las que no tienen actividad allí. Por otra parte, esperamos que la evolución de la economía estadounidense se refleje en el mercado de acciones estadounidense y que tenga un efecto significativo en las empresas con actividad en Sudamérica, y este es un segundo mecanismo a través del cual esperamos encontrar que las empresas españolas con actividad en Sudamérica tengan un mayor comovimiento con el mercado de acciones estadounidense. En la investigación que presentamos en el capitulo 4 encontramos que efectivamente las empresas españolas con actividad en Sudamérica tienen un mayor comovimiento con el mercado de acciones estadounidense.

En resumen, la evidencia empírica presentada en esta tesis sugiere que: i) Hay procesos generadores de información, relacionados con la actividad comercial que realizan las empresas globales alrededor del mundo, que constituyen un determinante importante de la persistencia en la volatilidad encontrada en la rentabilidad de las acciones. ii) Esos procesos generadores de información, también constituyen un determinante importante de los patrones intradia que presenta la volatilidad de la rentabilidad de las acciones. Parece haber información relacionada con la actividad del día a día de las empresas que se incorpora en el precio de las acciones en el muy corto plazo. iii) Hay indicios de que puede haber factores regionales que influyen en el precio de las empresas que realizan actividades en esas regiones, y estos factores podrían explicar una parte de la transmisión entre mercados financieros con acciones de empresas que realizan actividades en una misma región económica. Y por último, la evidencia empírica presentada en esta tesis sugiere que la globalización de la economía real afecta a algunas estructuras presentes en la rentabilidad de las acciones, por lo tanto, futuras investigaciones sobre la integración de mercados financieros teniendo en cuenta la globalización real deberían ser provechosas.

La investigación que se presenta en esta tesis puede mejorarse en varios aspectos, que se dejan como futuras extensiones del trabajo. Por ejemplo: i) en el capitulo 2, realizamos todo el análisis con modelos de volatilidad autoregresiva univariantes, por lo tanto, una posibilidad seria repetir el análisis con modelos multivariantes y comprobar si obtenemos los mismos resultados. Por otra parte podríamos realizar el análisis con acciones de la misma nacionalidad para comprobar la relevancia de la nacionalidad en los resultados obtenidos. ii) En el capitulo 3, se deja para un futuro análisis, estudiar si teniendo en cuenta la distribución geográfica de los negocios de las empresas se obtienen resultados diferentes en trabajos relacionados como los de Chan et al (1994) o Werner y Kleidon (1997)[4]. iii) Y en los capítulos 3 y 4 se deja para un futuro trabajo, estudiar si los inversores españoles recogen esa información relevante para las empresas españolas con actividad en Sudamérica, directamente desde Sudamérica o bien si infieren esa información a través de los movimientos del mercado de acciones estadounidense.

[4] El primero trata sobre los determinantes de la volatilidad de la rentabilidad en las acciones y el segundo sobre segmentación de mercados financieros, y en ambos casos no se tiene en cuenta la distribución geográfica de los negocios de las empresas.

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CONTENTS

Chapter 1:

Introduction

The growing international integration of financial markets has prompted several recent empirical studies to examine the mechanism through which stock market movements are transmitted around the world. These studies evaluate how stock returns in one national stock market influence those of another stock market and their implications for pricing of securities within those markets, for hedging and other trading strategies, and for regulatory policies within their financial markets.

On the one hand, hedging and other trading strategies using assets quoted on different markets, have received increasing attention since Grubel (1969) pointed out the benefits of international diversification.

On the other hand, the October 1987 international crash showed large and correlated price movements across most stock markets. As a result, some regulations and institutional rules were implemented to dampen the cross-market impact of large stock price movements[5]. However, in spite of those regulatory policies and institutional rules, new financial crisis occurred since 1987 that were transmitted also across different countries' financial markets. As an example, the financial crisis in Asia in 1998 had a significant impact on the behavior of Latin-American financial markets.

Therefore, detecting the transmission of market movements across stock markets is a relevant issue to be studied, and it is well documented in the literature[6]. Furthermore, it is also interesting to study the reasons behind this transmission of movements. For example, after the adoption by the New York Stock Exchange (NYSE) in 1988 of limits on large negative daily price movements, known as *circuit breakers*, the Toronto Stock Exchange (TSE) adopted circuit breaker rules identical to those of the NYSE. Interestingly, though, the TSE's circuit breakers were triggered, similarly to those of the NYSE, by down moves of the Dow Jones Industrial Average and not of any TSE-based aggregate. The rationale behind that regulatory policy was the observed strong correlation between the NYSE and the TSE stock returns. It was thought that financial storms happened first on the NYSE. However, Karolyi (1995) used more efficient econometric techniques to calculate this

[5] See Roll (1989) for a survey on these regulatory policies.
[6] See for example Hamao, Masulis and Ng (1990), Francis and Leachman (1996), Booth, Martikainen and Tse (1997), or Peiro, Quesada and Uriel (1998).

correlation and demonstrated that it was weaker than previously thought and diminished over time, so that the rationale behind that regulatory policy should be seriously re-examined. Knowing more about the fundamentals driving the transmission of movements between stock markets could be used in this case to detect changes in those fundamentals and to implement a more accurate regulatory policy.

The literature presents several contributions regarding the arguments that explain the transmission of stock price movements between financial markets. One explanation is based on the Ross (1976) asset valuation model, known as APT, in which it is assumed that some common factors explain asset returns in different markets. These common factors are the origin of the transmission of movements between markets. See, for example, King, Sentana and Wadhwani (1994), who tested a model where they assumed that there are observable factors and unobservable factors, and concluded that only a small proportion of transmission of movements is explained by observable factors[7]. Another explanation, mentioned in Engle, Ito, and Lin (1990), is that there could be some chartist analysis techniques causing transmission of movements from one market to another, but this would contravene the market efficiency hypothesis and they do not study the relevance of this explanation. Finally it has been argued that stochastic policy co-ordination or policy competition between countries could be behind some of the transmission observed; Francis and Leachman (1996), among others, explained this for the stock exchange market. Ito, Engle, and Lin (1992) tested the relevance of such explanation for the foreign exchange market, concluding that it is not a major cause.

The common factor explanation fails in identifying these common factors. Even so, it seems to be the most-used approach to the transmission of movements between markets. For example, based on it, King and Wadhwani (1990) presented a contagion model for the transmission of movements between stock markets. Their model has two stock markets in which stock prices are affected by one idiosyncratic factor, which only affects one market,

[7] They take into account the following macroeconomic variables to construct their factors; Short Interest Rate, Long Interest Rate, Dollar/Yen Exchange Rate, Dollar/DM Exchange Rate, Industrial Production, Inflation, US Trade Account, Real Money Supply, Oil Price, Commodity Prices. In a related line of research Karolyi and Stulz (1996) look for significant variables to explain the comovement between US stocks and Japanese stocks quoted as ADR in the US. They take into account the following variables; a Monday dummy, News announcement dummys, daily closing returns on the Chicago Mercantile Exchange Yen/Dollar currency Futures, Chicago Mercantile Exchange Treasure bill futures, a Center for Research in Security Prices value-weighted Portfolio, overnight returns on the Nikkei, daytime returns on the S&P 500, and demeaned trading volume on Nikkei stocks and on S&P 500 stocks. Finally, they find some of those variables to

and a common factor that affects both markets. In their model, traders observe the common and idiosyncratic factors' movements during the local market trading period, but just observe price movements in the foreign market and try to infer the common factor component in stock price movements there. In this process traders may overestimate the common factor and overreact to the foreign stock price movements; this is the origin of the contagion effect.

It is important noting that all this literature just takes into account one side of the economic globalization, namely the financial globalization. Indeed, one observes that an increasing number of firms are cross-listed in different stock markets around the world, that the modern technology available allows instantaneous capital flows, etc. However, little attention has been paid to the other side of the globalization, that is the real economy globalization that relates to the increase in the number of firms that operate in several markets simultaneously. Multinational firms have their markets spread around the world. An example is the Japanese firms quoted on the US stock market, which have a great proportion of their net sales in the US. In 1998, the net sales of Honda motors in the US represented 46,6% of their total net sales, in the case of Sony they were 29,9%, they were 21,3% for Kyrocera, and so on. At the same time, multinational firms tend to locate their production where there are cost advantages. Thus, our intuition suggests that the relevance of the home country of those firms (nationality) might become less important over time as a determinant of stock return behavior across stock markets[8].

This thesis intents to be the first step of a research project to study the issue of the relation between the real economy globalization and the financial globalization. The mechanisms through which stock price fluctuations in one financial market are transmitted to other financial markets is an issue not solved yet. Our research intents to study whether taking into account real economy globalization makes a contribution on this. In this thesis we present three empirical papers that study the relevance of the firms' business geographical distribution as a determinant of some structures in stock returns.

The following pages are organized as follows. In Chapter 2 we study the effect of multinational firms' business geographical distribution on stock return volatility

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be significant, like the Nikkei or the S&P 500 returns, but they do not measure the relevance of these variable for explaining the full comovement found, as done by King, Sentana and Wadhwani (1994).

[8] See for example, Chan et al (1996) for a paper taking the stocks nationality as a determinant of stock return behaviour.

persistence. We compare stock returns of multinational firms quoted in the two main stock markets around the world: The New York Stock Exchange and the Tokyo Stock Exchange. We construct two portfolios: i) One with stocks of firms that do have significant business activities in the New York and in the Tokyo geographical time zones (global firms), and ii) another with firms that do have business activity in just one geographical time zone (non-global firms). We find volatility persistence or volatility transmission from one stock market to the other to be significantly higher in global firms than in non-global firms. This volatility persistence is explained by two main causes: a) Market dynamics[9] or b) data generating processes. Our results are consistent with data generating processes, related to the firm's business activity around the world, to be the main reason of the volatility transmission or volatility persistence found in our sample.

A key assumption to understand our results in Chapter 2 is that information related with the firm's business daily activity is introduced into stock prices in the short run. However, as far as we know, the literature does not provide neither empirical nor theoretical contributions that could strengthen the validity of our assumption. Hence, the second part of our research, included in Chapter 3, is to study the validity of this assumption in the real world. In Chapter 3 we examine the Spanish Stock Exchange. It is especially well suited for our purpose because most of the Spanish multinational firms' activity is concentrated in South America. The trading period in the Spanish Stock Exchange, during the data sample we use for this study, was from 10:00 a.m. to 5:00 p.m., Spanish time. And at 3:30 p.m. in Spain it is the opening time in the NYSE, 9:30 a.m. in New York time, or 10:30 a.m. in Buenos Aires (Argentina) time. Thus, if information related with business activity is introduced into stock prices in the short run we expect that Spanish multinational firms with business activity in the Americas have a higher proportion of their daily volatility when it is business time there. This is precisely the result we found.

If information that is related to the firms' business activity is introduced into stock prices in the short run, we could expect all firms with business activity in an economic region to be moved by generic information relevant for that region. Regional factors could incorporate this information. These factors would be common for all firms with business activity in that region and could explain some comovement between financial markets with

[9] See for example, Kyle (1985) or Admati and Pfleiderer (1988) for theoretical models explaining market dynamics that

firms with business activity in that region. In Chapter 4 we deal with this hypothesis. Our objective is to make some contribution on the identification of those common factors that could explain transmission of movements between financial markets. We study the comovements between the Spanish Stock Exchange and the US stock market. This is a good sample for our purpose because: i) Spanish multinational firms have concentrated their foreign activity in South America. ii) There are large US companies investing in South America (most of them are included in US stock market indexes like the S&P 500). iii) And the South American exports are mainly directed to the US.

We expect the stock prices of all firms with business in South America to be moved by the regional factors that reflect information relevant for South America; this could justify a higher comovement between a US stock market index and Spanish firms with business in South America than other firms. Also, we expect US economic evolution to be reflected in the US stock market and to have a significant effect on firms with business in South America. Hence, this is a second mechanism through which we expect Spanish firms with business in the Americas to have a higher comovement with the US stock market. In this chapter we find Spanish firms with business in South America to have a higher positive comovement with the US stock market than other Spanish firms.

Summarizing, the empirical evidence presented in this thesis suggest that: i) Data generating processes, related to the firm's business geographical distribution around the world, are a significant determinant of stock return volatility persistence. ii) These data generating processes are also a significant determinant of intraday volatility patterns. Information related to the firm's business activity is introduced into stock prices in the very short run. iii) There seems to be regional factors affecting stock returns of firms with business activity in their region, and this could explain some stock return comovement between stock markets that have firms with business activity in the same economic region. Hence, our general conclusion is that real economy globalization seems to have an effect on stock return structures and that further research on financial markets integration taking it into account should be profitable.

Further research should be done to improve and enlarge our results. For example: i) In Chapter 2, we obtain our results using univariate autoregresive heteroskedasticity models,

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can cause volatility persistence.

thus one possibility is to study whether we get the same results using multivariate models. Also, to test the relevance of the stock's nationality, we could study whether we obtain the same results within stocks of the same nationality. ii) In Chapter 3, it is left for future research a deeper analysis to study whether we get different results in related empirical research like the one of Chan et al (1994) or Werner and Kleidon (1996)[10] when taking into account the firms' business activity geographical distribution. iii) And in Chapter 3 and 4, further research should be done to know whether Spanish traders gather South American information relevant for those Spanish firms with business activity there, directly from South America or whether they infer that information from the US stock market.

We have made an effort to present each of the chapters as a self-contained paper. The reader should have no problem reading only a selection of the chapters or altering the order. Readers of the whole thesis should excuse me if this is accomplished at the cost of slight reiteration of some of the arguments.

[10] Related papers on stock return volatility determinants and financial markets segmentation that do not take into account the firms' business geographical distribution.

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Chapter 2:

Volatility Transmission Between Stock Markets. An Application to Study the Determinants of Stock Return Volatility Persistence.

Volatility Transmission Between Stock Markets. An Application to Study the Determinants of Stock Return Volatility Persistence [11].

Abstract

Volatility transmission between a stock quoted in different non-overlapping markets is analysed in this paper. Evidence is found that the more global the commercial side of a firm, the more the volatility transmission. This fact supports the idea that this volatility transmission can be due to, among other reasons, the data generating process, in line with the model of Ito, Engle and Lin (1992). There may be other reasons behind this volatility persistence, such as asymmetric information between agents and slow processing of information by the agents, but we find evidence that data generating processes could be of greater importance than market dynamics for explaining volatility transmission among stocks quoted in different markets.

[11] The author thanks Jorge Yzaguirre of the *Sociedad de Bolsas* (Madrid Stock Exchange) for providing the stock price data. The author is grateful, too, to Gordon M. Bodnar of the University of Pennsylvania for helpful comments at the 1999 EFMA Meeting, to Ignacio Peña, Mikel Tapia and others present in a seminar at the *Universidad Carlos III de Madrid,* and to Elíseo Navarro, Juan Nave and others present in a seminar at the *Universidad de Castilla la Mancha* for helpful comments on earlier verisons of the paper. Finally, thanks to Jorge Pérez-Rodríguez of the *Universidad de Las Palmas de Gran Canaria* for helpful comments on econometrics. The content of this paper is the sole responsibility of the author.

1. INTRODUCTION

Studying volatility transmission between financial markets is especially relevant in two fields. One field is hedging and other trading strategies, and the other field is regulatory policy within financial markets.

For the field of hedging and trading strategies, using assets quoted in different markets, it is needed the covariance matrix between asset returns in those markets. There is a huge literature on GARCH models (Generalized Autoregressive Heteroskedasticity), started by Engle (1982) and Bollerslev (1986), proving that this matrix is variable and can be forecasted with an autoregressive process. So, it is relevant to take those econometric models into account, a key point being that such strategies require a good forecast of the covariance matrix. If there is volatility transmission between those markets, we can use volatility within each market to improve volatility forecasts for other markets. And it could be relevant to know the reason for that transmission in order to get better volatility forecasts, even if there are structural changes that econometric models do not take into account.

For regulatory policy, it is important to know structures in volatility, and to know the reasons behind those structures, to be able to forecast the effect of changes in economic fundamentals on the volatility structures. A documented example related to volatility transmission is the case of the Toronto Stock Exchange. The adoption by the New York Stock Exchange (NYSE) in 1988 of limits on large negative daily price movements, known as "circuit breakers", led to the introduction of similar measures on the Toronto Stock Exchange. But in this case, trading halts happened when there was a large negative movement in the Dow Jones Industrials Average, not in a Toronto Stock Exchange index. The rationale behind that policy regulation was a high correlation between the NYSE and the Toronto stock returns; it was thought that financial storms happened first on the NYSE. But in 1995 Karolyi used more efficient econometric techniques to calculate this correlation, GARCH models, and demonstrated that the correlation was weaker than previously thought and diminished over time, so that the rationale behind these regulatory policies should be seriously re-examined.

The existence of volatility transmission between stock markets is well-documented in the literature. See, for example, Hamao, Masulis and Ng (1990), who study volatility transmission between Tokyo, London and New York, or Francis and Leachman (1996), who study volatility transmission between G-7 countries. In the Spanish case, see, for example, Peña and Ruiz (1995), who study international financial integration effects on the Spanish stock market.

In the volatility transmission literature, we can see transmission between markets with overlapping trading, as in Hogan and Melvin (1994) in the foreign exchange market, or transmission between markets with non-overlapping trading, as in Booth, Martikainen and Tse (1997) in the stock market. In the case of transmission between overlapping stock markets, some volatility transmission is because some assets are quoted in both markets and arbitrage takes place, so movements in those assets' prices should be equal in both markets.

In this literature, we can also differentiate between volatility transmission among the same asset quoted in different markets, as in Engle, Ito and Lin (1990) in the foreign exchange market, and volatility transmission between different assets, as in Koutmos and

Booth (1995) in the stock market. When stock market volatility transmission is studied we can see the two kinds of transmission. Different firms' stocks are different assets, and some stocks are quoted in different stock markets. The greater part of the literature on stock market volatility transmission is about transmission between market indexes, and given that the greater part of market indexes takes into account national firms only, it is about volatility transmission between different assets. In this stock market literature, some papers study transmission between overlapping markets and some between non-overlapping markets. In the foreign exchange literature, the greater part of the papers study transmission among the same asset quoted in non-overlapping markets.

In the literature on volatility transmission between financial markets, we can find explanations of transmission such as the following: i) A first explanation is based on the Ross (1976) asset valuation model, known as APT, where it is assumed that some factors explain asset returns in different markets. These common factors are the origin of volatility transmission. One market opens first and receives the common factor volatility, then the second market opens and also receives the common factor volatility. See, for example, King, Sentana and Wadhwani (1994). They assume that there are observable factors and unobservable factors. Finally, they conclude that only a small proportion of volatility and volatility transmission is explained by observable factors. ii) Another explanation is stochastic policy coordination. See, for example, Ito, Engle and Lin (1992), who study the relevance of volatility transmission due to stochastic policy coordination in the foreign exchange market and conclude that this explanation is not a major cause. Another example is from Francis and Leachman (1996), who think that economic policy competition could be another source of volatility transmission. iii) Additional explanations, that break market efficiency, are based on chartist analysis. See, for example, Engle, Ito, and Lin (1990) that pointed out that it could be that some of those techniques cause volatility transmission. iv) In volatility transmission between the same asset quoted in different non-overlapping markets, we find two major explanations. a) It may be that information comes in clusters, as if information was arriving like a meteor shower onto the earth as the earth rotates on its own, and causes volatility transmission between financial markets. b) Or it may be that there are market dynamics that cause volatility persistence, and in this case, volatility transmission between markets. See, for example, Kyle (1985) and Admati and Pfleiderer (1988) for theoretical models explaining market dynamics that can cause volatility persistence; these are noisy rational expectation models[12]. Another case of market dynamics explaining volatility persistence is a relaxing of the market efficiency hypothesis; it could be that traders have heterogeneous expectations and take too long to agree on price responses to new information. A relevant paper in this literature is Engle, Ito and Lin (1990), in the foreign exchange market. They think of these two major explanations for volatility transmission, but they do not measure the relative importance of each one. Hogan and Melvin (1994) study the impact of heterogeneous expectations about US trade balance on volatility transmission in the foreign exchange market. They find that heterogeneous expectations have a significant effect, but this effect explains only a small proportion of volatility transmission. Finally it is worth mentioning Ederington and Lee (1995). They

[12] The basic idea behind these models is to assume that there are two major kinds of traders, informed traders and uninformed noisy traders. Informed traders maximize their profit by disseminating information into prices gradually, and that is the explanation for volatility persistence. For the relation between volatility and information incorporation into prices, see, for example, Ross (1989), Ederington and Lee (1995), and Donders and Vorst (1996).

study the impact of scheduled macroeconomic news releases on interest rates and foreign exchange rates. They find persistence in volatility and explain it by the same two major reasons mentioned above. In the case of persistence in volatility due to the data generating process, they argue that the media usually release the main figures first and take some time to release further details. This can justify persistence in volatility, at least for a few minutes.

In this paper we study volatility transmission among the same stock quoted in different non-overlapping markets. In this case, this is equivalent to study persistence in volatility. As we mentioned before, there are two major explanations in the literature for this transmission of volatility, that is i) market dynamics and ii) data generating processes. Little attention has been paid to the last explanation, and to the measurement of the relative importance of each explanation. In this paper we identify data generating processes that can explain persistence and transmission of volatility between non-overlapping markets, those processes are related to the firm's business geographical distribution. Also, we get a first measure of the importance of these data generating processes in relation to market dynamics for explaining that volatility persistence, and we obtain that the data generating processes are the main determinant.

In the next section we present the theoretical fundamentals. Section 3 gives the data summary. Section 4 reports on the empirical analysis. And the final section summarizes the main conclusions of this paper.

2. THEORETICAL FUNDAMENTALS

In order to identify the data generating processes that could explain volatility transmission among a stock quoted in different non-overlapping markets, we use a modelling technique similar to the one used by King and Wadhwani (1990) and Ito, Engle and Lin (1992).

So, let us suppose a stock quoted in a local market and in a foreign market. The local market opens first and closes before the opening of the foreign one. Every market is open for 12 hours. $P_{t,0}$ is the closing price in the local market on day t. And $P_{t,1}$ is the closing price in the foreign market on day t.

There are news releases relevant to stock prices during 24 hours. The news releases during the first 12 hours are reflected in the local market, and the news releases during the second 12 hours period are reflected in the foreign market.

$P_{t,0}- P_{t-1,1}$ - Innovation reflecting all the news released during the local market trading period.

$P_{t,1}-P_{t,0}$ - Innovation reflecting all the news released during the foreign market trading period.

Let us suppose that stock price movements can be explained by some indexes, in a way similar to the Ross (1976) APT model.

$$P_{t,i} = f(I_1, I_2, I_3,................, I_k) \qquad i=0,1 \tag{1}$$

Supposing two types of indexes, one type can have innovations at any time, and the other type can have innovations during the trading hours of one market only. The type 1 indexes could be those reflecting generic aspects, not related to any market, as, for example, indexes reflecting technological evolution. The type 2 indexes could be those reflecting information released when only one market is open, as, for example, indexes reflecting the demand evolution in a specific geographical area. Demand is on the products sold by the firm whose stock we are pricing.

Let us suppose a stock price can be linearly projected on three indexes.

$$P_{t,i} = \alpha_0 X_{t,i}+ \alpha_1 Y_{t,i} +\alpha_2 Z_{t,i} \quad i=0,1 \tag{2}$$

Suppose those indexes follow the following stochastic processes during the trading hours in every market.

$$Z_{t,0} = Z_{t-1,1}+ \varepsilon_{t,0} \qquad \varepsilon_{t,0} \mid \Psi_{t-1,1} \sim D(0,\sigma^2) \tag{3.1}$$

$$Z_{t,1} = Z_{t,0}+ \varepsilon_{t,1} \qquad \varepsilon_{t,1} \mid \Psi_{t,0} \sim D(0,\sigma^2) \tag{3.2}$$

$$X_{t,0}= X_{t-1,0} + \eta_{t,0}+ \eta^*_{t-1,1} (\rho + \zeta_{t,0}) \qquad \eta_{t,0} \mid \Psi_{t-1,1} \sim D(0,\sigma^2_\eta),$$

$$\zeta_{t,0} \mid \Psi_{t-1,1} \sim D(0,\sigma^2_\zeta) \qquad (4.1)$$

$$X_{t,1}= X_{t,0} \qquad (4.2)$$

$$Y_{t,0}= Y_{t-1,1} \qquad (5.1)$$

$$Y_{t,1}= Y_{t-1,1} + \eta^*_{t,1} + \eta_{t,0} (\rho^* + \zeta^*_{t,1}) \qquad \eta^*_{t,1} \mid \Psi_{t,0} \sim D(0,\sigma^2_{\eta^*}),$$

$$\zeta^*_{t,1} \mid \Psi_{t,0} \sim D(0,\sigma^2_{\zeta^*}) \qquad (5.2)$$

Where D is any probability distribution, Ψ is the conditioning set of information at every point in time, and there is no correlation among the specified innovations.

Index X changes take place during local market trading only, while index Y changes take place during foreign market trading period only. Finally, index Z changes take place at any time.

Knowing the stochastic process followed by those indexes we can see that:

$$P_{t,0}- P_{t-1,1} = \alpha_2\varepsilon_{t,0} +\alpha_0[\eta_{t,0}+ \eta^*_{t-1,1} (\rho + \zeta_{t,0})] \qquad (6.1)$$

$$P_{t,1}-P_{t,0} = \alpha_2\varepsilon_{t,1} + \alpha_1[\eta^*_{t,1} + \eta_{t,0} (\rho^* + \zeta^*_{t,1})] \qquad (6.2)$$

Equation 6.1 reflects the innovation that takes place in the stock price during the trading period in the local market, and likewise for equation 6.2 in the foreign market. It is worth mentioning that innovations in X index have an effect on innovations on Y index and vice versa, but it is a stochastic effect. So we have transmission of movement in the level of the price series.

These price change variances are:

$$VAR(P_{t,0}- P_{t-1,1}) = \alpha_2^2\, \sigma^2 + \alpha_0^2\sigma^2_\eta + \alpha_0^2\, (\eta^*_{t-1,1})^2\, \sigma^2_\zeta \qquad (7.1)$$

$$VAR(P_{t,1}-P_{t,0}) = \alpha_2^2\, \sigma^2 + \alpha_1^2\sigma^2_{\eta^*} + \alpha_1^2\, (\eta_{t,0})^2\, \sigma^2_{\zeta^*} \qquad (7.2)$$

Equation 7.1 shows how price change variance during trading hours in the local market is increased by the previous day innovation in index Y during the foreign market trading period ($\eta^*_{t-1,1}$). Similarly, this happens with the variance in the price changes during the foreign market trading hours. There is volatility transmission. And the reason is that the innovation effect of the previous market index on the present market price change is stochastic. That is, $\sigma^2_{\zeta}>0$ in the local market, and $\sigma^2_{\zeta*}>0$ in the foreign market.

As we have seen up until now, volatility transmission can be explained by the existence of type 2 indexes in the equation of price formation, equation 1.

Do these type of indexes exist in the real world? Let us suppose that we are trying to price the stock of a firm that sells its product J in the local market and in the foreign market geographic areas. Let us suppose that the X index reflects the demand evolution of J in the local market geographical area and that the Y index does the same but for the demand in the foreign market geographical area. Let us think about news that affects J's demand, independent of the geographical location of that demand. Suppose a new piece of information affecting J's demand has been released during the local market trading and, therefore, has an effect on the firm's stock price in the local market. This piece of information will also affect J's demand in the foreign market geographical area. But we do not know how much of an effect until trading occurs in the foreign market. Traders in the local market will discount the expected value of this effect during the trading period in the local market, but uncertainty about the direction and extent of this effect will remain until trading occurs in the foreign market. So even if there is a discounting of the expected effect, there will remain transmission in mean and in variance. In appendix A, there are equations reflecting the discounting made by traders.

We can think of examples of news affecting the firm's product demand in both countries, such as the launching of an advertising campaign in both countries, the launching a new product in both countries, a generalised change in product price, an environmental disaster due to the firm's behaviour, etc. Demand reaction does not have to be the same in every country. Every country has its own culture, its own customs, its own way of life. And there will always be uncertainty in forecasts about demand reaction to a new piece of information.

The firm's product demand example of type 2 indexes is an obvious one. But it is possible that there are other cases of type 2 indexes related to other aspects of a firm's activity. For example, if a firm decides to reduce wages, the conflict it creates on its workers reduces the firm's profits. If this measure is released in the local market, local traders will introduce into the stock price the level of conflict this measure generates in the firm's local workers and what they expect is going to be the reaction of the firm's foreign workers. Then in the foreign market, traders will introduce into the stock price the level of conflict generated in the firm's foreign workers that was not expected by local traders. The level of conflict generated on the firm's workers in each country is another example of type 2 indexes related to another aspect of the firm's activity. For another example type 2 indexes see Ito, Engle and Lin (1992) in the foreign exchange market. They study whether stochastic policy coordination could be an explanation of volatility transmission between markets. In the stock market case, this could provide a reason for volatility transmission. Just think of indexes which reflect the effect on stock prices of each country economic policy.

Under the argumentation of this section, volatility transmission is due to the stochastic process followed by the indexes affecting the stock price. This source of volatility transmission does not imply market inefficiency. It is not due to the existence of asymmetric information or to traders taking too long to agree on the effect of a new piece of information. It is a case of information arriving like a meteor shower, meteors that hit the earth as it rotates on its own. There is a new main piece of information, and then there is a gradual release of complementary news that is incorporated into prices. This is volatility transmission due to the data generating process.

Finally, it is worth mentioning that activity is required in the time-zone geographical areas of both markets where the stock is quoted in order to have volatility transmission of this type in a firm's stock[13]; this transmission type is due to the existence of type 2 indexes related to the firm's activity in specific geographical areas. Like transmission due to type 2 indexes reflecting product demand evolution in each market or the level of conflict generated on the firm's workers in each country. These indexes are not observable for us. So, an indirect way to test the importance of such type 2 indexes in reality is to test whether there is more volatility transmission, the more global a firm is[14].

On the other hand, the main part of news affecting non-global firms will be released in their local market, so market dynamics will produce volatility transmission from the local market to the foreign market. In global firms, there will also be volatility transmission due to market dynamics, but in this case there will be transmission from the local market to the foreign one and vice versa (assuming that news affecting global firms is released in both markets, because there is activity in both markets). There could exist other type 2 indexes not related to geographical area activity. So, supposing that market dynamics and that "other" type 2 indexes equally affect both types of firms (global and non-global), the difference between volatility transmission in both types of firms from the local market (local for non-global firms) to the foreign market, will be due to type 2 indexes related to the firm's activity in specific geographical areas. And so we can evaluate the importance of a specific source of volatility transmission due to the data generating process. The remaining volatility transmission will be due to other sources related to the data generating process and to market dynamics.

3. THE DATA

Given that we are trying to study volatility transmission between non-overlapping markets, we study transmission between the Tokyo Stock Exchange (TSE) and the New York Stock Exchange (NYSE). During the beginning of the Nineties, 29.4% of the world market value was quoted on the NYSE, and 46.3% on the TSE[15]. Those are the biggest markets in market value. We found, through the Internet, listings of foreign companies listed on the TSE and on the NYSE, which were quoted in both markets at the start of 1998. Our target company sample included US, Japanese and European companies quoted on the TSE and on the NYSE. We had stock price data of 43 companies[16]. But because of data

[13] The same analysis can be expanded to *n* markets. We present the case of two markets only for exposition simplicity.
[14] It is understood that the larger the percentage of activity in the foreign market, the more global a firm is.
[15] Peña and Ruiz (1995).
[16] In our sample there are just US, UK, Spanish and Japanese stocks. It has been left for future research to include in the sample other countries' companies, which are quoted on the TSE and on the NYSE. Data limitations make it impossible to have those company quotations for this paper. Even so, we would like to remark that at the beginning of 1998, there were just 59 foreign companies listed on the TSE. It could be that some of those 59 companies are not listed on the NYSE. So, our sample represents a big percentage of the total number of stocks dually listed on the NYSE and on the TSE.

limitations in their financial statements, we had to restrict our company sample to 31 of the 43 mentioned above.

Our empirical analysis was aimed at determining if there is more volatility transmission in companies that have activity in both markets' time-zone geographical areas than in companies that have activity in only one market time-zone geographical area. To do this empirical analysis, we had to classify companies into two categories: i) what we call international companies are those that have activity in both markets' time-zone areas, and ii) what we call non-international companies are those that have activity in only one market time-zone area.

Within the Tokyo time-zone area, we include Asia and the Pacific Ocean. Within the New York time-zone area, we include America, Africa and Europe. We include Africa and Europe in the New York time zone because, in Madrid time (Spain), New York opens at 15:30 and closes at 22:00 hours. All the news released in Europe during this period of time will be reflected in New York quotes, and similarly with Africa. Also, in Madrid time, Tokyo opens at 01:00 and closes at 07:00 hours, so that in Europe and Africa, there is a smaller proportion of daily activity during the TSE trading period when compared with the proportion of daily activity during the NYSE trading period. In addition, the greatest part of daily activity in Asia is during the Tokyo trading period. Australia, New Zealand and New Guinea are in the Tokyo time-zone area, and get the major part of the economic activity in the Pacific Ocean area.

To classify companies into international and non-international, we use the 1996 or 1997 financial statements[17]. All these statements were found on the company's Web pages. The general criterion for classifying those companies was the revenue distribution between the New York time-zone geographical area and the Tokyo time-zone geographical area. When we could not obtain that information, we classified companies by their profits, their assets, or, as in the case of the Spanish banking sector, their interest and other assimilated yields as distributed between the New York and the Tokyo time-zone geographical areas. Then we calculated the percentage of revenues, assets, profits, or interest and other assimilated yields in the time-zone geographical area of the foreign market, and we take that percentage as an indicator of real activity in the foreign market. We calculated this indicator's mean, and we classified as internationals all the companies with a bigger percentage. On the other hand, there were some companies that have only an abstract of the financial statements on their Web pages, and we could not get the geographical distribution of any of the chosen quantities to evaluate the company's activity in a geographical area. To classify these companies, we followed another criterion. We read the information on the company's Web pages, and we classified these companies as international or non-international only when there was a very clear choice. As a result, we applied this second method in only two cases. Of the 43 companies we had stock price data about and where traded on the NYSE and on the TSE, we end up with 31. Table 3.1 lists the company distribution quartiles, which orders the sample by the percentage of activity in the foreign market, the maximum and the minimum of that percentage in each quartile, and other relevant data related to the classification between international and non-international companies.

Table 3.1. Sample Descriptive Statistics.

Quartiles	USA [d]	Europe [d]	Japanese	Minimum [a]	Maximum
First quartile	2	5	0	0.35%	9.65%
Second quartile	5	2	0	9.99%	17.47%
Third quartile	5	0	2	18.00%	32.40%
Fourth quartile	3	0	5	34.26%	80.57%
Total	15	7	7		
Threshold [b]	24.02%				
Maximum in non-international companies [c]	19.42%				
Minimum in international companies	25.63%				

a. Minimum percentage of activity in the foreign market.

b. Percentage of activity in the foreign market that separates between international and non-international companies.

c. Maximum percentage of activity in the foreign market in the non-international companies.

d. There is a European company and an USA company where we couldn't get numerical information of any of the selected magnitudes to use as an indicator of activity in the foreign market. Those companies are not included in the table. Both are classified as non-internationals.

We have the daily opening price and the daily closing price of each stock from the 26 April 1996 to 22 May 1998.

We make an equally weighted portfolio with the 11 stocks classified as internationals, which we call the international portfolio, and another equally weighted portfolio with the 20 stocks classified as non-internationals, which we call the non-international portfolio.

We take the logarithm of the closing price minus the logarithm of the opening price as the daily return. We omit weekends and holiday days in either of both markets, and we take as a null return any time when there is no trading. Then we calculate the daily portfolio return as the arithmetic mean of the stock's daily return in each portfolio. So we end up with two returns' time series for each portfolio, the one in New York and the one in Tokyo. Each time series has 494 observations.

It is worth mentioning that we have returns for the trading period only; we do not have overnight returns. The reason is that we want to relate news released during the trading period in each market with returns in that market.

In appendix B we have the listing of all the companies included in our sample and their industrial sectors.

[17] We used the last financial statement available for each firm.

4. EMPIRICAL ANALYSIS

4.1. Descriptive Analysis and Mean Modeling.

We want to determine if the international portfolio (IP) has more volatility transmission between Tokyo and New York than the non-international portfolio (NIP), as we can extrapolate from the theoretical analysis.

We have two returns' time series for each portfolio, one for the NYSE and one for the TSE. These series basic statistics are shown in table 4.1.

Table 4.1 Basic Statistics

Series	Mean	Standard Error	Skewness	E-Kurtosis
IP-NYSE	0.000991007	0.006087077	1.3054	33.48252
	(0.00032687)		(0)	(0)
IP-TOKYO	0.000031376	0.006188757	0.05309	1.05797
	(0.91032643)		(0.63102785)	(0.00000188)
NIP-NYSE	0.000897005	0.008141196	2.17297	31.53085
	(0.01467673)		(0)	(0)
NIP-TOKYO	-0.000123833	0.001772034	-0.09279	1.17192
	(0.12101685)		(0.40126745)	(0.00000013)

- E-kurtosis is the kurtosis above the Normal distribution kurtosis.
- Between brackets we present the P-value of the T test. The null hypothesis is a zero value.

There are significant mean returns and skewness in the NYSE only. The greatest difference between both portfolios is in volatility. The non-international portfolio has more differences in volatility between the TSE and the NYSE than the international portfolio.

We have chosen the following method to analyse the differences in volatility transmission between the international portfolio and the non-international portfolio. We estimate a univariate Autoregressive Conditional Heteroscedastic model for each return time series. Then we use these models to estimate volatility time series, and then we see if there is more correlation between volatility in the NYSE and the TSE in the international portfolio than in the non-international portfolio. More correlation means more volatility transmission. Given that we want to compare a measure of volatility transmission among our two portfolios, we think that this method is more appropriated than a bivariate model for each portfolio. It is because in the bivariate model the measure of volatility transmission is a regression coefficient that is not bounded and it makes difficult to do comparisons between portfolios. The correlation coefficient is bounded between -1 and 1.

First of all, we need to see if there is an Autoregressive Conditional Heteroscedastic process in each return's time series. So we estimate a univariate model for each return time series under the assumption of homoscedasticity, and then we apply the McLeod and Li (1983) test to the squared residuals to see if there is an autoregresive process in variance. Having heteroscedasticity deteriorates efficiency but we still have consistency. So, by studying the abovementioned model residuals, we can see if there is an autoregressive process in volatility. In table 4.2 we show the estimated models under the homoscedasticity assumption. In table 4.3 we show the Ljung and Box (1978) test to detect autocorrelation in the residuals[18] and the McLeod and Li test to detect autocorrelation in the squared residuals. Finally in table 4.4 we show the e-kurtosis and the skewness of the abovementioned models' residuals.

Table 4.2 Estimated models under the homoscedasticity assumption.

	Constant	MA(1)	MA(17)	MA(22)	Durbin-Watson
IP-NYSE	0.000990871 (0.00004492)	-0.118834591 (0.00826506)			1.984825
IP-TOKYO		-0.079278716 (0.07931154)	-0.17598093 (0.00011557)		1.970689
NIP-NYSE	0.000897136 (0.00046652)	-0.283687598 (0)			1.960168
NIP-TOKYO				-0.109251790 (0.01993103)	2.093394

- The P-value of the T test is in brackets.

Table 4.3 Residual tests of the estimated models under the homoscedasticity assumption.

	IP-NYSE	IP-TOKYO	NIP-NYSE	NIP-TOKYO
Ljung-Box				
Q(5)	2.3851 (0.66532)	2.5655 (0.46357)	2.848 (0.58358)	4.1459 (0.38662)
Q(10)	6.9271 (0.64471)	9.4981 (0.30203)	6.7843 (0.65957)	12.6940 (0.17695)
Q(20)	21.8686 (0.29084)	18.6516 (0.41357)	19.4036 (0.43123)	23.7237 (0.20697)
Q(30)	28.7743 (0.47687)	24.7764 (0.63998)	27.4623 (0.54678)	33.2550 (0.26757)
McLeod-Li				
Q(5)	114.9457 (0.00000)	16.1896 (0.00632)	99.1557 (0.00000)	17.0494 (0.00441)
Q(10)	117.7783 (0.00000)	30.0476 (0.00084)	99.6634 (0.00000)	25.6079 (0.00430)
Q(20)	118.3647 (0.00000)	95.0658 (0.00000)	100.1168 (0.00000)	62.6990 (0.00000)
Q(30)	119.7657 (0.00000)	116.1625 (0.00000)	101.3096 (0.00000)	86.0367 (0.00000)

- The P- value of the Q test is in brackets[19].

[18] It is not the appropriate test when there is heteroscedasticity. We use it to have approximate results only. It is worth mentioning that Diebold (1987) showed that the Box-Pierce statistics are upward biased in the presence of autoregresive heteroscedasticity, so we are not wrong when we accept the no autocorrelation hypothesis.

[19] Under the null hypothesis of an ARMA(p,q) model with a strict white noise, the Q(h) statistic is asymptotically chi-square distributed with h-p-q degrees of freedom.

Table 4.4 Residual's e-kurtosis and skewness of the estimated models under the homoscedasticity assumption.

Series	E-kurtosis	Skewness
IP-NYSE	27.03049	0.56319
	(0)	(0.00000036)
IP-TOKYO	1.00245	0.11457
	(0.00000915)	(0.30853439)
NIP-NYSE	19.63187	0.81346
	(0)	(0)
NIP-TOKYO	1.07096	-0.09635
	(0.00000237)	(0.39377239)

- The P-value of the T test is in brackets.

All stocks have a similar liquidity on the NYSE. But on the TSE, Japanese companies are very liquid while there are big differences in liquidity between the other nationalities' stocks. So, we have portfolios composed of very different stocks in liquidity. Then the serial correlation found in Tokyo, with such high order MA(h) terms, possibly stems from the "Fisher effect" (nonsynchronous trading) and other frictions in the trading process, as discussed in Scholes and Williams (1977) and Lo and MacKinlay (1990). On the other hand we know that the Ljung-Box statistic is upward biased in the presence of autoregresive heteroscedasticity. So, could be some of the identified MA(h) terms are not in the true model. After modeling the variance, and using the Ljung-Box test on the standardized residuals, we will be able to detect such misspecification.

4.2. Volatility Modeling

For volatility modeling we take into account symmetric models and asymmetric models with Normal conditional distribution. Concretely, we consider the following cases:

- GARCH(1,1) with Normal conditional distribution (Bollerslev, 1986):

$$\varepsilon_t \approx N(0,h_t)$$

$$h_t = \alpha_0 + \alpha_1 h_{t-1} + \alpha_2 \varepsilon_{t-1}^2$$

- EGARCH(1,1) with Normal conditional distribution (Nelson, 1991):

$\varepsilon_t \approx N(0,h_t)$

$h_t = \exp(\alpha_0 + \alpha_1 \ln(h_{t-1}) + \alpha_2 g_{t-1})$

$$g_t = |Z_t| - \sqrt{\frac{2}{\pi}} - \alpha_3 Z_t$$

$$Z_t = \frac{\varepsilon_t}{\sqrt{h_t}}$$

- GJR(1,1) with Normal conditional distribution (Glosten, Jagannathan and Runkle, 1991):

$\varepsilon_t \approx N(0,h_t)$

$h_t = \alpha_0 + \alpha_1 h_{t-1} + \alpha_2 \varepsilon_{t-1}^2 + \alpha_3 g_t$

$g_t = \varepsilon_{t-1}^2$ if $\varepsilon_{t-1} < 0$

$g_t = 0$ if $\varepsilon_{t-1} > 0$

The asymmetric models are designed for modeling the so-called “leverage effect”; that is, negative shocks have bigger effect on variance than positive shocks. We use the errors of the models estimated under the assumption of homoscedasticity to detect this asymmetric effect. So we calculate the Ljung-Box statistic with the correlation coefficients between the squared error and the lagged error. Then, if we get significant correlation means that there is such asymmetric effect in the series. In table 4.5 we show this test.

Table 4.5 Test to detect asymmetries in the volatility process

Ljung-Box	IP-NYSE	IP-TOKYO	NIP-NYSE	NIP-TOKYO
$Q_3(1)$	69.0950	3.9330e-003	56.1949	0.9977
	(0)	(0.94999)	(0)	(0.31786)
$Q_3(2)$	75.9275	0.3472	62.0388	1.5654
	(0)	(0.84063)	(0)	(0.45716)
$Q_3(5)$	78.1571	4.6009	65.4196	2.6960
	(0)	(0.43020)	(0)	(0.74672)

- The P-value is in brackets.
- $Q_3(h)$ is the Ljung-Box statistic calculated with “corr(e_t^2,e_{t-1}), corr(e_t^2,e_{t-2}),......,corr(e_t^2,e_{t-h})” to determine the statistical significance of such coefficients. Where e_t is the error term in the estimated model under the assumption of homocedasticity.

In table 4.5 we see that the volatility process is asymmetric in the NYSE time series only. So we estimate the symmetric model for the Tokyo time series, and the asymmetric models for the NYSE time series.

It is worth mentioning that there was a mini crash during our sample time period. During the 27 of October of 1997 there was a drop in the Hong Kong Stock Exchange that caused a fall of more than 7% in the NYSE. On that day we see a big fall followed by a sharp rise the day after in our NYSE time series. We do not see such behavior in our Tokyo time series.

For volatility modeling we implemented two strategies, one is to ignore the existence of the crash, and the other is to use dummy variables to take account of it. The behavior of the series during the crisis suggest us that the outlier is in the variance level, so the most appropriated dummy variable seems to be in the variance constant term. We tried such model specification among others and we concluded that this is the best one. This dummy variable takes value 1 the 27 of October of 1997 and zero the otherwise.

As a performance measure of the specified models in each time series we have used three tests: the Ljung-Box test on the standardised residuals[20]; the McLeod and Li test on the squared standardised residuals; and the Engle and Ng (1991)[21] test to detect misspecification of the conditional variance function. In tables 4.6 to 4.9 we show the estimated models and the applied tests in each time series.

[20] So there is homoscedasticity in the null hypothesis, and we avoid the upward bias in the Q statistic under heteroscedasticity.

[21] To apply this test we need two dummy variables, the model residuals (e_t), and the implied variances (h_t). The first dummy variable (S_t^+) takes the value 1 when e_{t-1} is positive, and zero otherwise. The second dummy variable (S_t^-) takes value 1 when e_{t-1} is negative, and zero otherwise. We standardize the residuals dividing by the variance, so we get e_t^*. Then we regress e_t^* on an intercept, S_t^-, $S_t^- e_t$, and $S_t^+ e_t$ and test that the coefficient on the three constructed regressors is zero using an F statistic. This is a joint test. We use it because we want to test if the models explain the general process of the variance. The first regressor, S_t^-, represents the sign bias test which is intended to detect an asymmetric influence by the lagged negative and positive errors on the conditional variance, which may not be incorporated in the conditional variance function specified under the null hypothesis. The second regressor should be significant if the impact of large negative errors versus small negative errors on the conditional variance is different from the impact implied by the null h_t; this is the negative size bias test. The last regressor represents the positive size bias test.

Table 4.6.1.A Estimated Autoregressive Heteroscedastic Models in IP at the NYSE

IP-NYSE portfolio				
Coefficient	**EGARCH(1,1)**	**EGARCH(1,1) + dummy ****	**GJR(1,1)**	**GJR(1,1) + dummy**
Log-Likelihood	2365.41907	2381.74655	2366.50530	2379.45021
MEAN				
Constant	0.000845445	0.001027637	0.0009429024	0.0010583816
	(0.00019918)	(0.00001026)	(0.00006155)	(0.00000735)
	[1.22939e-005]	[3.89252e-006]	[7.40758e-005]	[2.09712e-004]
MA(1)	0.058765865	0.111244775	0.0673987352	0.0992686557
	(0.28353820)	(0.01538281)	(0.20746902)	(0.03183113)
	[0.34768]	[0.03936]	[0.27817]	[0.10405]
VARIANCE				
α_0	-3.332576233	-1.346904813	0.0000091586	0.0000058
	(0.00001111)	(0.00082263)	(0.00000124)	(0.00007334)
	[0.01210]	[0.00000]	[0.37886]	[0.09067]
α_1	0.683371193	0.874165241	0.4123823465	0.6517150542
	(0)	(0)	(0.00000001)	(0)
	[4.58465e-008]	[0.00000]	[0.39878]	[3.66976e-004]
α_2	0.447426776	0.143060118	0.0756027605	0.0455514921
	(0)	(0.00954861)	(0.18308055)	(0.19192869)
	[0.01680]	[0.05896]	[0.41939]	[0.58474]
α_3	0.429744126	0.361682545	0.4298463250	0.0926549524
	(0.00383256)	(0.17017554)	(0.00000026)	(0.19809291)
	[0.01680]	[0.30620]	[0.18504]	[0.29045]
Dummy		4.120080280		0.0015988775
		(0.00017622)		(0.29936201)
		[2.80662e-007]		[0.19528]

- The P-value of the T test is in brackets (....).
- The P-value of the robust T test is in brackets [.....].
- “Log-Likelihood” is the final value of the log likelihood function.
- ** The model has a dummy variable in the variance constant term that takes value 1 the day of the mini crash and zero otherwise.

Table 4.6.1.B Residual tests on the estimated Autoregressive Heteroscedastic Models in IP at the NYSE

IP-NYSE portfolio				
Coefficient	**EGARCH(1,1)**	**EGARCH(1,1) + dummy ****	**GJR(1,1)**	**GJR(1,1) + dummy**
E-Kurtosis	1.99224	0.75165	1.69333	0.86589
	(0)	(0.00071821)	(0)	(0.00009753)
Skewness	-0.30372	0.02414	-0.20469	0.02071
	(0.00605622)	(0.82728614)	(0.06434411)	(0.85152437)
Jarque-Bera Normality test	88.92907	11.62983	62.21665	15.40536
	(0)	(0.00298)	(0)	(0.000451525)
Ljung-Box				
Q(5)	3.43046	5.17665	3.30953	5.20142
	(0.48853)	(0.26965)	(0.50742)	(0.26725)
Q(10)	12.61998	10.21314	11.89157	10.25872
	(0.18057)	(0.33351)	(0.21949)	(0.32995)
Q(20)	24.06259	22.35834	23.84670	23.20667
	(0.19376)	(0.27159)	(0.20210)	(0.22836)
Q(30)	42.87984	36.10651	42.82331	37.24378
	(0.04671)	(0.17048)	(0.04727)	(0.14009)
McLeod-Li				
Q(5)	3.95776	3.72184	3.26741	3.18284
	(0.55551)	(0.59012)	(0.65884)	(0.67182)
Q(10)	9.57592	6.95694	7.81943	5.41558
	(0.47845)	(0.72950)	(0.64647)	(0.86175)
Q(20)	16.80180	13.65285	14.57370	14.07692
	(0.66580)	(0.84765)	(0.80026)	(0.82657)
Q(30)	33.26375	35.58261	34.76885	36.91977
	(0.31121)	(0.22206)	(0.25115)	(0.17949)
Engle Ng				
F(3,487)	1.84355	0.72752	1.04791	0.53342
	(0.13832736)	(0.53591386)	(0.37099916)	(0.65955406)

- The P-value of the T and Q tests is in brackets.
- Skewness and e-kurtosis are on the standardised residuals.
- ** The model has a dummy variable in the variance constant term that takes value 1 the day of the mini crash and zero otherwise.

All the estimated models in tables 4.6 have a significant e-kurtosis on the standardised residuals. It is a signal of non-normality in the real conditional distribution generating the data. As it is the Normality rejection in the Jarque-Bera test on the standardised residuals.

In the IP-NYSE time series case, we also tried to adjust GARCH(1,1) models with and without the dummy variable, and all the tests suggested that the models in tables 4.6 are the best ones. We also tried to estimate the same models as in tables 4.6.1 but without the MA(1) term, and the tests suggest that the MA(1) term is not needed when we do not use the dummy variable, as can be seen in tables 4.6.2.

Table 4.6.2 A Estimated Autoregressive Heteroscedastic Models in IP at the NYSE

IP-NYSE portfolio		
Coefficient	**EGARCH(1,1)**	**GJR(1,1)**
Log-Likelihood	2364.87401	2365.8187
MEAN		
Constant	0.000923321	0.0009847551
	(0.00000424)	(0.00000335)
	[1.54458e-006]	[8.94420e-006]
VARIANCE		
α_0	-3.487751045	0.0000092818
	(0.00000622)	(0.00000111)
	[6.58871e-006]	[0.21069]
α_1	0.668844809	0.3944948152
	(0)	(0.00000005)
	[6.92545e-021]	[0.26072]
α_2	0.470665618	0.1013406128
	(0)	(0.07882714)
	[2.42418e-004]	[0.28056]
α_3	0.390073605	0.4075521201
	(0.00313519)	(0.00000017)
	[0.02372]	[0.13689]

- The P-value of the T test is in brackets (....).
- The P-value of the robust T test is in brackets [.....].
- "Log-Likelihood" is the final value of the log likelihood function.

Table 4.6.2 B Residual tests on the estimated Autoregressive Heteroscedastic Models in IP at the NYSE

IP-NYSE portfolio		
Coefficient	**EGARCH(1,1)**	**GJR(1,1)**
E-Kurtosis	1.93355	1.63252
	(0)	(0)
Skewness	-0.28288	-0.18215
	(0.01057653)	(0.09973958)
Jarque-Bera Normality test	83.3725	57.47253
	(0)	(0)
Ljung-Box		
Q(5)	5.10	5.44210
	(0.4035)	(0.36434)
Q(10)	15.41	15.23017
	(0.1177)	(0.12389)
Q(20)	27.31	27.97271
	(0.1265)	(0.11005)
Q(30)	46.02	46.58896
	(0.0309)	(0.02728)
McLeod-Li		
Q(5)	3.99	3.56041
	(0.5502)	(0.61427)
Q(10)	9.28	7.68379
	(0.5048)	(0.65969)
Q(20)	16.88	14.60727
	(0.6602)	(0.79842)
Q(30)	33.89	35.61638
	(0.2848)	(0.22091)
Engle Ng		
F(3,487)	1.3418	0.94950
	(0.26004)	(0.41644717)

- The P-value of the T and Q tests is in brackets.
- Skewness and e-kurtosis are on the standardised residuals.

In tables 4.6 we see that there is a problem with the Ljung-Box test with 30 lags in the models without dummy variable. It could be that the estimated variance models does not fully reflect the dynamics of the true process and leaves unexplained some autocorrelation in variance for high lags. The problem arises at a very high lag. We are working with daily data, with no observations for the weekends. So, the fundamental part of the variance process is reflected in the estimated model. If we compare the Q statistics in the McLeod-Li test that we get in table 4.3 with the ones in tables 4.6, we see that the estimated model reflects the fundamental part of the real variance process.

Table 4.7.A Estimated Autoregressive Heteroscedastic Models in NIP at the NYSE

NIP-NYSE portfolio				
Coefficient	**EGARCH(1,1)**	**EGARCH(1,1) + dummy****	**GJR(1,1)**	**GJR(1,1) + dummy**
Log-Likelihood	2216.56677	2226.38159	2221.68420	2228.82953
MEAN				
Constant	0.000737252 (0.00595613) [0.00134]	0.000831050 (0.00114876) [0.00705]	6.9825e-004 (0.01322062) [0.15731]	8.0145e-004 (0.00387606)
MA(1)	-0.144555233 (0.00464303) [0.00685]	-0.153018928 (0.00204436) [0.00276]	-0.1048 (0.01004161) [0.00214]	-0.1067 (0.00288846)
VARIANCE				
α_0	-3.744799019 (0.00005904) [0.01707]	-2.734143867 (0.00730405) [0.28494]	2.1638e-005 (0.00000069) [1.92122e-017]	2.3445e-005 (0.00013588)
α_1	0.623849662 (0) [8.46742e-005]	0.728012198 (0) [0.00530]	0.4134 (0.00026706) [1.39553e-010]	0.4365 (0.00627471)
α_2	0.296701880 (0.00000265) [1.97667e-004]	0.111300730 (0.18225777) [0.28950]	-0.0731 (0.00024031) [0.03131]	-0.0948 (0.00012664)
α_3	0.975611813 (0.00142720) [0.00175]	1.457831149 (0.16588766) [0.42805]	0.4750 (0) [0.01631]	0.2755 (0.00516666)
Dummy		4.272360674 (0.00129697) [0.06700]		2.0869e-003 (0.20558162)

- The P-value of the T test is in brackets (....).
- The P-value of the robust T test is in brackets [.....].
- "Log-Likelihood" is the final value of the log likelihood function.
- ** The model has a dummy variable in the variance constant term that takes value 1 the day of the mini crash and zero otherwise.
- With our methodology, and after a lot of trials we could not calculate the robust T statistic in the case of the GJR model with dummy.

Table 4.7.B Residual tests on the estimated Autoregressive Heteroscedastic Models in NIP at the NYSE

NIP-NYSE portfolio				
Coefficient	**EGARCH(1,1)**	**EGARCH(1,1) + dummy****	**GJR(1,1)**	**GJR(1,1) + dummy**
E-Kurtosis	0.66718	0.32660	0.58174	0.29558
	(0.00267851)	(0.14163161)	(0.00884665)	(0.18347057)
Skewness	-0.20350	-0.15194	-0.24586	-0.17419
	(0.06591649)	(0.16971432)	(0.02629227)	(0.11545538)
Jarque-Bera Normality test	12.52095	4.079772	11.89430	4.27909
	(0.00191)	(0.13005)	(0.00261)	(0.11771)
Ljung-Box				
Q(5)	1.26468	1.01368	1.87166	2.13069
	(0.86734)	(0.90771)	(0.75935)	(0.71174)
Q(10)	6.01513	5.04855	6.20838	5.78194
	(0.73840)	(0.83006)	(0.71890)	(0.76153)
Q(20)	23.42607	20.73107	24.72173	23.08361
	(0.21910)	(0.35185)	(0.16991)	(0.23368)
Q(30)	27.88319	25.64120	29.51131	28.62304
	(0.52417)	(0.64459)	(0.43869)	(0.48482)
McLeod-Li				
Q(5)	5.72813	3.54601	9.90296	3.64753
	(0.33358)	(0.61644)	(0.07803)	(0.60119)
Q(10)	14.83625	10.50886	19.55036	12.59576
	(0.13815)	(0.39704)	(0.03380)	(0.24716)
Q(20)	21.82942	23.44957	29.21070	29.39768
	(0.34984)	(0.26726)	(0.08369)	(0.08022)
Q(30)	40.53215	50.79701	49.16645	52.41778
	(0.09496)	(0.01023)	(0.01511)	(0.00686)
Engle Ng				
F(3,487)	2.34559	0.24133	1.17773	0.48409
	(0.07209727)	(0.86750060)	(0.31765383)	(0.69348481)

- The P-value of the T and Q tests is in brackets.
- Skewness and e-kurtosis are on the standardised residuals.
- ** The model has a dummy variable in the variance constant term that takes value 1 the day of the mini crash and zero otherwise.

In the NIP-NYSE case, the EGARCH(1,1) model has a better performance in the Ljung-Box test and in the McLeod and Li test than the GJR model. Both models pass the Engle and Ng test at the 5% significance level. The EGARCH model seems better because the JGR seems to leave more unexplained autocorrelation in variance, as the McLeod-Li test shows. As in the previous case we also tried to estimate GARCH(1,1) models with and without the dummy variable and the models on table 4.7 have better performance. We estimated the same models as in table 4.7 but without the MA(1) term and we got a worse performance, meaning that the identified MA(1) term is not due to the bias in the Ljung-Box statistic in the presence of heterocedasticity.

Table 4.8.A Estimated Autoregressive Heteroscedastic Models in IP at the TSE.

IP-TOKYO portfolio				
Coefficient	**GARCH(1,1)**	**GARCH(1,1) + dummy****	**GARCH(1,1)**	**GARCH(1,1) + dummy**
Log-Likelihood	2133.08471	2133.57331	2283.86189	2284.50694
MEAN				
MA(1)	-0.1078 (0.02356847) [0.00773]	-0.1071 (0.02326801) [0.00269]		
MA(17)	-0.1643 (0.00134985) [1.00470e-005]	-0.1619 (0.00161478) [3.67354e-007]		
VARIANCE				
α_0	3.2621e-007 (0.29107057) [0.16965]	4.1214e-007 (0.25541490) [0.04773]	3.81043e-007 (0.20985007) [0.28777]	4.66240e-007 (0.18002323) [0.15015]
α_1	0.9382 (0) [0.00000]	0.9381 (0) [0.00000]	0.93328 (0) [0.00000]	0.93372 (0) [0.00000]
α_2	0.0545 (0.00651645) [5.91766e-006]	0.0504 (0.01184538) [1.47084e-005]	0.05756 (0.00241165) [0.00424]	0.05263 (0.00479371) [0.00228]
Dummy		4.4612e-005 (0.27718926) [0.50660]		5.58172e-005 (0.25248007) [0.47199]

- The P-value of the T test is in brackets (....).
- The P-value of the robust T test is in brackets [.....].
- "Log-Likelihood" is the final value of the log likelihood function.
- ** The model has a dummy variable in the variance constant term that takes value 1 the day of the mini crash and zero otherwise.

Table 4.8.B Residual tests on estimated Autoregressive Heteroscedastic Models in IP at the TSE.

IP-TOKYO portfolio				
Coefficient	**GARCH(1,1)**	**GARCH(1,1) + dummy****	**GARCH(1,1)**	**GARCH(1,1) + dummy**
E-Kurtosis	0.34122	0.24139	0.38153	0.29421
	(0.13777070)	(0.29374047)	(0.08599168)	(0.18550538)
Skewness	0.02189	-0.02776	-0.06568	-0.11269
	(0.84833739)	(0.80838398)	(0.55283142)	(0.30848718)
Jarque-Bera normality test	2.25847	1.17079	3.34451	2.82156
	(0.32328)	(0.55688)	(0.18782)	(0.24395)
Ljung-Box				
Q(5)	4.19352	4.53485	5.18850	5.30024
	(0.38045)	(0.33844)	(0.26850)	(0.25785)
Q(10)	9.77205	9.64510	10.16317	9.70426
	(0.36925)	(0.37997)	(0.33744)	(0.37495)
Q(20)	17.38022	17.37725	31.24881	30.53994
	(0.56413)	(0.56433)	(0.03791)	(0.04532)
Q(30)	21.48541	21.48971	35.79126	34.98670
	(0.84086)	(0.84069)	(0.17973)	(0.20498)
McLeod-Li				
Q(5)	1.82241	1.60251	2.01829	2.01140
	(0.87313)	(0.90095)	(0.84661)	(0.84757)
Q(10)	3.34697	3.44286	4.83672	4.57601
	(0.97204)	(0.96900)	(0.90182)	(0.91765)
Q(20)	16.50501	16.80059	14.52462	14.64276
	(0.68484)	(0.66588)	(0.80293)	(0.79647)
Q(30)	32.19076	33.57203	29.13620	29.50221
	(0.35871)	(0.29826)	(0.51045)	(0.49135)
Engle Ng				
F(3,455)	0.12630	0.10476	1.24737	1.14397
	(0.94451084)	(0.95727672)	(0.29193643)	(0.33083065)

- The P-value of the T and Q tests is in brackets.
- Skewness and e-kurtosis are on the standardised residuals.
- ** The model has a dummy variable in the variance constant term that takes value 1 the day of the mini crash and zero otherwise.

As we deduced from the behavior of the series in Tokyo, there is not an outlier on the crisis day. So in the IP in Tokyo, the dummy variable is not statistically significant, and we do not have a significant performance improvement in the residual tests when we use this variable in the model. Without the MA(h) terms we do not pass the Ljung-Box test at 20 lags, so it seems that the MA(h) terms are necessary to get the dynamics of the IP in Tokyo.

There is a problem with the adjusted models in the IP in Tokyo because the constant term does not seem to be significant, and that means a zero unconditional variance. But in a GARCH model, all the parameters must be positive in order to avoid negative variances. So the right T test is not bilateral, and then it is not so clear that the constant term is not significant.

Table 4.9.A Estimated Autoregressive Heteroscedastic models in NIP at the TSE

NIP-TOKYO portfolio				
Coefficient	**GARCH(1,1)**	**GARCH(1,1) + dummy****	**GARCH(1,1)**	**GARCH(1,1) + dummy**
Log-Likelihood	2897.23305	2637.29608	2897.23305	2898.70076
MEAN				
MA(22)	-0.0849 (0.08068959) [0.03594]	-0.0760 (0.13052364) [0.07982]		
VARIANCE				
α_0	4.6225e-008 (0.14228273) [0.12142]	5.2577e-008 (0.09267665) [0.15754]	3.82597e-008 (0.12274841) [0.19742]	4.40235e-008 (0.07405402) [0.15949]
α_1	0.9303 (0) [0.00000]	0.9320 (0) [0.00000]	0.93092 (0) [0.00000]	0.93311 (0) [0.00000]
α_2	0.0575 (0.00145300) [0.00445]	0.0511 (0.00273302) [0.02529]	0.05895 (0.00072618) [0.00311]	0.05190 (0.00124362) [0.01716]
Dummy		4.1211e-006 (0.40464374) [0.14317]		4.68411e-006 (0.35140545) [0.11428]

- The P-value of the T test is in brackets (....).
- The P-value of the robust T test is in brackets [.....].
- "Log-Likelihood" is the final value of the log likelihood function.
- ** The model has a dummy variable in the variance constant term that takes value 1 the day of the mini crash and zero otherwise.

Table 4.9.B Residual tests on the estimated Autoregressive Heteroscedastic models in NIP at the TSE

NIP-TOKYO portfolio				
Coefficient	**GARCH(1,1)**	**GARCH(1,1) + dummy****	**GARCH(1,1)**	**GARCH(1,1) + dummy**
E-Kurtosis	0.63474	0.69160	0.64366	0.69000
	(0.00632893)	(0.00293174)	(0.00377254)	(0.00190191)
Skewness	-0.06556	-0.05390	-0.07969	-0.06910
	(0.57102154)	(0.64140126)	(0.47143944)	(0.53232362)
Jarque-Bera Normality test	7.8913	9.16580	9.03216	10.17236
	(0.01965)	(0.01023)	(0.01093)	(0.00618)
Ljung-Box				
Q(5)	2.03422	1.61998	1.53088	1.10927
	(0.72946)	(0.80520)	(0.82116)	(0.89280)
Q(10)	8.08184	7.29837	9.41608	8.38879
	(0.52592)	(0.60609)	(0.39979)	(0.49549)
Q(20)	15.09531	14.49561	17.60752	16.55487
	(0.71652)	(0.75407)	(0.54878)	(0.62000)
Q(30)	21.56696	21.29584	28.59010	27.04341
	(0.83767)	(0.84815)	(0.48656)	(0.56936)
McLeod-Li				
Q(5)	6.08128	5.91599	6.05530	6.01192
	(0.29839)	(0.31448)	(0.30087)	(0.30506)
Q(10)	8.75119	8.79797	9.08375	9.21473
	(0.55587)	(0.55138)	(0.52417)	(0.51185)
Q(20)	17.98780	19.31772	20.64373	21.94197
	(0.58821)	(0.50127)	(0.41836)	(0.34367)
Q(30)	22.64975	23.75527	25.74254	26.97994
	(0.82938)	(0.78298)	(0.68821)	(0.62432)
Engle Ng				
F(3,445)	0.25419	0.09155	0.16531	0.09052
	(0.85835162)	(0.96468095)	(0.91973046)	(0.96525127)

- The P-value of the T and Q tests is in brackets.
- Skewness and e-kurtosis are on the standardised residuals.
- ** The model has a dummy variable in the variance constant term that takes value 1 the day of the mini crash and zero otherwise.

In the NIP in Tokyo case we pass all the residuals tests without the MA(22) term, so it seems that we identified that term because of the upward bias in the Ljung-Box test in the presence of autoregresive heteroscedasticity.

As in the IP in Tokyo case, the dummy variable is not significant, confirming our intuition. And in the models without the dummy variable we have again the same problem of significance in the constant term, but as we have seen before, the problem is not as large as it seems.

4.3. Robust Standard Errors

As we have seen in the previous section, we do not have a Normal conditional distribution in each analyzed series. We have estimated those models by Maximum Likelihood, and we have made an inference about a parameter's significance by the "Outer product" estimation of the information matrix[22]; that is, by the information matrix estimated from the vector containing the derivatives of the log likelihood function with respect to the parameters, with the derivatives evaluated at the maximum likelihood estimation. If we estimate by maximum likelihood, using the true conditional distribution, that which is generating the data, we get maximum likelihood estimators distributed in the following way:

$$\bar{\theta} \approx N\left(\theta_0, T^{-1}\Omega_0^{-1}\right)$$

Where the information matrix (Ω_0) can be estimated in two ways, we can get the "outer product" estimation or the "second-derivative" estimation. The "second derivative" estimation is obtained from the second derivative of the log likelihood function with respect to the parameters, evaluating the second derivatives at the maximum likelihood estimation.

Given that we have doubts about the normality of the conditional distribution generating the data, we are estimating by Quasi-Maximum Likelihood (QML). The asymptotic distribution of the Quasi-Maximum Likelihood estimators is as follows:

$$\bar{\theta} \approx N\left(\theta_0, T^{-1} A_0^{-1} B_0 A_0^{-1}\right)$$

Where $\bar{\theta}$ is the estimators' vector, θ_0 is the true parameter vector, A_0 is the "second-derivative" estimation of the information matrix, and B_0 is the "outer product" estimation of the information matrix. Good references on this topic are Hamilton (1994) and Gouriéroux (1997).

We have used the BHHH (Berndt, Hall, Hall, and Hausman (1974)) algorithm to maximize the log likelihood function, and we get B_0 from its last iteration. To get A_0, we maximized the log likelihood function again, but using the BFGS (Broyden, Fletcher, Goldfarb and Shanna[23]) algorithm, and we get A_0 from its last iteration, but only when the number of iterations is higher than the number of parameters to be estimated. If not, we cannot get A_0 from its last iteration. So whenever it is that both algorithms get the same estimation, and the number of iterations when maximizing by BFGS is higher than the number of parameters, we can obtain the QML estimators' asymptotic variance-covariance matrix. We have used this non-standard technique to obtain the QML estimators' asymptotic variance-covariance matrix. Because it is a non-standard and non-exact technique, we report on the appendix C the results of maximizing by BHHH and by BFGS,

[22] The P-value of the non-robust T test shown in tables 4.6 to 4.9.
[23] Method used in RATS software, from Estima. The reference they use in the RATS version 4.3 User's Manual is Press, Flannery, Teukolsky and Vettering (1988).

and the number of iterations taken. So, the reader can evaluate if we can consider both estimated parameters as the same estimation.

The P-values of the robust T test shown in tables 4.6 to 4.9 are obtained using this methodology.

Using the robust inference, we get different conclusions about the parameters' significance in some cases. The major part of these cases is using the GJR model. In some of the estimated GJR(1,1) models we do not have significant parameters in the variance specification. But, as in the GARCH model case, the variance parameters cannot be negative in order to avoid negative variances. So the right T test is unilateral, and though the variance parameters are not significant, their true significance level is higher than it seems at first glance.

4.4. Volatility Transmission Estimation

To estimate the volatility transmission between Tokyo and New York, we have calculated the implied variances in the estimated models, and then we have calculated the correlation coefficient between the volatility in New York and the volatility in Tokyo. We interpret that the correlation coefficient between the volatility in Tokyo on day *h* and the volatility in New York on day *h* is an estimation of the volatility transmission from the TSE to the NYSE. And that the correlation coefficient between the volatility in Tokyo on day *h+1* and the volatility in New York on day *h* is an estimation of the volatility transmission from the NYSE to the TSE.

In both portfolios we fitted the GARCH models without the dummy variable in the TSE time series, given that it is not significant in any case, confirming our intuition. In the NYSE time series case we have fitted all the models we have shown in tables 4.6 to 4.9. We have estimated the implied volatility in those models and then we have calculated the correlation coefficient between the volatility in Tokyo and the volatility in New York. In tables 4.10 and 4.11 we show these correlation coefficients and two significance tests. The first significance test is the Ljung-Box statistic to test cross correlation with one lag. This statistic does not take into account heteroscedasticity and autocorrelations. We obtain our measures of volatility from Autoregresive Conditional Heteroscedasticity models, so we know that the time series we correlate are autocorrelated. In order to take this problem into account we applied a second significance test assuming that those correlation coefficients are normally distributed and then using the Newey and West (1987) standard errors robust to heteroscedasticity and autocorrelation till lag 25[24]. That in our case, with daily time series without weekends, is about a month.

[24] To calculate those standard errors we followed the methodology used in Kofman and Martens (1987), see the appendix of that paper for a good description of the methodology.

Table 4.10. Correlation coefficients between volatility in Tokyo and volatility in New York in the IP.

IP-NYSE	IP-TOKYO			
	GARCH(1,1)		GARCH(1,1), MA|1,17|[e]	
	Tokyo - New York	New York - Tokyo	Tokyo – New York	New York - Tokyo
EGARCH(1,1)	0.20328309 [a]	0.19773863	0.20343152	0.20005931
Q(1)[b]	20.49696	19.39412	19.16124	18.53125
P-value[f]	(5.97259e-006) **	(1.06334e-005) **	(1.20128e-005) **	(1.67142e-005) **
Robust test P-value[g]	[0.0008486] **	[0.0006209] **	[0.0009868] **	(0.0007709) **
EGARCH(1,1), ma(1)[c]	0.20946099	0.20445934	0.20906109	0.20606296
Q(1)	21.76173	20.73485	20.23641	19.66016
P-value	(3.08697e-006) **	(5.27472e-006) **	(6.84378e-006) **	(9.25102e-006) **
Robust test P-value	[0.0008268] **	[0.0006047] **	[0.0009726] **	[0.0007578] **
EGARCH(1,1), ma(1), D[d]	0.20282109	0.19806282	0.20219201	0.19400330
Q(1)	20.40390	19.45776	18.92845	17.42631
P-value	(6.27018e-006) **	(1.02849e-005) **	(1.35713e-005) **	(2.98664e-005) **
Robust test P-value	[0.0084643] **	[0.0069027] **	[0.0096444] **	[0.0078601] **
GJR(1,1)	0.21259867	0.20898250	0.21200203	0.20920812
Q(1)	22.41858	21.66241	20.80976	20.26489
P-value	(2.19243e-006) **	(3.25099e-006) **	(5.07237e-006) **	(6.74267e-006) **
Robust test P-value	[0.0017976] **	[0.0013311] **	[0.0020749] **	[0.0016397] **
GJR(1,1), ma(1)	0.21850074	0.21552805	0.21732888	0.21492722
Q(1)	23.68061	23.04064	21.86865	21.38799
P-value	(1.13723e-006) **	(1.58612e-006) **	(2.91965e-006) **	(3.75114e-006) **
Robust test P-value	[0.001699] **	[0.0012672] **	[0.0019757] **	[0.001564] **
GJR(1,1), ma(1), D	0.23181822	0.22910283	0.22930580	0.22318607
Q(1)	26.65521	26.03442	24.34542	23.06329
P-value	(2.43194e-007) **	(3.35384e-007) **	(8.05181e-007) **	(1.56755e-006) **
Robust test P-value	[0.0079891] **	[0.0065516] **	[0.0091789] **	[0.0075532] **

a. Is the correlation coefficient between the volatility in the NYSE on day *h* and the volatility in the TSE on day *h*, fitting an EGARCH(1,1) model for the NYSE, and a GARCH(1,1) model for the TSE.
b. Is the Ljung-Box statistic to test the statistical significance of each correlation coefficient.
c. Means that the model has a moving average term of order one in the mean equation.
d. Means that the model has a dummy variable in the constant term of the variance equation. Such dummy variable takes value 1 the 27 of October of 1997 and zero otherwise.
e. Is a moving average with two terms in the mean equation, one of order 1 and one of order 17.
f. Probability value of the correlation coefficient using the Ljung-Box statistic.
g. Probability value of the correlation coefficient assuming it is normally distributed and using the Newey-West standard errors robust to heteroscedasticity and autocorrelation till lag 25.
- All the fitted models in the NYSE have a constant term in the mean equation.
- The models fitted in the TSE do not have a constant term in the mean equation.

** Significance at the 5% level.
* Significance at the 10% level.

Table 4.11. Correlation coefficients between volatility in Tokyo and volatility in New York in the NIP.

	NIP-TOKYO			
NIP-NYSE	**GARCH(1,1)**		**GARCH(1,1), MA|22|[e]**	
	Tokyo – New York	New York - Tokyo	Tokyo – New York	New York - Tokyo
EGARCH(1,1), ma(1)[c]	0.05632064 [a]	0.09181690	0.05446019	0.09082757
Q(1)[b]	1.57334	4.18150	1.34358	3.73715
P-value[f]	(0.20972)	(0.04087) **	(0.24640)	(0.05322) *
Robust test P-value[g]	[0.1537894]	[0.0609878] *	[0.2034151]	[0.085250] *
EGARCH(1,1), ma(1), D[d]	0.02854364	0.04708025	0.03183834	0.05327764
Q(1)	0.40412	1.09942	0.45920	1.28586
P-value	(0.52497)	(0.29439)	(0.49800)	(0.25681)
Robust test P-value	[0.0849227] *	[0.052218] *	[0.0791083] *	[0.0491601] **
GJR(1,1), ma(1)	0.02750443	0.06429413	0.02740567	0.06505450
Q(1)	0.37523	2.05036	0.34024	1.91716
P-value	(0.54017)	(0.15217)	(0.55969)	(0.16617)
Robust test P-value	[0.240507]	[0.0565732] *	[0.2827004]	[0.0736413] *
GJR(1,1), ma(1), D	0.02194432	0.04931275	0.02564105	0.05579546
Q(1)	0.23885	1.20616	0.29784	1.41027
P-value	(0.62504)	(0.27209)	(0.58524)	(0.23501)
Robust test P-value	[0.1423898]	[0.059063] *	[0.1264852]	[0.0561131] *

a. Is the correlation coefficient between the volatility in the NYSE on day *h* and the volatility in the TSE on day *h*. Fitting an EGARCH(1,1), ma(1) model for the NYSE and a GARCH(1,1) model for the TSE.
b. Is the Ljung-Box statistic to test the statistical significance of each correlation coefficient.
c. Means that the model has a moving average term of order one in the mean equation.
d. Means that the model has a dummy variable in the constant term of the variance equation. Such dummy variable takes value 1 the 27 of October of 1997 and zero otherwise.
e. Is a moving average with one term of order 22 in the mean equation.
f. Probability value of the correlation coefficient using the Ljung-Box statistic.
g. Probability value of the correlation coefficient assuming it is normally distributed and using the Newey-West standard errors robust to heteroscedasticity and autocorrelation till lag 25.
- All the fitted models in the NYSE have a constant term in the mean equation.
- The models fitted in the TSE do not have a constant term in the mean equation.

** Significance at the 5% level.
* Significance at the 10% level.

In tables 4.10 and 4.11 we see that there is a clear difference in volatility transmission between the international portfolio and the non-international portfolio. The correlation coefficient can take values from -1 to 1 only. So the correlation coefficients in the IP are considerably larger than in the NIP.

In the IP there is significant volatility transmission in both directions, from Tokyo to New York and viceversa, no matter which significance test we use. In the NIP we get different results in each significance test. With the Ljung-Box test we get significant volatility transmission with the first EGARCH model only, and from New York to Tokyo only. With the test robust to heteroscedasticity and autocorrelation we get more significant coefficients, at least at the 10% level. In this case, at the 10% significance level, volatility transmission from New York to Tokyo is significant in all cases. In the NIP, the EGARCH models have the best performance in the residual tests. So we can consider that under any significance test there is volatility transmission from New York to Tokyo when we ignore the existence of the mini crash.

It is worth mentioning that 20 stocks comprise the NIP and only one is Japanese. Those stocks belong to non-international firms, so the majority of news will be released in the local market, which is New York. And because of market dynamics, there will be volatility transmission from New York to Tokyo, as is reflected in our data analysis. Firms having activity in both markets compose the IP, so news is probably released in both markets. And there will be market dynamics causing volatility transmission in both directions. Under the assumption that the other factors[25] equally affect both portfolios, the difference between the IP and the NIP in volatility transmission from New York to Tokyo will be due to the Type 2 indexes related to the activity that a firm has in each specific geographical area. And given that the correlation coefficient between volatility in New York on day h and volatility in Tokyo on day $h+1$ in the IP is about twice that in the NIP (considering the biggest coefficient in the NIP), we can consider that, as a first approximation, volatility transmission due to the data generating process is about half of the volatility transmission in the international firm's case.

On the other hand, it is worth mentioning that a substantial body of studies from the forward exchange market, as well as other financial markets, addresses the evidence that the time varying risk premium for risky assets held by risk averse investors is related to the conditional variance. For the capital market, see Engle, Lilien and Robins (1987), and Bollerslev, Engle and Wooldridge (1988). If this is the case, then the volatility will be significant in the mean return equation. In order to check the robustness of our findings for this possibility, we have tried to include the volatility in the mean equation, and then we have estimated the volatility transmission in each portfolio again.

We conclude that for both portfolios, volatility is significant in the mean equation for New York only, but only when we eliminate the constant term. So we have estimated the volatility transmission between New York and Tokyo again, but fitting models without the constant term and with the volatility as a regressor in the mean equation for the NYSE time series. We find the same results as above. In appendix D, we show these results.

To test the robustness of our conclusions we used the median as the criterion to distribute stocks among the IP and the NIP. In this case we have moved four stocks from the NIP to the IP. Using this criterion the biggest percentage of activity in the foreign market for the NIP is 17,47%, and the smallest for the IP is 18,00%. The results are similar with those that we found above, but in the IP, the correlation coefficients tend to be lower. And in the NIP, those coefficients are lower and not significant in any case. This is consistent with the hypothesis that the bigger the percentage of activity in the foreign market the more volatility transmission. The smaller coefficients in the IP seem to be because the incorporation of firms with smaller percentage of activity in the foreign market, that have smaller volatility transmission. The smaller coefficients in the NIP seem to be because we removed the firms with biggest percentage of activity in the foreign market. And it seems that, although not significant, there are still market dynamics causing volatility transmission from New York to Tokyo because the volatility transmission in the

[25] Market dynamics and other type 2 indexes that are not related to the activity a firm has in a specific geographical area.

NIP is always bigger from New York to Tokyo than vice versa. In appendix E we show these results.

These last results make us change our initial valuation of the volatility transmission due to market dynamics. The first valuation was under the assumption that there was no data generating process causing volatility transmission in the NIP. As shown by these last results, this assumption was not true. And if we do the same assumption again, but under these last results, the conclusion is that the most volatility transmission found in our data is due to the data generating process. It seems that market dynamics do not cause significant volatility transmission when we analyse daily returns. Could be market dynamics are more relevant in shorter time period returns.

5. CONCLUSIONS

In this paper we study volatility transmission among the same stock quoted in different non-overlapping markets. In this case, this is equivalent to study persistence in volatility. As we mentioned in the introduction, there are two major explanations in the literature for this transmission of volatility, that is market dynamics and data generating processes. Little attention has been paid to the last explanation, and to the measurement of the relative importance of each explanation. In this paper we identify data generating processes that can explain persistence and transmission of volatility between non-overlapping markets, those processes are related to the firm's business geographical distribution. Also, we get a first measure of the importance of these data generating processes in relation to market dynamics for explaining that volatility persistence.

In order to get empirical evidence of the relevance that those data generating processes could have in the real world we study the volatility transmission between Tokyo and New York among stocks quoted in both markets. We construct two portfolios, one with global firms, that we call international portfolio, and another with non-global firms, that we call non-international portfolio. We find that there is more volatility transmission in the international portfolio than in the non-international portfolio. And, under the assumption of market dynamics equally affecting both portfolios[26], the difference between the IP and the NIP in volatility transmission from New York to Tokyo is due to the specific data generating process related to the activity a firm has in a specific geographical area. With the empirical evidence we obtain in this paper, we can consider that, as a first approximation, the identified data generating process causes the most volatility transmission found.

Future research will include a more detailed study of the effect of market dynamics on both portfolios, an analysis of intra-daily dynamics, the application of a similar analysis to other asset types, such as foreign exchange rates, interest rates, etc., or an increase in the sample time period and the number of stocks included in our sample.

[26] To prove that the data generating process is a significant source of volatility transmission, we just need to assume that market dynamics equally affects both portfolios. To evaluate the importance of volatility transmission due to the existence of type 2 indexes related to the activity a firm has in a specific geographical area, we also need to suppose that "other" type 2 indexes equally affect both portfolios. Given that those "other" type 2 indexes are not related to the activity a firm has in a specific geographical area, it seems difficult that those "other" type 2 indexes would affect both portfolios differently.

Also, to test the relevance of the stock's nationality, it is left for future research to study whether we obtain the same results within stocks of the same nationality. For this study we will need a bigger sample with stocks from more nationalities.

Finally, it is worth mentioning that the econometric models we use in this paper are univariate autoregresive heteroskedasticity models, it is left for future research to test whether we get the same results using multivariate models.

APPENDIX A

The Y and X indexes have innovations during the trading period in their own markets only. Traders will take into account the relation between those two indexes, if they are rational. We can reflect this behaviour by introducing a new index in equation 2:

$$P_{t,i} = \alpha_0 X_{t,i} + \alpha_1 Y_{t,i} + \alpha_2 Z_{t,i} + V_{t,i} \qquad i=0,1 \tag{8}$$

$$V_{t,0} = \alpha_1 \eta_{t,0} \rho^* \tag{8.1}$$
$$V_{t,1} = \alpha_0 \eta^*_{t,1} \rho \tag{8.2}$$

Prices reflect the expected effect in trading on the following market of a piece of information released in the present market. Changes in prices are:

$$P_{t,0} - P_{t-1,1} = \alpha_2 \varepsilon_{t,0} + \alpha_0 (\eta_{t,0} + \eta^*_{t-1,1} \zeta_{t,0}) + \alpha_1 \eta_{t,0} \rho^* \tag{9.1}$$

$$P_{t,1} - P_{t,0} = \alpha_2 \varepsilon_{t,1} + \alpha_1 (\eta^*_{t,1} + \eta_{t,0} \zeta^*_{t,1}) + \alpha_0 \eta^*_{t,1} \rho \tag{9.2}$$

Today's Indexes innovations' expected effect is reflected on prices today. Variance equations are:

$$VAR(P_{t,0} - P_{t-1,1}) = \alpha_2^2 \sigma^2 + (\alpha_0 + \alpha_1 \rho^*)^2 \sigma^2_\eta + \alpha_0^2 (\eta^*_{t-1,1})^2 \sigma^2_\zeta \tag{10.1}$$

$$VAR(P_{t,1} - P_{t,0}) = \alpha_2^2 \sigma^2 + (\alpha_1 + \alpha_0 \rho)^2 \sigma^2_{\eta^*} + \alpha_1^2 (\eta_{t,0})^2 \sigma^2_{\zeta^*} \tag{10.2}$$

The unanticipated index innovation effect in the following market is still the source of spillovers in mean. And index innovations in the previous market continue to cause an increase in volatility in the following market. There is uncertainty about the direction and extent of the demand reaction (or other aspects of a firm's activity) in the following market to an innovation that happens in the present market.

APENDIX B

1. US firms	Sector
PepsiCo, Inc.	Foods.
The Dow Chemical Company.	Chemicals
Minnesota Mining and Manufacturing Company.	Chemicals
The Procter & Gamble Company.	Chemicals
Eli Lilly and Company.	Pharmaceutical
Mobil Corporation.	Oil & Coal Products
Intermnational Business Machines Corporation.	Electric Appliances
Motorola, INC.	Electric Appliances
The Boeing Company.	Transportation Equipment
GTE Corporation.	Communication
McDonald´s Corporation.	Retail Trade
Citicorp.	Banks
J.P. Morgan & Co. Incorporated	Banks
Merrill Lyinch & Co.,Inc.	Securities & Commd. Futur.
AFLAC Incorporated	Insurance
Lincoln National Corporation	Insurance

2. European firms	Sector
Barclays PLC.	Banks Retail
British Petroleum Co PLC.	Oil Integrated
Glaxo Wellcome PLC	Pharmaceuticals
National Westminster Bank PLC.	Bank Retail
Banco Bilbao Vizcaya	Banks
Banco Central Hispano Americano	Banks
Banco Santander, S.A.	Banks
Telefónica de España, S.A.	Communications

3. Japanese firms	Sector
Hitachi, Ltd.	DiversifiedElec.Machin.Mfg
Honda Motor Co.,Ltd.	Auto/Motorcycles Mfg.
Kyocera Corporation	Ceramic/Electronic products
Bank of TOKIO-Mitsubishi, Limited.	Banking.
Pioneer Electronic Corporation.	Consumer Electronics.
Sony Corporation	Electronics/Entertainment
TDK Corporation	Electronic Components Mfg

APPENDIX C

IP NYSE

Table C.1.1 Robust standard errors in the estimated models for IP in the NYSE

IP-NYSE portfolio GJR(1,1)				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	**P-value**
Iterations	62	35		
Log-Likelihood	2365.81870596	2365.81870600		
MEAN				
Constant	0.0009847551	0.0009847480	4.44124	8.94420e-006
VARIANCE				
α_0	0.0000092818	0.0000092827	1.25167	0.21069
α_1	0.3944948152	0.3944474280	1.12468	0.26072
α_2	0.1013406128	0.1013439072	1.07907	0.28056
α_3	0.4075521201	0.4075795833	1.48747	0.13689

Table C.1.2 Robust standard errors in the estimated models for IP in the NYSE

IP-NYSE portfolio GJR(1,1), ma(1), dummy				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	**P-value**
Iterations	39	37		
Log-Likelihood	2379.45021419	2379.45021420		
MEAN				
Constant	0.0010583816	0.0010583815	3.70702	2.09712e-004
MA(1)	0.0992686556	0.0992686781	1.62553	0.10405
VARIANCE				
α_0	0.0000058000	0.0000057999	1.69190	0.09067
α_1	0.6517150541	0.6517186585	3.56276	3.66976e-004
α_2	0.0455514921	0.0455515972	0.54647	0.58474
α_3	0.0926549524	0.0926544440	1.05713	0.29045
Dummy	0.0015988775	0.0015987045	1.29511	0.19528

Table C.1.3 Robust standard errors in the estimated models for IP in the NYSE

IP-NYSE portfolio GJR(1,1), ma(1)				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	**P-value**
Iterations	67	42		
Log-Likelihood	2366.50530359	2366.50530365		
MEAN				
Constant	0.0009429024	0.0009428912	3.96280	7.40758e-005
MA(1)	0.0673987352	0.0673978070	1.08443	0.27817
VARIANCE				
α_0	0.0000091586	0.0000091599	0.88000	0.37886
α_1	0.4123823465	0.4123184051	0.84380	0.39878
α_2	0.0756027605	0.0756056803	0.80748	0.41939
α_3	0.4298463250	0.4298845925	1.32539	0.18504

Table C.1.4 Robust standard errors in the estimated models for IP in the NYSE

IP-NYSE portfolio EGARCH (1,1)				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	**P-value**
Iterations	39	28		
Log-Likelihood	2364.87401918	2364.87401300		
MEAN				
Constant	0.000923319	0.000923331	4.80538	1.54458e-006
VARIANCE				
α_0	-3.487737404	-3.488487078	-4.50656	6.58871e-006
α_1	0.668846016	0.668774751	9.37488	6.92545e-021
α_2	0.470667266	0.470700322	3.67014	2.42418e-004
α_3	0.390074910	0.390073891	2.26171	0.02372

Table C.1.5 Robust standard errors in the estimated models for IP in the NYSE

IP-NYSE portfolio EGARCH (1,1), ma(1), dummy				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	**P-value**
Iterations	23	11		
Log-Likelihood	2381.74655173	2381.72637428		
MEAN				
Constant	0.001027648	0.001027985	4.61704	3.89252e-006
MA(1)	0.111242468	0.111127253	2.06039	0.03936
VARIANCE				
α_0	-1.346901014	-1.457155901	-107.13113	0.00000
α_1	0.874165599	0.863831323	674.62465	0.00000
α_2	0.143057676	0.148357288	1.88852	0.05896
α_3	0.361699577	0.362495257	1.02322	0.30620
Dummy	4.120057744	4.204672313	5.13599	2.80662e-007

Table C.1.6 Robust standard errors in the estimated models for IP in the NYSE

IP-NYSE portfolio EGARCH (1,1), ma(1)				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	**P-value**
Iterations	37	27		
Log-Likelihood	2365.41907658	2365.41905221		
MEAN				
Constant	0.000845442	0.000845326	4.37231	1.22939e-005
MA(1)	0.058765280	0.058742041	0.93909	0.34768
VARIANCE				
α_0	-3.332561064	-3.335091620	-2.50916	0.01210
α_1	0.683372487	0.683132657	5.46671	4.58465e-008
α_2	0.447429881	0.447544391	3.42833	0.01680
α_3	0.429746100	0.429727676	2.39105	0.01680

NIP NYSE

Table C.2.1 Robust standard errors in the estimated models for NIP in the NYSE

NIP-NYSE portfolio GJR (1,1), ma(1)				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	**P-value**
Iterations	42	18		
Log-Likelihood	2221.68420212	2221.72857949		
MEAN				
Constant	6.9825e-004	4.3868e-004	1.41418	0.15731
MA(1)	-0.1048	-0.0967	-3.07067	0.00214
VARIANCE				
α_0	2.1638e-005	2.1967e-005	8.49846	1.92122e-017
α_1	0.4134	0.3839	6.41638	1.39553e-010
α_2	-0.0731	-0.0778	-2.15316	0.03131
α_3	0.4750	0.5607	2.40194	0.01631

Table C.2.2 Robust standard errors in the estimated models for NIP in the NYSE

NIP-NYSE portfolio EGARCH(1,1), ma(1)				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	**P-value**
Iterations	31	51		
Log-Likelihood	2216.56677022	2216.56681230		
MEAN				
Constant	0.000737240	0.000736966	3.20776	0.00134
MA(1)	-0.144555380	-0.144577532	-2.70417	0.00685
VARIANCE				
α_0	-3.744641543	-3.756132670	-2.38513	0.01707
α_1	0.623865561	0.622698050	3.93077	8.46742e-005
α_2	0.296689858	0.297359022	3.72198	1.97667e-004
α_3	0.975604005	0.976311759	3.12954	0.00175

Table C.2.3 Robust standard errors in the estimated models for NIP in the NYSE

NIP-NYSE portfolio EGARCH(1,1), ma(1), dummy				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	**P-value**
Iterations	27	42		
Log-Likelihood	2226.38089294	2226.38065544		
MEAN				
Constant	0.000831596	0.00083357	2.69464	0.00705
MA(1)	-0.153397928	-0.153417454	-2.99339	0.00276
VARIANCE				
α_0	-2.785459529	-2.783704344	-1.06928	0.28494
α_1	0.722911948	0.723082408	2.78837	0.00530
α_2	0.109800109	0.111469337	1.05922	0.28950
α_3	1.488418545	1.463263350	0.79254	0.42805
Dummy	4.307139111	4.307596293	1.83166	0.06700

IP TOKYO

Table C.3.1 Robust standard errors in the estimated models for IP in Tokyo

IP-TOKIO portfolio GARCH(1,1), ma|1,17|, dummy				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	
Iterations	22	38		
Log-Likelihood	2133.57331136	2133.57331143		
MEAN				
MA(1)	-0.1071	-0.1071	-3.00108	0.00269
MA(17)	-0.1619	-0.1619	-5.08514	3.67354e-007
VARIANCE				
α_0	4.1214e-007	4.1215e-007	1.97976	0.04773
α_1	0.9381	0.9381	88.90118	0.00000
α_2	0.0504	0.0504	4.33301	1.47084e-005
Dummy	4.4612e-005	4.4634e-005	0.66414	0.50660

Table C.3.2 Robust standard errors in the estimated models for IP in Tokyo

IP-TOKIO portfolio GARCH(1,1), dummy				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	
Iterations	12	24		
Log-Likelihood	2284.50694806	2284.50695254		
VARIANCE				
α_0	4.66245e-007	4.66178e-007	1.43900	0.15015
α_1	0.93372	0.93373	48.97675	0.00000
α_2	0.05263	0.05262	3.05063	0.00228
Dummy	5.57972e-005	5.59543e-005	0.71924	0.47199

Table C.3.3 Robust standard errors in the estimated models for IP in Tokyo

IP-TOKIO portfolio GARCH(1,1)				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	
Iterations	9	23		
Log-Likelihood	2283.86189720	2283.86189725		
VARIANCE				
α_0	3.81043e-007	3.81014e-007	1.06302	0.28777
α_1	0.93328	0.93329	37.97278	1.62408e-315
α_2	0.05756	0.05756	2.85991	0.00424

Table C.3.4 Robust standard errors in the estimated models for IP in Tokyo

IP-TOKIO portfolio GARCH(1,1), ma|1,17|				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	**P-value**
Iterations	15	24		
Log-Likelihood	2133.08471868	2133.08471860		
MEAN				
MA(1)	-0.1078	-0.1078	-2.66359	0.00773
MA(17)	-0.1643	-0.1643	-4.41616	1.00470e-005
VARIANCE				
α_0	3.2621e-007	3.2625e-007	1.37334	0.16965
α_1	0.9382	0.9382	67.06464	0.00000
α_2	0.0545	0.0545	4.52931	5.91766e-006

NIP TOKYO

Table C.4.1 Robust standard errors in the estimated models for NIP in Tokyo

NIP-TOKIO portfolio GARCH(1,1), ma|22|				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	**P-value**
Iterations	13	17		
Log-Likelihood	2636.15795839	2636.15795841		
MEAN				
MA(22)	-0.0849	-0.0849	-2.09755	0.03594
VARIANCE				
α_0	4.6225e-008	4.6225e-008	1.54886	0.12142
α_1	0.9303	0.9303	41.45573	0.00000
α_2	0.0575	0.0575	2.84445	0.00445

Table C.4.2 Robust standard errors in the estimated models for NIP in Tokyo

NIP-TOKIO portfolio GARCH(1,1)				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	**P-value**
Iterations	9	23		
Log-Likelihood	2897.23305840	2897.23305849		
VARIANCE				
α_0	3.82597e-008	3.82576e-008	1.28893	0.19742
α_1	0.93092	0.93093	41.60944	0.00000
α_2	0.05895	0.05894	2.95618	0.00311

Table C.4.3 Robust standard errors in the estimated models for NIP in Tokyo

NIP-TOKIO portfolio GARCH(1,1), dummy				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	**P-value**
Iterations	16	28		
Log-Likelihood	2898.70076858	2898.70076889		
VARIANCE				
α_0	4.40235e-008	4.40297e-008	1.40680	0.15949
α_1	0.93311	0.93310	38.47442	0.00000
α_2	0.05190	0.05190	2.38318	0.01716
Dummy	4.68411e-006	4.68783e-006	1.57924	0.11428

Table C.4.4 Robust standard errors in the estimated models for NIP in Tokyo

NIP-TOKIO portfolio GARCH(1,1), ma|22|, dummy				
Coefficient	**BHHH**	**BFGS**	**T-Robust**	**P-value**
Iterations	13	33		
Log-Likelihood	2637.29608779	2637.29608805		
MEAN				
MA(22)	-0.0760	-0.0760	-1.75174	0.07982
VARIANCE				
α_0	5.2582e-008	5.2576e-008	1.41338	0.15754
α_1	0.9320	0.9320	36.97007	0.00000
α_2	0.0511	0.0511	2.23701	0.02529
Dummy	4.1209e-006	4.1222e-006	1.46407	0.14317

APPENDIX D

Volatility is a significant regressor only in the mean equation for New York, but just when we exclude the constant term in the mean equation. So we estimate the new models for both portfolios of the NYSE. And then, to estimate the volatility transmission between New York and Tokyo, we fit the GARCH models without volatility in the mean equation for Tokyo. In tables C.1 and C.2, we show the correlation coefficients used to estimate the volatility transmission between Tokyo and New York and the significance tests of those correlation coefficients. There we show that our conclusions are robust to the inclusion of the volatility in the mean equation. Volatility transmission in the IP from New York to Tokyo is about twice that in the NIP (considering the biggest coefficient in the NIP).

Table D.1 Correlation coefficients between volatility in Tokyo and volatility in New York in the IP.

	IP-TOKYO			
IP-NYSE	**GARCH(1,1)**		**GARCH(1,1), MA|1,17|[e]**	
	Tokyo - New York	New York - Tokyo	Tokyo - New York	New York - Tokyo
EGARCH(1,1), σ[f]	0.19832523 [a]	0.19237383	0.19802720	0.19425973
Q(1)[b]	19.50936	18.35604	18.15670	17.47240
P-value[g]	(1.00108e-005) **	(1.83237e-005) **	(2.03453e-005) **	(2.91508e-005) **
Robust test P-value[h]	[0.0008329] **	[0.0006154] **	[0.0009711] **	[0.0007654] **
EGARCH(1,1), ma(1)[c], σ	0.20588684	0.20053568	0.20530282	0.20191081
Q(1)	21.02540	19.94667	19.51538	18.87584
P-value	(4.53236e-006) **	(7.96327e-006) **	(9.97931e-006) **	(1.39508e-005) **
Robust test P-value	[0.0007916] **	[0.0005829] **	[0.000935] **	[0.0007333] **
EGARCH(1,1), ma(1), σ ,D[d]	0.20296705	0.19816994	0.20226878	0.19405711
Q(1)	20.43328	19.47882	18.94283	17.43598
P-value	(6.17466e-006) **	(1.01722e-005) **	(1.34695e-005) **	(2.97149e-005) **
Robust test P-value	[0.0083975] **	[0.0068434] **	[0.0095922] **	[0.0078164] **
GJR(1,1), σ	0.20649803	0.20201137	0.20569806	0.20226834
Q(1)	21.15041	20.24131	19.59059	18.94275
P-value	(4.24610e-006) **	(6.82628e-006) **	(9.59406e-006) **	(1.34700e-005) **
Robust test P-value	[0.0018282] **	[0.0013554] **	[0.0021092] **	[0.0016814] **
GJR(1,1), ma(1), σ	0.21186019	0.20807053	0.21067646	0.20759295
Q(1)	22.26310	21.47376	20.55035	19.95319
P-value	(2.37731e-006) **	(3.58703e-006) **	(5.80833e-006) **	(7.93615e-006) **
Robust test P-value	[0.00176990.] **	[0.0013291] **	[0.0020525] **	[0.0016489] **
GJR(1,1), ma(1), σ, D	0.22804823	0.22511775	0.22568305	0.21948896
Q(1)	25.79529	25.13660	23.58224	22.30553
P-value	(3.79614e-007) **	(5.34096e-007) **	(1.19687e-006) **	(2.32536e-006) **
Robust test P-value	[0.0083825] **	[0.0068955] **	[0.0096249] **	[0.0079561] **

a. Is the correlation coefficient between the volatility in the NYSE on day *h* and the volatility in the TSE on day *h*. Fitting an EGARCH(1,1), σ, model for the NYSE and a GARCH(1,1) model for the TSE.
b. Is the Ljung-Box statistic to test the statistical significance of each correlation coefficient.
c. Means that the model has a moving average term of order one in the mean equation.
d. Means that the model has a dummy variable in the constant term of the variance equation. Such dummy variable takes value 1 the 27 of October of 1997 and zero otherwise.
e. Is a moving average with two terms in the mean equation, on of order 1 and one of order 17.
f. Means that the model has the volatility as a regressor in the mean equation.
g. Probability value of the correlation coefficient using the Ljung-Box statistic.
h. Probability value of the correlation coefficient assuming it is normally distributed and using the Newey-West standard errors robust to heteroscedasticity and autocorrelation till lag 25.

\- All the fitted models do not have a constant term in the mean equation.

** Significance at the 5% level.

* Significance at the 10% level.

Table D.2 Correlation coefficients between volatility in Tokyo and volatility in New York in the NIP.

	NIP-TOKYO			
NIP-NYSE	**GARCH(1,1)**		**GARCH(1,1), MA|22|[e]**	
	Tokyo - New York	New York - Tokyo	Tokyo - New York	New York - Tokyo
EGARCH(1,1), ma(1)[c],σ[f]	0.05644959 [a]	0.09163939	0.05454014	0.09061878
Q(1)[b]	1.58055	4.16535	1.34753	3.71998
P-value[g]	(0.20868)	(0.04126) **	(0.24571)	(0.05376) *
Robust test P-value[h]	[0.1525829]	[0.0609397] *	[0.2023539]	[0.085338] *
EGARCH(1,1), ma(1), σ, D[d]	0.02560888	0.04271449	0.02868852	0.04876354
Q(1)	0.32529	0.90498	0.37284	1.07720
P-value	(0.56845)	(0.34145)	(0.54146)	(0.29933)
Robust test P-value	[0.0902267] *	[0.0539284] *	[0.0834338] *	[0.0503584] *
GJR(1,1), ma(1), σ	0.02726928	0.06399025	0.02729501	0.06487749
Q(1)	0.36884	2.03102	0.33750	1.90675
P-value	(0.54364)	(0.15412)	(0.56128)	(0.16733)
Robust test P-value	[0.2456501]	[0.0574459] *	[0.2854283]	[0.0740362] *
GJR(1,1), ma(1), σ, D	0.02209555	0.05004402	0.02588497	0.05658207
Q(1)	0.24216	1.24220	0.30353	1.45031
P-value	(0.62265)	(0.26505)	(0.58168)	(0.22848)
Robust test P-value	[0.1430776]	[0.0590593] *	[0.1264992]	[0.0560581] *

a. Is the correlation coefficient between the volatility in the NYSE on day *h* and the volatility in the TSE on day *h*. Fitting an EGARCH(1,1), ma(1), σ, model for the NYSE and a GARCH(1,1) model for the TSE.
b. Is the Ljung-Box statistic to test the statistical significance of each correlation coefficient.
c. Means that the model has a moving average term of order one in the mean equation.
d. Means that the model has a dummy variable in the constant term of the variance equation. Such dummy variable takes value 1 the 27 of October of 1997 and zero otherwise.
e. Is a moving average with one term of order 22 in the mean equation.
f. Means that the model has the volatility as a regressor in the mean equation.
g. Probability value of the correlation coefficient using the Ljung-Box statistic.
h. Probability value of the correlation coefficient assuming it is normally distributed and using the Newey-West standard errors robust to heteroscedasticity and autocorrelation till lag 25.
- All the fitted models do not have a constant term in the mean equation.

** Significance at the 5% level.
* Significance at the 10% level.

APPENDIX E

When we use the median as a criterion to distribute stocks among the IP and the NIP, we still have significant volatility transmission in both directions in the IP. But the correlation coefficients tend to be smaller. In the NIP there are no significant volatility transmission, and we get smaller correlation coefficients.

Table E.1 Correlation coefficients between volatility in Tokyo and volatility in New York in the IP.

	IP-TOKYO	
IP-NYSE	**GARCH(1,1)**	
	Tokyo - New York	New York - Tokyo
EGARCH(1,1)	0.20338505[a]	0.20645381
Q(1)[b]	20.43480	21.05611
P-value[d]	(6.16976e-006) **	(4.46028e-006) **
Robust test P-value[e]	[0.0006722] **	[0.0005268] **
EGARCH(1,1), D[c]	0.11019467	0.10814097
Q(1)	5.99865	5.77714
P-value	(0.01432) **	(0.01624) **
Robust test P-value	[0.0206196] **	[0.0181663] **
GJR(1,1)	0.15859025	0.15994276
Q(1)	12.42468	12.63751
P-value	(4.23697e-004) **	(3.78083e-004) **
Robust test P-value	[0.0015345] **	[0.0012742] **
GJR(1,1) D	0.13869635	0.13723950
Q(1)	9.50304	9.30445
P-value	(0.00205) **	(0.00229) **
Robust test P-value	[0.014073] **	[0.0122779] **

a. Is the correlation coefficient between the volatility in the NYSE on day *h* and the volatility in the TSE on day *h*. Fitting an EGARCH(1,1), model for the NYSE and a GARCH(1,1) model for the TSE.
b. Is the Ljung-Box statistic to test the statistical significance of each correlation coefficient.
c. Means that the model has a dummy variable in the constant term of the variance equation. Such dummy variable takes value 1 the 27 of October of 1997 and zero otherwise.
d. Probability value of the correlation coefficient using the Ljung-Box statistic.
e. Probability value of the correlation coefficient assuming it is normally distributed and using the Newey-West standard errors robust to heteroscedasticity and autocorrelation till lag 25.
- All the fitted models in the NYSE have a constant term in the mean equation.
- The fitted models in the TSE do not have a constant term in the mean equation.

** Significance at the 5% level.
* Significance at the 10% level.

Table E.2 Correlation coefficients between volatility in Tokyo and volatility in New York in the NIP.

	NIP-TOKYO	
NIP-NYSE	**GARCH(1,1)**	
	Tokyo - New York	New York - Tokyo
EGARCH(1,1), ma(1)[c]	0.01891199[a]	0.02050758
Q(1)[b]	0.1766	0.20776
P-value[e]	(0.67424)	(0.64853)
Robust test P-value[f]	[0.6616214]	[0.6472]
EGARCH(1,1),ma(1) D[d]	0.01006345	0.01355613
Q(1)	0.05003	0.09078
P-value	(0.82301)	(0.76318)
Robust test P-value	[0.4567511]	[0.3520802]
GJR(1,1), ma(1)	0.00935869	0.01442216
Q(1)	0.04327	0.10275
P-value	(0.83522)	(0.74855)
Robust test P-value	[0.7275944]	[0.604709]
GJR(1,1), ma(1), D	0.00844006	0.01333638
Q(1)	0.03519	0.08787
P-value	(0.85120)	(0.76690)
Robust test P-value	[0.4666469]	[0.3090486]

a. Is the correlation coefficient between the volatility in the NYSE on day *h* and the volatility in the TSE on day *h*. Fitting an EGARCH(1,1), ma(1) model for the NYSE and a GARCH(1,1) model for the TSE.
b. Is the Ljung-Box statistic to test the statistical significance of each correlation coefficient.
c. Means that the model has a moving average term of order one in the mean equation.
d. Means that the model has a dummy variable in the constant term of the variance equation. Such dummy variable takes value 1 the 27 of October of 1997 and zero otherwise.
e. Probability value of the correlation coefficient using the Ljung-Box statistic.
f. Probability value of the correlation coefficient assuming it is normally distributed and using the Newey-West standard errors robust to heteroscedasticity and autocorrelation till lag 25.
- All the fitted models in the NYSE have a constant term in the mean equation.
- The fitted models in the TSE do not have a constant term in the mean equation.

** Significance at the 5% level.
* Significance at the 10% level.

If we try to use the volatility as a regressor in the mean equation, we also find that it is significant only in the NYSE time series, and just when removing the constant term. So we estimated the NYSE models again but with a mean equation without the constant term and with the volatility as a regressor. Then we calculated the correlation coefficients between the TSE and the NYSE volatility time series, estimated from the previous models for the NYSE, and from the original models (without volatility as a regressor) for the TSE. In tables E.3 and E.4 we present the results. There we see that our conclusions do not change. Our findings are robust to the inclusion of the volatility as a regressor in the mean equation.

Table E.3 Correlation coefficients between volatility in Tokyo and volatility in New York in the IP.

	IP-TOKYO	
IP-NYSE	**GARCH(1,1)**	
	Tokyo - New York	New York - Tokyo
EGARCH(1,1), σ[d]	0.20041736[a]	0.20359190
Q(1)[b]	19.84280	20.47639
P-value[e]	(8.40787e-006) **	(6.03715e-006) **
Robust test P-value[f]	[0.0006788] **	[0.0005349] **
EGARCH(1,1), D[c], σ	0.10855012	0.10656672
Q(1)	5.82094	5.61016
P-value	(0.01584) **	(0.01786) **
Robust test P-value	[0.0211339] **	[0.0186618] **
GJR(1,1), σ	0.18209030	0.18488186
Q(1)	16.37970	16.88577
P-value	(5.18374e-005) **	(3.96980e-005) **
Robust test P-value	[0.0018164] **	[0.0015029] **
GJR(1,1), D, σ	0.14054752	0.13918024
Q(1)	9.75840	9.56946
P-value	(0.00179) **	(0.00198) **
Robust test P-value	[0.0141156] **	[0.0123396] **

a. Is the correlation coefficient between the volatility in the NYSE on day *h* and the volatility in the TSE on day *h*. Fitting an EGARCH(1,1), σ, model for the NYSE and a GARCH(1,1) model for the TSE.
b. Is the Ljung-Box statistic to test the statistical significance of each correlation coefficient.
c. Means that the model has a dummy variable in the constant term of the variance equation. Such dummy variable takes value 1 the 27 of October of 1997 and zero otherwise.
d. Means that the model has the volatility as a regressor in the mean equation.
e. Probability value of the correlation coefficient using the Ljung-Box statistic.
f. Probability value of the correlation coefficient assuming it is normally distributed and using the Newey-West standard errors robust to heteroscedasticity and autocorrelation till lag 25.
- All the fitted models do not have a constant term in the mean equation.

** Significance at the 5% level.
* Significance at the 10% level.

Table E.4 Correlation coefficients between volatility in Tokyo and volatility in New York in the NIP.

	NIP-TOKYO	
NIP-NYSE	**GARCH(1,1)**	
	Tokyo - New York	New York - Tokyo
EGARCH(1,1), ma(1)[c], σ	0.01842776[a]	0.02001326
Q(1)[b]	0.16776	0.19786
P-value[f]	(0.68211)	(0.65645)
Robust test P-value[g]	[0.6714889]	[0.6534092]
EGARCH(1,1), ,ma(1), D[d], σ[e]	0.00960618	0.01311719
Q(1)	0.04559	0.08500
P-value	(0.83093)	(0.77063)
Robust test P-value	[0.459187]	[0.3497537]
GJR(1,1), ma(1), σ	0.00898459	0.01391919
Q(1)	0.03988	0.09571
P-value	(0.84172)	(0.75704)
Robust test P-value	[0.7436715]	[0.6247007]
GJR(1,1), ma(1), D, σ	0.00828860	0.01298202
Q(1)	0.03394	0.08326
P-value	(0.85384)	(0.77293)
Robust test P-value	[0.4494901]	[0.2962372]

a. Is the correlation coefficient between the volatility in the NYSE on day *h* and the volatility in the TSE on day *h*. Fitting an EGARCH(1,1), ma(1), σ, model for the NYSE and a GARCH(1,1) model for the TSE.
b. Is the Ljung-Box statistic to test the statistical significance of each correlation coefficient.
c. Means that the model has a moving average term of order one in the mean equation.
d. Means that the model has a dummy variable in the constant term of the variance equation. Such dummy variable takes value 1 the 27 of October of 1997 and zero otherwise.
e. Means that the model has the volatility as a regressor in the mean equation.
f. Probability value of the correlation coefficient using the Ljung-Box statistic.
g. Probability value of the correlation coefficient assuming it is normally distributed and using the Newey-West standard errors robust to heteroscedasticity and autocorrelation till lag 25.

\- All the fitted models do not have a constant term in the mean equation.

** Significance at the 5% level.

* Significance at the 10% level.

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Chapter 3:

The Effect of Multinational Firms' Activity on the Intraday Patterns of Stock Return Volatility. The Case of the Spanish Stock Exchange.

The Effect of Multinational Firms' Activity on the Intraday Patterns of Stock Return Volatility. The Case of the Spanish Stock Exchange[27].

Abstract

This paper studies the effect that multinational firms' activity in a foreign country could have on stock prices in the short run. One explanation of this potential effect is that news about daily business activity matters for stock pricing. To gather empirical evidence we used the Spanish Stock Exchange (SSE), which is especially well suited because most of its firms' international activity is concentrated in South America. In this market, under the hypothesis that daily business activity news affects stock prices in the short run, we expect firms with higher real activity in the Americas to have a higher proportion of their daily volatility concentrated at the opening of the SEE and during the day in the Americas. These are indeed the results we found. Werner and Kleidon (1996) found that UK stocks dually listed on the New York Stock Exchange (NYSE) have more volatility during the overlapping trading period. We repeated the analysis without the Spanish stocks listed on the NYSE, and with just those dually listed stocks, and the results are the same. Our contribution is the finding of empirical evidence supporting the hypothesis that the geographical distribution of firm's real activity affects stock prices in the short run.

[27] This paper has been done during a stay in the Business Economics department of the *Universidad Carlos III de Madrid*. The author thanks this department for all its support for doing this paper. The author is also grateful to Mikel Tapia of the *Universidad Carlos III de Madrid,* to Miguel A. Martínez of the *Universidad del País Vasco,* and to Elíseo Navarro, Juan Nave and others present in a seminar at the *Universidad de Castilla la Mancha* for helpful comments on earlier versions of the paper. The content of this paper is the sole responsibility of the author.

1. INTRODUCTION

In the literature studying the stock return volatility determinants there have been identified four potentially important determinants: Trading noise, public information, private information and trading mechanisms. To identify the relative importance of these determinants, contributions to the literature have focused on experiments that exploit differences in trading mechanisms, in the arrival of public information, and in whether markets are open. For example French and Roll (1986) use the suspension of trading in some Wednesday to compare non-trading days with trading days with similar rates of arrival of public information. Barclay et al. (1990) uses the fact that there were some Saturdays with trading in the Tokyo Stock Exchange to investigate whether additional private information revealed through trading on Saturdays affects volatility. Stoll and Whaley (1990) show that the opening mechanism affects stock return volatility. Amihud and Mendelson (1991) use the fact that the Tokyo Stock Exchange has two trading periods to argue that higher opening volatility is mostly the result of the incorporation of overnight information. Chan et al (1996) assume that European and Japanese stocks quoted on US markets have different patterns in public information releases to investigate volatility determinants.

Chan et al (1996) base their analysis on the assumption that the rate of arrival of public information differs predictably across stocks during the trading day. They compare the intraday return behavior, during the US trading day, of European, Japanese, and American stocks listed on the New York Stock Exchange (NYSE) or the American Stock Exchange (AMEX). Their argument is that public information is mostly released during the business day in the firm's country. Thus for European Stocks, the arrival of public information drops off at the end of the morning in the US as the European Business day comes to an end. And for Japanese stocks, the arrival of public information is uniformly low during the US trading day because the business day in Japan does not overlap with the trading day in the US. They assume that little private information about foreign stocks is expected to become known during the US trading day. They found US stocks intraday behavior to be close to Japanese and European intraday behavior. Their conclusion is that there is trading based on public information[28] and that the foreign stocks' volatility is due to trading based on public information released in the foreign market after the closing of the US market the day before.

What is not taken into account in previous literature is the multinational activity of some foreign firms quoted on a stock market. In the case of the US, the most of the Japanese stocks quoted on the NYSE have a high proportion of their sales in the US. For example, in 1998 the net sales of Honda motors in the US represented 46,6% of their total net sales, in the case of Sony they were 29,9%, they were 21,3% for Kyocera, and so on. These are foreign firms but they have a great part of their business in the US. If daily business activity news is introduced into prices, as private or public information, we would expect those firms' stocks to have intraday volatility patterns close to those of US stocks, as

[28] See Harris and Raviv (1993) for a model of trading on pubic information.

found by Chan et al (1996)[29]. However, in this case the evaluation of trading on public information as a determinant of intraday stock behavior could be different.

The study of the effect multinational firms' activity on stock return volatility is relevant for other fields too. For example, it could be relevant in the research on financial markets integration. For example, Werner and Kleidon (1996) study whether the US and UK stock markets are segmented by examining British stocks dually listed in the US. They find dually listed securities to have U-shaped patterns in volatility and in volume in both markets, despite the overlapping period. Under the hypothesis of integrated markets they expected one U-shaped pattern from the opening in the UK to the US closing. Their theory is that new private information is introduced into prices in the US during the overlapping period, this information is transmitted to the UK market through arbitrage and it causes an increase in volume in London during the overlap. They argue that both markets are segmented because US traders with private information wait for US trading to exploit their information instead of trading earlier in London. A key point in this explanation is that US traders could trade in UK earlier in the morning in order to take profit of their information. But, what if US traders did not have the information till the US marked opening? In this case we can not argue that the evidence is supportive of market segmentation. This argument could be broken if daily business activity is incorporated into prices and UK dually listed stocks have a significant proportion of their business in the US time zone geographical area. If it were the case one could think that the main new information that US traders introduce into prices of UK dually listed stocks is related to the firm's daily business activity. And they do not have this information until business activity in the US, hence it could not be previously incorporated in the UK stock market. Being consistent with the evidence presented by Werner and Kleidon (1996), it could be that the UK and US stock markets are more integrated than what they concluded.

The object of this paper is to study the effect of multinational firms' activity on intraday volatility patterns. We expect an effect when the multinational firms' activity is distributed among different time zones. If it is relevant, future research on stock return volatility determinants based in differences across stocks using intraday data should take into account the geographical distribution of the firms' business activity. Also, our findings could be relevant for other fields in financial markets research such as financial markets integration.

The Spanish Stock Exchange (SSE) is especially well suited for this research because the international activity of Spanish multinational firms is mainly concentrated in South America. Thus we find two clearly defined periods during the trading time in the SSE, one when it is still night in the Americas, during the morning in the SSE, and another when it is day there, during the afternoon in the SSE.

We estimate the intraday volatility patterns of a sample of stocks that meet certain liquidity requirements. We follow the estimation technique of Andersen and Bollerslev (1997) that isolates the intraday volatility patterns from any daily volatility process, and implies normalization across stocks, allowing us to make comparisons between them[30]. We use a variable called "percentage of American activity" that refers to the importance of the firms' business activities in the Americas, and we proxy it mostly with the percentage of

[29] Even closer for US stocks with significant business activity in the Japan time zone geographical area.

[30] This separation between the daily process and the intraday process in variance was not taken into account in previous research to estimate the intraday volatility patterns; see for example Chan et al (1996), Foster and Viswanathan (1993) or Kofman and Martens (1997).

total sales in the Americas. We then study the effect of this variable on intraday volatility patterns. We find that firms with more American activity have a higher proportion of their intraday volatility in the first 15-minute trading periods, which we think is due to the greater business activity in those firms since the SSE closing the day before. After the SSE opening and during the night in the Americas those firms with more American activity have a lower proportion of their intraday volatility, we think it is because those firms have a great part of their business inactive. And finally, we find that those firms have a higher proportion of their intraday volatility during the day in the Americas, our interpretation is that it is because a great part of their business become active in this period.

Some of the Spanish firms with more American activity are dually listed on the SSE and the NYSE. Werner and Kleidon (1996) found British stocks dually listed in the US to have a concentration of their daily volatility during the overlapping period of trading in the US and the UK. Their empirical evidence is consistent with the idea that information incorporated into British stocks during US trading is motivated by the firms' business activity in the US time zone geographical area, but it is also consistent with this information not being related to the firms' business activity there. In the latter case our results could be due to the fact that Spanish dually listed securities are among the group with higher American activity, so that we might think we have detected the effect of the American activity when there is no such effect. It could be that the explanation for our empirical evidence is that it is information coming from the US that has nothing to do with the firms' American activity that is causing a concentration of volatility in the afternoon in the dually listed stocks. In order to discern which is the real explanation we have repeated the analysis without the dually listed stocks and with just the dually listed stocks. In these analyses we get the same results. Daily volatility is concentrated in the afternoon for firms with a higher percentage of American activity.

We conclude that the geographical distribution of firms' business has a significant effect on intraday volatility patterns. Our assumption is that this is because information about daily business activity is incorporated into stock prices. Finally, our empirical evidence suggest that further research on stock return volatility determinants and in other fields such as financial stock markets segmentation should take into account the geographical distribution of firm's business.

The paper proceeds as follows. In section 2, we present theoretical fundamentals that could explain why daily business activity information could be relevant for stock pricing in the short run. In section 3, we present the data and methodology. In section 4 we present the results, and in section 5 the conclusions.

2. THEORETICAL FUNDAMENTALS

There are two main approaches for stock pricing, Fundamental analysis and Chartist analysis[31]. In the fundamental approach, investors use all the economic information relevant for the firm in order to know the state and the foreseeable evolution of the firm's business. One key information that fundamental investors could use is the firm's strategies and plans, being private information or not. The fundamentalists will evaluate those strategies and plans and will price the stock. It seems sensible to think that information about firm's strategies and plans will be released from the firm's matrix. When something affecting the business of the firm changes, there is a reaction from the managers, the information about this reaction will be released, publicly or not, from the firm's matrix and probably will have an effect on the stock price. If all the information that traders introduce into prices is information about the managers reaction, or the plans and the strategies they want to implement, it seems sensible to use the nationality of the stock or the nationality of the owners of the stock to explain the intraday volatility pattern. During the night in Tokyo there will be few information of this type about the Japanese stocks. So during the night in Tokyo there will be little volatility in the Japanese stocks quoted on the NYSE. However, could be those fundamentalists are continuously evaluating the implementation of those strategies and plans or the effect on business of the managers reaction to any innovation affecting the firm. In this case, could be that they use information about the evolution of the firm's business. If this happens, firm's daily business activity will have an effect on stock prices. Any information about the evolution of business will be used to revise the initial evaluation of the plans, strategies and reactions of the managers to an innovation that affects the firm. If a firm have branches abroad, traders will get information about the evolution of business in these branches, and will evaluate whether the plans have or will have the expected result or not in the actual situation. Whether the implementation of the strategies in those branches is made as was expected or not, and so on.

If this is the case, we expect volatility of Japanese stocks quoted on the NYSE to be positively related to the business activity of those firms in the US time zone geographical area. Furthermore, traders can get information about the evolution of business at a higher frequency than information about plans, strategies and managers reactions to innovations affecting the firm. Hence, it seems sensible to expect this kind of information being the reason of a substantial percentage of the intraday volatility that we find in the data. However, the revision of evaluations of plans and strategies are expected to have a lower effect on prices than the plans and strategies by them selves. Hence, they are not expected to be the main reason of the stock's volatility in the log run[32]. But these small effects could be very frequent and explain a substantial proportion of the volatility we find in higher frequencies like in intraday data.

Let us take the Spanish Stock Exchange. Most of the foreign activity of Spanish multinational firms is concentrated in the Americas. If the business information of branches in the Americas is relevant for stock pricing we expect more information arriving about the Spanish multinational firms when it is day in the Americas. Furthermore, the Spanish Stock Market closes, more or less, at noon in the Americas. Hence, some business information

[31] In the literature we can find some theoretical models studying the stock price dynamics when some investors use one of the approaches and some investors the other. A good example is Frankel and Froot (1990)

[32] That is the volatility that traders could use to price stocks for a long period investment.

could be generated during the SSE overnight period. As it is shown in papers like Ross (1989), information is incorporated into prices via volatility. So we expect multinational firms' stock return volatility to be higher during day in the Americas, that is afternoon in the SSE. And, we expect also multinational firms to have more volatility at the SSE opening. As suggested by Amihud and Mendelson (1991) the higher stock return volatility at the opening found in the empirical literature can be due to the slow processing of overnight information. Hence, our idea is that more overnight information will generate more opening volatility.

To see how can this work we use a modeling technique similar to the one of King and Wadhwani (1990) and Ito, Engle and Lin (1992). Let us suppose we can price a stock with some indexes, in a way similar to the Ross (1976) APT model:

$$Pt=\alpha_1*I_{1,t}+\alpha_2*I_{2,t}+I_{3,t}$$

Suppose that Index I_1 reflects the evolution of the firm's business in Europe, Index I_2 reflects the evolution of the firm's business in the Americas, and I_3 reflects all the other factors that can affect the price of the stock but that are not the object of our analysis. We can divide the trading period in the Spanish Stock Exchange (SSE) in two periods, night in the Americas and day in the Americas. In the first period there will be index I_1 and I_3 affecting prices and in the second period there will be I_1, I_3 and I_2.

Taking N intraday periods, define $P_{t,n}$ the price on day t at the intraday period n, and the same for $I_{1t,n}$, $I_{2t,n}$, and $I_{3t,n}$. Suppose we take 15-minute periods, so in a 24 hors day we have 96 periods. Suppose that it is day during 10 hours, that is 40 intraday periods. Suppose that n=0 is at the SSE opening and that it is the beginning of the day in Spain. Suppose that n=28 is at the SSE closing and n=40 is when becomes night in the SSE, n=22 is when it becomes day in America, and it becomes nigh in America at n=62. In table 1 we present the assumed time schedule in relation to Spain, America and the SEE.

Table 1. Time schedule in relation to Spain, the Americas and the SEE

Spanish local time	n	Event
10:00	0*	SEE Opening and beginning of daytime in Spain
15:30	22	Beginning of daytime in the Americas
17:00	28	Closing SSE
20:00	40	Beginning of nighttime in Spain
01:30	62	Beginning of nighttime in the Americas
9:45	95	One period before the SEE opening and beginning of daytime in Spain

*Notice that n=96 would be the same as n=0. Thus, n=0 is at the end of the last 15-minute period of the 24 hours Spanish day, and n=1 is at the end of the first period of the Spanish day. The number n is situated at the end of each 15-minute period.

Suppose that the indexes follow the following stochastic process:

$I_{1(t,n)}=I_{1(t,n-1)}+e_{1(t,n)}$	if $n>1$	
$I_{1(t,n)}=I_{1(t-1,40)}+e_{1(t,n)}$	if $n=1$	$e_{1(t,n)} \cong D(0,\sigma_1)$ and is i.i.d
$e_{1(t,n)}=0$	if $n>40$ or $n=0$	
$I_{2(t,n)}=I_{2(t,n-1)}+e_{2(t,n)}$	if $n>23$	
$I_{2(t,n)}=I_{2(t-1,62)}+e_{2(t,n)}$	if $n=23$	$e_{2(t,n)} \cong D(0,\sigma_2)$ and is i.i.d
$e_{2(t,n)}=0$	from $n=0$ to $n=22$ and	from $n=63$ to $n=95$
$I_{3(t,n)}=I_{3(t,n-1)}+e_{3(t,n)}$	if $n>0$	
$I_{3(t,n)}=I_{3(t-1,95)}+e_{3(t,n)}$	if $n=0$	$e_{3(t,n)} \cong D(0,\sigma_3)$ and is i.i.d

Where D is any probability distribution and:

$Cov(e_{i(t,n)},e_{j(t',n')}) = \sigma_{ij}$	if $t=t'$ and $n=n'$	$i,j=1,2,3$
$Cov(e_{i(t,n)},e_{j(t',n')}) = 0$	if $t\neq t'$ or $n\neq n'$	

In this context the price variation during the SSE overnight period will be:

$$P_{t,0} - P_{t-1,28} = \alpha_1 \sum_{i=29}^{40} e_{1(t-1,i)} + \alpha_2 \sum_{j=29}^{62} e_{2(t-1,j)} + \sum_{k=29}^{95} e_{3(t-1,k)} + e_{3(t,0)}$$

After the SSE opening and before the daytime in America the price change every 15-minute period will be:

$$P_{t,n} - P_{t,n-1} = \alpha_1 \cdot e_{1(t,n)} + \cdot e_{3(t,n)} \qquad \text{For } 23>n>=1$$

And from the moment when starts the day time in America to the SSE closing:

$$P_{t,n} - P_{t,n-1} = \alpha_1 \cdot e_{1(t,n)} + \alpha_2 \cdot e_{2(t,n)} + \cdot e_{3(t,n)} \qquad \text{For } 28>=n>=23$$

For simplicity we can assume that $\sigma_{13}=\sigma_{23}=0$. Then we get that the variance in the price changes at every moment will be:

$$Var(P_{t,0} - P_{t-1,28}) = \alpha_1{}^2 12 \cdot \sigma_1{}^2 + \alpha_2{}^2 34 \cdot \sigma_2{}^2 + 68 \cdot \sigma_3{}^2 + 24\alpha_1\alpha_2\sigma_{12}$$

$$Var(P_{t,n} - P_{t,n-1}) = \alpha_1{}^2 \cdot \sigma_1{}^2 + \sigma_3{}^2 \qquad \text{For } 23>n>=1$$

$$Var(P_{t,n} - P_{t,n-1}) = \alpha_1{}^2 \cdot \sigma_1{}^2 + \alpha_2{}^2 \cdot \sigma_2{}^2 + \sigma_3{}^2 + 2\alpha_1\alpha_2\sigma_{12} \qquad \text{For } 28>=n>=23$$

We assume that there is no dynamic correlation between indexes, that is e_1 and e_2 could be correlated at the same point of time but not otherwise. It is because $\alpha_1 e_1$ and $\alpha_2 e_2$ are the effect of news on prices. If they were correlated in different points of time, the effect of later news could be forecasted with the effect that news have on prices now. In an efficient market it is incorporated into prices now, all that is known that will have an effect on prices.

In this framework, if news about evolution of business in the Americas and in Europe are not correlated, or are positively correlated we get that the overnight volatility will be higher in firms with American activity. Also those firms will have more volatility during the day in the Americas than during the night in the Americas. We will use these conclusions to test whether the business activity information is relevant to price stocks or not.

In the following sections we will study whether there is a positive relation between the percentage of American activity, the overnight period volatility and the volatility during the day in the Americas. If firm's business activity information is not relevant or contemporaneous news about firm's business in the Americas is negatively correlated with news about firm's business in Europe, we should not find those relations. Hence, finding no positive relations does not prove that business activity information is irrelevant for stock pricing. But finding positive relations proves that this information maters for stock pricing.

In the theoretical model we expect the overnight information to be incorporated into prices overnight. That is, the model assumes the opening price to reflect all the overnight information. On the other hand, as is shown in papers like Lin et al (1994) or Amihud and Mendelson (1991) the overnight information is incorporated into prices during the first trading periods of the day, but not in the opening price. Amihud and Mendelson (1991) argue it is due to the slow processing of overnight information. So in order to test whether there is a positive relation between the volatility and the overnight information due to the American activity we will use the volatility in the first trading periods. On the other hand we do not expect to observe this relation for the most liquid stocks[33]. Hence it is not a powerful test to detect the effect of having business in the Americas. We just expect to find a positive relation between volatility in the first periods of trading and the percentage of American activity for samples with stocks that do not trade very often.

On the other hand, it is shown in previous literature that there is a U-shaped intraday pattern in the stock return volatility[34]. If we want to test whether volatility in the SSE is higher during daytime in the Americas the more activity a firm has in the Americas or not, we need to take the U-shaped pattern into account. We can not compare the volatility of the multinational firms, quoted on the SSE, during the morning with the volatility during the afternoon. To solve this problem we take control stocks and we compare the intraday volatility pattern of multinational firms with the intraday volatility pattern of firms without American activity. Concretely we take into account all the stocks quoted on the Continuous Trading System of the Spanish Stock Exchange, we estimate the intraday volatility pattern

[33] They incorporate information faster. Thus, we think that their opening price should incorporate a greater proportion of the overnight information.

[34] To explain the higher volatility at the opening we can fin explanations like the one of Amihud and Mendelson (1991) that attributes it to the slow processing of overnight information. Also, the theoretical models of Foster and Viswanathan (1993) and Holden, Subrahamanyam (1992) predict that informed traders with long-lived information trade more aggressively at the opening. To explain the high volatility at the closing there are explanations like that traders are not allowed to have high open positions overnight, see for example Hsieh and Kleidon (1996).

in each stock and then we estimate the effect of an indicator of each firm's American activity on these volatility patterns. In this way we can test the significance of the American activity in the entire intraday volatility pattern.

3. DATA AND METHODOLOGY

Our sample period is 1997-1998. Given that we are studying the process of information incorporation into prices, we drop from the sample all the stocks not quoted on at least 95% of the trading days or that go untraded for 5 consecutive days, and we end up with 99 stocks. We then analyze those firms' annual financial reports[35] to obtain their percentage of American activity. Because some of the firms had not yet approved their 1998 annual report we have just the 1997 annual report for some. For the firms with an annual report for both years there is no substantial change in the percentage of American activity from 1997 to 1998, so that to obtain the percentage of American activity we used the last annual report we have. As a proxy of the percentage of American activity we used the percentage of American net sales. If we could not get this datum we used the percentage of gross sales, gross profits or net profits in the Americas.

The geographical distribution of the net sales must be in one of the notes to the annual accounts, but Spanish law allows not quoting this data in full detail when this might be damaging for the firm. Thus we have firms with no data or with few data, such as the distribution of sales between exports and imports. In these cases we used all the information in the annual report to infer the proportion of sales in the Americas, or any other of the magnitudes we used as an indicator of American activity. In some cases we could get only an approximate percentage of American activity, such as the maximum or the minimum percentage of American activity that the firm could have, or we were simply not sure about the accuracy of the estimation. We end up with two categories of firms, 19 on which we could get only limited information about the percentage of American activity and 53 on which we could get this percentage with accuracy.

We have to point out that most of the firms are the matrix of a group, and in those cases we analyzed the annual report of the consolidated group. Under Spanish law, when the matrix have 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 activity we have calculated is not exact. It is and additional source of inaccuracy in the percentage. Even so, we think that taking into account just the sales of firms in which the parent has a high interest we made an accurate enough calculation of the percentage of American activity, at least for the purposes of this paper.

We have tick-by-tick transaction data on all the stocks included in our sample for 1997 and 1998[36]. All the stocks in the sample are traded in the "continuous trading system" of the SSE. We make fifteen-minute returns trough the logarithm of the final price minus the

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[35] We could obtain this information form the Information Services of the Madrid Stock Exchange.

[36] We obtained these data from the *Sociedad de Bolsas* of the Spanish Stock Exchange.

logarithm of the initial price of the period. To make those returns we divide the sample into periods of fifteen minutes and take the last price of the period as the price at the last moment of the period. The fist price of the day is assigned to the first moment of trading whenever the transaction takes place during the first 15-minute period. The trading period in the continuous trading system of the SSE is from 10 a.m. to 5 p.m., so we have 28 returns per day. In order to evaluate the accuracy of this method we calculate the difference between the time a transaction actually took place and the time the price is assigned[37]. In appendix B we show the mean of this magnitude for each stock. Whenever there is no trading in one 15-minute period we suppose that the price at the end of this period is equal to the last price. We also calculate the percentage of 15-minute periods with trading, drop from the sample all the stocks for which this percentage lower than 50%, and end up with 56 stocks.

To construct time series of 15-minute returns we make three adjustments, one for dividends, one for increases in capital, and one for splits. In the Spanish Stock Exchange the right to perceive the dividend belongs to the owner of the stock at the end of the day before the dividend payment. The effect of the dividend payment on the stock return must be an extraordinary overnight return. Given that we do not work with overnight returns we do not have to make any adjustment. However, because of the method used to construct the 15-minute return series, whenever there is no trading in the first fifteen minutes of the payment day we will have the extraordinary return in the first 15-minute period with trading. Hence, whenever there is no trading in the first period of the payment day we suppose that the first price of this day is the price at the end of the previous day less the dividend. We do something similar when there is an increase in capital. The preferment rights of subscription to buy the new shares also mean a lower stock price. These rights start to be quoted at the beginning of the day they come into being, so the effect on returns is an overnight effect, but whenever there is no trading in the first period of that day we have the same problem as with the dividends. The adjustment we make is to take the price at the end of the previous day, less the theoretical value of this right, as the first price of the day[38]. 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, in the literature there is research that finds abnormal behavior in stock prices whenever a split is effected; see for example Grinblatt, Masulis, and Titman (1984). A recent study in the case of Spain is the paper by Gomez-Sala (1999), who finds abnormal returns principally on the day the split is effected. We therefore eliminate from the sample, for each stock, all days when a split is effected.

It is worth mentioning that we do not have data for 23 October 1997 in our tick-by-tick databases. There was trading during this day but for an unknown reason there are no data in the tick-by-tick databases. Our data provider, the *Sociedad de Bolsas* of the Spanish Stock Exchange, could not give us an explanation of this phenomenon, nor did they have tick-by-tick data for this day in their databases.

[37] The end of a fifteen-minute period.

[38] The *Sociedad de Bolsas* of the Spanish Stock Exchange has calculated this theoretical value of the right to buy new shares.

3.1. INTRADAY VOLATILITY PATTERNS

To estimate the intraday volatility patterns we use the methodology of Andersen and Bollerlev (1997), in which it is supposed that intraday returns can be decomposed in the following way:

$$R_{t,n} = E(R_{t,n}) + \frac{\sigma_t s_{t,n} Z_{t,n}}{N^{1/2}} \tag{1}$$

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 returns intervals per day, $s_{t,n}$ is the intraday seasonal factor, σ_t the return volatility on day t and $Z_{t,n}$ is a random variable with $E(Z_{t,n})=0$ and $Var(Z_{t,n})=1$. If this is the case, the conditional variance of the stock returns could be decomposed in the following way:

$$VAR(R_{t,n})_{t,n} = \frac{\sigma^2{}_t s^2{}_{t,n} VAR(Z_{t,n})}{N} \tag{2}$$

So that $s_{t,n}$ are the intraday seasonal factors determining the intraday seasonal patters in the return volatility. Andersen and Bollerslev (1997) use a Fourier flexible functional form to model the patterns of intraday returns. These Fourier flexible functional forms were introduced by Gallant (1981, 1982), and have been also applied in finance by Pagan and Shwert (1990). For estimating intraday volatility patterns, Kofman and Martens (1997) used these functional forms.

Following the methodology of Andersen and Bollerslev (1997) to estimate the seasonal volatility patterns, from Eq (1), define:

$$x_{t,n} \equiv 2\log\left[\left|R_{t,n} - E(R_{t,t})\right|\right] - \log\sigma^2{}_t + \log N = \log s^2{}_{t,n} + \log Z^2{}_{t,n} \tag{3}$$

The modeling approach is based on a non-linear regression in the intraday time interval, n, and the daily volatility factor, σ_t:

$$x_{t,n} = f(\theta : \sigma_t, n) + u_{t,n} \tag{4}$$

It is worth mentioning that from Eq (3) we see that the $R_{t,n}$ is a random variable because $Z_{t,n}$ is a random variable, while the other variables are deterministic. Thus we have:

$$E(\log s^2{}_{t,n} + \log Z^2{}_{t,n}) = f(\theta : \sigma_t, n) \tag{5}$$

$$u_{t,n} = \log s^2{}_{t,n} + \log Z^2{}_{t,n} - E(\log s^2{}_{t,n} + \log Z^2{}_{t,n}) \tag{6}$$

And because $s_{t,n}$ is not a random variable:

$$u_{t,n} = \log Z^2{}_{t,n} - E(\log Z^2{}_{t,n}) \quad (7)$$

Therefore $u_{t,n}$ is a i.i.d random variable with mean zero. In Andersen and Bollerslev (1997) the non-linear regression function is approximated by a flexible Fourier functional form like the one proposed by Gallant (1981, 1982), but they allow this functional form to vary with the daily volatility level. This is the approach that we take, but we also allow a regression of dummy variables, one for each intraday time period, that 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 expressed in the following equation[39]:

$$f(\theta:\sigma_t, n) = \sum_{j=0}^{J} \sigma_t^j \left[\mu_{0j} + \mu_{1j}\frac{n}{N} + \mu_{2j}\frac{n^2}{N^2} + \sum_{i=1}^{D} \lambda_{ij} I_{n=i} + \sum_{p=1}^{P} \left(\gamma_{pj} \cos\frac{pn2\pi}{N} + \delta_{pj} sin\frac{pn2\pi}{N} \right) \right] \quad (8)$$

Where we allow j to be 0 or 1, and p to be from 1 to 6. And the dummy variable regression is:

$$f(\theta:\sigma_t, n) = \sum_{j=0}^{J} \sigma_t^j \left[\sum_{i=1}^{28} \lambda_{ij} I_{n=i} \right] \quad (9)$$

Where we allow j to be 0 or 1. Finally, we use the Akaike model selection criterion to choose the model to be used to estimate the intraday seasonal factors. With this criterion we select one model from all the models we estimate, that is, the twelve models implied in equation 8 and the two models implied in equation 9. 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 penalize models with more variables, but not too much, in order to keep models with a good fit to estimate intraday volatility patterns.

Kofman and Martens (1997) also use the flexible Fourier functional form approach to estimate intraday volatility patterns, but do not differentiate the daily process in variance from the intraday process in variance as assumed in Eq. 1. Hence Kofman and Martens (1997) propose the following model:

$$|e_{t,n}| = f(\theta:\sigma_t, n) + u_{t,n}$$

Where $e_{t,n}$ comes from a first filtering of the returns time series with an ARMA model. Andersen and Bollerslev (1997) show that intraday financial data are consistent with the idea of two processes in variance, a daily process and an intraday process. Therefore, we follow the Andersen and Bollerslev (1997) approach, that is:

$$2\log\left[\left| R_{t,n} - E(R_{t,n}) \right| \right] - \log\sigma^2{}_t + \log N = f(\theta:\sigma_t, n) + u_{t,n} \quad (10)$$

[39] 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 μ_1 and μ_2, both polynomials can reproduce the same functional forms.

Where $E(R_{t,n})$ is the unconditional mean of the returns time series. However, we are using transaction prices and transaction prices are subject to fluctuations between the bid and the ask. As is shown in the literature, this behavior induces 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 1 to calculate the expected return. For a related reason, Kofman and Marteens (1997) use an ARMA filter. We decided to use a moving average of order 1 in all cases for the following reasons: First, it is a short memory-process[40]. The spurious negative autocorrelation induced by bid-ask bouncing seems to be more consonant with a short-memory process. For example, Roll (1984) just uses first order serial covariance of price changes to construct his measure of the Spread. In any event, we expect low coefficients in the moving average process[41], and in this case there is little difference from an autoregresive process. Second, as is shown by Diebold (1987), the presence of autoregresive heterocedasticity produces an upward bias in the usual statistics for determining the order of autocorrelation, so that before the elimination of the intraday and the daily volatility process it is difficult to evaluate the autocorrelation order, and it is even difficult to isolate the spurious autocorrelation induced by bid-ask bouncing from any other autocorrelacion that may be in the data. For these reasons we prefer to determine a priori the filter to eliminate the spurious bid-ask induced autocorrelation[42]. If there is bouncing between the bid and the ask, we expect the moving average term to be negative. Indeed, all the moving average terms we have estimated are negative. The following is the model we use to calculate the $E(R_{t,n})$:

$$E(R_{t,n})_t = c + \beta_1 I_n e_{t-1,28} + \beta_2 (1 - I_n) e_{t,n-1} \qquad \begin{array}{l} I_n = 1 \text{ if } n=1 \\ I_n = 0 \text{ if } n>1 \end{array} \qquad (11)$$

In the end, we are using the same methodology as Andersen and Bollerslev (1997), but taking the filtered returns for the spurious autocorrelation induced by the bid-ask bouncing as the true price process, and leaving the possibility of dummy regressions to estimate the intraday process. Another difference with Andersen and Bollerlev (1997) is that they use GARCH[43] 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 instead of using models like the GARCH.

Let $\overline{f}_{t,n} = f(\overline{\theta}; \overline{\sigma}_t, n)$ denote the resulting estimate of the non-linear function, by the flexible Fourier functional forms or by the dummy variable regression. Let T denote the total number of 15-minute periods, so that [T/N] is the number of days. Andersen and Bollerslev (1997) suggest the following estimator of the intraday seasonal factor for interval n on day t:

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[40] An autoregresive process has long-memory.

[41] Indeed, all moving average coefficients are small. The highest do not exceed 0.3.

[42] In appendix C we present the whole paper's results when we do not use this ma(1) filter. That is when we take the unconditional mean as the expected return in Eq. 10. There, we show that we get very close results.

[43] These are models that modelize the autoregresive process in variance. Engel (1982) introduced the ARCH models and Bollerslev (1986) generalized the ARCH models with the GARCH models.

$$\hat{s}_{t,n} = \frac{T \cdot \exp(\overline{f}_{t,n} / 2)}{\sum_{t=1}^{[T/N]} \sum_{n=1}^{N} \exp(\overline{f}_{t,n} / 2)} \tag{12}$$

Given Eq. 5 and that the intraday seasonal factor is not a random variable we have:

$$\hat{s}_{t,n} = \frac{T \cdot \exp(\overline{E(Z_{t,n})} / 2) \cdot \exp(\overline{s}_{t,n} / 2)}{\exp(\overline{E(Z_{t,n})} / 2) \sum_{t=1}^{[T/N]} \sum_{n=1}^{N} \exp(\overline{s}_{t,n} / 2)} \tag{13}$$

So that the random variable $Z_{t,n}$ disappears from the equation. This estimator implies normalization because:

$$\frac{\sum_{n=1}^{N} \sum_{t=1}^{[T/N]} \hat{s}_{t,n}}{T} = 1 \tag{14}$$

For each 15-minute intraday period we take the mean of the intraday seasonal factors estimated in Eq. 13. as an estimation of each of the 28 intraday seasonal factors. With this method we can compare the intraday seasonal patterns of different stocks because we always get 28 factors that sum 28.

3.2. THE EFFECT OF AMERICAN ACTIVITY ON INTRADAY STOCK RETURN VOLATILITY PATTERNS

We use the previous methodology to estimate the 28 intraday seasonal factors of each of the 56 stocks for which we have data about their percentage of American activity. Thus we end up with a database of 28 intraday seasonal factors for each stock. To investigate the effect of the percentage of American activity on the intraday seasonal patterns of stock returns volatility, we calculate the correlation coefficient between each intraday seasonal factor and the percentage of American activity. To calculate the statistical significance of those coefficients we assume they are normally distributed and then we use the White (1980) standard errors, robust to heteroskedasticity[44]. The correlation coefficient is bounded between -1 and 1, so it gives us an idea about the direction and the intensity of the effect.

The continuos trading system of the Spanish Stock Exchange trades from 10 a.m. to 5 p.m., so denote fact1015 to be the intraday seasonal factor in volatility at 10:15 a.m., factt1030 at 10:30 a.m. and so on, and denote America as the percentage of American activity for each stock. Thus we have calculated:

Corr(fact1015, America)
Corr(fact1030, America)
....
....
Corr(fact1645, America)
Corr(fact1700, America)

In a previous version of this paper we did this analysis with one regression model for each intraday 15-minute period, where the dependent variable was the intraday volatility factor and the independent variable was the percentage of American activity. In that case we got very close results to the ones presented in this version of the paper. We think it is better to do the analysis with correlation coefficients instead with regression coefficients because coefficients are not bounded and do not allow us to compare directly the effect of the American activity in different intraday periods. The correlation coefficient is bounded and, for example, allows us to compare the intensity of the American activity effect on the first intraday volatility factor with the intensity of the effect on the intraday volatility factor at 3:00 p.m. The regression coefficient has the advantage that many corrections could be easily implemented to avoid spurious results such as for heteroskedasticity. However, our inference about the correlation coefficients is robust to heteroskedasticity, and we think that this is the main problem that could be in our data.

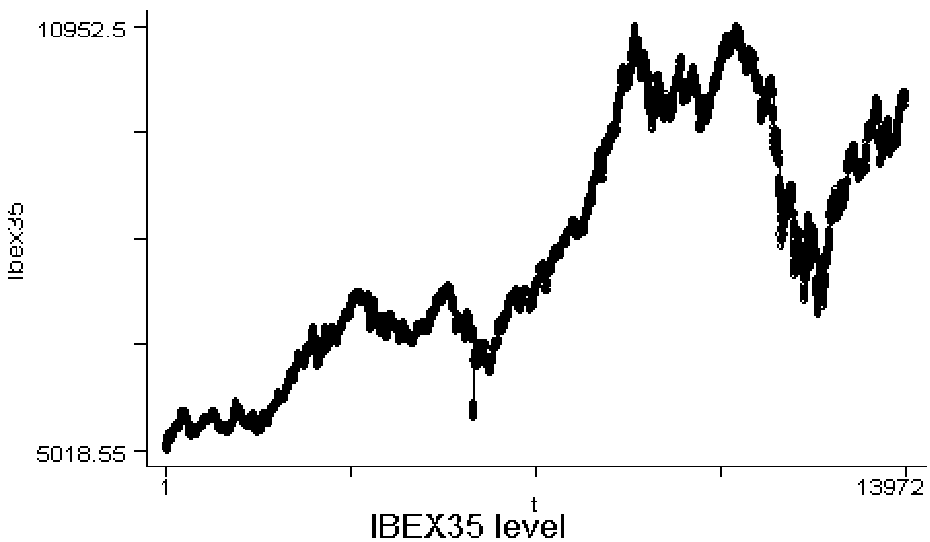
[44] To calculate these standard errors we followed the methodology used in Kofman and Marteens (1997). See the appendix of that paper for a good description of this methodology.

4. RESULTS

4.1. SPANISH STOCK EXCHANGE MARKET INDEX

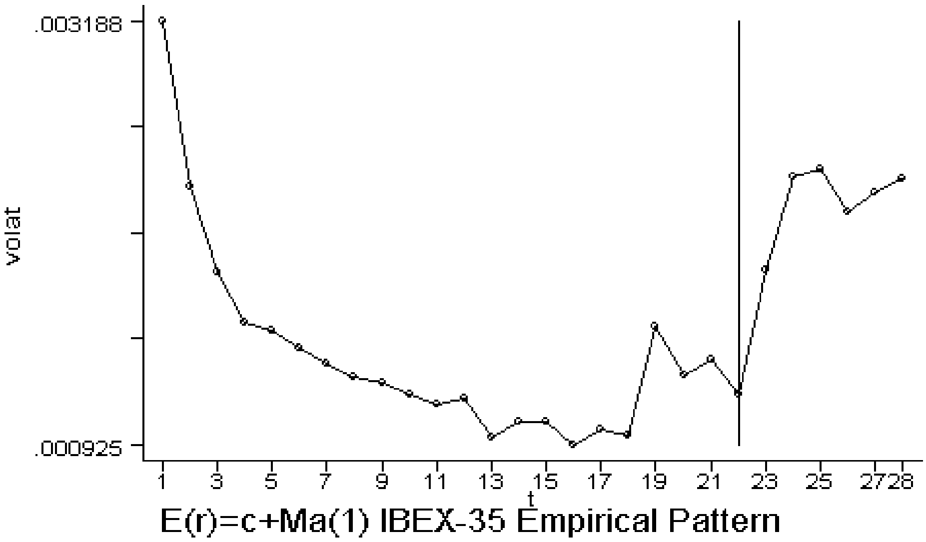
We use the methodology exposed in section 3.1 to estimate the intraday seasonal pattern in the return volatility of the IBEX-35, the main stock price index of the SSE. In figure 1 we show the level of the index measured every fifteen minutes for 1997-1998. There, we can observe an extraordinary movement on 29 October 1997 at 10:15 a.m. On 27 October 1997 there was a crisis in the Hong Kong financial market that was transmitted to the New York Stock Exchange on the same day. This crisis affected the Spanish Stock Exchange just after the NYSE, so that the first reaction of the Spanish Stock Exchange was in the overnight period, and the second effect was on 29 October 1997 in the first periods of the trading session. As is shown in the literature, for example in King and Wadwani (1990), there is usually a contagion effect between markets during crisis periods, that is, transmission of stock price movements that do not respond to information. We wished to detect the effect of information from the Americas on the Spanish Stock Exchange, and given this contagion effect we thought that the crisis week must introduce noise in our study. We therefore decided to eliminate the crisis week from the sample and did all the following analysis without it.

Figure 1. IBEX35 level for 1997 and 1998 every fifteen minutes



In figure 2 we present the empirical estimated intraday seasonal pattern in the IBEX-35 returns volatility. We adjust an MA(1) model with constant term to estimate the expected return, then we take the deviation from the expected return and we take the absolute value of this unexpected return as a measure of volatility, finally we calculate the mean of this absolute value in each intraday period as an estimation of each intraday volatility factor[45].

Figure 2. Empirical Intraday Pattern in the IBEX35 fifteen minutes return volatility.

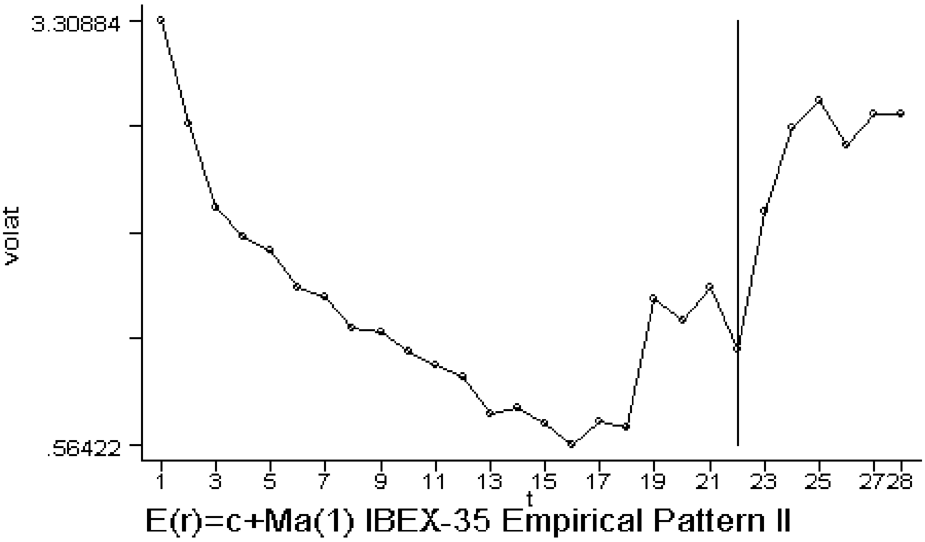


If the process generating the data follows Eq. 1, that is, there are two processes in variance, a daily process and an intraday process, in figure 2 we are mixing both variance processes. In order to be consistent with the model laid out in Eq. 1, and to separate the intraday process from the daily process in variance, we estimate a second version of the empirical intraday pattern in the IBEX-35 fifteen minutes return volatility. To do it we construct a new variable equal to the right-hand side of Eq. 3, that is, standardizing the unexpected return by the daily volatility level. And then we calculate the mean of this variable at each intraday period to obtain the intraday pattern in volatility without mixing it with the daily process in variance. In figure 3 we present the intraday pattern calculated in this way, using Eq. 11 to calculate the expected return[46].

---

[45] Without the MA(1) we get a very close pattern.
[46] Without the MA(1) term we get a very close pattern.

Figure 3. Empirical Intraday Pattern in the IBEX35 fifteen minutes return volatility standardized by the daily volatility.

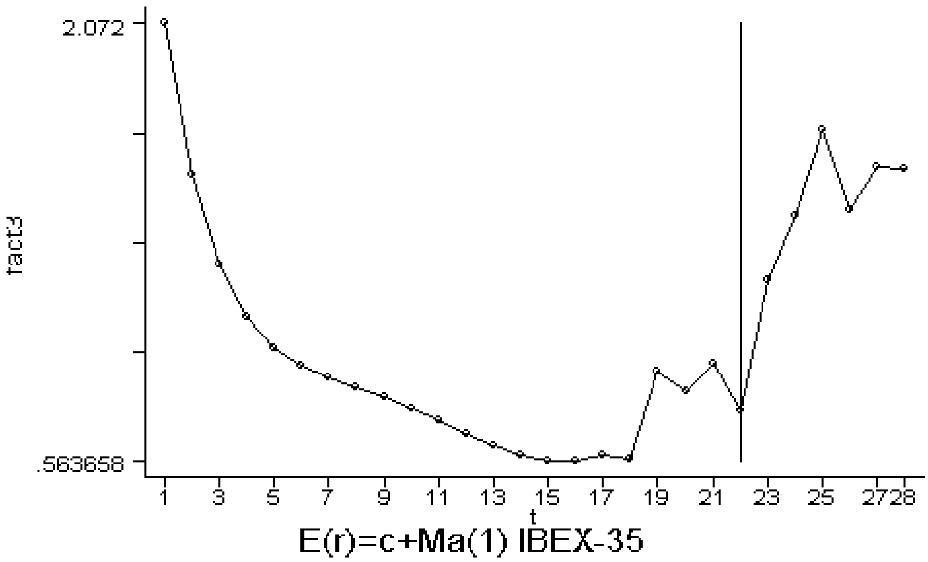


In figures 2 and 3 we can observe the U-shaped pattern in the intraday volatility process that is common in others markets, as is shown in papers such as Harris (1986) or Wood, McInish and Ord (1985). In these figures we also see a recovery in volatility prior to the opening of the NYSE, followed by a drop at the opening of this market. The opening of the NYSE is at 9:30 a.m. that in Madrid local time is 3:30 p.m[47]. Our interpretation is that expectations about the NYSE opening generate the rise in volatility in the periods before that opening. Werner and Kleidon (1996) found a similar behavior in the British dually listed stocks on the US stock market. In these figures we also see that for the Spanish market we have to take special notice of two periods that do break the nice U-shape in the intraday volatility pattern, that is, around the opening of the NYSE and at the end of the trading day. Hence in order to estimate the intraday seasonal patterns, when using the flexible Fourier functional forms that come from Eq. 8 we use 9 dummy variables that take value 1 for one certain intraday period and zero otherwise. These dummy variables are for the following intraday moments: 2:15 p.m., 2:30 p.m., 2:45 p.m., 3:00 p.m., 3:15 p.m., 3:30 p.m., 4:30 p.m., 4:45 p.m., and 5:00 p.m.

In figure 4 we show the estimated intraday seasonal pattern in the IBEX35 returns volatility using the method exposed in section 3.1:

[47] The opening of the NYSE is specially market on those graphs.

Figure 4. Intraday Seasonall Pattern in IBEX35 return volatility



In figure 4 we get a normalized estimation of the intraday volatility pattern, the sum of the 28 intraday factors is equal to 28. From the 14 models that we use to estimate the intraday volatility patterns, 12 with the Eq. 8[48] and 2 with the Eq. 9, we have chosen, with the Akaike Selection Criteria, the model that comes from Eq. 8 with j=0 and p=2[49]. The advantage of using a normalized estimation of the intraday volatility patterns is that we can compare it across stocks to investigate the effect of the firm's American activity.

4.2. THE EFFECT OF THE FIRM'S AMERICAN ACTIVITY ON THE INTRADAY VOLATILITY PATTERNS

We use the methodology exposed in section 3.1 to estimate the normalized intraday volatility patterns of each of the 56 stocks for which we have information about its American activity. Given the pattern found in the market index we use Eq. 8 with the same 9 dummy variables than in the market index as exogenously given.

In the case of the stock by stock analysis we have an additional problem that is the lack of liquidity. Some stocks have days without trading. On those days we have zero daily volatility and we get a missing observation in the variable equal to the left-hand side of Eq. 10. In order to avoid those missing observations we calculate the minimum value in the

[48] All the estimated models using Eq. 8 contain the 9 dummy variables. Given the empirical pattern found, we take those 9 dummy variables as exogenously given.

[49] Without the MA(1) term we chose the same model and we get a very close pattern.

daily volatility series when it is larger than zero and replace the zero daily volatility values by this minimum. We did trials with and without this replacement and got close results.

Given the amount of firms for which we estimate the intraday volatility patterns we do not report them here. All of them have a U-shaped form and are available from the author on request.

Then we apply the methodology presented in section 3.2 to estimate the effect of the American activity on the intraday volatility patterns.

We have calculated the percentage of 15-minute periods with trading, including the crisis week, as a measure of liquidity, and we constructed groups of stocks according to this percentage. This liquidity indicator is to detect the frequency of trade in order to see which stocks get the information into prices faster[50]. For example, Low and Muthuswamy (1996) and Lo and Mackinlay (1988) found empirical evidence indicating that the more traded assets incorporate information faster.

On the other hand we have two kinds of stocks, the ones with an accurate estimation of the percentage of American activity and the ones with a non-accurate percentage. So we have done the analysis for ten samples. In table 2 there is the description of those samples.

Table 2. Summary statistics of the percentage of American activity

			Percentiles[5]						
Sample	**Number Obs.**[3]	**Mean America**[4]	**95%**	**90%**	**75%**	**50%**	**25%**	**Max**[6]	**Min**
50%-clean[1]	42	8.65%	50.70%	30.73%	12.50%	0.00%	0.00%	54.30%	0.00%
60%-clean	37	8.60%	52.93%	30.73%	12.50%	0.00%	0.00%	54.30%	0.00%
70%-clean	30	10.29%	52.93%	40.71%	14.83%	0.82%	0.00%	54.30%	0.00%
80%-clean	25	12.35%	52.93%	50.70%	19.12%	3.59%	0.00%	54.30%	0.00%
90%-clean	23	13.40%	52.93%	50.70%	21.01%	4.50%	0.00%	54.30%	0.00%
50%[2]	56	8.69%	50.70%	30.73%	10.89%	1.76%	0.00%	54.30%	0.00%
60%	50	8.79%	50.70%	30.36%	12.45%	2.26%	0.00%	54.30%	0.00%
70%	41	10.40%	50.70%	30.73%	13.23%	3.59%	0.00%	54.30%	0.00%
80%	32	12.26%	52.93%	31.60%	20.06%	4.05%	0.00%	54.30%	0.00%
90%	28	13.63%	52.93%	50.70%	21.25%	5.65%	0.00%	54.30%	0.00%

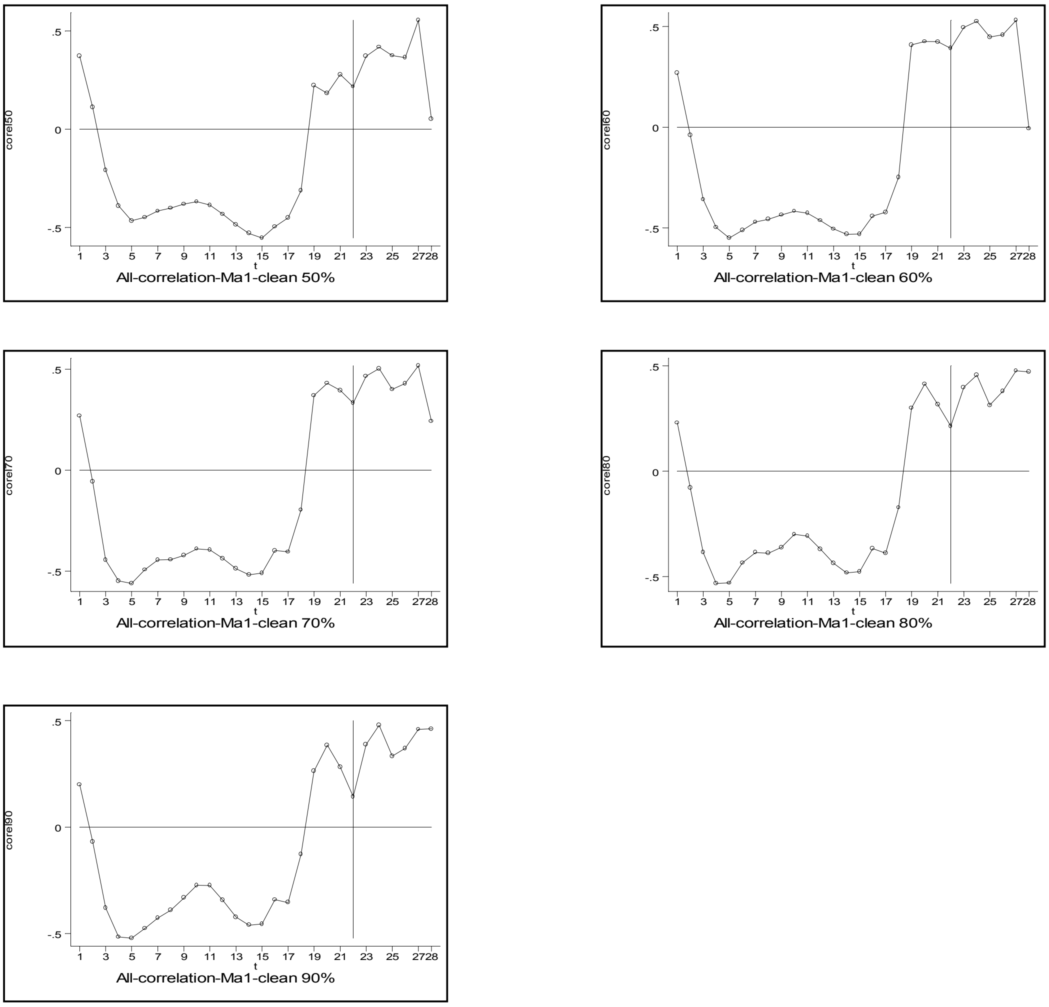
1. Sample with the firms for witch we have an accurate estimation of the percentage of American activity and have a percentage 15-minute periods with trading greater than 50%.
2. Sample including firms with and without an accurate estimation of the percentage of American activity and have a percentage 15-minute periods with trading greater than 50%.
3. Number of firms in each sample.
4. Mean percentage of American activity in each sample.
5. Percentilic distribution of the percentage of American activity, in each sample.
6. Maximum percentage of American activity that a firm has, in each sample.

As can be seen in table 2, the sample size becomes smaller as the liquidity indicator increases. Thus the faster is the acquisition of information by the stocks in the sample the smaller is the sample and the more difficult is to get statistically significant effects.

[50] This is not to detect liquidity in the sense of price responses to trade. In this last sense a stock is liquid when its price response to trade is small. We do not want to detect stocks with small price reaction to trade. We want to detect stocks with prices getting information faster.

In figure 5 there are the correlation coefficients between the percentage of American activity and each intraday seasonal factor in volatility.

Figure 5. Correlation coefficients between each intraday seasonal factor in volatility and the percentage of American activity. This is for the 5 samples with an accurate estimation of this percentage.

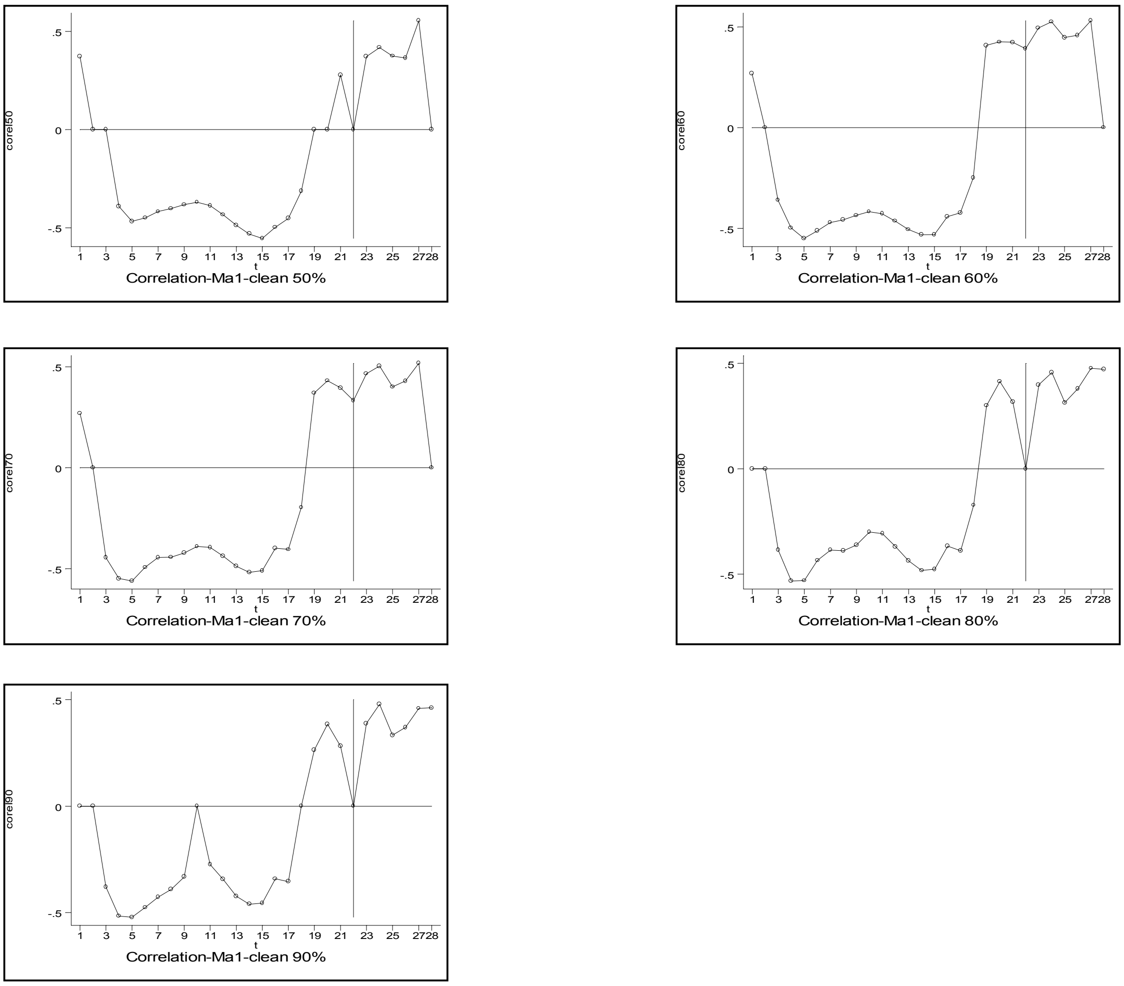


- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

In figure 5 we see that there are the two trading periods we expected to find in the SEE. In the first period the higher the percentage of American activity the smaller the intraday seasonal volatility. In the second period the higher the percentage of American activity, the higher the seasonal volatility.

In order to test the significance of the relations found we estimate the White (1980) standard errors of those coefficients, robust to heteroskedasticiy. In figure 6 we present the same correlation coefficients presented in figure 5, but whenever a coefficient is not significant at the 5% level we replace it by zero.

Figure 6. Correlation coefficients between each intraday seasonal factor in volatility and the percentage of American activity. Non-significant coefficients are replaced by zero. This is for the 5 samples with an accurate estimation of this percentage.

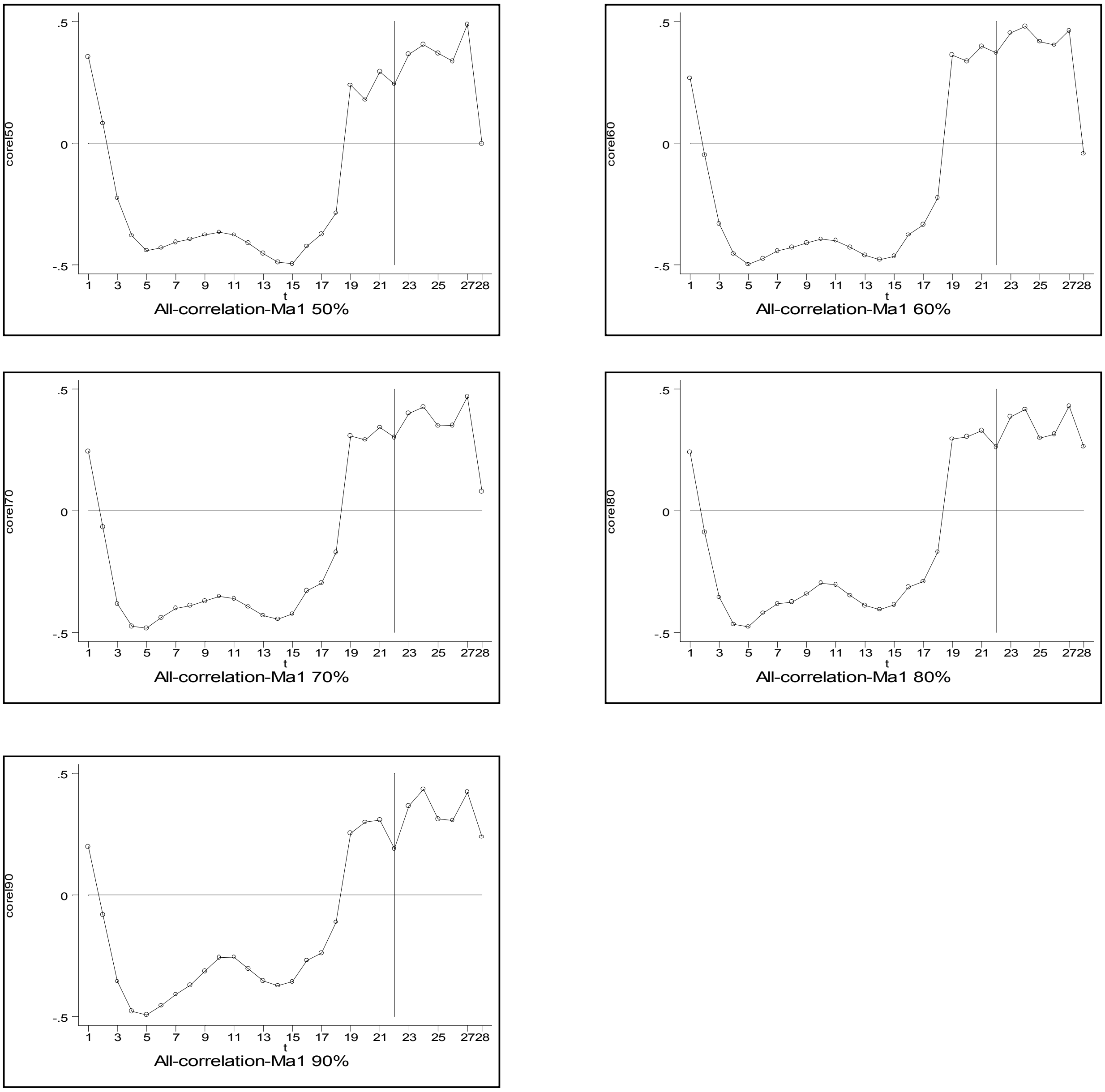


- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility. But whenever a coefficient is not significant at the 5% level it is replaced by zero. Inference is based on the White (1980) standard errors, robust to heteroskedasticity.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

In figure 6 we confirm the existence of the two trading periods in the SEE. In the first trading period, volatility is negatively correlated the American activity, and in the second it is positively correlated. The threshold between trading periods is around 14:45 Madrid time, that is, at 8:45 in New York or 9:45 in Buenos Aires (Argentina). Firms with American activity tend to have a lower proportion of their intraday volatility than other firms when it is night in the Americas and tend to have a higher proportion than other firms when it is day there. Also, as we expected, we find the first 15-minute period volatility to represent a higher proportion of intraday volatility for firms with American activity. Those firms have business information generated in the Americas after the SSE closing the day before. The evidence is consistent with the idea that this business information generated in the Americas is causing the higher opening volatility in firms with American activity. This higher concentration of volatility at the opening for firms with American activity disappears for the most liquid samples. In those samples we expect information to be incorporated into prices faster. We think this is the reason for the non-significant higher concentration of volatility at the opening in highly liquid firms with American activity. Another interesting point is that volatility at the NYSE opening is significantly related to the American activity in just two samples. We think this could be because at the NYSE opening all traders are awaiting the NYSE opening price, which could affect all stocks no matter whether the firms have American activity or not.

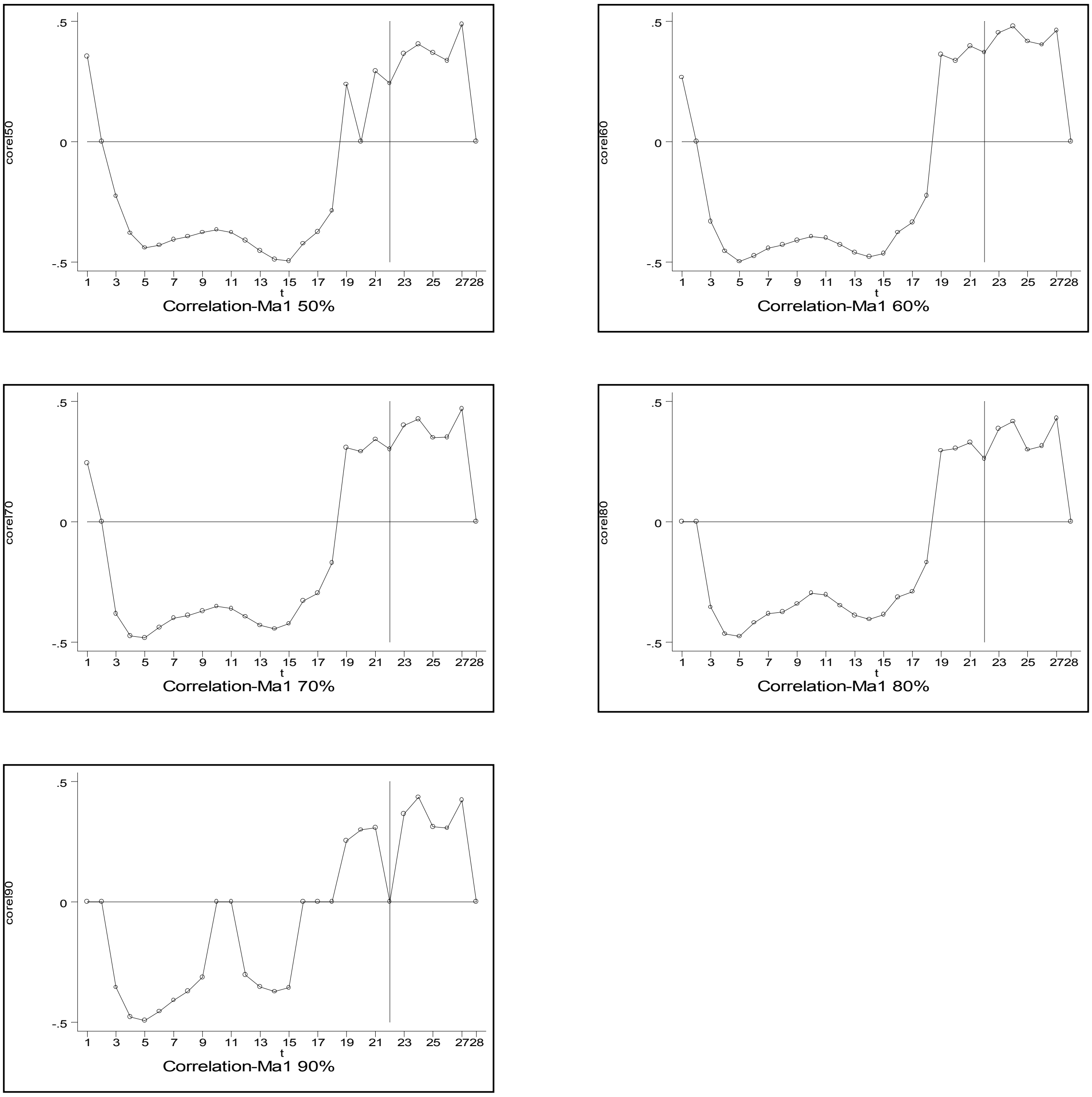
In order to expand the sample size we repeated the analysis incorporating the firms with a non-accurate estimation of the percentage of American activity. We show this results in figures 7 and 8.

Figure 7. Correlation coefficients between each intraday seasonal factor in volatility and the percentage of American activity. This is for the 5 samples including firms with an inaccurate estimation of this percentage.



- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

Figure 8. Correlation coefficients between each intraday seasonal factor in volatility and the percentage of American activity. Non-significant coefficients are replaced by zero. This is for the 5 samples including firms with an inaccurate estimation of this percentage.



- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility. But whenever a coefficient is not significant at the 5% level it is replaced by zero. Inference is based on the White (1980) standard errors, robust to heteroskedasticity.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

The results including the stocks with an inaccurate estimation of the American activity are very close to the first results. The main difference is that in all cases we get a non-significant relation between volatility and the percentage of American activity in the last trading period. We think the results are very close to the first results because the inaccuracy in the estimation of the firm's American activity is smaller than expected. However, this is just an intuition and a deeper analysis of this inaccuracy should be done in order get more conclusive results.

We think this non-significant relation in the last trading period, that we find in some cases in figure 5 and in all cases in figure 7, could be because other factors, that affect all stocks, originate higher closing volatility. For example Hsieh and Kleidon (1996) explain the higher closing volatility by arguing that traders are not allowed to have high open positions overnight. If it affects all stocks, it could dilute the effect of higher volatility in firms with American activity originated by information related with the firms' business in the Americas. In the analysis that do not include firms with an inaccurate percentage of American activity, we get a positive and significant relation between closing volatility and the American activity for the most liquid samples. It suggests to us that these other factors that cause higher closing volatility are not so determinant for liquid stocks. For example, the explanation of Hsieh and Kleidon (1996) seems to affect less liquid stocks more.

4.3 DUALLY LISTED SECURITIES

There are 7 Spanish stocks quoted on the NYSE. Two of them have the highest percentage of American activity from all the 56 stocks in our sample. In the sample with accurate estimation of the American activity there are 12 stocks with a percentage of American activity greater than 10%, and 5 of them are dually listed stocks. Werner and Kleidon (1997) found British stocks dually listed in the US to have a concentration of their daily volatility and volume during the overlapping period of trading in the UK and the US stock markets. Their theory is that information from US traders is incorporated into British dually listed stocks during the overlap. They did not study the origin of this information, whether it is information related to those British firms' business activity in the US time zone geographical area or not. The key point in their argumentation is that US traders had that information during the early morning trading period in the UK but they did prefer to trade in the US than in the UK. Informed traders with short-lived private information should trade in London instead to wait till the opening of US trading. Werner and Kleidon (1996) suggest that this is evidence of market segmentation. It seems that they thought about short-lived private information that is known before the beginning of US business activity. And it suggests that they were not thinking about information related to the firm's business activity in the US. The Spanish firms dually listed in the NYSE are among the group with higher percentage of American activity. Thus, it could be that our previous results are spurious[51] and we are interpreting the effect of the dually listing as the effect of the firm's American activity. Indeed, we have studied the effect of the dually listing on the

[51] Given the Werner and Kleidon (1996) results, our results could be spurious, just if the higher volatility in the overlapping period for the dually listed stocks is not related to the firm's business American activity.

intraday volatility patterns and the result is that dually listed firms have a higher proportion of their intraday volatility during the daytime in the Americas than other stocks. We present those results in appendix A. Thus what we do in this section is to do the same analysis done in the previous section, but without the dually listed securities and just with the dually listed securities. If the higher volatility comes from the higher American activity we expect the other securities, and dually listed securities as a group, to behave in the same way as in the previous section with dually and no-dually listed stocks mixed. Having more proportion of intraday volatility when it is day in the Americas the more activity they have there. So if we get similar results to the ones found in the previous section our conclusion will be that the real American activity is the origin of the higher volatility when it is day in the Americas in the firms with higher American activity. On the other hand, notice the special relevance of the analysis with just the dually listed stocks. It is because having similar results in this case, it will shed some light in the origin of the information generated in the US detected by Werner and Kleidon (1996) for the British stocks.

We can not incorporate a dummy variable for the dually listed securities in a regression model with the percentage of American activity to explain each intraday volatility factor, because this dummy variable is highly correlated with the percentage of American activity. Depending on the sample this correlation coefficient ranges from 54.37% to 60.33%. These high coefficients also confirm our concern to discern the dually listing effect from the American activity effect on the intraday seasonal pattern in volatility. In table 3 it is the description of the samples in which we apply the analysis.

Table 3. Summary statistics of the percentage of American activity it is in each analyzed sample without the dually listed stocks, and in the samples with just dually listed stocks.

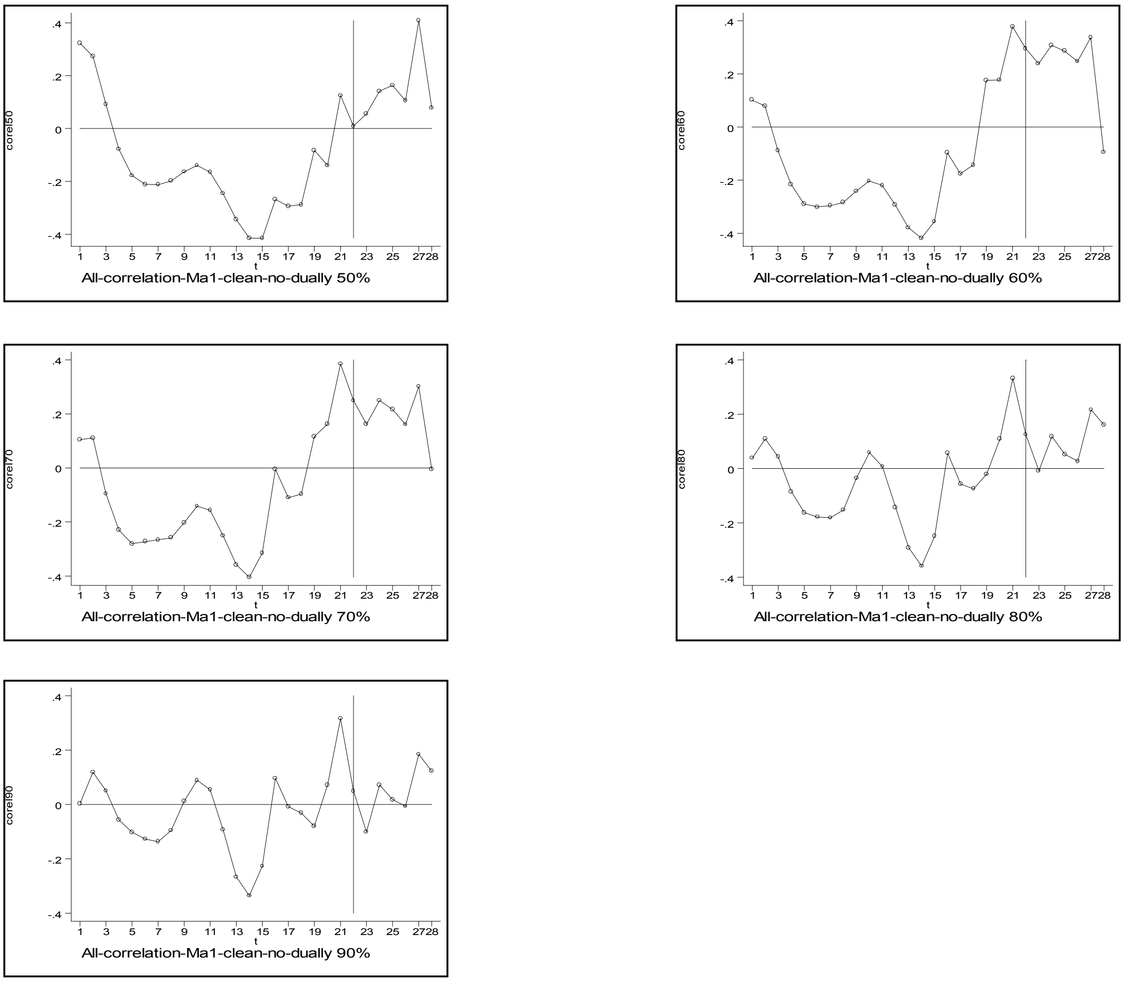
			Percentiles[5]						
Sample	**Number Obs.**[3]	**Mean America**[4]	**95%**	**90%**	**75%**	**50%**	**25%**	**Max**[6]	**Mini**
50%-clean[1]	36	5.19%	42.50%	19.12%	3.10%	0.00%	0.00%	50.70%	0.00%
60%-clean	31	4.57%	21.01%	14.83%	3.59%	0.00%	0.00%	50.70%	0.00%
70%-clean	24	5.51%	21.01%	19.12%	5.19%	0.00%	0.00%	50.70%	0.00%
80%-clean	19	6.96%	50.70%	21.02%	13.23%	0.67%	0.00%	50.70%	0.00%
90%-clean	17	7.75%	50.70%	21.02%	13.23%	0.97%	0.00%	50.70%	0.00%
50%[2]	49	5.72%	31.60%	19.12%	6.90%	0.00%	0.00%	50.70%	0.00%
60%	43	5.42%	21.01%	14.83%	7.19%	0.00%	0.00%	50.70%	0.00%
70%	34	6.47%	31.60%	19.12%	8.17%	1.24%	0.00%	50.70%	0.00%
80%	25	7.43%	31.60%	21.05%	8.89%	1.50%	0.00%	50.70%	0.00%
90%	21	8.34%	31.60%	21.01%	13.23%	1.50%	0.00%	50.70%	0.00%
Dually[7]	7	29.49%	54.30%	54.30%	52.93%	30.0%	12.5%	54.30%	4.50%
Dually-clean	6	29.41%	54.30%	54.30%	52.93%	26.1%	12.5%	54.30%	4.50%

1. Is the sample without dually listed stocks, with the firms for witch we have an accurate estimation of the percentage of American activity and have a percentage 15-minute periods with trading greater than 50%.
2. Is the sample without dually listed stocks, including firms with and without an accurate estimation of the percentage of American activity and have a percentage 15-minute periods with trading greater than 50%.
3. The number of firms it is in each sample.
4. The mean percentage of American activity it is in each sample.
5. The percentilic distribution of the percentage of American activity it is in each sample.
6. The maximum percentage of American activity that a firm has in each sample.
7. Is the sample with just dually listed stocks in the SSE and in the NYSE.

In table 3 we can see that in the Spanish stock market the dually listed stocks have a great proportion of the real American activity. Hence, without those stocks we get samples with a substantial reduction in the weight of stocks with significant American activity.

In figures 9 and 10 we present the correlation coefficients between the American activity and the intraday seasonal factors in volatility. In figure 10 we replace by zero the non-significant correlation coefficients.

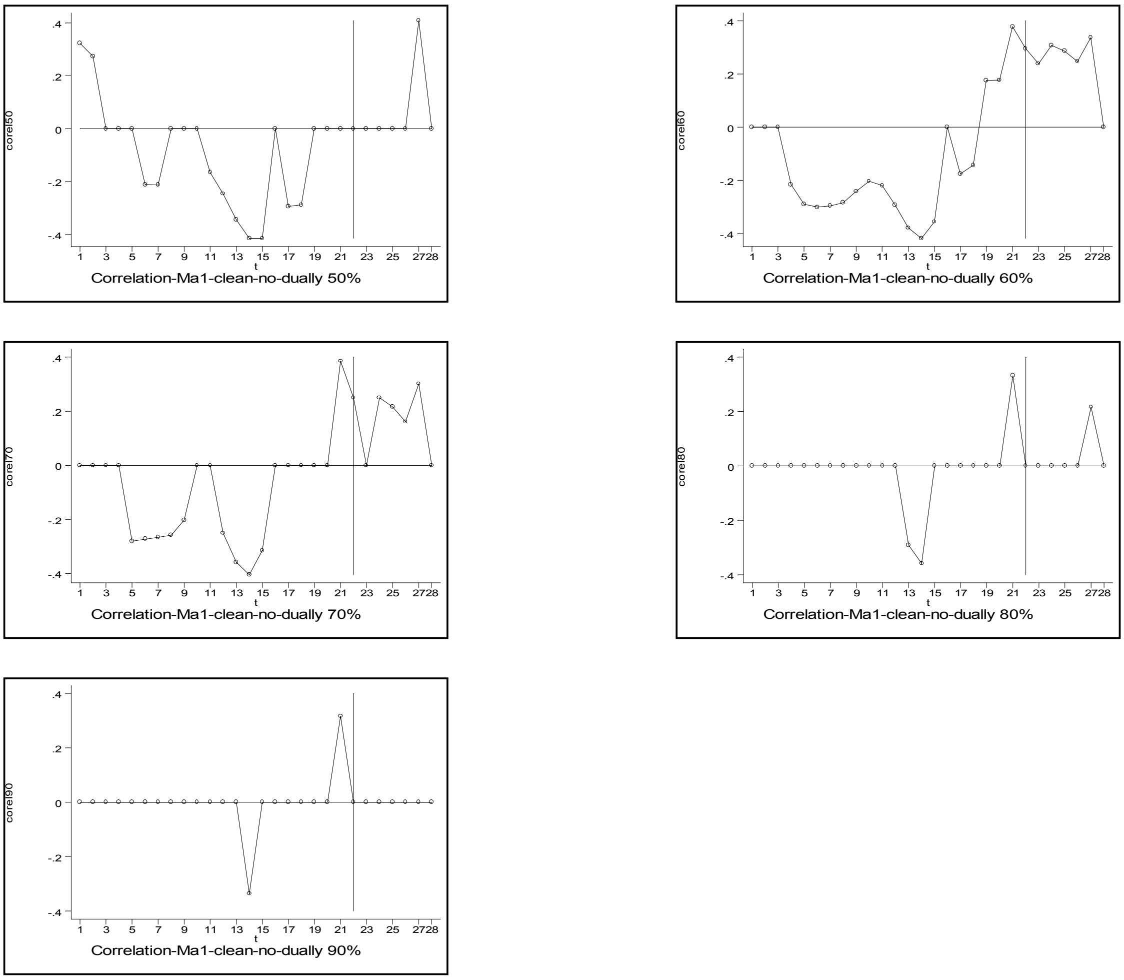
Figure 9. Correlation coefficients between each intraday seasonal factor in volatility and the percentage of American activity. This is for the 5 samples with an accurate estimation of this percentage without dually listed stocks.



- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

In figure 9 we observe a similar behavior than the one found in the previous section. Only in the highly liquid samples there are some correlation coefficients with an unexpected sign. These samples have a big reduction in the variability of the percentage of American activity. We think it could make difficult to make inference.

Figure 10. Correlation coefficients between each intraday seasonal factor in volatility and the percentage of American activity. Non-significant coefficients are replaced by zero. This is for the 5 samples with an accurate estimation of this percentage without dually listed stocks.

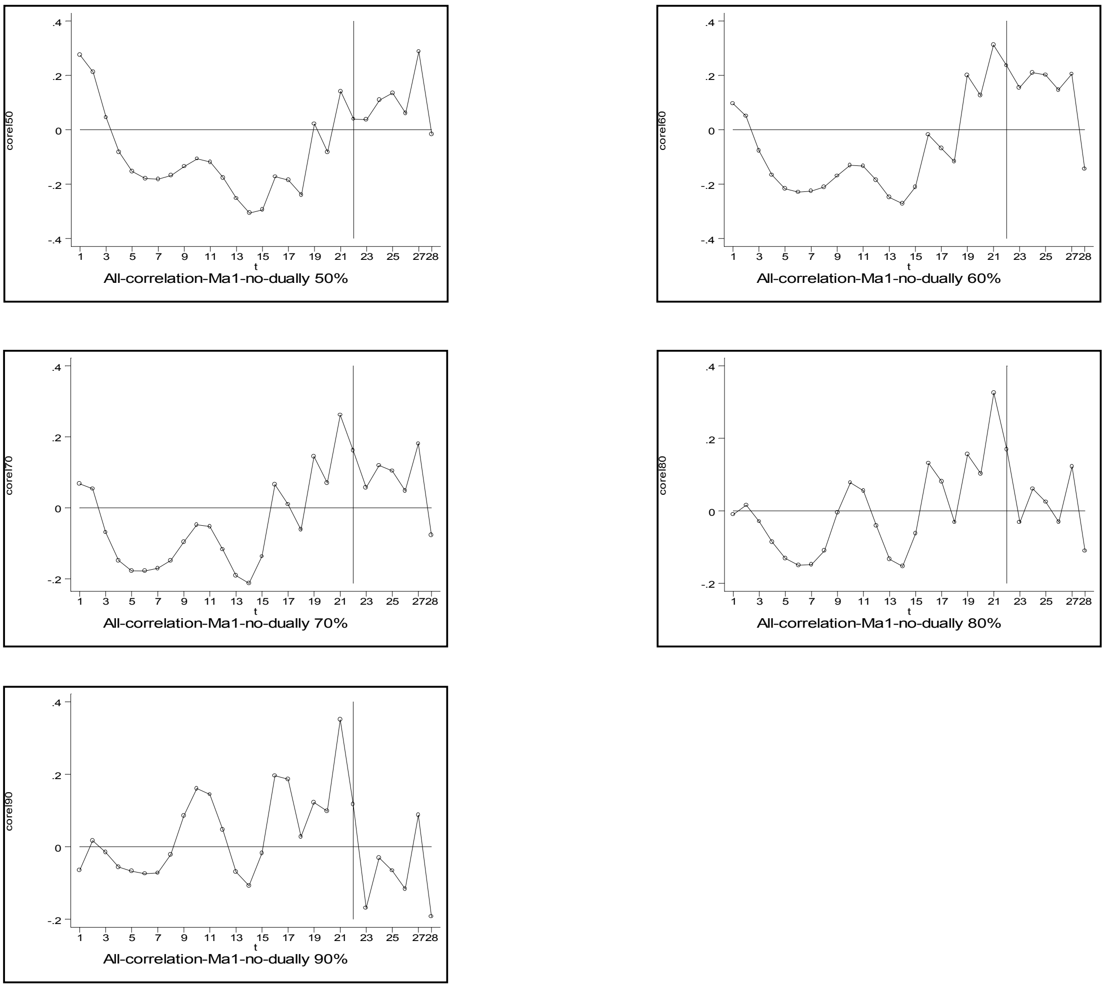


- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility. But whenever a coefficient is not significant at the 5% level it is replaced by zero. Inference is based on the White (1980) standard errors, robust to heteroskedasticity.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

In figure 10 we see that, in the analysis without the dually listed stocks, we get less significant coefficients. As we mentioned before, this could be because the lower variability of the percentage of American activity. Even so, all significant coefficients have the expected sign. The relation between the American activity and the intraday volatility factors seems to be positive during the day in the Americas and negative during the night there. Also, as was expected in section 2, in the less liquid samples there is a positive relation between intraday volatility and the American activity at the opening.

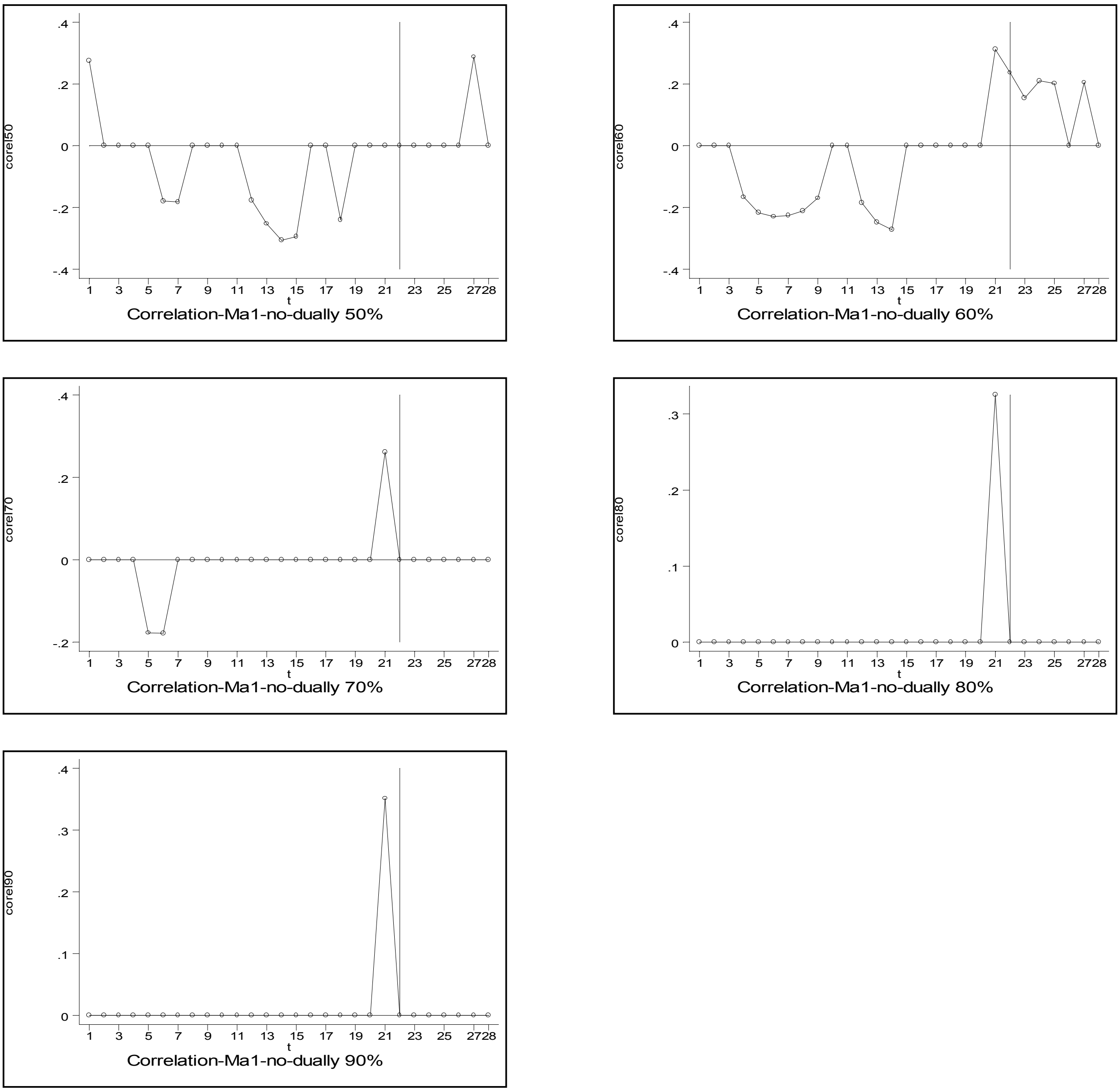
In figures 11 and 12 we present the results with the samples including stocks with an inaccurate estimation of the American activity.

Figure 11 Correlation coefficients between each intraday seasonal factor in volatility and the percentage of American activity. This is for the 5 samples including firms with an inaccurate estimation of this percentage without the dually listed stocks.



- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

Figure 12. Correlation coefficients between each intraday seasonal factor in volatility and the percentage of American activity. Non-significant coefficients are replaced by zero. This is for the 5 samples including firms with an inaccurate estimation of this percentage without the dually listed stocks.



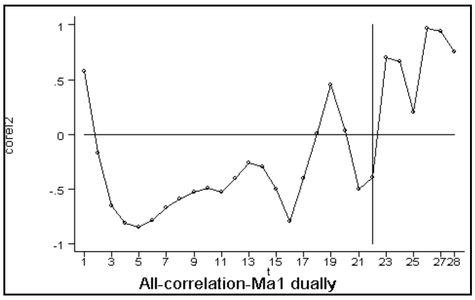
- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility. But whenever a coefficient is not significant at the 5% level it is replaced by zero. Inference is based on the White (1980) standard errors, robust to heteroskedasticity.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

Comparing figures 9 and 10 with figures 11 and 12 we get the same conclusions. The main difference is the fewer significant coefficients in figure 12 than in figure 10. If the bias in the estimated percentage of American activity were randomly upward or downward, it could be argued that the bias is the reason of the fewer significant coefficients.

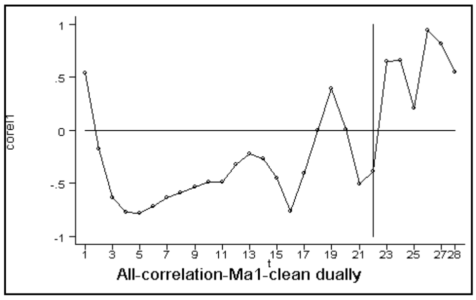
In figure 13 we present the results with just the Spanish stocks dually listed in US.

Figure 13. The case of dually listed stocks. There is a dually listed stock with an inaccurate estimation of the percentage of American activity. Graphs a and c are with this stock and graphs b and d are without this stock.

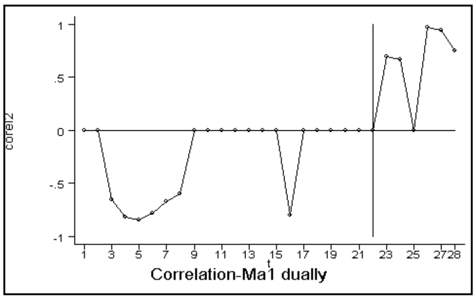
a



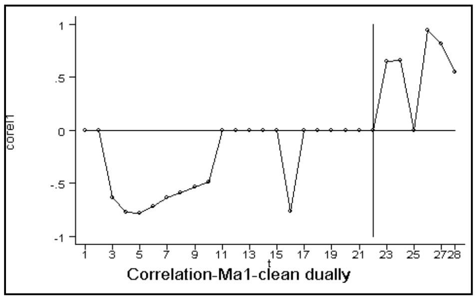
b



c



d



- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility. In figures c and d, whenever a coefficient is not significant at the 5% level it is replaced by zero. Inference is based on the White (1980) standard errors, robust to heteroskedasticity.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

In figure 13 we see the same relation between the American activity and the intraday volatility as in the other samples. Dually listed stocks with American activity have a lower proportion of their daily volatility during the night in the Americas and a higher proportion of their daily volatility during the day in the Americas. In this case the threshold between the positive and the negative relation is at the NYSE opening. The information included into prices during the overlapping period is related to the firm's American activity. We do not know whether this information is first introduced in the US and then transmitted to the SSE via arbitrage or not. But if this were the case, as argued by Werner and Kleidon (1996) for British stocks, it would mean that US traders were introducing information about daily business activity into stock prices. If this information is mostly available during the business hours in America, US traders could not trade earlier in Spain. So we get new results that are able to cast some doubt on the Werner and Kleidon (1996) explanation of this effect by market segmentation. In any event, a further and deeper study should be done to study whether taking into account firm's multinational activity we get different conclusions about international market segmentation.

The evidence we found in this section is supportive of our idea that firms with American activity have a higher proportion of their daily volatility during the day in the Americas. In the previous section we got this result with dually and non-dually listed stocks in the US. And in this section we get that this relation is maintained without the dually listed stocks and just with the dually listed stocks. Under this evidence it could not be argued that we have confused the effect of the dually listing with the effect of the American activity. However, in figure 13, with just dually listed stocks, we get bigger correlation coefficients. We think this could be because the sample with dually listed stocks have a high variability in the variable that measures the activity in the Americas, in the full sample with stocks not listed on the NYSE there are many firms with no activity in the Americas. However, further research should be done to understand why in dually listed stocks we get bigger values, even if these values are of the expected sign.

5. CONCLUSION

We have studied the effect that multinational firms' activity in a foreign country could have on stock prices. One explanation of this potential effect is that news about daily business activity matters for stock pricing. In section 2 we presented an argument that could explain why this news could matter for stock pricing in the short run. That is to continuously evaluate the strategies, plans and reactions of the firm's managers. To gather empirical evidence of the existence of this effect, and of the validity of the argument explaining it, we used the Spanish Stock Exchange. It is especially well suited because the international activity of their multinational firms is mainly concentrated in South America. In the case of Spanish Stock Exchange (SSE), and under the hypothesis that daily business activity news affects stock prices in the short run, we expect firms with higher real American activity to have a higher proportion of their daily volatility concentrated at the opening of the SEE and during the day in the Americas. These are indeed the results we found.

On the other hand, Werner and Kleidon (1996) found that UK stocks dually listed on the NYSE have more volatility during the overlapping trading period of the UK and the US stock markets. Their empirical evidence is consistent with the idea that information about the British firms' daily business activity in the US time zone is incorporated in these stocks in the US. But it is also consistent with the idea that the information being incorporated into prices in the US is not related with the firms' activity in the US time zone geographical area. Thus, it could be that our results are spurious. It could be that our results are explained with the theory that during the overlapping period between the US and the Spanish stock markets, Spanish stocks dually listed on the NYSE incorporate information from the US not related to the firms' business American activity. In order to disentangle which is the right explanation, we repeated the analysis without those stocks listed on the NYSE, and the results are the same. On the other hand we find that dually listed stocks have a higher proportion of their daily volatility during the overlapping period than other stocks. But we find also empirical evidence indicating that, in the dually listed stocks, the higher proportion of daily volatility during the day in America is positively related to the firm's American activity. Hence, we conclude our results are not spurious.

The contribution of this paper is its finding of empirical evidence supporting the hypothesis that the geographical distribution of firms' real activity affects stock prices.

Previous research in finance using intraday data did not take into account the geographical distribution of firms' business. Given our results, further research could be done taking it into account. For example, in the case of the US stock market, it could be that public and private information is incorporated into foreign stock prices for firms with high American activity, even if the foreign market is closed. This could modify the conclusions in Chan et al (1994) about the relevance of private information as an intraday stock behavior determinant. In the US stock market again, it could be that information US traders introduce into British stocks is mainly related to those firms' daily business activity in the Americas. It could be that this information is available for them during business hours there, so that during the early morning trading in London they do not have the information yet. If this is the case, the conclusions about market segmentation in Werner and Kleidon (1996) could be modified.

It is left for future research to study whether the geographical distribution of firms' real activity also affects the dynamics of intraday stock return volatility. Also left for future research a deeper analysis to study whether taking into account the firms' business activity geographical distribution we get different results in empirical research like the one of Chan et al (1994) or Werner and Kleidon (1996)[52]. Finally, it left for future research to study whether Spanish traders gather South American information relevant for those Spanish firms with business activity there, directly from South America or they infer that news from the US stock market movements.

[52] Their topics of research are volatility determinants and financial markets integration.

APPENDIX A

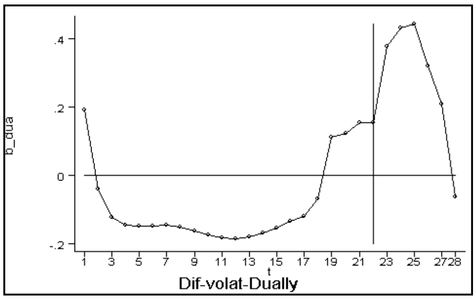
To study whether dually listed stocks have a concentration of their daily volatility during the day in America, we have estimated the following regression for each intraday volatility factor:

$$Fact_i = b_0 + b_1\ dually_i$$

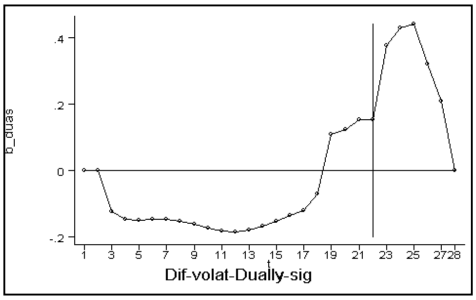
Where dually is a dummy variable that takes value 1 for dually listed stocks and zero otherwise. Hence, b_1 measures the difference between the mean factor in the non-dually listed stocks and in the dually listed stocks. Inference about the significance of b_1 is based on the White (1980) standard errors, robust to heteroscedasticity. In figure A, we present the estimated value of b_1 for each intraday volatility factor. In graph b of figure A, all non-significant coefficient at the 5% level are replaced by zero.

Figure A. Difference between each intraday volatility factor for non-dually listed stocks and for dually listed stocks.

a.



b.



- The estimated regressions are: "$Fact_i = b_0 + b_{1i}$ dually i=1,.....,28". Where $Fact_i$ represent one specific intraday volatility seasonal factor and dually is a dummy variable that takes value one for dually listed stocks and zero otherwise. In the vertical axis figure the b_1 coefficients and in the horizontal axis figure the corresponding intraday period. In graph b, when a coefficient is not significant at the 5% level, using the White (1980) standard errors, it is replaced by zero.

APPENDIX B

Table B.1. Control variable and sample, according to liquidity, of each Spanish stock.

Company Name	Sample**	Mean*
TELEFONICA	90%	0.4
ENDESA	90%	0.6
REPSOL	90%	0.6
BANCO BILBAO VIZCAYA	90%	0.7
BANCO DE SANTANDER	90%	0.7
ARGENTARIA	90%	1.0
IBERDROLA	90%	1.1
BANCO CENTRAL HISPANO	90%	1.1
BANCO POPULAR	90%	1.6
TUBACEX	90%	1.9
TABACALERA	90%	2.0
UNION ELECTRICA-FENOSA	90%	2.0
BANCO ESPAÑOL DE CREDITO (BANESTO)	90%	2.1
DRAGADOS Y CONSTRUCCIONES	90%	2.3
GAS NATURAL SDG	90%	2.4
ACERINOX	90%	2.4
AMPER	90%	2.5
BANCO INTERCONTINENTAL ESPAÑOL	90%	2.6
AUTOPISTAS CONCESIONARIA ESPAÑOLA	90%	2.8
PRYCA	90%	2.9
TELE PIZZA	90%	3.0
CORPORACION MAPFRE	90%	3.1
AUTOPISTAS DEL MARE NOSTRUM	90%	3.3
CONSTRUCCIONES LAIN	80%	3.3
VALLEHERMOSO	90%	3.4
FUERZAS ELECTRICAS DE CATALUÑA	90%	3.5
SEVILLANA DE ELECTRICIDAD	90%	3.6
C.C. CONTINENTE	90%	3.7
AGUAS DE BARCELONA	90%	3.8
HIDROELECTRICA DEL CANTABRICO	80%	4.1
LA SEDA DE BARCELONA	70%	4.2
AGROMAN	80%	4.3
ENERGIA E IND. ARAGONESAS	80%	4.3
SOTOGRANDE	70%	4.3
INMOBILIARIA URBIS	70%	4.4

- * Mean of the control variable calculated as difference between the moment when a price happened and the moment when it is supposed to happen in order to construct 15 minutes return time series. This variable is measured in minutes. It is measured including the crisis week and the days with splits.
- ** Indicates the highest liquid sample at witch pertains the stock when we make samples that keep stocks with a minimum percentage of 15-minute periods with trading, as in tables 2, 3 and 4.

Table B.1 Continuation

Company Name	Sample**	Mean*
TAVEX ALGODONERA	70%	4.5
PRIMA INMOBILIARIA	60%	4.7
FILO	70%	4.7
BANCO DE VALENCIA	70%	4.8
ZARDOYA OTIS	70%	4.8
EL AGUILA	60%	4.9
METROVACESA	70%	4.9
PROSEGUR	60%	5.1
INMOBILIARIA ZABALBURU	50%	5.1
MARCO IBERICA, D.E. -MIDESA-	60%	5.1
CIA. ESPAÑOLA DE PETROLEOS	70%	5.2
CORTEFIEL	60%	5.2
VIDRALA	60%	5.3
ABENGOA, S.A.	50%	5.3
EUROPISTAS CONCESIONARIA ESPAÑOLA	60%	5.3
BANCO PASTOR	60%	5.4
GAS Y ELECTRICIDAD	50%	5.5
MAPFRE VIDA	50%	5.6
BANCO ZARAGOZANO	60%	5.6
ELECTRICAS REUNIDAS DE ZARAGOZA	50%	5.8
PORTLAND VALDERRIVAS	50%	5.9

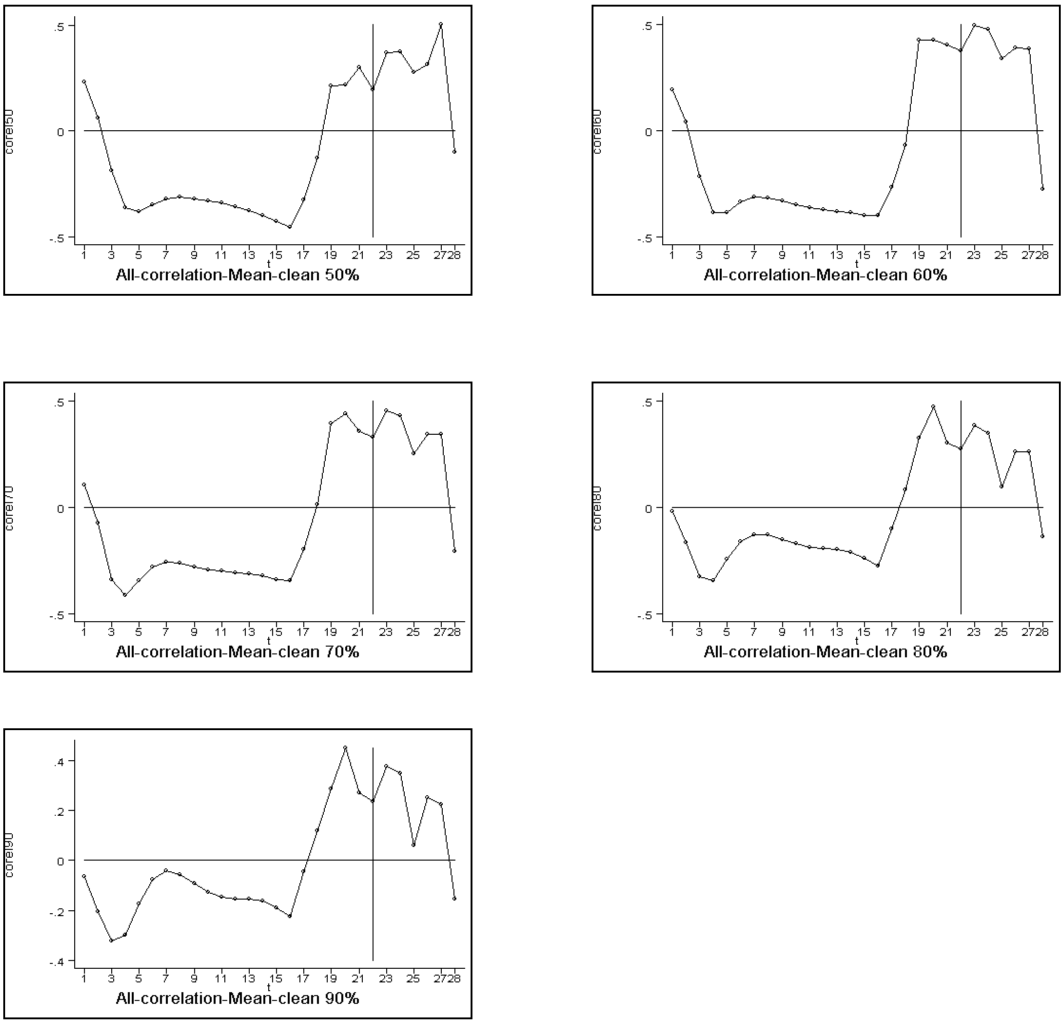
- * Mean of the control variable calculated as difference between the moment when a price happened and the moment when it is supposed to happen in order to construct 15 minutes return time series. This variable is measured in minutes. It is measured including the crisis week and the days with splits.
- ** Indicates the highest liquid sample at witch pertains the stock when we make samples that keep stocks with a minimum percentage of 15-minute periods with trading, as in tables 2, 3 and 4.

APPENDIX C

In this appendix we present the results when there is not a previous filtering of the transaction prices for the spurious autocorrelation induced by the bid-ask bouncing. That is when we take the unconditional mean as the expected return in Eq. 10. In figures C.1 to C.4 there is the analysis with the dually listed stocks. The results are close to the ones found with the expected return calculated with Eq. 11. The main difference is that in this case we find some significant negative correlation coefficients in the last period of trading[53]. In figures C.5 to C.8 there is the analysis without the dually listed stocks. In this case results are more different but in general the significant correlation coefficients lead to the same conclusion. That is, the firms with business American activity tend to have a lower proportion of their daily volatility during the night in the Americas, and a higher proportion during the day there. And the main differences are in the most liquid samples where we get a negative correlation in the first period of trading, and in the most liquid sample we find a positive correlation during the first periods of trading. These results contradict the theory presented in section 2. Finally, in figure C.9 there is the analysis with just dually listed stocks. The significant coefficients lead us to the same conclusion as when we use Eq. 11 to calculate the expected return. Hence, in the end, with some significant correlation coefficients that are inconsistent with the predictions in section 2, the results suggest us that the firms' American activity affect intraday volatility patterns in the way predicted in section 2. However, in this case the results are not as conclusive.

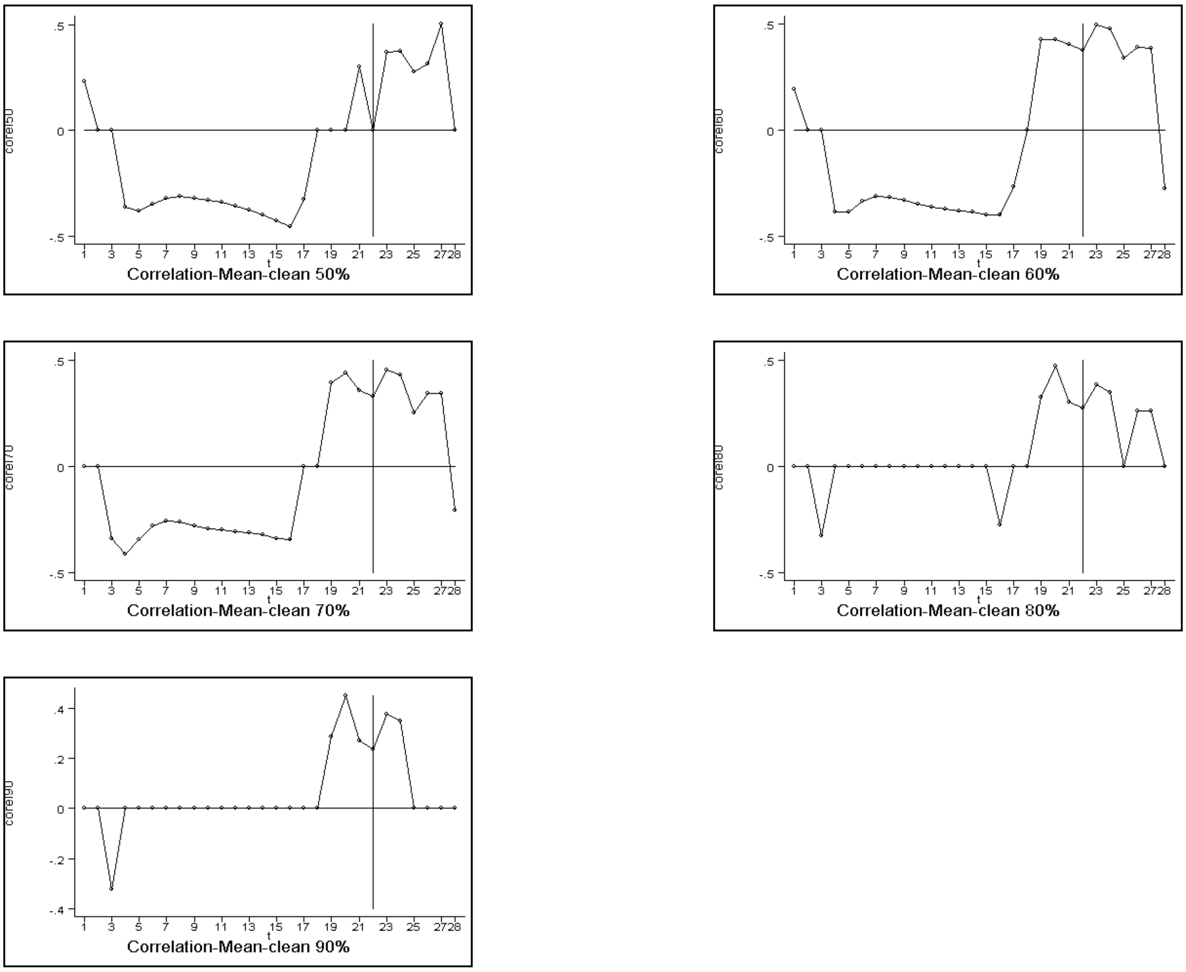
[53] If the main reason for the higher volatility at the closing is that traders are not allowed to have high open positions overnight, as suggested by Hsieh and Kleidon (1996), we would expect the less liquid stocks to be more affected by this restriction. Since the firms with American activity are among the most liquid firms, it could be argued that it causes the negative correlation between closing volatility and the percentage of American activity. If this were the case, this correlation would be spurious.

Figure C.1. Correlation coefficients between each intraday seasonal factor in volatility and the percentage of American activity. This is for the 5 samples including firms with an accurate estimation of this percentage.



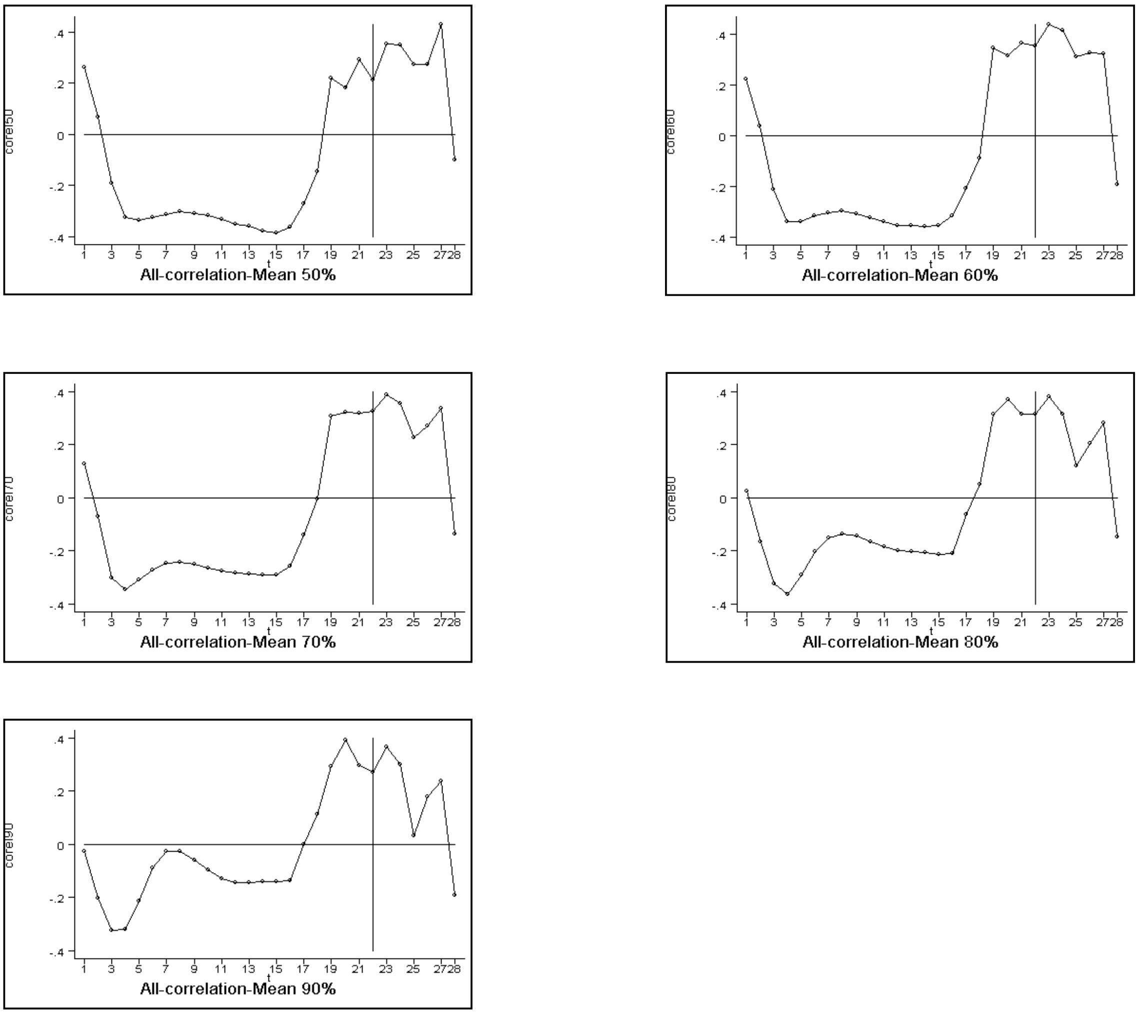
- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

Figure C.2. Correlation coefficients between each intraday seasonal factor in volatility and the percentage of American activity. Non-significant coefficients are replaced by zero. This is for the 5 samples with an accurate estimation of this percentage.



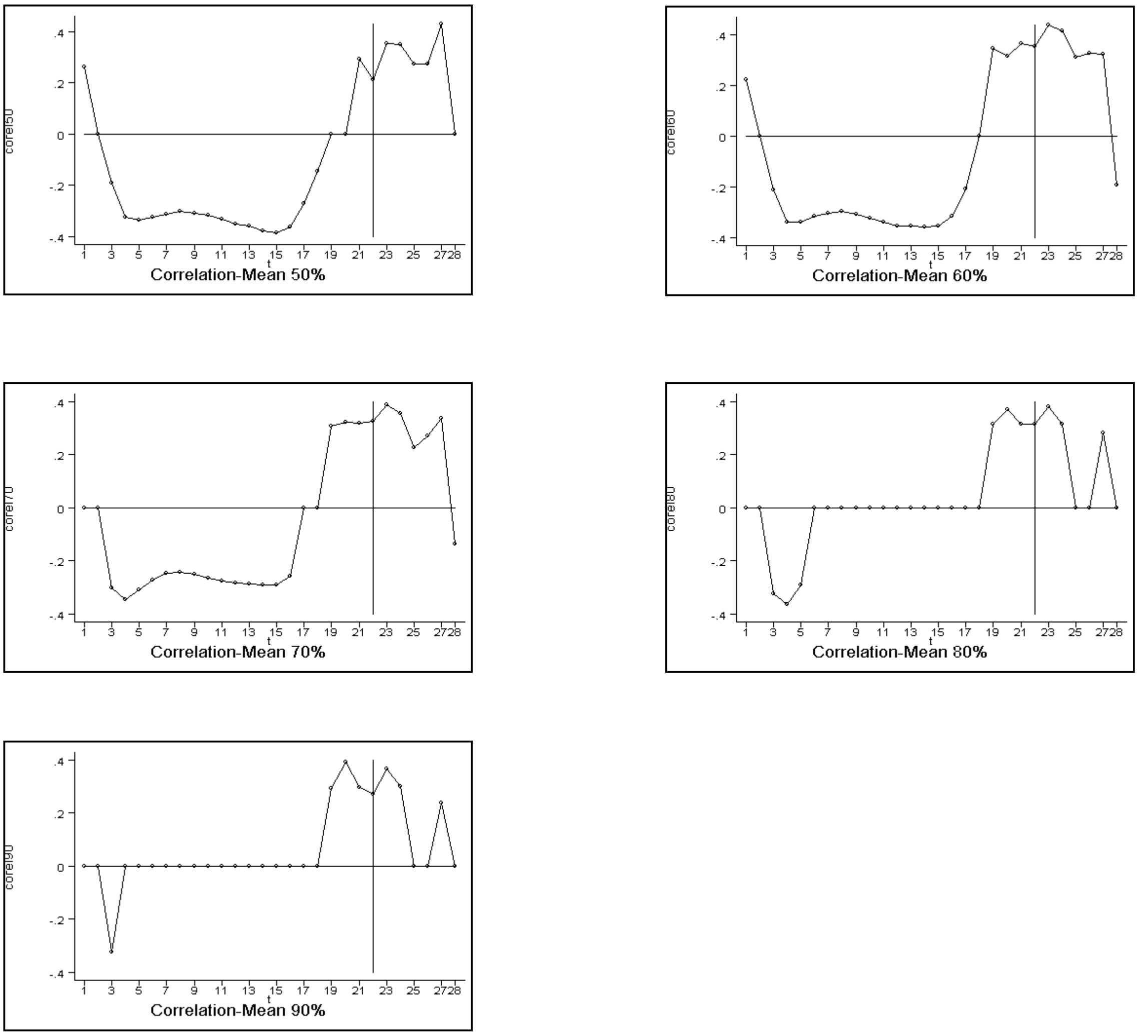
- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility. But whenever a coefficient is not significant at the 5% level it is replaced by zero. Inference is based on the White (1980) standard errors, robust to heteroskedasticity.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

Figure C.3. Correlation coefficients between each intraday seasonal factor in volatility and the percentage of American activity. This is for the 5 samples including firms with an inaccurate estimation of this percentage.



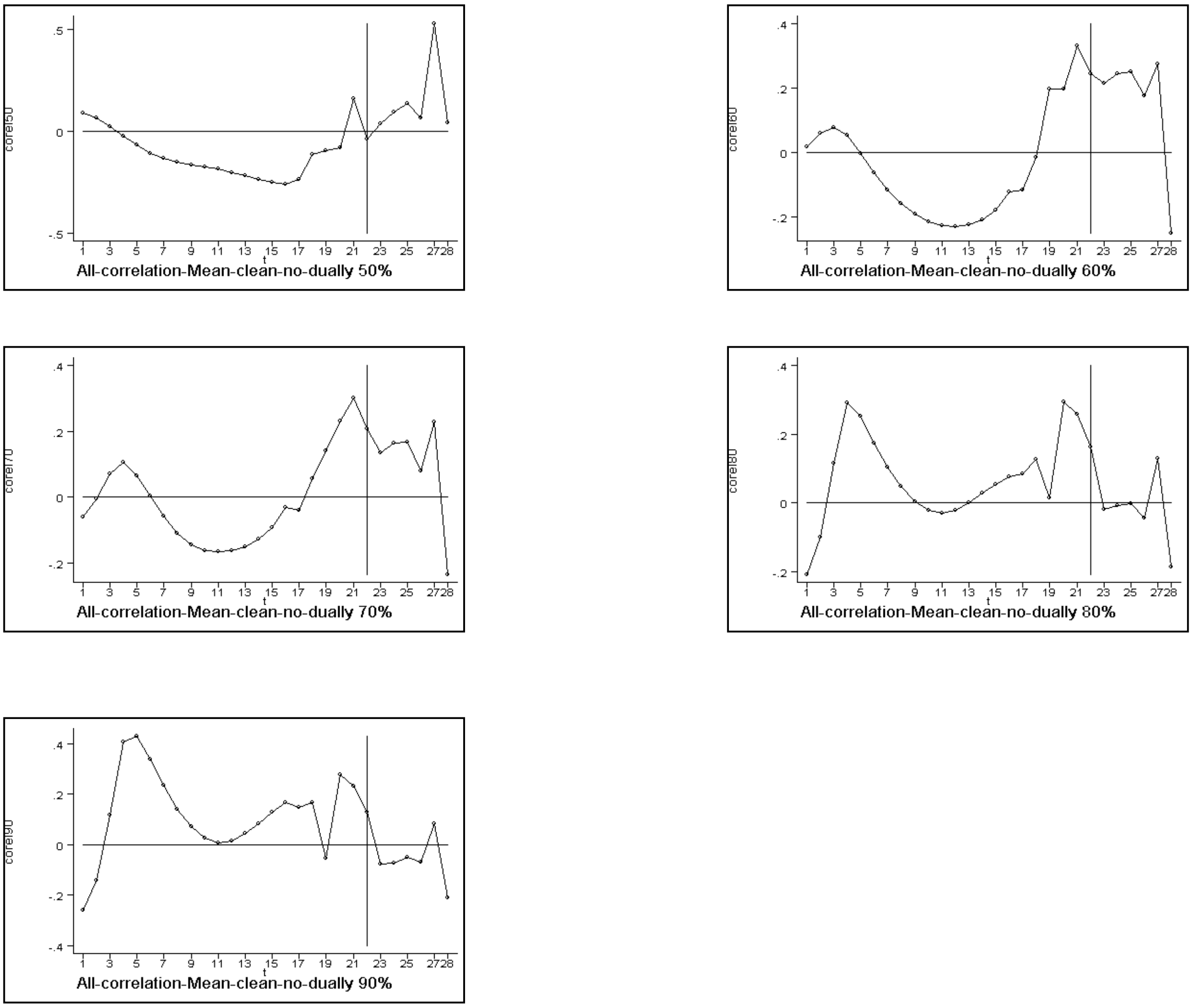
- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

Figure C.4. Correlation coefficients between each intraday seasonal factor in volatility and the percentage of American activity. Non-significant coefficients are replaced by zero. This is for the 5 samples including firms with an inaccurate estimation of this percentage.



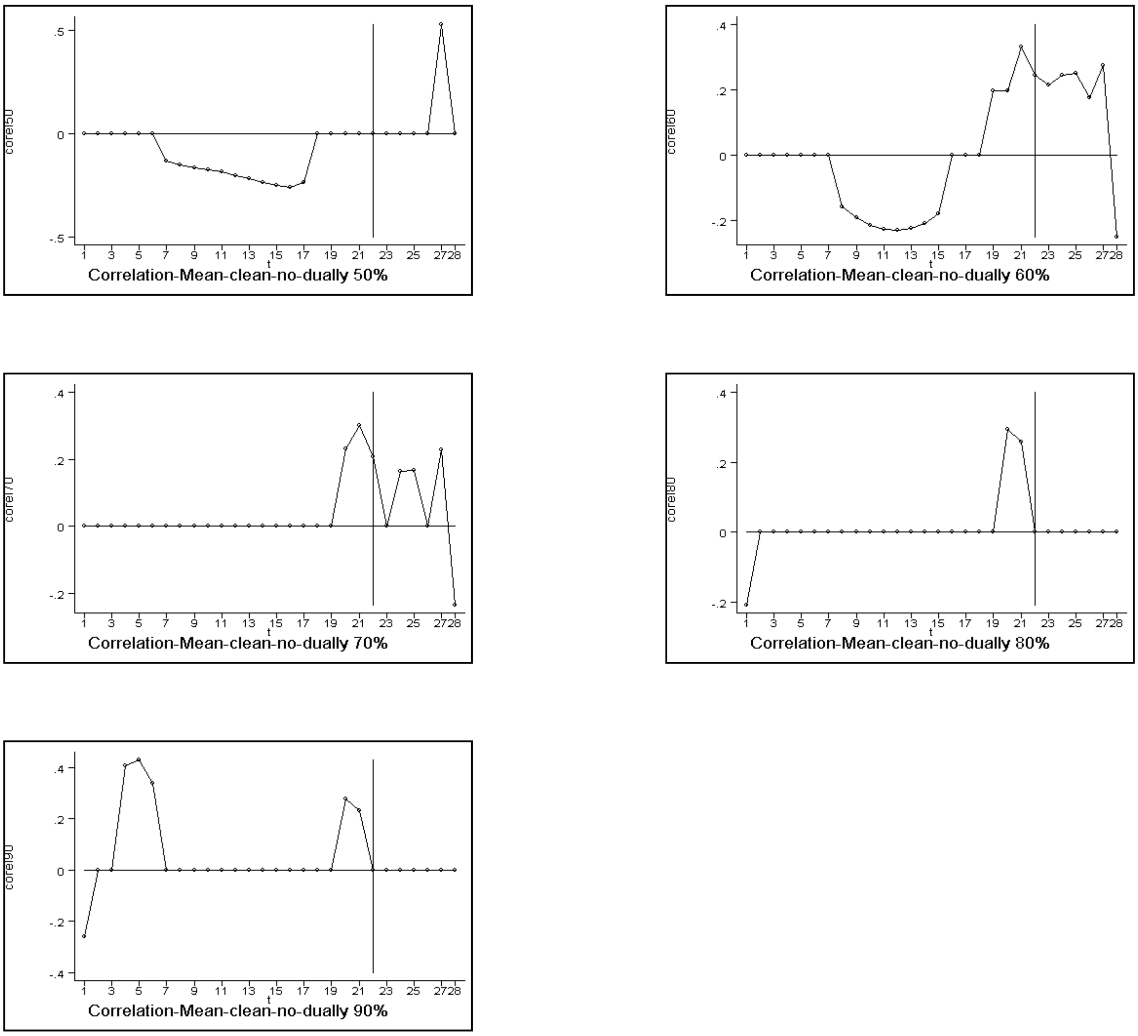
- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility. But whenever a coefficient is not significant at the 5% level it is replaced by zero. Inference is based on the White (1980) standard errors, robust to heteroskedasticity.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

Figure C.5. Correlation coefficients between each intraday seasonal factor in volatility and the percentage of American activity. This is for the 5 samples with an accurate estimation of this percentage without dually listed stocks.



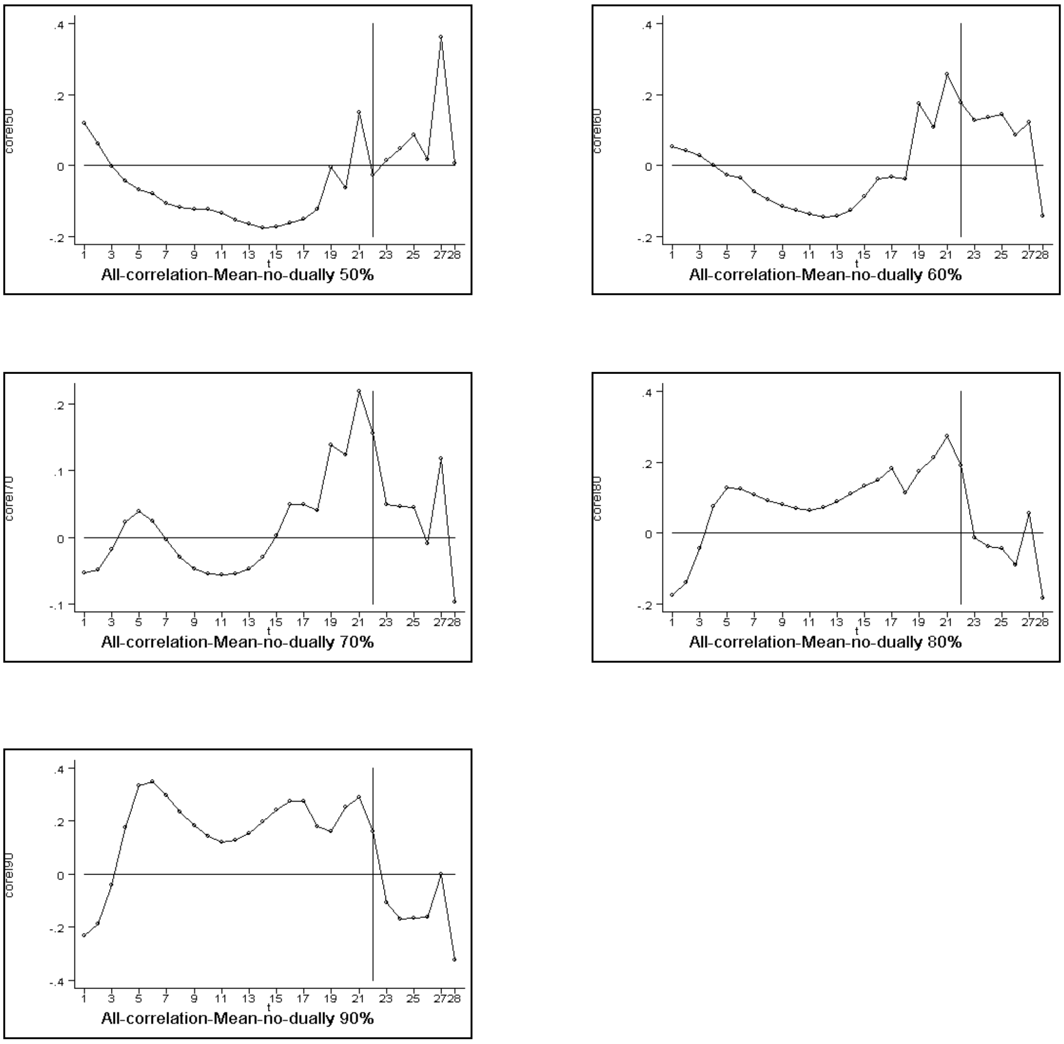
- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

Figure C.6. Correlation coefficients between each intraday seasonal factor in volatility and the percentage of American activity. Non-significant coefficients are replaced by zero. This is for the 5 samples with an accurate estimation of this percentage without dually listed stocks.



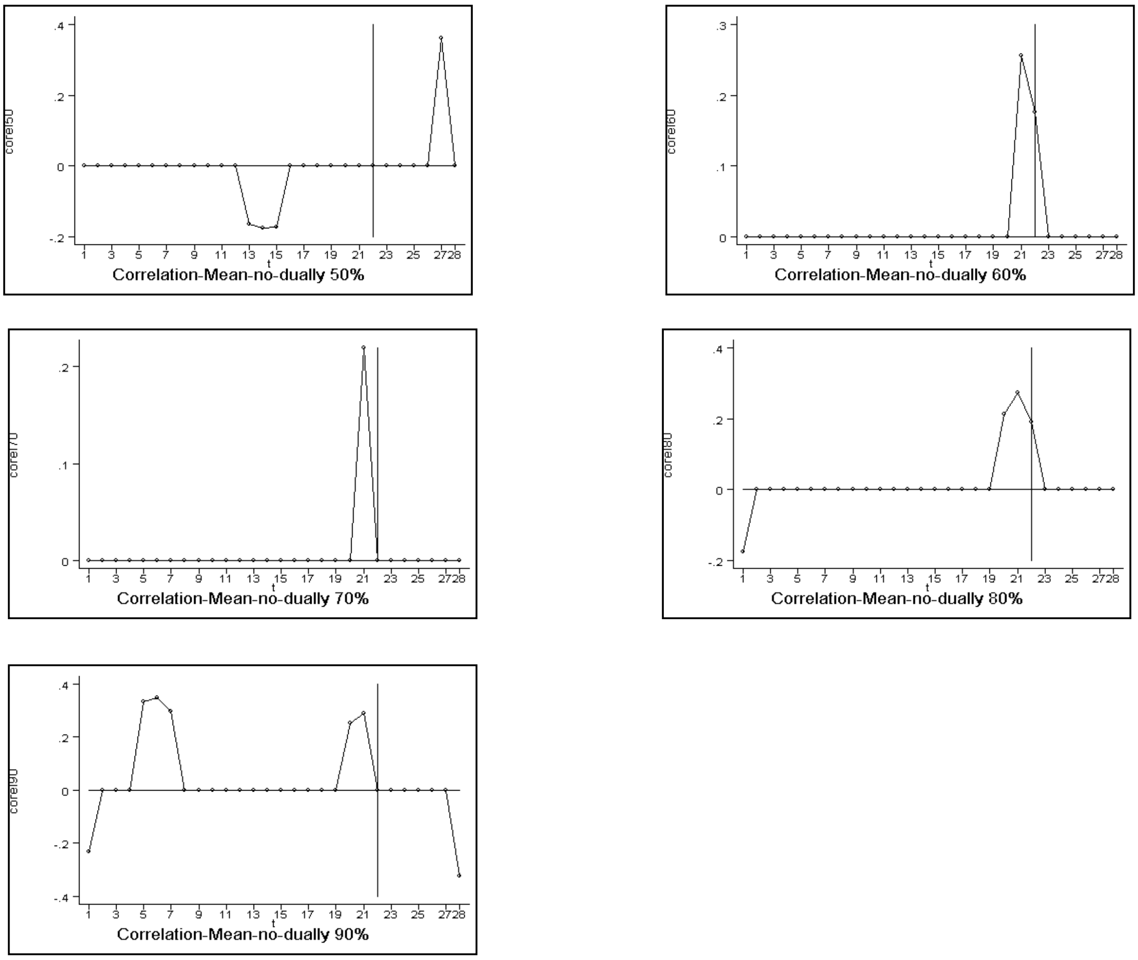
- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility. But whenever a coefficient is not significant at the 5% level it is replaced by zero. Inference is based on the White (1980) standard errors, robust to heteroskedasticity.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

Figure C.7 Correlation coefficients between each intraday seasonal factor in volatility and the percentage of American activity. This is for the 5 samples including firms with an inaccurate estimation of this percentage without the dually listed stocks.



- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

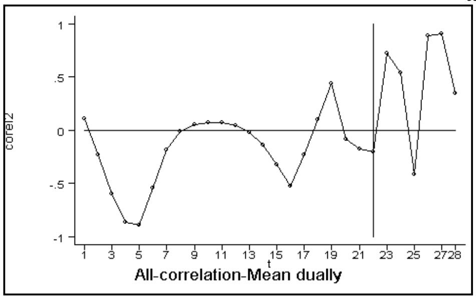
Figure C.8. Correlation coefficients between each intraday seasonal factor in volatility and the percentage of American activity. Non-significant coefficients are replaced by zero. This is for the 5 samples including firms with an inaccurate estimation of this percentage without the dually listed stocks.



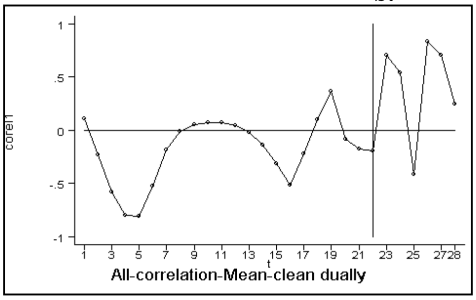
- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility. But whenever a coefficient is not significant at the 5% level it is replaced by zero. Inference is based on the White (1980) standard errors, robust to heteroskedasticity.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

Figure C.9. The case of dually listed stocks. There is a dually listed stock with an inaccurate estimation of the percentage of American activity. Graphs a and c are with this stock and graphs b and d are without this stock.

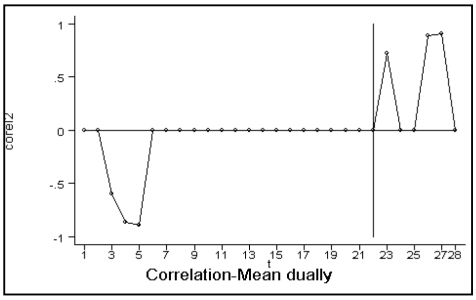
a.



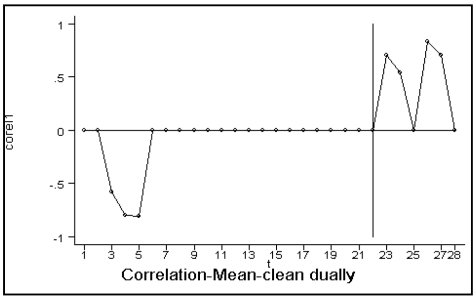
b.



c.



d.



- In the vertical axis there is the correlation coefficient between the percentage of American activity and each intraday factor in volatility. In figures c and d, whenever a coefficient is not significant at the 5% level it is replaced by zero. Inference is based on the White (1980) standard errors, robust to heteroskedasticity.
- In the horizontal axis there is each intraday period. The period number 22 is at 3:30 p.m., Madrid time, that is the NYSE opening.

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Chapter 4:

Does the expansion of Spanish firms into South America affect the price relations between the US and the Spanish Stock Markets?

Does the expansion of Spanish firms into South America affect the price relations between the US and the Spanish Stock Markets?[54]

Abstract

This paper analyses whether Spanish multinational firms' concentration of activity abroad in South America has an effect on stock price relations between the US and the Spanish stock markets. In order to detect the effect of information that could affect both stock markets simultaneously, we study the stock price relations of both stock markets in their overlapping trading period. We use the Kofman and Martens (1997) methodology to construct a measure of the stock price relations between each Spanish stock and the US stock market. We find stock prices of Spanish firms with American activity to have a higher positive relation with US stock market prices than other Spanish stocks have. We repeat the analysis without the Spanish stocks quoted on the NYSE, and with only those stocks, to take into account the possibility that these stocks move like the US stock market just because they are listed there, and we get the same results. Our hypothesis is that this is due to regional factors that affect stock prices of firms with business in the Americas.

[54] This paper was partially done during a stay in the Business Economics department of the *Universidad Carlos III de Madrid*. The author thanks this department for all its support for doing this paper. The author is also grateful to Mikel Tapia of the *Universidad Carlos III de Madrid,* and to Amado Peiró of the *Universidad de Valencia* for helpful comments. The content of this paper is the sole responsibility of the author.

1. INTRODUCTION

The growing international integration of financial markets has prompted several recent empirical studies that examine the mechanism through which stock market movements are transmitted around the world. These studies evaluate how stock returns in one national market influence those of another and their implications for securities pricing within those markets, for hedging and other trading strategies, and for regulatory policies within financial markets. Hedging and other trading strategies, using assets quoted on different markets, have received increasing attention since Grubel (1968), Levy and Sarnat (1970), and Solnik (1974) pointed out the benefits of international diversification. To implement these strategies, the covariance matrix between stock returns in those markets is needed, that is, to know how stock returns in one market influence those of other markets. The October 1987 international crash saw large, correlated price movements across most stock markets. As a result, various regulations and institutional rules were introduced to dampen the cross-market impact of large stock price movements. See Roll (1989) for a survey of these regulatory policies.

It is therefore relevant to detect transmission of movements across stock markets, and it is well documented in the literature; see for example Hamao, Masulis and Ng (1990), Francis and Leachman (1996), Booth, Martikainen and Tse (1997), or Peiro, Quesada and Uriel (1998).

It is also interesting to know the reasons behind this transmission of movements. For example, on the Toronto Stock Exchange (TSE) there were trading halts[55] when there was a large negative movement in the Dow Jones Industrials Average, not in a TSE index. The rationale behind that regulatory policy was the high correlation between the New York Stock Exchange (NYSE) and the TSE stock returns. It was thought that financial storms happened first on the NYSE. However, Karolyi (1995) used more efficient econometric techniques to calculate this correlation and demonstrated that it was weaker than previously thought and diminished over time, so that the rationale should be seriously re-examined. Knowing more about the fundamentals driving the transmission of movements between stock markets could be used in this case to detect changes in those fundamentals and to implement a more appropriate regulatory policy.

In the literature we can find some explanations for the transmission of stock price movements between markets. One explanation is based on the Ross (1976) asset valuation model, known as APT, in which it is assumed that certain common factors explain asset returns in different markets. These factors are the origin of the transmission of movements between markets. See for example, King, Sentana and Wadhwani (1994), who assume that there are observable and unobservable factors, and conclude that only a small proportion of transmission of movements is explained by observable factors. Another explanation, advanced by Engle, Ito, and Lin (1990), is that there could be some chartist analysis techniques causing transmission of movements from one market to another, but this would contravene the market efficiency hypothesis and they do not study the relevance of this explanation. Finally it has been argued that stochastic policy co-ordination or policy competition between countries could be behind some of the transmission found; see for

[55] Known as circuit breakers.

example Francis and Leachman (1996) for the stock exchange market. Ito, Engle, and Lin (1992) study the relevance of this explanation for the foreign exchange market and conclude that it is not a major cause.

The common factor explanation lacks the identification of these common factors. Even so, it seems to be the most-used approach to the transmission of movements between markets. For example, based on it, King and Wadhwani (1990) presented a contagion model for the transmission of movements between stock markets. They propose a model with two stock markets in which stock prices are affected by one idiosyncratic factor that affects only one market and a common factor that affects both. In this model, traders just observe price movements in the other market and try to infer the common factor component in stock price movements there. In this process they may overestimate this common factor and overreact to the foreign stock price movements; this is the origin of the contagion effect.

Also following the common factor explanation, Roll (1992) explains differences in stock prices behavior between different stock markets by the industrial composition of each stock market. The basic idea behind this is the existence of common factors related to the industrial sectors. Arshanapalli, Doukas and Lang (1997) use the common ARCH-feature testing methodology developed by Engle and Kozicki (1993) to test whether industry-return series located in different economic regions of the world exhibit intra-industry common time-varying volatility processes. Their results are consistent with Roll (1992).

In a related line of research, other papers mention geographical proximity, institutional currency relationships, partnership in trade, cultural similarity, or similarity of the economic bases of the countries as possible explanations for the price relations between stock markets; see for example Jeon and Furstenberg (1990). However, we have found no paper studying the relevance of these explanations.

Roll (1992) and Arshanapalli, Doukas and Lang (1997) deal with the problem of identification of the common factors that could explain transmission of movements between stock markets, but there remains research to do in order to identify these factors. In this paper we wish to make a contribution on the identification of those common factors. As we mentioned before, the real economic relations between countries or economic regions seem to be behind those common factors; see Jeon and Fustenberg (1990). In this paper we wish to study whether multinational firms' activity abroad, in another country or economic region, has any effect on price relations between stock markets. For this study the Spanish and the US stock markets are a good sample because Spanish multinational firms have their foreign activity concentrated in South America. Thus we will study whether it can have an effect on the relation between the Spanish Stock Exchange (SSE) and the US stock market. We think it can because the US stock market is the main stock market in the American time zone, and the US economy has a large influence on the South American economies. The US has been the main foreign investor in South America since the Second World War, and this investment has doubled during the nineties[56]. Furthermore, South American exports are mainly to the US. For example, in 1997, 49.4% of South American merchandise exports were to the US (24.8% excluding Mexico). It could thus be argued that there is news affecting the US economy and reflected in the US stock market that has an effect on South American economies. This news will have larger effect on Spanish firms having business in

[56] See "The Foreign Investment in Latin America and the Caribbean". 1998 report of the Economic Commission for Latin America and the Caribbean (ECLAC). United Nations.

the Americas than on other Spanish firms[57]. Likewise, given the US investment in South American economies, we expect some South American news to be reflected in the US stock market. There are large US companies investing in South America; most of them are included in US stock market indexes like the S&P 500, for example General Motors, Ford, Coca-Cola, PepsiCo, Philip Morris, IBM, Exxon, Kimberly Clark, or Wal-Mart Stores[58]. We also expect that South American news should have a larger effect on Spanish firms with American activity. Thus finding Spanish firms with real activity in the Americas to have more comovement with the US stock market will mean that the geographical distribution of the firm's business is a relevant variable for explaining stock markets' comovements, and that some of the common factors driving the comovements between stock markets are related to economic regions. Firms with business in an economic region are affected by that region's factors.

To do this study we calculate a measure of the Spanish firms' American activity, calculate a measure of the relation of each specific Spanish stock and the US stock market, and finally study whether this measure of American activity is able to explain the differences among stocks in their relation with the US stock market.

For a measure of Spanish firms' American activity we mainly use the proportion of their sales in the Americas; as an indicator of US stock market prices we use prices of the Future contract on the Standard and Poors 500 (S&P 500) stock market index.

The Spanish Stock Exchange shares one hour and a half of overlapping trading with the New York Stock Exchange. To construct a measure of the relation between each Spanish stock and the Future on the S&P 500 we use Kofman and Martens' methodology (1997). They study the transmission of movements between the London and New York Stock Exchanges during their 2 hours' overlapping trading period. Their methodology consists of using the correlation coefficient between returns and a measure of volatility in those stock markets in the overlapping period. We think this methodology is especially appropriate for our purposes because it allows us to obtain a measure of the relation between the S&P 500 and each Spanish stock that is comparable among the Spanish stocks. Furthermore, given that we relate simultaneous returns, it allows us to detect Spanish stocks that incorporate more information that is also incorporated in the US stock market[59]. For example, Lin et al. (1994) compare overlapping returns[60] on the Tokyo Stock Exchange and on the NYSE to detect whether information that is released in one stock market is also incorporated into the other market's stock prices.

Our results show a positive relation between firms' American activity and the relation with the US stock market. However, some Spanish firms with more American activity are dually listed on the SSE and on the NYSE, and papers like Werner and Kleidon (1996) or Chan et al. (1994) suggest that new information is introduced into foreign stocks during US trading, which could cause those stocks to be more correlated with the US stock market. Hence if the dual listing were the main reason for the stock price relation with the US stock market our results could be spurious. In order to determine whether this is the case we have

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[57] Papers like Peiro, Quesada and Uriel (1998) show that the US stock market has the greatest ability to influence the other stock markets around the world, one of them the Spanish Stock Exchange. Hence we expect the US stock market to have an effect on all the Spanish stocks.

[58] See "Latin American and the Caribbean in the world economy". 1998 report of the Economic Commission for Latin America and the Caribbean (ECLAC). United Nations.

[59] Due to the modern information technology we think that information could be reflected almost simultaneously in both stock markets.

[60] The daily return in one market and the overnight return in the other.

repeated the analysis without dually listed stocks and with only the dually listed stocks, and we found the same positive relation between firms' American activity and the stock price relation with the US stock market.

This paper proceeds as follows. In section 2 we present argumentation that could explain the effect of multinational firms' activity abroad on the price relations between stock markets. In section 3 we present the data, in section 4 the methodology, in section 5 the results, and in section 6 the conclusions.

2. A Simple Framework for Understanding the Potential Effect of the Multinational Firms' Activity Abroad on the Price Relations Between Stock Markets

In this section we wish to study how the multinational activity of some firms could affect price relations between stock markets. Among all the explanations found in the literature for the transmission of price movements between stock markets, we think that the common factor explanation is the most appropriate for our purposes. For example, Roll (1992) relates financial markets' similarities and differences to national industrial composition, and the idea behind this is the existence of common factors related to the industrial sectors. The common factor explanation thus seems an appropriate way to look for the effect of national economies' characteristics on price relations in those countries' financial markets. In our case we wish to study the effect of commercial relations between countries on stock market price relations. We have a large stock market and a small stock market and we wish to determine whether or not a firm's particular characteristics in the small market could affect the relation in prices between those markets.

The common factor explanation assumes the existence of common factors that affect both markets and idiosyncratic factors that affect just one market. This explanation is based on the Ross (1976) APT model for stock pricing. Hence we can similarly assume two stock markets with prices behaving in the following way[61]:

$$P_1= U+V_1$$
$$P_2= U+V_2$$

Where U is the common factor and V_1 and V_2 are the idiosyncratic factors of each market. These factors may be composed of other factors. We are studying the relation of one stock market index with every stock quoted on the other stock market. At a stock level we could get different returns for different stocks if those stocks are affected by different factors, or if the factors' weights are different between stocks, or both, so that in our case each Spanish stock equation could be:

$$P_i= \alpha_{1i}\, U_1+\alpha_{2i}\, U_2 \ldots\ldots\ldots +\alpha_{ni}\, U_n+ b_i\, V_i \quad i=1,\ldots\ldots,m$$

Where U factors are factors in common with the US stock market and V factors are idiosyncratic factors. The covariance between the US stock market index[62] and each

[61] Karolyi and Stulz (1996) used a close approach.
[62] The Future contract on the S&P 500.

Spanish stock will depend on the number of factors in common with the US stock market and the loading of those factors.

Assuming the following equation for the Future contract on the S&P 500:

$$SP = a_1 U_1 + a_2 U_2 + \dots\dots\dots + a_n U_n + V_{sp}$$

Assuming:

$$U_{j,t} - U_{j,t-1} = e_{j,t} \qquad j=1, 2, \dots\dots\dots n$$
$$V_{k,t} - V_{k,t-1} = \varepsilon_{k,t} \qquad k=sp, i$$

$e_{j,t} \approx D(0, var(e_j))$ and is i.i.d
$\varepsilon_{k,t} \approx D(0, var(\varepsilon_k))$ and is i.i.d
$Cov(e_{j,t,} \varepsilon_{k,t}) = 0$
$Cov(e_{m,t}, e_{f,t}) = 0$ For $m \neq f$,

Where D is any probability distribution. Define $r_{i,t}$ as the stock return for each Spanish firm and $r_{sp,t}$ as the return for the Future contract on the S&P 500:

$$r_{i,t} = P_{it} - P_{it-1} = \alpha_{1i} e_{1,t} + \alpha_{2i} e_{2,t} \dots\dots\dots + \alpha_{ni} e_{n,t} + b_i \varepsilon_{i,t} \qquad i=1,\dots\dots,m$$

$$r_{sp,t} = SP_t - SP_{t-1} = a_1 e_{1,t} + a_2 e_{2,t} + \dots\dots\dots a_n e_{n,t} + \varepsilon_{sp,t}$$

Then the covariance between each Spanish stock return and the Future contract on the S&P 500 index return is:

$$Cov(r_i, r_{sp}) = E[(r_{i,t} - E(r_i))(r_{sp,t} - E(r_{sp}))] = E[(r_{i,t})(r_{sp,t})] =$$

$$= E[(\alpha_{1i} e_{1,t} + \alpha_{2i} e_{2,t} \dots\dots\dots + \alpha_{ni} e_{n,t} + b_i \varepsilon_{i,t})(a_1 e_{1,t} + a_2 e_{2,t} + \dots\dots\dots a_n e_{n,t} + \varepsilon_{sp})]$$

$$Cov(r_i, r_{sp}) = a_1 \alpha_{1i} var(e_1) + a_2 \alpha_{2i} var(e_2) + \dots\dots\dots + a_n \alpha_{ni} var(e_n)$$

Thus the existence of common factors could be the reason for the covariance between the US stock market and each Spanish stock. It could be that there are some regional factors for American economies[63]. It seems sensible to think that those factors could be just affecting stock prices of firms with American activity, or that those factors have a greater weight for those firms.

In order to compare the relevance of those common factors for different Spanish firms we could use the correlation coefficient between stock returns for each Spanish firm with

[63] Those factors affecting the US stock market and the Spanish stocks with American activity could be factors reflecting the US economy's evolution, since the South American exports are mainly to the US. More South American exports mean more South American wealth to be spent in Spanish firms with business there, so the effect of the US economy's evolution will be higher on Spanish firms with business in South America. On the other hand, those factors could be reflecting the South American economies' evolution, since the US is the main investor in South America, and many large companies included in US stock market indexes do have business in South America. Hence we could think about broader regional factors for American economies instead of factors just for the South American economies.

returns in the US stock market. This is because the correlation coefficient is bounded between -1 and 1. It is also the measure used in the Kofman and Martens (1997) methodology.

If the movement of these common factors is driven by news about American economies we expect them to have greater movement during the day in the Americas. During the afternoon in Madrid it is the morning in the Americas and there is trading on the US stock market and on the SSE. Hence in order to detect the effect of these potential common factors on stock returns, we could compare the US stock market returns and the Spanish stock returns during the overlapping trading period. In this period we can observe return movements in both markets during the high activity in the potential common factors that are driven by news about American economies. Due to the modern information technology we think that information reflected in those common factors could be detected comparing simultaneous intraday return movements in both stock markets.

We do not know whether those regional factors exist for America, but finding Spanish stocks with American activity to be more correlated with the US stock market would mean they might. Thus with this study we could shed some light on identifying the common factors that could explain transmission of stock price movements between financial markets.

3. DATA

Our sample period is 1997-1998. We relate each stock quoted on the SSE with the Future on the S&P 500, quoted on the Chicago Mercantile Exchange. Given that we are studying the process of information incorporation into prices, we drop from the sample all Spanish stocks not quoted on at least 95% of the trading days or that go untraded for 5 consecutive days, and end up with 99 Spanish stocks. We then analyze those firms' annual financial reports[64] to obtain their percentage of American activity. Because some of the firms had not yet approved their 1998 annual report we have just the 1997 annual report for some. For the firms with an annual report for both years there is no substantial change in the percentage of American activity from 1997 to 1998, so that to obtain the percentage of American activity we used the last annual financial report we have. As a proxy of the percentage of American activity we used the percentage of American net sales. If we could not get this data we used the percentage of gross sales, gross profits or net profits in the Americas.

The geographical distribution of net sales must be released in one of the notes to the annual accounts, but Spanish law allows not quoting this data in full detail when this might be damaging for the firm. Thus we have firms with no data or with few data, such as the distribution of sales between exports and imports. In these cases we used all the information in the annual report to infer the proportion of sales in the Americas, or any other of the magnitudes we used as an indicator of American activity. In some cases we could get only an approximate percentage of American activity, such as the maximum or the minimum percentage of American activity that the firm could have, or we were simply

[64] We could get this information form the Information Services of the Madrid Stock Exchange.

not sure about the accuracy of the estimation. We end up with two categories of firms, 19 on which we could get only limited information about the percentage of American activity and 53 on which we could get this percentage accurately.

We have to point out that most of the firms are the parent company of a group, and in those cases we analyzed the annual report of the consolidated group. Under Spanish law, when the parent has 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 parent 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 activity we have calculated is not exact[65]. This is an additional source of inaccuracy in the percentage. Even so, we think that taking into account just the sales of firms in which the parent has a high interest we made an accurate enough calculation of the percentage of American activity, at least for the purposes of this paper.

We have tick-by-tick transaction data on all the stocks included in our sample for 1997 and 1998[66]. All the stocks in the sample are traded in the "continuous trading system" of the SSE. We make fifteen-minute returns trough the logarithm of the final price minus the logarithm of the initial price of the period. To make those returns we divide the sample into periods of fifteen minutes and take the last price of the period as the price at the last moment of the period. The fist price of the day is assigned to the first moment of trading whenever the transaction takes place during the first 15-minute period. The trading period in the continuous trading system of the SSE is from 10 a.m. to 5 p.m., so we have 28 returns per day. In order to evaluate the accuracy of this method we calculate the difference between the time a transaction actually took place and the time the price is assigned[67]. In appendix D we show the mean of this magnitude for each stock. Whenever there is no trading in one 15-minute period we suppose that the price at the end of this period is equal to the last price. We also calculate the percentage of 15-minute periods with trading, drop from the sample all the stocks for which this percentage is lower than 50%, and end up with 56 Spanish stocks.

To construct time series of 15-minute returns for the Spanish stocks we make three adjustments, one for dividends, one for increases in capital, and one for splits. In the Spanish Stock Exchange the right to perceive the dividend belongs to the owner of the stock at the end of the day before the dividend payment. The effect of the dividend payment on the stock return must be an extraordinary overnight return. Given that we do not work with overnight returns we do not have to make any adjustment. However, because of the method used to construct the 15-minute return series, whenever there is no trading in the first fifteen minutes of the payment day we will have the extraordinary return in the first 15-minute period with trading. Hence whenever there is no trading in the first period of the payment day we suppose that the first price of this day is the price at the end of the previous day less the dividend. We do something similar when there is an increase in capital. The preferential rights of subscription to buy the new shares also mean a lower stock price. These rights start to be quoted at the beginning of the day they come into being, so the effect on returns is an overnight effect, but whenever there is no trading in the first period of that day we have the same problem as with the dividends. The adjustment we make is to take the price at the end of the previous day, less the theoretical value of this

[65] The proxy used as an indicator of the percentage of American activity has been calculated inaccurately.
[66] We obtained these data from the *Sociedad de Bolsas* of the Spanish Stock Exchange.
[67] The end of a fifteen-minute period.

right, as the first price of the day[68]. 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, in the literature there is research that finds abnormal behaviour in stock prices whenever a split is effected; see for example Grinblatt, Masulis, and Titman (1984). A recent study in the case of Spain is the paper by Gómez-Sala (1999), who finds abnormal returns principally on the day the split is effected. We therefore eliminate from the sample, for each stock, all days when a split is effected.

It is worth mentioning that we do not have data for 23 October 1997 in our tick-by-tick databases for the SSE. There was trading during this day but for an unknown reason there are no data in the tick-by-tick databases. Our data provider, the *Sociedad de Bolsas* of the Spanish Stock Exchange, could not give us an explanation of this phenomenon, nor did they have tick-by-tick data for this day in their databases.

As a representative index of the US stock market we use the Future contract on the S&P 500, quoted on the Chicago Mercantile exchange[69]. We use the future contract instead of the cash index to avoid the nonsynchronous trading problem found in stock market indexes. See for example Sholes and Williams (1977) and Lo and Mackinlay (1990). The problem is that stock market indexes are composed of stocks traded with different frequencies, so that at a given moment there are stocks that reflect all the information available while others have not traded since the information release and do not yet reflect the information. This problem is especially severe for the opening price of the stock indexes. The stock index's opening price is usually very close to the closing price of the day before, because when the opening price is calculated there are stocks in the index that have not traded since that day. In our case, the nonsynchronous trading problem is especially relevant because we are relating contemporaneous intraday returns in US and in Spain during the overlapping trading period, and this period begins at the US stock market's opening.

In order to get an idea of the relation between the Spanish Stock Exchange and the US stock market we use two Spanish stock market indexes, the IBEX-35 and the Future contract on the IBEX-35. The IBEX-35 is the main stock market index of the SSE continuous trading system[70].

To construct the return time series in the futures contract we use the contract with higher volume. In the S&P 500 it is the contract nearest to delivery, except for one week before expiration, when liquidity goes to the contract second nearest to delivery. In the IBEX-35 it is the contract nearest to delivery, but in this case liquidity goes to the second contract on the delivery day, and on this day the most liquid contract is sometimes the contract nearest to delivery. We construct 15-minute returns as was previously mentioned for the Spanish stocks, but in the cases of the futures contracts and of the IBEX-35 there are no adjustments for dividends, increases in capital or splits.

On 27 October 1997 there was a crisis in the Hong Kong financial market that was transmitted to the NYSE on the same day. This crisis affected the SSE just after the NYSE, so that the first reaction of the SSE was in the overnight period, and the second effect was

[68] The *Sociedad de Bolsas* of the Spanish Stock Exchange has calculated this theoretical value of the right to buy new shares.

[69] We got this data from the Futures Industry Institute, Washington, DC, USA.

[70] We got the IBEX-35 data from the *Sociedad de Bolsas*, and the Future contract on the IBEX-35 data from the Market Information System of *MEFF Renta Variable*.

on 29 October 1997 in the first periods of the trading session. As is shown in the literature, for example in King and Wadwani (1990), there is usually a contagion effect between markets during crisis periods, that is, transmission of stock price movements that do not respond to information. We wished to detect the effect of information from business activity of Spanish firms in the Americas on the price relations between the Spanish and the US stock markets, and given this contagion effect we thought that the crisis week must introduce noise in our study. We therefore decided to eliminate the crisis week from the sample and did all the analysis without it.

In the NYSE there are some days with special closing before 2:00 p.m. We eliminate those days from our analysis for any abnormal relation that they might cause.

4. METHODOLOGY

In the overlapping period between the SSE and the US stock market[71], we have estimated the relation between the 15-minute returns in the Future on the S&P 500 and in each of the Spanish stocks in our sample.

We studied the relation between returns in mean and in variance, using the methodology of Kofman and Martens (1997). Hence as a measure of the relation between the means of the series we have used the correlation coefficient between those returns, and in the case of the variance, we have used the correlation coefficients between the absolute values of those returns. To infer the significance of each of these correlation coefficients we assumed they are normally distributed and then used the Newey-West (1987) standard errors, which are robust to heteroskedasticity and autocorrelation. We calculated these standard errors robust to autocorrelation till lag six, because we have six 15-minute periods in the overlapping trading time. We call these correlation coefficients US connection in mean and in variance. This methodology is especially useful for our purposes because the correlation coefficient goes from -1 to 1, and allows us to compare the US connection of different Spanish stocks.

We assumed all the correlation coefficients not significant at the 5% level were equal to zero. We ended up with a database with the US connection in mean and in variance and the percentage of American activity for each firm. We calculated the correlation coefficient between the percentage of American activity and the US connection for the different samples we have of Spanish stocks. Then we used this last correlation coefficient to evaluate the effect of the firms' American activity on the price relation between the SSE and the US stock markets, in mean and in variance[72]. To infer the significance of this last coefficient we assumed it is normally distributed and then used the White (1980) standard errors[73], robust to heteroskedasticity.

[71] The overlapping period between the SSE and the US stock market goes from 3:30 p.m. to 5:00 p.m. Spanish time. The transition to daylight saving time in the US is in the first week of April, while in Spain it is one week before, so for that week the overlapping period is reduced to 30 minutes. In October, the transition to standard time is on the same day in US and in Spain.

[72] We use a correlation coefficient instead of a regression coefficient because the correlation coefficient is bounded and this allows us make comparisons between samples.

[73] We use the method used in Kofman and Martens (1997) to calculate the White standard errors and the Newey-West standard errors, robust to heteroskedasticity and autocorrelation. We describe their method in appendix C.

To calculate the US connection for each Spanish stock, as is done by Kofman and Martens (1997), we took into account two stylised facts in intraday financial data. The first is the presence of negative stock return autocorrelation caused by bid-ask bouncing, as illustrated in Roll (1984). The second is the U-shaped intraday volatility pattern. See for example Harris (1986) or Wood, McInish and Ord (1985).

In order to purge the US connection of any spurious characteristic in the time series processes, to detect the purest US connection in the 15-minute periods, we take into account the following possibilities: First, if daily volatility levels move in the same way in the Spanish stock and in the US market, this could cause correlation in the 15-minute variance that is not due to information released during these 15-minute periods[74]. Second, as Pierce and Haugh (1977) show, similar autoregressive processes might lead to spurious cross-correlation estimates. Thus we will purge these effects.

It is worth mentioning that this analysis is only to compare the US connection in stocks that have American activity with stocks that do not have American activity. We simply wish to detect Spanish stocks that share more common factors with the US stock market or on which those factors have a higher weight. The analysis is done with Spanish and US simultaneous returns, so the stock price relations could be due to common factors that move the Spanish stock and the US stock market at the same time.

5. RESULTS

In the Spanish stocks sample, we calculated the percentage of 15-minute periods with trading, including the crisis week, as a measure of liquidity, and we constructed groups of stocks according to this percentage. This liquidity indicator is to detect the frequency of trade in order to see which stocks get the information into prices faster[75]. The Future on the S&P 500 is highly liquid, and we think that Spanish stocks' liquidity could affect the results. For example, Low and Muthuswamy (1996) and Lo and Mackinlay (1990) found empirical evidence indicating that the more-traded assets get information faster.

It is worth mentioning that there are seven Spanish stocks listed on the NYSE. Those stocks are among the ones with the highest percentage of American activity. Papers like Werner and Kleidon (1996) or Chan et al. (1994) suggest that new information is introduced into foreign stocks during US trading, and could cause those stocks to be more correlated with the US stock market. Hence if the dual listing were the main reason for the stock price relation with the US stock market, that is, if information that moves the US stock market also moves those Spanish stocks just because they are listed in the US, our results could be spurious. To determine whether this is the case we repeated the analysis without the dually listed stocks and with only the dually listed stocks. Finding positive results in the latter case would suggest that the firm's American business activity is a significant determinant of the price relation between the US stock market and the Spanish stocks. Werner and Kleidon (1996) and Chan et al. (1994) did not study the origin of the

[74] We wish to detect correlation between the Spanish stock and the US stock market that is due to the incorporation of the same information released at the same time.

[75] This is not to detect liquidity in the sense of price responses to trade. In this last sense a stock is liquid when its price response to trade is small.

information incorporated into foreign stocks quoted on the US stock market during the US trading period, so it could be that the information incorporated into the Spanish stocks during US stock market trading is related to the firm's American business activity. We have not found empirical evidence or a theoretical model in the literature for dual listing per se as a determinant of the stock price relations we can find between the Spanish stocks quoted in the US and the US stock market.

We cannot incorporate a dummy variable for the dually listed securities in a regression model with the percentage of American activity to explain our measure of the price relation between the Spanish stocks and the US stock market, because this dummy variable is highly correlated with the percentage of American activity. Depending on the sample, this correlation coefficient ranges from 54.37% to 60.33%. These high coefficients also justify our concern to distinguish any dual listing effect from the real American activity effect on the price relations between the Spanish stocks and the US market.

Because we have two kinds of Spanish stocks, the ones with an accurate estimation of the percentage of American activity and the ones with an inaccurate percentage, we do the analysis once including all stocks and again including just the stocks with an accurate estimation. We have done the analysis for 22 samples of Spanish stocks, whose description is found in table 1.

Table 1. Summary statistics for the percentage of American activity of the Spanish firms

Sample	Number Obs.[3]	Mean America[4]	Percentiles[5] 95%	90%	75%	50%	25%	Max[6]	Min
50%-clean[1]	42	8.65%	50.70%	30.73%	12.50%	0.00%	0.00%	54.30%	0.00%
60%-clean	37	8.60%	52.93%	30.73%	12.50%	0.00%	0.00%	54.30%	0.00%
70%-clean	30	10.29%	52.93%	40.71%	14.83%	0.82%	0.00%	54.30%	0.00%
80%-clean	25	12.35%	52.93%	50.70%	19.12%	3.59%	0.00%	54.30%	0.00%
90%-clean	23	13.40%	52.93%	50.70%	21.01%	4.50%	0.00%	54.30%	0.00%
50%[2]	56	8.69%	50.70%	30.73%	10.89%	1.76%	0.00%	54.30%	0.00%
60%	50	8.79%	50.70%	30.36%	12.45%	2.26%	0.00%	54.30%	0.00%
70%	41	10.40%	50.70%	30.73%	13.23%	3.59%	0.00%	54.30%	0.00%
80%	32	12.26%	52.93%	31.60%	20.06%	4.05%	0.00%	54.30%	0.00%
90%	28	13.63%	52.93%	50.70%	21.25%	5.65%	0.00%	54.30%	0.00%
Nd-50%-clean[7]	36	5.19%	42.50%	19.12%	3.10%	0.00%	0.00%	50.70%	0.00%
Nd-60%-clean	31	4.57%	21.01%	14.83%	3.59%	0.00%	0.00%	50.70%	0.00%
Nd-70%-clean	24	5.51%	21.01%	19.12%	5.19%	0.00%	0.00%	50.70%	0.00%
Nd-80%-clean	19	6.96%	50.70%	21.02%	13.23%	0.67%	0.00%	50.70%	0.00%
Nd-90%-clean	17	7.75%	50.70%	21.02%	13.23%	0.97%	0.00%	50.70%	0.00%
Nd-50%[8]	49	5.72%	31.60%	19.12%	6.90%	0.00%	0.00%	50.70%	0.00%
Nd-60%	43	5.42%	21.01%	14.83%	7.19%	0.00%	0.00%	50.70%	0.00%
Nd-70%	34	6.47%	31.60%	19.12%	8.17%	1.24%	0.00%	50.70%	0.00%
Nd-80%	25	7.43%	31.60%	21.05%	8.89%	1.50%	0.00%	50.70%	0.00%
Nd-90%	21	8.34%	31.60%	21.01%	13.23%	1.50%	0.00%	50.70%	0.00%
Dually[9]	7	29.49%	54.30%	54.30%	52.93%	30.0%	12.5%	54.30%	4.50%
Dually-clean	6	29.41%	54.30%	54.30%	52.93%	26.1%	12.5%	54.30%	4.50%

1. Sample with the firms for witch we have an accurate estimation of the percentage of American activity and have a percentage 15-minute periods with trading greater than 50%.
2. Sample including firms with and without an accurate estimation of the percentage of American activity and have a percentage 15-minute periods with trading greater than 50%.
3. Number of firms in each sample.
4. Mean percentage of American activity in each sample.
5. Percentilic distribution of the percentage of American activity, in each sample.
6. Maximum percentage of American activity that a firm has, in each sample.
7. Sample without dually listed stocks, with the firms for witch we have an accurate estimation of the percentage of American activity and have a percentage 15-minute periods with trading greater than 50%.
8. Sample without dually listed stocks, including firms with and without an accurate estimation of the percentage of American activity and have a percentage 15-minute periods with trading greater than 50%.
9. Sample with just dually listed stocks in the SSE and in the NYSE.

5.A. RESULTS AT THE STOCK LEVEL.

5.A.1 Results with raw returns.

In the first step of studying the relation between the US connection of each Spanish firm and its American activity, we calculate the US connection with the raw returns of each Spanish stock and the Future contract on the S&P 500. Using the Newey-West standard errors, robust to heteroskedasticity and autocorrelation till lag 6, we replace with zero the coefficients not significant at the 5% level. Then we calculate the correlation coefficient between the US connection and the percentage of American activity. The significance of this last coefficient is evaluated with the White standard errors, robust to heteroskedasticity.

In table 2.a. we present the correlation coefficient between the US connection in mean and the percentage of American activity. In table 2.b we present these correlation coefficients for the US connection in variance. In table 2.c we present the results for the dually listed securities, in mean and in variance. In all cases the inference about the significance of each coefficient has been done with the White standard errors, robust to heteroskedasticity.

Table 2.a Results in mean with raw returns.

Correlation between the US connection in mean for each Spanish stock and their percentage of American activity.

Sample	Inac+dually	Inac-no-dually[3]	Accurate+dually[4]	Accurate-no-dually
Corr-50[1]	0.4757	0.1986	0.4664	** 0.1861
P-value[2]	0.000	0.046	0.000	0.098
Corr-60	0.5335	0.2719	0.5492	0.3033
P-value	0.000	0.002	0.000	0.002
Corr-70	0.4977	0.1858	0.5450	0.2607
P-value	0.000	0.023	0.000	0.007
Corr-80	0.4938	** 0.1250	0.5100	** 0.1188
P-value	0.000	0.070	0.000	0.141
Corr-90	0.5139	** 0.0535	0.5112	** 0.0568
P-value	0.000	0.504	0.000	0.509

1. Correlation coefficient between the US connection in mean and the percentage of American activity for the Spanish stocks sample with stocks that trade at least for the 50% of the 15-minute trading periods.
2. Probability value of the correlation coefficient, calculated with the White standard errors.
3. Samples of Spanish stocks that include Spanish firms with an inaccurate estimation of their percentage of American activity.
4. Samples of Spanish stocks that just include stocks with an accurate estimation of the percentage of American activity. Dually listed stocks in the SSE and in the NYSE are included in the sample.

** Not significantly different from zero at the 5% significance level.

In table 2.a we see a positive relation in all cases, but it is weaker for samples without the dually listed stocks. In the samples with an accurate estimation of the percentage of American activity the relation is weaker still. This lower significance could be due to the reduction of variability in the percentage of American activity for samples without dually listed stocks, or because the dually listed securities are a key point in the relation.

Table 2.b Results in variance with raw returns.

Correlation between the US connection in variance for each Spanish stock and their percentage of American activity.

Sample	Inac+dually	Inac-no-dually[3]	Accurate+dually[4]	Accurate-no-dually
Corr-50[1]	0.5601	0.3086	0.5791	0.3329
P-value[2]	0.000	0.001	0.000	0.002
Corr-60	0.5963	0.3414	0.6314	0.3953
P-value	0.000	0.000	0.000	0.001
Corr-70	0.5700	0.2863	0.6215	0.3656
P-value	0.000	0.002	0.000	0.002
Corr-80	0.5795	0.2364	0.6224	0.2915
P-value	0.000	0.009	0.000	0.008
Corr-90	0.5991	0.2510	0.6292	0.3093
P-value	0.000	0.012	0.000	0.008

1. Correlation coefficient between the US connection in variance and the percentage of American activity for the Spanish stocks sample with stocks that trade at least for the 50% of the 15-minute trading periods.
2. Probability value of the correlation coefficient, calculated with the White standard errors.
3. Samples of Spanish stocks that include Spanish firms with an inaccurate estimation of their percentage of American activity.
4. Samples of Spanish stocks that just include stocks with an accurate estimation of the percentage of American activity. Dually listed stocks in the SSE and in the NYSE are included in the sample

** Not significantly different from zero at the 5% significance level.

In table 2.b we see that in all cases there is a positive and significant relation between the percentage of American activity and the correlation between US market and each Spanish stock variance. The relation between the American activity and the US connection in variance remains even without dually listed stocks.

Table 2.c Results for dually listed stocks with raw returns.

Correlation between the US connection for each Spanish stock dually listed in the NYSE and their percentage of American activity. It is with the US connection in mean and in variance.

	Dually with inaccurate[4]	Dually without inaccurate
Mean[1]	0.7029	0.7029
P-value	0.010	0.017
Variance[2]	0.6474	0.6760
P-value[3]	0.016	0.022

1. Correlation coefficient between US connection in mean and the percentage of American activity.
2. Correlation coefficient between the US connection in variance and the percentage of American activity.
3. Probability value of the correlation coefficient, calculated with the White standard errors.
4. Sample with just dually listed stocks in the NYSE that includes one stock with an inaccurate estimation of the percentage of American activity.

** Not significantly different from zero at the 5% significance level.

In table 2.c we see that the percentage of American activity is significant to explain the US connection in the dually listed stocks, in mean and in variance. These samples are composed of 6 and 7 stocks, but even so we get a significant relation. This suggests to us that even if the dual listing were increasing the US connection, the percentage of American activity is a significant variable to explain it.

5.A.2 Results after the first filter.

In this section we present the results with returns filtered for the spurious autocorrelation induced by bid-ask bouncing.

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 behaviour induces 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 behaviour into account we use a moving average of order one to calculate the expected return. Kofman and Martens (1997) use an ARMA filter. We decided to use a moving average of order one in all cases for the following reasons: First, it is a short memory process, and an autoregressive process has long memory. The spurious negative autocorrelation induced by bid-ask bouncing seems to be more consonant with a short memory process. For example, Roll (1984) just uses first order serial covariance of price changes to construct his measure of the Spread. In any event we expect low coefficients in the moving average process[76], and in this case there is little difference with an autoregressive 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, so that before the elimination of the intraday and daily volatility processes it is difficult to evaluate the autocorrelation order, and it is even difficult to isolate the spurious autocorrelation induced by bid-ask bouncing from any other autocorrelation that may be in the data. For those reasons we prefer to determine a priori the filter to eliminate the spurious bid-ask induced autocorrelation[77]. If there is bouncing between the bid and the ask, we expect the moving average term to be negative. Indeed, all the moving average terms we have estimated are negative. The following is the moving average model of order one that we use to filter the series:

$$R_{t,n} = c + \beta_1 I_n e_{t-1,N} + \beta_2 (1 - I_n) e_{t,n-1} + e_{t,n} \qquad \begin{array}{l} I_n = 1 \text{ if } n=1 \\ I_n = 0 \text{ if } n>1 \end{array}$$

Where N is the total number of intraday 15-minute periods. It is 28 for the Spanish stocks and 27 for the Future on the S&P 500. The filtered time series are $e_{t,n}$.

In tables 3.a, 3.b and 3.c we present the results of the analysis applied to those series filtered for the spurious autocorrelation induced by bid ask bouncing.

[76] Indeed all moving average coefficients are small. The highest do not exceed 0.3.

[77] We have repeated the analysis of the full paper without this filtering for the spurious autocorrelation induced by bid-ask bouncing and we found similar results. We present these results in appendix B.

Table 3.a Results in mean after the first filter.

Correlation between the US connection in mean for each Spanish stock and their percentage of American activity. Returns have been filtered for the spurious autocorrelation induced by bid-ask bouncing.

Sample	Inac+dually	Inac-no-dually[3]	Accurate+dually[4]	Accurate-no-dually
Corr-50[1]	0.4707	0.1999	0.4606	** 0.1865
P-value[2]	0.000	0.046	0.000	0.099
Corr-60	0.5279	0.2733	0.5425	0.3033
P-value	0.000	0.002	0.000	0.002
Corr-70	0.4916	0.1882	0.5376	0.2616
P-value	0.000	0.023	0.000	0.006
Corr-80	0.4871	** 0.1276	0.5026	** 0.1191
P-value	0.000	0.066	0.000	0.132
Corr-90	0.5116	** 0.0583	0.5073	** 0.0588
P-value	0.000	0.460	0.000	0.482

1. Correlation coefficient between the US connection in mean and the percentage of American activity for the Spanish stocks sample with stocks that trade at least for the 50% of the 15-minute trading periods.
2. Probability value of the correlation coefficient, calculated with the White standard errors.
3. Samples of Spanish stocks that include Spanish firms with an inaccurate estimation of their percentage of American activity.
4. Samples of Spanish stocks that just include stocks with an accurate estimation of the percentage of American activity. Dually listed stocks in the SSE and in the NYSE are included in the sample

** Not significantly different from zero at the 5% significance level.

In table 3.a wee see that in mean we get similar results to those with raw returns. The significance becomes problematic again when we drop dually listed securities.

Table 3.b Results in variance after the first filter.

Correlation between the US connection in variance for each Spanish stock and their percentage of American activity. Returns have been filtered for the spurious autocorrelation induced by bid-ask bouncing.

Sample	Inac+dually	Inac-no-dually[3]	Accurate+dually[4]	Accurate-no-dually
Corr-50[1]	0.5581	0.3074	0.5780	0.3316
P-value[2]	0.000	0.001	0.000	0.002
Corr-60	0.5912	0.3401	0.6253	0.3907
P-value	0.000	0.000	0.000	0.001
Corr-70	0.5635	0.2857	0.6133	0.3604
P-value	0.000	0.002	0.000	0.002
Corr-80	0.5768	0.2378	0.6158	0.2843
P-value	0.000	0.008	0.000	0.008
Corr-90	0.5964	0.2493	0.6245	0.3008
P-value	0.000	0.012	0.000	0.009

1. Correlation coefficient between the US connection in variance and the percentage of American activity for the Spanish stocks sample with stocks that trade at least for the 50% of the 15-minute trading periods.
2. Probability value of the correlation coefficient, calculated with the White standard errors.
3. Samples of Spanish stocks that include Spanish firms with an inaccurate estimation of their percentage of American activity.
4. Samples of Spanish stocks that just include stocks with an accurate estimation of the percentage of American activity. Dually listed stocks in the SSE and in the NYSE are included in the sample

** Not significantly different from zero at the 5% significance level.

In table 3.b we see that in variance we still have positive and significant correlation in all cases.

Table 3.c Results for the dually listed stocks after the first filter.

Correlation between the US connection for each Spanish stock dually listed in the NYSE and their percentage of American activity. It is with the US connection in mean and in variance. Returns have been filtered for the spurious autocorrelation induced by bid-ask bouncing.

	Dually with inaccurate[4]	Dually without inaccurate
Mean[1]	0.6879	0.6879
P-value	0.012	0.019
Variance[2]	0.6330	0.6712
P-value[3]	0.019	0.023

1. Correlation coefficient between US connection in mean and the percentage of American activity.
2. Correlation coefficient between the US connection in variance and the percentage of American activity.
3. Probability value of the correlation coefficient, calculated with the White standard errors.
4. Sample with just dually listed stocks in the NYSE that includes one stock with an inaccurate estimation of the percentage of American activity.

** Not significantly different from zero at the 5% significance level.

In table 3.c we see that all the coefficients remain significant in the dually listed securities although these coefficients are a little smaller.

5.A.3 Results after the second filter.

In this section we present the results with returns filtered for the spurious autocorrelation induced by bid-ask bouncing and for the U-shape in intraday volatility patterns.

The second stylised fact that we wish to take into account is the U-shaped pattern found in stock return intraday volatility. See for example Harris (1986) or Wood, McInish and Ord (1985). In the overlapping period, intraday volatility is increasing in the SEE and decreasing in the US market. Thus in order to get a more accurate estimation of the relations in variance we estimate the intraday volatility pattern in each of the asset returns we have. We used the methodology of Andersen and Bollerslev (1997) to estimate the intraday volatility patterns. This methodology assumes two processes in variance, a daily process and an intraday process. To estimate the intraday volatility patterns we use the return series filtered for the spurious autocorrelation induced by bid-ask bouncing[78], because by eliminating autocorrelation we improve the consistency of intraday volatility patterns estimation. In appendix A we present the details of these estimations. Dividing the filtered return time series we got in the previous section by the estimated seasonal volatility factors we obtain return time series that do not have the intraday U-shaped volatility pattern.

[78] In appendix B we present the results of this section without this filtering. That is, the results when we apply the methodology of Andersen and Bollerslev (1997) to the raw returns, as they do.

In tables 4.a, 4.b and 4.c we present the results of the analysis applied to those series cleaned of the spurious autocorrelation induced by bid-ask bouncing and the U-shaped pattern in variance.

Table 4.a Results in mean after the second filter.

Correlation between the US connection in mean for each Spanish stock and their percentage of American activity. Returns have been filtered for the spurious autocorrelation induced by bid-ask bouncing and for the U-shaped pattern in variance.

Sample	Inac+dually	Inac-no-dually[3]	Accurate+dually[4]	Accurate-no-dually
Corr-50[1]	0.4550	** 0.1809	0.4464	** 0.1667
P-value[2]	0.000	0.116	0.000	0.219
Corr-60	0.5334	0.2884	0.5558	0.3318
P-value	0.000	0.001	0.000	0.002
Corr-70	0.4999	0.2105	0.5527	0.2989
P-value	0.000	0.015	0.000	0.004
Corr-80	0.4933	0.1511	0.5269	0.1765
P-value	0.000	0.044	0.000	0.048
Corr-90	0.5166	** 0.0993	0.5265	** 0.1352
P-value	0.000	0.242	0.000	0.145

1. Correlation coefficient between the US connection in mean and the percentage of American activity for the Spanish stocks sample with stocks that trade at least for the 50% of the 15-minute trading periods.
2. Probability value of the correlation coefficient, calculated with the White standard errors.
3. Samples of Spanish stocks that include Spanish firms with an inaccurate estimation of their percentage of American activity.
4. Samples of Spanish stocks that just include stocks with an accurate estimation of the percentage of American activity. Dually listed stocks in the SSE and in the NYSE are included in the sample.

** Not significantly different from zero at the 5% significance level.

In table 4.a we see that with this filtering we get more significant correlation. The non-significant correlation coefficients are for the largest and the smallest samples without the dually listed securities.

Table 4.b Results in variance after the second filter.

Correlation between the US connection in variance for each Spanish stock and their percentage of American activity. Returns have been filtered for the spurious autocorrelation induced by bid-ask bouncing and for the U-shaped pattern in variance.

Sample	Inac+dually	Inac-no-dually[3]	Accurate+dually[4]	Accurate-no-dually
Corr-50[1]	0.5104	0.2595	0.5630	0.3194
P-value[2]	0.000	0.017	0.000	0.016
Corr-60	0.5608	0.3303	0.6367	0.4395
P-value	0.000	0.001	0.000	0.000
Corr-70	0.5362	0.2880	0.6355	0.4337
P-value	0.000	0.006	0.000	0.001
Corr-80	0.5357	0.2546	0.6469	0.4169
P-value	0.000	0.023	0.000	0.004
Corr-90	0.5717	0.2947	0.6536	0.4448
P-value	0.000	0.026	0.000	0.005

1. Correlation coefficient between the US connection in variance and the percentage of American activity for the Spanish stocks sample with stocks that trade at least for the 50% of the 15-minute trading periods.
2. Probability value of the correlation coefficient, calculated with the White standard errors.
3. Samples of Spanish stocks that include Spanish firms with an inaccurate estimation of their percentage of American activity.
4. Samples of Spanish stocks that just include stocks with an accurate estimation of the percentage of American activity. Dually listed stocks in the SSE and in the NYSE are included in the sample.

** Not significantly different from zero at the 5% significance level.

Table 4.b shows that all correlation coefficients between the US connection and the percentage of American activity are still positive and significant.

Table 4.c Results for dually listed stocks after the second filter.

Correlation between the US connection for each Spanish stock dually listed in the NYSE and their percentage of American activity. It is with the US connection in mean and in variance. Returns have been filtered for the spurious autocorrelation induced by bid-ask bouncing and for the U-shaped pattern in variance.

	Dually with inaccurate[4]	Dually without inaccurate
Mean[1]	0.6784	0.6835
P-value	0.011	0.016
Variance[2]	** 0.4024	** 0.4594
P-value[3]	0.209	0.169

1 Correlation coefficient between US connection in mean and the percentage of American activity.
2 Correlation coefficient between the US connection in variance and the percentage of American activity.
3 Probability value of the correlation coefficient, calculated with the White standard errors.
4 Sample with just dually listed stocks in the NYSE that includes one stock with an inaccurate estimation of the percentage of American activity.

** Not significantly different from zero at the 5% significance level.

In table 4.c we see a new result, which is the non-significant result in variance for the dually listed stocks.

5.A.4 Results after the third filter.

In this section we present the results with returns filtered for the spurious autocorrelation induced by bid-ask bouncing, for the U-shape in intraday volatility patterns, and further filtered for the presence of any remaining autoregressive structure, as was done by Kofman and Martens (1997). For example, Pierce and Haugh (1977) show that similar autoregressive processes might lead to spurious cross-correlation estimates. Hence we take the series filtered for the bid-ask bouncing effect and the U-shaped intraday volatility pattern, and we apply the Schwarz model selection criterion to determine the number of lags of any remaining autoregressive structure in those filtered return time series and in the absolute value of those return time series[79]. We restrict the number of lags to the number of 15-minute periods per day, 28 for the Spanish stocks and 27 for the Future contract on the S&P 500. Other selection criteria like the Akaike do not penalise the number of lags so much, but we prefer models with fewer lags to avoid overparametrization, and because in an efficient stock market there should be no autoregressive structures in returns, since this implies the opportunity to predict future returns. We estimate a moving average model with the lags determined by the Schwarz selection criterion. In the absolute value time series there are cases where the moving average model is not appropriate. By the Schwarz selection criterion applied to the residuals of these last models we see that there remains an autoregressive structure. In this case we adjust an autoregressive process instead of a moving average process. A priori we use a moving average process because it is a short memory process, but the existence of long memory processes in variance is well documented in the literature. See for example Bollerslev (1986). We think this is the reason for finding the autoregressive models to be more appropriate just in the absolute value return time series.

We take the residuals of these models, applied to the returns filtered for the bid-ask bounce and for the U-shaped intraday volatility pattern, as the further filtered series. Then we apply again the analysis calculating the US connection with this further filtered time series. The US connection in mean is calculated with the further filtered series of returns, and the US connection in variance is calculated with the further filtered series of absolute returns.

In tables 5.a, 5.b, and 5.c we show the results using this further filtered returns time series.

[79] In appendix B we present the results of this section when we do not apply the filter for the spurious autocorrelation induced by the bid-ask bouncing.

Table 5.a Results in mean after the third filter.

Correlation between the US connection in mean for each Spanish stock and their percentage of American activity. Returns have been filtered for the spurious autocorrelation induced by bid-ask bouncing, for the U-shaped pattern in variance, and a further filter has been applied to eliminate any remaining autoregresive structure in mean.

Sample	Inac+dually	Inac-no-dually[3]	Accurate+dually[4]	Accurate-no-dually
Corr-50[1]	0.4664	** 0.2050	0.4601	** 0.1959
P-value[2]	0.000	0.054	0.000	0.115
Corr-60	0.5330	0.2913	0.5550	0.3345
P-value	0.000	0.001	0.000	0.001
Corr-70	0.4990	0.2140	0.5520	0.3025
P-value	0.000	0.014	0.000	0.003
Corr-80	0.4926	0.1566	0.5263	0.1830
P-value	0.000	0.039	0.000	0.042
Corr-90	0.5168	** 0.1066	0.5265	** 0.1420
P-value	0.000	0.210	0.000	0.128

1. Correlation coefficient between the US connection in mean and the percentage of American activity for the Spanish stocks sample with stocks that trade at least for the 50% of the 15-minute trading periods.
2. Probability value of the correlation coefficient, calculated with the White standard errors.
3. Samples of Spanish stocks that include Spanish firms with an inaccurate estimation of their percentage of American activity.
4. Samples of Spanish stocks that just include stocks with an accurate estimation of the percentage of American activity. Dually listed stocks in the SSE and in the NYSE are included in the sample

** Not significantly different from zero at the 5% significance level.

In table 5.a we see that we do not have different results in mean with the further filtering. We think this is because few autoregressive structures were remaining in the mean of the return time series filtered for the spurious autocorrelation induced by bid-ask bouncing and for the U-shaped pattern in intraday variance.

Table 5.b Results in variance after the third filter.

Correlation between the US connection in variance for each Spanish stock and their percentage of American activity. Returns have been filtered for the spurious autocorrelation induced by bid-ask bouncing, for the U-shaped pattern in variance, and a further filter has been applied to eliminate any remaining autoregresive structure in the absolute value of returns.

Sample	Inac+dually	Inac-no-dually[3]	Accurate+dually[4]	Accurate-no-dually
Corr-50[1]	0.4575	0.1961	0.5005	0.2453
P-value[2]	0.000	0.031	0.000	0.020
Corr-60	0.4870	0.2230	0.5490	0.3047
P-value	0.000	0.015	0.000	0.004
Corr-70	0.4410	** 0.1499	0.5260	0.2600
P-value	0.000	0.101	0.000	0.013
Corr-80	0.4169	** 0.0543	0.4901	** 0.1047
P-value	0.000	0.544	0.000	0.358
Corr-90	0.4226	** 0.0360	0.4950	** 0.1164
P-value	0.000	0.733	0.000	0.336

1. Correlation coefficient between the US connection in variance and the percentage of American activity for the Spanish stocks sample with stocks that trade at least for the 50% of the 15-minute trading periods.
2. Probability value of the correlation coefficient, calculated with the White standard errors.
3. Samples of Spanish stocks that include Spanish firms with an inaccurate estimation of their percentage of American activity
4. Samples of Spanish stocks that just include stocks with an accurate estimation of the percentage of American activity. Dually listed stocks in the SSE and in the NYSE are included in the sample

** Not significantly different from zero at the 5% significance level.

The results in table 5.b suggest that the spurious cross-correlation problem is more severe in variance. We think this is because there were more autoregressive structures in variance, as is usual in financial data. See for example Bollerslev, Chou, and Kroner (1992).

Table 5.c Results for dually listed stocks after the third filter.

Correlation between the US connection for each Spanish stock dually listed in the NYSE and their percentage of American activity. It is with the US connection in mean and in variance. Returns have been filtered for the spurious autocorrelation induced by bid-ask bouncing, for the U-shaped pattern in variance, and for the existence of remaining autoregresive structures.

	Dually with inaccurate[4]	Dually without inaccurate
Mean[1]	0.6668	0.6726
P-value	0.011	0.017
Variance[2]	0.4357	** 0.4416
P-value[3]	0.043	0.056

1. Correlation coefficient between US connection in mean and the percentage of American activity.
2. Correlation coefficient between the US connection in variance and the percentage of American activity.
3. Probability value of the correlation coefficient, calculated with the White standard errors.
4. Sample with just dually listed stocks in the NYSE that includes one stock with an inaccurate estimation of the percentage of American activity.

** Not significantly different from zero at the 5% significance level.

In table 5.c we see that with this further filtering we get just one non-significant result in variance. Even it is significant at the 6% level.

5.A.5 Results after the fourth filter.

In this section we present the results with returns filtered for the spurious autocorrelation induced by bid-ask bouncing and for the U-shape in intraday volatility patterns, standardised by the daily volatility level, and further filtered for the presence of any remaining autoregressive structure.

It could be that the daily volatility level in the Spanish stocks moves as in the US stock market. In this case we could get higher correlation coefficients between our measures of volatility in the US stock market and in each Spanish stock return. In order to isolate the correlation in variance due to information releases in the overlapping trading period, we standardize our filtered returns by the daily volatility level.

Like Andersen and Bollerslev (1997), we assume stock return behaviour like the following:

$$R_{t,n} = E(R_{t,n}) + \frac{\sigma_t s_{t,n} Z_{t,n}}{N^{1/2}} \tag{1}$$

Where t indicates the day and n indicates the intraday period, N is the total number of intraday periods, σ_t is the daily variance, $s_{t,n}$ is the intraday volatility factor for day t and intraday period n, $Z_{t,n}$ is a random variable with zero mean, and $E(R_{t,n})$ is the expected return. Andersen and Bollerslev (1997) used the unconditional mean as the expected returns. We introduce the moving average of order one to filter for the spurious negative autocorrelation induced by bid-ask bouncing[80]. Then we estimate the intraday volatility factors and we divide the unexpected return by those factors. Thus we have:

$$\frac{R_{t,n} - E(R_{t,n})}{s_{t,n}} = \frac{\sigma_t Z_{t,n}}{N^{1/2}} \tag{2}$$

Now to cleanse the series even more of the correlation that could be in 15-minute variances induced by similar processes of daily volatility levels in the US stock market and in the Spanish firms, we divide the filtered returns by $\sigma_t/N^{1/2}$, and we get:

$$\frac{(R_{t,n} - E(R_{t,n}))N^{1/2}}{s_{t,n}\sigma_t} = Z_{t,n} \tag{3}$$

The method we use to estimate the intraday volatility factors takes into account the possibility of different volatility patterns depending on the daily volatility level. We estimate different models for the intraday volatility factors, one group of them with the

[80] However, in appendix B we present the results of the full paper when we take the unconditional mean as the expected return.

intraday volatility factors varying with the daily volatility level. Then with a model selection criterion we choose the model that fits the data best. Kofman and Martens (1997) estimate the intraday volatility patterns in a similar way but do not differentiate the intraday process in variance from the daily process in variance as in Eq. 1. Thus the way they use to take into account the spurious correlation in variance that could come from daily volatility levels moving in the same way in both markets is to force the intraday volatility factors to depend on the daily volatility level in both markets. Andersen and Bollerslev's (1997) empirical evidence is consistent with the idea of two processes in variance as in Eq. 1. Our approach is thus to leave the data to say whether the daily volatility level modifies the intraday volatility factors, but we then standardise by the daily volatility level.

Finally we apply the same further filtering that was applied in the previous section for any remaining autoregressive process that could exist in the data.

In tables 6.1, 6.b, and 6.c we show the results of our analysis applied on these purest 15-minute return and variance time series.

Table 6.a Results in mean after the fourth filter.

Correlation between the US connection in mean for each Spanish stock and their percentage of American activity. Returns have been filtered for the spurious autocorrelation induced by bid-ask bouncing, for the U-shaped pattern in variance, have been standardized by the daily volatility level, and a further filter has been applied to eliminate any remaining autoregresive structure in those returns.

Sample	Inac+dually	Inac-no-dually[3]	Accurate+dually[4]	Accurate-no-dually
Corr-50[1]	0.4406	** 0.1575	0.4373	** 0.1548
P-value[2]	0.000	0.118	0.000	0.194
Corr-60	0.5050	0.2348	0.5360	0.2891
P-value	0.000	0.003	0.000	0.003
Corr-70	0.4670	** 0.1435	0.5307	0.2462
P-value	0.000	0.052	0.000	0.007
Corr-80	0.4494	** 0.0533	0.4954	** 0.0885
P-value	0.000	0.372	0.000	0.240
Corr-90	0.4603	** -0.0718	0.4910	** 0.0095
P-value	0.000	0.403	0.001	0.905

1. Correlation coefficient between the US connection in mean and the percentage of American activity for the Spanish stocks sample with stocks that trade at least for the 50% of the 15-minute trading periods.
2. Probability value of the correlation coefficient, calculated with the White standard errors.
3. Samples of Spanish stocks that include Spanish firms with an inaccurate estimation of their percentage of American activity.
4. Samples of Spanish stocks that just include stocks with an accurate estimation of the percentage of American activity. Dually listed stocks in the SSE and in the NYSE are included in the sample

** Not significantly different from zero at the 5% significance level.

In table 6.a we see that this last filtering increases the significance problems in the US connections in mean for samples without dually listed stocks. The problem is larger for the most liquid samples. Even though this filtering was designed to purge the US connection in variance it has a significant effect on mean.

Table 6.b Results in variance after the fourth filter.

Correlation between the US connection in variance for each Spanish stock and their percentage of American activity. Returns have been filtered for the spurious autocorrelation induced by bid-ask bouncing, for the U-shaped pattern in variance, have been standardized by the daily volatility level, and a further filter has been applied to eliminate any remaining autoregresive structure in the absolute value of those returns.

Sample	Inac+dually	Inac-no-dually[3]	Accurate+dually[4]	Accurate-no-dually
Corr-50[1]	0.4127	** 0.0535	0.4338	** 0.0922
P-value[2]	0.000	0.492	0.000	0.332
Corr-60	0.4670	** 0.1128	0.5107	0.1931
P-value	0.000	0.091	0.000	0.021
Corr-70	0.4116	** 0.0022	0.4771	** 0.1155
P-value	0.000	0.974	0.000	0.167
Corr-80	0.3565	** -0.1737	0.4076	** -0.1150
P-value	0.009	0.079	0.011	0.308
Corr-90	0.3198	** -0.2830	0.3796	** -0.1629
P-value	0.039	0.050	0.022	0.206

1. Correlation coefficient between the US connection in variance and the percentage of American activity for the Spanish stocks sample with stocks that trade at least for the 50% of the 15-minute trading periods.
2. Probability value of the correlation coefficient, calculated with the White standard errors.
3. Samples of Spanish stocks that include Spanish firms with an inaccurate estimation of their percentage of American activity
4. Samples of Spanish stocks that just include stocks with an accurate estimation of the percentage of American activity. Dually listed stocks in the SSE and in the NYSE are included in the sample

** Not significantly different from zero at the 5% significance level.

In table 6.b we see a large reduction of significance in samples without the dually listed stocks. This suggests to us that daily volatility levels move in the same way in both stock markets. It also suggests that dual listing could be a key point for the relation of the Spanish stocks with the US stock market.

Table 6.c Results for dually listed stocks after the fourth filter.

Correlation between the US connection for each Spanish stock dually listed in the NYSE and their percentage of American activity. It is with the US connection in mean and in variance. Returns have been filtered for the spurious autocorrelation induced by bid-ask bouncing, for the U-shaped pattern in variance, have been standardized by the daily volatility level, and a further filter has been applied to eliminate any remaining autoregresive structure.

	Dually with inaccurate[4]	Dually with out inaccurate
Mean[1]	0.6732	0.6741
P-value	0.017	0.026
Variance[2]	** 0.5528	** 0.5527
P-value[3]	0.089	0.107

1. Correlation coefficient between US connection in mean and the percentage of American activity.
2. Correlation coefficient between the US connection in variance and the percentage of American activity.
3. Probability value of the correlation coefficient, calculated with the White standard errors.
4. Sample with just dually listed stocks in the NYSE that includes one stock with an inaccurate estimation of the percentage of American activity.

** Not significantly different from zero at the 5% significance level.

In table 6.c we observe a significant relation in mean but not in variance. Even so the results in variance are close to significant. The significant relations found in this case support the idea of firms' American business activity as a determinant to explain stock price relations between the US stock market and each Spanish stock.

5.B General results and results at the stock index level

In order to evaluate the effectiveness of the filters applied to the series we present in table 7 the mean US connection in mean and in variance.

Table 7. Descriptive statistics of the US connection in mean and in variance.

	Mean US connection in mean	Mean US connection in variance
Raw returns	0.2056	0.1312
Ma(1)[1]	0.2094	0.1360
$Ma(1)/s_{t,n}$ [2]	0.2013	0.1401
$ARMA(Ma(1)/s_{t,n})$[3]	0.2028	0.0847
$ARMA(Ma(1)/s_{t,n}\sigma_t)$[4]	0.2055	0.0640

1. Mean results for the series corrected for the spurious negative autocorrelation induced by bid-ask bouncing.
2. Mean results for the series corrected for the spurious negative autocorrelation induced by bid-ask bouncing and for the U-shaped pattern in intraday volatility.
3. Mean results for the series corrected for the spurious negative autocorrelation induced by bid-ask bouncing, for the U-shaped pattern in intraday volatility, and where a further ARMA filter has been applied eliminate any remaining autocorrelation in mean and in variance.
4. Mean results for the series corrected for the spurious negative autocorrelation induced by bid-ask bouncing, for the U-shaped pattern in intraday volatility, for similar daily volatility levels in both markets, and where a further ARMA filter has been applied eliminate any remaining autocorrelation in mean and in variance.

In table 7 we can observe the effect of each of the applied filters. The main effect is on the US connection in variance. When we clean for the U-shaped intraday volatility pattern in both stock markets, we get a higher correlation between intraday variances in the US stock market and each Spanish stock. Using a further filtering with the ARMA models we observe a reduction in the US connection in variance but not in mean. We think this is because the autocorrelation structures are mainly present in variance. Finally, the reduction in the mean US connection in variance, shown in the last row of table 7, suggests to us that some US connection in variance is due to the daily volatility levels in the US stock market and in each Spanish stock moving in a similar way, rather than to information released during the overlapping period of trading in the US and the Spanish stock markets.

Table 8. Index results. The price relation between the Future contract on the S&P 500 and the Future contract on the Ibex-35, and the Ibex-35.

	FUTIB[6]	IBEX[7]
Raw returns mean	**0.6323**	**0.6211**
P_val	**0.000**	**0.000**
Raw returns variance	0.4600	0.4590
P_val	0.000	0.000
MA(1) returns mean[1]	**0.6317**	**0.6212**
P_val	**0.000**	**0.000**
MA(1) returns variance	0.4603	0.4592
P_val	0.000	0.000
MA(1) / $S_{t,n}$ returns mean	**0.6028**	**0.5894**
P_val	**0.000**	**0.000**
MA(1) / $S_{t,n}$ returns variance[2]	0.4381	0.4348
P_val	0.000	0.000
ARMA[MA(1)/$S_{t,n}$] returns mean[3]	**0.6036**	**0.5885**
P_val	**0.000**	**0.000**
ARMA[MA(1)/$S_{t,n}$] returns variance	0.3283	0.3071
P_val	0.000	0.000
ARMA[MA(1)/$S_{t,n}\sigma_t$] returns mean	**0.6056**	**0.5915**
P_val	**0.000**	**0.000**
ARMA[MA(1)/$S_{t,n}\sigma_t$] returns variance[4]	0.3201	0.3086
P_val[5]	0.000	0.000

1. Results for the series corrected for the spurious negative autocorrelation induced by bid-ask bouncing.
2. Results for the series corrected for the spurious negative autocorrelation induced by bid-ask bouncing and for the U-shaped pattern in intraday volatility.
3. Results for the series corrected for the spurious negative autocorrelation induced by bid-ask bouncing, for the U-shaped pattern in intraday volatility, and where a further ARMA filter has been applied eliminate any remaining autocorrelation.
4. Results for the series corrected for the spurious negative autocorrelation induced by bid-ask bouncing, for the U-shaped pattern in intraday volatility, for similar daily volatility levels in both markets, and where a further ARMA filter has been applied eliminate any remaining autocorrelation.
5. Newey-west standard errors, robust to heteroskedasticity and autocorrelation till lag 6 in the case of the Ibex-35 and till lag 7 in the case of the future contract on the Ibex-35. The future contract on the Ibex-35 is traded for one 15-minute period more after the closing in the Spanish Stock Market.
6. Results for the correlation coefficients between the Future contract on the S&P 500 and the Future contract on the Ibex-35, in mean and in variance.
7. Results for the correlation coefficients between the Future contract on the S&P 500 and the Ibex-35, in mean and in variance.

In table 8 we can see that the relation at the index level is positive and statistically significant in all cases. The relation is higher in mean than in variance, and it is higher between futures contracts. This last fact suggests to us that the relations found at the stock level should be higher with futures contracts on each Spanish stock. Furthermore, the filters applied have a greater effect on the variance relations.

6. CONCLUSION

In this paper we have studied whether multinational firms' activity abroad, in a foreign country or economic region, have any effect on price relations between stock markets. We have analyzed the relations between the Spanish and the US stock markets. This is a good sample because Spanish multinational firms have their activity abroad concentrated in South America, the main stock market in the South American time zones is the US stock market, and the US economy has a big influence on the South American economies. Our intuition is that the common factor theory of stock price relations between the US and the Spanish stock markets could explain an effect of the Spanish firms' business in the Americas on the relations between those stock markets. It could be that there exist some common factors that reflect information relevant for American economies. These common factors should have a larger effect on firms with business in the Americas. The strong relation between the US economy and the South American economies could explain the effect of these common factors on the US stock market. The highest movement activity of these common factors should be during the day in the Americas. Thus to detect whether news driving the movements in those factors simultaneously drives stock movements in the US stock market and in the Spanish stocks of firms with American activity, we compare returns in the overlapping trading period.

We used the Kofman and Martens (1996) methodology to calculate a measure of the price relations between each Spanish stock and the US stock market in mean and in variance, which we called US connection in mean and in variance. These measures are calculated with simultaneous returns during the overlapping trading period in the US and Spanish stock markets. We then constructed a measure of the Spanish firm's American activity and calculated the correlation of this measure with the US connection in mean and in variance.

Like Kofman and Martens (1997), we applied filters to the returns time series to obtain non-spurious measures of the relation between Spanish and US stock returns, and to detect relations due to intraday news releases that could affect stock prices in both stock markets simultaneously.

We take into account the fact that seven Spanish firms' stocks are quoted on the NYSE and these firms are among the ones with the highest American activity. Werner and Kleidon (1996) and Chan et al. (1994) suggest that there is information incorporated into foreign stocks quoted in the US during US trading. If this information is incorporated into Spanish stocks quoted on the NYSE just because these stocks are quoted there, we could get spurious results. As we mentioned before, we did not find empirical evidence in the literature supporting this last theory. Even so, we did the analysis without the dually listed stocks and with only the dually listed stocks.

In the samples including the dually listed stocks we find a positive and significant relation between the US connection, in mean and in variance, and the firm's American activity. These results hold for all samples and after any filter.

In the samples without the stocks dually listed on the NYSE, all the significant correlation coefficients between the US connection and the firm's American activity are positive. After the application of any filter there are some positive and significant correlation coefficients, but the results are not as determinant as with the dually listed stocks. We think this could be because by dropping the dually listed stocks we lose variability in the variable that measures the firm's American activity, but this is just an intuition. Finally, when we do the analysis with just the dually listed stocks we get a significant positive relation between US connection and the firm's American activity. This happens in all cases for the US connection in mean. In the case of the US connection in variance all coefficients are positive but some are non-significant, although close to significant, at least after cleaning for any autoregressive structure in variance. Hence the analysis with just dually listed stocks suggests that our results including dually listed stocks are not spurious and the firm's American activity is a determinant magnitude for the price relations between the US stock market and the Spanish stock market.

Our conclusion is that multinational firms' activity abroad has an effect on the stock price relations between stock markets[81]. Our results are consistent with the theory of the existence of regional factors affecting the stock prices of all firms with business activity in their region. These factors could explain some stock price relations between stock markets. Our results shed some light on the nature of the common factors behind the transmission of movements between stock markets. Those common factors are not yet fully identified. See for example King, Sentana and Wadhwani (1994)

Spanish multinational firms' expansion into South America has begun during the last few years, and the process is still going on. Hence a time dimensional analysis to study whether the stock price relations with the US stock market of the Spanish multinational firms with American activity were weaker when those firms had no American activity is left for future research. Finally, it left for future research to study whether Spanish traders gather South American information relevant for those Spanish firms with business activity there, directly from South America or they infer that news from the US stock market movements.

[81] In the case of the SSE, it could be argued that their multinational firms' concentration of activity in South America has contributed to increasing the positive stock price relations between the US stock exchange and the SSE. From a US portfolio manager's point of view, it could be argued that Spanish multinational firms' concentration of activities in South America has reduced the appeal of the SSE for diversification purposes.

APPENDIX A

INTRADAY VOLATILITY PATTERNS

To estimate the intraday volatility patterns we use the methodology of Andersen and Bollerlev (1997), in which it is supposed that intraday returns can be decomposed in the following way:

$$R_{t,n} = E(R_{t,n}) + \frac{\sigma_t s_{t,n} Z_{t,n}}{N^{1/2}} \tag{1}$$

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 returns intervals per day, $s_{t,n}$ is the intraday seasonal factor, σ_t the return volatility on day t and $Z_{t,n}$ is a random variable with $E(Z_{t,n})=0$ and $Var(Z_{t,n})=1$. If this is the case, the conditional variance of the stock returns could be decomposed in the following way:

$$VAR(R_{t,n})_{t,n} = \frac{\sigma^2{}_t s^2{}_{t,n} VAR(Z_{t,n})}{N} \tag{2}$$

So that $s_{t,n}$ are the intraday seasonal factors determining the intraday seasonal patters in the return volatility. Andersen and Bollerslev (1997) use a Fourier flexible functional form to modelize the patterns of intraday returns. These Fourier flexible functional forms were introduced by Gallant (1981, 1982), and it have been also applied in finance by Pagan and Shwert (1990). For estimating intraday volatility patterns, Kofman and Martens (1997) used these functional forms.

Following the methodology of Andersen and Bollerslev (1997) to estimate the seasonal volatility patterns, from Eq (1), define:

$$x_{t,n} \equiv 2\log\left[\left|R_{t,n} - E(R_{t,t})\right|\right] - \log\sigma^2{}_t + \log N = \log s^2{}_{t,n} + \log Z^2{}_{t,n} \tag{3}$$

The modeling approach is based on a non-linear regression in the intraday time interval, n, and the daily volatility factor, σ_t:

$$x_{t,n} = f(\theta : \sigma_t, n) + u_{t,n} \tag{4}$$

It is worth mentioning that from Eq (3) we see that the $R_{t,n}$ is a random variable because $Z_{t,n}$ is a random variable, while the other variables are deterministic. So we have:

$$E(\log s^2{}_{t,n} + \log Z^2{}_{t,n}) = f(\theta : \sigma_t, n) \tag{5}$$

$$u_{t,n} = \log s^2{}_{t,n} + \log Z^2{}_{t,n} - E(\log s^2{}_{t,n} + \log Z^2{}_{t,n}) \tag{6}$$

And because $s_{t,n}$ is not a random variable:

$$u_{t,n} = \log Z^2{}_{t,n} - E(\log Z^2{}_{t,n}) \qquad (7)$$

Therefore $u_{t,n}$ is a i.i.d random variable with mean zero. In Andersen and Bollerslev (1997) the non-linear regression function is approximated by a flexible Fourier functional form like the one proposed by Gallant (1981, 1982), but they allow this functional form to vary with the daily volatility level. This is the approach that we take, but we also allow a regression of dummy variables, one for each intraday time period, that 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 expressed in the following equation[82]:

$$f(\theta : \sigma_t, n) = \sum_{j=0}^{J} \sigma_t^j \left[\mu_{0j} + \mu_{1j} \frac{n}{N} + \mu_{2j} \frac{n^2}{N^2} + \sum_{i=1}^{D} \lambda_{ij} I_{n=i} + \sum_{p=1}^{P} \left(\gamma_{pj} \cos \frac{pn2\pi}{N} + \delta_{pj} sin \frac{pn2\pi}{N} \right) \right] \qquad (8)$$

Where we allow j to be 0 or 1, and p to be from 1 to 6. And the dummy variable regression is:

$$f(\theta : \sigma_t, n) = \sum_{j=0}^{J} \sigma_t^j \left[\sum_{i=1}^{28} \lambda_{ij} I_{n=i} \right] \qquad (9)$$

Where we allow j to be 0 or 1. Finally, we use the Akaike model selection criterion to choose the model to be used to estimate the intraday seasonal factors. With this criterion we select one model from all the models we estimate, that is, the twelve models implied in equation 8 and the two models implied in equation 9. 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 penalize models with more variables, but not too much, in order to keep models with a good fit to estimate intraday volatility patterns.

Kofman and Martens (1997) also use the flexible Fourier functional form approach to estimate intraday volatility patterns, but do not differentiate the daily process in variance from the intraday process in variance as assumed in Eq. 1. Hence Kofman and Martens (1997) propose the following model:

$$\left| e_{t,n} \right| = f(\theta : \sigma_t, n) + u_{t,n}$$

Where $e_{t,n}$ comes from a first filtering of the returns time series with an ARMA model. Andersen and Bollerslev (1997) show that intraday financial data are consistent with the

[82] 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 μ_1 and μ_2, both polynomials can reproduce the same functional forms.

idea of two processes in variance, a daily process and an intraday process. Therefore, we follow the Andersen and Bollerslev (1997) approach, that is:

$$2\log\left[\left|R_{t,n}-E(R_{t,n})\right|\right]-\log\sigma^2{}_t+\log N=f(\theta:\sigma_t,n)+u_{t,n} \tag{10}$$

Where $E(R_{t,n})$ is the unconditional mean of the returns time series. However, we are using transaction prices and transaction prices are subject fluctuations between the bid and the ask. As is shown in the literature, this behavior induces 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 moving average of order 1 to calculate the expected return[83]. Hence, the following is the model we use to calculate the $E(R_{t,n})$:

$$E(R_{t,n})_t=c+\beta_1 I_n e_{t-1,28}+\beta_2(1-I_n)e_{t,n-1} \qquad I_n=1 \text{ if } n=1 \tag{11}$$
$$I_n=0 \text{ if } n>1$$

In the end, we are using the same methodology of Andersen and Bollerslev (1997), but taking the filtered returns for the spurious autocorrelation induced by bid-ask bouncing as the true price process, and leaving the possibility of dummy regressions to estimate the intraday process. Another difference with Andersen and Bollerlev (1997) is that they use GARCH[84] 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 instead of using models like the GARCH.

Let $\bar{f}_{t,n}=f(\bar{\theta};\bar{\sigma}_t,n)$ denote the resulting estimate of the non-linear function, by the flexible Fourier functional forms or by the dummy variable regression. Let T denote the total number of 15-minute periods, so that [T/N] is the number of days. Andersen and Bollerslev (1997) suggest the following estimator of the intraday seasonal factor for interval n on day t:

$$\hat{s}_{t,n}=\frac{T\cdot\exp(\bar{f}_{t,n}/2)}{\sum_{t=1}^{[T/N]}\sum_{n=1}^{N}\exp(\bar{f}_{t,n}/2)} \tag{12}$$

[83] Given that it is not a standard technique to eliminate this spurious autocorrelation we repeated the analysis taking the unconditional mean as the expected return, as Andersen and Bollerlev (1997). And we present those results in Appendix B

[84] These are models that modelize the autoregresive process in variance. Engel (1982) introduced the ARCH models and Bollerslev (1986) generalized the ARCH models with the GARCH models.

Given Eq. 5 and that the intraday seasonal factor is not a random variable we have:

$$\hat{s}_{t,n} = \frac{T \cdot \exp(\overline{E(Z_{t,n})}/2) \cdot \exp(\bar{s}_{t,n}/2)}{\exp(\overline{E(Z_{t,n})}/2) \sum_{t=1}^{[T/N]} \sum_{n=1}^{N} \exp(\bar{s}_{t,n}/2)} \tag{13}$$

So that the random variable $Z_{t,n}$ disappears from the equation. This estimator implies normalization because:

$$\frac{\sum_{n=1}^{N} \sum_{t=1}^{[T/N]} \hat{s}_{t,n}}{T} = 1 \tag{14}$$

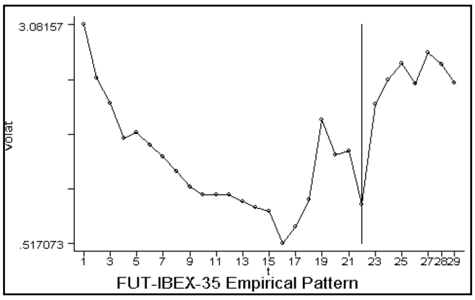
In Eq. 8 to estimate intraday volatility factors there are dummy variables to fit any behaviour in the patterns that breaks the nice U-shaped pattern and that is difficult to fit adding sines and cosines to the flexible Fourier functional form. In the case of the Spanish firms, we estimate an empirical intraday volatility pattern for the IBEX-35 to detect the intraday periods where a dummy variable is needed for the IBEX-35 and for each Spanish stock. This empirical pattern is estimated as the mean in each intraday period of a variable equal to the left-hand side of Eq. 10. Thus for the IBEX-35 and each of the Spanish firms in the sample these dummy variables were for moments around the NYSE opening and in the last trading periods of the SSE.

For the Future contract on the IBEX-35 these moments were also around the NYSE opening and in the last periods of trading, but fewer dummy variables were enough. In the Future contract on the S&P 500 these moments were in the first and last trading periods.

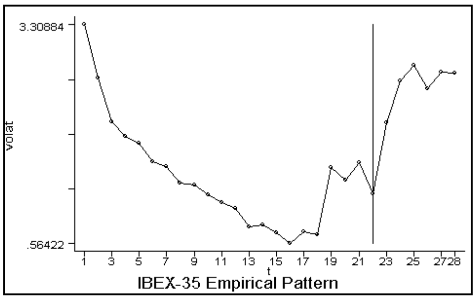
In figure a.1 we present the empirical intraday volatility patterns for the IBEX-35, the Future contract on the IBEX-35 and the Future contract on the S&P 500.

Figure a.1 Intraday volatility patterns

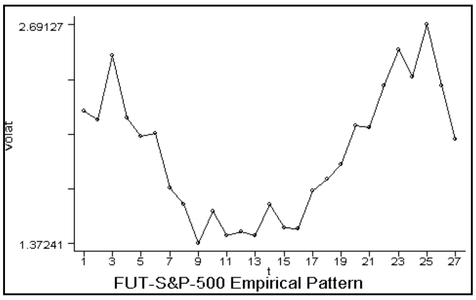
a.



b.



c.



- The intraday volatility pattern has been calculated as the mean of the left-hand side of Eq. 10 in each intraday period[85]. In a it is the pattern for the Future contract on the IBEX-35, in b for the IBEX-35, and in c for the Future contract on the S&P 500. In the case of the Spanish indexes it is especially marked, with a vertical bar, the NYSE opening.

The dummy variables identified with the empirical pattern for the IBEX-35 were used for all the Spanish stocks, so we used more dummy variables for them than for the Future contract on the IBEX-35. With the Future contract on the S&P 500, we find some of the largest movements in our sample around 10:00 a.m. New York time. Dropping these large movements we got a decreasing intraday volatility since the opening.

Finally, it is worth mentioning that in the case of the stock by stock analysis we have an additional problem, that is the lack of liquidity. Some stocks have days without trading. On those days we have zero daily volatility and we get a missing observation in the variable equal to the right-hand side of Eq. 10. In order to avoid those 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 did trials with and without this replacement and got close results.

[85] Taking the unconditional mean as the expected return we get very similar patterns. The graphs of those patterns are available from the author on request.

APPENDIX B

The analysis presented in sections 5.A.3, 5.A.4, 5.A.5, and 5.B is done with return time series filtered by a moving average of order one to eliminate the spurious autocorrelation induced by bid-ask bouncing in transaction prices. Because this is not a standard technique for eliminating this spurious autocorrelation, in order to evaluate the effect of this filtering on the final results of the paper we repeated the analysis without this filter. The results are very close and led us to the same conclusions.

Table B.1.a. Results in mean, equivalent to section 5.A.3.

Correlation between the US connection in mean for each Spanish stock and their percentage of American activity. Returns have been filtered for the U-shaped pattern in variance.

Sample	Inac+dually	Inac-no-dually[3]	Accurate+dually[4]	Accurate-no-dually
Corr-50[1]	0.4651	** 0.1827	0.4570	** 0.1650
P-value[2]	0.000	0.098	0.000	0.197
Corr-60	0.5426	0.2857	0.5634	0.3206
P-value	0.000	0.001	0.000	0.002
Corr-70	0.5101	0.2053	0.5591	0.2793
P-value	0.000	0.012	0.000	0.005
Corr-80	0.5027	0.1377	0.5299	** 0.1455
P-value	0.000	0.049	0.000	0.084
Corr-90	0.5182	** 0.0817	0.5258	** 0.1028
P-value	0.000	0.307	0.000	0.242

1. Correlation coefficient between the US connection in mean and the percentage of American activity for the Spanish stocks sample with stocks that trade at least for the 50% of the 15-minute trading periods.
2. Probability value of the correlation coefficient, calculated with the White standard errors.
3. Samples of Spanish stocks that include Spanish firms with an inaccurate estimation of their percentage of American activity.
4. Samples of Spanish stocks that just include stocks with an accurate estimation of the percentage of American activity. Dually listed stocks in the SSE and in the NYSE are included in the sample.

** Not significantly different from zero at the 5% significance level.

Table B.1.b Results in variance, equivalent to section 5.A.3.

Correlation between the US connection in variance for each Spanish stock and their percentage of American activity. Returns have been filtered for the U-shaped pattern in variance.

Sample	Inac+dually	Inac-no-dually[3]	Accurate+dually[4]	Accurate-no-dually
Corr-50[1]	0.5378	0.2874	0.5961	0.3539
P-value[2]	0.000	0.002	0.000	0.001
Corr-60	0.5720	0.3277	0.6474	0.4272
P-value	0.000	0.000	0.000	0.000
Corr-70	0.5535	0.2938	0.6403	0.4145
P-value	0.000	0.003	0.000	0.001
Corr-80	0.5427	0.2450	0.6335	0.3721
P-value	0.000	0.017	0.000	0.005
Corr-90	0.5656	0.2816	0.6418	0.4076
P-value	0.000	0.022	0.000	0.005

1. Correlation coefficient between the US connection in variance and the percentage of American activity for the Spanish stocks sample with stocks that trade at least for the 50% of the 15-minute trading periods.
2. Probability value of the correlation coefficient, calculated with the White standard errors.
3. Samples of Spanish stocks that include Spanish firms with an inaccurate estimation of their percentage of American activity.
4. Samples of Spanish stocks that just include stocks with an accurate estimation of the percentage of American activity. Dually listed stocks in the SSE and in the NYSE are included in the sample

** Not significantly different from zero at the 5% significance level.

Table B.1.c Results for dually listed stocks, equivalent to section 5.A.3.

Correlation between the US connection for each Spanish stock dually listed in the NYSE and their percentage of American activity. It is with the US connection in mean and in variance. Returns have been filtered for the U-shaped pattern in variance.

	Dually with inaccurate[4]	Dually without inaccurate
Mean[1]	0.6967	0.7049
P-value	0.008	0.013
Variance[2]	** 0.4428	** 0.4662
P-value[3]	0.151	0.143

1. Correlation coefficient between US connection in mean and the percentage of American activity.
2. Correlation coefficient between the US connection in variance and the percentage of American activity.
3. Probability value of the correlation coefficient, calculated with the White standard errors.
4. Sample with just dually listed stocks in the NYSE that includes one stock with an inaccurate estimation of the percentage of American activity.

** Not significantly different from zero at the 5% significance level.

Table B.2.a Results in mean, equivalent to section 5.A.4.

Correlation between the US connection in mean for each Spanish stock and their percentage of American activity. Returns have been filtered for the U-shaped pattern in variance, and a further filter has been applied to eliminate any remaining autoregresive structure in mean.

Sample	Inac+dually	Inac-no-dually[3]	Accurate+dually[4]	Accurate-no-dually
Corr-50[1]	0.4572	** 0.1840	0.4485	** 0.1654
P-value[2]	0.000	0.095	0.000	0.193
Corr-60	0.5343	0.2868	0.5541	0.3197
P-value	0.000	0.001	0.000	0.002
Corr-70	0.5007	0.2074	0.5482	0.2786
P-value	0.000	0.012	0.000	0.005
Corr-80	0.4931	0.1397	0.5198	** 0.1437
P-value	0.000	0.046	0.000	0.085
Corr-90	0.5105	** 0.0810	0.5172	** 0.0982
P-value	0.000	0.312	0.000	0.259

1. Correlation coefficient between the US connection in mean and the percentage of American activity for the Spanish stocks sample with stocks that trade at least for the 50% of the 15-minute trading periods.
2. Probability value of the correlation coefficient, calculated with the White standard errors.
3. Samples of Spanish stocks that include Spanish firms with an inaccurate estimation of their percentage of American activity.
4. Samples of Spanish stocks that just include stocks with an accurate estimation of the percentage of American activity. Dually listed stocks in the SSE and in the NYSE are included in the sample.

** Not significantly different from zero at the 5% significance level.

Table B.2.b Results in variance, equivalent to section 5.A.4.

Correlation between the US connection in variance for each Spanish stock and their percentage of American activity. Returns have been filtered for the U-shaped pattern in variance, and a further filter has been applied to eliminate any remaining autoregresive structure in the absolute value of returns.

Sample	Inac+dually	Inac-no-dually[3]	Accurate+dually[4]	Accurate-no-dually
Corr-50[1]	0.4622	0.2091	0.5073	0.2565
P-value[2]	0.000	0.008	0.000	0.002
Corr-60	0.4771	0.2097	0.5346	0.2744
P-value	0.000	0.013	0.000	0.004
Corr-70	0.4324	** 0.1374	0.5075	0.2199
P-value	0.000	0.097	0.000	0.017
Corr-80	0.3923	** 0.0425	0.4480	** 0.0598
P-value	0.001	0.608	0.001	0.496
Corr-90	0.3966	** 0.0444	0.4614	** 0.0883
P-value	0.002	0.655	0.001	0.332

1. Correlation coefficient between the US connection in variance and the percentage of American activity for the Spanish stocks sample with stocks that trade at least for the 50% of the 15-minute trading periods.
2. Probability value of the correlation coefficient, calculated with the White standard errors.
3. Samples of Spanish stocks that include Spanish firms with an inaccurate estimation of their percentage of American activity
4. Samples of Spanish stocks that just include stocks with an accurate estimation of the percentage of American activity. Dually listed stocks in the SSE and in the NYSE are included in the sample

** Not significantly different from zero at the 5% significance level.

Table B.2.c Results for dually listed stocks, equivalent to section 5.A.4.

Correlation between the US connection for each Spanish stock dually listed in the NYSE and their percentage of American activity. It is with the US connection in mean and in variance. Returns have been filtered for the U-shaped pattern in variance, and for the existence of remaining autoregresive structures in returns and in absolute value of returns.

	Dually with inaccurate[4]	Dually without inaccurate
Mean[1]	0.6837	0.6957
P-value	0.009	0.014
Variance[2]	** 0.4085	** 0.4210
P-value[3]	0.066	0.072

1. Correlation coefficient between US connection in mean and the percentage of American activity.
2. Correlation coefficient between the US connection in variance and the percentage of American activity.
3. Probability value of the correlation coefficient, calculated with the White standard errors.
4. Sample with just dually listed stocks in the NYSE that includes one stock with an inaccurate estimation of the percentage of American activity.

** Not significantly different from zero at the 5% significance level.

Table B.3.a Results in mean, equivalent to section 5.A.5.

Correlation between the US connection in mean for each Spanish stock and their percentage of American activity. Returns have been filtered for the U-shaped pattern in variance, have been standardized by the daily volatility level, and a further filter has been applied to eliminate any remaining autoregresive structure in those returns.

Sample	Inac+dually	Inac-no-dually[3]	Accurate+dually[4]	Accurate-no-dually
Corr-50[1]	0.4553	** 0.1623	0.4551	** 0.1612
P-value[2]	0.000	0.105	0.000	0.174
Corr-60	0.5204	0.2444	0.5504	0.2969
P-value	0.000	0.002	0.000	0.002
Corr-70	0.4825	0.1537	0.5482	0.2554
P-value	0.000	0.039	0.000	0.007
Corr-80	0.4708	** 0.0659	0.5207	** 0.1030
P-value	0.000	0.275	0.000	0.194
Corr-90	0.4873	** -0.0478	0.5201	** 0.0327
P-value	0.000	0.572	0.000	0.699

1. Correlation coefficient between the US connection in mean and the percentage of American activity for the Spanish stocks sample with stocks that trade at least for the 50% of the 15-minute trading periods.
2. Probability value of the correlation coefficient, calculated with the White standard errors.
3. Samples of Spanish stocks that include Spanish firms with an inaccurate estimation of their percentage of American activity.
4. Samples of Spanish stocks that just include stocks with an accurate estimation of the percentage of American activity. Dually listed stocks in the SSE and in the NYSE are included in the sample.

** Not significantly different from zero at the 5% significance level.

Table B.3.b Results in variance, equivalent to section 5.A.5.

Correlation between the US connection in variance for each Spanish stock and their percentage of American activity. Returns have been filtered for the U-shaped pattern in variance, have been standardized by the daily volatility level, and a further filter has been applied to eliminate any remaining autoregresive structure in the absolute value of those returns.

Sample	Inac+dually	Inac-no-dually[3]	Accurate+dually[4]	Accurate-no-dually
Corr-50[1]	0.4331	** 0.0467	0.4575	** 0.0849
P-value[2]	0.000	0.543	0.000	0.368
Corr-60	0.4944	** 0.1145	0.5410	0.1933
P-value	0.000	0.090	0.000	0.030
Corr-70	0.4446	** 0.0021	0.5144	** 0.1156
P-value	0.000	0.975	0.000	0.217
Corr-80	0.4002	** -0.1727	0.4573	** -0.109
P-value	0.005	0.100	0.007	0.394
Corr-90	0.3825	** -0.2466	0.4447	** -0.1268
P-value	0.017	0.083	0.010	0.352

1. Correlation coefficient between the US connection in variance and the percentage of American activity for the Spanish stocks sample with stocks that trade at least for the 50% of the 15-minute trading periods.
2. Probability value of the correlation coefficient, calculated with the White standard errors.
3. Samples of Spanish stocks that include Spanish firms with an inaccurate estimation of their percentage of American activity.
4. Samples of Spanish stocks that just include stocks with an accurate estimation of the percentage of American activity. Dually listed stocks in the SSE and in the NYSE are included in the sample.

** Not significantly different from zero at the 5% significance level.

Table B.3.c Results for dually listed stocks, equivalent to section 5.A.5.

Correlation between the US connection for each Spanish stock dually listed in the NYSE and their percentage of American activity. It is with the US connection in mean and in variance. Returns have been filtered for the U-shaped pattern in variance, have been standardized by the daily volatility level, and a further filter has been applied to eliminate any remaining autoregresive structure.

	Dually with inaccurate[4]	Dually with out inaccurate
Mean[1]	0.7383	0.7383
P-value	0.007	0.013
Variance[2]	0.6729	0.6754
P-value[3]	0.016	0.026

1. Correlation coefficient between US connection in mean and the percentage of American activity.
2. Correlation coefficient between the US connection in variance and the percentage of American activity.
3. Probability value of the correlation coefficient, calculated with the White standard errors.
4. Sample with just dually listed stocks in the NYSE that includes one stock with an inaccurate estimation of the percentage of American activity.

** Not significantly different from zero at the 5% significance level.

Table B.4 . Descriptive statistics of the US connection in mean and in variance.

	Mean US connection in mean	Mean US connection in variance
Raw returns[1]	0.2056	0.1312
$R_{t,n}/s_{t,n}$ [2]	0.1929	0.1321
$ARMA(R_{t,n}/s_{t,n})$[3]	0.1981	0.0752
$ARMA(R_{t,n}/s_{t,n}\sigma_t)$[4]	0.2048	0.0600

1. Mean results for the raw return series.
2. Mean results for the series corrected for the U-shaped pattern in intraday volatility.
3. Mean results for the series corrected for the U-shaped pattern in intraday volatility, and where a further ARMA filter has been applied eliminate any remaining autocorrelation in mean and in variance.
4. Mean results for the series corrected for the U-shaped pattern in intraday volatility, for similar daily volatility levels in both markets, and where a further ARMA filter has been applied eliminate any remaining autocorrelation in mean and in variance.

Table B.5 Index results. There is the price relation between the Future contract on the S&P 500 and the Future contract on the Ibex-35, and the Ibex-35.

	FUTIB[6]	IBEX[7]
Raw returns mean[1]	**0.6323**	**0.6211**
P_val	**0.000**	**0.000**
Raw returns variance	0.4600	0.4590
P_val	0.000	0.000
$R_{t,n}$ / $S_{t,n}$ returns mean	**0.6021**	**0.5896**
P_val	**0.000**	**0.000**
$R_{t,n}$ / $S_{t,n}$ returns variance[2]	0.4374	0.4369
P_val	0.000	0.000
ARMA[$R_{t,n}/S_{t,n}$] returns mean[3]	**0.6028**	**0.5898**
P_val	**0.000**	**0.000**
ARMA[$R_{t,n}/S_{t,n}$] returns variance	0.3302	0.3104
P_val	0.000	0.000
ARMA[$R_{t,n}/S_{t,n}\sigma_t$] returns mean	**0.6058**	**0.5920**
P_val	**0.000**	**0.000**
ARMA[$R_{t,n}/S_{t,n}\sigma_t$] returns variance[4]	0.3200	0.3082
P_val[5]	0.000	0.000

1. Results for the raw return time series.
2. Results for the series corrected for the U-shaped pattern in intraday volatility.
3. Results for the series corrected for the U-shaped pattern in intraday volatility, and where a further ARMA filter has been applied eliminate any remaining autocorrelation.
4. Results for the U-shaped pattern in intraday volatility, for similar daily volatility levels in both markets, and where a further ARMA filter has been applied eliminate any remaining autocorrelation.
5. Newey-west standard errors, robust to heteroskedasticity and autocorrelation till lag 6 in the case of the Ibex-35 and till lag 7 in the case of the future contract on the Ibex-35. The future contract on the Ibex-35 is traded for one 15-minute period more after the closing in the Spanish Stock Market.
6. Results for the correlation coefficients between the Future contract on the S&P 500 and the Future contract on the Ibex-35, in mean and in variance.
7. Results for the correlation coefficients between the Future contract on the S&P 500 and the Ibex-35, in mean and in variance.

APPENDIX C

A "NEWEY-WEST"/"WHITE" STANDARD ERROR FOR THE CROSS-CORRELATION

To calculate the "Newey-West" or the "White" standard error for the cross-correlation coefficient, we use the methodology used in Kofman and Martens (1997). They describe the methodology in the appendix of their paper. However, because it is a non-standard technique we describe the methodology in this appendix.

Suppose we have two time series, y_t and x_t (with zero mean[86]), for which we need to estimate the cross-correlation, as well as a heteroskedasticity and autocorrelation consistent standard error. Consider the following two regressions:

$$y_t = \rho_1 x_t + u_{1t} \tag{C.1}$$

$$x_t = \rho_2 y_t + u_{12t} \tag{C.2}$$

In this case the OLS estimators for ρ_1 and ρ_2 are:

$$\hat{\rho}_1 = \frac{\sum_{t=1}^{T} x_t y_t}{\sum_{t=1}^{T} x_t^2} = \frac{\operatorname{cov}(x_t, y_t)}{\operatorname{var}(x_t)} \tag{C.3}$$

$$\hat{\rho}_2 = \frac{\sum_{t=1}^{T} x_t y_t}{\sum_{t=1}^{T} y_t^2} = \frac{\operatorname{cov}(x_t, y_t)}{\operatorname{var}(y_t)} \tag{C.4}$$

Where T is the number of observations. Thus, an estimator for the cross-correlation between x_t and y_t is then:

$$\hat{\rho}_{xy} = \frac{\sum_{t=1}^{T} x_t y_t}{\sqrt{\sum_{t=1}^{T} x_t^2 \sum_{t=1}^{T} y_t^2}} = \frac{\operatorname{cov}(x_t, y_t)}{\sqrt{\operatorname{var}(x_t)\operatorname{var}(y_t)}} = sign(\operatorname{cov}(x_t, y_t))\sqrt{\hat{\rho}_1 \hat{\rho}_2} \tag{C.5}$$

[86] Remember that: $corr(x, y) = corr(x - \bar{x}, y - \bar{y})$. Where $\bar{x}$ is the mean of x and $\bar{y}$ is the mean of y.

Based upon the above Kofman and Martens (1997) apply the following procedure. Regressions C.1 and C.2 will be estimated simultaneously with:

$$z = \begin{pmatrix} y_1 \\ . \\ . \\ . \\ y_T \\ x_1 \\ . \\ . \\ . \\ x_T \end{pmatrix} = \begin{pmatrix} x_1 & 0 \\ . & . \\ . & . \\ . & . \\ x_T & 0 \\ 0 & y_1 \\ . & . \\ . & . \\ . & . \\ 0 & y_T \end{pmatrix} \begin{pmatrix} \rho_1 \\ \rho_2 \end{pmatrix} + \begin{pmatrix} u_{11} \\ . \\ . \\ . \\ u_{1T} \\ u_{21} \\ . \\ . \\ . \\ u_{2T} \end{pmatrix} = X\rho + u \qquad \text{(C.6)}$$

If we denote the rows of the matrix X with X_t (t=1.....2T), then the Newey-West variance-covariance matrix is equal to:

$$\hat{V}\left[\hat{\rho}\right] = (X^{'}X)^{-1}\left[\sum_{t=1}^{2T} \hat{u}_t^2 X_t X_t^{'} + \sum_{j=1}^{H-1} w_j \sum_{s=j}^{2T} \hat{u}_s \hat{u}_{s-j}(X_s X_{s-j}^{'} + X_{s-j} X_s^{'})\right](X^{'}X)^{-1} \qquad \text{(C.7)}$$

$$\hat{V}\left[\hat{\rho}\right] = \begin{bmatrix} Var(\hat{\rho}_1) & Cov(\hat{\rho}_1 \hat{\rho}_2) \\ Cov(\hat{\rho}_1 \hat{\rho}_2) & Var(\hat{\rho}_2) \end{bmatrix} \qquad \text{(C.8)}$$

Where w_j=1-j/H, and $E[u_t u_{t-j}]=0$ for j≥H for a given value of H. For H=0 this gives the White (1980) variance-covariance matrix. Using equation (C.5) we can construct a "Newey-West" or a "White"[87] standard error for the cross-correlation by applying the well-known "delta-method". See for example, Bishop et al (1975) page 486. Let :

$$f(\rho_1, \rho_2) = \sqrt{\rho_1 \rho_2} \qquad \text{(C.9)}$$

Then, the gradient will be:

$$\nabla f = \begin{pmatrix} \frac{\partial f}{\partial \rho_1} & \frac{\partial f}{\partial \rho_2} \end{pmatrix} = \begin{pmatrix} \frac{1}{2}\sqrt{\frac{\rho_2}{\rho_1}} & \frac{1}{2}\sqrt{\frac{\rho_1}{\rho_2}} \end{pmatrix} \qquad \text{(C.10)}$$

[87] Depending on the value of H.

And (using the estimates for the parameters in (C.10)) the Kofman and Martens (1997) estimation of the "Newey-West" or "White" standard error for the cross-correlation coefficient is:

$$\sqrt{\mathrm{var}(\rho_{xy})} = \sqrt{\nabla\hat{f}\hat{V}\left[\hat{\rho}\right]\nabla\hat{f}'} \qquad \text{(C.11)}$$

APPENDIX D

Table D.1. Control variable and sample, according to liquidity, of each Spanish stock.

Company Name	Sample**	Mean*
TELEFONICA	90%	0.4
ENDESA	90%	0.6
REPSOL	90%	0.6
BANCO BILBAO VIZCAYA	90%	0.7
BANCO DE SANTANDER	90%	0.7
ARGENTARIA	90%	1.0
IBERDROLA	90%	1.1
BANCO CENTRAL HISPANO	90%	1.1
BANCO POPULAR	90%	1.6
TUBACEX	90%	1.9
TABACALERA	90%	2.0
UNION ELECTRICA-FENOSA	90%	2.0
BANCO ESPAÑOL DE CREDITO (BANESTO)	90%	2.1
DRAGADOS Y CONSTRUCCIONES	90%	2.3
GAS NATURAL SDG	90%	2.4
ACERINOX	90%	2.4
AMPER	90%	2.5
BANCO INTERCONTINENTAL ESPAÑOL	90%	2.6
AUTOPISTAS CONCESIONARIA ESPAÑOLA	90%	2.8
PRYCA	90%	2.9
TELE PIZZA	90%	3.0
CORPORACION MAPFRE	90%	3.1
AUTOPISTAS DEL MARE NOSTRUM	90%	3.3
CONSTRUCCIONES LAIN	80%	3.3
VALLEHERMOSO	90%	3.4
FUERZAS ELECTRICAS DE CATALUÑA	90%	3.5
SEVILLANA DE ELECTRICIDAD	90%	3.6
C.C. CONTINENTE	90%	3.7
AGUAS DE BARCELONA	90%	3.8
HIDROELECTRICA DEL CANTABRICO	80%	4.1
LA SEDA DE BARCELONA	70%	4.2
AGROMAN	80%	4.3
ENERGIA E IND. ARAGONESAS	80%	4.3
SOTOGRANDE	70%	4.3
INMOBILIARIA URBIS	70%	4.4

- * Mean of the control variable calculated as difference between the moment when a price happened and the moment when it is supposed to happen in order to construct 15-minute return time series. This variable is measured in minutes. It is measured including the crisis week and the days with splits.
- ** Indicates the highest liquid sample at witch pertains the stock when we make samples that keep stocks with a minimum percentage of 15-minute periods with trading.

Table D.1 Continuation

Company Name	Sample**	Mean*
TAVEX ALGODONERA	70%	4.5
PRIMA INMOBILIARIA	60%	4.7
FILO	70%	4.7
BANCO DE VALENCIA	70%	4.8
ZARDOYA OTIS	70%	4.8
EL AGUILA	60%	4.9
METROVACESA	70%	4.9
PROSEGUR	60%	5.1
INMOBILIARIA ZABALBURU	50%	5.1
MARCO IBERICA, D.E. -MIDESA-	60%	5.1
CIA. ESPAÑOLA DE PETROLEOS	70%	5.2
CORTEFIEL	60%	5.2
VIDRALA	60%	5.3
ABENGOA, S.A.	50%	5.3
EUROPISTAS CONCESIONARIA ESPAÑOLA	60%	5.3
BANCO PASTOR	60%	5.4
GAS Y ELECTRICIDAD	50%	5.5
MAPFRE VIDA	50%	5.6
BANCO ZARAGOZANO	60%	5.6
ELECTRICAS REUNIDAS DE ZARAGOZA	50%	5.8
PORTLAND VALDERRIVAS	50%	5.9

- * Mean of the control variable calculated as difference between the moment when a price happened and the moment when it is supposed to happen in order to construct 15-minute return time series. This variable is measured in minutes. It is measured including the crisis week and the days with splits.
- ** Indicates the highest liquid sample at witch pertains the stock when we make samples that keep stocks with a minimum percentage of 15-minute periods with trading.

Table D.2 Stock market indexes control variable

Index Name	Mean*
Future contract on the S&P 500	0.108
Future contract on the IBEX-35	0.403
IBEX-35	0.128

- * Mean of the control variable calculated as difference between the moment when a price happened and the moment when it is supposed to happen in order to construct 15-minute return time series. This variable is measured in minutes. It is measured including the crisis week. In the case of the Future contract on the S&P 500, Kofman and Martens (1997) found this measure to take a value of 7.8 seconds in a different time period. In our case this measure takes value 6.57 seconds.

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