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Methods For Extracting Information From Financial Markets

Doctoral Dissertation Presented by

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A Papá y Mamá,
por vuestro apoyo incondicional,
por todo el cariño, por cuidar de mí,
y sobre todo, por animarme tanto a llegar hasta aquí.

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Summary

The financial research literature has evolved significantly on the development of methodologies to extract the information content on financial data. The extraction of accurate information from financial data has important implications for the market participants and analysts, and it is also essential for monetary authorities given the implications that the deeper knowledge of the functioning of financial markets might have for the financial stability. This doctoral dissertation aims to contribute to the literature in financial research in four different topics related to market behavior and information transmission among markets.

Concretely, the four topics are the following:

- First, we implement a new methodology to detect episodes of abnormal market behavior.
- Next, we propose an indicator for the strength of the market movements and a new indicator of representative market returns.
- Then, we compare the performance of this new measure of market return with the traditional return based on closing prices by assessing the different impact that relevant news have when taking each of these measures as the representative market return.
- Finally, and getting deeper into the information transmission field, we try to assess the effect that relevant news from emerging economies might have on global financial markets.

The first chapter aims to improve the assessment of market expectations by providing a new

methodology to detect episodes of abnormal market behavior. This new procedure is based on:

a) the literature on implied density functions that provides the framework to extract market expectations from option prices and,

b) the bootstrap resampling technique, which is helpful to replicate the market conditions within the same trading date so that we can calculate a benchmark for the market behavior.

The idea is to obtain a daily benchmark for the skewness statistic of the implied probability density function in option prices, which is used as a proxy of negative outcomes priced by the market. This methodology allows us to identify three different types of market behavior: normal, fuzzy and abnormal ones. The empirical application is based on the Spanish Ibex-35 index over the period 1997 to 2005.

The second chapter analyzes the strength of the market movement using the information content in the trading volume. We start from the fact that prices and volumes reflect investors' opinion on future asset prices. However, instruments of financial analysis sometimes underuse the information embedded in the trading volume. Therefore, this chapter proposes a new indicator of the Strength of the Market Movement based on prices and volumes and shows that its distribution is a helpful instrument to identify the market opinion on the prices' evolution. Moreover, we introduce the Movement Strength Weighted Return as a measure to improve the information content of the data used for market analysis. The empirical analysis is performed using intra-day data from the Spanish Future on the IBEX-35 index during 2004.

Then, on the third chapter we try to compare this new measure of Movement Strength Weighted Return (also denominated Volume Weighted Return) with the traditional return based on closing prices. Then, we evaluate the impact that relevant news from developed and emerging markets linked to the Spanish economy have when assessing the market evolution using as the representative market return: (a) the volume weighted return or, (b) the return based on closing prices.

The empirical findings suggest that this new measure of market performance provides more moderate estimates of the impact of the relevant news coming from abroad, thus it might be significant to evaluate accurately the impact that other economies exert on the Spanish market.

Finally, on the last chapter we analyze the transmission of emerging market shocks to global equity markets. Namely, we analyze whether, and to what extent, emerging market economies (EMEs) have systemic importance for global financial markets, above and beyond their influence during crises episodes. Using a novel database of exogenous economic and political shocks for 14 systematically relevant EMEs, we find that EME shocks not only have a statistically but also economically significant impact on global equity markets.

The economic significance of EME shocks is in particular underlined by their remarkably persistent effects over time. Importantly, EMEs are found to influence global equity markets about just as much in "good" times as in "bad" times, i.e. during crises or periods of financial turbulence. Finally, we detect a large degree of heterogeneity in the transmission of EME shocks to individual countries' equity markets, stressing the different degrees of financial exposure, which is relatively higher for European equity markets.

The main contributions of this doctoral dissertation are summarized as follows:

a) Enhance the evaluation of market expectations by introducing and implementing a new technique that appraises market participants' expectations about a decline in prices that is not supported by the information available in the market.

b) Test that the abnormal market behavior indicator seems to be a reliable indicator of significant market movements.

c) Propose an indicator that mixes price and trading volume, named Strength of the Market Movement in order to identify the degree of support for a certain trend.

d) Using the last indicator indicator, also propose the Distribution of the Strength across Returns, which constitutes a useful technique to quickly identify opinions from investors.

e) Suggest a new method of computing the daily representative return as the Movement Strength Weighted Return that accurately reflects the market trend during the day.

f) Test empirically on the Spanish IBEX-35 index that the indicator of the Strength of the Market Movement and the Distribution of the Strength across Returns can help investors to obtain information on the aggregate opinion in the market. Also test empirically that the Movement Strength Weighted Return can improve the analysis of time series using a complete and representative measure of the market evolution.

g) Analyze the market performance using the Volume Weighed Return (Market Strength Weighted Return) as the representative market return and evaluate the impact that other economies exert on the Spanish market, especially US and Latin America using a standard GARCH (1,1) model.

h) Provide a database for shocks arising in 14 emerging countries that has the key advantage of containing largely exogenous shocks that are specific to individual emerging economies.

i) Estimate the transmission of these shocks to 29 mature economies and emerging markets and find that EME shocks have a statistically and economically significant impact on global equity markets.

Resumen

La investigación en el campo de las finanzas ha avanzado significativamente en el desarrollo de metodologías para extraer la información contenida en datos financieros. La obtención de información precisa es fundamental para los agentes y analistas del mercado, y también es esencial para las autoridades monetarias dadas las implicaciones que puede tener el conocimiento del funcionamiento de los mercados financieros para la estabilidad financiera. Esta tesis doctoral pretende contribuir a la literatura financiera en cuatro temas relacionados con el comportamiento del mercado y la transmisión de información entre mercados.

Concretamente, estos cuatro temas son los siguientes:

- En primer lugar, se desarrolla una nueva metodología para detectar episodios de comportamiento anormal del mercado.
- A continuación, se propone un indicador de la fortaleza de movimiento del mercado y una nueva medida de rendimiento representativo de los cambios de precios en el mercado.
- Más adelante, se compara esta nueva medida de rendimiento frente al rendimiento basado en precios de cierre y se evalúa el diferente impacto que tienen las noticias procedentes del exterior cuando se utiliza cada uno de estos indicadores como rendimiento representativo.
- Finalmente, y profundizando en el campo de la transmisión de información entre mercados, se trata de evaluar el impacto que las noticias procedentes de economías emergentes tienen sobre los mercados financieros globales.

El objetivo del primer capitulo es mejorar la evaluación de las expectativas de mercado desarrollando una metodología para detectar comportamiento anormal en el mercado. Este nuevo procedimiento se basa en:

a) la literatura sobre distribuciones de probabilidad implícitas en los precios de las opciones, que constituye el marco para la extracción de expectativas a partir de los precios de las opciones y,

b) el bootstrap como técnica estadística de remuestreo que ayuda a replicar las condiciones del mercado dentro del mismo día de negociación, de modo que podemos calcular un punto de referencia para el comportamiento de mercado.

El objetivo es obtener diariamente un punto de referencia para la asimetría de la distribución de probabilidad implícita, que se utiliza como aproximación a los resultados negativos valorados por el mercado. Esta metodología permite identificar tres tipos de comportamiento de mercado: normal, confuso y anormal. La aplicación empírica se realiza a partir de datos del índice bursátil español Ibex 35 en el periodo comprendido entre 1997 y 2005.

El segundo capítulo analiza la fortaleza del movimiento del mercado utilizando la información contenida en el volumen de negociación. Se parte del hecho de que el precio y el volumen negociado de un activo contienen información sobre la opinión de los inversores en relación al precio del activo en el futuro. Sin embargo, en ocasiones, los instrumentos de análisis financiero infrautilizan la información disponible en el volumen de negociación. Este capítulo propone un nuevo indicador de fortaleza de movimiento del mercado basado en la información contenida en los precios y volúmenes negociados y muestra que su distribución constituye un instrumento útil para identificar la opinión del mercado sobre la evolución futura de los precios. Adicionalmente, este capítulo introduce el rendimiento ponderado por la fortaleza de movimiento, medida que pretende mejorar el contenido de la información utilizada para el análisis de los mercados. El análisis empírico se realiza sobre datos intradía del mercado español de futuros sobre el índice Ibex 35 durante el año 2004.

A continuación, el tercer capítulo compara la nueva medida de rendimiento ponderado por la fortaleza de movimiento (también denominado rendimiento ponderado por volumen relativo) con la medida convencional de rendimiento basada en los precios de cierre. Así, se evalúa el diferente impacto que tienen las noticias relevantes procedentes de economías desarrolladas y emergentes que están ligadas a la economía española considerando dos tipos diferentes de rendimientos:(a) rendimiento ponderado por volumen relativo, y (b) redimiento basado en precios de cierre. Los resultados empíricos sugieren que la nueva medida ofrece estimaciones más moderadas del impacto de otras economías y, por tanto, puede resultar significativo a la hora de evaluar el efecto que dichas economías tienen sobre el mercado español.

Finalmente, el último capítulo analiza la transmisión de shocks procedentes de países emergentes a los mercados globales de valores. En concreto, este capítulo analiza en qué medida las economías emergentes (EMEs) tienen una importancia sistémica en los mercados globales más allá de la influencia que llegan a tener durante los episodios de crisis. Utilizando una nueva base de noticias domésticas de carácter económico y político procedentes de 14 países emergentes, encontramos que los shocks procedentes de las EMEs no sólo tienen impacto estadístico sino también económico en los mercados globales de valores.

La relevancia económica de estos shocks queda subrayada por la remarcable persistencia de sus efectos en el tiempo. En concreto, encontramos que las EMEs influyen en los mercados globales de valores tanto en periodos de crisis y turbulencias como en periodos de mayor tranquilidad. Finalmente, detectamos un grado elevado de heterogeneidad en la transmisión de los shocks procedentes de las EMEs a los mercados individuales de países, marcando los diferentes niveles de exposición financiera, que es relativamente mayor para los mercados europeos.

Las principales contribuciones de esta tesis doctoral se resumen a continuación:

a) Mejorar la evaluación de las expectativas de mercado desarrollando una nueva técnica que mide el grado en que las expectativas de los agentes del mercado sobre una caída de precios no se sustentan con la información disponible en el mercado.

b) Contrastar empíricamente que el nuevo indicador de comportamiento anormal de mercado constituye un indicador fiable de movimientos de mercado significativos.

c) Proponer un indicador mixto de precios y volumen negociado, denominado Fortaleza de Movimiento de Mercado, para identificar el grado de soporte que una determinada tendencia tiene en el mercado.

d) Mediante este indicador, proponer la denominada Distribución de la Fortaleza por Rendimiento para identificar con rapidez la opinión de los inversores.

e) Sugerir un nuevo método para el cálculo del rendimiento diario representativo, denominado Rendimiento Ponderado por la Fortaleza de Movimiento (o también Rendimiento Ponderado por Volumen) que refleja de modo preciso la tendencia del mercado durante el día.

f) Contrastar empíricamente (utilizando datos del índice bursátil español, Ibex 35) que el indicador de Fortaleza de Movimiento de Mercado y la Distribución de Fortaleza por Rendimiento pueden ayudar a los inversores a obtener información sobre la opinión agregada del mercado. También, se contrasta empíricamente que el Rendimiento Ponderado por Volumen puede mejorar el análisis de las series temporales dado que constituye una medida más completa y representativa de la evolución del mercado.

g) Analizar la evolución del mercado utilizando el Rendimiento Ponderado por Volumen Negociado como rendimiento representativo del mercado y evaluar mediante un modelo GARCH el impacto que tienen otras economías (especialmente Estados Unidos y América Latina) sobre el mercado español.

h) Proporcionar una base de datos con shocks procedentes de países emergentes cuya ventaja fundamental es la de contener principalmente shocks exógenos que son específicos de determinadas economías emergentes.

i) Estimar la transmisión de estos shocks a un conjunto de 29 economías desarrolladas y emergentes y detectar que los shocks procedentes de EMEs tienen un impacto significativo en los mercados globales de valores.

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Chapter 1

Detecting Abnormal Market Behavior

1.1 Introduction

Option prices contain information about the market participants' expectations on the future price of the underlying asset. The implied probability density function in option prices (PDF) is an useful tool to extract price prospects for the underlying asset and its statistics might provide valuable information (e.g., Söderlind and Svensson, 1997; Deutsche Bundesbank, 2001).

After the stock market crash in October 1987, the negative skewness and leptokurtosis in the implied PDF raised notably (e.g. Jackwerth and Rubinstein, 1996; Bates, 2003). Since then, the lognormal distribution function is less accurate as a benchmark to estimate the shape of the PDFs. Compared to the lognormal distribution, the excess negative skewness shows that there are more negative than positive outcomes priced by the market, whereas excess leptokurtosis indicates the presence of extreme outcomes.

The aim of the chapter is to improve the assessment of market expectations by providing a new method to test if the market expects a downward movement in prices and whether this behavior is consistent with the information available. Specifically, we apply Breeden and Litzenberger

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(1978) and Shimko (1993) results to characterize the implied PDF. Then, we use the paired bootstrap to calculate a benchmark for the skewness of the implied PDF, which is used as a proxy of the market expecting a decline in prices.

If the market had no clue about the future and had no crash aversion, one would expect a similar number of trading operations considering an upward trend and downward trend in prices. Thus, the PDF should be rather symmetric in these cases. In a similar way of reasoning, the more trading operations that consider a downward trend in prices, the more negative skewed the PDF will be. In this chapter we use the negative skewness of the implied PDF to approximate a market that is pricing more negative than positive outcomes. Thus, we use this statistic as a proxy of the market that expects a decline in prices.

We cannot determine whether the negative skewness is at normal levels considering the lack of accurate benchmark for the distribution of the PDFs. Then, we aim to develop a new methodology to calculate a daily benchmark for the skewness of the PDF as a proxy for the market participants' expectations about a decline in prices. Namely, we wonder whether the observed skewness is consistent with the information present in the market. If the data observed in the market constitute an outlier for this daily benchmark, we classify it as abnormal market behavior (AMB) given that it is inconsistent with the information available in the market. In particular, we consider this behavior as inconsistent because the same information set produces bootstrap replications of the skewness of the PDF that are not similar to the observed skewness.

To be precise, the method proposed to assess the regularity of the skewness of the PDF is based on the calculation of the confidence intervals based on bootstrap percentiles for this statistic. Therefore, the fact that the observed statistic exceeds certain threshold on its bootstrap distribution can be interpreted as a warning signal of an abnormal market behavior. In this way, this new methodology can help to detect abnormal trading dates in the sense that the expectation of a decline in prices does not seem to be supported by the information set available in the market.

The bootstrap technique has gained importance in financial literature during recent years probably due to the fact that it does not rely on distributional assumptions. For instance, among other empirical studies, Andersson and Lomakka (2005) and Yatchew and Härdle (2006) use the bootstrap residual approach (e.g., Tibshirani, 1996) on the option pricing formula. Nevertheless, Brownstone and Valetta (2001) prove that, under the bootstrap residual approach, OLS estimation results are inconsistent when the true errors are heteroscedastic or not normally distributed, and they affirm that the results become consistent under the paired bootstrap approach. Following this conclusion, we apply the paired bootstrap approach when assessing the confidence intervals for the skewness statistic of the PDF.

In summary, we provide a new methodology to calculate a benchmark for the AMB that relies on a) the results of the literature on implied PDFs and b) on the confidence intervals based on bootstrap percentiles for the PDF skewness, as a proxy for the market participants' expecting a decline in prices.

The remainder of the chapter is organized as follows: section 2 presents the literature review on implied density functions and on the bootstrap resampling technique. Section 3 describes the data and the methodology applied. Section 4 presents the results; and finally, Section 5 presents the main concluding remarks.

1.2 A method to assess market behavior

In their seminal paper on implied density functions, Breeden and Litzenberger (1978) prove that the probabilities associated to the different future underlying asset prices can be derived from option prices. Since then, many articles have discussed different approaches to derive the PDF. Jackwerth and Rubinstein (1996) catalogue the different approaches according to a parametric vs. non parametric classification. We will follow their view on this chapter.

The parametric approach sets that the PDF follows a lognormal or mixture of lognormal distributions. Therefore, the estimation of its parameters is performed assuming a particular functional relation between the observed variables and statistical parameters such as volatility, skewness and kurtosis. The non-parametric method recovers the implied probabilities from contemporaneous market prices of the associated derivatives without pre-specification of the distribution function of the implied PDF.

Regarding the parametric techniques, Bahra (1997) revises several methods for estimating the implied PDF. He states that a weighted average of two lognormal distributions is the best method to deal with LIFFE equity index options, interest rate options and Philadelphia SE currency options.

The parametric approach has been widely used in empirical studies on crises during the nineties. Thus, for instance, Melick and Thomas (1997) use American options prices to estimate the corresponding empirical PDFs in the Gulf crisis (1990-1991) and show that a mixture of lognormal distributions provides more accurate results than a lognormal one. Nielsen (2001) assumes a mixture of two lognormal distributions to analyze the three-month Euribor during the ECB interventions on the exchange rate in 2000.

As a counter-example, Campa, Chang and Refalo (2002) use the Breeden and Litzenberger (1978) results to estimate the implied PDF. These authors take the expected future exchange rates as a measure of the credibility of the Brazilian Real crawling peg between 1994 and 1999. They base their calculation on the quadratic approximation for volatility proposed by Shimko (1993), which we will use in this chapter.

The non-parametric approach is applied by Andersson and Lomakka (2005), who compare the double lognormal (parametric) and the (non parametric) smoothing spline methods for estimating the implied PDF. They analyze the Swedish market concluding that the non-parametric approach produces more accurate PDF's estimations. Besides, Clews et al. (2000) also apply the non parametric approach to quantify the market uncertainty about the future evolution of short-term interest rates.

The seminal contribution to the bootstrap resampling technique is Efron (1979, 1981 and 1982). The most frequent application of the bootstrap technique to the literature on implied PDFs consists on applying the bootstrap to the error term of the volatility equation by re-sampling with replacement from a normal distribution (e.g., Andersson and Lomakka, 2005).

Besides, other researchers apply this resampling technique to the error term on the option pricing equation (e.g., Yatchew and Härdle, 2006). These two applications of the bootstrap to the error terms on the different equations rely on the fact that the error term is assumed to be normally distributed. However, the normality assumption is not always supported by the data. In this sense, Brownstone and Valetta (2001) argue in favor of the paired bootstrap to avoid the problems arisen from both the parametric and the non-parametric bootstrap residual approaches. The paired bootstrap approach used in this chapter for building the thresholds is consistent with Brownstone and Valetta (2001).

The new methodology proposed in this chapter could be combined to the existing measures of market anxiety, as the VIX index (e.g. CBOE, 2003) to detect episodes in which the market expects a decline in prices and does not behave consistently according the available information. The VIX index uses index option prices to measure the market's expectation of volatility. The reason why the VIX is usually called the "investor fear gauge" is that its highest historical levels are achieved during times of financial turmoil and investor fear. As markets recover and investor fear subsides, VIX levels tend to drop.[1] Therefore, the combination of our new method to detect abnormal market behavior and the "investor fear gauge" could lead to a measure of the "investor fear gauge" that might not be supported by the information available in the market and this, could be closely related to the crash-phobia.

As the value of an option depends on the probability of the option finishing in the money, Bates (1997) argues that prices of European call (put) options will reflect conditions in the upper (lower) tail of the risk neutral distribution. Under conditions of symmetric risk neutral distribution prices of out of the money call options should be identical to otherwise similar out of the money European put options. The prices deviate only if the underlying distribution is skewed. Consequently, a shift in the skewness of the underlying distribution can provide information about the market's perception of future movements in the underlying asset price. This is an extremely useful approach when assessing skewness at certain degree of moneyness. In a sense, this is a static measure since the skewness premium has to be computed for each moneyness degree. The new method proposed in this chapter takes into account the skewness statistic of the implied PDF, thus, considers the entire range of moneyness. Besides, Bliss and

[1] For more details, see http://www.cboe.com/micro/vix/vixwhite.pdf

Panigirtzoglou (2004) develop a method to calculate the risk aversion parameter implied in option prices by using the risk neutral and the subjective implied distribution functions.

Therefore, the new methodology proposed in this study does not target to create an indicator of risk aversion, but to detect abnormal market behavior. In this way, this methodology can be an additional tool for the market analysis.

1.2.1 Extracting information from option prices

Options contracts are used to speculate or hedge against a certain risk related to future prices. The prices at which options are traded contain information on the market participants' uncertainty about future underlying prices. Under certain assumptions the information in options prices can be expressed in terms of the probability that the price of the underlying asset will lie within particular ranges. This is the implied probability density function (PDFs) for future asset values.

PDFs do not necessarily provide the actual probabilities of an asset price realizing particular values in the future. Instead they can provide an idea of the probabilities that option market participants in aggregate attach to different outcomes. One assumption in the calculations is that market participants do not require compensation for risk (they are 'risk neutral').

One of the implications of extracting implied PDFs from option prices by assuming investors are risk neutral is a lower mean than that in a risk-averse world. Turning to the higher moments of implied PDFs (dispersion, asymmetry and kurtosis), work thus far suggests that, outside of periods of extreme market turbulence, the assumption of risk neutrality has little impact. Overall, this means that the risk neutral assumption seems to be more important for the location of an implied PDF than for the shape of the distribution.

We use both, call and put options by using the put-call parity condition to convert put option prices into call option prices. The shape of the implied PDF depends, among other factors, on the time to expiration of the option contracts. Then, we calculate the (daily) implied PDF for all option contracts with the same time to expiration. For simplicity on the presentation and given that we use settlement prices, we do not indicate the time parameter subscript in the equations.

As a first step to derive the implied PDF we analyze the relation between the moneyness degree (strike to futures price ratio) and the implied volatility using a quadratic approximation:[2]

$$\sigma_k = \beta_0 + \beta_1 \cdot moneyness_k + \beta_2 \cdot (moneyness_k)^2 \tag{1.1}$$

where,

- σ_k denotes the observed implied volatility for the option with strike k,
- β_0 denotes a constant parameter,
- $moneyness_k$ is the observed moneyness degree of the option with strike k,
- $k = 1, \ldots, K$ is the sequence of strikes with open positions observed in the market.

Once the parameters are estimated, we simulate a new series for equally spaced strike prices, $\widehat{x_k}$, and their corresponding moneyness degree, m_k. The maximum and minimum strikes observed in the market data are considered as upper and lower bounds for the simulated strike prices.

Then, the implied volatilities associated to the simulated moneyness degree are calculated according to the relation estimated in (1), that is:

$$\hat{\sigma_k} = \hat{\beta}_0 + \hat{\beta}_1 \cdot m_k + \hat{\beta}_2 \cdot (m_k)^2 \tag{1.2}$$

Where, $\hat{\sigma_k}$ designates the implied volatility calculated from the simulated moneyness degree and the estimated parameters in (1), $\beta_i, i = 0, \ldots, 2$ denotes the estimated parameters in (1) m_k indicates the simulated moneyness degree.

Option prices on futures on an index are calculated applying the Black (1976) model. Then, we get:

$$\hat{c_k} = e^{-r_f \cdot \tau} \cdot [f \cdot \Phi(d_1) - x \cdot \Phi(d_2)] \tag{1.3}$$

[2] Same approach as in Shimko (1993) and Bliss and Panigirtzoglou (2002).

where,

$$d_1 = \frac{ln(\frac{f}{\hat{x_k}}) + \frac{1}{2} \cdot \frac{\hat{\sigma}_k^2}{\tau}}{\hat{\sigma}_k \sqrt{\tau}},\ d_2 = d_1 - \hat{\sigma}_k \sqrt{\tau}$$

and,

- f designates the futures´ price,
- $\widehat{x_k}$ denotes the strike price
- Φ is the distribution function of a standard normal variable
- $\hat{\sigma}_k$ is the estimated implied volatility for the option with strike k.
- r_f denotes the continuously compounded risk free interest rate,
- τ stands for the option's time to expiration.

Finally, to compute the PDF as a function of the option price, we apply Breeden and Litzenberger (1978) according to the following equation:

$$P(\hat{m_k}) = \frac{(\hat{c_{k+1}} - \hat{c_k}) - (\hat{c_k} - \hat{c_{k-1}})}{(\Delta k)^2} \tag{1.4}$$

We use the skewness of the implied PDF to monitor the asymmetry of the distribution provided that an excess negative skewness could signal disproportionate number of negative outcomes prices by the market.

However, the application of the skewness as a proxy for market behavior is pointless unless there is a benchmark to use as reference. In this regard, the bootstrap resampling method helps to compute this benchmark for the skewness as long as it replicates the same information structure observed in the market.

As explained before, the new indicator could be combined to other existing measures of market anxiety as the skewness premium (Bates, 1997) or the VIX index (e.g. CBOE, 2003). The main advantage of our method is that it is able to detect when the market does not behave consistently according to the available information.

Finally, the current observed skewness could be compared to its historical standard deviation instead of computing the bootstrap percentiles. However, this benchmark would be less accurate than the one we propose especially during high volatility episodes.

The following subsection briefly summarizes the bootstrap literature and presents the methodology used to calculate the bootstrap percentiles for the skewness of the implied PDF.

1.2.2 Computation of the bootstrap percentiles

The bootstrap resampling technique is applied to compute a threshold for the skewness of the implied PDF. This technique allows us to estimate the distribution of the skewness of the implied PDF using the same information structure observed in the market.

The bootstrap method consists on the following steps:

1. We start resampling with replacement from the original dataset, $Y = \{y_1, y_2, \ldots, y_k, \ldots, y_K\}$, to build a bootstrap data set, $Y_1^* = \{y_2^*, y_5^*, \ldots, y_{70}^*, \ldots, y_K^*\}$, generally of the same number of observations as the original dataset. The bootstrap dataset that contains the same information structure than the original data.
2. Repeat the re-sampling process B times until we obtain B bootstrap datasets, $\{Y_1^*, Y_2^*, \ldots, Y_b^*, \ldots, Y_B^*\}$.
3. Compute the summary statistic of interest, s , for each of the bootstrap datasets. In this way we get B bootstrap statistics, $\{s_1^*, s_2^*, \ldots, s_b^*, \ldots, s_B^*\}$.
4. Finally, we compute the $\alpha - bootstrap$ confidence interval by calculating the α and $1 - \alpha$ percentiles of $\{s_1^*, s_2^*, \ldots, s_b^*, \ldots, s_B^*\}$.

In more detail, we calculate the implied PDF and the bootstrap distribution for its skewness statistic on a daily basis. To do so, we first calculate de implied PDF and the associated skewness from the original dataset:

Table A. Original dataset

Obs.	Option Strike	Option price	Implied volatility	Futures price
1	8000	1892	44.56	9893
2	8050	1842	44.19	9893
...	...	...	...	...
k	9100	794	36.42	9893
...	...	...	...	...
K-1	10550	1	27.25	9893
K	10650	0	26.75	9893

Then, we apply the paired bootstrap to the original data, by resampling with replacement the characteristics of the strikes. Namely, we build a new dataset that selects a strike and the associated option price, implied volatility and future price as shown in Table B. The next step is to calculate the implied PDF and the corresponding skewness for the bootstrap dataset.

Table B. Bootstrap dataset

Obs.	Option Strike	Option price	Implied volatility	Futures price
49	10400	5	28	9893
7	8300	1592	42.34	9893
2	8050	1842	44.19	9893
51	10500	2	27.5	9893
18	8850	1043	38.27	9893
39	9900	123	30.5	9893
...	...	...	...	...
46	10250	18	28.75	9893

We repeat the process 1000 times and obtain 1000 bootstrap samples to ensure the accuracy of the estimations. Finally, to compute the bootstrap percentiles, we erase those PDFs not satisfying the condition $0.99 \leqslant \sum_{k=1}^{K} P(\hat{m}_k) \leqslant 1$.

In order to find the normal levels in terms of skewness, we compute the percentile where the observed skewness lays within its bootstrap distribution. Then, we consider that there is evidence of abnormal market behavior if the observed statistic is not very similar to that obtained in the bootstrap samples. That is, we consider that there is evidence of abnormal market behavior if the skewness exceeds certain threshold. Thus, any time the skewness falls below a lower bound, we interpret that there is a signal of the market expecting a decline in prices that is not consistent with the information available. The threshold must be settled by the analyst according to the specific market characteristics and to the desirable sensitiveness of the warning signal. We consider the 20^{th} percentile as the threshold for the abnormal market behavior.[3]

1.3 Empirical Application to the Spanish Ibex 35

1.3.1 Data Sources

We use daily data on settlement prices and their corresponding implied volatilities for European call options on the IBEX 35 over the period $January 2^{nd}$, 1997, through $July 12^{th}$, 2005. These data were obtained from MEFF (Mercado Español de Futuros Financieros).[4]

We analyze options with expiration smaller than 30 days to get the information of the more liquid contracts in the market. We have 102 expiration dates in our sample period. The database contains 2,029 trading dates (expiration dates are excluded), although 20 out of them are excluded from the later analysis due to some data problems that impede the PDF calculation. Table 1 lists, on a yearly basis, some statistics for the main variables:

[INSERT TABLE 1 AROUND HERE]

[3] If we took the 10^{th} (30^{th}) percentile, we would have too few (many) warning signals. We checked the performance of this threshold and it works well, but we insist that some calibration may be needed depending on the market and analyst's purposes.

[4] We selected settlement prices rather than closing prices since the former provide further information on market expectations, given that any open position is signaling certain opinion about the future evolution of the underlying asset price. Also, settlement prices are stated at the same instant for any strike with open positions, while the closing prices may be set at different trading hours and thus, causing asynchronous quotes estimation problems.

Finally, the discount factors are computed using daily data on the 3-month Madrid Interbank Offered Rate (MIBOR) interest rates, obtained from Datastream.

1.3.2 Estimation

The methodology detailed previously is applied to study the evolution of the implied PDF skewness statistic on the Spanish IBEX-35. The classification supports three different types of days according to market behavior: fuzzy, abnormal and normal.

1. Fuzzy market behavior: days in which there are not enough open positions at different strike prices to characterize the PDF accurately. In these cases, the cumulative probability of the implied PDF is smaller than 0.99. The intuition is that possibly, the wait-and-see trading strategies (when agents close their positions in the market and wait until they have more information on contemporaneous events) dominate the market. We think that in these cases agents do not have enough reliable information to operate in the market. As a consequence, the range of strikes with open positions narrows and it causes problems to compute the PDF. These trading dates are considered (and labeled) as fuzzy market behavior.

2. We consider either normal or abnormal market behavior if and only if the PDF can be completely characterized, so that we can calculate their corresponding summary statistics. The distinction between both behaviors is as follows:

   (a) Normal market behavior takes place when the observed skewness lays above the 20^{th} percentile threshold.

   (b) On the contrary, abnormal market behavior takes place when the observed skewness falls below the 20^{th} bootstrap percentile. In this case, the observed skewness is different than the bootstrap replications obtained from the same information set. Thus, we defend that the observed skewness is not very consistent with the information available in the market.

Figures 1 to 3 show these three types of behavior found in the data. The expiration date is set to 21 days on these figures. We can highlight the following facts:

1. The normal market behavior presents an implied PDF with a wide range of moneyness degree. The probability is concentrated in the interval $[0.9, 1.1]$, that is, close to the at the money options.

   [INSERT FIGURE 1 AROUND HERE]

2. Abnormal market behavior: in this case the implied PDF presents a flatter shape with clearly fatter tails. Market participants' expectations about future price are far more heterogeneous than in the previous case. Additionally, the range of moneyness is narrower compared to the normal behavior. A possible explanation is that the abnormal market behavior might be accompanied by "wait and see strategies" when market participants abandon the market and wait until more information is available.

   [INSERT FIGURE 2 AROUND HERE]

3. Finally, the implied PDF in the fuzzy market behavior is similar to the abnormal market behavior case except that the implied PDF cannot be completely characterized. Comparing to the normal behavior, the shape of the distribution is flatter and the tails are also significantly fatter, showing a greater heterogeneity among market participants' expectations about the future underlying price. However, in this case there is a narrower range of moneyness traded in the market. A possible explanation is that the "wait and see strategies" (whereby agents cancel their open positions until they have further information on events) become dominant for the extreme events on this type of trading dates. Therefore, there is evidence something odd takes place in the market during the fuzzy market behavior trading dates.

   [INSERT FIGURE 3 AROUND HERE]

1.4 Results

As mentioned before, we identify two possible deviations from the normal market behavior (NMB): abnormal market behavior (AMB) and fuzzy market behavior (FMB). Both of them seem to be associated to “wait and see” strategies, and the difference between them is that, under AMB, the PDF can be completely characterized whereas, under FMB, there is no enough information in the market to accurately compute the implied PDF.

We present a benchmark based on the same trading date information set.[5] Table 2 summarizes he results for the whole sample period. For presentation purposes, the results are detailed on a yearly basis:

[INSERT TABLE 2 AROUND HERE]

The main findings are the following:

- The more frequent abnormal and fuzzy market behavior trading dates during the 1997-1998 period could be explained by a simultaneous market immaturity and the sequence of events related to the crises contagion that took place in those years. The period under study witnessed the Asian, Russian, Argentinean, and Turkish crises. Also, Banco de España interventions to correct the evolution of the Spanish Peseta against the German Mark caused several episodes of AMB. By the end of 1998, the impact of the Iraq attack on the market behavior provoked another episode of AMB. Since 1999, the FMB decreases significantly indicating, probably, a different stage of the market maturity.
- In 1999, FMB days diminish notably. In return for this, the Brazilian crisis, the lack of confidence on the Euro, the Kosovo War, several declarations of the IMF regarding

[5]However, any other reference period (keeping constant time to expiration) could be an alternative. The requirement of keeping constant the time to expiration relates to the changing characteristics of the implied PDF across time.

the stock markets overvaluation plus the subsequent market correction, and the high US commercial deficit along with a depreciation of the US Dollar set a maximum on the AMB records over the entire sample period .

- In 2000, the Dot-com crisis happened. Besides, the continuous increase in oil prices and the disappointing evolution of the Euro[6] were other factors that could impact the market behavior. While the AMB is still high on this year, the FMB drops dramatically. This fact might be due to a different market reaction to the bubble burst compared to other crisis types that involved higher degree of uncertainty. The Argentinean crisis in 2001 and the beginning of a large series of accounting scandals in 2001 (Enron), 2002 (WorldCom, Andersen and AOL among others) could introduce a large degree of uncertainty in the markets, explaining the higher level of FMB with respect to the AMB.
- In 2003, the Invasion of Iraq could cause the abnormal market behavior. The market started an upward trend by the end of 2002, after a three-year period decrease in market prices. There are no FMB days recorded in 2003 and 2004, and the AMB registered correspond to the first increase in US interest rates in four years, the impact of the Abbey Bank acquisition by Banco Santander Central Hispano and the increase in oil prices up to historical maximums.
- Finally, in 2005, several episodes of AMB can be provoked by the oil price evolution and the uncertainty associated due to its impact on the world economy.

We test the relation between the indicator of market behavior and the market volatility.[7]In this exercise we follow a similar approach as Kaminsky and Smuckler (1999). To do this, we regress the proxy for the market behavior on the historical market volatility and a dummy variable for relevant news that could impact significantly on the market. In more detail, we use the indicator of market behavior is approximated by the bootstrap percentile where the skewness based on real data lays. The dummy variable for relevant news coming from abroad takes value 1 any time there are significant news released on abnormal market behavior days and zero otherwise.[8]

[6]This required a joint intervention by the European Central Bank, US Federal Reserve and Bank of Japan.

[7]In this exercise we follow a similar approach as Kaminsky and Smuckler (1999).

[8]To avoid the selection bias, news were obtained from the Bekaert and Campbell (1998, 2004) database for relevant economic and political news from the US and emerging countries.

Figure 4 graphs a line for the daily skewness bootstrap percentile and bars for the dates when relevant news were released to the market at the same time that the skewness went below the 20^{th} percentile threshold. There seems to be a negative relation between the skewness percentile and the release of relevant news. Thus we expect a negative relation between the dummy for news and the skewness percentile. On the same vein, we also expect a negative relation between the market volatility and the market behavior proxy.

[INSERT FIGURE 4 AROUND HERE]

Then, we obtain the following equation:

$$\begin{aligned} market\ behavior_t = {} & \underset{(0.0064)}{0.4424} - \underset{(0.0242)}{0.1699} \cdot market\ volatility_t - \underset{(0.0048)}{0.2553} \cdot dummy_t + \epsilon_t \\ & R^2 = 0.249,\ F - Test = 0.000 \end{aligned}$$

We find that both explanatory variables are statistically significant. As expected, the market behavior is negatively related to the market volatility, so that the higher the volatility (market uncertainty) the lower the skewness percentile tends to be. This makes sense provided that higher market volatility would cause lower skewness percentiles indicating that the market prices more negative outcomes. In addition, the dummy variable for selected news is also negative and statistically significant.

Finally, we test the prediction capability of the AMB indicator, which seems to be quite satisfactory. The daily return on IBEX-35 exceeds (in absolute terms) 1% in 92 out of the 109 AMB cases within the following 3 days after the AMB signal appears over the entire 1997 - 2005 period.[9]

Table 3 summarizes the results for significant market movements after an AMB indicator. In short, this table shows the number of days in which returns exceed 1% (in absolute value) that appear 1, 2 or 3 days after the AMB signal. It seems that the AMB can be a good predictor

[9]Following the advice of market practitioners, we take the 1% threshold as a significant market movement.

of significant market movements. Additionally, we insist that this methodology is not able to capture all the significant market movements. However, the utility of the new methodology proposed to assess the market behavior, and the use of the AMB signal as predictor of returns exceeding 1% (in absolute terms), is notable.

[INSERT TABLE 3 AROUND HERE]

1.5 Conclusions

This chapter tried to enhance the evaluation of market expectations by introducing and implementing a new technique that appraises market participants' expectations about a decline in prices that is not supported by the information available in the market. This new method is built on the basis of previous literature on implied PDFs that provides a framework to obtain market expectations from option prices.

Changing market conditions make difficult the characterization of normal behavior patterns. To overcome this problem, this chapter suggests the bootstrap resampling technique to reproduce market conditions within the same trading date. The approach is quite general, allowing for different definitions of normal market behavior depending on the researcher's interest and providing flexible thresholds to distinguish among the different behavior patterns. In this sense, the method can be applied to different markets and to diverse stages of market maturity. This methodology should be useful to analysts who wish to avoid the introduction of additional information structure rather than market data.

Market data reflects three different types of market behavior: normal, fuzzy and abnormal. The main qualitative conclusion of the empirical application shows that the abnormal market behavior indicator seems to be a reliable indicator of significant market movements.

Tables and Figures

Table 1

Call Options on IBEX-35 Futures - Summary Statistics by Year

This table presents the main trading figures per year. Namely, it present the total number of trading days, the average number of option contracts with open positions per trading day, the minimum and maximum strikes traded, the maximum option price and maximum option implied volatility, and the minimum and maximum prices for the future contract.

		Call options					Futures	
			Strike		Price	Volatility	Price	
Year	Days	N./d	Min	Max	Max	Max	Min	Max
1997	236	64	3500	8900	3290	59.02	4982	7328
1998	236	115	4000	13500	4744	98.36	7153	10933
1999	238	111	6000	13000	5526	70.86	9131	11740
2000	238	144	5000	15200	6450	71.2	8841	12804
2001	238	146	4000	15500	4850	70.17	6453	10167
2002	238	134	2000	13500	4738	83.6	5361	8483
2003	238	109	3000	11000	4025	66.56	5458	7730
2004	239	96	3700	10800	4673	62.08	7586	9091
2005	128	96	4500	11400	5131	38.12	8942	9641

Table 2
Trading Dates Classification per Year

This table presents the total number of trading days classified among the three categories of market behavior calculated according to new method proposed in this paper.

	Year									
Type	1997	1998	1999	2000	2001	2002	2003	2004	2005	Total
Abnormal	16	22	30	18	4	4	8	3	4	109
Fuzzy	69	48	23	3	17	16	0	0	1	177
Normal	151	166	185	217	208	207	230	236	123	1723
Total	236	236	238	238	229	227	238	239	128	2009

Table 3
Abnormal Market Behavior: Significant Market Movements

This table summarizes the results for the significant market movements after an AMB day. In short, column AMB shows the total number of Abnormal Market Behavior days registered per year. The column "Next day" shows the number of days that show a return exceeding 1% (in absolute value) following an AMB signal. Columns "Within 2 days" and "Within 3 days" contain the number of days where return exceed 1% (in absolute value) 2 and 3 days after the AMB signal.

Year	AMB signals	Next day	Within 2 days	Within 3 days
1997	16	6	11	13
1998	22	12	17	21
1999	30	12	22	22
2000	18	16	18	18
2001	4	2	3	4
2002	4	1	2	2
2003	8	4	8	8
2004	3	2	2	3
2005	4	0	0	1
Total	109	55	83	92

Figure 1
Normal Market Behavior, August 27^{th} 2004

In the case of Normal Market Behavior, the PDF is rather symmetric, with a wide range of moneyness degree quoted in the market. The probability is concentrated in the moneyness interval [0.9, 1.1]. This can be interpreted as that the market agrees on the future price being a 10% far from the strike price at the expiration date.

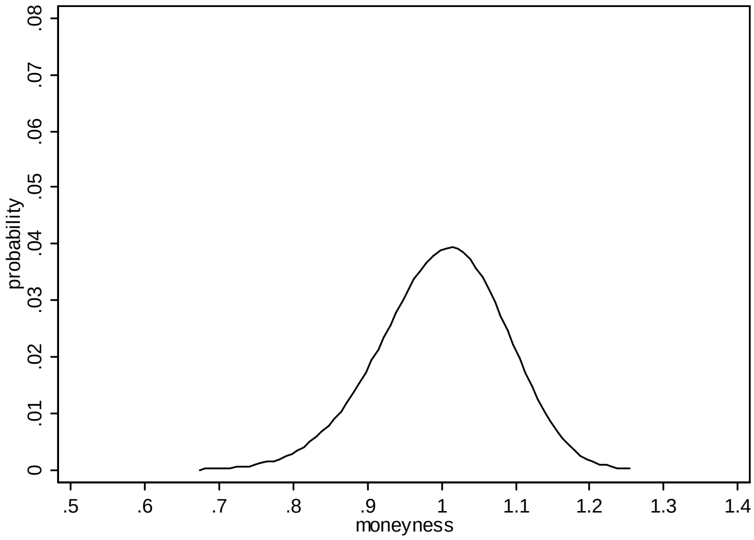


Figure 2
Abnormal Market Behavior, March 27^{th} 2003

In the Abnormal Market Behavior case the PDF shows a flatter shape with clearly fatter tails signaling greater heterogeneity on the market consensus about future price than in the previous case.

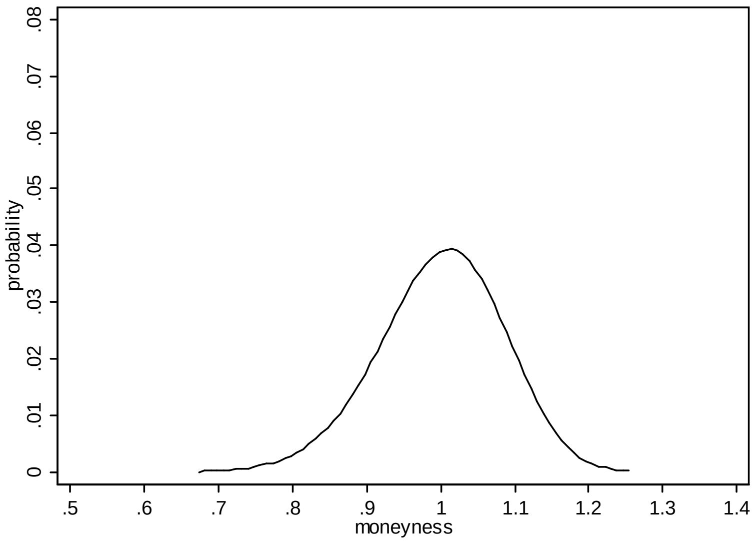


Figure 3
Fuzzy Market Behavior, October 26^{th} 2001

In the Fuzzy Market Behavior case the PDF cannot be completely characterized, in the sense that the probability do not add up to unity. Therefore, these cases are erased from the sample in order to calculate the statistics.

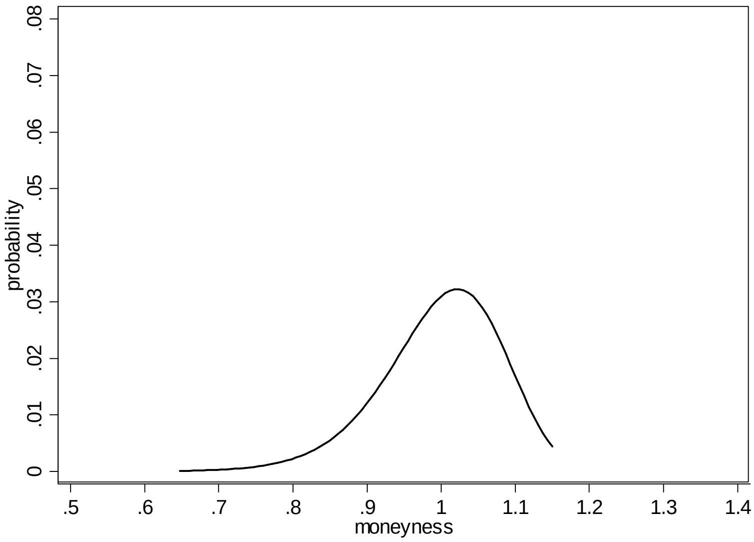
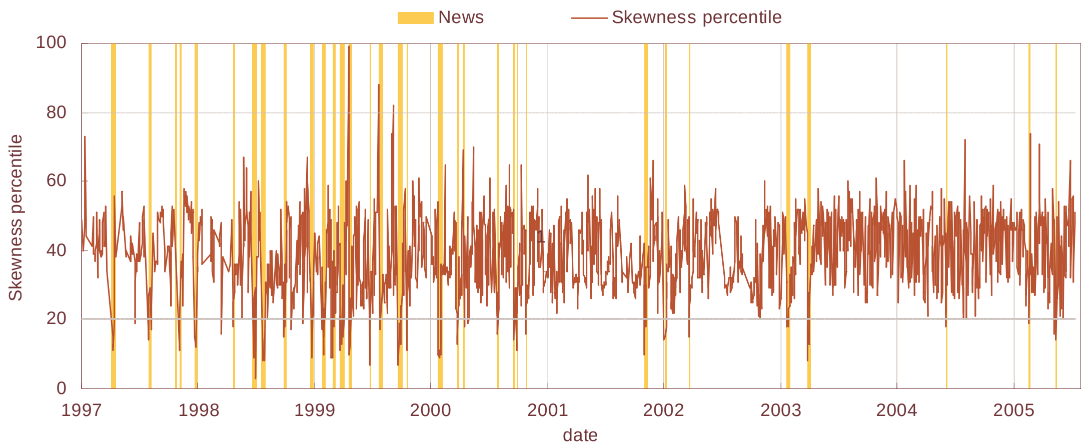


Figure 4
Market Behavior and Relevant News

This figure shows the percentile in which the observed skewness falls within its bootstrap distribution and the dates when relevant news where released to the market while at the same time the observed skewness exceeded the lower bound.



Chapter 2

Analysis of the Strength of the Market Movement Using the Information Content in the Trading Volume

2.1 Introduction

Over the last years, the evolution of the markets shows that the assumptions that the asset pricing models make on nonexistent transaction costs, market efficiency and rational behavior of the agents are systematically violated. The literature on behavioral finance focuses on the last factor: the breach of the assumption of agents' rational behavior on the financial markets, and contributes to explain and predict the systematic implications of the cognitive processes of decision making present in financial markets (Olsen, 1996; Thaler, 1999).

This stream of research began as a response to the increasing interest of practitioners on the impact that cognitive processes exert on decision criteria (Slovic, 1972; and Tversky and Kahneman, 1974), and argue that certain financial phenomena are better understood by introducing non-rational agents on the asset pricing models.

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There are two main pillars of the behavioral finance literature (Shleifer and Summers, 1990): a) limits to arbitrage, whereby a substantial impact might exist if there is any interaction between rational and non-rational agents (Mullainathan and Thaler, 2000); and b) cognitive psychology, which catalogues the kind of deviations from the rational behavior assumed by the market efficiency hypothesis (Fromlet, 2001).

The solutions proposed by this literature are useful for the individual investor since they widen the perspective on her environment and provide a deeper knowledge of the consequences implied by certain behavior patterns on the asset prices. From the authorities perspective, the advances in this research field facilitate the adoption of ex-ante measures that avoid abrupt endings associated to non-rational behavior such as, for instance, a stock market crash originated by a herd behavior and non supported by the real economic situation.

The main aim of this chapter is to provide some tools to detect episodes of herding or information cascades right at the beginning. In this way, these instruments could be of help for investors and monetary authorities to react in time to extreme market reactions. The basic idea idea behind the model in this chapter is that there exists a certain threshold upon which agents do not follow their own pricing rules but follow the market stream in order to avoid being trapped in their initial positions as on the information cascades or herding episodes.

Therefore, this article aims to contribute to the psychological perspective by: first, developing a new indicator for the strength of the market movement that identifies the degree of market support to a certain trend. Second, we use this new indicator of movement strength to calculate the distribution of strength across returns, which offers a global perspective of the importance associated to each possible return at any point in time. Finally, we propose a new approach to calculate the representative market return as the market strength weighted return, which improves the information content and the robustness of the measures for the evolution of market.

The remaining of this chapter is organized as follows: Section 2 presents an overview of the literature while section 3 develops the model of agents' behavior. Section 4 details the empirical analysis and, finally, section 5 summarizes the main concluding remarks.

2.2 Literature Review

Behavioral Finance aims to explain many reactions of financial markets that seem to be contrary to conventional theory and thus, can make an important contribution to avoidance of serious mistakes (Fromlet, 2001). The psychology approach included in the literature on Behavioral Finance (Barberis and Thaler, 2003) typifies the various deviations from rational behavior observed in human actions.

Some examples of these deviations are: imitation processes (Scharfstein and Stein, 1990; Bannerjee, 1992); disposition effect (Shefrin and Statman, 1985) heuristics dealing with information, varying availability of information, preference for certain news, differences in interpretation, the psychology of sending messages and anchoring (Fromlet, 2001); gender and overconfidence (Barber and Odean, 1998); control illusion (Shiller, 1999; Gervais and Odean, 2001); disposition effect (Odean, 1998); and following the herd (Eguiluz and Zimmermann, 2000).

In addition, the literature on Prospect theory initiated by Kahneman and Tversky (1979) analyses factors such as loss aversion (Kahneman and Tversky, 1992) and mental accounting (Shiller, 1999). These are some of the behavior patterns observed in financial markets that systematically violate the rational assumptions made by the neoclassical school.

This chapter contributes to the literature on Behavioral Finance by proposing a new indicator of Strength of the Market Movement based on a model for herding behavior. All the above mentioned issues, especially information cascades and herding are somehow reflected on financial variables such as returns, trading volumes or volatilities. We focus on the first two elements, returns and trading volumes, to build a new indicator that reflects agents' opinion on the market evolution, and that can constitute a helpful tool to detect episodes of herding behavior on the very short run.

In panic situations, certain decisions that are rational at an individual level cause an irrational result at an aggregate level. For instance, the classical example of a cinema fire shows how the individual rational decision of "leaving among the firsts" turns out to be chaotic and irrational when a relatively big group of people try to “leave among the firsts” at the same time. This type of chaotic situation also takes place in financial markets. As we will explain in detail, under certain circumstances the rational individual decision of selling a certain asset might trigger the massive sale of such asset at any price. This phenomenon is known as Irrational Exuberance (Greenspan, 1996; Shiller, 2000).

Herding behavior is an indication of the imitation processes that take place in the market and that can be observed in both upward and downward trends. In an upward trend, only quite a few assets increase their price. This is due to investors that think that these assets are underpriced (that is, that the asset is relatively cheap) and therefore they buy it at higher prices until the new equilibrium price. Meanwhile, other investors observe the upward trend and do not want to lose the opportunity of making profits even if they do not believe that the asset is cheap.

Nevertheless, herding behavior is more interesting on downward trends. Any time prices follow a downward trend, some analysts will justify it due to certain causes while some other analysts will not be able to justify the movement. If the downward trend strengthens, both those who think that there are information that supports the movement as well as those that think that the movement has no support will tend to adjust their portfolios to avoid any losses as far as this adjustment is still possible.

Fromlet (2001) distinguishes two different types of herding behavior: voluntary and enforced. The voluntary herding corresponds to those agents whose assessments are in line with the herd, and the enforced herding behavior is that of the players on financial markets that might think that is not worth while to fight against the herd, and follow the trend of the market to avoid being trampled on their initial positions. In this sense, countertendency investors might slow down the downward trend, although is very unlikely that they could invert the market trend. Besides, institutional investors would enhance the herding behavior. However, the role of the institutional investors shall be taken carefully given that they accede to a better quality information, and thus, can contribute to the information cascades rather than to the herding behavior.

The fact that we cannot distinguish between information cascades or herding behavior does not affect to the analysis implemented here. The purpose of the chapter is to provide tools to detect episodes of information cascades or herding at the very beginning, but not to determine whether these market movements are due to information cascades or herding, which we think that should be tackled in future research.

Herding behavior is reinforced by two phenomena: the varying availability of information and the preference for certain news. Information is not easily available to all agents in the market. Moreover, it is also possible that some agents do not have the skills or the intuition to apply it in an appropriate way (Fromlet, 2001). In this sense, if only a few investors know about a very negative piece of news (such as a Government inability to pay its external debt) they will trade discreetly in the market selling the Government bonds that they hold in their portfolios. As long as the trading volume increases and / or prices decrease in the process of getting rid of these Government bonds, there will be sharp uninformed agents that will perceive this discreet flight. They will follow the flight, making this movement even more evident to the rest of the market participants until prices finally tumble.

Especially regarding market stability, the preference for certain news also plays an important role among the factors that boost the herding behavior. This phenomenon reflects the fact that agents are reluctant to change their predictions and recommendations. This attachment to their first assessment might underestimate the importance of new information, particularly in the presence of relatively unimportant news that supports the old forecast (Fromlet, 2001).

Finally, the formation of speculative bubbles is closely related to the preference for certain news. If neither specialists nor authorities perceive in time the divergence among the real economy indicators and the evolution of market prices, or even if they cannot act effectively to reduce this divergence, then the stability of the financial markets might be jeopardized. On the bubble limit, some agents will revise their positions and expectations and they will start selling at perceptibly lower prices. If the volume of these operations at lower prices increases and a herding behavior shows up, then the probability of the bubble to burst increases.

In sum, the detection of herding behavior in time is of interest to investors to maintain the value of their portfolios. This is also of interest to authorities in order to maintain the stability of the financial system. In the following sections, we will develop a simple model that serves a basis to construct an indicator that can be of help in detecting herding behavior episodes in advance: the distribution of the market strength across returns.

2.3 Methodology

This section presents a new model for herding behavior that serves as the basis for the construction of the indicator of the strength of the market movement. This new indicator detects herd behavior in the very short run; therefore, it can be useful to avoid in extremis the possible extreme outcomes of such behavior.

Herding behavior is highly noticeable during stock market crashes in which information has not been incorporated to prices at the right time or when there is an overreaction of the market. When this herding behavior becomes evident, the asset prices are severely depreciated and the trading volumes are quite high. At this point, one could say that the market movement is very strong since it is not only that some operations support the fall in prices, but also that the vast majority of them sustain such movement. This is due to agents who want to leave the market as soon as possible and offer increasing volumes at lower and lower prices to avoid being tramped. However, there is a time interval in which the herding behavior is non evident and where authorities can intervene to transmit tranquility to the markets.

Below we present a model that considers the individual behavior pattern to assess asset prices and then, we explain the functioning of the market as a result of the individual patterns. Afterwards we describe the indicator of the strength of the market movement.

2.3.1 Behavior of the individual investor

To explain the asset-pricing model it is necessary to make certain assumptions on the criteria that agents use. We will assume that each investor has her own criteria such that the price of an asset can be decomposed on a reference value plus a second component that considers all the individual factors that correct the reference value. Then, the asset price is given by:

$$p_i = \nu + \psi_i, \tag{2.1}$$

where,

- $p_i \in \mathbb{N}$ is the price assigned by the investor i to the asset.
- $\nu \in \mathbb{N}$ denotes the reference value, it constitutes a key element of the model.
- $i = 1, ..., N$, where $N \in \mathbb{N}$ is the total number of investors that participate in the market.
- $\psi_i \in \mathbb{R}$ indicates the adjustment to the reference value.

The selection of the reference value, ν, is a fundamental issue in the model. Among the different possibilities to assess the reference value, ν, we discuss three of them:

[a] The present value of all future cash flows, which would be the ideal reference if we exactly knew the flows and the discount factors. Unfortunately, it is not possible to know any of these magnitudes accurately and its estimation is subject to significant biases.

[b] The asset value determined by the fundamental analysis, which is also subject to severe estimation biases given that the frequency of the data included in this analysis is much lower than the appropriate in technical analysis.

[c] The last option is to consider a neutral price, for instance, the opening price for the trading day. The main advantage of this option is that it does not incorporate any estimation bias. Also, and comparing to the closing price of the previous day, is that this is consistent with the calculation of the relative volume.

The adjustment that each agent applies to the reference value, ψ_i, considers all the subjective components considered by the individual investor in her valuation rule. Among these components, those of special relevance are characterized for being non-rational such as the preference for certain news, overconfidence and control illusion, imitation processes, and herding behavior or information cascades. This adjustment term depends, among other factors, on the following variables:

- The asset price during a given period, which might vary among agents, π_i
- The evolution of other asset prices used as benchmark for valuation, κ_i
- The interpretation of news, η_i
- The fact that the portfolio is running profit or losses at that time, d_i
- The individual's risk preferences, λ_i.

It should be noted that the importance of each component might vary between agents. Therefore, the importance assigned by each individual to each of the factors can be different. Moreover, the relation between the factors provided by $f(\circ)$ might be non-linear:

$$\psi_i = f(\pi_i, \kappa_i, \eta_i, d_i, \lambda_i). \tag{2.2}$$

As a result, each individual investor expects the market price to rely between an upper and lower bound. Therefore, the agent's own interval for the prices is given by:

$$p_t \in [p_i^{low}, p_i^{up}]. \tag{2.3}$$

Any time the condition in (3) is not satisfied (so that the price exceeds the upper or lower bound) will make the investor to revise his expectations and justify the change in the thresholds. If she succeeds, she will establish new upper and lower bounds on the threshold. Nonetheless, if she finds no explanation for the price variation, then she will probably follow the market trend.

2.3.2 Behavior of the market

We assume that each agent follows her own pricing criteria as long as the market price relies between the upper and lower bounds of the agent's valuation interval. However, according to the literature on herding behavior, as soon as the price falls out of the valuation interval, the agent will follow the market dominant trend to avoid being trapped in her initial position, that is:

$$p_i = \begin{cases} \nu + \psi_i & if \ p_t \in [p_i^{low}, p_i^{up}] \\ \nu + \psi_{market} & otherwise \end{cases}, \tag{2.4}$$

where ψ_{market} is the adjustment to the reference value observed in the market. We consider two possibilities in this model:

1. A balanced market behavior in which agents maintain their valuation rules:

$$\psi_{market} = \sum_{i=1}^{n} \psi_i \approx \varepsilon, \tag{2.5}$$

   where ε denotes a smooth market movement based on the public and private information available to the agents.

2. However, in some cases when a negative piece of news arrives at the market, the asset prices may go beyond the lower bound, and agents could follow the market trend if the information publicly available is not sufficient to explain such a big change. In this way, the strongest market trend, ψ_d, will dominate the weakest one, ψ_{nd}. Therefore, the adjustment to the reference value will be given by:

$$\psi_{market} = \sum_{i=1}^{n} \psi_i^d + \sum_{i=1}^{n} \psi_i^{nd} \not\approx \varepsilon, \tag{2.6}$$

The fact that one trend dominates the other depends, among other factors, on the messages that the market receives: those renowned persons or entities with high credibility have a greater ability to influence investors' perception about the market circumstances. Besides, there are private and public institutions (such as central banks, institutional investors or private investors with outstanding financial conditions) that are capable to influence the evolution of market prices.

The spillover of the dominant trend among agents follows the next mechanism: each individual has a different interval where the upper and lower bounds are given by $[p_i^{low}, p_i^{up}]$. Therefore the herding behavior takes place on a sequential basis provided that not all the agents detect at the same time the herding behavior since. Concretely, as long as the market prices go beyond the investors' thresholds bounds, more and more agents will follow the dominant market trend.

Taking all the above mentioned factors into account, we propose to calculate the strength of the market movement (i.e. the proportion of the market following a certain trend), $\vartheta_{d,\tau}$, as the ratio of the market correction of the trading operations that follow that given trend (i.e. ψ_i^d) relative to the correction of the reference value of the market, ψ_{market}:

$$\vartheta_{d,\tau} = \frac{\sum_{i=1}^{n} \psi_i^d}{\psi_{market}}. \tag{2.7}$$

But, how to measure ψ_i? Agents' preferences regarding risk, the period and the prices used as reference, or the benchmark assets are not easy to model and this target would go beyond the scope of this chapter. However, if we assume that we have a representative agent, all those aspects may be well reflected (although probably not completely) on the trading prices and volumes. The obvious indicator to assess ψ_i is the price change with respect to the reference value, however, this calculation would omit the information content in the trading volume.

We then calculate ψ_i as the product of the price change with respect to the reference price times the trading volume of the operation. Besides, to avoid that positive and negative price changes compensate each other, we calculate the absolute value of the price changes. Therefore, the correction of the reference value observed on each trading operation is given by:

$$\psi_i = |ln(\frac{price_i}{reference\_price})| \times volume_i. \tag{2.8}$$

In order to calculate the strength of the market movement for each return interval, d, and time interval, τ, we use equations (7) and (8) to get the following expression:

$$\vartheta_{d,\tau} = \frac{\sum_{i=1}^{d} |return_{i,\tau}| \times volume_{i,\tau}}{\sum_{i=1}^{D} |return_{i,\tau}| \times volume_{i,\tau}} \times 100, \tag{2.9}$$

where the sequence $i = 1, ..., d, ..., D$, identifies the operations ordered according to their associated return, so that the d first operations support the analyzed trend and D represents the total number of operations recorded in the time interval, τ. The parameter $\vartheta_{d,\tau}$ measures the strength of the market movement and ranges from 0 (indicating there are no operations supporting that trend) to 100 (where all operations support the trend).

For illustrative purposes, we present a very simplistic example on Table 1, which shows the daily reference value (opening price), quoted price, and trading volume for a given asset between 9.30am and 10.30am. To calculate the strength of the market movement supporting certain trend (for instance, a decrease in prices by more than X%, then $r \leq X\%$), we have to compute the coefficient $\vartheta_{d,\tau}$ defined above:

[INSERT TABLE 1 AROUND HERE]

- Example 1: Decrease higher than 2%. The table above contains seven operations, out of which, four of them indicate a decrease in the market higher or equal to -2%. According to this table, the strength of this movement is computed as follows:

$$\vartheta_{r \leq -2\%, 9:30-10:30} = \frac{+6+72+6+6}{110} \times 100 = 81.82\%$$

- Example 2: Decrease higher than 6%. In this case, just two of the seven quoted operations support this possibility. However, the volume traded in these operations is important and, then, the impact on the movement strength is significant. In fact, the result says that the 70.91% of the volume traded in the market is providing a return smaller than 6%. The computation is as follows:

$$\vartheta_{r \leq -6\%, 9:30-10:30} = \frac{+6+72}{110} \times 100 = 70.91\%$$

The above examples are exaggerated but they help to understand the empirical exercise developed in the next section.

2.4 Empirical application

2.4.1 Data

The empirical analysis is performed over the Spanish futures on IBEX-35, for which data were obtained from the official market for these futures, Mercado Español de Futuros Financieros de Renta Variable. A stock index future reflects the market evolution and, in contrast to the index, the future is traded. Then, there is a trading volume available.

The database includes all trading operations between January 2^{nd}, 2004 and September 29^{th}, 2004. In more detail, we consider the price and trading volume for the nearest maturity, as they provide the highest liquidity.

2.4.2 Empirical results

This section shows the usefulness of the new indicator of strength of the market movement to identify the distribution of strength across returns and to calculate a representative return that improves the robustness of the indicators employed up to now. The results indicate that in days of relative calmness the closing price seems to be a good indicator of what has happened during the day. However, when there is an important discount of relevant information and herding behavior appears on the market, the return based on closing prices may not be representative of what has happened during the day die to odd operations with low trading volume and big changes in prices that frequently take place at the market closing times.

Based on our findings, we propose to use the market strength weighted return as representative return as it is a more robust estimate of the market evolution during the day. This way of computing the market return can improve the information used in the financial analysis and can help to mitigate the jumps in the series originated by punctual trading operations with small volume and big changes in prices at market closing times.

Strength of the Market Movement

By computing the strength of the market movement, we obtain an indicator that mixes the price and volume evolution, which incorporates further information to the classical methods used in technical analysis. For illustrative purposes we present a candlestick chart on Figure 1, which includes some representative prices (open, high, low and last price), as well as the total trading volume for each time period within the trading date.

As Table 2 illustrates, using this instrument we can not distinguish the proportion of the market that supports each potential market trend. As for example, on March 15^{th} 2004, in the time period between 9:00am and 9.30am, more than 4,524 contracts with prices between 7,778 and 7,914 were traded. However, this graph does not help to identify the trading volume related to each price movement. As shown later, the analysis of the strength of the market movement can provide this information.

[INSERT FIGURE 1 and TABLE 2 AROUND HERE]

Using equation (9) we proceed to calculate the strength of the market movement per each return interval on March 15^{th} 2004, for each 30 minutes interval, which is reported on Table 3. Note that trading started in a large interval for returns because of the substantial information published that morning related to a) the unforeseen result of the Spanish general elections and b) the confusion created by the terrorist attack that happened in Madrid 4 days before.

Between 9:00am and 9.30am, most of the trading operations imply positive returns. However, one can see a small proportion of trading operations with associated negative returns. Some herding behavior arose as the market was assimilating the news. In a way, on that date the market was continuously correcting the initial positions, closing the trading day with a decrease close to -2%.

[INSERT TABLE 3 AROUND HERE]

Distribution of the Strength across Returns

The distribution of the strength across returns provides a general overview of what the market considers in each time period. In this way, one can see the price interval in which the market is moving and obtain a relevant measure of the volume related to each price. Figure 2 shows this distribution of the market strength across returns for some time intervals on March 15^{th} 2004. It provides significant information on the market activity. For instance, the curve observed between 9:00am and 9.30am is especially interesting as one can identify a number of trading operations whose prices are much smaller than the average price of this time period.

[INSERT FIGURE 2 AROUND HERE]

As described in the model, in presence of a herding behavior episode, we expect a different shape for the distribution of the strength across returns given the evolution of the market. Taking into account that on March 15^{th} 2004, the market was discounting a large set of information after the terrorist attacks in Madrid and the unexpected result in the general elections in Spain, one observes what can be described as herding behavior or information cascade. Between 9:00am and 9.30am, the distribution of the strength across returns seems to reflect that a certain group of investors was closing positions or arriving at a new equilibrium price. In fact, these operations pointed to a significant decrease in prices (see Figure 2).

A quiet behavior in the market is related to a smooth movement of the prices, it is also associated with an homogeneous distribution of the strength across returns. As Figure 3 illustrates, this is the case of September 21^{st} 2004, when all the contracts were traded in a rather narrow interval of returns (i.e. between -0.2% and 0.3%).

[INSERT FIGURE 3 AROUND HERE]

In contrast to a quiet day, Figure 4 shows a day (March 11^{th}, 2004) characterized by high uncertainty and a significant discount of information. On this date, the city of Madrid suffered a dramatic terrorist attack, three days before the Spanish general elections on March 14^{th}. Although the day started with very different opinions and with returns between -0.8% and +0.3%, the Distribution of the Strength of Market Movement between 12.00 and 12.30 is very significant. The motivation may be related to the first official release of the number of victims, which caused the returns to move to the interval $[-2.0, -0.6]$.

[INSERT FIGURE 4 AROUND HERE]

In summary, there is relevant information embedded in the trading volume that is underused by the traditional methods of financial analysis. This information helps to obtain a clearer view of the potential trends that the investors are considering. Using the new methodology introduced in this chapter, an investor could assess whether her strategy equates that of the market and then, take later decisions.

Representative Market Return: the Market Strength Weighted Return

Figures 2 to 4 question the validity of summarizing the daily facts in a single price (opening, maximum, minimum or closing). In short, we propose as a representative market return, the sum of intraday returns weighted by the movement strength, which is computed as follows:

$$msw\_r_{t,t+1} = \sum_{return=-\infty}^{+\infty} return_{(t,t+1]} \times \vartheta_{r,(t,t+1]} \tag{2.10}$$

Compared to the return based on closing prices, the market strength weighted return shows a very similar evolution in calm trading days while, at the same time, this new calculation for the representative return mitigates the impact of trading operations with extreme prices and small trading volumes. This type of operations could occur in days with high degree of uncertainty and correspond to potentially non-representative data. As shown on Figure 5, one could test that the return based on closing prices is more extreme than the market strength weighted return.[1]

[1] This is an important note as we are interested in obtaining an objective measure of the behavior of the market on a given date.

[INSERT FIGURE 5 AROUND HERE]

Finally, Figure 6 reports the accumulated probability distributions for the market strength weighted return and for the return based on closing prices. It should be clear the presence of more extreme values when considering the return computed using the closing price, while the market strength weighted return decreases the impact of the extreme quotes if their volume is relatively small with respect to the total daily trading volume.

[INSERT FIGURE 6 AROUND HERE]

Considering the importance that must be given to trading operations with small volume, it seems reasonable to use the market strength weighted return as a daily representative return provided that this indicator takes into account not just the impact of the price change but also, the relative size of the operation. In this way, an extreme closing price with a small volume traded would have little impact on the representative return. Then, the representative price of the day is closer to that of the trading operations with a significant trading volume in relation to the total daily trading volume.

2.5 Conclusions

Investors' opinion on the market evolution is reflected not just in prices but also in trading volumes. However, the information embedded in those trading volumes is frequently underused by the traditional methods of financial analysis.

This chapter proposes an indicator that combines the information content in prices and trading volumes, labeled strength of the market movement, which constitutes a helpful instrument to identify the degree of support in the market for a certain trend. We then present the distribution of the strength across returns as a useful tool to quickly identify the opinion of investors about the asset price per time interval. Finally, we suggest that the market strength weighted return may be a more robust measure of the evolution of the market -the next chapter tackles this issue in detail-. The empirical analysis is performed on the futures on IBEX-35 over the period between January and September 2004.

The results support the fact that there is relevant information embedded in the trading volume, and that this information may be relevant to assess the evolution of the market. The distribution of the strength across returns behaves differently on calm and nervous trading dates, and helps to detect the market opinion about the evolution of prices in the very short term. Besides, the market strength weighted return seems to be more robust than the return based on closing prices on the estimation of the evolution of the market. Nevertheless, further research on this last issue should be implemented to analyze the behavior of the market strength weighted return.

All in all, the tools presented in this chapter could be of help for investors in order to obtain information on the aggregate opinion in the market. and they could be also useful for the monetary authorities in sustaining market stability. Last, but not least, the market strength weighted return could improve the analysis of time series using a more complete and representative measure of the market evolution.

Tables and Figures

Table 1

Calculation of the support for a market trend

This table illustrates the calculation of the market strength indicator for a given date and time interval. The first columns contains the time, the second contains the reference value for the day, ν, which in this case is the daily opening price. The third column shows the quoted price, p_t, and the fourth presents the trading volume, V. The last two columns contain the correction for the reference value, ψ_i, calculated as the percentage deviation of the quoted prices from the reference value, the final column presents the product of the price correction times the trading volume for each operation.

Time	Ref.Val.	Price	Volume	ψ_m	$\lvert\psi_m \times V\rvert$	$r \leq -2\%$	$r \leq -6\%$
9:30	5,000	4,950	3	-1.0	3		
9:40	5,000	4,900	2	-2.0	6	6	
9:50	5,000	5,075	10	1.5	15		
10:00	5,000	4,700	12	-6.0	72	72	72
10:10	5,000	5,100	1	2.0	2		
10:20	5,000	4,850	2	-3.0	6	6	
10:30	5,000	4,700	1	-6.0	6	6	6
TOTAL					110	90	78
$\vartheta_{r \leq X\%,\tau}$						81.82%	70.91%

Table 2
Market Evolution on March 15^{th} 2004

This table shows the market evolution in terms of trading volume, opening price, maximum and minimum prices, and closing price for each 30 minutes time interval on March 15^{th} .

T.interval	Trading Volume	Open	Maximum	Minimum	Close
09.00-09.30	4,524	7,830	7,914	7,778	7,871
09.30-10.00	2,757	7,870	7,872	7,845	7,852
10.00-10.30	1,741	7,853	7,862	7,838	7,838
10.30-11.00	1,315	7,838	7,840	7,806	7,820
11.00-11.30	1,218	7,820	7,820	7,800	7,809
11.30-12.00	1,642	7,811	7,816	7,792	7,797
12.00-12.30	2,080	7,794	7,796	7,772	7,772
12.30-13.00	1,290	7,773	7,784	7,748	7,761
13.00-13.30	855	7,761	7,786	7,760	7,779
13.30-14.00	988	7,778	7,781	7,758	7,768
14.00-14.30	551	7,770	7,786	7,761	7,781
14.30-15.00	869	7,780	7,796	7,771	7,785
15.00-15.30	903	7,785	7,808	7,784	7,796
15.30-16.00	970	7,795	7,798	7,777	7,784
16.00-16.30	1,355	7,783	7,784	7,764	7,773
16.30-17.00	4,029	7,772	7,772	7,727	7,728
17.00-17.30	5,058	7,727	7,727	7,683	7,691
17.30-18.00	1,654	7,688	7,690	7,647	7,679

Table 3
Distribution of the Strength across Returns, March 15^{th} 2004

The table reports the strength of the market movement for each return interval and for each 30 minutes interval. When considering one single time interval, we obtain the Distribution of the Strength across Returns.

	Time interval																	
Return interval	09.00-09.30	09.30-10.00	10.00-10.30	10.30-11.00	11.00-11.30	11.30-12.00	12.00-12.30	12.30-13.00	13.00-13.30	13.30-14.00	14.00-14.30	14.30-15.00	15.00-15.30	15.30-16.00	16.00-16.30	16.30-17.00	17.00-17.30	17.30-18.00
[1.1, 1.2)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[1, 1.1)	3.2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[0.9, 1.0)	6.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[0.8, 0.9)	25.5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[0.7, 0.8)	12.5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[0.6, 0.7)	13.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[0.5, 0.6)	30.9	6.0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[0.4, 0.5)	2.5	24.2	0.4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[0.3, 0.4)	0.1	48.3	53.0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[0.2, 0.3)	0.4	21.3	29.6	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[0.1, 0.2)	0.8	0.3	17.1	4.5	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[0, 0.1)	0.2	-	-	7.7	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[-0.1, 0.0)	0.5	-	-	7.1	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[-0.2, -0.1)	1.3	-	-	41.8	7.52	0.52	-	-	-	-	-	-	-	-	-	-	-	-
[-0.3, -0.2)	0.9	-	-	36.6	45.6	36.3	-	-	-	-	-	-	2.96	-	-	-	-	-
[-0.4, -0.3)	1.7	-	-	2.3	46.8	44.5	-	-	-	-	-	-	25.6	-	-	-	-	-
[-0.5, -0.4)	0.0	-	-	-	-	18.7	10.1	-	-	-	-	16.5	33.1	17.5	-	-	-	-
[-0.6, -0.5)	0.3	-	-	-	-	-	45.4	0.1	1.6	-	6.87	48.4	38.3	63.6	0.06	-	-	-
[-0.7, -0.6)	0.3	-	-	-	-	-	39.7	22.9	46.1	3.5	24.3	23.1	-	18.9	26.4	-	-	-
[-0.8, -0.7)	-	-	-	-	-	-	4.8	18.5	36.9	7.8	58.9	12	-	-	61.4	1.93	-	-
[-0.9, -0.8)	-	-	-	-	-	-	-	20.2	15.4	86.4	9.92	-	-	-	12.2	9.61	-	-
[-1, -0.9)	-	-	-	-	-	-	-	22.9	-	2.2	-	-	-	-	-	29	-	-
[-1.1, -1.0)	-	-	-	-	-	-	-	15.4	-	-	-	-	-	-	-	38.9	-	-
[-1.2, -1.1)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	12.9	-	-
[-1.3, -1.2)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	7.55	-	-
[-1.4, -1.3)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.19	4.97	-
[-1.5, -1.4)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	7.97	-
[-1.6, -1.5)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	8.42	-
[-1.7, -1.6)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	33.3	-
[-1.8, -1.7)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	23.4	-
[-1.9, -1.8)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	21.9	28.8
[-2, -1.9)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	46.1
[-2.1, -2.0)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	5.5
[-2.2, -2.1)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	8.62
[-2.3, -2.2)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	9.38
[-2.4, -2.3)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1.58
[-2.5, -2.4)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Figure 1
Candlestick chart as of March 15^{th}, 2004

This figure shows the usual candlestick chart from technical analysis where trading volume is in bars (left axis) and the open, high, low and last prices (right axis) per 30 minutes time interval on March 15^{th}, 2004.

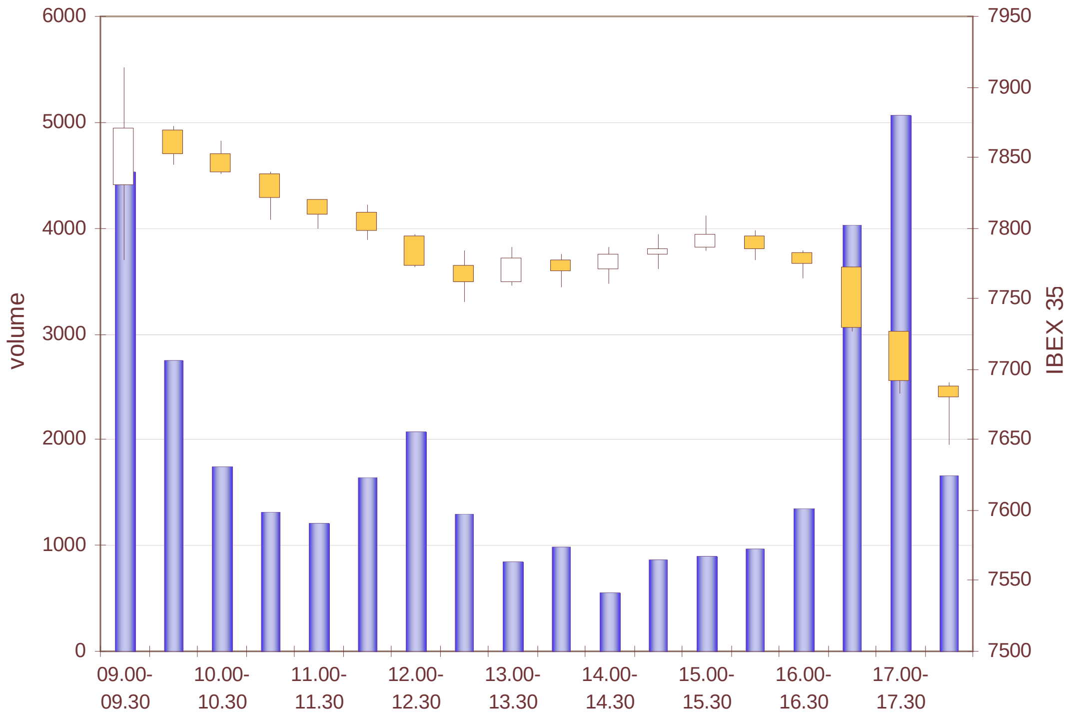


Figure 2
Distribution of Strength across Returns
March 15^{th} 2004

This figure presents various Distributions of the Strength across Returns for several time intervals on March 15^{th} 2004.

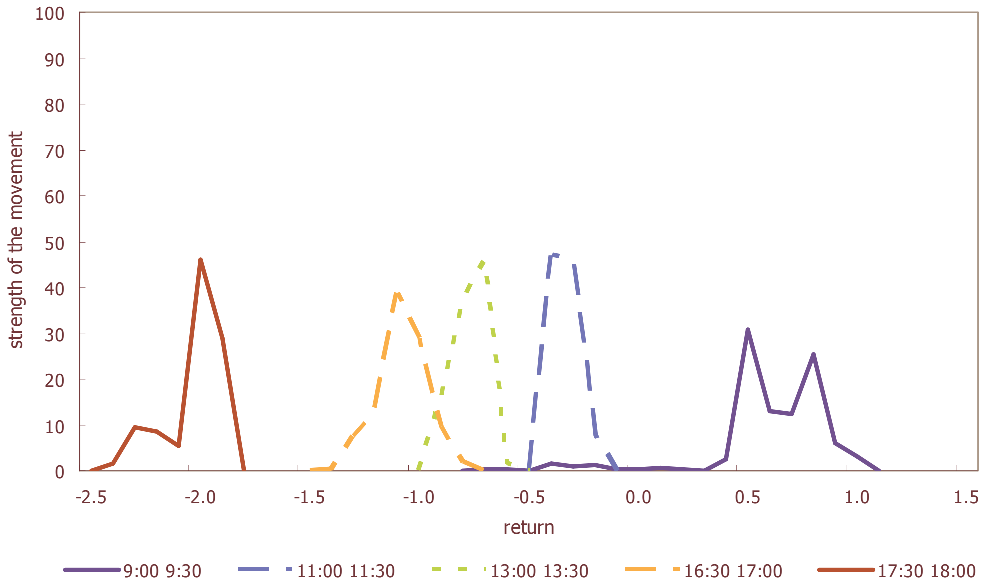


Figure 3
Distribution of Strength across Returns
Sept. 21^{st} 2004

The figure shows a tranquil day with similar Distributions of the Strength across Returns during the day.

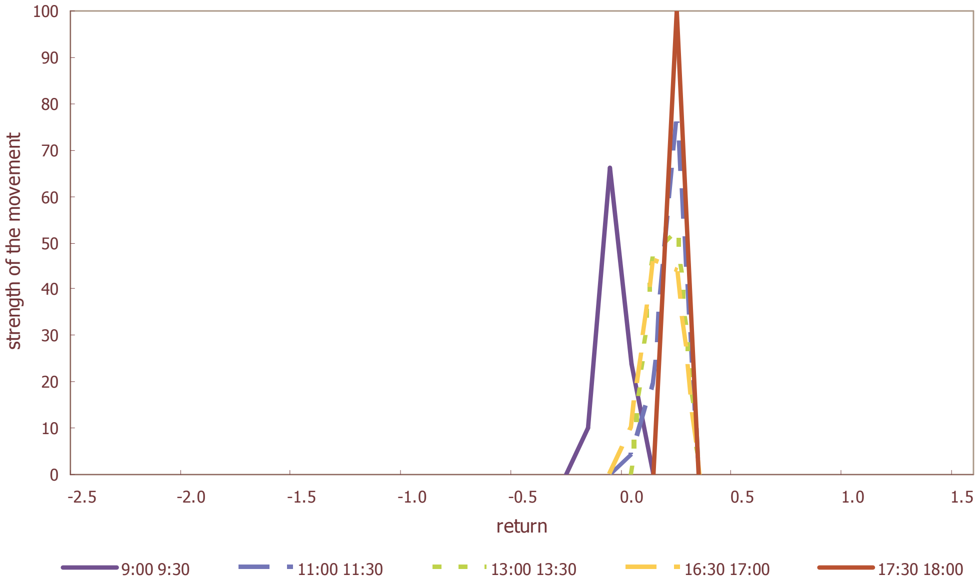


Figure 4
Distribution of Strength across Returns
March 11^{th} 2004

The figure shows a high uncertainty trading date in which relevant news was released to the market.

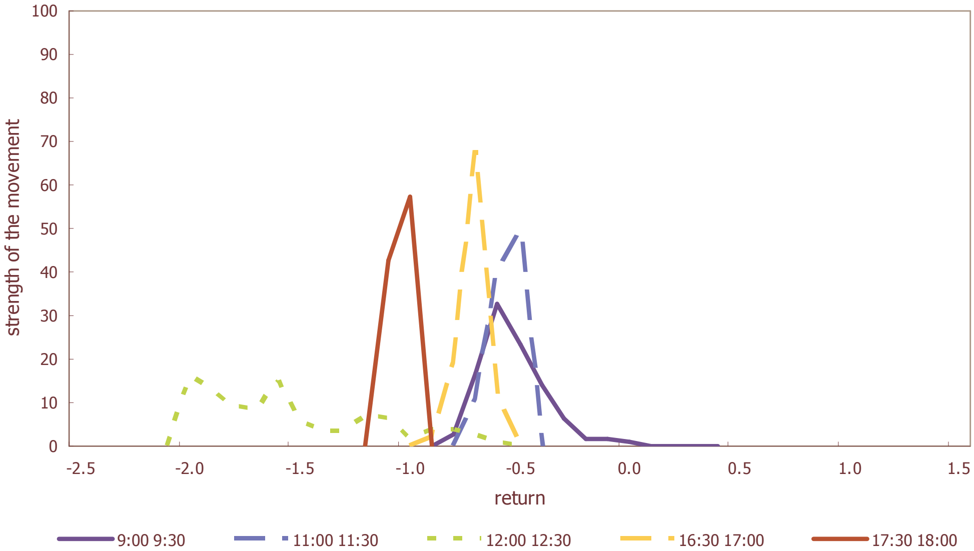


Figure 5
Movement Strength Weighted Return vs.
return based on closing prices

The figure shows the relationship between the Movement Strength Weighted Return and the return based on closing prices over the period from January to September 2004.

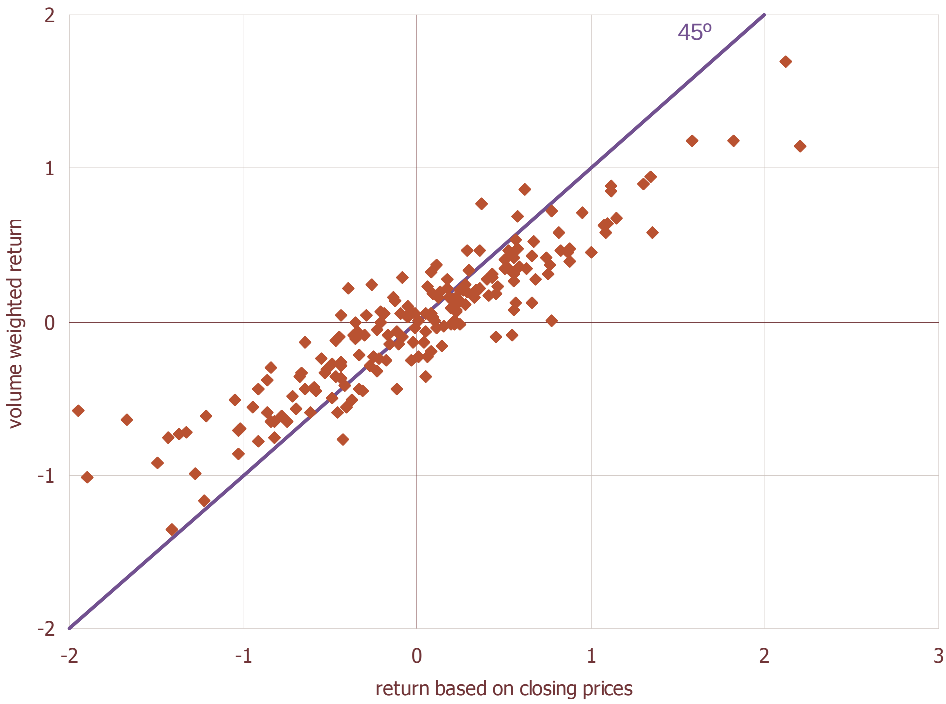
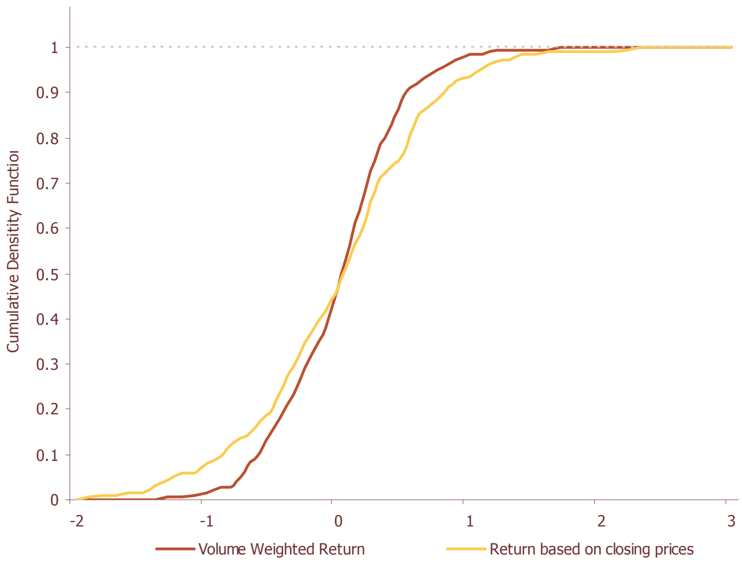


Figure 6
Accumulated distribution function of returns
January to September, 2004

This figure displays the accumulated probability distributions for the Movement Strength Weighted Return and the return based on the closing price over the period from January to September 2004.



Chapter 3

GARCH Modeling of Robust Market Returns

3.1 Introduction

Arrival of new information at the market changes expectations of investors on the future evolution of financial variables and, from a practical point of view, it may be interesting to analyze the effect of this information on how investors build and diversify their portfolios. The assessment of market evolution has developed significantly thanks to the advances in the literature on the GARCH family models. However, daily financial market returns may be significantly biased due to operations with low trading volume and high change in prices frequently traded at market closing times.

In this sense, we claim that the estimation of impact that other economies exert on a financial market calculated by the returns based on closing prices could be overestimated due to the bias caused by odd trading operations at closing times. Therefore, this chapter proposes a set of new and more accurate measures for the representative market return, which are based on the movement strength weighted return presented by Cuadro-Sáez and Moreno (2007) (see Chapter 2).

This chapter has been coauthored with Manuel Moreno. The authors gratefully acknowledge the helpful comments by Vasyl Golosnoy.

Concretely, in this chapter we develop four different specifications for the new indicator of volume weighed return that include the information content in prices and trading volumes. In this way, the new measures might be more robust to operations with low trading volumes and big changes in prices than the return based on closing prices. Next, we analyze the market evolution using the new set of volume weighted returns as the representative market returns. Namely, for each specification of the volume weighted return we estimate a standard GARCH(1, 1) model that includes shocks arising from developed and emerging market countries that are linked to the Spanish economy.

It should be emphasized that the goal of this chapter is not identifying the relation between prices and volumes but analyzing what happens when assuming that both variables are important to assess the market evolution. Therefore, this chapter should be distinguished from others that have analyzed such relationship as, for instance, Hiemstra and Jones (1994), who find evidence of significant bidirectional nonlinear causality between both variables. Similarly, and analyzing the role of trading volume on international financial markets studying the links between stock market return, Avouyi-Dovi and Jondeau (2000) suggest that the unexpected trading volume has a strong positive impact on all market returns and volatilities, although unexpected volume appears to have asymmetric effects on return as well as on volatility.

Our findings suggest that the new indicators of market evolution proposed in this chapter provide more moderate than the return based on closing prices when assessing the impact of spillovers from developed and emerging markets countries to the Spanish stock market.

These findings could be relevant from a monetary policy perspective provided that the use of the volume weighted return, as a more accurate measure of the market evolution, could shed some light on the understanding of the links between financial markets in one country and other countries. Besides, these findings on the linkages between different economies could also be helpful to design diversification strategies for investors especially interested in building multi-country portfolios.

The reminder of the chapter is organized as follows: Section 2 reviews the literature, Section 3 presents the new measures and the methodology applied, while Section 4 details the data and the results of the empirical analysis. Finally, Section 5 summarizes the main concluding remarks.

3.2 Literature Review

Given that the main objective of this chapter is threefold (i.e. present a new set of measures for the market return that accounts for the information content in volumes and prices; test its performance on a GARCH model specification compared to the traditional measure of market returns; to assess international spillovers to the Spanish market), the review of the literature is based on three different pillars: first, the measure of market returns; second, the use of volume information on GARCH models; and finally, the analysis of international spillovers in the literature.

As for the measurement of the market evolution, the new set of measures presented in this chapter is based on Cuadro-Sáez and Moreno (2007) (see Chapter 2), which proposes a new indicator of the Strength of the Market Movement based on prices and trading volumes and introduce the market strength weighted return as a measure to improve the information content of the data used for market analysis. The main qualitative conclusion in that chapter is that the distribution of the new measure is a helpful instrument to identify the market opinion on the prices' evolution.

Departing from this measure, we recognize the importance of the trading volume information content and we use it to assess the impact of news stories on financial markets using both, prices and the trading volume information. Concretely, we use some variations of the volume weighted return proposed by Cuadro-Sáez and Moreno (2007) to analyze the Spanish market using intra-day data from the Spanish Future on the IBEX-35 index during 2004.

The second pillar focuses on the role of the trading volume in GARCH models. Previous research has already explored this field by first, analyzing the role of the information content on the trading volume: attempting to explain the trading volume in terms of the new information arrival (Andersen, 1996; and Brock and LeBaron, 1996); using the trading volume contains information to predict volatility in a market microstructure framework (Suominen, 2001); or providing a theoretical benchmark for the trading volume that connects trading activity in individual stocks with market-wide volume (Tkac, 1999).Then, several previous studies have evaluated the impact of trading volume on the GARCH volatility equation, aiming to incorporate the arrival of new information by using a GARCH specification.

In order to empirically analyze volume versus GARCH effects on daily data, Lamoureux and Lastrapes (1990) finds that the variance of stock returns is explained at a high extend by the daily trading volume (used as a proxy for information arrival time). Besides, their findings suggest that ARCH effects tend to disappear when the volume is included in the variance equation.[1]. A subsequent paper studies the ability of volume data to explain persistence in stock-return volatility and find that their procedure cannot accommodate serial dependence in squared returns(Lamoureux and Lastrapes, 1994).

The effects of trading activity on market volatility is also analyzed in Gallo and Pacini (2000), which reexamines the question of excessive implied persistence of volatility estimates when GARCH type models are used, and corroborate that the estimated persistence decreases when the trading volume is inserted in the (E)-GARCH specification for returns.

Finally, the third pillar relates to the analysis of international spillovers using GARCH models. Some papers have analyzed directly the impact of news by using some type of (generalized) ARCH assumption. The seminal paper is Engle and Ng (1993) that defines the news impact curve to measure how new information is incorporated into volatility estimates with especial emphasis on the (potential) asymmetric response of the volatility to news.

In the same vein, Andersen and Bollerslev (1998) show that a substantial fraction of return variability (both at the intraday and daily level) can be explained by the intraday activity patterns, the macroeconomic announcements, and the volatility persistence using a sample of five-minute returns on the deutsche mark-dollar foreign exchange market.

[1] The results of Lamoureux and Lastrapes (1990) are extended by Omran and Mckenzie (2000) to the UK stock market and find that GARCH modeling captures the serial dependence in the trading volume and the existence of a strong association in the timing of innovational outliers in returns and volume.

Moreover, Nofsinger and Prucyk (2003) examines the impact of 21 different types of scheduled macroeconomic news announcements on S&P 100 stock-index option volume and implied volatility. One of their findings is that there is a two hours delay after the announcement before volume increases. However, there is an immediate increase in volatility, which slowly dissipates over several hours. Further analysis shows that most of the high volume and volatility after announcements come from the "bad" announcements whereas good news elicits lower volume and is not associated with higher volatility.

In addition, Hayo and Kutan (2005) consider six emerging markets and examine the reaction of stock market returns and volatilities to a set of IMF events. The focus of this paper is to analyze whether the IMF induces "investor panics" on the days of negative IMF events causing a significant drop in stock market returns. The main qualitative conclusion is that IMF news influence daily stock returns but do not have a significant impact on the volatility of stock markets. Thus, empirical evidence does not seem to support the hypothesis of IMF induced "investor panics".

Finally, Nikkinen et al. (2006) investigates how global stock markets react to the U.S. macroeconomic news announcements. To this end, they analyze the behavior of GARCH volatilities around ten important U.S. macroeconomic news announcements on six regions, for a total of 35 local stock markets. The main conclusion is that the G7 countries, the European countries other than G7 countries and Asian countries (developed and emerging) are closely integrated with respect to these news stories, while Latin America and Transition Economies are not affected. These results support that market integration is high among the major stock markets while some emerging markets are segmented.[2]

[2] Similar findings were obtained in previous papers as, for instance, Bekaert and Harvey (1995) and Rockinger and Urga (2001). Obviously, this result has important implications for international investors as they can obtain diversification benefits by investing in those segmented emerging regions.

3.3 Methodology

To reconsider the importance of the information content in volumes and prices to assess market evolution, we base our analysis on the market strength weighted return (see equation 1) presented by Cuadro-Sáez and Moreno (2007) to calculate de volume weighted return, and we use this measure as a representative market return.

Departing from the above mentioned market strength weighted return, we present four different specifications of the volume weighted return depending on the reference price (previous day closing price versus same day opening price) and on the time frequency used to calculate the return (tick data versus 5-minutes interval data).[3] Concretely, we define:

$$WO\_tick_t = \sum_{n=1}^{N} \frac{v_n}{V_t} \cdot ln(F_{n,t}/F_{1,t}) \cdot 100, \tag{3.1}$$

$$WO\_5min_t = \sum_{i5=1}^{I} \frac{v_{i5}}{V_t} \cdot ln(F_{i5,t}/F_{1,t}) \cdot 100, \tag{3.2}$$

$$WC\_tick_t = \sum_{n=1}^{N} \frac{v_n}{V_t} \cdot ln(F_{n,t}/F_{N,t-1}) \cdot 100, \tag{3.3}$$

$$WC\_5min_t = \sum_{i5=1}^{I} \frac{v_{i5}}{V_t} \cdot ln(F_{i5,t}/F_{N,t-1}) \cdot 100. \tag{3.4}$$

Where,

- WO_tick_t stands for the volume weighted return based on the same day opening price using tick-data, WO_5min_t represents the volume weighted return based on the same day opening price using 5 minute interval data, WC_tick_t is the volume weighted return based on the previous day closing price using tick-data, and WC_5min_t is the volume weighted return based on the previous day closing price using 5 minute interval data.
- N is the total number of trading operations during the day,
- I is the total number of 5-minutes intervals during the day,

[3]The authors gratefully acknowledge Vasyl Golosnoy for suggesting the use of 5-minutes interval data to avoid microstructure problems.

- V_t is the daily total trading volume,
- v_n denotes the trading volume on the nth intraday trading operation,
- v_{i5} denotes the cumulated trading volume within the ith 5-minutes interval,
- $F_{n,t}$ is the futures price of the n-th intraday trading operation,
- $F_{i5,t}$ is the last futures price of the ith 5-minutes interval, and
- $F_{N,j}$ ($F_{1,j}$) is the closing (opening) price at day j ($j = t-1, t$).
- The return based on closing prices is calculated as the difference in log prices, $U_t = ln(F_{N,t}/F_{N,t-1}) \cdot 100$.

Using equations (1) to (4) we calculate the four different specifications of the volume weighted return and we compare them to the return based on closing prices using scatter plots for illustrative purposes. As can be seen in Figures 1 to 4, compared to the return based on closing prices, the volume weighted return shows a very similar evolution in calm market days while, at the same time, this new calculation for the representative return mitigates the impact of trading operations with extreme prices and small trading volumes. This type of operations could occur in days with high degree of uncertainty and could also correspond to potentially non-representative data.

The presence of more extreme values when considering the return based on closing prices is clear compared to each specification of the volume weighted return (see Figures 1 to 4). The volume weighted return reduces the impact of the extreme prices if their associated volume is relatively small with respect to the total daily trading volume. In sum, the assessment of the impact of certain events on the market could be overestimated when using the return based on closing prices as the representative market return.

[INSERT FIGURES 1 TO 4 AROUND HERE]

The use of the volume weighted return as a daily representative return provides a better estimation of the market evolution considering the relative importance that must be given to trading operations with small volume and big changes in prices. In this way, an extreme closing price with a small trading volume would have little impact on the representative return of the day. Therefore, the volume weighted return is closer to that of the trading operations with a significant volume in relation to the total daily trading volume.

In the analysis of the market evolution we compare the performance of the four specifications of the volume weighted return to that of the return based on closing prices. Namely, we analyze the representative market return as a function of the shocks from developed markets, using the shocks from the US as a main global market driver, and also, as a function of shocks coming from emerging markets countries where Spain has economic interests. Concretely, we estimate a GARCH (1,1) model of the form:

$$return_t = \beta_0 + \sum_{c=1}^{C} [\beta_{positive} \cdot D\_P_{i,t} + \beta_{negative} \cdot D\_N_{i,t}] + e_t \tag{3.5}$$

Where:

$$\sigma^2_{e,t} = \alpha_0 + \alpha_1 \cdot \sigma^2_{e,t-1} + \alpha_2 \cdot e^2_{t-1},\ e_t = \sigma_{e,t} \cdot u_t,\ u_t \sim white\ noise.$$
$$c = \{Developed,\ Latin\ America,\ Eastern\ Europe,\ Asia\}.$$

Regarding the definition of the shocks, we take into account those coming from the US as well as those coming from emerging markets where Spain has economic interests. To do this, we perform three steps on the calculation: first, and focusing on the emerging markets countries, we select the country sample including the main Spanish trading partners, as well as the main Spanish net recipients of Foreign Direct Investment (both in terms of flows and stocks).

Then, for all the regions, we classify the shocks between positive and negative according to the sign of the local return where the domestic news were released. That is, if there is news from Argentina, we consider the positive or negative reaction of the Latin American return for the dummy of Latin America to classify the shock as positive or negative.

Finally, we only consider those shocks that exceed certain threshold to avoid the inclusion of irrelevant shocks in the database. This is a delicate procedure since the various possible definitions of thresholds might distort the analysis. Thus, we proceed to define several thresholds to ensure the reliability of the results. Namely, we define the release of news (threshold=0%) and 6 different fixed thresholds to determine whether there is a shock or not. We do this by considering the cases in which the return exceeds (in absolute terms) 0.5%, 1%, 1.5%, 2%, 2.5% or 3%. The argument for these criteria is that they are easy to handle and they are somehow comparable to standard references as the normal distribution assumed for the asset returns. In the following section, we will describe in detail the dummies obtained by applying these criteria.

3.4 Empirical application

3.4.1 Data

We apply the methodology to estimate the evolution of the Spanish futures contract on the Ibex-35. The dependent variable, the volume weighted return, is built on the basis of intraday data on prices and trading volumes for the futures contract on the Ibex 35. We take the data on futures contract corresponding to the closest time to expiration provided its higher liquidity. Then, we compare the results of the four specifications for the volume weighted return to the daily return based on closing prices.[4] As for the control variables, we use daily returns on four aggregate regional market indices obtained from FTSE (developed markets, Latin America, Asia ex-Japan and Emerging Europe). We perform the empirical analysis over the period August 1st 2003 to July 31st 2004. Table 1 summarizes the main statistical properties of the data on returns.

[INSERT TABLE 1 AROUND HERE]

News stories were collected from Bekaert and Harvey (2000, 2004). For that news stories for which these authors do not indicate the exact date, we put a date on them using several newspapers' libraries and other Internet sources (BBC, El Mundo, Comisión Andina de Juristas, El País and Factiva among others).

[4]The data are obtained from the Mercado Español de Futuros Financieros de Renta Variable (MEFF-RV).

To analyze the countries that might have a stronger impact on the Spanish stock market, we consider the relevant news from the US as main driver of global and developed stock markets. We also consider the emerging countries that are main trading partners of Spain and those that are net recipients of FDI (either in terms of flows or stocks) from Spain.[5] All main trading partners and main net FDI recipients are considered as potential sources of disturbances for the Spanish market.[6]

3.4.2 Empirical results

The volume weighted return is quite similar to the return based on closing prices on calm days. However, this new method to calculate the representative return mitigates the impact of trading operations with extreme prices and small trading volumes that often occur at closing hours (see Figure 1). The idea is that some of these trading operations with small trading volume and large change in prices could correspond to potentially non-representative data and thus, provide a biased assessment of the evolution of the market.

We propose the volume weighted return as a daily representative market return. This indicator takes into account not just the impact of prices but also the relative size of the trading operations when assessing the market evolution. In this way, an extreme closing price with a small trading volume associated would have little impact on the representative return of the day. Hence, the assessment of the market evolution depends more on the trading operations with higher trading volume relative to the total daily trading volume.

Regarding the definition of the dummy variables, some countries seem to be overrepresented in the sample of news stories, as Mexico (see the first column in Table 2). We transform the news into shocks to ensure that the news stories included in the database are important for the domestic market where they were released, at least, to a certain extent. Therefore, we reject the

[5] The data on trade and foreign direct investment has been obtained from the Spanish Ministry of Industry, Tourism and Trade.

[6] Namely, in Latin America we consider Argentina, Brazil, Colombia, Chile, Mexico, Peru, and Venezuela; in Eastern Europe: Czech Republic, Hungary, Poland, Russia and Turkey; finally, in Asia we include South Korea, China, India and Indonesia.

news stories that do not have a significant impact in their local market. As explained before, we use seven different threshold criteria (0%, 0.5%, 1%, 1.5%, 2%, 2.5% and 3%). Table 2 shows the number of shocks that we obtain after applying these thresholds to filter news stories and delete those that are not relevant in the local market where they are released.

[INSERT TABLE 2 AROUND HERE]

The empirical results confirm our intuition that the volume weighted return produces a more moderate assessment of how other economies affect the Spanish market. In general, we find that the use of the volume weighted return produces more moderate estimates of the impact of the shocks on the Spanish market and improves the significance of the parameters of the dummies. The regional analysis shows the following features when we consider the volume weighted return as representative market return (see Tables 3 to 6):

[INSERT TABLES 3 to 6 AROUND HERE]

Moreover, we find that there are no significant differences when using tick data or 5-minutes interval data so that the results based on tick data seem to be robust to the possible microstructure problems. Besides, we also find a stronger impact when considering the previous day closing price as reference price for the calculation of the volume weighted return. This makes sense provided that the volume weighted return measures based on the opening price are not accounting for the information released overnight, and thus, may provide a smaller impact than that obtained when using also the overnight information. Therefore, and for simplicity on the discussion of the results, we will compare the results based on the use of the tick data.

3.4.3 Discussion

This subsection deals with the linkages between the Spanish market and other economies that are found on the empirical results, according to the different measures of the volume weighted returns based on tick data (see Tables 3 to 6).

As expected, relevant news stories from the US affect the Spanish market. However, the size and the impact of positive an negative news differ in the following aspects:

(i) Positive news stories from the US are always relevant. The size of the impact increases as the impact on the US market also increases. These results also suggest that using the volume weighted return as the representative market return, the average impact is about 58% of the average impact calculated using the return based on closing prices as the representative return. That is, the use of the return based on closing prices overestimates the effect of positive news form the US on the Spanish market.

(ii) It seems that negative news affect the Spanish market if the impact on the US market is at least -1.0%. Unfortunately, the model does not contain enough information to derive a consistent conclusion when comparing to the return based on closing prices.

News stories coming from Latin America always affect the Spanish market. However, the impact of the negative news is larger than the impact of positive news, particularly in the case of shocks that largely affect the Latin American market. The results point to the following facts:

(i) On the one hand, positive shocks do affect the Spanish market. Concretely, if relevant news stories are released in a Latin American country, they have an average impact on the Spanish volume weighted return of 0.16% (using WO_tick) or 0.18% (using WC_tick). However, these coefficients vary according to the strength of the impact on the Latin American local market. Contrary to the usual pattern, it is not always the case that the stronger the impact on the local Latin American market, the stronger the impact on the Spanish market. Among the possible explanations, one of the reasons could be that the stronger the impact on the Latin American market, the more likely is that "odd" operations will take place at closing times. The asynchrony of trading between the Latin American and the Spanish markets may play an important role. Further research on this issue is needed. Namely, the next step would be to calculate the volume weighted return considering only the time period where the Latin American market and Spanish market are opened simultaneously. In addition, the volume weighted return produces, on average, an impact that is 59% of that calculated using the return based on closing prices.

(ii) On the other hand, in the case of the negative shocks, the impact on the Spanish market raises as the impact on the Latin American local market increases. If a Latin American country releases a negative and relevant news story, it has an average impact of -0.26% (for WO_tick) and -0.45% (for WC_tick) on the Spanish market, but this impact increases (up to -0.87% -WO_tick-, and -1.02% -WC_tick-) as the effect of the news on the Latin American market also increases (up to 3%). Besides, the size of the impact of negative shocks is smaller (around 63% on average) compared to the results of the return based on closing prices.

Shocks from Eastern European countries seem to affect the Spanish market only in the case of positive news and only if the impact of the shock on the Eastern European local market is quite high (at least 2.5%). This result could be explained by the fact this period witnessed part of the process of integration of many of these countries on the European Union. In the case of the Eastern European countries, the impact of positive shocks calculated using the volume weighted return is approximately 67% of the impact calculated using the return based on closing prices.

As regards shocks from Asia, they present a similar pattern to that of Latin America and US in the following aspects:

(i) First, positive shocks from Asia do impact more on the Spanish market the stronger the impact on the Asian market is. However, compared to the return based on closing prices, the volume weighted return provide a slightly more moderate estimation of the impact of the Asian shocks (87% of the impact calculated using the return based on closing prices).

(ii) Second, there is not much information to assess the influence of negative shocks and we find some statistically significant negative impact on the Spanish stock market for moderate shocks. However, the lack of observations causes some counter-intuitive results for stronger shocks that are not considered in the conclusions.[7] They matter

[7] The results for shocks with an impact on the local Asian market larger than -2% are represented by only one

even if the shock has a weak impact on the Asian market, but we think that the scarcity of observations made the coefficients statistically insignificant when assessing the effect of shocks with a larger impact on Asia.

Concerning the asymmetry between positive and negative shocks from the regions analyzed, we find that according to the new indicators, the news stories from the US have the strongest and most symmetric effect on the Spanish market if we use the opening price as reference (around 45bp for positive and -0.45bp for negative shocks on average), although the impact becomes asymmetric if we account for the overnight information (103bp for positive and -16bp for negative news). Then, Latin America is the emerging region with the strongest impact on the Spanish market, which also presents asymmetries between positive and negative news (27bp and -51bp when using the same day opening price as reference price and 31bp and -78bp when using the previous day closing price as reference). The impact of shocks arising in Eastern Europe is more moderate than in US and Latin America (14bp and -8bp, opening price; and 15bp and -17bp, closing price). Also, Asia presents a similar moderate impact of shocks on the Spanish market (10bp and -12bp, opening price; and 23bp and -16bp, closing price) present, on average, much more moderate impacts on the Spanish market for both positive and negative shocks.

In sum, our findings support the fact that the volume weighted returns, as representative measures of market evolution, provide more moderate estimates of the impact of the relevant news coming from abroad. In this sense, the difference on the impact of news from abroad estimated using the return based on closing prices instead of the volume weighted returns - depending on the specification of the volume weighted return- may range between 1.2 to 1.5 for news from Eastern Europe and positive news from Asia, and it may range between 1.6 to 1.9 for news from US and Latin America. The impact of negative news from Asia may be about 3 times larger if we use the return based on closing prices rather than the volume weighted return.

piece of news. Therefore, we do not consider this as a relevant result.

3.5 Conclusions

Non-representative operations with low trading volumes and big changes in prices at market closing times frequently distort the return based on closing prices as the representative market return. This chapter analyzes the effect of adjusting daily returns by volume information to minimize this distortion. For this purpose, and extending the approach of Cuadro-Sáez and Moreno (2007), we use the four different specifications of the volume weighted return as the representative market returns to analyze the Spanish IBEX-35 futures market, using a standard GARCH(1,1) model over the period between August 2003 and July 2004. In our approach, we control for shocks coming from developed and emerging markets countries that are linked to the Spanish economy, which allows us to explore the linkages between the Spanish market and other economies using a better estimation of market returns.

The results support the fact that the volume weighted returns, as the representative measures of market evolution, provide more moderate estimates than the return based on closing prices when analyzing spillovers from other countries. In this sense, our main finding point out that the use of the return based on closing prices could provide misleading conclusions about the sensitivity of financial markets, and that this problem could be mitigated using the volume weighted returns as the representative market returns. Using these new and more robust indicators of market evolution, we analyze the Spanish stock market and find that the most influential regions for the Ibex-35 futures market are the US and Latin America, followed by Eastern Europe and Asia, in line with the results obtained using the return based on closing prices. However, we also find that the size of the impact is overestimated when using the return based on closing prices instead of a more robust measure of market evolution, as the volume weighted returns.

These findings could be interesting, from a monetary policy perspective, to get a deeper knowledge of the linkages between financial markets in one country and other countries. It could be especially relevant in the case of countries where Spain has economic interests and therefore, has a higher exposition to their domestic shocks as is the case of many Latin American countries. Besides, on the linkages between countries, it could also be helpful to design diversification strategies for investors especially interested in building multi-country portfolios.

Tables and Figures

Table 1

Summary statistics for market returns

The table contains the main summary statistics for the return indexes used on the empirical analysis over the period between August 2003 and July 2004. The first row contains the summary statistics for the volume weighted return based on the same day Opening price using tick-data (WO_tick), the second row contains volume weighted return based on the same day Opening price using 5 minute interval data (WO_5min); row 3 shows the results for the volume weighted return based on the previous day Closing price using tick-data (WC_tick), row 4 row contains volume weighted return based on the previous day Closing price using 5 minute interval data (WC_5min); and row 5 contains the return based on closing prices (U). Rows 6 to 9 contain the summary statistics for the regions and aggregates used in the analysis.

	Obs.	Mean	Median	Std. Dev.	Min	Max.	Skew.	Kurt.
Volume Weighted Returns								
WO_ tick	261	0.014	0.052	0.491	-1.449	1.691	0.062	3.242
WO_ 5min	261	0.005	0.016	0.438	-1.132	1.223	-0.053	3.049
WC_ tick	261	0.051	0.104	0.717	-3.063	1.880	-0.632	4.520
WC_ 5min	261	0.051	0.105	0.721	-3.057	1.883	-0.628	4.492
Based on closing prices								
U	261	0.057	0.160	0.916	-4.432	2.333	-0.630	5.030
Regions and aggregates								
Developed markets	261	0.056	0.107	0.624	-2.360	2.044	-0.344	3.865
Latin America	261	0.114	0.192	1.268	-5.194	4.471	-0.676	5.637
Eastern Europe	261	0.116	0.209	1.483	-6.442	5.807	-0.419	5.225
Asia	261	0.077	0.150	0.826	-3.911	3.085	-0.783	6.162

Table 2
Number of news / shocks per region and impact on the local market

The table contains the number of news / shocks recorded over the period August 2003 to July 2004. The conditions for the dummy Shock=1 are: (a) news are released in that day, and (b) the daily return on the region where the domestic news is released is bigger (in absolute terms) than {0.5%, 1%, 1.5%, 2%, 2.5%, 3%}.

	News	Shocks					
	$\geqslant 0.0\%$	$\geqslant 0.5\%$	$\geqslant 1.0\%$	$\geqslant 1.5\%$	$\geqslant 2.0\%$	$\geqslant 2.5\%$	$\geqslant 3.0\%$
Positive shocks							
Developed markets	10	2	1	0	0	0	0
Latin America	49	30	16	7	2	2	0
Eastern Europe	36	27	22	11	4	1	1
Asia	25	7	3	1	0	0	0
Negative shocks							
Developed markets	6	3	1	1	0	0	0
Latin America	34	21	14	9	4	2	2
Eastern Europe	32	24	14	8	6	4	3
Asia	21	13	7	3	1	0	0

Table 3
Impact of news/shocks on Volume Weighted Returns

The table contains the regression results for robust standard GARCH(1,1) model in equation (5) for the cases where the impact of the news stories on the local market of origin is (in absolute terms) greater than 0.0% and 0.5%. The first column contains the result for the volume weighted return based on the same day Opening price using tick-data (WO_tick), the second column contains volume weighted return based on the same day Opening price using 5 minute interval data (WO_5min); column 3 shows the results for the volume weighted return based on the previous day Closing price using tick-data (WC_tick), column 4 column contains volume weighted return based on the previous day Closing price using 5 minute interval data (WC_5min); finally, the regression results for column 5 contains the return based on closing prices (U). ***, **, * indicate significantly different from zero at the 1, 5, and 10 percent level, respectively.

	|local return| ⩾ 0.0%					|local return| ⩾ 0.5%				
Dependent variable	WO_tick	WO_5min	WC_tick	WC_5min	U	WO_tick	WO_5min	WC_tick	WC_5min	U
Mean equation										
DP US	0.232**	0.239**	0.484***	0.486***	0.582***	0.493***	0.393***	1.055***	1.061***	1.284***
DN US	-0.017	-0.041	0.277	0.284	0.001	-0.235	-0.183	0.493	0.496	0.233
DP Latin America	0.163**	0.084	0.183**	0.186**	0.208*	0.337***	0.265***	0.317***	0.323***	0.428**
DN Latin America	-0.261***	-0.220***	-0.453***	-0.456***	-0.674***	-0.383***	-0.332***	-0.584***	-0.587***	-0.915***
DP Eastern Europe	-0.050	0.014	0.045	0.046	0.102	-0.064	-0.003	0.010	0.010	0.154
DN Eastern Europe	-0.002	0.025	-0.116	-0.118	-0.056	-0.058	-0.012	-0.155	-0.156	-0.047
DP Asia	0.112	0.114	0.193*	0.194*	0.037	0.130	0.191	0.067	0.070	-0.050
DN Asia	-0.104	-0.067	-0.191	-0.190	-0.170	-0.157	-0.135	-0.289*	-0.289*	-0.277
Constant	0.025	0.007	0.073	0.072	0.124	0.035	0.013	0.102**	0.101**	0.120*
Variance equation										
L.arch	0.096*	0.063*	0.133*	0.132*	0.164*	0.144*	0.076*	0.173*	0.173*	0.223*
L.garch	0.765***	0.794***	0.726***	0.729***	0.682***	0.630***	0.765***	0.582***	0.583***	0.547***
Constant	0.031	0.026	0.063	0.062	0.118*	0.048**	0.027*	0.107**	0.108*	0.172**
Regression statistics										
Observations	261.0	261.0	261.0	261.0	261.0	261.0	261.0	261.0	261.0	261.0
Akaike IC	362.9	310.1	535.2	537.9	670.3	344.9	294.0	531.3	534.0	660.4
Schwarz C	405.7	352.9	578.0	580.7	713.1	387.6	336.8	574.0	576.8	703.2
Wald-test(chi2)	27.31	18.22	62.14	62.89	50.33	135.63	56.76	76.89	77.48	68.89
p-value	0.001	0.020	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	-169.4	-143.0	-255.6	-256.9	-323.1	-160.4	-135.0	-253.6	-255.0	-318.2

Table 4
Impact of news/shocks on Volume Weighted Returns (*Cont.*)

This table contains the regression results for robust standard GARCH(1,1) model in equation (5) for the cases where the impact of the news stories on the local market of origin is (in absolute terms) greater than 1.0% and 1.5%. The first column contains the result for the volume weighted return based on the same day Opening price using tick-data (WO_tick), the second column contains volume weighted return based on the same day Opening price using 5 minute interval data (WO_5min); column 3 shows the results for the volume weighted return based on the previous day Closing price using tick-data (WC_tick), column 4 column contains volume weighted return based on the previous day Closing price using 5 minute interval data (WC_5min); finally, the regression results for column 5 contains the return based on closing prices (U). ***, **, * indicate significantly different from zero at the 1, 5, and 10 percent level, respectively.

	|local return| $\geqslant$ 1.0%					|local return| $\geqslant$ 1.5%				
Dependent variable	WO_tick	WO_5min	WC_tick	WC_ 5min	U	WO_tick	WO_5min	WC_tick	WC_5min	U
Mean equation										
DP US	0.632***	0.534***	1.537***	1.546***	1.986***					
DN US	-0.768***	-0.827***	0.542	0.569	-0.217	-0.771***	-0.833***	-1.947*	0.553	-2.346
DP Latin America	0.342***	0.326***	0.382***	0.388***	0.462***	0.326**	0.179	0.459**	0.476***	0.504*
DN Latin America	-0.482***	-0.413***	-0.705***	-0.711***	-1.045***	-0.550***	-0.483***	-0.583***	-0.588***	-0.878***
DP Eastern Europe	-0.060	-0.009	0.042	0.042	0.125	0.028	0.092	0.184	0.179	0.241
DN Eastern Europe	-0.157	-0.147	-0.346*	-0.349*	-0.344	-0.303*	-0.288	-0.482	-0.484	-0.384
DP Asia	0.130**	0.165***	0.444**	0.445**	0.515**	0.045	0.126***	0.214***	0.217***	0.298***
DN Asia	-0.112	-0.034	-0.013	-0.011	-0.029	0.046	0.094	0.353	0.359	0.394
Constant	0.045	0.023	0.091**	0.090**	0.109*	0.048	0.030	0.085**	0.084**	0.103*
Variance equation										
L.arch	0.118	0.061	0.178	0.180	0.135	0.146	0.062	0.195	0.196	0.140
L.garch	0.694***	0.789***	0.471	0.464	0.619**	0.617***	0.746***	0.575**	0.575**	0.694***
Constant	0.041*	0.025	0.155	0.158	0.178	0.054*	0.034	0.112	0.113	0.136
Regression statistics										
Observations	261.0	261.0	261.0	261.0	261.0	261.0	261.0	261.0	261.0	261.0
Akaike IC	351.2	291.9	534.8	537.6	666.2	357.1	300.2	553.1	553.8	686.0
Schwarz C	386.9	327.6	574.0	576.8	705.4	389.2	332.3	592.3	589.5	721.6
Wald - test (chi2)	825.12	900.99	1714.27	1713.94	1848.92	719.95	1139.50	54.84	52.39	60.04
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	-165.6	-136.0	-256.4	-257.8	-322.1	-169.5	-141.1	-265.5	-266.9	-333.0

Table 5
Impact of news/shocks on Volume Weighted Returns (*Cont.*)

This table contains the regression results for robust standard GARCH(1,1) model in equation (5) for the cases where the impact of the news stories on the local market of origin is (in absolute terms) greater than 2.0% and 2.5%. The first column contains the result for the volume weighted return based on the same day Opening price using tick-data (WO_tick), the second column contains volume weighted return based on the same day Opening price using 5 minute interval data (WO_5min); column 3 shows the results for the volume weighted return based on the previous day Closing price using tick-data (WC_tick), column 4 column contains volume weighted return based on the previous day Closing price using 5 minute interval data (WC_5min); finally, the regression results for column 5 contains the return based on closing prices (U). ***, **, * indicate significantly different from zero at the 1, 5, and 10 percent level, respectively.

	|local return| ⩾ 2.0%					|local return| ⩾ 2.5%				
Dependent variable	WO_tick	WO_5min	WC_tick	WC_ 5min	U	WO_tick	WO_5min	WC_tick	WC_5min	U
Mean equation										
DP US										
DN US										
DP Latin America	0.231***	0.111***	0.392***	0.397***	0.777***	0.239***	0.118***	0.403***	0.409***	0.795***
DN Latin America	-0.921***	-0.783***	-1.089***	-1.101***	-1.458***	-0.810***	-0.634***	-1.002***	-1.007***	-1.353***
DP Eastern Europe	0.200	0.276	0.060	0.058	-0.025	0.448***	0.413***	0.339***	0.350***	0.432***
DN Eastern Europe	-0.185	-0.212	-0.174	-0.172	-0.176	0.017	-0.004	0.026	0.026	-0.064
DP Asia										
DN Asia	0.456*	0.507**	0.307	0.317	0.507					
Constant	0.038	0.020	0.086**	0.086**	0.097*	0.030	0.014	0.077**	0.076*	0.087*
Variance equation										
L.arch	0.122*	0.060	0.123	0.121	0.114	0.118*	0.078*	0.128*	0.127*	0.126
L.garch	0.638***	0.712***	0.698***	0.703***	0.749***	0.694***	0.753***	0.725***	0.728***	0.746***
Constant	0.055**	0.041	0.087	0.086	0.113*	0.045	0.032	0.073	0.073	0.107*
Regression statistics										
Observations	261.0	261.0	261.0	261.0	261.0	261.0	261.0	261.0	261.0	261.0
Akaike IC	364.0	306.4	554.7	559.6	688.1	370.7	311.8	558.6	559.5	688.4
Schwarz C	392.5	334.9	583.2	591.7	716.6	399.2	336.7	587.1	584.5	713.3
Wald - test (chi2)	532.69	2723.16	1033.07	1005.29	604.67	388.88	799.17	3829.87	3037.68	158.07
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log-likelihood	-174.0	-145.2	-269.4	-270.8	-336.1	-177.4	-148.9	-271.3	-272.8	-337.2

Table 6
Impact of news/shocks on Volume Weighted Returns (*Cont.*)

Notes: this table contains the regression results for robust standard GARCH(1,1) model in equation (5) for the case where the impact of the news stories on the local market of origin is (in absolute terms) greater than 3.0% . The first column contains the result for the volume weighted return based on the same day Opening price using tick-data (WO_tick), the second column contains volume weighted return based on the same day Opening price using 5 minute interval data (WO_5min); column 3 shows the results for the volume weighted return based on the previous day Closing price using tick-data (WC_tick), column 4 column contains volume weighted return based on the previous day Closing price using 5 minute interval data (WC_5min); finally, the regression results for column 5 contains the return based on closing prices (U). ***, **, * indicate significantly different from zero at the 1, 5, and 10 percent level, respectively.

	$\lvert$local return$\rvert \geqslant 3.0\%$				
Dependent variable	WO_tick	WO_5min	WC_tick	WC_ 5min	U
Mean equation					
DP US					
DN US					
DP Latin America					
DN Latin America	-0.870***	-0.724***	-1.012***	-1.019***	-1.398***
DP Eastern Europe	0.448***	0.414***	0.336***	0.348***	0.430***
DN Eastern Europe	0.142	0.189	0.042	0.045	0.025
DP Asia					
DN Asia					
Constant	0.030	0.013	0.079**	0.079**	0.089*
Variance equation					
L.arch	0.118*	0.080*	0.131*	0.130*	0.130
L.garch	0.694***	0.759***	0.719***	0.723***	0.741***
Constant	0.045	0.030	0.075	0.075	0.109*
Regression statistics					
Observations	261.0	261.0	261.0	261.0	261.0
Akaike IC	368.8	309.4	557.2	560.2	689.6
Schwarz C	393.7	330.8	582.1	585.1	714.6
Wald - test (chi2)	718.96	877.62	7285.55	5850.68	175.73
p-value	0.000	0.000	0.000	0.000	0.000
Log-likelihood	-177.4	-148.7	-271.6	-273.1	-337.8

Figure 1
WO_tick vs. return based on closing prices

This figure represents the volume weighted return against the return based on closing prices during the period August 2003−July 2004. The specification for the volume weighted return is WO_tick, based on tick data and using the same day opening price as reference price.

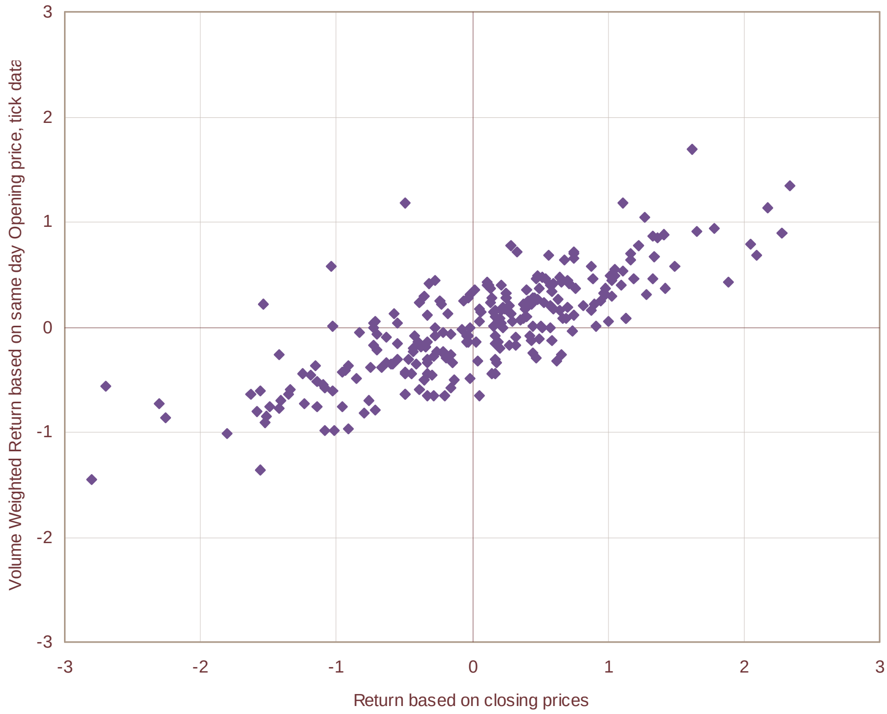


Figure 2
WO_5min vs. return based on closing prices

This figure represents the volume weighted return against the return based on closing prices during the period August 2003−July 2004. The specification for the volume weighted return is WO_5min, based on 5-minutes interval data and using the same day opening price as reference price.

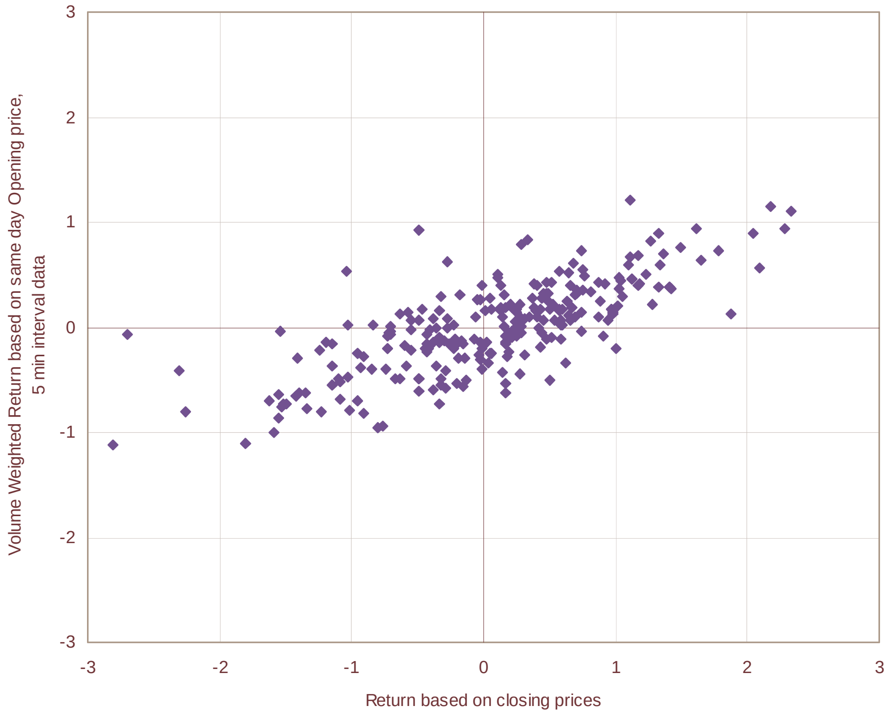


Figure 3
WC_tick vs. return based on closing prices

This figure represents the volume weighted return against the return based on closing prices during the period August 2003−July 2004. The specification for the volume weighted return is WC_tick, based on tick data and using the previous day closing price as reference price.

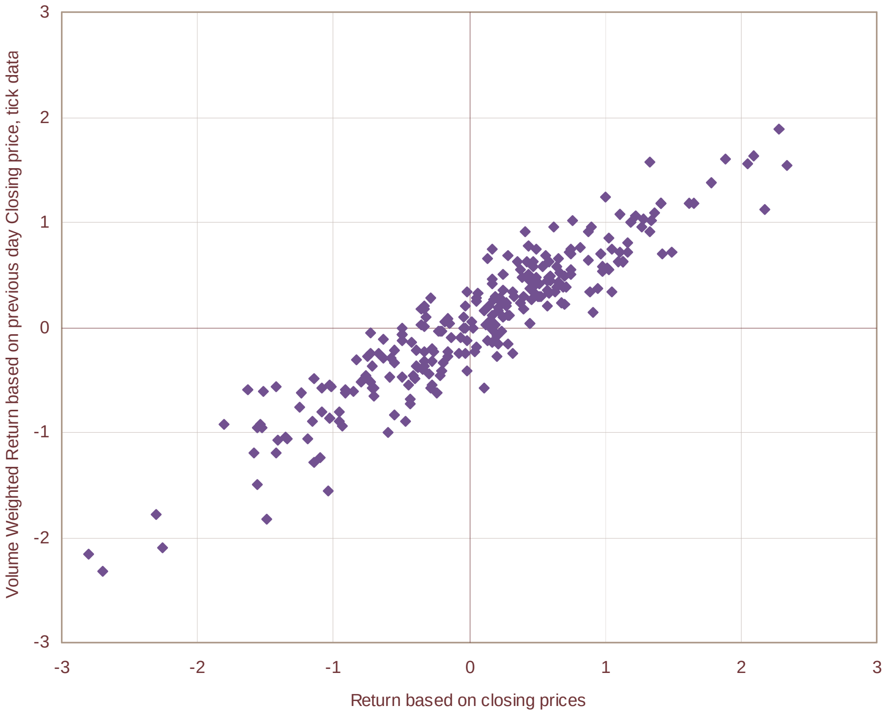
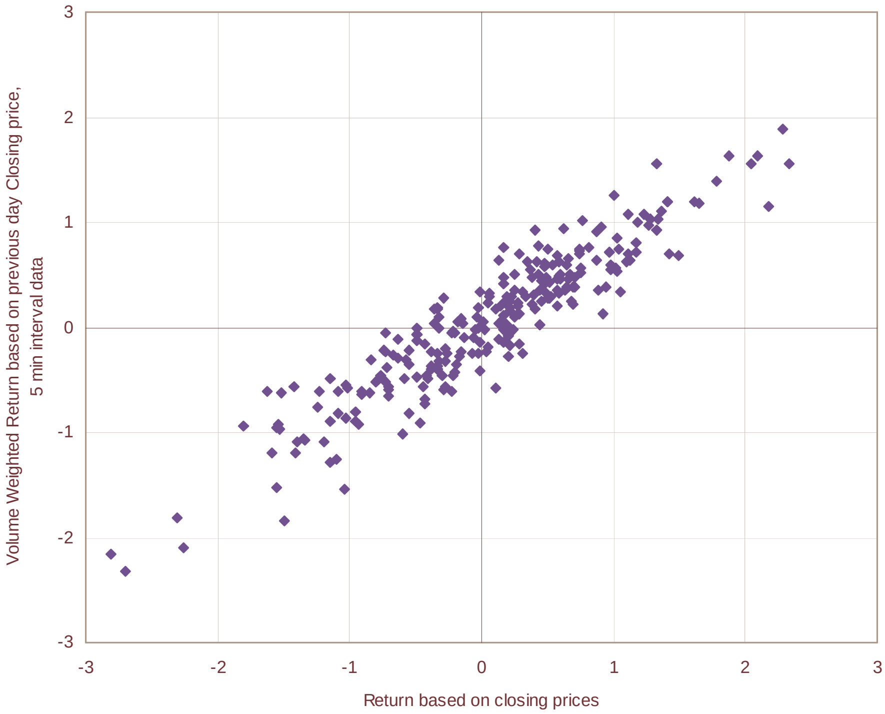


Figure 4
WC_5min vs. return based on closing prices

This figure represents the volume weighted return against the return based on closing prices during the period August 2003−July 2004. The specification for the volume weighted return is WC_5min, based on 5-minutes interval data and using the previous day closing price as reference price.



Chapter 4

The Transmission of Emerging Market Shocks to Global Equity Markets

4.1 Introduction

Do emerging market economies (EMEs) matter for global and mature economies' financial markets? The general perception is that EMEs are relevant for global financial markets mainly when they experience financial crises, thus inducing an abrupt portfolio rebalancing that also affects investment decisions and thus returns in markets of mature economies. In fact, there is a large literature focusing on and indeed finding evidence for the international transmission of EME shocks and for contagion during crises in emerging markets, foremost the Latin American crises of 1994-95 the Asian crisis of 1997-98 and the Russian default of August 1998 (see e.g. Kaminsky and Schmukler 1999, Baig and Goldfajn 1998, Rigobon 2002, Wongswan 2003).

However, there have been no major crises in systematically relevant emerging markets since 1998 - apart from the Turkish and Argentine crises of 2000 and 2001, which arguably have had little systemic repercussions for global financial markets (Krueger 2002, Fischer 2002, and Hall and Taylor 2002). At the same time, emerging markets' assets have become an increasingly important asset class over the past decade, in particular also for investors in mature economies

This chapter has been coauthored with M. Fratzscher and C. Thimann.

including the United States and Europe. Emerging markets have, moreover, developed into an ever more relevant driver of global economic growth, as for instance much of global growth in the last few years being attributable to economies in Emerging Asia and also those in Latin America and Emerging Europe. And finally, EMEs are increasingly intertwined with mature economies via FDI and the relocation of production.

The present chapter asks whether, and to what extent, EMEs have systemic importance for global financial markets, above and beyond their influence during crises episodes. Such an analysis is complicated by an identification problem, i.e. the difficulty to distinguish financial market developments in emerging markets from those in mature economies. We use a novel database of shocks that are truly idiosyncratic and specific to EMEs. These shocks comprise a set of economic and political events in 14 systemically relevant EMEs over the period 2000-2004. They are based on and extracted from "exogenous" sources, i.e. on International Finance Corporation reports (factbooks, quarterly reviews, and monthly reviews of emerging markets, among others), as well as Bekaert and Harvey (1998, 2004) and various IMF reports. The news reported in these sources have been selected based on their country-specific nature and overall economic and political importance, and not based on their financial market impact.

More specifically, the database comprises a broad range of important political and economic events such as announcements of new regulations, monetary and fiscal policy announcements, the default of a financial institution or the election or resignation of politicians in individual EMEs. The database not only covers negative events that drive markets lower, but also "positive" news that e.g. indicate better than expected economic growth or the announcement of important economic reforms. Given the focus on important idiosyncratic events in EMEs, the number of identified shocks is limited to, on average, about 6 to 7 shocks per emerging market per year.

Using daily data over the period 2000-2004, we analyze the transmission of these shocks from the 14 EMEs to 15 mature economies' equity markets - covering the 12 euro area countries, the United States, Japan and the UK - plus global equity market returns, as well as the intra-regional and extra-regional spillover across EMEs. Thus the analysis based on such identified EME shocks allows a very rich analysis of the transmission of different types of shocks, and during tranquil rather than only crises periods.

The empirical analysis yields a number of striking findings. A first revealing stylized fact is that there is a strong correlation between global equity returns and EME shocks even when taking a medium-term perspective: the correlation coefficient between quarterly global equity returns and the net sum of all EME shocks during that quarter is as high as 70%. While this obviously does not necessarily imply causality, it underlines that developments in EMEs strongly co-move with those in global equity markets. Turning to the issue of transmission, i.e. causality, we find that, on a daily frequency, EME shocks have a significant and sizeable effect, inducing on average a 0.3% change in global equity returns on the day a shock occurs, and rising to around 0.5% cumulated after 5 days.

Second, our analysis shows that EME-specific shocks are so important overall for global equity returns that their effect is still statistically significant after several weeks. While it is difficult to quantify precisely the overall explanatory power of the EME shocks for global equity markets, in particular the persistence of the effects stresses the economic relevance and systemic importance of emerging markets for global equity markets.

A third key finding of the chapter is that global equity markets react almost as strongly to positive EME news as to negative news, with this result being robust across EMEs and over time. This underlines that EMEs matter for global financial markets not only during crises or other less favorable episodes, but that investors in mature economies also share the gains from positive developments in EMEs.

Finally, there are a number of intriguing cross-country differences: although EME equity markets generally react more strongly to shocks in other EMEs of the same region, mature economies overall react mostly more strongly to EME shocks than emerging markets from other regions. Among mature economies, US equity returns respond much more to shocks in Latin America than to those in Emerging European and Asian EMEs, while Japanese markets are most sensitive to Asian EMEs. By contrast, euro area and UK markets not only show the strongest exposure and overall reaction to EME shocks, but they appear to be roughly equally sensitive to shocks from all the three EME regions of Asia, Emerging Europe and Latin America.

Overall, the findings of the chapter emphasize the emergence and relevance of EMEs for global and in particular mature economies' financial markets. This reflects the growing economic integration of EMEs in the world economy and their rising trade and financial linkages with mature economies. This is an important result, and constitutes the intended contribution of the chapter to the literature, as it underlines that emerging markets can no longer be considered as a minor player in global financial markets that matter only in times of crisis or financial market turbulence. Given the importance and ongoing increase of cross-border financial investment as a transmission channel and the rapid growth of EMEs as an asset class, the results suggest that EMEs are likely to continue becoming an even more important factor for the determination of global asset prices in the years to come.

The chapter is organized as follows. We start with a brief review of related literature in section 2, before proceeding to a detailed presentation and some stylized facts of our dataset in section 3. Section 4 presents the empirical methodology as well as the benchmark empirical results for the transmission of EME shocks. Section 5 then discusses various extensions to the benchmark model and several robustness tests. Section 6 concludes.

4.2 Related literature

The empirical literature has pointed towards a rapidly increasing degree of financial market integration, at least over the past decade. In the early 1990s, most evidence pointed towards no or little market integration, as shown e.g. by King et al. (1994) who find evidence against the null hypothesis of integrated capital markets, or Bekaert and Campbell (1995) who only find a partial integration of equity markets, in particular of EMEs, based on an international CAPM modeling framework. However, in recent years the evidence on financial integration has changed. For instance, Kim et al. (2005) find that the increase in stock market integration in Europe over the period 1999-2003 has been significantly driven in part, by macroeconomic convergence associated with European Economic and Monetary Union. In addition, Albuquerque et al. (2005) point out that increased market integration leads to a greater role for worldwide sources of risk.

For the context of the present chapter, we are particularly interested in the evidence of financial integration and interdependence of emerging markets. Much of the focus on EMEs in this context over the past decade has been on crises and contagion in and their impact on mature economies. The definition of contagion is not unanimous and rather controversial. Karolyi (2003) observes that the perception of market contagion is not always consistent with the empirical evidence. Along these lines, some researchers define contagion as an increase in the degree of interdependence, and find that little of such an increase has taken place in financial crises of the 1990s (Forbes and Rigobon, 2002). By contrast, focusing on the channels of contagion, Kaminsky and Reinhart (2002) find that financial turbulence in Brazil, Russia, and Thailand in the late 1990s spread globally when it affected asset markets in one or more of the world's financial centers.

Similarly, Kaminsky and Schmukler (1999) analyze the sources of the largest daily swings in markets during the Asian crisis by testing the impact of news on daily returns, and show that large swings affect local and international markets due to herding behavior. In the same vein, Baig and Goldfajn (1998) test for contagion during the Asian crisis and suggest that there exist discernible patterns of contagion during periods of financial market instability when market participants tend to move together across a set of countries. More recently, Rigobon (2002) supports the idea that the transmission of shocks was intensified during the Russian and the Asian crises, as well as Cappiello et al. (2005) who find that co-movements in equity returns tend to increase significantly during crises.

Concerning the speed of the transmission, the general consensus is that the transmission occurs very rapidly and is intensified during crisis periods, as shown in Ederington and Lee (1993), Fleming and Remolona (1999), and Andersen et al. (2003). These findings are in line with Ehrmann, Fratzscher and Rigobon (2005) who find that there are substantial international spillovers, and that the international propagation of shocks is strengthened in times of recession.

A second important strand relevant for the present chapter is the transmission of macroeconomic shocks. The key argument here is that asset prices are determined simultaneously and thus it is difficult to identify which individual markets are the drivers of global markets. Several studies have therefore taken macroeconomic announcements or news to identify shocks, and to analyze their transmission. The most frequent approach in the literature has been to study the impact of US and/or other developed market economies news on global financial markets. Canova (2005) find that US monetary shocks produce significant fluctuations in Latin America, but real demand and supply shocks do not. Wongswan (2003) finds a large and significant association between emerging-economy equity volatility and trading volume and developed-economy macroeconomic announcements at short-time horizons. Other studies focusing on the impact of US news on asset prices and foreign exchange rates include Andersen et al. (2003), Miniane and Rogers (2003) and Ehrmann and Fratzscher (2004). For instance, Andersen et al. (2003) analyze the response of the US market on exchange rates and find that the markets react in an asymmetric fashion to good and bad news, since bad news cause a greater impact than good news.

A third strand relevant for the present chapter focuses on the role of financial and real integration as a determinant of the financial transmission process. For instance, considering the linkages among financial markets, Dungey and Martin (2006) provide evidence that cross market linkages played a key role during the Asian crisis. In this sense, the consensus in the literature is that trade and financial channels are important factors in determining how crises are transmitted internationally (Forbes 2004, Eichengreen et al. 1996, Glick and Rose 1999, Forbes and Chinn 2004). Focusing on the US during tranquil times, Ehrmann and Fratzscher (2006) link the strength of the transmission of US monetary policy shocks to the underlying asset holdings and find that the degree of global integration of countries is a key determinant for the transmission process.

In summary, the literature has so far primarily concentrated on measuring the degree of integration of EMEs into global financial markets or generally on how various EMEs respond to external and internal shocks. As to the relevance of EMEs for global financial markets, the focus has been on crisis periods and on contagion issues. To our knowledge, there is no systematic work so far assessing how important EMEs are as drivers of global financial markets overall, and not only during crises episodes. The analysis of this issue constitutes the aim of the present chapter and its intended contribution to the literature.

4.3 The Data

A key difficulty with every type of analysis of financial market linkages is identification: as asset prices are determined simultaneously, with shocks often triggering reactions of several asset prices within minutes, it is difficult to identify the source of asset price movements and the corresponding direction of causality.

We solve this identification issue by using mostly purely exogenous events occurring in EMEs. The list of events for each of the 14 EMEs mostly comes from reports by the International Finance Corporation (IFC) and the IMF, which have partly been collected and summarized by Bekaert and Harvey (1998, 2004). In most cases these databases do not list the exact day, so that we use newswire services to attribute each of the events to that particular day when it occurred and was first reported.

We believe that using these sources helps mitigate the identification problem as they are reliable and, importantly, the news reported in these sources have been selected based on their country-specific nature and overall economic and political importance, and not based on their financial market impact. This selection criterion implies that these news are largely exogenous and specific to the identified EMEs. Given the focus on important idiosyncratic events in EMEs, the number of identified shocks is limited to, on average, only about 6 to 7 shocks per emerging market per year.

Our database includes economic and political news, and also not only covers negative events, but also "positive" news that e.g. indicate better than expected economic growth or the announcement of important economic reforms. The shocks to emerging market j at time t are coded as follows:

$$S_{jt} = \begin{cases} +1, & \textit{positive shock} \\ 0, & \textit{no shock} \\ -1, & \textit{negative shock} \end{cases}$$

Annex 1 provides an overview and some specific examples of our database for the case of

Argentina. The news include events such as announcements of new regulations, monetary and fiscal policy announcements, the collapse of a financial institution or the election or resignation of a politician in individual EMEs.

It should be stressed again that the “exogeneity” of the events, or shocks, captured by the IFC/IMF database is of fundamental importance for the validity of the analysis of the chapter. As Annex 1 illustrates for the case of Argentina, most of the news indeed appear to be country-specific and exogenous in the sense that their origin is primarily a domestic and not a foreign one. Moreover, although some of the news may not come entirely unexpected by the markets, at least part of the news and their timing are likely to be unanticipated.

We are also comforted by the fact that the primary source of the data is the IFC and the IMF, and their stated purpose is to identify country-specific events that have large economic relevance, and not primarily those that have a global market impact. For all these arguments, we believe this database provides the best possible identification method for EME-specific shocks in order to conduct our analysis of the impact of EMEs on global equity markets. As we will discuss further below, we also include for a set of “global” shocks in order to control for a possible correlation of EME shocks with other unrelated global developments.

As to the country coverage, the database covers 14 EMEs, four in Latin America (Argentina, Brazil, Chile and Mexico), four in Emerging Europe (Czech Republic, Poland, Russia and Turkey) and six in Asia (India, Indonesia, Korea, Malaysia, Taiwan and Thailand), while the time period is 1 January 2000 to 31 July 2004. This list covers most of the systemically important EMEs, possibly with the exception of China. Hong Kong and Singapore are also not included, partly due to data availability and partly also as they may not be considered as emerging markets any longer given their degree of development and also financial market depth.

[INSERT TABLE 1 AROUND HERE]

Table 1 gives a summary for the distribution of the shocks across EMEs. Overall, there are 424 days with shocks for all 14 EMEs over the whole sample period. This means that on average each EME had about 30 shocks over the close to 5-year sample period, or about 6 to 7 shocks per year. While some countries experience significantly more shocks over that period - these are e.g. as expected countries such as Argentina, Mexico and Russia - other have experienced very few shocks that are captured. Moreover, the shocks can mostly relatively easily be classified as political or economic shocks, and as positive or negative shocks. In the few cases where the sign of the news cannot be readily identified, we use the direction of the domestic stock market reaction to sign the news.

Figure 1 shows the distribution of the shocks over time, quarter by quarter since 2000. The key point of this chart is that both positive and negative shocks are distributed relatively equally over time. Hence this underlines that the empirical findings are not driven by individual episodes during the sample period. This point is further investigated and confirmed in section 4 when analyzing the time variations in the transmission of EME shocks.

[INSERT FIGURE 1 AROUND HERE]

Equity market returns come from Datastream market price indices. We chose Datastream indices as they have a very broad coverage of stocks within individual markets and are most readily comparable across countries. Datastream market indices are also available for a broad set of countries, thus providing an ideal source for our analysis of equity market spillovers. An additional advantage of Datastream indices is that also sectoral indices are available. We will go into detail about sectoral spillovers as an extension in section 4.[1]

The empirical analysis is based on daily financial market data, using closing quotes of the respective national stock markets in local currency. It is important to consider this timing issue in the empirical modeling due to the fact that several equity markets do not have an overlap in trading times so that e.g. yesterday's shocks in Latin American EMEs need to be used to analyze the effects on Asian markets today.

[1] However, there are also some potential drawbacks of Datastream indices, such as that for instance IFC equity indices may in some instances be of higher quality - see e.g. Sarno and Taylor (1999) for a detailed discussion. However, the need for indices that cover a broad set of countries and are directly comparable with one another point to Datastream indices as our preferred choice.

A final caveat is the issue of cross-listing of firms as in particular multinational firms may be listed in several markets simultaneously. Thus, for instance, a strong reaction of a particular market may at least in part reflect such cross-listing. To control for this issue, the ideal way would be to exclude foreign cross-listed firms from domestic equity return indices. Unfortunately, such data is not available for all of the 14 EMEs and 15 mature markets in our sample. A test for those few markets where such information is available, however, suggests that the transmission effects from EMEs are affected only moderately. Part of the explanation for these limited effects is that cross-listing primarily occurs among mature economies, and much less so with EMEs.

4.4 Empirical results

This section constitutes the core of the chapter, providing the empirical results for the transmission of EME shocks to global equity markets. We start with the benchmark model and results in section 4.1, discuss their economic relevance (section 4.2) and then present several extensions and robustness tests in section 4.3.

4.4.1 Methodology

As the first step of the analysis, we want to measure the transmission of shocks in emerging market country j to the equity market of country i. Our benchmark empirical specification looks as follows:

$$r_{it} = \alpha_i + \sum_{j=1}^{14} (\beta_j \cdot S_{jt}) + \delta \cdot X_{it} + \varepsilon_{it} \tag{4.1}$$

which estimates the response of the equity return of country i, r_{it}, to the shocks emanating from the 14 EMEs in the sample, S_{jt}, and to a vector of controls, X_{it}, such as own past returns and day-of-the-week effects. Note that this model is estimated in a panel for all 29 countries i in our sample, including a country fixed effect α_i. The model thus yields transmission coefficients β_j for each of the 14 EMEs, which measure the average effects of each of the 14 EMEs on the other 29 countries.[2]

It is important to emphasize that ideally one would like to control for all other relevant factors in the vector of controls X_{it} which may affect global equity markets, in particular "global" shocks. In order to control for such shocks as much as possible, we include two sets of proxies for global shocks in the vector of controls X_{it}. First, we follow Andersen et al. (2003) and Ehrmann and Fratzscher (2006) and include 10 of the most important US macroeconomic shocks, as measured through the news or unanticipated component of US macroeconomic announcement,[3] as a proxy for global economic shocks. Although these macroeconomic shocks are US-based in nature, they have been shown by in the literature to have a substantial effect on global FX and equity markets.

Second, we include a measure of global risk aversion, measured by the Chicago Board Options Exchange's SPX Volatility Index, which reflects a market estimate of future volatility, based on the weighted average of implied volatilities for a wide range of strike prices. The rationale for including this proxy for risk aversion is that the strength in the transmission may differ over time and may in part depend on the overall risk attitude of investors.[4]

An even more general specification of model (1) is one in which we average also across all EME source countries of shocks:

$$r_{it} = \alpha_i + \beta \sum_{j=1}^{14} (\beta_i j \cdot S_{jt}) + \delta \cdot X_{it} + \varepsilon_{it} \tag{4.2}$$

so that in this case measures the average effect of all EME shocks on equity returns. Alternatively, instead of obtaining the average response of a number of country returns to EME shocks,

[2] Note that we ensure in the estimation that shocks from countries j are excluded when these same countries are included as country i in the estimation.

[3] These shocks are the surprise component of the announcements of the 10 US macroeconomic news: monetary policy, GDP advance release, industrial production, CPI, retail sales, trade balance, non-farm payroll employment, ISM business confidence, consumer confidence, and housing starts. The surprise component of each of these variables is calculated as the difference between the announced value and the expected value, where this latter is measured as the median expectation from surveys conducted by Money Market Services (MMS) International.

[4] As these are controls and not the focus of this chapter, the results for these shocks are not shown in the tables below, but are available upon request. Most of the macroeconomic shocks and the risk-aversion proxy are found to exert a statistically significant effect on global and most regional equity markets.

we extract the effect on each individual equity return r_{it} by estimating for each equity return i separately:

$$r_{it} = \alpha + \beta_i \sum_{j=1}^{14} (S_{jt}) + \delta \cdot X_{it} + \varepsilon_{it} \tag{4.3}$$

to get the average transmission of all 14 EMEs to equity return r_{it}, or:

$$r_{it} = \alpha + \sum_{j=1}^{14} (S_{jt}) + \delta \cdot X_{it} + \varepsilon_{it} \tag{4.4}$$

in order to obtain the response of r_{it} to each of the 14 EMEs separately. Note that we use an OLS estimator with panel-corrected standard errors (PCSE) throughout the chapter for the estimations in order to take account of and to correct for the heteroskedasticity as well as the cross-sectional correlation in the data. Using such an estimator is important in order to obtain correct variance-covariance matrices as otherwise we would underestimate the true standard errors of the coefficients.

4.4.2 Benchmark results

Table 2 shows the benchmark result for models (2) and (3) for a select number of global, regional and mature economies' equity markets. The market reaction of "world" shows the coefficient for model (3) when using the Datastream world market return index. The subsequent rows show the response of regional equity market return indices for Latin America, Emerging Asia and Emerging Europe, as well as the return indices of the large mature markets of the euro area, Japan, UK and the USA. The last row titled "all countries (panel)" shows the panel estimates based on model (2), i.e. indicating the average response of the 29 equity markets in the sample.[5]

[INSERT TABLE 2 AROUND HERE]

[5] This panel estimate is comparable to the first row of using the world market index itself, only that the 29 countries in our sample do not constitute the whole global equity market - though they account for well over 90% of it - and that they are "unweighted" in the sense that in the panel regression each equity market return r_{it} has an equal influence on the coefficient, i.e. independent of their actual share in global equity market capitalisation.

Table 2 indicates that global equity returns react by 0.30% on average in response to a shock in one of the 14 EMEs. Global returns appear to be most sensitive to shocks in the Latin American EMEs, though they also sensitive to shocks in Emerging Asia and in Emerging Europe. The panel estimates in the last row are similar in magnitude when all EME shocks are taken together, giving a point estimate of 0.32%, though there are different responses from the world index to shocks from different regions.

Looking at the response of mature economies sheds light on these different regional effects and provides a number of interesting results. In particular, US, Japanese and European markets react very differently to regional EME shocks. US equity markets change substantially more in response to Latin American than to Asian or Emerging European shocks. By contrast, Japanese markets appear to respond most to Asian shocks, and not at all to shocks emanating from Emerging Europe. The euro area and the UK are very different again in that their reaction is very similar to shocks from all three EME regions. For instance, euro area and UK markets react substantially more to shocks from Emerging Europe then do the United States and Japan.

A final point relates to the reaction of EME stock markets to shocks in other EMEs. Table 2 nicely illustrates that EME equity markets react very strongly to shocks in the own region; this is the case for Latin America (0.59%), Asia (0.41%) and Emerging Europe (0.97%). However, there are some, though more limited cross-regional spillovers also for EMEs.

[INSERT TABLE 3 AROUND HERE]

Table 3 shows the full matrix of spillover of the 14 EMEs to the 29 countries, plus the regional averages. As for Table 2, the point estimates of the row called "all countries (panel)" are based on panel estimates of models (1) and (2), while all other estimates are based on individual country regressions of models (3) and (4).

Table 3 confirms the results of Table 2, only that it provides a much more detailed breakdown of the country-by-country transmission of shocks. For instance, the findings in the table confirm that EME spillovers to other EMEs are much stronger within regions than across regions, though cross-regional spillovers do exist and are sometimes sizeable.

An additional interesting point of Table 3 is that it shows the breakdown of the responses of the 12 euro area countries to EME shocks. Apart from Finland - most likely reflecting the technology dependence of the country - the euro area countries with the largest overall reaction to EME shocks are France, Netherlands, Germany and Spain, i.e. countries that are relatively integrated or exposed both financially and in terms of trade to EMEs. The countries with the overall lowest response are Ireland, Luxemburg, Portugal, Greece and Austria.[6] For many of the euro area countries it is also confirmed that they appear to respond about equally to shocks stemming from any of the three EME regions.

[INSERT TABLES 4 to 6 AROUND HERE]

As the final step of the analysis, we analyze the presence of various asymmetries in the transmission process. In particular, we investigate whether negative EME shocks have a larger effect than positive one. As discussed above, this hypothesis has been emphasized in particular in the literature on financial crises, which frequently suggests that negative EME shocks may have a much larger relevance for mature financial markets. Moreover, we also compare different types of shocks, i.e. political versus economic shocks.

Table 4 shows that negative EME shocks only have a slightly larger effect on the global equity market index (-0.33%) than positive events (0.28%). This underlines that also positive EME developments induce financial spillovers. There are again a number of revealing cross-country differences. Japanese and euro area equity markets, for instance, are even more responsive to positive shocks than to negative EME events, while the opposite is the case for US markets. Another revealing dimension relates to the shocks emanating from different EME regions. Negative shocks in Latin America and Asia appear to have a significantly larger impact than positive news. By contrast, positive shocks emanating from Emerging Europe in all cases have larger spillovers to other regions, including the euro area, than negative shocks.

[6] The finding for Austria appears somewhat surprising, especially given the countries financial exposure to several Emerging European countries, though recall that these include only the Czech Republic, Poland, Russia and Turkey in our sample.

Table 5 distinguishes between economic and political shocks, showing that there is no substantial difference in the relevance between these types of shocks. Tables 6.a and 6.b then combine the type of news with the direction of the shocks. It appears that in particular negative political news have the largest overall impact on foreign equity markets, though in general again all categories of shocks have significant spillover effects.

In summary, we find significant and sizeable spillovers from EMEs to global equity markets, with world equity returns responding on average 0.3% to EME shocks. The disaggregation of the shocks by source EME and by affected countries shows a highly heterogeneous picture, with mature economies being most sensitive to EME shocks from their own region, with the exception of Europe which appears to be roughly equally responsive to all thee EME regions.

4.5 Sensitivity

As a final step, this section presents various extensions and robustness checks (section 5.2) and discusses the overall economic relevance of EMEs shocks for global equity markets (section 5.1).

4.5.1 Economic relevance of EMEs for global equity markets

How permanent and long-lasting are the effects of EME shocks on global equity markets? This is an important question because a key issue of interest is not only whether the effect of EMEs on global financial markets is statistically significant, but also whether it is economically relevant. From a more general perspective, EME events may have a statistically significant effect on global equity markets on a particular day, but they may in the medium- to long-run - e.g. over several weeks or months - be dominated by other developments, like economic and political developments in mature economies, such that EMEs may play only a small overall role for global equity markets.

This issue is hard to tackle because our data includes only a small, albeit relevant fraction of EME events that affects global financial markets. In other words, our data includes only "shocks", i.e. well identified, mostly unanticipated events while many other unanticipated or anticipated EME developments are clearly not captured by our data. This means that it is impossible to determine precisely how much of global equity market movements are explained by developments in EMEs and how much by mature economies or truly common shocks.

As a first test in order to gauge the overall relevance of EME shocks for global markets, an interesting stylized fact is to plot the "net" number of shocks per quarter - subtracting the total number of negative shocks from the total number of positive shocks across all 14 EMEs - together with the global equity market return during that quarter. Figure 2 shows a remarkably high degree of comovement between both, in particular since the end of 2002. In fact, the correlation coefficient between the two series is 0.70 for the whole sample period. It should be stressed that while this obviously does not necessarily imply causality, it underlines that developments in EMEs strongly co-move with those in global equity markets. While this is merely indicative of the overall importance of EMEs, it appears to be a striking stylized fact of the data.

[INSERT FIGURE 2 AROUND HERE]

Given this limitation, and in order to turn to a more formal test, we can gauge the importance of EMEs for global equity markets also by analyzing the permanence of the transmission of EME shocks. The intuition is as follows: if EMEs are an important driver of global equity markets and if our data captures relevant EME events, then the impact of our EME shocks on global equity markets should be detectable in the data at least for several days or even weeks. We test for this permanence in two alternative ways. First, we estimate a dynamic version of model (3) by including and testing for the lagged effects of EME shocks:

$$r_{it} = \alpha + \sum_{k=0}^{K} \beta_{ik} \sum_{j=1}^{14} (S_{jt-k}) + \delta \cdot X_{it} + \varepsilon_{it} \tag{4.5}$$

with k as the number of lags. Figure 3 shows the cumulated coefficients up to 3 months (65 days), while testing the null hypothesis $H_0 : \sum_{k=0}^{K} \beta_k = 0$, for the returns of the world equity index, as well as for the United States', the euro area' and the emerging markets' equity indices.

The key finding is that there is a high degree of persistence or permanence in the spillover effects of EME shocks. For the world, US and euro area indices the effect increases for a number of days after a shock occurs and then stabilizes. Most importantly, statistically the impact of EME shocks is mostly significant even still after 1 month, or about 20 business days. This is somewhat less the case for the US equity markets, but for which the effects of EME shocks are still statistically significant for up to 10 days, or 2 weeks.

[INSERT FIGURES 3 and 4 AROUND HERE]

A second and alternative way of testing for the permanence of the effects is to use different data frequencies. For this exercise, we repeat the estimation of model (3) using different data frequencies starting with daily data (as in the benchmark model), then moving to two-day frequencies and so on up to using 65-day or quarterly frequency. Figure 4 gives the results again for four of the equity market indices. This second exercise gives us essentially the same results as the first one: the effect of EME shocks appears to increase slightly in the first few days and then levels off. Again, the key result is that the effect of EME shocks on global equity markets is present in the data even when using quarterly data. Both of the tests underline the overall economic importance of EMEs for global equity markets.

4.5.2 Extensions and robustness

We now turn to various extensions and robustness tests of the benchmark results. A first important issue is that of time-variations in the transmission process. Do EMEs matter for global equity markets only in some periods rather than others? As discussed above, much of the literature appears to indirectly or directly suggest that EMEs have the largest impact on global markets during financial crises. Recall that our sample period of 2000-2004 had no major EME crisis of systemic importance, especially when compared to the Latin American crisis of 1994-95, the Asian financial crisis of 1997-98, or the Russian default and the LTCM episode in the second half of 1998. Nevertheless, the Argentine default of late 2001 and the Turkish crisis of 2001 were two relevant events during our sample period.

To test for the presence of time variations in the transmission process, we modify the benchmark models (2) and (3) to allow for different spillover coefficients for each of the five years of our data:[7]

$$r_{it} = \alpha_i + \sum_{t=1}^{5} \beta_t D_t \sum_{j=1}^{14} (S_{jt}) + \delta \cdot X_{it} + \varepsilon_{it} \tag{4.6}$$

with $D_t = 1$ for a particular year, and $D_t = 0$ otherwise, so that in this case β_t measures the average effect of all EME shocks on global equity returns in year t.

[INSERT FIGURE 5 AROUND HERE]

Figure 5 plots the coefficients for the panel estimation of model (6). The figure shows a slight decrease in the effects, indicating that the strongest transmission of shocks from EMEs to global equity markets occurred in 2000 and 2001, while the smallest effects are recorded for 2003 and 2004. However, it should be stressed that the transmission is statistically significant and sizeable for all years. Hence EME shocks have continuously exerted an influence on global equity markets throughout the sample period, amid relatively small variations in the precise magnitude of the transmission.[8]

Turning to a second important issue, it is possible that the cross-country difference in the transmission process, as highlighted in Table 3, may in part be explained by the very different sector composition of countries' equity indices. Some sectors, such as the financial or technology sectors may be more open and exposed to foreign developments. Hence countries' stronger reaction to EME shocks may partly reflect the fact that different sectors have different weights in individual countries' equity indices. For instance, the fact that Spain is affected relatively strongly by shocks in Latin America may be explained e.g. by the fact that it is highly integrated financially with many Latin American economies but it could also be due to the fact that Spain's equity market index is dominated by some sectors rather than others.

[7]Note that using a higher frequency, such as quarterly or even monthly data, is not feasible due to the relative few EME shocks in our dataset at such frequencies.

[8]Note that this pattern of the time variations in the spillover coefficients is not driven by some specific markets' responses, as it is very similar also when looking only at mature economies.

[INSERT TABLE 7 AROUND HERE]

Given the relevance of financial institutions in the transmission process, an obvious hypothesis is that countries where financial institutions are relatively important and constitute a large share of the equity index also respond more strongly to EME shocks. We test this by re-estimating models (2) and (3) using Datastream financial sector sub-indices. Table 7 reveals that we can broadly reject this hypothesis as financial sector returns are generally not more sensitive to EME shocks than the market index as whole (see Table 2). In fact, the overall effect of EME shocks on global financial sector returns is with 0.269% somewhat lower than the impact on the overall market index.

[INSERT TABLE 8 AROUND HERE]

Third and finally, we want to check the effect of large and important shocks, and thus restrict the sample to those news that triggered a significant domestic market movement. To determine the threshold, we choose a 1% cut-off, although we conducted robustness tests for the 0.5% and 1.5% cut-offs. We do this to check how the results of the benchmark model change when using a narrower set of shocks. The corresponding Table 8, however, shows that this is not the case and that most spillover coefficients increase significantly for this narrower sample. Indeed, the increase in the magnitude of the transmission is consistent with the argument that news that have a larger effect on the domestic market should also have a greater impact on other markets.

4.6 Conclusions

How important are emerging markets as drivers of global financial markets? While there is a large literature and plenty of evidence for the role and impact of EMEs during financial crises, much less attention has been paid to the systemic importance of global financial markets overall, including during "normal" or tranquil times. In fact, the last few years have been marked by the absence of major crises or systemic turbulence in EMEs as well as the strong emergence, or re-emergence, of EMEs as a key asset class for investors in mature economies.

This chapter has focused on the importance of EMEs for global financial markets by analyzing the transmission of EME shocks to global equity markets. Our database for this analysis has the key advantage of containing largely exogenous shocks that are specific to individual emerging economies. We have estimated the transmission of these shocks to 29 mature economies and emerging markets and find that EME shocks have a statistically and economically significant impact on global equity markets. On average, shocks to the 14 EMEs in our sample move world equity markets by 0.3% on the day they occur. Importantly, the persistence of these effects is found to be remarkably long as the impact of EME shocks is statistically significant even one month after they occur. Moreover, EMEs influence global equity markets not just in “bad” times but also in “good” times. In fact, the average effect of positive shocks stemming from EMEs is in many cases very similar to that of negative events.

A second key result of the chapter is that we detect a large degree of heterogeneity in the response of individual countries’ equity markets to EME shocks. For mature economies, US equity markets appear to be more sensitive to developments in Latin America than in Emerging Asia or Emerging Europe, while the Japanese market reacts the strongest to shocks elsewhere in Asia. By contrast, an interesting finding is that European (euro area and UK) equity markets appear to be different as they are exposed the strongest and also roughly equally responsive to shocks in all three emerging market regions.

Overall, the findings underline the importance of emerging markets as drivers of global asset price developments in recent years. In many ways, this is what one would expect given the substantial contribution of EMEs to global economic growth and their rapidly increasing clout in global financial markets as investors. Understanding the evolution of EMEs as a global player in financial markets is an important topic from a financial market angle, but also from a policy perspective given their rapid emergence and the rising economic interdependence between mature and emerging market economies.

Tables and Figures

Annex1
Data Description and Examples

Date	News
24 February 2000	A strike is called against the labor market reform proposal, stipulating decentralization of collective labor contracts.
10 March 2000	IMF Board approves Stand-By Arrangement with Argentina.
6 June 2000	A national strike is called.
17 August 2000	Responding to public denunciations, President De La Rúa creates a special commission, chaired by Vice PresidentCarlos Álvarez, to investigate the bribery charges associated with the Senate approval of the labor reform law.
6 October 2000	Vice President Carlos Álvarez resigns.
5 March 2001	Ricardo López Murphy is appointed Minister of Economy.
29 March 2001	Minister Cavallo secures “emergency powers” from Congress.
16 April 2001	Minister Cavallo announces a modification of the convertibility law, with the replacement of the dollar by an equallyweighted basket of the dollar and the euro.
26 April 2001	The Central Bank Governor is replaced over alleged money laundering charges.
8 May 2001	A national strike is called against the labor reform.
11 July 2001	Standard & Poor’s lowers Argentina’s long-term sovereign rating further from B+ to B.
21 August 2001	A zero deficit plan is announced, with a mandatory reduction in expenditures to balance the budget.
3 December 2001	IMF announces planned augmentation of Stand-By Arrangement by $8 billion.
6 December 2001	The government introduces a partial deposit freeze (corralito) and capital controls.
10 December 2001	Minister Cavallo travels to the United States to meet with IMF management.
19 December 2001	Minister Cavallo resigns.
20 December 2001	President Fernando De La Rúa resigns over death of demonstrators. Ramón Puerta, President of the Senate, becomes interim President.
3 January 2002	President Duhalde announces the end of convertibility, and the introduction of a dual foreign exchange regime.
7 January 2002	The convertibility law ceases to be in effect. A dual exchange rate regime is introduced, one fixed at 1.40 pesos to a dollar for foreign trade, and the other determined in the free market.
8 March 2002	The pesoization of government debt under Argentine law is decreed.
5 March 2003	The Supreme Court ruled that conversion to pesos was illegal. According to the Central Bank, approximately to 8,760 million US dollars are at stake.
10 September 2003	Argentine finance officials reached an agreement with the IMF for a three-year, US$ 12.6 billion stand-by credit. Under the terms of the new arrangement, the government pledges to raise the consolidated primary fiscal surplus
14 June 2004	Roberto Lavagna sent a "fiscal responsibility" bill to Congress to set limits on spending by provincial governments.
2 July 2004	Argentina obtained regulatory approval in the U.S. for a debt exchange to restructure some $100 billion in defaulted debt.

Source: Factiva, Datastream Bekaert and Campbell (2004) and Independent Evaluation Office, International Monetary Fund (2004). *The IMF and Argentina, 1991–2001.*

Table 1
Summary Statistics

The table shows the number of news, economic news and political news recorded for each country and region. Sources: IMF; IFC; Bekaert and Harvey (1998, 2002); Factiva.

	Shocks			Economic shocks			Political shocks		
	Total	*Positive*	*Negative*	*Total*	*Positive*	*Negative*	*Total*	*Positive*	*Negative*
Emerging markets	424	204	220	308	152	156	176	80	96
Latin America:	214	113	101	146	77	69	76	39	37
Argentina	58	24	34	29	11	18	29	13	16
Brazil	39	22	17	34	19	15	5	3	2
Chile	38	22	16	20	14	6	18	8	10
Mexico	92	50	42	67	35	32	25	15	10
Emerging Asia:	152	67	85	99	45	54	55	23	32
India	48	19	29	27	12	15	21	7	14
Indonesia	35	10	25	16	4	12	19	6	13
Korea	40	21	19	19	10	9	21	11	10
Malaysia	21	9	12	12	4	8	9	5	4
Taiwan	31	17	14	20	11	9	11	6	5
Thailand	26	15	11	24	14	10	2	1	1
Emerging Europe:	168	81	87	123	61	62	55	24	31
Czech Republic	28	14	14	15	9	6	13	5	8
Poland	56	30	26	44	24	20	12	6	6
Russia	77	32	45	56	22	34	21	10	11
Turkey	24	13	11	15	8	7	9	3	6

Table 2
Transmission of EME Shocks - All shocks, by Region

The table shows the transmission coefficients for EME shocks based on models (1)-(4). *** , **, * indicate statistical significance at the 99%, 95%, and 90% levels.

Transmission of EME shocks, all shocks by region

Event shock to:	All 14 EMEs		Latin America 4		Emerging Asia 6		Emerging Europe 4	
Market reaction of:	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*
World	0.300 ***	0.04	0.362 ***	0.06	0.149 **	0.07	0.268 ***	0.07
Latin America	0.402 ***	0.06	0.592 ***	0.07	0.101	0.09	0.315 ***	0.10
Emerging Asia	0.302 ***	0.05	0.220 ***	0.07	0.407 ***	0.09	0.234 ***	0.08
Emerging Europe	0.635 ***	0.08	0.400 ***	0.10	0.329 ***	0.13	0.966 ***	0.16
Euro area	0.354 ***	0.06	0.307 ***	0.08	0.278 ***	0.11	0.373 ***	0.10
Japan	0.216 ***	0.07	0.238 ***	0.10	0.212 *	0.12	0.072	0.11
United Kingdom	0.318 ***	0.05	0.315 ***	0.07	0.234 ***	0.10	0.292 ***	0.10
United States	0.328 ***	0.06	0.457 ***	0.08	0.107	0.10	0.271 ***	0.10
All countries (panel)	0.323 ***	0.03	0.274 ***	0.04	0.263 ***	0.04	0.334 ***	0.05

Table 3
Transmission of EME Shocks by Country

The table shows the transmission coefficients for EME shocks based on models (1)-(4). *** , **, * indicate statistical significance at 99%,95%,and 90%.

Event shock to:	Aggregate				Latin America 4				Emerging Asia 6						Emerging Europe 4			
Market reaction of:	All 14 EMEs	Latin America 4	Emerging Asia 6	Emerging Europe 4	Argentina	Brazil	Chile	Mexico	India	Indonesia	Korea	Malaysia	Taiwan	Thailand	Czech Rep.	Poland	Russia	Turkey
World	0.300 ***	0.362 ***	0.149 **	0.268 ***	0.151	0.378 ***	0.201	0.520 ***	0.274 ***	0.093	0.101	-0.081	0.246	0.186	0.293 *	0.100	0.260 ***	0.571 ***
Latin America	0.402 ***	0.592 ***	0.101	0.315 ***	0.427 ***	0.952 ***	0.375 **	0.617 ***	0.305 **	0.146	0.126	-0.238	-0.010	0.144	0.444 **	0.064	0.266 ***	0.926 ***
Emerging Asia	0.302 ***	0.220 ***	0.407 ***	0.234 ***	0.092	0.007	0.520 ***	0.317 ***	0.426 ***	0.314	0.676 ***	0.189	0.754 ***	0.389 ***	0.511 ***	0.093	0.175	0.378 *
Emerging Europe	0.635 ***	0.400 ***	0.329 ***	0.966 ***	0.358 *	0.512 **	0.160	0.388 ***	0.153	0.700 **	0.224	0.204	0.479	0.182	0.457	0.299	0.933 ***	3.177 ***
Euro area	0.354 ***	0.307 ***	0.278 ***	0.373 ***	-0.049	0.397 ***	0.107	0.571 ***	0.115	0.354 *	0.205	-0.049	0.692 ***	0.432 **	0.502 **	0.247	0.330 ***	0.543 *
Japan	0.216 ***	0.238 ***	0.212 *	0.072	-0.016	0.047	0.601 ***	0.279 **	0.197	0.107	0.635 ***	0.587 *	0.056	0.260	-0.062	0.033	0.124	0.048
United Kingdom	0.318 ***	0.315 ***	0.234 ***	0.292 ***	0.109	0.340 **	0.240	0.471 ***	0.231	0.204	0.081	-0.035	0.500 **	0.315 *	0.309	0.238	0.331 ***	0.222
United States	0.328 ***	0.457 ***	0.107	0.271 ***	0.254 *	0.526 ***	0.128	0.633 ***	0.394 ***	-0.052	-0.099	-0.131	0.104	0.120	0.273	0.051	0.248 ***	0.796 ***
All countries (panel	0.323 ***	0.274 ***	0.263 ***	0.334 ***	0.130	0.273 ***	0.232 ***	0.374 ***	0.180 ***	0.385 ***	0.297 ***	0.111 **	0.412 ***	0.308 ***	0.396 ***	0.149 ***	0.317 ***	0.728 ***
Latin America:																		
Argentina	0.377 ***	0.826 ***	0.019	0.062	2.412 ***	0.175	0.449	0.234	0.035	0.280	0.220	0.619	-0.268	-0.402	-0.041	-0.563 *	0.561 ***	0.262
Brazil	0.508 ***	0.642 ***	0.136	0.496 ***	0.405 *	1.419 ***	0.358	0.557 ***	0.353	0.216	0.239	-0.552	0.216	0.120	0.765 **	0.135	0.393 **	1.312 **
Chile	0.243 ***	0.348 ***	0.074	0.214 ***	0.008	0.521 ***	0.657 ***	0.369 ***	0.118	0.081	0.066	0.114	0.281 *	-0.166	0.315 ***	0.182	0.165	0.452 *
Mexico	0.365 ***	0.651 ***	0.079	0.183 *	0.342 **	0.742 ***	0.295 *	0.951 ***	0.375 ***	0.035	0.094	-0.102	-0.363	0.368 **	0.195	-0.028	0.143	0.835 ***
Emerging Asia:																		
India	0.288 ***	0.082	0.510 ***	0.311 ***	-0.511 ***	0.308	0.584	0.195	1.286 ***	0.267	0.513 *	-0.223	0.090	0.427 *	0.697 ***	-0.006	0.496 ***	-0.209
Indonesia	0.311 ***	-0.006	0.724 ***	0.235	-0.071	-0.644 **	0.492 *	0.172	0.461 *	2.236 ***	0.604 **	-0.085	0.370	0.225	-0.125	0.239	0.235	0.382
Korea	0.368 ***	0.292 **	0.413 **	0.289 *	0.252	-0.104	0.432	0.483 ***	0.381	0.296	1.577 ***	0.327	0.784 *	0.441	0.764 **	-0.001	0.193	0.683
Malaysia	0.087 *	-0.035	0.179 **	0.131 *	-0.124	-0.199	0.191	0.034	0.082	0.255	0.037	0.502 ***	0.312	-0.031	0.078	0.093	0.082	0.355 ***
Taiwan	0.335 ***	0.258 *	0.612 ***	0.137	0.145	-0.115	0.666 *	0.461 ***	0.309	0.067	0.737 ***	0.448	2.094 ***	0.414	0.250	0.054	-0.006	0.685
Thailand	0.231 ***	0.140	0.270 **	0.264 *	-0.148	-0.050	0.596 ***	0.175	-0.102	0.287	0.821 ***	0.445	0.110	1.133 ***	0.449 *	0.211	0.221	0.234
Emerging Europe:																		
Czech Republic	0.271 ***	0.078	0.285 ***	0.376 ***	0.142	0.142	-0.294	0.118	0.233	0.594 ***	0.290	0.263	0.154	0.153	1.330 ***	0.110 ***	0.315 ***	0.173
Poland	0.444 ***	0.254 ***	0.302 ***	0.576 ***	0.240	0.141	0.290	0.303 **	0.148	0.389	0.595 ***	0.342	0.109	0.673 ***	0.301	0.957	0.370 ***	0.632 ***
Russia	0.723 ***	0.587 ***	0.400 ***	0.946 ***	0.530 ***	0.865 ***	0.231	0.531 ***	0.451 *	0.579	0.268	0.156	0.768 **	-0.062	0.190	0.120	1.389 ***	1.870 ***
Turkey	0.780 ***	0.300	0.409	1.410 ***	0.259	0.226	0.446	0.265	-0.552	1.184 **	-0.095	0.072	0.879	1.007	1.167	0.420	0.432	7.728 ***
Euro area:																		
Austria	0.016	-0.063	0.046	0.080	-0.157	0.047	-0.097	-0.087	-0.115	0.174	0.136	-0.070	0.153	0.251 **	0.187	0.041	0.063	0.108
Belgium	0.211 ***	0.240 ***	0.066	0.220 ***	0.037	0.206	0.148	0.386 ***	0.014	0.187	-0.019	0.017	0.275	0.025	0.444 *	0.200	0.229 *	-0.117
Finland	0.616 ***	0.461 ***	0.677 ***	0.524 ***	-0.022	0.808 **	-0.088	0.750 ***	0.289	0.823 **	0.894 ***	-0.058	1.500 ***	0.781 *	0.838 *	0.092	0.345	1.626 ***
France	0.376 ***	0.354 ***	0.303 ***	0.355 ***	-0.068	0.351 *	0.219	0.683 ***	0.157	0.417 *	0.251	0.033	0.668 **	0.442 *	0.519 *	0.218	0.307 *	0.443
Germany	0.381 ***	0.356 ***	0.217 *	0.455 ***	-0.046	0.513 ***	0.065	0.652 ***	0.106	0.234	0.180	-0.419	0.761 ***	0.469 ***	0.619 **	0.359 **	0.364 ***	0.670 ***
Greece	0.203 ***	0.218 ***	0.123	0.243 **	0.231	0.084	-0.031	0.379 ***	0.141	0.385	0.305	0.107	-0.085	0.181	0.213	0.218	0.362 ***	0.046
Ireland	0.154 ***	0.061	0.147	0.226 ***	-0.245	0.264	-0.038	0.230 ***	0.036	0.259	-0.053	0.212	0.263	0.210	0.025	0.140	0.302	0.463
Italy	0.285 ***	0.155 *	0.322 ***	0.334 ***	-0.168	0.268 *	-0.029	0.397 ***	0.120	0.433	0.021	0.071	0.708	0.392	0.397	0.197	0.341	0.481
Luxemburg	0.109 *	0.017	0.102	0.134	-0.109	0.142	0.018	0.003	-0.181	0.421	-0.299	0.279	0.075	0.088	0.325	0.064	0.328	-0.322
Netherlands	0.358 ***	0.340 ***	0.247 **	0.362 ***	0.000	0.318 *	0.204	0.637 ***	0.072	0.229	0.173	0.099	0.653	0.467	0.431	0.341	0.333	0.392
Portugal	0.131 ***	0.085	0.122	0.158 **	-0.037	0.108	0.018	0.125	0.077	0.144	0.201	-0.094	0.272	0.203	0.411	0.053	0.158	0.219
Spain	0.327 ***	0.302 ***	0.249 **	0.321 ***	0.082	0.452 ***	-0.068	0.519 ***	0.053	0.428	0.251	0.195	0.473	0.340	0.290	0.192	0.346	0.538

Table 4 - Asymmetries
Positive vs. Negative Shocks

The table shows the transmission coefficients for EME shocks based on models (1)-(4), but further distinguishing between positive and negative shocks. *** , **, * indicate statistical significance at the 99%, 95%, and 90% levels.

Positive shocks

Event shock to:	All 14 EMEs		Latin America 4		Emerging Asia 6		Emerging Europe 4	
Market reaction of:	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*
World	0.284 ***	0.06	0.272 ***	0.08	-0.008	0.09	0.378 ***	0.10
Latin America	0.446 ***	0.09	0.589 ***	0.10	-0.007	0.14	0.404 ***	0.14
Emerging Asia	0.321 ***	0.07	0.242 ***	0.09	0.338 ***	0.12	0.278 ***	0.11
Emerging Europe	0.802 ***	0.11	0.674 ***	0.13	0.100	0.15	1.108 ***	0.20
Euro area	0.381 ***	0.08	0.285 ***	0.11	0.182	0.15	0.490 ***	0.13
Japan	0.249 ***	0.10	0.304 **	0.13	0.112	0.18	0.143	0.15
United Kingdom	0.289 ***	0.08	0.288 ***	0.11	0.060	0.12	0.318 ***	0.12
United States	0.299 ***	0.09	0.305 ***	0.12	-0.080	0.13	0.410 ***	0.16
All countries (panel)	0.332 ***	0.04	0.286 ***	0.04	0.132 ***	0.04	0.393 ***	0.06

Negative shocks

Event shock to:	All 14 EMEs		Latin America 4		Emerging Asia 6		Emerging Europe 4	
Market reaction of:	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*
World	-0.331 ***	0.06	-0.464 ***	0.08	-0.275 ***	0.11	-0.148	0.09
Latin America	-0.368 ***	0.08	-0.595 ***	0.11	-0.189	0.13	-0.219 *	0.13
Emerging Asia	-0.289 ***	0.08	-0.196 *	0.11	-0.462 ***	0.14	-0.187	0.13
Emerging Europe	-0.480 ***	0.12	-0.090	0.16	-0.515 ***	0.21	-0.811 ***	0.23
Euro area	-0.338 ***	0.09	-0.332 ***	0.12	-0.354 **	0.16	-0.245	0.15
Japan	-0.181 *	0.11	-0.164	0.17	-0.292 *	0.16	0.005	0.16
United Kingdom	-0.361 ***	0.09	-0.346 ***	0.10	-0.373 ***	0.15	-0.264 *	0.15
United States	-0.380 ***	0.09	-0.630 ***	0.12	-0.258 *	0.15	-0.121	0.12
All countries (panel)	-0.320 ***	0.03	-0.261 ***	0.05	-0.369 ***	0.04	-0.270 ***	0.05

Table 5 - Asymmetries
Political vs. Economic Shocks

The table shows the transmission coefficients for EME shocks based on models (1)-(4), but further distinguishing between economic and political shocks. *** , **, * indicate statistical significance at the 99%, 95%, and 90% levels.

Political shocks

Event shock to:	All 14 EMEs		Latin America 4		Emerging Asia 6		Emerging Europe 4	
Market reaction of:	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*
World	0.291 ***	0.06	0.309 ***	0.09	0.230 **	0.11	0.260 ***	0.11
Latin America	0.501 ***	0.08	0.629 ***	0.11	0.205	0.13	0.529 ***	0.15
Emerging Asia	0.321 ***	0.08	0.355 ***	0.13	0.390 ***	0.13	0.176	0.15
Emerging Europe	0.445 ***	0.11	0.347 **	0.17	0.379 *	0.21	0.496 ***	0.19
Euro area	0.257 ***	0.09	0.248 *	0.13	0.204	0.16	0.245	0.18
Japan	0.123	0.10	0.103	0.16	0.143	0.20	0.020	0.16
United Kingdom	0.282 ***	0.08	0.265 ***	0.11	0.235 *	0.14	0.217	0.16
United States	0.367 ***	0.09	0.425 ***	0.12	0.277	0.17	0.328 **	0.15
All countries (panel)	0.274 ***	0.03	0.266 ***	0.05	0.256 ***	0.04	0.242 ***	0.04

Economic shocks

Event shock to:	All 14 EMEs		Latin America 4		Emerging Asia 6		Emerging Europe 4	
Market reaction of:	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*
World	0.288 ***	0.05	0.370 ***	0.07	0.100	0.09	0.261 ***	0.08
Latin America	0.327 ***	0.07	0.534 ***	0.09	0.045	0.12	0.224 *	0.12
Emerging Asia	0.296 ***	0.06	0.164 **	0.08	0.419 ***	0.12	0.259 ***	0.10
Emerging Europe	0.696 ***	0.10	0.382 ***	0.11	0.300 *	0.17	1.167 ***	0.20
Euro area	0.388 ***	0.07	0.328 ***	0.09	0.312 **	0.14	0.409 ***	0.12
Japan	0.220 ***	0.08	0.277 **	0.13	0.239 *	0.13	0.089	0.13
United Kingdom	0.321 ***	0.06	0.317 ***	0.09	0.215 *	0.13	0.325 ***	0.11
United States	0.293 ***	0.07	0.450 ***	0.10	0.012	0.12	0.238 **	0.12
All countries (panel)	0.333 ***	0.03	0.265 ***	0.04	0.264 ***	0.04	0.373 ***	0.06

Table 6.a - Asymmetries
Positive vs. Negative Economic Shocks

The table shows the transmission coefficients for EME shocks based on models (1)-(4), but further distinguishing between positive economic and negative economic shocks. *** , **, * indicate statistical significance at the 99%, 95%, and 90% levels.

Positive economic shocks

Event shock to:	All 14 EMEs		Latin America 4		Emerging Asia 6		Emerging Europe 4	
Market reaction of:	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*
World	-0.307 ***	0.07	-0.511 ***	0.09	-0.174	0.14	-0.153	0.11
Latin America	-0.334 ***	0.10	-0.564 ***	0.13	-0.145	0.17	-0.219	0.16
Emerging Asia	-0.279 ***	0.09	-0.148	0.11	-0.486 ***	0.19	-0.202	0.15
Emerging Europe	-0.585 ***	0.15	-0.115	0.17	-0.525 *	0.27	-1.085 ***	0.30
Euro area	-0.383 ***	0.11	-0.384 ***	0.14	-0.307	0.20	-0.377 **	0.19
Japan	-0.081	0.13	-0.190	0.20	-0.192	0.19	0.157	0.21
United Kingdom	-0.386 ***	0.10	-0.412 ***	0.12	-0.240	0.20	-0.434 **	0.19
United States	-0.339 ***	0.10	-0.695 ***	0.14	-0.106	0.18	-0.084	0.14
All countries (panel)	0.334 ***	0.05	0.313 ***	0.04	0.181 ***	0.06	0.370 ***	0.07

Negative economic shocks

Event shock to:	All 14 EMEs		Latin America 4		Emerging Asia 6		Emerging Europe 4	
Market reaction of:	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*
World	0.267 ***	0.08	0.250 **	0.11	0.008	0.12	0.355 ***	0.12
Latin America	0.316 ***	0.10	0.530 ***	0.13	-0.079	0.17	0.235	0.16
Emerging Asia	0.310 ***	0.08	0.192 *	0.12	0.338 **	0.16	0.309 ***	0.13
Emerging Europe	0.798 ***	0.14	0.644 ***	0.16	0.021	0.18	1.243 ***	0.27
Euro area	0.391 ***	0.10	0.286 **	0.14	0.319	0.21	0.438 ***	0.15
Japan	0.353 ***	0.11	0.362 **	0.17	0.298	0.19	0.299 *	0.17
United Kingdom	0.256 ***	0.09	0.239 *	0.13	0.185	0.17	0.235 *	0.14
United States	0.245 **	0.11	0.237	0.15	-0.105	0.16	0.373 **	0.19
All countries (panel)	-0.327 ***	0.04	-0.273 ***	0.07	-0.327 ***	0.05	-0.323 ***	0.06

Table 6.b - Asymmetries
Positive vs. Negative Political Shocks

The table shows the transmission coefficients for EME shocks based on models (1)-(4), but further distinguishing between positive political and negative political shocks. *** , **, * indicate statistical significance at the 99%, 95%, and 90% levels.

Positive political shocks

Event shock to:	All 14 EMEs		Latin America 4		Emerging Asia 6		Emerging Europe 4	
Market reaction of:	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*
World	0.222 ***	0.08	0.260 **	0.12	-0.011	0.14	0.365 ***	0.14
Latin America	0.592 ***	0.12	0.682 ***	0.14	0.132	0.23	0.795 ***	0.23
Emerging Asia	0.285 ***	0.10	0.314 **	0.14	0.338 *	0.19	0.186	0.18
Emerging Europe	0.507 ***	0.13	0.604 ***	0.20	0.256	0.26	0.571 ***	0.13
Euro area	0.244 **	0.12	0.221	0.17	-0.039	0.21	0.527 ***	0.20
Japan	-0.050	0.14	0.101	0.20	-0.188	0.32	-0.244	0.22
United Kingdom	0.270 ***	0.11	0.310 *	0.16	-0.122	0.15	0.460 ***	0.19
United States	0.286 ***	0.12	0.379 **	0.17	-0.003	0.19	0.422 *	0.22
All countries (panel)	0.251 ***	0.05	0.282 ***	0.07	0.098 *	0.05	0.326 ***	0.07

Negative political shocks

Event shock to:	All 14 EMEs		Latin America 4		Emerging Asia 6		Emerging Europe 4	
Market reaction of:	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*
World	-0.353 ***	0.10	-0.399 ***	0.14	-0.413 ***	0.16	-0.176	0.18
Latin America	-0.410 ***	0.11	-0.609 ***	0.17	-0.260	0.17	-0.304	0.20
Emerging Asia	-0.350 ***	0.13	-0.418 *	0.23	-0.431 ***	0.18	-0.173	0.23
Emerging Europe	-0.376 **	0.19	-0.067	0.28	-0.472	0.30	-0.461	0.36
Euro area	-0.263 *	0.15	-0.309	0.21	-0.389 *	0.23	-0.009	0.29
Japan	-0.284 *	0.16	-0.128	0.27	-0.393	0.26	-0.250	0.22
United Kingdom	-0.290 **	0.13	-0.236	0.17	-0.508 ***	0.20	-0.014	0.26
United States	-0.438 ***	0.13	-0.518 ***	0.19	-0.490 **	0.25	-0.252	0.22
All countries (panel)	-0.291 ***	0.03	-0.268 ***	0.04	-0.375 ***	0.05	-0.179 ***	0.05

Table 7
Extension - Financial Sector

The table shows the transmission coefficients for EME shocks based on models (1)-(4), focusing only on the Datastream financial sector return indices. ***, **, * indicate statistical significance at the 99%, 95%, and 90% levels.

Event shock to:	All 14 EMEs		Latin America 4		Emerging Asia 6		Emerging Europe 4	
Market reaction of:	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*
World	0.269 ***	0.04	0.226 ***	0.06	0.202 ***	0.08	0.271 ***	0.07
Latin America	0.415 ***	0.06	0.562 ***	0.09	0.188 *	0.10	0.259 ***	0.10
Emerging Asia	0.227 ***	0.05	0.095	0.07	0.297 ***	0.09	0.306 ***	0.08
Emerging Europe	0.550 ***	0.10	0.255 **	0.12	0.344 **	0.18	0.900 ***	0.19
Euro area	0.269 ***	0.06	0.161 *	0.09	0.252 **	0.12	0.324 ***	0.10
Japan	0.200 **	0.09	0.147	0.13	0.207	0.15	0.143	0.14
United Kingdom	0.297 ***	0.06	0.224 ***	0.09	0.271 **	0.12	0.294 ***	0.11
United States	0.322 ***	0.06	0.330 ***	0.09	0.172	0.11	0.295 ***	0.11
All countries (panel)	0.277 ***	0.03	0.183 ***	0.05	0.253 ***	0.05	0.327 ***	0.05

Table 8
Extension - “important” shocks

The table shows the transmission coefficients for EME shocks based on models (1)-(4), focusing on ”important” shocks, i.e. only on those news that moved the domestic equity market by 1% or more. *** , **, * indicate statistical significance at the 99%, 95%, and 90% levels.

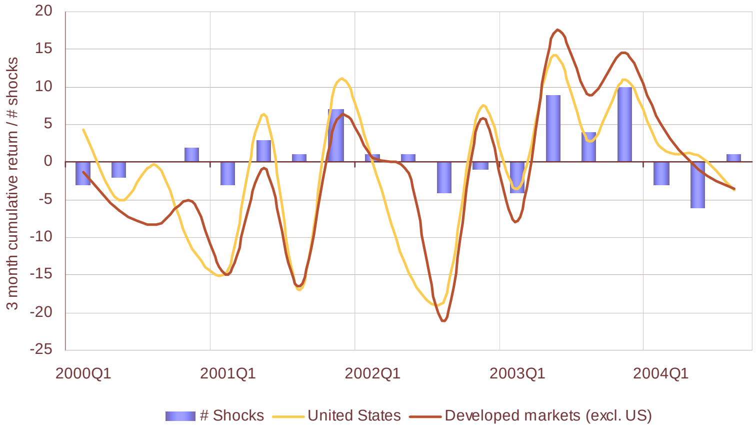
Event shock to:	All 14 EMEs		Latin America 4		Emerging Asia 6		Emerging Europe 4	
Market reaction of:	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*	coef.	*std.err.*
World	0.496 ***	0.06	0.684 ***	0.09	0.323 ***	0.09	0.422 ***	0.10
Latin America	0.715 ***	0.08	1.141 ***	0.12	0.359 ***	0.12	0.525 ***	0.14
Emerging Asia	0.542 ***	0.08	0.395 ***	0.13	0.903 ***	0.15	0.383 ***	0.13
Emerging Europe	1.120 ***	0.14	0.701 ***	0.20	0.658 ***	0.18	1.795 ***	0.27
Euro area	0.618 ***	0.08	0.629 ***	0.12	0.558 ***	0.14	0.626 ***	0.14
Japan	0.320 ***	0.10	0.345 **	0.17	0.440 ***	0.17	0.170	0.17
United Kingdom	0.586 ***	0.08	0.590 ***	0.12	0.544 ***	0.12	0.583 ***	0.13
United States	0.534 ***	0.09	0.905 ***	0.13	0.189	0.14	0.426 ***	0.14
All countries (panel)	0.573 ***	0.06	0.570 ***	0.08	0.538 ***	0.08	0.572 ***	0.10

Figure 1
Distribution of EME shocks over time

The figure shows the cumulated positive and negative shocks in a quarterly basis.

Figure 2
EME shocks and global equity returns - 3-months cumulated

The figure shows the cumulated net shocks (cumulated difference between positive and negative shocks) and the cumulated stock market return in a quarterly basis.



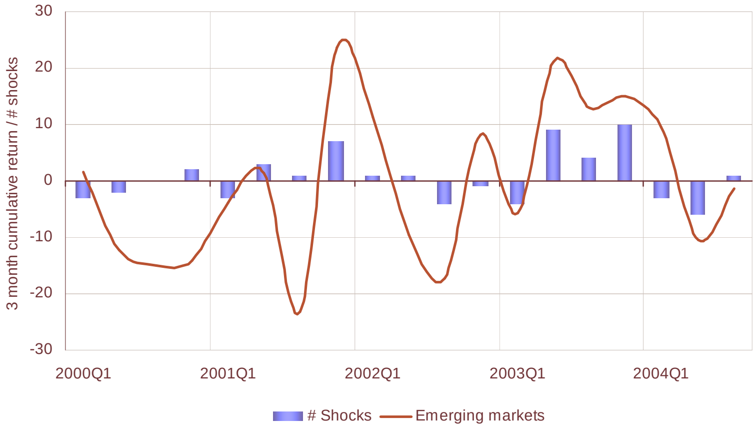


Figure 3

Shock transmission to World, US, Euro Area and EMEs - cumulated dynamic effects up to 3 months (65 days)

The figure is based on model (5) and shows the cumulated coefficients up to k days, testing the null hypothesis $H_0 : \sum_{k=0}^{K} \beta_k = 0$, for the returns of the world equity index, as well as for the United States', the euro area' and the emerging markets' equity indices. The dotted lines show the 90% confidence intervals.

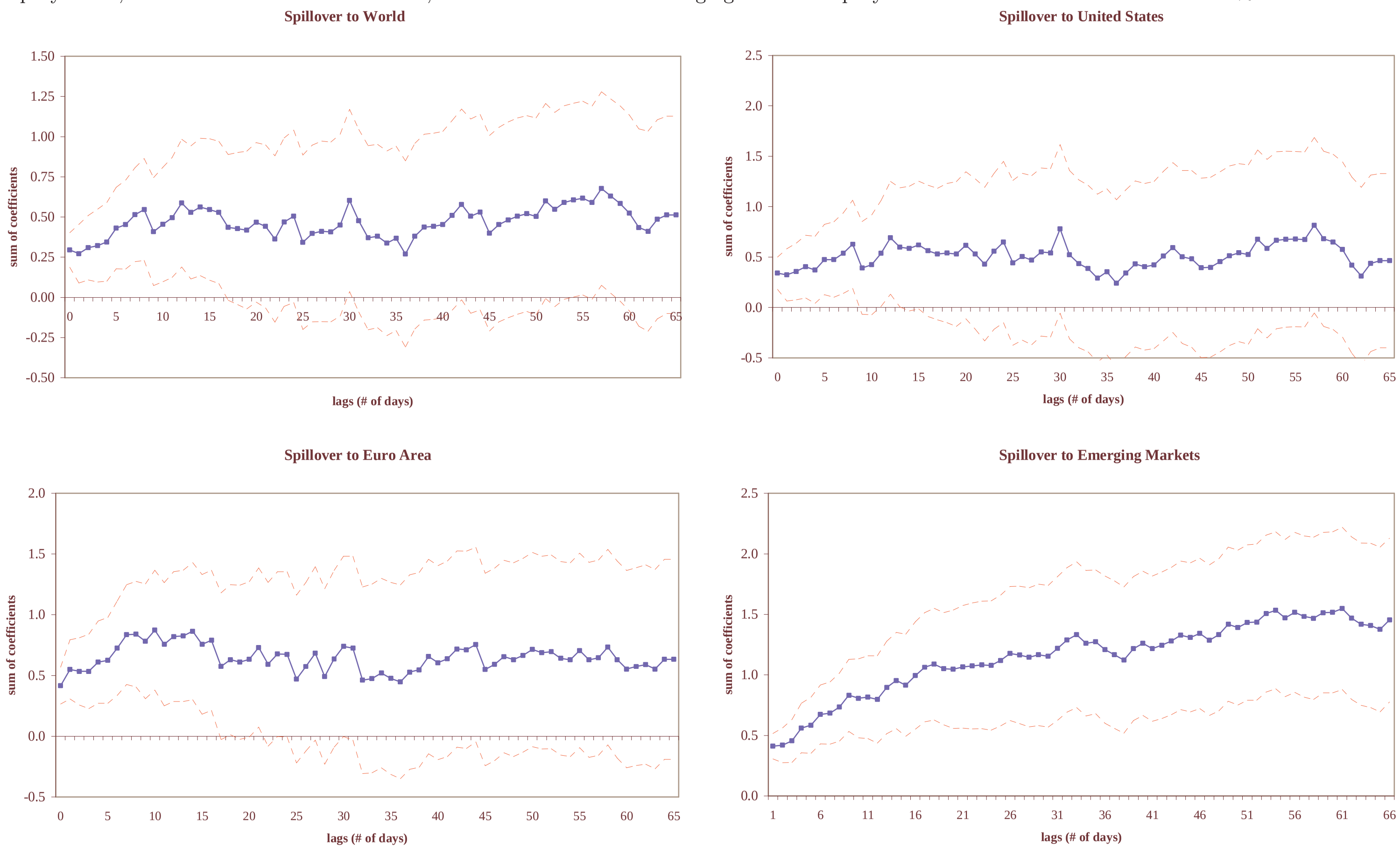


Figure 4
Shock transmission to World, US, Euro Area and EMEs - data frequency up to 3 months (65 days)

The figure is based on model (3) for different data frequencies ranging from 1 day to 65 days, showing the transmission coefficient for the returns of the world equity index, as well as for the United States', the euro area' and the emerging markets' equity indices. The dotted lines show the 90% confidence intervals.

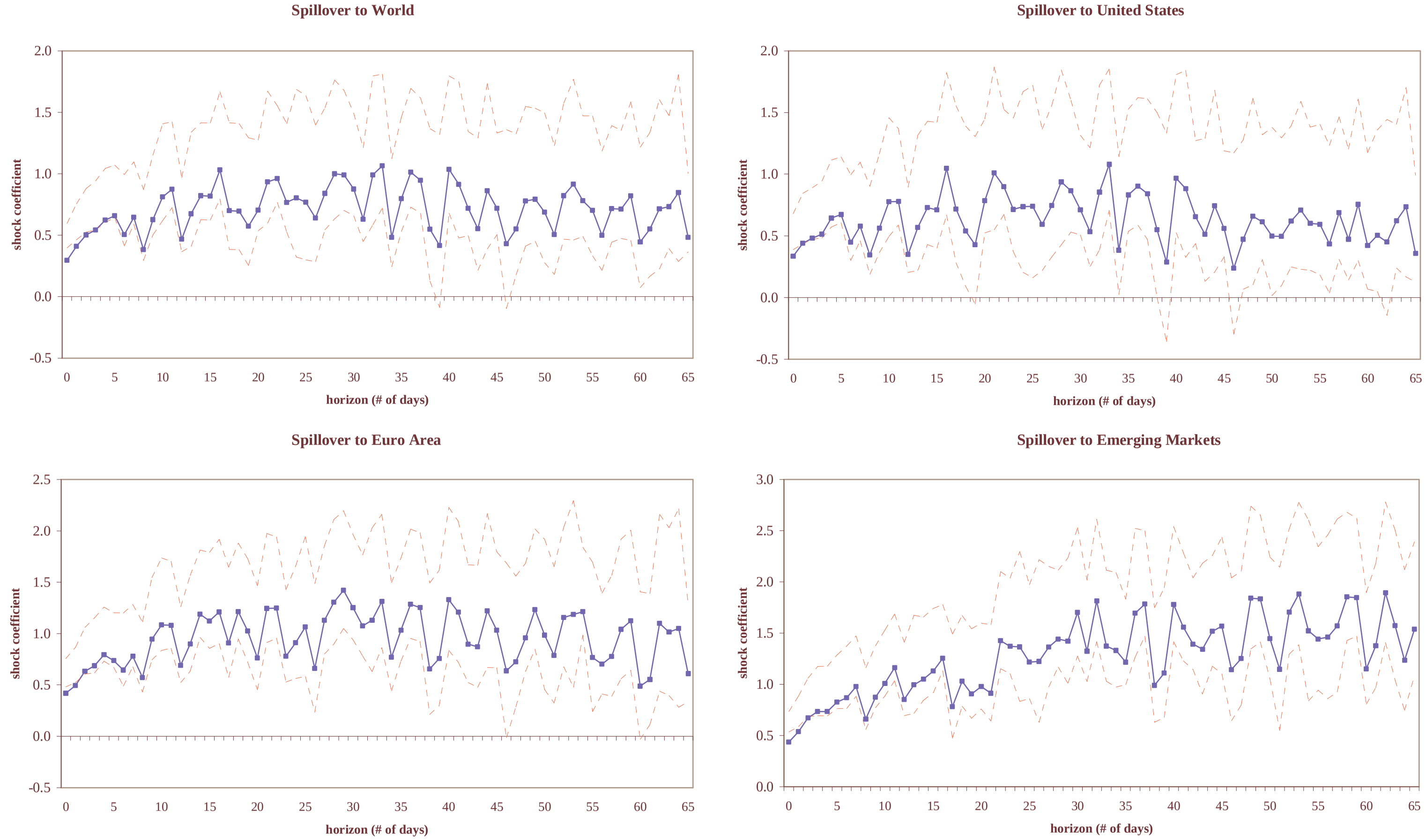
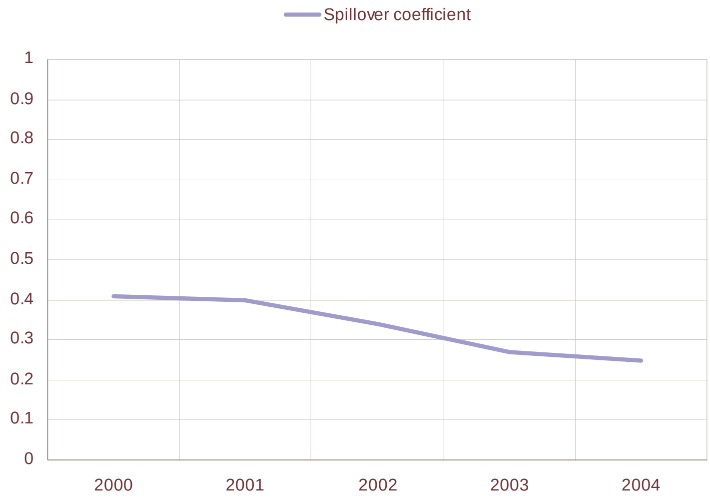


Figure 5
Asymmetry of shock transmission - changes over time

The figure is based on model (6) estimated with annual dummies.



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