# Cointegration between $R^2$ and Volatility in the Mexican Stock Exchange Stock Prices[1]

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# *Cointegración entre $R^2$ y Volatilidad para acciones de la Bolsa Mexicana de Valores*


## Resumen

Cuando se enfrentan a un ambiente de incertidumbre, los inversionistas se comportan de acuerdo con lo que podría describirse como conducta "de rebaño", la cual resulta en una mínima selectividad en sus decisiones de compra-venta de títulos bursátiles. Santillán-Salgado (2011) encontró evidencia de una tendencia a la reducción del coeficiente de determinación ($R^2$) en las regresiones de MCO del Modelo del Mercado en el largo plazo para una muestra de acciones y el Índice de Precios y Cotizaciones (IPC) de la Bolsa Mexicana de Valores (BMV), con observaciones diarias para el periodo 2000-2010. Sin embargo, aun cuando el $R^2$ disminuyó durante los primeros seis años del periodo, aumentó nuevamente durante los siguientes cuatro. La explicación presentada por ese autor fue que, como resultado de la mayor estabilidad macroeconómica y la modernización de la regulación del mercado, la eficiencia informacional de la BMV había mejorado en el tiempo, lo cual explicaba la tendencia a la baja observada durante los primeros seis años del análisis pero, durante la última parte del decenio la inflexión de la tendencia debía ser explicada por la conducta de "rebaño" resultante de la extraordinaria turbulencia del mercado ocasionada por la Crisis Financiera de 2007-2009.

Este trabajo introduce una prueba más rigurosa de la explicación anterior, e incorpora la utilización de otras pruebas para detectar rupturas estructurales y análisis de cointegración, al tiempo que amplía la base de datos sobre la cual se apoya el análisis empírico. La nueva base de datos incluye todas las series de precios de las acciones cotizadas en la Bolsa Mexicana de Valores que cumplieron cierto criterio de selección para el periodo de abril de 1992 a marzo de 2011, resultando en 86 series útiles. La hipótesis central fue que, en presencia de volatilidad intensa en el mercado, existe una tendencia de la $R^2$ del Modelo del Mercado a aumentar, pero cuando la calma regresa al mercado, los inversionistas se comportan nuevamente de manera selectiva (y la $R^2$ regresa a su tendencia a la baja de largo plazo).


Clasificación JEL: G11, G12, G14

**Palabras clave:** Eficiencia de mercados; Periodos de volatilidad; El modelo del mercado

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## Abstract

*When faced with market uncertainty, investors' buy and sell decisions tend to follow a 'herd' behavior which results in a minimal selectivity of the securities they include in their portfolio. Santillán-Salgado (2011) found evidence that there was a long-run reduction of the Coefficient of Determination ($R^2$) of Market Model's OLS regressions for a sample of stocks traded at the Mexican Stock Exchange (MSE), using daily observations for the period 2000-2010. However, while the $R^2$ moved downwards during the first six years of the period, it rose again during the last four. In an attempt to explain that seeming inconsistency, the author argued that, as a result of improved macroeconomic stability and the modernization of market regulation, the MSE's informational efficiency improved over time, explaining the downward trend observed during the first six years of the period of analysis but, during the last years of the decade the inflection of the trend could be explained by the "herd" behavior resulting from the extraordinary market turbulence generated by the 2007-2009 financial crisis.*

*This work introduces a more rigorous test of the previous explanation, incorporating the use of structural breaks detection and cointegration analysis, and expands the database that supports the empirical analysis. The new database included all the MSE stocks' price series that met a selection criteria for the period from 1992 to 2011, resulting in a sample of 86 useful series. The central hypothesis was that, in the presence of intense market volatility, there is a tendency for the $R^2$ of the Market Model to increase but, when calm returns to the market, investors behave again in a more selective way (and $R^2$ goes back to its long-term downward trend).*


*JEL classification:* ***G11, G12, G14***

***Key Words:*** *Market Efficiency; Volatility periods; The market model.*

## 1. Introduction

The Mexican Stock Exchange (MSE) has often been one of the most profitable stock exchanges among the Emerging Markets, but its significance as a source of funding for private firms has not developed accordingly. The limited economic importance of the MSE as a source of funding for Mexican private firms may be explained by a variety of institutional and psychological factors. One of the dimensions that always results in an increased interest to invest in stocks among domestic and international investors is the confirmation of an improvement in informational efficiency, according to Roll (1988) and Durnev *et al*. (2000). In this work we aim to reveal additional evidence in the sense that the Mexican Exchange is gradually becoming more efficient, although atypical, externally originated turbulence may temporarily seem to contradict that fact.

Santillán-Salgado (2011) proposed to measure the efficiency of the Mexican Stock Exchange for the 2000-2010 period following Durnev *et al*. (2000) methodology, i.e., by empirically measuring the sensitivity of a sample stocks returns to the overall market returns, as measured by a composite index, representing a proxy measurement of the Market Portfolio (e.g., similar to the Market Model, or the CAPM). If individual stock returns' Market Model-type regressions' $R^2$s decreased over time, it could be considered as a confirmation that the stock returns increasingly respond to fundamental information (which is specific to the issuer), and less and less to the overall general market conditions. So he studied a sample of the most liquid stocks traded in the MSE and showed that the level of individual stock information incorporated in the formation of prices increased during the first six years of the century (2000-2006), but decreased again towards the end of the decade. While a reduction in the Market Model $R^2$ of an individual stock returns with respect to a market proxy may be interpreted as an increase in the relative importance of stock-specific information and a reduction in the relative weight of general market information (again, in the sense of Roll (1988) and Durnev *et al*. (2000)), when the decreasing tendency changes one could easily conclude that the opposite occurred. However, considering that Market Efficiency should improve as a market matures institutionally and its participants earn greater experience, a change in tendency demands a more analytical interpretation.

In this paper we report evidence that confirms the existence of a second-level influence on the degree of association between an individual stock price's returns and a market proxy that reflects environmental factors common to all stocks, in addition to informational efficiency changes that may be interpreted as results of a more mature market activity. We refer to the results reported by Santillan-Salgado (2011) with respect to an increasing importance of idiosyncratic information in the formation of prices for a small sample of stocks traded in the MSE, and present evidence that the inflection observed during the last sub-period of his analysis (2007-2010) may well be explained as a result of the "herd" psychology of the market during the period of turmoil and uncertainty that resulted from the Subprime Mortgage Crisis in the United States.

## 2. The Efficient Markets Hypothesis: is it "testable"?

During recent decades the "Efficient Markets Hypothesis" (EMH) is one of most often researched subjects in the literature of empirical finance studies. Its main postulate is that a stock's price is permanently in equilibrium and correctly priced because at any moment it has already incorporated all the relevant information that market participants can have access to, and they have acted accordingly–buying if the most recent information is favorable and selling in the opposite case. By doing so, they incorporate the new information in the price. For example, Fama (1970, 1991) argued that Capital Markets allow the formation of stock prices in the most efficient way when information flows freely and there are no impediments to the trading activity of investors. Dyckman and Morse (1986) suggested that the dissemination and analysis of information that is relevant to the pricing of financial securities contributes to the development of new expectations about future prices and determines the degree of efficiency in the market. Wurgler (2000) as well as Durnev *et al*. (2004) reported evidence that countries with more advanced financial markets allow a better allocation of capital in the economy since those countries increase their investment in growing industries and reduce it in declining industries; by contrast, countries with less-developed financial systems both over-invest in their declining industries and under-invest in growing industries.

Based on that background, this work proposes that the “degree of efficiency” with which an individual stock price incorporates relevant information specific to the issuer can be measured with the coefficient of determination of a regression ajusted between individual stock price changes and the contemporaneous stock market index returns. Accordingly, a high $R^2$ is interpreted in the sense that a larger proportion of the volatility of a stock’s returns is explained by common factors that influence the returns for all the stocks included in the market index, but only a small proportion of the volatility is the result of specific information.

According to Roll (1988), a low $R^2$ for common asset pricing models means firm-specific variations are not highly related to general information, implying that either specific information has a significant influence on stock prices or, alternatively, it may be due to stock market ‘noise’ interference in trading decisions.

Durnev *et al*. (2000) tested Roll’s hypothesis for low $R^2$ and reported that the stocks with low market model $R^2$ statistics show a greater degree of association between current returns and future earnings. That finding supports Roll’s argument in the sense that firm-specific returns is not associated with the market’s general performance. Morck *et al*. (2000) argued that the measure in which stock returns tend to move in parallel depends on the relative importance of firm-level and market-level information that is incorporated and capitalized into the stock prices. To that end, they used the Market Model.[1] With their work, they gave additional support to the idea that a large independence of a stock price variation (low Market Model $R^2$), may be interpreted in terms that the markets are more efficient. They also presented evidence supporting the assertion that stock prices in economies with high per capita GDP tend to move in an unsynchronized manner, but stock prices in low per capita GDP economies show a much higher degree of synchronization.

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1 The Market Model is a theoretical representation of the possible relationship between the returns of the stock market index, and an individual stock’s performance. Also known as the “Single Index Model”, the Market Model is estimated using an Ordinary Least Squares regression, whose coefficient (the beta) is a measure of the responsiveness (elasticity) of the individual stock returns to changes in the main stock market index fluctuations.

While the empirical evidence presented by Morck *et al*. (2000) is incontrovertible, the interpretation of their results depend on the approach taken. For example, if the magnitude of the $R^2$ can be interpreted as the degree in which an individual stock's price incorporates information that reflects the general sentiment of the market, but not the specific information of the firm that issued the stock, then a high $R^2$ means less market efficiency, i.e., less idiosyncratic information is reflected in the individual price's behavior. It is in that sense that the relative magnitude of the coefficient of determination and its evolution through time is interpreted as an indirect measure of the efficiency of the pricing mechanism of stocks for the Mexican Stock Exchange, and that is the way we interpret it in this study.

Durnev *et al*. (2004) argue that the traditional interpretation of stock market efficiency promoted by finance economists distinguishes "weak, strong and semi-strong forms of the efficient markets hypothesis according to whether or not portfolio managers can 'beat the market' using extant information about prices and volumes, all existing information, or all existing publicly available information". However, while that approach may be of some relevance to financial managers, from an economic point of view the most relevant aspect is whether or not the stock market allocates capital to its highest value uses. The fact that stock prices rise when the new information containing positive news for the expected future performance of the issuer reaches the market and, alternatively, they descend when information is negative, is a gauge that can guide investment decisions in a very efficient way, thus contributing to a better allocation of society's resources.

The Market Efficiency measurement problem may also be treated from the point of view of "herding" behavior. An increasing number of Works have addressed herding behavior in financial markets. In general, herding behavior is characterized by correlated actions of investors where investors ignore their personal beliefs or expectations about market fundamentals and mimic the behavior of others. Bikhchandani and Sharma (2001) produced an excellent overview of the theoretical and empirical research on rational herd behavior in financial markets, and looked into the meaning of herding, what are possible causes of rational herd behavior, what success existing studies have had in identifying it, and what effect such behavior has on financial markets. They concluded that more empirical work needs to be done on emerging markets where one is likely to find a greater tendency to herd. In these markets, they argue, where the environment is not clear because of weak reporting requirements, lower accounting standards, lax enforcement of regulations, and costly information acquisition, information cascades and reputational herding are more likely to arise. Balciar *et al*. (2012) propose a Markov-Switching test of herding behavior in China's segmented stock markets under a regime-changing environment. Their findings suggested the presence of three market regimes (low, high and extreme or crash volatility) in all Chinese market segments with the common volatility transmission order of Low, High and Crash regimes, and that herding behavior is asymmetric, observed during the high and crash volatility periods only. Kremer and Nautz (2013) provided evidence on the causes and consequences of herding by institutional investors using a database that contained every transaction made by financial institutions in the German stock market, and showed that institutions exhibit herding behavior on a daily basis. According to these authors, herding intensity depended on stock characteristics, including past returns and volatility. They interpreted return reversals as a destabilizing impact of herds on stock prices in the short term. Finally, they suggest, through a panel regression analysis, that herding may be interpreted as unintentional and partly driven by the use of similar risk models and, for that reason, their findings confirmed the importance of macro-prudential regulation. Jegadeesh and Jim (2010) developed and implemented a new test to research whether sell-side analysts herd around the consensus when they make stock recommendations and find empirical results that support the herding hypothesis. Stock price reactions following recommendation revisions are stronger when the new recommendation is far from the consensus than when it is closer to it, indicating that the market recognizes analysts' tendency to herd. They also report that, according to their results, analysts from larger brokerages, analysts following stocks with smaller dispersion across recommendations, and analysts who make less frequent revisions are more likely to herd. Lastly, Blasco et al. (2012) analysed the impact of herding which, they wrote, may be interpreted as one of the components of uninformed trading, on the volatility of the Spanish stock market. Herding is examined at the intraday level, considered the most reliable sampling frequency for detecting this type of investor behavior. Different volatility measures (historical, realized and implied) are employed. The results confirm that herding has a direct linear impact on volatility for all of the volatility measures considered, although the corresponding intensity is not always the same. In fact, herding variables seem to be useful in volatility forecasting and therefore in decision making when volatility is considered a key factor.

While Santillán-Salgado (2011) reported evidence of an average decreasing $R^2$ for the MSE market during the first six years of the 21st century, this study represents and extension of that study where the aim is to test if the renewed increase of the MSE average Market Model $R^2$ observed during the 2007-2010 period. This behavior may be explained by the presence of a relationship between the magnitude of the $R^2$ and the volatility of the MSE; i.e., we search for an explanation of the seemingly contradictory evidence that after a period of decreasing $R^2$ (and thus, increasing efficiency), a renewed increase of the Market Model's coefficient of determination (which would mean decreasing efficiency) happened. More explicitly, the explanation that this work offers is that besides increasing (or decreasing) efficiency (Wurgler 2000; Durnev *et al*. 2000 and 2004; Morck 2000) , there is a second factor that influences the relationship between the individual stock's price returns and the market as a whole (and thus, the $R^2$ levels), consisting in the "herd" behavior that reflects the risk-averse psychology of investors when uncertainty in the market is abnormally high.

## 3. *Methodology, database, analysis, and results*

According to different authors, (e. g., Wurgler 2000; Durnev *et al*. 2000 and 2004; Morck 2000), an improvement in the efficiency of stock prices' formation can be indirectly measured by observing the proportion of the variance of individual stocks' returns explained by the market portfolio proxy's returns, i.e., one should observe a decreasing $R^2$ for the Market Model. However, if it may be argued that efficiency is at the same time related to an increasingly liquid market and to improved transparency, as well as to greater institutional maturity, it would be puzzling to observe a renewed increase in the value of the Market Model's $R^2$ statistics over time. Thus, if there is significant evidence to support the argument that, in addition to informational efficiency, there are other factors that help explain the evolution of Market Model's $R^2$, an interpretation of the seemingly contradictory results observed by Santillán-Salgado (2011) may be confirmed.

While it is not the purpose of this work to develop a detailed analysis of the psychological mechanisms that explain investors' "herd behavior", the argument this research postulates is that the average investor becomes less selective regarding its securities' buy and sell decisions during turbulent times, and attempts to follow the ups and downs of a highly volatile market, trying to minimize its losses (and, if possible, to earn some speculative profits). That argument may explain why in the case of the MSE there was a decreasing trend in the Market Model $R^2$ during "normal" times and an increasing $R^2$ during times of uncertainty and high volatility of the market. A similar argument was presented by Santillán-Salgado (2011) to explain a diminishing Market Model $R^2$ for a sample of stocks traded at the MSE during the first six years of the new century, and a newly increasing $R^2$ during the 2007-2010 period, in this study we present additional econometric evidence that supports that line of reasoning.

The initial database included 135 series of prices for stocks traded at the MSE, for a period of observation that goes from April 1991 through March 2011. After eliminating 49 series that did not fulfill the criteria of a minimum number of observations and/or that showed discontinuities in the time series, the number of stocks that was workable was 86.

Since our study covers almost twenty years of observations, using the MSE's Indice de Precios y Cotizaciones, it could have been subject to a survival bias. For that reason, it was replaced with a new comprehensive weighted average portfolio, named "Market Proxy Sample Portfolio" (MPSP), and calculated following the same methodology used to obtain the IPC, but widening the size of its sample including all the series that remained after the initial selection. The IPC is a value weighted index, where the capitalization value of each share divided by the sum of all-shares-in-the-sample capitalization value represents its weight in the portfolio, and is obtained according to the following formula:

$$I_t = I_{t-1}\left(\frac{\sum P_{it} * Q_{it}}{\sum P_{it-1} * Q_{it-1} * F_{it}}\right)$$

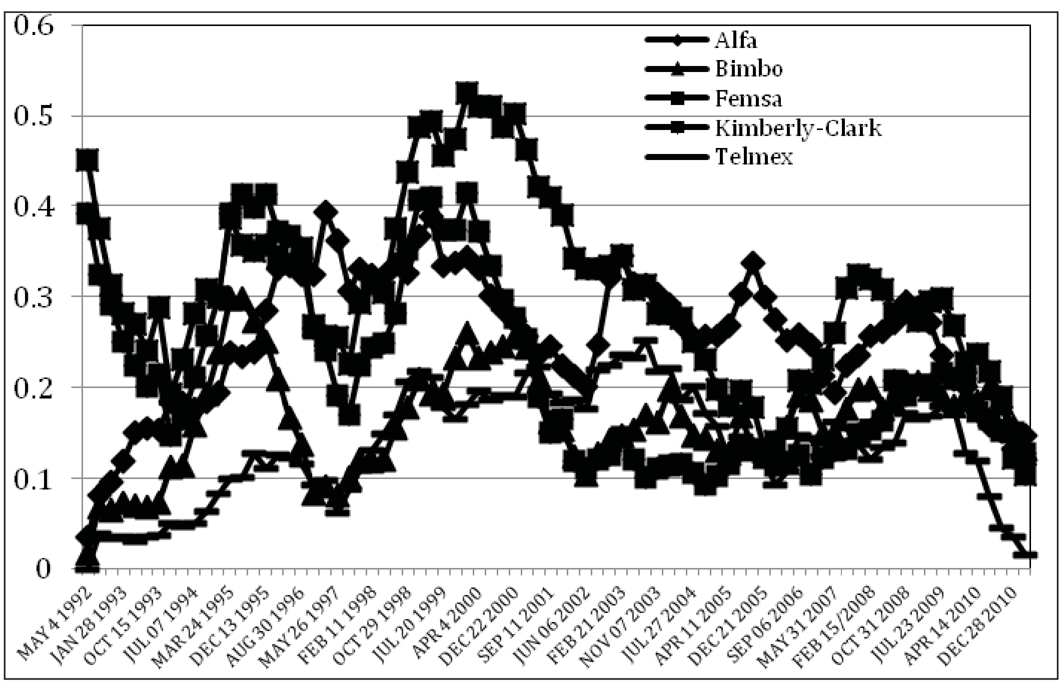
Where:

$$I_t = IPyC \ in \ time \ t$$
$$P_{it} = Price \ of \ stock \ i \ in \ time \ t$$
$$Q_{it} = Number \ of \ i \ shares \ traded \ in \ day \ t$$
$$F_{it} = Adjustment \ factor \ for \ ex-rights$$

For the purposes of this study, the MPSP was "fine-tuned", controlling for the influence that was to be expected from the regressed stock returns on the MPSP returns. The MPSP was adjusted on a case by case basis, by excluding one stock at a time, to obtain its corresponding Individually Adjusted Market Index (IAMI). Thus, individual IAMIs were built as a value weighted average of daily returns for the remaining n-1 stock price returns for each stock. That adjustment eliminated the possibility that when running Market Model's regressions, there could be spurious results due to the presence of a stock's daily returns in both, the regressor and the regressand.

Market Model's $R^2$ were obtained by estimating an OLS regression between a stock's returns and its corresponding IAMIs, for subsequent, non-overlapping series of 60 trading days (see summary results for the regression outputs in Table 1.A in the Appendix). Depending on the stock,

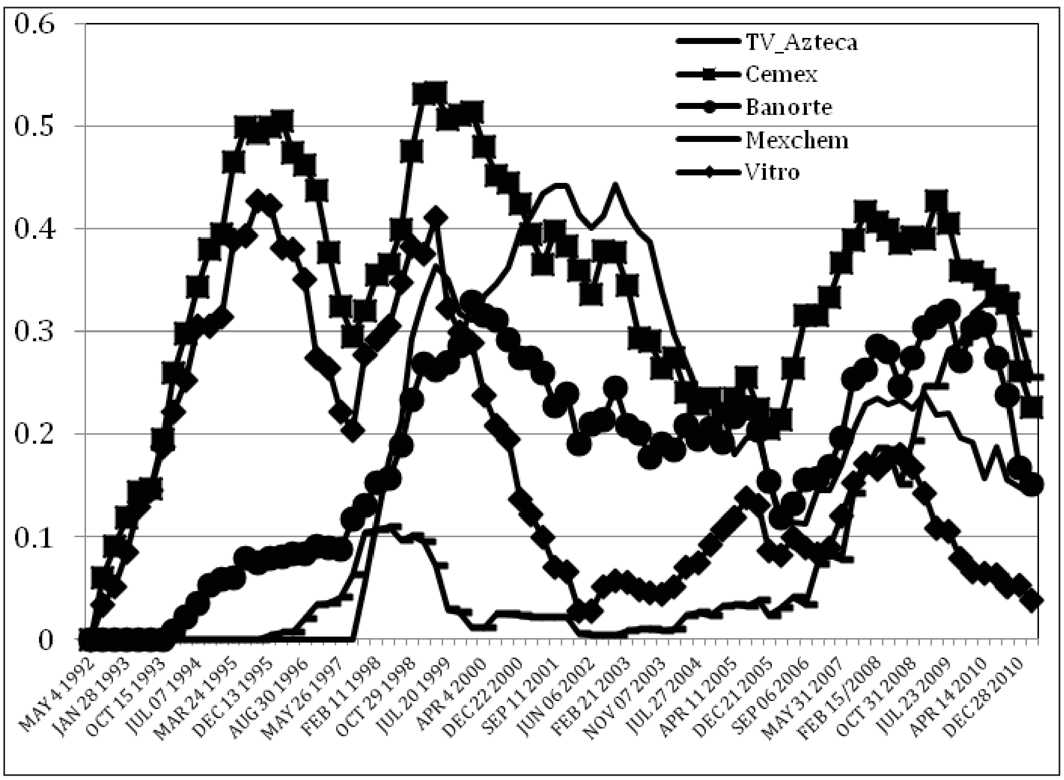
Exhibit 1A: Evolution of the $R^2$ for the Highest Liquidity Subsample.



there was a maximum of 80 possible observations during the period that goes from May 1992 through March 2011 (8 series), and a minimum of 30 observations (1 series). Finally, the volatility of the corresponding IAMI for the same sub-periods, was measured as the standard deviation from the mean, and used as the second variable of the regression.

In an initial graphical screening of the evolution of the $R^2$ for the whole sample of observations there was visual evidence of a tendency for that statistic to rise during periods of market uncertainty, e.g.: *a*) during the months surrounding the December 1994 Mexican Peso devaluation;

Exhibit 1B: Evolution of the $R^2$ for the Highest Liquidity Subsample.




Note: The dates on the horizontal axis represent the last day for the 60 day observation period used to estimate the R2 coefficients.

Source: Bloomberg and Bolsa Mexicana de Valores

*b*) during the months after the beginning of the 1997 South Eastern Asia Financial Crisis, showing an initial decreasing tendency that curved up again after the September 2001 Terrorist Attacks in New York; and, finally, *c*) a new rising tendency beginning during the last months of 2006. Graphical

Exhibit 2A: $R^2$ vs. IAMI Volatility for Alfa.

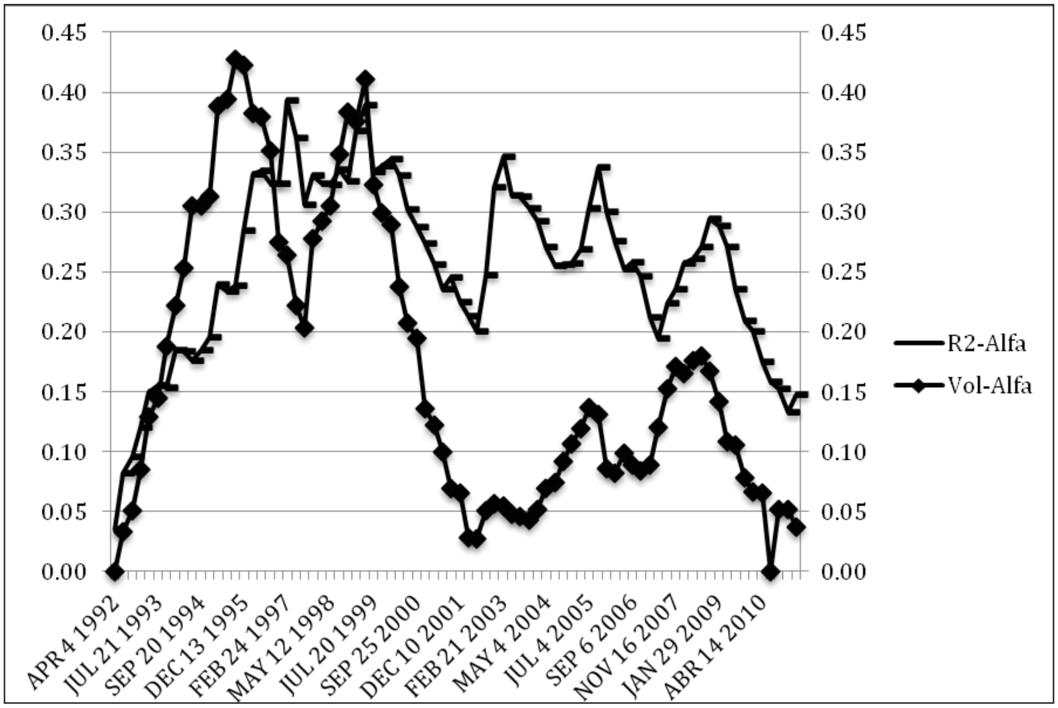



Exhibit 2B: $R^2$ vs. IAMI Volatility for Bimbo.

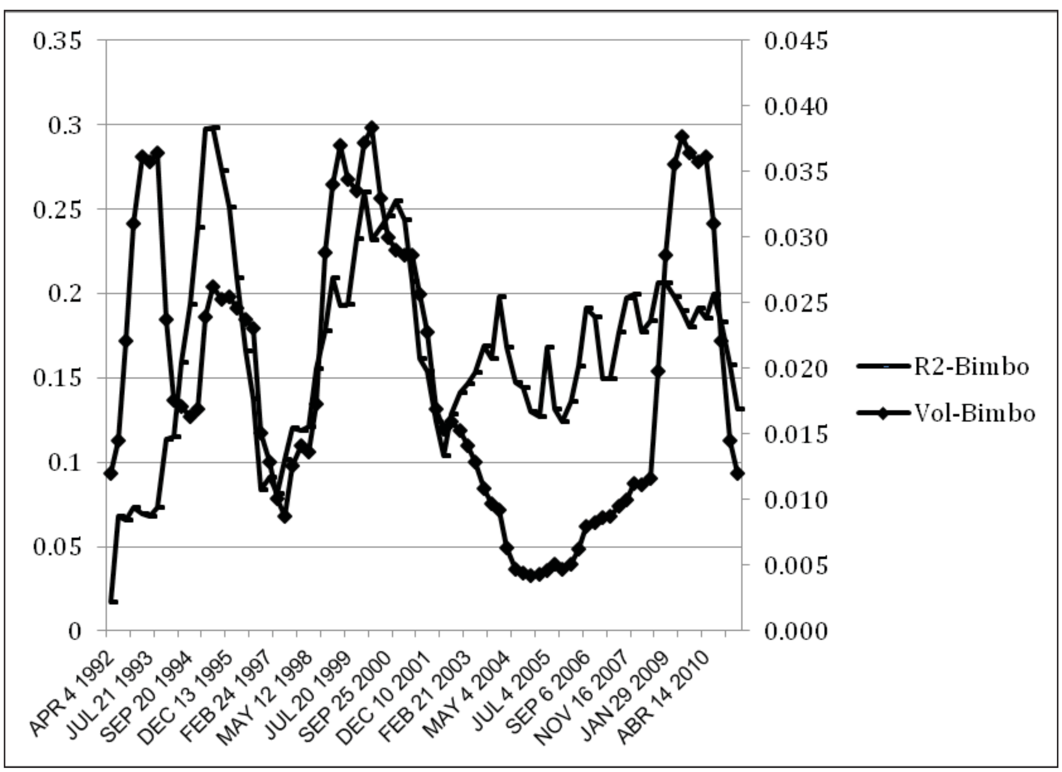
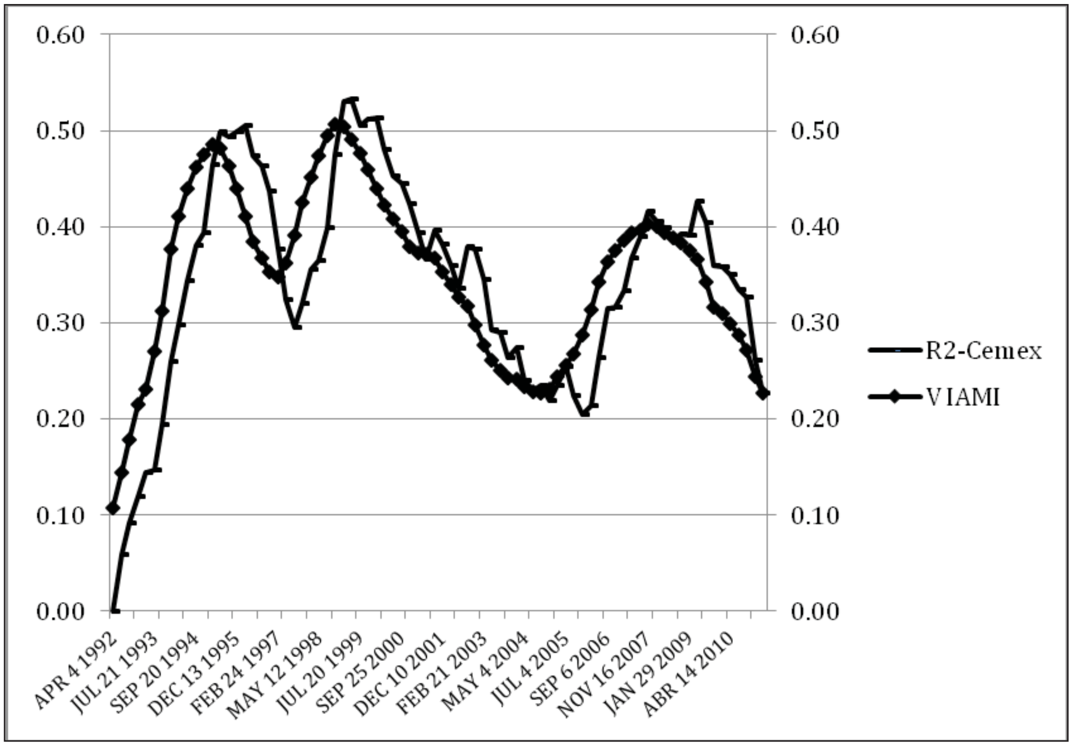


Exhibit 2C: $R^2$ vs IAMI Volatility for Cemex.




Note: The dates on the horizontal axis represent the last day for the 60 day observation period used to estimate the $R^2$ coefficients. The right axis measures the individual stock's $R^2$ and the right axis measures the VIAMI.

Source: Bloomberg and Bolsa Mexicana de Valores.

representations for the Market Model $R^2$ of groups with the stocks with the highest liquidity-in-trading is presented in Exhibits 1A and 1B, showing "peaks" in the above mentioned dates.

The main contention of this work is that there exists a strong statistical relationship between the Coefficient of Determination and the Market's Proxy Volatility, so a graphical analysis, similar in a sense to Exhibits 1A and 1B, but this time built with 60 trading days sub-periods' Market Model $R^2$s for individual stocks, contrasted with the evolution of their IAMI's variance. Exhibits 2A through 2C show the graphs for three actively traded stocks (Alfa, Bimbo, and Cemex) $R^2$s *vs*. IAMI Volatility series. The patterns observed for these stocks, shed further light on the association between the two variables.

A more rigorous confirmation of the existence of a significant statistical relationship between the Coefficients of Determination and the Volatility of the Individual Adjusted Market Index (VIAMI) was performed by using Cointegration Analysis with the inclusion of possible structural breaks. In order to proceed, and as a necessary preliminary step, Perron's (1989) test was used to confirm the presence of unit roots in $R^2$s and VIAMIs, as well as to detect structural breaks in the series.

According to Perron (1989) a given series $\{y_t\}$ of which T+1 observations are available, is a realization of a time series process characterized by the presence of a unit root and possibly a nonzero drift. However, that approach may be generalized to allow a one-time change in the structure of the series occurring at a time $T_1$ $(1 < T_1 < T+1)$. Perron's approach suggests three different possibilities (and tests): *a*) one that permits an exogeneous change in the level of the series (a "crash"); *b*) one that permits an exogenous change in the rate of growth (slope of the series); and, *c*) one that allows both changes simultaneously: These hypotheses are parameterized as follows:

Model (A) $y_t = \mu + dD(TB)_t + y_{t-1} + e_t$

Model (B) $y_t = \mu_1 + y_{t-1} + (\mu_2 - \mu_1)DU_t + e_t$

Model (C) $y_t = \mu_1 + y_{t-1} + dD(TB)_t + (\mu_2 - \mu_1)DU_t + e_t$

where:

$D(TB)_1 = 1$, if $t = T_B+1$, and 0 otherwise;

$DU_t=1$, if $t > T_B$, and 0 otherwise; and

$A(L)\ e_t = B(L)\ v_t$, $v_t \sim$ i.i.d. $(0, s^2)$, with A(L) and B(L) $p^{th}$ and $q^{th}$ order polynomials, respectively, in the lag operator L.

The innovation series $(e_t)$ is taken to be of the ARMA(p, q) type with the orders p and q possibly unknown, so this postulate allows the series $\{y_t\}$ to represent quite general processes.

Instead of considering the *Ha* that $y_t$ is a stationary series around a deterministic linear trend with time invariant parameters, Perron's test analyzes the following models:

Model (A) $y_t = \mu_1 + \beta t + (\mu_2 - \mu_1) DU_t + e_t$

Model (B) $y_t = \mu + \beta_1 t + (\beta_2 - \beta_1) DT^*_t + e_t$

Model (C) $y_t = \mu + \beta_1 t + (\mu_2 - \mu_1) DU_t + (\beta_2 - \beta_1) DT_t + e_t$

Model (A)'s null hypothesis of a unit root is characterized by a dummy variable which takes the value one at the time of the break. Under the alternative, of a "trend-stationary" system, it allows for a one-time change in the intercept of the trend function. Model (B) is referred to as the "changing growth" model. Under the alternative hypothesis, a change in the slope of the trend function without any sudden change in the level at the time of the break is allowed. Finally, Model (C) allows for both effects to take place simultaneously, i.e., a sudden change in the level followed by a different growth path (Perron 1989).

Perron's test results allowed the detection of coincident structural breaks that permitted the grouping of the different series in a few categories. Interestingly enough, the test results indicated that the structural breaks for most of the VIAMI corresponded to macroeconomic episodes of high turbulence for the MSE, i.e., a) the period immediately before the December 1994 devaluation of the peso (15 series); b) the period of the Russian crisis in 1998 (9 series); c) the most turbulent months of the

Table 1. Perron's United Root Test Results for the $R^2$ and the VIAMI Series.

| | R2 | | | | VIAMI | | | |
|---|---|---|---|---|---|---|---|---|
| | Do not reject | Reject | | | Do not reject | Reject | | |
| | | 1% | 5% | 10% | | 1% | 5% | 10% |
| A | 17 | 61 | 4 | 3 | 24 | 31 | 21 | 9 |
| B | 16 | 59 | 7 | 3 | 3 | 37 | 43 | 2 |
| C | 18 | 60 | 5 | 2 | 24 | 30 | 25 | 6 |

**A: Series has a unit root with structural break in the intercept**
**B: Series has a unit root with structural break in both, the intercept and the slope**
**C: Series has a unit root with structural break in the slope**

Source: Authors' calculations, with data from Bloomberg and the MSE..

year 2008 (58 series); only three series could not be grouped in any of the above three categories. (see Tables A3 and A4 in the Appendix).

Besides the identification of the dates of the series' structural breaks, Perron's test confirmed that most of the series were stationary, i.e., there was no unit root, as reported in Table 1.

In the case of the $R^2$ coefficients series, Perron's test results indicated that between 16 and 17 series were not stationary, while the rest were stationary. For the VIAMI, the results suggested that not more than 24 series were non-stationary; i.e., the results validated that most of the series were stationary.

To incorporate the effects of structural breaks into the cointegration analysis and to validate the long-term association between the $R^2$ and the VIAMI for individual stocks, we selected an Engle-Granger Single Equation Cointegration Test. To that end, the information extracted from

Table 2A:Engle-Granger Cointegration Tests
Ho: Series are not Cointegrated (First Part).

| | First group: months before the 1994 peso devaluation (Tequila Crisis) | | | Second group: months surrounding the 1998 South East Asia Financial (Dragon) Crisis | |
|---|---|---|---|---|---|
| Number | Stock | P Value | Number | Stock | P Value |
| 1 | ALFA | 0.0000000 | 1 | ACCELSA | 0.00740 |
| 2 | BIMBO | 0.0000000 | 2 | FINAMEX | 0.00000 |
| 3 | CERAMIC | 0.0000000 | 3 | GENSEG | 0.00000 |
| 4 | CONTAL | 0.7467000 | 4 | GFINTER | 0.00000 |
| 5 | FEMSA | 0.0003000 | 5 | ICH | 0.00000 |
| 6 | GCARSO | 0.0027000 | 6 | MAXCOM | 0.00000 |
| 7 | GEUPEC | 0.0000000 | 7 | MEXCHEM | 0.00000 |
| 8 | GISSA | 0.0012000 | 8 | SAVIA | 0.00520 |
| 9 | GPH | 0.0193000 | 9 | TEKCHEM | 0.00000 |
| 10 | KIMBER | 0.0003000 | | | |
| 11 | KUO | 0.0001000 | | | |
| 12 | LAMOSA | 0.0147000 | | | |
| 13 | LIVEPOL | 0.0000000 | | | |
| 14 | PE&OLES | 0.0002000 | | | |
| 2 | HERDEZ | 0.7520000 | | | |

Source: Authors' calculations, with data from Bloomberg and the MSE.

the Perron tests results regarding the identification of structural breaks in the series gave support to the construction of dummy variables in which 1's corresponded to the periods in which structural breaks were detected by any of the three variations of the Perron test, and zeros elsewhere. The dummy variables were then introduced as deterministic regressors in the

Table 2B: Engle-Granger Cointegration Tests
Ho: Series are not Cointegrated (Second Part).

| Third group: the most turbulent months of 2008 (2007-2009 Financial Crisis) | | | | | |
|---|---|---|---|---|---|
| Number | Stock | P Value | Number | Stock | P Value |
| 1 | CEMEX | 0.000000 | 30 | CONVER | 0.9928000 |
| 2 | CNCI | 0.000700 | 31 | CYDSASA | 0.2023000 |
| 3 | GMARTI | 0.000000 | 32 | EDOARDO | 0.0068000 |
| 4 | ICA | 0.000000 | 33 | ELEKTRA | 0.0000000 |
| 5 | POSADAS | 0.000000 | 34 | FRAGUA | 0.0065000 |
| 6 | SANLUIS | 0.000000 | 35 | GEO | 0.0007000 |
| 7 | SANMEX | 0.000000 | 36 | GFINBUR | 0.0000000 |
| 8 | SORIANA | 0.022700 | 37 | GFNORTE | 0.1948000 |
| 9 | TELMEX | 0.021900 | 38 | GMD | 0.0017000 |
| 10 | TMM | 0.063900 | 39 | GMEXICO | 0.0098000 |
| 11 | VASCONI | 0.000400 | 40 | GNP | 0.0000000 |
| 12 | VITRO | 0.391600 | 41 | GPROFUT | 0.0000000 |
| 13 | WALMEX | 0.000000 | 42 | GRUMA | 0.0000000 |
| 14 | ALSEA | 0.000000 | 43 | HILASAL | 0.0000000 |
| 15 | AMX | 0.000000 | 44 | HOGAR | 0.0000000 |
| 16 | ARA | 0.000000 | 45 | HOMEX | 0.7336000 |
| 17 | ARCA | 0.053800 | 46 | IASASA | 0.0909000 |
| 18 | ASUR | 0.000000 | 47 | INVEX | 0.0000000 |
| 19 | azteca | 0.705700 | 48 | MEDICA | 0.0000000 |
| 20 | BACHOCO | 0.000000 | 49 | NUTRISA | 0.0000000 |
| 21 | BAFAR | 0.000000 | 50 | PINFRA | 0.0000000 |
| 22 | C | 0.000000 | 51 | POCHTEC | 0.0000000 |
| 23 | CABLE | 0.000000 | 52 | Q | 0.0000000 |
| 24 | CIDMEGA | 0.000000 | 53 | RCENTRO | 0.0000000 |
| 25 | CIE | 0.220800 | 54 | SAB | 0.0000000 |
| 26 | CMOCTEZ | 0.000200 | 55 | SARE | 0.7172000 |
| 27 | CMR | 0.007900 | 56 | SIMEC | 0.0137000 |
| 28 | COLLADO | 0.000200 | 57 | TS | 0.1171000 |
| 29 | COMERCI | 0.000200 | 58 | VALUEGF | 0.0000000 |

Source: Authors' calculations, with data from Bloomberg and the MSE.

Engle-Granger Cointegration Tests, to find that most of the pairs of $R^2$s and VIAMIs, with few exceptions, cointegrated in the presence of structural breaks. Table 2 presents the summarized results of Engle-Granger tests for pairs of $R^2$ and VIAMI for individual stocks, grouped according to the structural break dates detected with the Perron tests.

Out of the total sample of 86 pairs of series, in 44 cases the Engle-Granger test was rejected at the 1% confidence level, in 2 cases it was rejected at a 5% confidence level and in 1 case at a 10% confidence level. That means that in 47 out of the 86 pairs of series, in which the null hypothesis was rejected there was strong evidence of cointegration between the $R^2$s and the VIAMIs; in 39 pairs of series, the null could not be rejected with a minimum of 10% confidence level.

## Conclusion

The argument of Durnev *et al*. (2000) that a Market Model Regression's $R^2$ is a good measure of informational efficiency suggests that as markets become more mature and thus, more efficient, one should observe a declining value on the average $R^2$ for the Market Model regressions because the performance of a stock's price will increasingly respond to its fundamentals, as well as any other relevant public announcements likely to affect the issuer's future expected cash flows and/or risk, and less so to the more general information about the economy.

While the Market Portfolio, (measured with the different market indices, e.g., the *Indice de Precios y Cotizaciones* for the MSE case) reflects the general perception of investors regarding the future profits and dividend payments of those firms included in its calculation, there are many new items that are more relevant to one or several firms than to the rest of the market. As individual stock prices respond more rapidly and intensely to information that may be considered specific to their valuation, their evolution becomes increasingly different with respect to the Market Portfolio, and with it the Market Model's $R^2$.

Emerging Markets stock exchanges gradually improve their liquidity and informational efficiency as the number of firms listed grows, there are better regulatory standards and better information dissemination mechanisms. Accordingly, one could expect to observe a declining absolute value for the Market Model $R^2$ for the general stock case. While there is strong evidence that this is the case in many countries (e.g., Durnev *et al*. 2000), Santillán-Salgado (2011) found a puzzling evolution of the average $R^2$ for a small sample of stocks traded in the MSE. While there was evidence of a gradual reduction of $R^2$ throughout a period from the years 2000 to 2006, during the next four years of that decade a renewed increment of the $R^2$ average was observable, apparently contradicting the underlying assumption of gradual improvement in the efficiency of the stock market. The explanation of investors' less selective behavior during times of turmoil, based on the logical argument that during such periods investors "buy when the market rises" and "sell when the market falls" to minimize losses and maximize potential profits, has been reported elsewhere.

In this study we formalized the relationship between the absolute magnitude of $R^2$ and the volatility trends in the market by implementing cointegration analyses that takes into account the presence of structural breaks in the series to test for the existence of a long term relationship between individual stock price returns and a comprehensive value-weighted market index, built omitting the information for each stock being considered so as to avoid potentially conflictive information contained in the dependent (the stock returns) and in the independent variable (the comprehensive value weighted market index).

The results from the cointegration analyses were consistent with our initial postulate. We may, thus, conclude that the degree of efficiency of the MSE, measured in terms of the Market Model R2 for individual stocks has improved through time, but that during periods of high turbulence there is a pattern of "herd" behavior that increases individual stocks' degree of association with the general market trends. A change in the tendency of R2 does not necessarily mean a reverse in an Emerging Market's evolution towards superior stages of efficiency (and development). It may be an expression of fear and opportunism of investors who prefer to follow (and reinforce) the market trends until there is more stability that allows a more informed trading activity.

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# APPENDIX

Table A1: Summarized Market Model Regressions' Results for Individual Stocks
(60 days observation non-overlapping windows, from 1992 to 2011).
(First Part)

| | | Mean | | Maximum | | Minimum | | Std. Dev. | | Skewness | | Kurtosis | | Jarque-Bera | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| EMPRESA | | R2 | Beta | R2 | Beta | R2 | Beta | R2 | Beta | R2 | Beta | R2 | Beta | R2 | Beta |
| 1 | ACCELSA | 0.034 | 0.204 | 0.274 | 1.181 | 0.000 | -0.834 | 0.054 | 0.356 | 2.721 | 0.769 | 8.088 | 1.220 | 327.800 | 15.483 |
| 5 | ALFA | 0.253 | 0.929 | 0.595 | 2.193 | 0.001 | -0.196 | 0.137 | 0.417 | 0.426 | 0.039 | -0.149 | 0.357 | 2.539 | 0.257 |
| 6 | ALSEA | 0.110 | 0.455 | 0.580 | 1.491 | 0.000 | -0.494 | 0.120 | 0.473 | 1.687 | 0.195 | 3.702 | -0.749 | 176.225 | 13.626 |
| 7 | AMX | 0.205 | 0.900 | 0.464 | 1.519 | 0.025 | 0.138 | 0.120 | 0.396 | 0.245 | -0.106 | -0.898 | -0.998 | 12.802 | 9.466 |
| 8 | ARA | 0.213 | 0.837 | 0.536 | 1.679 | 0.013 | 0.271 | 0.129 | 0.365 | 0.446 | 0.649 | -0.489 | -0.493 | 6.223 | 3.219 |
| 9 | ARCA | 0.061 | 0.271 | 0.230 | 0.971 | 0.000 | -0.387 | 0.061 | 0.279 | 1.313 | 0.224 | 1.000 | 0.822 | 129.463 | 44.805 |
| 11 | ASUR | 0.014 | 0.100 | 0.113 | 0.702 | 0.000 | -0.407 | 0.022 | 0.214 | 2.814 | 0.324 | 9.218 | 1.083 | 1156.835 | 65.283 |
| 14 | azteca | 0.270 | 1.066 | 0.663 | 2.758 | 0.016 | 0.148 | 0.152 | 0.566 | 0.382 | 0.574 | -0.131 | 0.074 | 5.697 | 5.444 |
| 15 | BACHOCO | 0.058 | 0.148 | 0.665 | 0.929 | 0.000 | -0.618 | 0.114 | 0.353 | 3.689 | 0.284 | 15.481 | -0.279 | 1758.310 | 9.026 |
| 16 | BAFAR | 0.025 | 0.061 | 0.184 | 0.966 | 0.000 | -0.441 | 0.037 | 0.204 | 2.522 | 1.504 | 7.374 | 6.389 | 461.433 | 361.131 |
| 19 | BIMBO | 0.164 | 0.647 | 0.444 | 2.128 | 0.001 | 0.000 | 0.110 | 0.314 | 0.590 | 1.540 | -0.597 | 5.964 | 5.953 | 135.846 |
| 20 | C | 0.193 | 0.952 | 0.439 | 3.254 | 0.005 | 0.067 | 0.130 | 0.763 | 0.307 | 1.406 | -1.142 | 1.872 | 18.438 | 93.726 |
| 21 | CABLE | 0.011 | 0.002 | 0.077 | 0.279 | 0.000 | -0.398 | 0.017 | 0.122 | 2.402 | -0.545 | 6.910 | 3.274 | 1428.950 | 476.031 |
| 22 | CEMEX | 0.350 | 1.178 | 0.767 | 2.103 | 0.000 | 0.000 | 0.161 | 0.413 | 0.075 | 0.012 | -0.333 | 0.011 | 0.541 | 0.993 |
| 23 | CERAMIC | 0.021 | 0.036 | 0.130 | 1.102 | 0.000 | -0.695 | 0.028 | 0.267 | 2.064 | 0.719 | 4.113 | 3.387 | 136.197 | 61.829 |
| 26 | CIDMEGA | 0.017 | 0.036 | 0.087 | 1.010 | 0.000 | -1.301 | 0.021 | 0.398 | 1.697 | -0.716 | 2.347 | 2.721 | 118.826 | 79.732 |
| 27 | CIE | 0.192 | 0.775 | 0.754 | 2.639 | 0.000 | -0.252 | 0.194 | 0.615 | 0.970 | 0.620 | -0.052 | 0.613 | 22.210 | 10.571 |
| 28 | CMOCTEZ | 0.039 | 0.146 | 0.619 | 0.718 | 0.000 | -0.549 | 0.090 | 0.222 | 5.225 | 0.328 | 32.353 | 1.265 | 7089.628 | 29.644 |
| 29 | CMR | 0.036 | 0.271 | 0.261 | 2.804 | 0.000 | -1.698 | 0.053 | 0.600 | 2.579 | 0.881 | 6.781 | 6.395 | 429.365 | 284.895 |
| 30 | CNCI | 0.069 | 0.610 | 0.644 | 5.111 | 0.000 | -0.963 | 0.119 | 1.106 | 2.951 | 1.934 | 10.990 | 5.368 | 1282.907 | 453.980 |
| 31 | COLLADO | 0.039 | 0.338 | 0.281 | 3.262 | 0.000 | -0.349 | 0.064 | 0.589 | 2.757 | 3.031 | 7.869 | 12.775 | 851.591 | 1648.778 |
| 32 | COMERCI | 0.022 | 0.041 | 0.247 | 1.646 | 0.000 | -0.767 | 0.042 | 0.381 | 3.871 | 1.439 | 17.658 | 6.234 | 3078.633 | 554.314 |
| 35 | CONTAL | 0.026 | 0.169 | 0.233 | 1.308 | 0.000 | -1.057 | 0.036 | 0.365 | 2.886 | -0.212 | 12.583 | 2.600 | 581.879 | 19.811 |
| 36 | CONVER | 0.018 | 0.062 | 0.132 | 0.533 | 0.000 | -1.579 | 0.028 | 0.315 | 2.341 | -2.968 | 5.910 | 15.691 | 558.544 | 2129.626 |
| 37 | CYDSASA | 0.017 | 0.059 | 0.133 | 0.531 | 0.000 | -1.581 | 0.028 | 0.314 | 2.364 | -2.996 | 6.089 | 15.853 | 579.179 | 2193.938 |
| 39 | EDOARDO | 0.034 | 0.281 | 0.451 | 2.127 | 0.000 | -1.451 | 0.075 | 0.537 | 4.285 | 0.618 | 21.845 | 4.731 | 4811.122 | 263.889 |
| 40 | ELEKTRA | 0.228 | 1.059 | 0.666 | 2.254 | 0.008 | 0.157 | 0.166 | 0.583 | 0.624 | 0.267 | -0.500 | -1.033 | 7.584 | 4.682 |
| 41 | FEMSA | 0.300 | 1.037 | 0.923 | 2.639 | 0.015 | -0.384 | 0.181 | 0.515 | 0.854 | 0.564 | 1.040 | 1.342 | 12.407 | 9.015 |
| 42 | FINAMEX | 0.028 | -0.073 | 0.247 | 0.721 | 0.000 | -3.585 | 0.051 | 0.560 | 2.929 | -4.378 | 8.797 | 26.479 | 649.040 | 4463.849 |
| 44 | FRAGUA | 0.038 | 0.130 | 0.295 | 0.776 | 0.000 | -0.140 | 0.056 | 0.190 | 2.607 | 1.093 | 7.911 | 1.308 | 550.708 | 65.630 |
| 49 | GCARSO | 0.286 | 1.017 | 0.769 | 2.001 | 0.000 | -0.105 | 0.179 | 0.416 | 0.507 | -0.373 | -0.060 | 0.341 | 3.445 | 2.044 |
| 51 | GENSEG | 0.020 | -0.019 | 0.112 | 0.373 | 0.000 | -0.768 | 0.024 | 0.227 | 1.787 | -1.030 | 3.306 | 1.790 | 186.634 | 87.865 |
| 52 | GEO | 0.209 | 0.976 | 0.571 | 2.155 | 0.000 | -0.046 | 0.138 | 0.491 | 0.348 | -0.104 | -0.363 | -0.090 | 4.009 | 2.276 |
| 53 | GEUPEC | 0.037 | 0.061 | 0.924 | 0.888 | 0.000 | -0.809 | 0.110 | 0.224 | 7.137 | 0.454 | 56.304 | 5.052 | 10925.000 | 86.205 |
| 55 | GFINBUR | 0.140 | 0.594 | 0.644 | 1.412 | 0.000 | -0.387 | 0.118 | 0.409 | 1.375 | -0.338 | 3.395 | -0.183 | 54.649 | 1.831 |
| 56 | GFINTER | 0.020 | 0.083 | 0.145 | 0.890 | 0.000 | -0.691 | 0.033 | 0.308 | 2.497 | 0.960 | 6.587 | 1.930 | 714.496 | 151.577 |
| 57 | GFMULTI | 0.022 | -0.005 | 0.204 | 3.875 | 0.000 | -1.746 | 0.045 | 0.717 | 3.102 | 3.727 | 9.751 | 22.745 | 1683.981 | 6590.269 |
| 58 | GFNORTE | 0.200 | 0.998 | 0.511 | 2.360 | 0.006 | 0.126 | 0.134 | 0.464 | 0.538 | 0.591 | -0.651 | 0.549 | 5.802 | 0.795 |
| 60 | GISSA | 0.101 | 0.363 | 0.923 | 1.252 | 0.000 | -1.639 | 0.136 | 0.380 | 3.345 | -1.398 | 16.509 | 9.147 | 994.558 | 241.319 |
| 62 | GMARTI | 0.016 | 0.045 | 0.096 | 0.917 | 0.000 | -0.573 | 0.022 | 0.242 | 1.967 | 0.750 | 3.653 | 2.807 | 192.629 | 99.448 |
| 63 | GMD | 0.029 | 0.218 | 0.202 | 1.821 | 0.000 | -2.253 | 0.038 | 0.671 | 2.199 | -0.480 | 6.163 | 3.019 | 291.151 | 57.948 |
| 65 | GMEXICO | 0.184 | 1.006 | 0.532 | 2.677 | 0.001 | -0.151 | 0.144 | 0.529 | 0.740 | 0.590 | -0.380 | 0.619 | 9.820 | 2.137 |
| 67 | GNP | 0.017 | -0.033 | 0.094 | 0.425 | 0.000 | -1.555 | 0.021 | 0.271 | 1.947 | -3.083 | 4.164 | 16.911 | 188.016 | 2052.266 |

Source: Authors' calculations, with data from Bloomberg and the MSE.

Table A2: Summarized Market Model Regressions' Results for Individual Stocks (60 days observation non-overlapping windows, from 1992 to 2011). (Second Part)

| | EMPRESA | R2 | Beta | R2 | Beta | R2 | Beta | R2 | Beta | R2 | Beta | R2 | Beta | R2 | Beta |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 68 | GOMO | 0.0274 | 0.0335 | 0.2009 | 2.3939 | 0.0000 | -1.5536 | 0.0387 | 0.7904 | 2.6812 | 0.3738 | 8.8490 | 1.0102 | 949.3628 | 60.9153 |
| 69 | GPH | 0.0247 | 0.0773 | 0.1929 | 1.1537 | 0.0000 | -0.3723 | 0.0353 | 0.2361 | 2.7642 | 2.1253 | 9.4741 | 7.5529 | 543.4569 | 417.1304 |
| 70 | GPROFUT | 0.0152 | -0.0154 | 0.0562 | 0.2066 | 0.0000 | -0.4450 | 0.0149 | 0.1394 | 1.0777 | -1.5165 | 0.4503 | 3.7271 | 178.1546 | 785.6184 |
| 71 | GRUMA | 0.1024 | 0.5091 | 0.4628 | 1.9977 | 0.0000 | -0.1936 | 0.1065 | 0.3731 | 1.5364 | 1.2353 | 1.9742 | 2.7178 | 52.6405 | 32.4270 |
| 72 | HERDEZ | 0.0758 | 0.2443 | 0.9238 | 1.5837 | 0.0000 | -0.6873 | 0.1400 | 0.4016 | 3.8879 | 0.7115 | 18.8641 | 1.1273 | 1290.2640 | 10.5966 |
| 73 | HILASAL | 0.0476 | 0.2597 | 0.4098 | 2.1578 | 0.0000 | -1.4437 | 0.0735 | 0.6363 | 2.7759 | -0.0775 | 10.0506 | 1.0879 | 751.9889 | 17.0829 |
| 74 | HOGAR | 0.0722 | 0.4481 | 0.4503 | 1.3951 | 0.0000 | -0.6539 | 0.1082 | 0.5189 | 2.3103 | -0.0363 | 4.8207 | -0.6338 | 286.4891 | 5.0384 |
| 75 | HOMEX | 0.2840 | 1.0972 | 0.6177 | 1.7596 | 0.0000 | 0.0030 | 0.1737 | 0.4154 | -0.0168 | -0.6425 | -1.0232 | 0.1535 | 31.6865 | 15.7096 |
| 76 | IASASA | 0.0182 | 0.0481 | 0.1306 | 1.9666 | 0.0000 | -2.2876 | 0.0270 | 0.7498 | 2.2831 | -0.5477 | 5.9361 | 3.5887 | 501.9997 | 186.7949 |
| 77 | ICA | 0.2733 | 1.1181 | 0.7342 | 2.5849 | 0.0003 | 0.0000 | 0.1618 | 0.5540 | 0.3976 | 0.4708 | -0.2530 | 0.0050 | 2.2734 | 1.8566 |
| 78 | ICH | 0.1407 | 0.5438 | 0.5626 | 2.1088 | 0.0001 | -0.3832 | 0.1469 | 0.4418 | 1.0754 | 0.5177 | 0.1962 | 0.7831 | 16.9942 | 5.2729 |
| 81 | INVEX | 0.0148 | 0.0452 | 0.0960 | 0.3713 | 0.0000 | -0.0817 | 0.0216 | 0.0814 | 2.1459 | 1.7447 | 4.5945 | 4.5137 | 198.3684 | 176.1904 |
| 82 | IXEGF | 0.0180 | 0.0253 | 0.0885 | 0.6429 | 0.0000 | -0.2606 | 0.0218 | 0.1698 | 1.5061 | 0.8421 | 1.8391 | 1.6942 | 86.7834 | 57.2675 |
| 83 | KIMBER | 0.2118 | 0.6711 | 0.9290 | 1.9198 | 0.0034 | 0.1162 | 0.1664 | 0.3524 | 1.6670 | 1.2699 | 3.7557 | 1.9509 | 77.4564 | 31.8407 |
| 85 | KUO | 0.0420 | 0.1720 | 0.2573 | 0.8292 | 0.0000 | -0.6281 | 0.0604 | 0.3083 | 1.9460 | 0.1884 | 3.2820 | 0.0886 | 90.4005 | 0.9531 |
| 87 | LAMOSA | 0.0332 | 0.1740 | 0.2161 | 0.9746 | 0.0000 | -0.7495 | 0.0480 | 0.3149 | 1.8123 | 0.3089 | 2.7205 | 1.0286 | 96.8320 | 10.4891 |
| 89 | LIVEPOL | 0.0342 | 0.1210 | 0.2442 | 0.7655 | 0.0000 | -0.5359 | 0.0491 | 0.2864 | 2.2952 | 0.3183 | 5.5778 | 0.2121 | 160.7372 | 1.3891 |
| 91 | MAXCOM | 0.1054 | 0.4931 | 0.4707 | 1.6909 | 0.0000 | -1.0250 | 0.1400 | 0.5548 | 1.4384 | 0.1076 | 0.9259 | 0.0750 | 59.5655 | 4.8494 |
| 92 | MEDICA | 0.0157 | 0.0898 | 0.1262 | 1.1399 | 0.0000 | -0.4731 | 0.0263 | 0.2465 | 2.7653 | 1.3499 | 7.6808 | 5.0030 | 570.5394 | 254.9224 |
| 94 | MEXCHEM | 0.1043 | 0.4845 | 0.4678 | 1.6411 | 0.0000 | -1.0309 | 0.1392 | 0.5507 | 1.4493 | 0.0872 | 0.9592 | 0.0759 | 60.7715 | 4.5568 |
| 98 | NUTRISA | 0.0199 | 0.0080 | 0.0986 | 0.9991 | 0.0000 | -0.6395 | 0.0261 | 0.2513 | 1.5080 | 1.0575 | 1.1718 | 5.9884 | 195.7901 | 679.4543 |
| 104 | PE&OLES | 0.1104 | 0.5791 | 0.5142 | 1.7699 | 0.0000 | -1.1093 | 0.1146 | 0.5391 | 1.3283 | -0.0685 | 1.3480 | 0.7359 | 28.1120 | 1.3732 |
| 105 | PINFRA | 0.1812 | 0.8871 | 0.5662 | 2.6421 | 0.0001 | -1.7274 | 0.1553 | 0.8067 | 0.5905 | -0.1964 | -0.6166 | 1.0895 | 15.2010 | 4.3496 |
| 106 | POCHTEC | 0.0303 | 0.2481 | 0.2113 | 2.3251 | 0.0000 | -1.4755 | 0.0442 | 0.6407 | 2.1904 | 1.1006 | 4.9062 | 2.8211 | 273.1171 | 113.6833 |
| 107 | POSADAS | 0.0284 | 0.1492 | 0.2290 | 0.9428 | 0.0000 | -0.2828 | 0.0472 | 0.2489 | 2.5561 | 1.0427 | 6.6189 | 1.2510 | 281.8046 | 29.3763 |
| 110 | Q | 0.0423 | 0.3022 | 0.3378 | 1.3989 | 0.0001 | -0.3962 | 0.0709 | 0.3908 | 3.2115 | 1.3759 | 12.2153 | 2.3815 | 4575.1560 | 590.9244 |
| 113 | RCENTRO | 0.0330 | 0.1324 | 0.5966 | 3.2871 | 0.0000 | -1.3836 | 0.0759 | 0.5600 | 6.1119 | 2.3905 | 43.7875 | 14.0701 | 7764.4820 | 891.3891 |
| 115 | SAB | 0.0546 | 0.2295 | 0.4742 | 1.9069 | 0.0000 | -0.6056 | 0.0858 | 0.4640 | 2.6285 | 0.9919 | 8.3248 | 1.5863 | 365.9857 | 30.6825 |
| 117 | SANLUIS | 0.0212 | 0.0870 | 0.1703 | 1.1344 | 0.0000 | -1.4288 | 0.0300 | 0.4049 | 2.6481 | -0.7474 | 9.0045 | 2.7140 | 351.4284 | 30.8334 |
| 118 | SANMEX | 0.0218 | -0.7330 | 0.1057 | 2.0303 | 0.0000 | -55.4061 | 0.0265 | 6.7979 | 1.5817 | -8.1212 | 1.6564 | 66.2880 | 63.2420 | 20899.5500 |
| 119 | SARE | 0.1583 | 0.8317 | 0.3782 | 1.8609 | 0.0011 | -0.0964 | 0.1178 | 0.4495 | 0.2820 | -0.0329 | -1.1347 | -0.2198 | 39.7283 | 20.7746 |
| 120 | SAVIA | 0.1421 | 0.6483 | 0.6403 | 3.8568 | 0.0000 | -1.0168 | 0.1715 | 0.7691 | 1.3580 | 1.2665 | 0.9664 | 4.5714 | 71.4170 | 154.8277 |
| 121 | SIMEC | 0.1236 | 0.9038 | 0.5458 | 3.2877 | 0.0002 | -0.5447 | 0.1247 | 0.7844 | 1.4032 | 0.9818 | 1.9243 | 1.6901 | 41.0595 | 21.4073 |
| 122 | SORIANA | 0.1968 | 0.8175 | 0.5982 | 1.7205 | 0.0000 | 0.0000 | 0.1587 | 0.3746 | 0.9019 | 0.1760 | -0.0764 | -0.3378 | 10.9139 | 0.5766 |
| 125 | TEKCHEM | 0.0335 | 0.0951 | 0.2383 | 1.6120 | 0.0001 | -1.6308 | 0.0553 | 0.5715 | 2.8048 | -0.2273 | 7.4650 | 1.5004 | 820.4993 | 58.3941 |
| 127 | TELMEX | 0.1378 | 0.7161 | 0.4433 | 1.9378 | 0.0000 | -0.0610 | 0.1086 | 0.4282 | 0.6256 | 0.5056 | -0.4373 | 0.3801 | 6.3405 | 2.9132 |
| 129 | TMM | 0.0448 | 0.1919 | 0.2835 | 1.5964 | 0.0000 | -0.8415 | 0.0709 | 0.4661 | 2.0921 | 0.2591 | 3.4538 | 0.0597 | 97.5343 | 1.1129 |
| 130 | TS | 0.0807 | 0.5185 | 0.4257 | 1.5658 | 0.0015 | -0.4964 | 0.1010 | 0.4357 | 1.9657 | 0.4311 | 3.7528 | 0.5230 | 512.7441 | 54.0662 |
| 132 | VALUEGF | 0.0280 | 0.0633 | 0.1829 | 0.4557 | 0.0000 | -0.4874 | 0.0387 | 0.1834 | 2.1392 | -0.7444 | 5.4734 | 1.7287 | 573.5165 | 61.7505 |
| 133 | VASCONI | 0.0201 | 0.1943 | 0.1337 | 1.2574 | 0.0000 | -0.3968 | 0.0310 | 0.3673 | 2.4256 | 0.9055 | 5.6298 | 0.3450 | 266.4782 | 24.1629 |
| 134 | VITRO | 0.1748 | 0.8236 | 0.7155 | 2.0763 | 0.0000 | -0.2961 | 0.1584 | 0.4553 | 1.1632 | 0.1072 | 1.1780 | -0.2324 | 22.2405 | 0.7135 |
| 135 | WALMEX | 0.2396 | 0.9353 | 0.6586 | 1.8570 | 0.0000 | 0.0000 | 0.1371 | 0.3762 | 0.5529 | -0.3008 | 0.3180 | -0.0575 | 3.4115 | 2.1329 |

Source: Authors' calculations, with data from Bloomberg and the MSE.

Table A3: Identification of Groups with Corresponding Structural Breaks in the R2-IAMI Series, using Perron's (1989) test.
(First Part)

| First group: months before the 1994 peso devaluation (Tequila Crisis) | | | Second group: months surrounding the 1998 South East Asia Financial (Dragon) Crisis | | |
|---|---|---|---|---|---|
| Number | Stock | Structural Break | Number | Stock | Structural Break |
| 1 | ALFA | 07/08/1994-09/30/1994 | 1 | ACCELSA | 08/05/1998-10/29/1998 |
| 2 | BIMBO | 07/08/1994-09/30/1994 | 2 | FINAMEX | 08/05/1998-10/29/1998 |
| 3 | CERAMIC | 07/08/1994-09/30/1994 | 3 | GENSEG | 08/05/1998-10/29/1998 |
| 4 | CONTAL | 07/08/1994-09/30/1994 | 4 | GFINTER | 08/05/1998-10/29/1998 |
| 5 | FEMSA | 07/08/1994-09/30/1994 | 5 | ICH | 08/05/1998-10/29/1998 |
| 6 | GCARSO | 07/08/1994-09/30/1994 | 6 | MAXCOM | 08/05/1998-10/29/1998 |
| 7 | GEUPEC | 07/08/1994-09/30/1994 | 7 | MEXCHEM | 08/05/1998-10/29/1998 |
| 8 | GISSA | 07/08/1994-09/30/1994 | 8 | SAVIA | 08/05/1998-10/29/1998 |
| 9 | GPH | 07/08/1994-09/30/1994 | 9 | TEKCHEM | 08/05/1998-10/29/1998 |
| 10 | KIMBER | 07/08/1994-09/30/1994 | | | |
| 11 | KUO | 07/08/1994-09/30/1994 | | | |
| 12 | LAMOSA | 07/08/1994-09/30/1994 | | | |
| 13 | LIVEPOL | 07/08/1994-09/30/1994 | | | |
| 14 | PE&OLES | 07/08/1994-09/30/1994 | | | |
| 2 | HERDEZ | 10/03/1994-12/29/1994 | | | |

Source: Authors' calculations, with data from Bloomberg and the MSE.

Table A4: Identification of Groups with Corresponding Structural Breaks in the R2-IAMI Series, using Perron's (1989) test.
(Second Part)

Third group: the most turbulent months of 2008 (2007-2009 Financial Crisis).

| Number | Stock | Structural Break | Number | Stock | Structural Break |
|---|---|---|---|---|---|
| 1 | CEMEX | 02/18/2008-05/15/2008 | 30 | CONVER | 05/16/2008-08/07/2008 |
| 2 | CNCI | 02/18/2008-05/15/2008 | 31 | CYDSASA | 05/16/2008-08/07/2008 |
| 3 | GMARTI | 02/18/2008-05/15/2008 | 32 | EDOARDO | 05/16/2008-08/07/2008 |
| 4 | ICA | 02/18/2008-05/15/2008 | 33 | ELEKTRA | 05/16/2008-08/07/2008 |
| 5 | POSADAS | 02/18/2008-05/15/2008 | 34 | FRAGUA | 05/16/2008-08/07/2008 |
| 6 | SANLUIS | 02/18/2008-05/15/2008 | 35 | GEO | 05/16/2008-08/07/2008 |
| 7 | SANMEX | 02/18/2008-05/15/2008 | 36 | GFINBUR | 05/16/2008-08/07/2008 |
| 8 | SORIANA | 02/18/2008-05/15/2008 | 37 | GFNORTE | 05/16/2008-08/07/2008 |
| 9 | TELMEX | 02/18/2008-05/15/2008 | 38 | GMD | 05/16/2008-08/07/2008 |
| 10 | TMM | 02/18/2008-05/15/2008 | 39 | GMEXICO | 05/16/2008-08/07/2008 |
| 11 | VASCONI | 02/18/2008-05/15/2008 | 40 | GNP | 05/16/2008-08/07/2008 |
| 12 | VITRO | 02/18/2008-05/15/2008 | 41 | GPROFUT | 05/16/2008-08/07/2008 |
| 13 | WALMEX | 02/18/2008-05/15/2008 | 42 | GRUMA | 05/16/2008-08/07/2008 |
| 14 | ALSEA | 05/16/2008-08/07/2008 | 43 | HILASAL | 05/16/2008-08/07/2008 |
| 15 | AMX | 05/16/2008-08/07/2008 | 44 | HOGAR | 05/16/2008-08/07/2008 |
| 16 | ARA | 05/16/2008-08/07/2008 | 45 | HOMEX | 05/16/2008-08/07/2008 |
| 17 | ARCA | 05/16/2008-08/07/2008 | 46 | IASASA | 05/16/2008-08/07/2008 |
| 18 | ASUR | 05/16/2008-08/07/2008 | 47 | INVEX | 05/16/2008-08/07/2008 |
| 19 | azteca | 05/16/2008-08/07/2008 | 48 | MEDICA | 05/16/2008-08/07/2008 |
| 20 | BACHOCO | 05/16/2008-08/07/2008 | 49 | NUTRISA | 05/16/2008-08/07/2008 |
| 21 | BAFAR | 05/16/2008-08/07/2008 | 50 | PINFRA | 05/16/2008-08/07/2008 |
| 22 | C | 05/16/2008-08/07/2008 | 51 | POCHTEC | 05/16/2008-08/07/2008 |
| 23 | CABLE | 05/16/2008-08/07/2008 | 52 | Q | 05/16/2008-08/07/2008 |
| 24 | CIDMEGA | 05/16/2008-08/07/2008 | 53 | RCENTRO | 05/16/2008-08/07/2008 |
| 25 | CIE | 05/16/2008-08/07/2008 | 54 | SAB | 05/16/2008-08/07/2008 |
| 26 | CMOCTEZ | 05/16/2008-08/07/2008 | 55 | SARE | 05/16/2008-08/07/2008 |
| 27 | CMR | 05/16/2008-08/07/2008 | 56 | SIMEC | 05/16/2008-08/07/2008 |
| 28 | COLLADO | 05/16/2008-08/07/2008 | 57 | TS | 05/16/2008-08/07/2008 |
| 29 | COMERCI | 05/16/2008-08/07/2008 | 58 | VALUEGF | 05/16/2008-08/07/2008 |

Source: Authors' calculations, with data from Bloomberg and the MSE.