Nonlinear Time Series and Finance

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This is the main purpose of this book, which offers a collection of studies related to economics and finance. The book is comprised by eleven chapters. All works were peer reviewed. Six of those chapters contain applied research related to Mexico. Other chapters focus on methodological issues and on applications of nonlinear time series models to diverse problems, all related to the economy and finance.

Centro Universitario de Ciencias Económico Administrativas
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Nonlinear Time Series and Finance

Coronado-Ramírez, Celso-Arellano y Trejo-Pech [editors]

Nonlinear
Time Series
and Finance

Universidad de Guadalajara

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[editors]

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Content

Preface

The application of nonlinear time series models in economic and finance has expanded rapidly lately. Thus, it becomes important to disseminate the latest research to scholars, practitioners and graduate students interested in this field. This is the main purpose of this book, which offers a collection of studies related to economics and finance.

The behavior of complex economic and financial markets has been modeled beyond traditional economics theory by borrowing techniques from fields such as physics, statistics or mathematics. Examples of such techniques include the Brownian motion, fractals, and the application of nonparametric statistics, among others.

This book is comprised by eleven chapters. All works were peer reviewed. Six of those chapters contain applied research on Mexico. Other chapters focus on methodological issues and on applications of nonlinear time series models to diverse problems, all related to the economy and finance. One exception is the work by He and Kyaw, on which linear models are applied to analyze public Chinese firms. He and Kyaw along with Gevorkyan and Gevorkyan were invited authors as recipients of the best paper award in the International Business and Economy Conferences 2011 and 2012 (Hawaii, USA and Caen, France). Their submissions were also peer reviewed.

A total of twenty four authors representing nineteen institutions contributed in this book. Affiliations of authors include Cornell University (NY, USA); Virginia Tech (Virginia, USA); Instituto Politécnico Nacional (Mexico City and Zacatenco, México); Instituto Tecnológico de Estudios Superiores de Monterrey (Guadalajara, Mexico); Universidad Nacional Autónoma de México (Mexico City, México); Marist College (NY, USA); New School University (NY, USA); Columbia University (NY, USA); Mississippi State University (Mississippi, USA); University of Groningen (The Netherlands); Universidad de Salamanca

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We hope this collection of chapters, containing original research, sheds some light on current applications to economic and financial behavior on diverse markets.

The Editors

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Abstracts

An ARFIMA Model for Volatility Does Not Imply Long Memory

Jiang and Tian (2010) have estimated an ARFIMA model for stock return volatility. We argue that this result does not imply actual 'long memory' in such time series - as any kind of instability in the population mean yields apparent fractional integration as a statistical artifact. Alternative high-pass filters for studying stock market volatility data are suggested.

Currency Crises in Mexico 1990 – 2009: An Early Warning System Approach

The Global Financial Crisis (GFC) has affected many countries including Mexico. The exchange rate depreciated sharply in the fall of 2008. This chapter investigates the experience of Mexico with currency crises since 1990. We estimate an Early Warning System, consisting of an ordered logit model to include the severity of currency crises, and a factor model to cope with the large number of crisis indicators. We find that Mexico's currency crises are driven primarily by domestic economy, external economy and debt indicators. Ex ante forecasts for 2008-2009 do not produce a currency crisis in late 2008, in sharp contrast with reality.

The Utilization of Logistic Regressions in Addition to Multivariate Analyses for More Reliable Test Results

To date, most of the prior accounting or finance related empirical studies were based solely on results of some forms of multivariate regressions. The reliability of their findings is subject to question. By definition, all forms of multiple regressions rely critically on some assumptions of the quality of the test data. The problem is that most of the financial data often violate some, and in some cases, all of these assumptions. Many times the authors themselves acknowledge the problem; however, they do not do anything to remedy the situation. In this chapter, I will try to promote the utilization of logistic regressions, in addition to any applicable multiple analyses, to provide the much needed reliability of study results. Based on these findings of this empirical tests, I will also discuss the development of The Logistic Indicator - a practical barometer and security investment tool for daily stock index trading.

Sovereign Credit Default Swap Spread Volatility: A Spectral Analysis of Risk Premiums of Common Currency and Standalone Economies

This study advances a relatively new technical approach of a country risk premium analysis focusing on a five year sovereign Credit Default Swap (CDS). The magnitude and diverse set of countries affected by the latest global crisis are both immense. In this study we look at four countries that may offer representative narratives: France, Spain, Hungary, and Poland. The paper relies on spectral analysis techniques exploring cyclicality of data. The analysis produces a co-spectrum (coherence, phase and power) of market returns and interest rates with sovereign CDS. These indicators may have a significant potential impact on CDS and data frequency demonstrates that in the frequency domain. Additionally, the paper analyzes individual sovereign CDS prices using harmonic analysis, where harmonic coefficients were obtained. The goal of this research is to explore correlations in financial series cyclicality of countries that are members of the monetary union and those that are standalone with somewhat comparable macroeconomic parameters.

Impact of Free Cash Flow on Overinvestment: An Empirical Evidence of Chinese Listed Firms

We investigates the relationship between free cash flow and over-investment of Chinese listed companies during 2003-2008 following Richardson's model. Consistent with agency cost explanation, over-investment is associated with higher free cash flows. Further examination of corporate ownership structures reveals that large block holders and mutual fund investors in Chinese corporations do not exert sufficient monitoring on corporate decisions towards mitigating overinvestment. As expected, the financially unconstrained firms tend to overinvest and the financially constrained firms are more sensitive to free cash flows when making overinvestment decisions. The valuation effect of overinvestment supports the U.S. evidence that overinvesting firms destroy value.

Oil Price Shocks and Business Cycles in Major OECD Economies

We find that oil shocks lower real GDP growth and raise inflation in the major oil importing OECD economies. Oil exporting UK's reactions are qualitatively similar, except for a moderate expansion within the first year. There is widespread evidence of non-linearities that amplify the macroeconomic effects of oil shocks. Historical decompositions reveal that higher oil prices impacted real activity during the recessions of the mid-1970s and early 1980s - both periods characterised by very high oil prices. Starting with the oil price spike of 1990-1991, oil shocks have exerted weaker effects on real output developments.

Long Memory Volatility and VaR for Long and Short Positions in the Mexican Stock Exchange

We analyze the relevance of models that capture the presence of long memory on the performance of Value at Risk (VaR) estimates Long Memory effects both for the case of returns and volatility in the Mexican Stock Index are captured employing autoregressive models with fractional integration. Volatility of returns are estimated applying FIGARCH, FIAPARCH and HYGARCH models, including for each model three different specifications for the error distribution. The evidence shows that for, daily VaR calculations, models that consider distributions other than gaussian, perform better than those that do, both for the short and long positions. The study covers the 1983-2009 period.

Characterization of Non-Linear Time Series of Spare Parts Demand in Service Companies

Telecommunication service providers, also called operators or carriers, must maintain 99.999% of their telecom network availability. To avoid or mitigate the effects of an outage in the network, carriers perform different activities to restore service. Spare parts management plays an important role in meeting the required service. Unfortunately, the closed - loop supply chain that supports the availability of spare parts experiences fluctuations (or "bullwhip effect") in its processes as a result of endogenous and exogenous variables that make matching the recovery process with the demand process difficult. Understanding the effect of the emergence of the bullwhip effect can help to guide the development of future mathematical models for the management of spare parts. In this chapter, a complex system approach is applied to characterize the emergence of the bullwhip effect.

Predictability of Exchange Rate: A Comparison of Stochastic Simulation Models

We test the hypothesis that the lower the development of financial markets, the greater the Central Bank intervention in the foreign exchange market. To do this, we will use both the Geometric Brownian Motion (GMB) and the Ornstein-Uhlenbeck Process (OU) as models for predicting the exchange rate variation. The performance of these two models will be compared with the following exchange rates: U.S. Dollar/Mexican Peso (USD/MXN), U.S. Dollar/British Pound (USD/GBP), U.S. Dollar/Euro (USD/EUR), and U.S. Dollar/Yuan (USD/CNY). Finally, we provide some recommendations regarding Central Bank intervention on the level of the foreign exchange rate.

Financial Time Series: Stylized Facts for the Mexican Stock Exchange Index Compared to Developed Markets'

We present some stylized facts exhibited by the time series of returns of the Mexican Stock Exchange Index (IPC) and compare them to a sample of both developed (USA, UK and Japan) and emerging markets (Brazil and India). The period of study is 1997-2011. The stylized facts are related mostly to the probability distribution function and the autocorrelation function (e.g. fat tails, non-normality, volatility clustering, among others). We find that positive skewness for returns in Mexico and Brazil, but not in the rest, suggest investment opportunities. Evidence of nonlinearity is also documented.

Geometric Brownian Motion and Efficient Markets in Mexico

It is constantly assumed that financial time series data follow a geometric Brownian motion (gBm). This assumption follows from the efficient market hypothesis, which in its weak form states that all markets participants, having access to publicly available information, cannot predict prices. Asset prices already incorporate that information. Failure to meet the gBm condition is also an indicator of market inefficiency, and creates biased results when pricing options using the Black-Sholes formula. Morever, if a time series follows a gBm, then its return are stationary, I(0), a critical condition for analyzing time series data. This analysis uses a scaled variance ratio test on several commodities and financial time series to test the hypothesis of gBm. We conclude that commodities follow a gBm path, but currency (Mexican peso/ US Dollar) does not follow a gBm at higher lags.

CHAPTER 1
An ARFIMA Model for Volatility Does Not Imply Long Memory

Richard A. Ashley
Douglas M. Patterson

Introduction

This chapter is motivated by Jiang and Tian (2010). They estimate ARFIMA models for stock return volatility. These models are used to forecast return volatility, with the goal of improving option valuation under the Statement of Financial Accounting Standards (SFAS) 123R. They show that when a fractional difference is incorporated into a vector-autoregressive (VAR) specification, superior volatility forecasts are obtained. Their fitted model includes, in addition to the ARFIMA fractional difference operator – $(1–B)^d$, $0<d<0.5$ – some common market factors such as the volatility of the S&P 500 index. They describe this as an "LM-VAR' model, in which the 'LM' term refers to 'long memory.'

Our purpose is not to criticize their identification or estimation of these LM-VAR models as volatility forecast models. However, we point out that the fractional difference operator $(1–B)^d$ at the heart of any *ARFIMA* (p, d, q) model, is only one of many high-pass filters suitable for modeling stock market volatility.

The unfortunate aspect of Jiang and Tian's paper is its assertion that their estimated *ARFIMA* model necessarily implies the existence of 'long memory' in stock return volatility data, where 'long memory' is intended to assert the existence of actual serial correlations in the data which die out only very slowly at long lags. That assertion is incorrect, basically because any estimated *ARFIMA* (p, d, q) (or test of $H_0 : d = 0$) in essence relies on sample autocovariances as consistent estimators of population autocovariances. But these sample autocovariance estimators are inconsistent in the presence of any time variation in the population mean of the time series. Thus, the apparent presence of fractional integration in a time series is more likely to be signaling the presence such time variation – structural shifts or weak trends – than to be an authentic indicator of 'long memory.'

Fractional integration and 'long memory.'

It is well known – e.g., Granger (1980), Granger and Joyeaux (1980), Beran (1994), and Baillie (1996) – that fractional integration of order d in a time series implies that its population autocorrelation at lag k decay slowly as k increases. In particular, if $0 < d < 1/2$, for the *ARFIMA* (p, d, q) model, then $\rho_k \propto k^{2d-1}$ *as* $k \rightarrow \infty$. Concomitantly, fractional integration of order d is equivalent, under certain conditions, to an exploding spectral density at zero frequency – i.e., to $s(\omega) \propto \omega^{-2d}$ *as* $\omega \rightarrow 0^+$, where $s(\omega)$ is the power spectrum of $\{x_t\}$.[1]

For this reason, observed slow decay in the sample autocorrelation function r_k, is taken to be evidence that $\{x_t\}$ is generated by an *ARFIMA* (p, d, q) model. Similarly, an observation that $\log[\hat{s}(\omega)]$ – the logarithm of the sample spectrum $\hat{s}(\omega)$ – goes to zero linearly $\log(\omega) \rightarrow 0$ as is also taken to be evidence that $\{x_t\}$ is generated by an *ARFIMA* (p, d, q) model. Indeed, the most popular ways to estimate d and to test the null hypothesis $H_0 : d = 0$ are based on regressing $\log[\hat{s}(\omega)]$ of $\{x_t\}$ against $\log(\omega)$ for low frequencies – see Geweke and Porter-Hudak (1983) and Robinson (1995).

This, in fact, is precisely how Jiang and Tain (2010) estimate the value of d in their *ARFIMA* (p, d, q) models for stock return volatility. And, in principle there is nothing wrong with estimating d is this way and using these estimates to identify and estimate short-term forecasting models for stock return volatility.

1. The power spectrum is defined as the Fourier transform of the autocovariance function; the corresponding population autocorrelation function $\rho_k \equiv \frac{cov(x_t, x_{t-k})}{\sqrt{var(x_t)\, var(x_{t-k})}}$ is a simple transform of the autocovariance function.

The problem arises when one interprets this modeling effort as implying the existence of actual long-range serial correlation in the data, as this interpretation is valid only if the d estimates are based on consistent estimates of $s(\omega)$ or, equivalently, on consistent estimators of the autocovariances underlying the ρ_k.

But these autocovariance estimates cannot be consistent if $E\{x_t\}$ varies over time. This proposition is proven in Ashley and Patterson (2010, Section 3.1); but this demonstration is so brief and straightforward that we repeat it here. The *population* autocovariance of $\{x_t\}$ with itself lagged k periods is defined as:

$$cov(x_t x_{t-k}) = \frac{1}{T}\sum_{t=1}^{T}[x_t - E\{x_t\}][x_{t-k} - E\{x_{t-k}\}], \tag{1}$$

whereas the *sample* autocovariance of $\{x_t\}$ with itself lagged k periods is defined as:

$$cov(x_t, x_{t-1}) = \frac{1}{T}\sum_{t=k+1}^{T}[x_t - \bar{x}][x_{t-k} - \bar{x}]. \tag{2}$$

But if $E\{x_t\}$ varies over time – due to either structural shifts or due to any kind of smooth variation or trend-like behavior – then the sample mean $\overline{x}$ cannot possibly be a consistent estimator of $E\{x_t\}$.[2] Thus, in that case, the sample autocovariances cannot possibly be consistent estimators of the population autocovariances. Hence, neither the autocovariances nor the power spectrum based on them is consistently estimated in that case.

This result rationalizes what otherwise might appear to be a contradiction between our acceptance of Jian and Tian's *ARFIMA* forecasting model and our rejection of their interpretation of this model as implying slowly decaying long-range linear dependence in these data. Their model might in this situation be a useful approximation for short-run forecasting, but their interpretation of their estimated model as implying that ρ_k is non-negligible for large k is not credible. As noted above, it is much more likely that the sample autocovariances underlying their estimated short-run model are inconsistent estimators of the population autocovariances because of time variation in $E\{x_t\}$ than it is that

2. See Ashley and Patterson (2010, Section 3.1).

there is any noticeable relationship between current stock return volatility and its distant past.

Dealing with a slowly-evolving $E\{x_t\}$

Like a fractionally integrated process, a process with a slowly evolving mean is also characterized by an autocorrelation function that slowly decays as the lag becomes large[3]. Given the similarity between these two models in the sample statistics, it becomes an empirical question as to whether or not the process is an example of fractional integration or a slowly evolving mean; a serial correlation coefficient that slowly decays is not a sufficient condition for fractional integration. In Ashley and Patterson (2010) we studied the weekly volatility of the CRSP value weighted stock index. There we present evidence based on the sample power spectrum that stock market volatility is not generated by a fractional difference process. In particular, the behavior of the spectrum at low frequencies is not indicative of a fractional difference process.

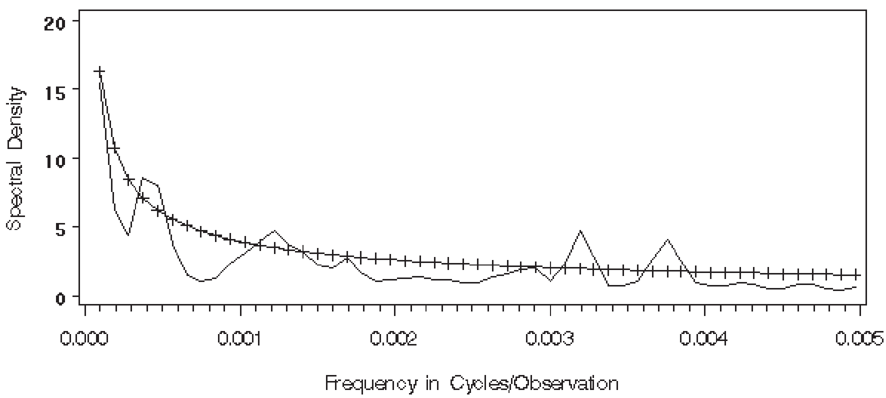

Figure 1. The sample power spectrum at very low frequencies from a generated approximation to a fractionally integrated model is plotted as the solid line. The theoretical spectrum for the fractionally integrated process is plotted with the "+" symbol.

3. This is proven in Theorem 2 of Ashley and Patterson (2010).

In Figure 1 we display the sample power spectrum at low frequencies from a generated approximation to a fractionally integrated (*ARFIMA*) model, using an *MA*(1,000,000)approximation to the *ARFIMA* process.[4] The *MA* model was truncated after 1,000,000 terms. For reference purposes in Figure 1, the theoretical spectrum for the fractionally integrated process is plotted with the "+" symbol. Contrast the plot in Figure 1 with Figure 2, where we plot the low frequency spectral behavior of the observed weekly volatility of returns to the value weighted CRSP index[5]. The sample period is the 2,705 weeks spanning March 1956 through the last week in December of 2007.

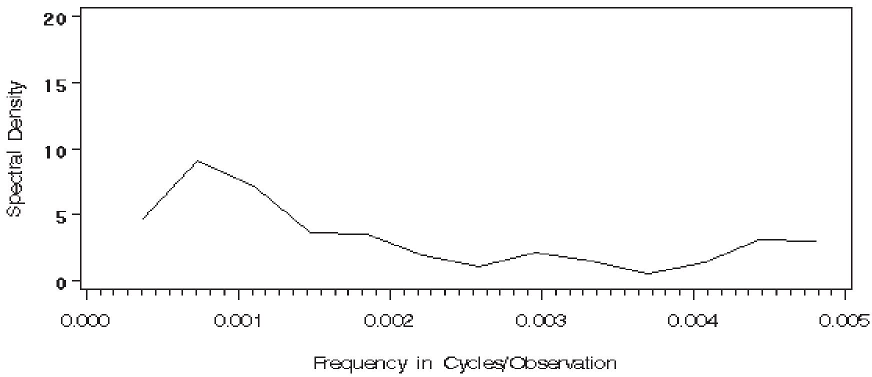

Figure 2. The sample power spectrum of the weekly volatility of the CRSP value weighted stock market index. The period shown are the 2,705 weeks from March 1956 through December 2007.

Figure 2 shows that the observed power spectrum of the CRSP return weekly volatility actually dips at the lowest frequencies, rather than

4. An *ARFIMA* process can be very compactly expressed using the $(1 - B)^d$ operator, but one of its awkward features is that the notion of actually differencing a time series a fractional number of times is intuitively opaque. Relatedly, another awkward feature is that *ARFIMA* processes can only be approximately simulated, using expansions of $(1 - B)^d$ or $(1 - B)^{-d}$ to obtain $AR(p)$ or $MA(q)$approximations to a fractionally integrated process. See Hamilton (1994, pp. 447-9) where formulas for these expansions are derived. These expansions converge very slowly, thus extremely large values of p or q are necessary in order for the expansion to yield an adequate approximation to the correlogram, spectrum, etc. of a fractionally integrated process.
5. Weekly volatility is measured as the root mean square of the daily returns during the calendar week.

exploding – per the fractional integration hypothesis and Figure 1 – as the frequency approaches zero from the right. Thus, a closer look at related sample evidence is actually not very supportive of the conclusion that weekly stock market index volatility is generated by an *ARFIMA* process. From this evidence the conclusion that stock market volatility is generated by an *ARFIMA* process is not exactly compelling.

Nevertheless, as Jiang and Tian (2010) observe, one can fit an *ARFIMA* model to the data and obtain useful short-term forecasting models. And this is by no means wrong, so long as one recognizes that one is not adducing evidence for 'long memory' in the actual data generating process.

Alternatively, one could estimate less elegant – but more easily interpretable and (perhaps) more appropriate – models for these data by observing that the fractional difference operator is in this context simply serving as a high-pass filter for the data.

Many alternative high-pass filters are well known in the time series analysis and Electrical Engineering literatures. These include:

1. Exponential Smoothing[6]
2. Moving Average[7]
3. Nonlinear Bandpass filtering[8]
4. Butterworth filter[9]
5. Non parametric time regression[10]

High-pass filtering of these types can eliminate a slow, smooth time variation in the mean of a financial return volatility series just as easily as does a fractional difference. Indeed, Ashley and Patterson (2007, 2010) used some of these filters to eliminate the sample evidence of fractional integration in several such time series.

Of course, some high pass filters are more intuitively appealing than others; some readers might even prefer the compactness of the fractional difference filter, despite its intuitive opaqueness. One would

6. See Granger and Newbold (1977) pages 162-165, and SAS/ETS User's Guide, Version 6, Second Edition (1995) Chapter 9, page 443.
7. See Ashley and Patterson (2007) for a simple example applied to weekly stock index volatility.
8. These are common in the macroeconomic time-series literature – see Baxter and King (1999).
9. See A. Antoniou, *Digital Filters: Analysis, Design, and Applications*, New York, NY: McGraw-Hill, 1993, and, S.K. Mitra, *Digital Signal Processing: A Computer-Based Approach*, New York, NY: McGraw-Hill, 1998.
10. See Ashley and Patterson (2010).

expect to obtain similar short-term forecasts from models based on any of these choices, so our main complaint with the *ARFIMA* approach is its concomitant implication of 'long memory' in the time series. We also note that the *ARFIMA* model eliminates any trends in the time series at the outset, whereas an analyst applying some other high-pass filter is more likely to also examine the trend which, albeit weak, might be of economic interest.

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Chapter 2
Currency Crises in Mexico 1990–2009: An Early Warning System Approach

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Introduction

The 2007 – 2009 Global Financial Crisis (GFC) has affected many countries including Mexico. In the fall of 2008, the Mexican pesos depreciated sharply by almost 50% vis-a-vis the US dollar, as can be seen in Figure 1. After reaching its highest point in February 2009, the Mexican peso appreciated and stabilized at approximately MXN12.50 per USD by the end of 2009.

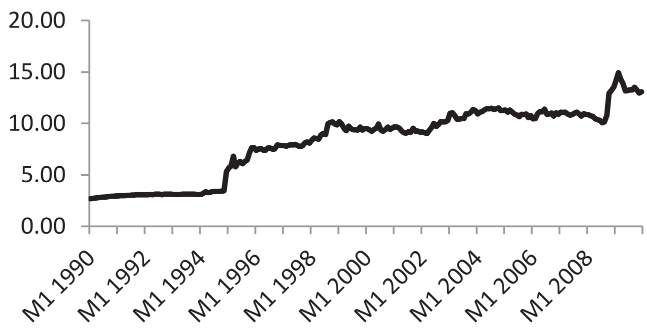

Figure 1. The nominal exchange rate of the Mexican peso versus the US dollar.

The Global Financial Crisis and its effects on other countries and currencies have been studied extensively, with different findings. Rose and Spiegel (2011) conclude that there is little hope to find a common statistical model to predict crises, because the causes differ between countries. They find that countries with current account surpluses seem to suffer less from slowdowns. Fratzscher (2009) finds that countries with low foreign reserves, weak current account positions and high financial exposure vis-à-vis the United States experienced larger currency depreciations. Frankel and Saravelos (2012) choose a wide range of variables from the EWS literature and find that international reserves and real exchange rate overvaluation are the most important leading indicators for the 2008-2009 crisis. Furthermore they note that there is promising research in revising how well Early Warning Systems perform out-of-sample. In other words: How well would an existing EWS perform to predict the GFC well ahead?

We investigate the experience of Mexico with currency crises since the 1990s. We address two questions. First, what were the main determinants for the currency crises and the run-up to currency crises? Second, does our model pick up the crisis in the aftermath of the fall of Lehman Brothers in September 2008, and more generally how did Mexico perform in the run up to and the aftermath of this event?

We model the probability of a currency crisis in an ordered logit model to include the severity of currency crises and use a factor model to cope with the large number of crisis indicators. In that respect our work is related to Jacobs, Kuper and Lestano (2008), who apply factor analysis to predict the Asia crisis. The factor model allows us to investigate the role of institutional, political, global and commodity-related indicators, as suggested by Alvarez Plata and Schrooten (2004) who investigate the Argentinean 2002 currency crisis. We estimate the ordered logit models from 1990 up to and including 2007, and present forecasts for 2008-2009. In our analysis we include only one country, so that we are not limited by country-specific heterogeneity, which is one of the major problems in EWS.

The remainder of the chapter is structured as follows. After a review of financial crises and models, early warning systems and empirical studies for Latin America, we discuss our method. The presentation of our data is followed by the empirical results, and the conclusion.

Literature review

Early Warning Systems

Early Warning Systems (EWS) are models that send signals or warnings well ahead of a potential financial crisis. The dozens of EWS that have been developed over the years differ widely in the crisis definition, the period of estimation, data frequency, the countries included in the database, the inclusion of indicators, the forecast horizon, and the statistical or econometric method. For extensive overviews see Kaminsky, Lizondo and Reinhart (1998) or Abiad (2003). Most studies use binary methods (logit or probit), the signals approach, Ordinary Least Squares, Markov Switching models, binary recursive trees, contingent claims analysis, or a combination of these methods.

The typical EWS is applied to a large number of emerging countries in order to obtain a sufficient number of crisis observations. This choice of the dataset has received criticism. To quote Abiad (2003): "The one-size-fits-all panel data approach used in estimating most Early Warning Systems (EWS) might be one of the causes of their only moderate success." Kaminsky (2006) confirms this and Beckmann, Menkhoff and Sawischlewski (2006) also suggest that differences between geographical regions justify a regional approach. A growing number of studies focuses on a geographic region – particularly South East Asia, Central Europe and Latin America.

Even within a region distinctions can be made. Van den Berg, Candelon and Urbain (2008) construct country clusters for six Latin American countries because of similarities between countries. In their study for the period 1985-2004, Argentina, Brazil and Peru are grouped in one cluster because of similar inflation patterns, while Mexico, Uruguay and Venezuela are grouped in the other cluster, due to important privatizations in the early 1990s.

Empirical studies for Mexico and Latin America

With its rich history of financial crises (Reinhart and Rogoff, 2009), Mexico has been included in many EWS studies. Studies with an exclusive focus on the region also exist. Kamin and Babson (1999) construct an EWS to predict currency crises for a pooled dataset of six Latin American countries for the period 1981-1998. They use a probit model to identify the deeper causes of Latin America's volatility and find that domestic policy and economic imbalances (large fiscal deficits, excessive money creation, overvalued exchange rate) have a stronger influence on currency crises than exogenous external shocks (increase in international real interest rates, recession in developed countries, decrease in commodity prices). Herrera and Garcia (1999) construct an EWS that can be updated every month at a low cost. For this reason they select a limited number of variables in their model: real effective exchange rate, domestic credit growth in real terms, ratio of M2 to international reserves, inflation and stock market index in real terms. They use the signals approach from Kaminsky et al. (1998), but with one difference: they first aggregate the indicators into a composite index and then generate signals depending on the behavior of this composite index. They apply their model to eight Latin American countries. Acknowledging that including external interest rates, commodity prices and the state of the real economy will probably improve the performance. To handle this, they suggest the use of factor models.

The Mexico 1994-1995 "tequila" crisis has been studied extensively. Sachs, Tornell and Velasco (1996) focus on contagion, and identify fundamentals that explain why some countries are hit and others not: high real exchange rate, lending boom and low reserves. Beziz and Petit (1997) use real time data for predicting the crisis. They find that the 1994 crisis could well have been foreseen with information available before the crisis, with the composite leading indicator which was constructed by the OECD in 1996 and which consists of financial series (total industrial production in USA, total imports from USA, share prices, real effective exchange rate and CPP), business surveys (production and employment tendencies) and employment in manufacturing.

The causes and consequences of the Global Financial Crisis in Latin America have been studied by Ocampo (2009), Porzecanski (2009) and Jara, Moreno and Tovar (2009). They agree that the Global Financial Crisis hit Latin America very hard, but that the financial impact was less severe. Various reasons have been provided. After a period of economic prosperity in the 2002 – 2007 boom, the initial situation was much better due to high commodity prices, increasing international trade and exceptional financing conditions. Other factors that played a role were reduced currency mismatches, a more flexible exchange rate regime, improved supervision on the banking sector, more credible monetary and fiscal policies, high foreign reserves and low sovereign external debt levels.

Our work builds upon previous empirical research on Latin America. Herrera and Garcia (1999) also use a factor model. Our choice to include a wide range of variables instead of preselecting explanatory variables is inspired by Kaminsky, Mati and Choueiri (2009), who find that no category dominates. Finally, we follow Cerro and Iajya (2009) and Alvarez Plata and Schrooten (2004) by including institutions as explanatory variables in our model.

Methodology

We first apply a factor model to extract the factors from a set of indicators, then we use the estimated factors as regressors in the ordered logit model, with a crisis dating dummy as dependent variable, and finally compute ex ante forecasts. Before we turn to these models, we first describe crisis dating.

Crisis dating

Identifying and dating currency crises has been debated since the mid 1990s. Two approaches can be distinguished: the successful attack and the speculative pressure approach.

In this study we opt for the latter, which was inspired by Girton and Roper (1977) and later adopted by Eichengreen, Rose and Wyplosz (1995) for currency crises, because it not only takes into account actual devaluations or depreciations of the currency, but also includes periods of great stress of the exchange rate.

We adopt the Exchange Market Pressure Index (EMPI) of Kaminsky and Reinhart (1999), defined as the weighted average of exchange rate changes and reserve changes, with weights such that the two components of the index have equal conditional volatilities. Kaminsky and Reinhart (1999) identify a crisis when the observation exceeds the mean by more than three standard deviations. We use this criterion to identify “very deep” crises. Similar to Cerro and Iajya (2009) we extend the definition of crises by introducing “deep” crises (which we define as two adjacent months exceeding between 2 and 3 times the standard deviation) and “mild” crises (which we define as two adjacent months exceeding between 1 and 2 times the standard deviation). The ordinal variable that indicates crises periods is constructed as follows: the value 0 indicates no crisis period, the value 1 is assigned to mild crises, 2 to deep crises and 3 to very deep crises. As is common in early warning systems of currency crisis, we assign the same dummy variable value for the run-up period to the crisis. In this work we choose a period of six months preceding the onset of a crisis. In case a crisis follows within six months after the previous crisis, then the second crisis is considered a continuation of the earlier one. If depths of crises overlap we assign the highest ordinal number to that crisis.

Factor models

In factor models an observable set of n variables is expressed as the sum of mutually orthogonal unobservable components: the common component (factors) and the idiosyncratic component. The primary reason for the popularity of factor models is that one can include a large number of variables and let the model reduce this into a much smaller number of factors ($n >> r$). This is a desirable feature since more and more data become available for policy makers and researchers at a more disaggregated level. The drawback of using factor models is the difficulty to interpret the results.

Several types of factor models are distinguished: exact and approximate, static and dynamic. When the factors and the idiosyncratic components are uncorrelated and i.i.d., then the model is *static*, *exact*, or *strict*. Exact factor models can be consistently estimated by maximum likelihood. However the restrictions on the model are often not met in empirical applications. When the number of variables goes to infinity, the correlation restrictions of the exact factor model can be relaxed and one can use the approximate factor model. In the static, approximate factor model the idiosyncratic components are (weakly) correlated, which covers cross-correlation and heteroskedasticity between the idiosyncratic errors and correlation between the common components and the idiosyncratic components (see e.g. Barhoumi, Darné and Ferrara, 2010).

Whereas static factor models only consider cross-sectional relations, the dynamic factor model also takes into account lags and leads. Most dynamic factor models are approximate. The dynamic factor model has the advantage that it takes into account both current and temporal relationships, which makes it–in theory–superior to the static model. However, empirical evidence is mixed. Barhoumi et al. (2010) for example conclude that dynamic factor models with a large number of variables do not necessarily produce better forecasting results of French GDP than static models with a small number of variables. Schumacher (2007) also mentions a number of studies with mixed empirical success for the dynamic factor model.For this reason we choose for the static factor model.

The static factor model

The static factor model has the following form:

$$X_{i,t} = \lambda_{i,1}F_{1,t} + \lambda_{i,2}F_{2,t} + \cdots + \lambda_{i,r}F_{r,t} + u_{i,t} = \Lambda F_t + u_t, \tag{1}$$

where Λ is an $n\ x\ r$ matrix of factor loadings, F_t is an $r\ x\ 1$ vector of factors in period t, $i = 1, 2, \ldots, n$ and $t = 1, 2, \ldots, T$. The assumptions for the *exact* static factor model are: $\mathrm{E}(u_t) = 0$; $\mathrm{E}(u_t u_t') = \Sigma = \mathrm{diag}(\sigma_1^2, \sigma_2^2, \ldots, \sigma_n^2)$; $E(F_t u_t') = 0$; and for the factors $\mathrm{E}(F_t) = 0$; $E(F_t F_t') = \Omega$.

The principal components method can be used to estimate the factors. The principal components of X_t are the factors:

$$F_t = S'X_t = (S_1, S_2, \ldots, S_r)'X_t, \tag{2}$$

where the factor estimates F_t are the first r principal components of X_t, and, S_j, $j = 1, 2, \ldots, r$, are the eigenvectors that correspond to the r largest eigenvalues.

Determination of the number of factors

One of the issues in factor analysis is the determination of the optimal number of factors. Various procedures have been proposed, e.g. the Bayesian Information Criterium, the Kaiser Criterium and Cattell's scree test (Cattell, 1966). The number of factors is better overestimated than underestimated, because in the first case the factors are still estimated consistently (Breitung and Eickmeier, 2006). However, there is debate whether using a large number of variables generate better forecasts than a model with a small number of variables (Barhoumi et al., 2010).

With the large dimensional factor models of recent years, many studies have proposed solutions and consistent estimators using different factor model and distributional assumptions. Here we employ the criterion of Otter, Jacobs and Den Reijer (2011), which is associated with Onatski's (2009) test statistic, and linked with the scree test.

Interpreting the factors

Using factor models comes at a cost. Determining the economic relevance of factors and interpreting the factors in a meaningful way is problematic. Most indicators feature in more than one factor, so focusing on a single factor only partially explains the full impact of an indicator on the probability of a crisis, and may even lead to counterintuitive results. We present two ways to "label" the factors: (i) contribution of the variable to the factor, which is obtained by squaring each individual element of the eigenvector, (ii) correlations between the factor and the individual indicator.

Ordered logit model

As our dependent variable can take four values ($y_t = 0$: no crisis; $y_t = 1$: mild crisis; $y_t = 2$: deep crisis, and $y_t = 3$: very deep crisis), we employ an ordered choice model, which extends the binary choice model, allowing for a natural ordering in the outcomes y. Assume that there are $K+1$ possible outcomes, then

$$y = \begin{cases} 0 \text{ if } y^* \leq \mu_{1,} \\ 1 \text{ if } \mu_1 < y^* \leq \mu_{2,} \\ 2 \text{ if } \mu_2 < y^* \leq \mu_{3,} \\ \vdots \\ K \text{ if } \mu_K < y^* , \end{cases} \tag{3}$$

where y is the observed ordinal variable, and y^* is the continuous latent variable that is equal to

$$y^* = \alpha + X\beta \tag{4}$$

The thresholds which separate the various outcomes, are estimated simultaneously with the parameters α and β. We use the ordered logit model, because the logistic distribution (logit model) has wider tails than the normal distribution (probit model). This is preferable if an event seldom occurs, as is the case with financial crises (Manasse, Roubini and Schimmelpfennig, 2003).

We estimate two versions of the ordered logit model. The first uses only static factors calculated from the data set, excluding institutional variables. The low variation of some discrete variables (particularly institutional variables) may cause quasi-complete separation (Zorn, 2005). This occurs when there is limited overlap in the values of (a set of) explanatory variables and the outcomes of the dependent variable. As a consequence, the coefficients have large estimates and standard errors. The second version of the model adds institutional and political variables to the static factors as separate regressors. Both models are estimated using data up to and including 2007.

Ex ante forecasts

We test the out-of-sample performance of the estimated models for the period 2008M1–2009M12. We estimate the factors for the out-of-sample period by combining the actual, monthly indicators for the out-of-sample period (2008 and 2009) with the factor loadings of the in-sample period (1990-2007). With these factors we estimate the ordered logit model for the out-of-sample period. We forecast the probabilities of a mild, deep and very deep crisis with our ordered logit model.

Data

Our sample starts in 1990, after the effects of spillovers of the 1980s Latin American debt crisis faded out. As explained above, we distinguish mild, deep and very deep crises. Figure 2 shows that very deep crises are rare; Mexico experienced only two very deep crises: December 1994 and October 2008. We split the sample in two periods: the period until and including December 2007 is used to estimate the models, and the period January 2008 until and including December 2009 is used to forecast currency crises. For the crisis identification we construct the EMPI, weighted with the standard deviations from 1990 to 2007. For the out-of-sample period we use the actual exchange rate and reserves, with the standard deviations from the in-sample period.

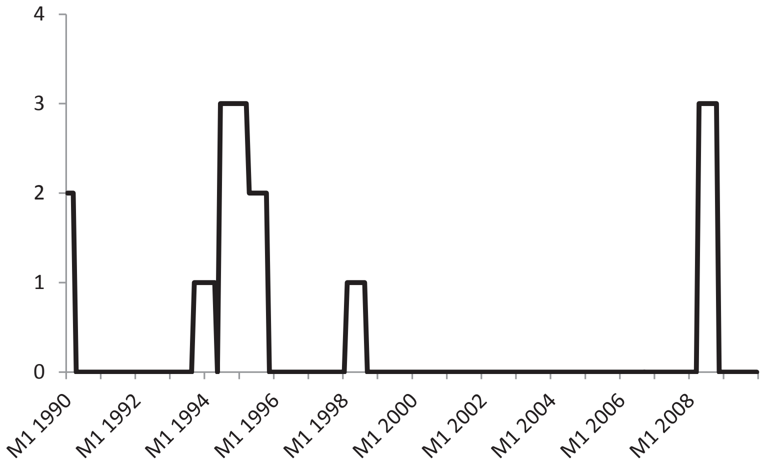

Figure 2. Ordered crisis dummy 1990-2009.

For the explanatory variables we select the "usual suspects" (the common macroeconomic and financial variables), institutional variables, commodity-related and global indicators. However some data limitations exist. Not all time series are sufficiently long which limits the selection of explanatory variables. The selected indicators can be classified into separate categories:

- 13 external economic indicators, including the deviation from real exchange rate trend, exchange rate volatility, growth of exports, imports and foreign reserves, import cover, and ratio of M2 to foreign reserves.
- 17 domestic economic indicators, including domestic real interest rate, inflation, M2 multiplier, industrial production, and the share market index return.
- 14 institutional indicators, including Herfindahl indices, political stability, corruption, investment profile, internal conflict, and election years.
- 10 debt indicators, including total debt, short term debt, debt service, and arrears.

- 11 banking sector indicators, including credit to public sector, credit to private sector, ROE, and deposits.
- 5 global and regional indicators, including world economic growth, US yield, and a contagion dummy for currency crises in Argentina or Brazil.
- 12 commodity related indicators, including prices of oil, metals, agricultural products, exports and imports of fuel, agricultural products, food and metals as percentage of GDP.

The main sources for the data are the International Financial Statistics (IFS) database of the IMF, the World Development Indicators (WDI) of the World Bank, International Country Risk Guide (ICRG) database of the Political Risk Services Group, and Beck, Demirguc-Kunt and Levine (2009).[1]

The series have been tested for non-stationarity using Augmented Dickey-Fuller tests and visually inspected for seasonal effects. Where necessary a transformation is made to render them stationary. To deal with mixed frequencies in the series, we apply simple quadratic interpolations. All series are normalized, i.e. demeaned and divided by their sample standard deviations.

Empirical results

We estimate the ordered logit model for Mexico for the period up to and including 2007. The criterion of Otter et al. (2011) suggests six factors for Mexico. In order to interpret the results we “label” the factors by different alternatives. Appendix A provides an overview of the different ways that we use to label the factors. Factor 1 is associated with the external economy (current account to GDP and deviation from real exchange rate) and to a lesser extent the banking sector (concentration and liquidity). Factor 2 is associated with the domestic economy (inflation) and debt. Factor 3 is related to domestic economy (interest rates) indicators. Factor 4 is related to US indicators (interest rates) and external indicators, Factor 5 is related to economic growth in the US,

1. For a complete overview, including definitions, transformations, and sources we refer to Boonman, Jacobs and Kuper (2012).

industrial production in Mexico and debt service, and factor 6 is associated with debt and global indicators.

Estimation results

The second column in Table 1 presents the estimation results for the period 1990M1 to 2007M12. Table 1 shows that factors 2, 3 and 5 are significant at a 1% level. The contagion dummy is significant at the 5% level. Currency crises in the period 1990-2007 are primarily associated with domestic economy variables (inflation, interest rate, industrial production), debt (external debt, debt service and use of IMF credit), and external economy (exchange rate volatility, foreign reserves) indicators. Also economic growth in the USA and contagion from currency crises in Argentina or Brazil are associated with currency crises in Mexico.

Table 1

Ordered logit estimation results for Mexico, with *p*-values in brackets

	Factors only	*Factors and institutional variables*
SF1	0.7834 (0.1059)	0.8426 (0.0616)*
SF2	1.9787 (0.0040) ***	2.1568 (0.0010)***
SF3	2.4690 (0.0000) ***	2.2886 (0.0000)***
SF4	-0.1793 (0.6377)	-0.1522 (0.6789)
SF5	1.7122 (0.0005) ***	1.5514 (0.0014)***
SF6	0.0809 (0.8299)	0.1063 (0.7790)
Contagion dummy: currency crisis in Argentina or Brazil	0.7685 (0.0152) **	0.7564 (0.0122)**
Year of elections for executive power		0.4912 (0.0983)*
Adjusted pseudo R^2	0.477	0.479

*** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Including institutional variables

In the second version of the model we add institutional variables as regressors. This extended model allows us to test whether the institutional variables contain additional information that is significant for currency crisis periods. The last column of Table 1 shows the regression outcomes including institutional indicators. The adjusted pseudo R^2 improves marginally. The fit can be improved by including more institutional variables (e.g. when we include bureaucratic quality, democratic accountability and investment profile the adjusted pseudo R^2 increases to 0.553), but this causes quasi complete separation. We opt for not including these institutional indicators because it causes large coefficients and standard deviations. Factors 2, 3 and 5 are significant at the 1% level, factor 1 and the election year are significant at the 10% level and contagion at the 5% level.

We conclude that currency crises in the period 1990-2007 are primarily associated with domestic economy variables (inflation, interest rate, industrial production), external economy (exchange rate volatility, deviation of the exchange rate trend, current account) and debt (external debt, debt service and use of IMF credit) indicators. Also economic growth in the USA and contagion from Argentina or Brazil are important indicators for currency crises in Mexico. Commodities, institutional and banking indicators play a less prominent role.

Out-of-sample performance

Figure 3 shows the performance of our first version of the EWS in the out-of-sample period: 2008M1- 2009M12.

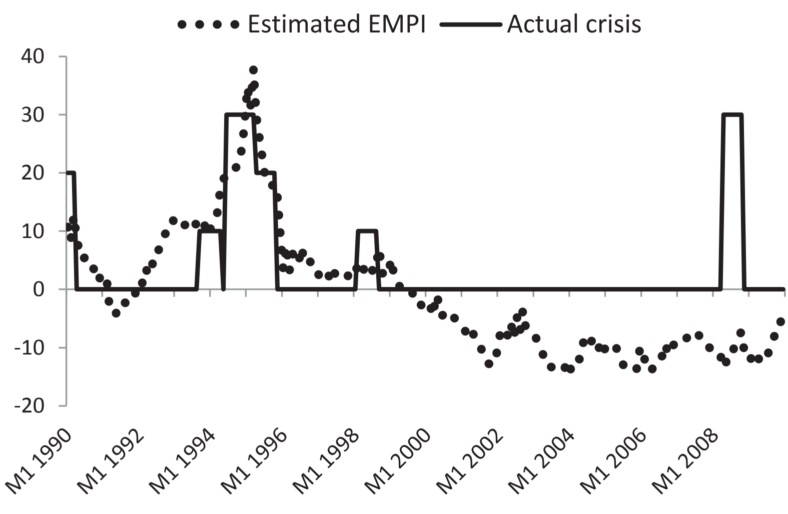

Figure 3. Actual and fitted data from the ordered logit model for Mexico 1990-2009.

Our EWS does not predict a currency crisis in Mexico. Nevertheless, Mexico experienced a deep currency crisis in October 2008. Comparing the GFC with earlier crises, in particular the 1994 crisis, we observe differences in the variables that our EWS associates with currency crises: in 2008 the external total and short-term debt was low, debt service to reserves was low, real interest rates were negative and the exchange rate regime was more flexible. These are some of the variables that Ocampo (2009), Porzecanski (2009) and Jara et al. (2009) identify when they explain why the GFC had a less severe impact on Latin America than previous crises.

Figure 3 shows another important feature: the estimated EMPI in the 1990s was positive, indicating an increased probability of a currency crisis. Since 1999 the estimated EMPI has been negative, indicating that a currency crisis is less likely to occur. We interpret this as follows: The conditions associated with currency crises in the 1990s have improved in the next decade, which demonstrates that Mexico has learned from its past crises. This does not mean that the currency is immune for external shocks, as the GFC has shown.

Conclusion

The fall of Lehman Brothers in September 2008 affected many countries and regions including Mexico. The Mexican peso depreciated by almost 50%. This chapter investigates the experience of Mexico with currency crises since the 1990s. We first determine which indicators are related to past currency crises, including the run-up to the crises. For that reason we develop an Early Warning System for currency crises, consisting of an ordered logit model, using a factor model to reduce the dimension of the information set. We find that Mexico's currency crises are driven primarily by domestic economy, external economy and debt indicators. Inflation, interest rate, current account balance, overvaluation of the currency and external debt to GDP are important indicators for crises. Institutional variables, commodity-related and banking indicators do not seem to play a central role.

Secondly, we use our EWS to forecast the probability of currency crises in 2008 and 2009, the period in which the GFC hit the region the hardest. Mexico experienced a currency crisis in 2008, which our model does not pick up. We attribute this to better conditions in the run-up to the GFC: low debt indicators, high reserves, negative real interest rates and a more flexible exchange rate regime. The GFC episode has different features compared to earlier currency crisis episodes, which leads us to conclude that this time was different (after Reinhart and Rogoff, 2009).

Appendix A: Labeling the factors

Table A.1
Variables with the highest share in the factor

Factor	*Highest contribution*	*Second highest*	*Third highest*
1	Current account to GDP (4.8%)	Bank concentration (4.6%)	Deviation from real exchange rate (4.4%)
2	Inflation (8.2%)	Use of IMF credit to GDP (7.7%)	Total debt to GDP (7.5%)
3	Real interest (8.1%)	Short term interest rate (5.8%)	Change in foreign reserves (5.6%)
4	T-bill rate (5.9%)	Terms of trade (5.1%)	US long term rate (5.1%)
5	US economic growth (7.4%)	Industrial production (7.1%)	Exchange rate volatility (5.7%)
6	Arrears on total debt (7.8%)	M2 to reserves (6.9%)	Long term private non-guaranteed debt (6.1%)

Table A.2
Five indicators with highest correlation coefficient (ρ) with the static factors

Factor 1	ρ	*Factor 2*	ρ
Ratio current account to GDP	-0.82	Inflation	0.95
Bank concentration	0.80	Use of IMF credit to GDP	0.92
Deviation from real exchange rate	-0.78	Total debt to GDP	0.91
Change in fuel exports	-0.74	Commercial bank lending to GDP	0.76
Change in liquid liabilities (bank)	0.73	Gross capital formation to GDP	-0.73

Factor 3	ρ	*Factor 4*	ρ
Real interest rate	0.80	T-bill rate	-0.58
Change in short term interest rate	0.67	US yield (10 years)	-0.54
Change in foreign reserves	-0.67	Terms of Trade	-0.54
Domestic credit to public sector	-0.67	World GDP volume change	-0.53
Change in deposit money bank assets to GDP	0.61	Debt reduction to total debt	0.52

Factor 5	ρ	*Factor 6*	ρ
US GDP growth	0.60	Arrears on total debt	0.54
Industrial production	0.59	Ratio of M2 to reserves	0.51
Exchange rate volatility	0.53	Long term private non-guaranteed debt	0.48
Ratio debt service to exports	0.49	Change in food imports	0.47
Ratio debt service to reserves	0.47	World GDP volume change	-0.44

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CHAPTER 3
The Utilization of Logistic Regressions in Addition to Multivariate Analyses for More Reliable Test Results

Jianing Fang

Introduction

For a long time, researchers have utilized various form of multivariate analysis as a statistic tool in most of accounting or finance related empirical studies. Since most of the prior empirical studies were based solely on results of some form of multiple regressions, the reliability of their findings is subject to question. By definition, all forms of multiple regressions rely critically on the assumptions of linearity, constant variance, absence of special causes, normality, and independence of the test data. The problem is that most of the financial data often violate some, and in some cases, all of these assumptions.

Taking guidance from the medical researchers, the main goal of this study is to promote the utilization of logistic regressions, in addition to any applicable multiple analyses, to provide the much needed reliability of study results. We will use an example with actual market closing indices on which we conducted dual tests on the same set of test data by running both the multiple regressions and logistic regressions. While the multiple regression results provide the necessary statistics as well as reference or comparison with prior studies, the logistic regression results provide confirmation of the reliability of the empirical findings.

Literature Survey

Long before the debate on the efficiency of the global security markets, the Efficient Market Hypothesis (EMH) was one of the most hotly contested topics among academic and finance professionals worldwide. By now the literature is so large that it is practically impossible to review all of the relevant literature in this article. Instead, we will only discuss the papers that we believe are the most relevant to this study. The debate about market efficiency was started in 1900 by Bachelier. By analyzing the movements of commodity prices, Bachelier presents convincing evidence that commodity speculation in France is a "fair game" because the price movements follow the pattern of a "random walk." This means that neither buyers nor sellers could expect to make significant profits. However, the "efficient market hypothesis" was first proffered by Fama (1970). His work motivated the quest for a viable economic theory for security investment. In this article, Fama also gives a thorough review of all the then existing theoretical and empirical studies on the subject.

The Three Forms of the EMH

Three forms of the EMH have evolved in the literature: (1) weak form, (2) semi-strong form, and (3) strong form. The differences between these three forms of market efficiency are succinctly explained by Brigham and Gapenski (1997):

Weak Form Efficiency: The weak form of the EMH states that all information contained in past price movements is fully reflected in current market prices. If this were true, then information about recent trends in stock prices would be of no use in selecting stocks—the fact that a stock has risen for the past three days, for example, would give us no useful clues as to what it will do today or tomorrow.

Semi-strong Form Efficiency: The semi-strong form of the EMH states that current market prices reflect all publicly available information. Therefore, if semi-strong form efficiency exists, it would do no good to study annual reports or other published data because market prices would have already been adjusted to any good or bad news contained in such reports, back when the news came out.

Strong Form Efficiency: The Strong form of the EMH states that current market prices reflect all pertinent information, whether publicly available or privately held. If this form holds, even insiders would find it impossible to earn abnormal returns in the stock market.

Related Anecdotal and Empirical Studies

Innumerable anecdotal and empirical studies followed the work of Fama. Fama, Fisher, Jensen and Roll (1969) show that the equity market reacts quickly to new information. They analyze 940 stock splits from January 1927 to December 1959. By running a natural logarithm regression on the monthly returns, they find that stock splits have often been followed closely by dividend increases, indicating that these companies were enjoying abnormally good business, generally during boom periods. Thus, a stock split can be a valuable indicator that the managers of a firm are optimistic about future business, profit, and cash flow prospects. The caveat is that the authors just "assume…the usual assumptions of the linear regression" are satisfied (pg. 4). The authors conclude that the results of their study support the weak form EMH because the information regarding a stock split is fully reflected in the share price very quickly.

Guo (1990) also studies the transmission of stock market movements among Hong Kong, the United States, Japan, and the United Kingdom. She performs VAR (vector autoregression) tests on daily market indices of these four security exchanges (HIS, CRSP, NSA, and FTIO respectively) for the 19-year testing period from 1970 to 1988. The empirical evidence shows that the U.S. market is the most influential in terms of innovation transmission.[1] Guo finds that the HKSE is highly vulnerable to external factors with the largest influence from the U.S. market.

The most recent scholarship includes an empirical analysis by Borgas who tests daily closing values of stock market indexes for UK, France, Germany, Spain, Greece and Portugal to test the weak form EMH from January 1993 to December 2007. Using a runs test and joint variance ratio tests, her test results suggest mixed evidence on EMH among the sample stock exchanges. Guidi examines the day-of-the-week effect on stock market prices using daily closing price indices for the Italian

1. 46.63% for U.K., 47.25% for Japan, and 37.25% for Hong Kong in a 20-day horizon. These rates changes for different test range of 2, 5, 10, and 20-day horizon.

stock market index (MIB) for the time period covering January 4, 1999 through March 5, 2009. He utilizes various forms of regression analyses such as GARCH-M and UVR. His test results do not support the weak form EMH because investors can earn above-normal profits by following the trend of the past price movement of the securities. Nevertheless, he acknowledges that his tests are only reliable "if there is no serial correlations among returns" (p. 21).

Logistic Regression Analysis

The foregoing not only reviews the EMH basic theory as well as the supporting and contradicting empirical tests, but also demonstrates that most of the prior studies rely on some form of regression analysis. Since most of the prior empirical studies were based solely on results of some form of multiple regressions, the reliability of their findings is subject to question. By definition, all forms of multiple regressions rely critically on the assumptions of linearity, constant variance, absence of special causes, normality, and independence of the test data.[2] The problem is that most of the financial data often violate some, and in some cases, all of these assumptions. Therefore, a contribution of this study is that I conduct dual tests on the same set of test data by running both the multiple regressions and logistic regressions. While the multiple regression results provide the necessary reference or comparison with prior studies, the logistic regression results provide confirmation of the reliability of the empirical findings.

Empirical Hypothesis, Sample Data, and Variables

Generally, once a company grows so large as to have excess production, capital, or other capabilities that are beyond the ability of its home market to absorb (market saturation), then it looks beyond its national borders for additional distribution channels and often further expands its operations. The activities of the giant global companies are aggregated together with trade volume of other companies, big and small, into various totals and indices for various periods for each country or

2. Outliers due to one-time situations have been removed from the data.

state. King and Wadhwani (1990) assert that all of these "globalization" activities are reflected on all the security exchange indices of the world; therefore, providing a major link between foreign trade and the capital markets.

Like a twin brother of global trade, the round-the-clock global security markets, as discussed in the introductory quote from Bose (1988), are not only real but also growing fast. They provide us endless investing opportunities as well as risks day and night. For the past few decades, investors and money managers have been investing in foreign economies or industry sectors growing faster than those in the United States (Littauer, 1995). Another reason to own foreign stocks is to manage portfolio risk by global diversification. Foreign markets fluctuate to a different rhythm. It is impossible to find that two markets act the same. In fact, each market advances or falls depending mainly on local economic, political, social, and other relevant conditions that are peculiar to that country (Slatter, 1995 and Guo, 1990). Global markets may mean global opportunities for investment, but they also mean global risks. While all the hoopla about electronic markets enabling us to buy shares in Hong Kong at breakfast-time, sell in London at lunch-time and then buy some more again at dinner-time as the Pacific exchanges open may sound exciting, they can be dangerously problematic as well. The Crash of 1987 tells the most vivid and horrible story—the Dow Jones Industrial Average, "the world's best-known stock market index" (Zweig, 1986, p. 25), declined "a record 508.32 points, 22.6 percent, which prompted the chairman of the exchange, John Phelan, to call it a meltdown" (Bose, 1988).

Empirical Hypothesis

The basic economic theory that my study to develop *The Logistic Indicator* is based on the contrarians' view of the efficient market hypothesis. Stocks are sold when they are considered out of favor or over-valued based on some calculation utilizing one of (or a combination of) the security analysis theories and/or techniques. The same stocks are bought because other investors considered the exact opposite probably after running some different, as well as similar, analyses. *The Logistic Indicator* is developed under the belief that stock prices are changing constantly as new information become available. But, all of the balancing and re-balancing take time, especially in the global market. A small foreign exchange often looks upon, and follows the leadership of the global markets. I concur that so far Wall Street has provided such leadership. Thus, I developed the following hypotheses:

> *H0:* The price movement of a particular stock exchange index is not correlated with any other foreign exchange indexes

> *HA:* The price movement of a particular stock exchange index is correlated with some other foreign exchange indexes

What is the current status of efficiency for the global security market? By testing these hypotheses with a large set of empirical data, I will show that there are strong links between foreign stock exchanges. I will show that the Hong Kong Stock Exchange (HKSE) is highly vulnerable to market movements of other major foreign stock exchanges with the greatest influence from the United States. I will show that there is a clear pattern of movement between HKSE and these related foreign stock exchange indexes. As the result, the empirical evidence should provide valid support for my argument against the semi-strong form of EMH in global security markets.

Empirical Data

The empirical tests use daily returns from January 1, 1988 to September 30, 1998 for 12 international stock exchanges obtained from Morgan Stanley's electronic database. One of the main purposes of this study is to test the validity of the semi-strong form of EMH by testing my hypothesis that the price movements of a particular stock exchange index are associated with one or more foreign stock exchange index(es). In all of the following analyses, Hong Kong's (second-day, or 1-day lag) Hang Seng Index (HK2) was selected to be the dependent variable because it occupies such a strategic position in the 24-hour global security market. The 1-day lag was selected for the sole purpose for comparing my empirical test results to existing studies of King and Wadhwani (1990), and Guo (1990).

The Explanatory Variables

For the purpose of establishing a practical baseline or reference for my research, I selected the same foreign stock exchange indexes that

Guo (1990) used in her study[3] as the independent variables for the first empirical test:

- Japan's Nikkei Average 225 Index (JAP)
- United States' S&P 500 Stock Index (S_P)
- United Kingdom's FTSE 100 Index (BRT)

These indexes represent the largest (in terms of market capitalization) and the most active stock exchanges in Asia, Europe, and the Americas in three different time zones.

An alert reader might wonder why factors such as a country's GDP, interest rates and other variables commonly used in most security evaluation models were not included among the independent variables in this model. The reason is that this study assumes that the efficient market theory (and arguments against it), capital asset pricing theory, and other theories mentioned in the Literature Survey section above are also valid on the global scale. Therefore, all of the factors affecting security values, whether they are political or economic, sentimental or fundamental, have already been reflected in the stock prices. A stock index is the representative average, weighted or un-weighted, arithmetic or geometric, of all the individual stocks traded in a particular exchange or group. In fact, if these variables were included among our predictors, they would have been eliminated because they are highly correlated with the existing independent variables. Furthermore, most of these factors such as GDP, interest rates, unemployment rates, etc., do not change, or are not published daily. Thus, they are not applicable for our dynamic, daily-changing model.

Empirical Results

The Baseline Test - Following the example of Guo (1990), I performed a multiple regression analysis on data covering the period from January 2, 1988 to September 30, 1998. As I have described in the last section, I selected Hong Kong's (second-day, or 1-day lag) Hang Seng Index (HK2) for the dependent variable and Japan's Nikkei Average 225

3. Guo's study uses data for the period of November 1, 1984 to November 1, 1988. My tests cover the period of January 2, 1988 to September 30,1998

(JAP), S&P 500 Stock Index (S_P), and United Kingdom FTSE 100 (BRT) as the independent variables. Tables 1 to 4 show all the relevant statistics for the test.

Table 1
Descriptive Statistics For Baseline Test

Variable	*Sample*				
(Market)	*Count*	*Minimum*	*Maximum*	*Mean*	*Standard Deviation*
BRT	2803	-4.863E-02	5.590E-02	4.223E-04	8.421E-03
HK2	2803	-2.174E-01	1.882E-01	5.839E-04	1.679E-02
JAP	2803	-6.795E-02	1.323E-01	-7.272E-05	1.394E-02
S-P	2803	-6.865E-02	5.115E-02	5.412E-04	8.508E-03

The data consist of 2803 daily returns of Hong Kong's (second-day, or 1-day lag) Hang Seng Index (HK2), Japan's Nikkei Average 225 Index (JAP), the United Kingdom's FTSE 100 Index (BRT), and the United States' S&P 500 Index (S_P), from January 2, 1988 to September 30, 1998.

Table 2
Correlation Matrix for Baseline Test

	Variable			
(Market)	*BRT*	*HK2*	*JAP*	*S_P*
BRT	1.000			
HK2	0.209	1.000		
JAP	0.243	-0.019	1.000	
S_P	0.358	0.324	0.088	1.000

Pearson Correlation coefficients at the 5% significance level for variables consisting of 2803 daily returns of Hong Kong's (second-day, or 1-day lag) Hang Seng Index (HK2), Japan's Nikkei Average(225) (JAP), the United Kingdom's FTSE100 (BRT), and the United States' S&P 500 Stock Index (S_P), from January 2, 1988 to September 30, 1998.

Table 1 contains all the relevant descriptive statistics for the sample variables. The sample population is 2,803 daily closing index values for each of the four sample stock exchanges. The correlation matrix is shown on Table 2. The Pearson correlation coefficient between particular pairs of indexes varies from a low of -0.019 (between HK2 and JAP) to a high of 0.358 (between BRT and S_P). However, for the purpose of my test, the only meaningful correlations are the ones between the dependent variable HK2 and each of the three independent variables—0.209 with BRT, -0.019 with JAP, and 0.324 with S_P.

Table 3
Regression Statistics for Baseline Test

Independent Variables	*Regression*		
(Market)	*Coefficient*	*Standard Error*	*T-Value **
Intercept	1.667E-04	2.984E-04	0.558
BRT	2.492E-01	3.889E-02	6.402
JAP	-9.070E-02	2.201E-02	-4.119
S_P	5.643E-01	3.748E-02	15.055

The data consist of 2803 daily returns of Hong Kong's (second-day, or 1-day lag) Hang Seng Index (HK2), Japan's Nikkei Average 225 Index (JAP), the United Kingdom's FTSE 100 Index (BRT), and the United States' S&P 500 Index (S_P), from January 2, 1988 to September 30, 1998. * This is the t-test value for testing the hypothesis that j=0 versus the alternative (after removing the influence of all other independent variables).

Table 3 shows the regression coefficients, standard errors and t-values[4] for the intercept and all the independent variables. Based on these coefficients, I derive the corresponding regression equation as follows:

$$HK2 = 1.667E-04 + 2.49E-01 * BRT - 9.07E-02 * JAP + 5.643E-01 * S\_P \quad (4)$$

Table 4
Multicollinearity Test for Baseline Test

Variable	*R-Squared Vs Other*
(Market)	*Independent Variables*
BRT	0.173
JAP	0.059
S_P	0.128

The data consist of 2803 daily returns of Japan's Nikkei Average 225 Index (JAP), the United Kingdom's FTSE 100 Index (BRT), and the United States' S&P 500 Index (S_P), from January 2, 1988 to September 30, 1998.

4. This is the *t*-test value for testing the hypothesis that *j*=0 versus the alternative (after removing the influence of all other independent variables.

The multicollinearity tests (R^2 versus other independent variables) of the independent variables (shown in Table 4) is acceptably low for each of the three independent variables. From this regression equation and the data in Tables 1 to Tables 4, we can see that the sample size is large enough to support a reliable empirical test. These statistics imply that the return (%) of the Hang Seng Index of Hong Kong (HK2) is correlated negatively with the prior-day return of Nikkei (225) Index of Japan (JAP), but positively with that of the FTSE (100) Index of the United Kingdom (BRT) and of the S&P (500) Index of the United States (S_P). Mathematically speaking, every unit of change in HK2 is correlated with 0.2492 of BRT, -0.0907 of JAP, 0.5643 of S_P, and a constant of 0.00017. This result is consistent with Guo's finding that the Hong Kong Stock Exchange (HKSE) is highly vulnerable to major foreign market innovation transmission with the largest influence from the United States.

The Logistic tests - Now we have found that HKSE is highly vulnerable to major foreign market innovation transmission with the largest influence from the United States. However, all the empirical tests so far violate most of the assumptions for multiple regression. And they still do not tell us when and how to make day-to-day investment decisions even if we turned a blind eye for these requirements. We need a practical and statistically reliable model as a guide for this important task and for verifying my test results of the multiple regression analyses. Fortunately, we can call upon Logistic Regression for the rescue. With this practical purpose in mind and based on the findings of the prior studies, I develop *The Logistic Indicator*--a practical barometer and security investment tool for daily stock index trading.

Using daily percentage changes of the indexes and modifying the data for the dependent variable into a binary format--0 for daily return less than 0.5 percent (triggering threshold), and 1 for daily return of 0.5 percent or more--I ran a logistic regression analysis with BRT, JAP, and S_P (the same group of independent variables I used for the baseline test discussed above). In Table 5, I provide all the relevant test statistics for the full sample period from January 2, 1988 to September 30, 1998.

Table 5
Logistic Regression Statistics

Independent Variables	*Sample*	*Regression*		*Prob.*		*– Errors (%) –*		*% Correctly*
(Market)	*Count*	*Coefficient*	*Intercept*	*Level**	*R-Squared*	*a*	*b*	*Classified*
–HK2 Up 0.5% or more–	2803		-8.313E-01	0.000	0.058	2.64	28.08	69.28
BRT	2803	2.741E+01		0.000				
JAP	2803	-8.685E+00		0.005				
S_P	2803	5.613E+01		0.000				
–HK2 Down 0.5% or more–	2803		-9.939E-01	0.000	0.054	1.39	25.19	73.42
BRT	2803	-2.971E+01		0.000				
JAP	2803	2.958E+00		0.364				
S_P	2803	-5.105E+01		0.000				

The data consist of 2830 daily returns of Hong Kong's (second-day, or 1-day lag) Hang Seng Index (HK2), Japan's Nikkei Average 225 Index (JAP), the United Kingdom's FTSE 100 Index (BRT), and the United States' S&P 500 Index (S_P), from January 2, 1988 to September 30, 1998. * This is the significance level of the test. If it is less than the predefined alpha level (0.05 in these tests), the variable is statistically significant.

Examining the information in Table 5, we can see that the sample count is still 2,803 observations, and the probability level[5] for the intercept and each of the independent variables ranges from 0 to 0.005 (< 0.05, all are statistically significant). The model has an $\mathbf{R^2}$ of 0.058, an α error of 2.64%, and a β error of 28.08%. The model has a pretty high rate of successful classification of 69.28%. The model's mathematical presentation is as follows:

$$P(HK2 \geq 0.5\%) = 1/(1 + \text{Exp}[\,-\{-0.8313\} + \{27.41 * BRT - \{8.685 * JAP\} + \{56.13 * S\_P\}\}]\,) \quad (5)$$

5. This is the significance level of the test. If it is less than the predefined alpha level (0.05 in all of these logistic regression tests), the variable is statistically significant.

At this point, the model only predicts whether or not the Hang Seng Index will close 0.5% or more above the level of the day before. We would also like to be able to make profits when the index moves down by shorting the index. Unfortunately, the statistics software does not have the ability to run a polychotomous logistic regression. However, in the absence of software that is capable of performing a polychotomous analysis, we can use the results of a combination of two individual logistic regressions, realizing of course that the resulting estimates are approximations to maximum likelihood estimates (Hosmer, 1989).

Thus, I further modified the data for the dependent variable into a binary format, 0 for daily decreases of less than 0.5 percent, and 1 for daily decreases of 0.5 percent or more. I ran a similar procedure for the "short" prediction as I described above and listed the statistics in the second portion of Table 5. In this test, the sample count stays at 2,803 observations, and the probability level for the intercept and each of the independent variables remains the same except for JAP which changes from 0.005 to 0.364 (> 0.05, not statistically significant). The model has an $\mathbf{R}^2$ of 0.054, an α error of 1.39%, and a β error of 25.19%. This model has a higher (73.42%) rate of successful classification than the "up" model. The "down" model's mathematical presentation is as follows:

$$P(HK2 \leq -0.5\%)= \\ 1/(1 + Exp[-0.994\} - \{29.71 * BRT\} + \{2.9858 * JAP\} - \{51.05 * S\_P\}) \qquad (6)$$

The Logistic Indicator - The finalized mathematical presentation of the model is:

$$(HK2 \geq 0.5\%) = \\ 1/(1 + Exp[-\{-0.7841\} + \{0.0474 * BRA\} + \{0.3188*BRT\}+\{0.6651*S\_P\}]) \qquad (7)$$

I also ran a similar test for a triggering threshold of 0.3percent with the same group of variables. The results show some significant changes--α error increased from 4.26% to 8.45%; β error decreased slightly from 26.74% to 26.60%; while the model classification rate decreased from 69.00% to 64.79%. These results signify that the model is more reliable with a higher triggering threshold. One logical explanation is that security markets are more sensitive with stronger innovation transmitions (King and Wadhwani, 1990).

For the "short" prediction, the model has an $\mathbf{R}^2$ of 0.074, an α error of 2.34%, and a β error of 25.91%. The model has a higher rate of successful classification of 71.75% than the "long" prediction. The model's mathematical presentation is changed to the following:

$$P(HK2 \le -0.5\%) =$$
$$1/(1 + \mathrm{Exp}[-\{-0.7945\} - \{0.0473 * BRA\} - \{0.312 * BRT\} - \{0.6440 * S\_P\}]) \quad (8)$$

Table 6

Logistic Regression Statistics. (HK2 Up 0.5% or more)

Independent Variables (Market)	*Sample Count*	*Regression Coefficient*	*Intercept*	*Prob. Level**	*R-Squared*	*– Errors (%) – a*	*b*	*% Correctly Classified*
(5- year Look-back period, 1993 to 1998)			-7.961E-01	0.000	0.098	4.28	24.88	70.85
BRA	1029	8.203E-02		0.001				
BRT	1029	2.650E-01		0.005				
S_P	1029	7.264E-01		0.000				
(2- year Look-back period, 1992 to 1994)			-7.276E-01	0.000	0.070	6.91	28.39	64.71
BRA	391	6.723E-02		0.036				
BRT	391	4.872E-01		0.001				
S_P	391	5.530E-01		0.012				
(2- year Look-back period, 1994 to 1996)			-1.003E+00	0.000	0.142	6.25	21.63	72.12
BRA	416	6.788E-02		0.130				
BRT	416	5.394E-01		0.007				
S_P	416	1.306E+00		0.000				
(2- year Look-back period, 1996 to 1998)			-6.950E-01	0.000	0.073	4.47	28.00	67.53
BRA	425	8.659E-02		0.100				
BRT	425	1.372E-01		0.271				
S_P	425	4.430E-01		0.001				
(1- year Look-back period, 1991 to 1992)			-7.608E-01	0.000	0.054	3.35	26.82	69.83
BRA	179	-1.850E-02		0.621				
BRT	179	3.908E-01		0.047				
S_P	179	4.293E-01		0.115				

Independent Variables (Market)	*Sample Count*	*Regression Coefficient*	*Intercept*	*Prob. Level**	*R-Squared*	*– Errors (%) – a*	*b*	*% Correctly Classified*
(1- year Look-back period, 1997 to 1998)			-5.801E-01	0.000	0.054	3.40	29.61	66.99
BRA	206	9.148E-02		0.169				
BRT	206	7.885E-02		0.601				
S_P	206	2.581E-01		0.140				

The data consists of daily returns of Brazil's Bovespa Index (BRA), the United Kingdom's FTSE 100 Index (BRT), and the United States' S&P 500 Index (S_P), from July 8, 1991 to September 30, 1998. * This is the significance level of the test. If it is less than the pre-defined alpha level (0.05 in these tests), the variable is statistically significant.

Before finalizing the model, for the purpose of verifying the consistency of the model, I ran the procedures described above (only for "long" predictions) for different time horizons (see Table 6)--5-year (1993 to 1998), 2-year (1992 to 1994, 1994 to 1996, and 1996 to 1998), and 1-year (1991 to 1992, and 1997 to 1998). Upon examining and comparing these results, I did not find any materially significant differences except for the 1-year and 2-year tests. In these tests most of the independent variables are not statistically significant (probability level > 0.05). Thus, I am quite confident that the model developed is statistically and practically stable as long as the sample period is long enough.

Weighing the significance in terms of the probability level, predictability of the model and the model errors, the independent variables selected for the final model make good sense on the basic economic grounds. The links, or correlations between these stock exchange indexes can be explained as follows:

- Britain has been one of the major trading partners of Hong Kong in merchandise and services. It ruled Hong Kong for almost a century until July 1, 1997. Even after the handover of Hong Kong to Mainland China, Britain still has significant financial and political links to its government, businesses, and people.
- Like Hong Kong, Brazil has been a light manufactory exporting country. In addition, it has been a raw material exporter whose products were purchased by other newly industrialized countries or states like Hong Kong.

- Wall Street has been the leader of the global financial market. Also, the United States has been one of the major trading partners of Hong Kong and China.

Thus, all the results of my empirical tests above reject the null hypotheses of this study that the price movement of a particular stock exchange index is not correlated with any other foreign exchange index(es) and accept the alternative hypotheses that the price movement of a particular stock exchange index is correlated with one or more other foreign exchange index(es). My empirical results imply that there is a clear pattern, or arbitrage opportunity for a knowledgeable investor to make meaningful profits. Thus, the semi-strong form of EMH is not supported in the global security market.

Conclusions

Although the findings based on any forms of multivariate regressions are not reliable, most of the prior accounting or finance related empirical studies were based solely on results of some forms of multivariate regressions. The reliability of their findings is subject to question because by definition, all forms of multiple regressions rely critically on some assumptions of the quality of the test data. The obvious problem is that most of the financial data often violate some, and in some cases, all of these assumptions. By running both the multivariate regressions and logistic regressions on a set of empirical data, this study shows that while the multiple regression results provide the necessary statistics as well as reference or comparison with prior studies, the logistic regression results provide confirmation of the much needed reliability of the empirical findings.

This study also shows that, today, the capital market has undeniably become part of a global game—most foreign stock exchanges are significantly linked, or correlated. Taking advantage of the linked, and round-the-clock global security market, a stock index day-trading model is developed based on the contrarian's view of the efficient market hypothesis and other economic and security analysis theories. *The Logistic Indicator* is both flexible and dynamic, and perfectly suitable for today's fast-paced, ever-changing global financing environment. With easy access to information and modern computing technology, the application of the model is not only simple and fast, but also can be easily modified for different user preferences. The model can also be easily modified to utilize findings of other studies (e.g. add more independent variables such as private information).

However, the model is newly developed; therefore, it lacks the much needed empirical data to support its reliability and applicability. Users are also cautioned to reevaluate the model whenever the market conditions affecting the relevant exchanges used as variables in the analysis changed.

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CHAPTER 4
Sovereign Credit Default Swap Spread Volatility: A Spectral Analysis of Risk Premiums of Common Currency and Standalone Economies

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Introduction

It is now clear that extremely volatile sovereign Credit Default Swap (CDS) segment of the modern financial markets have gone astray with countries' credit ratings. This only distorted a true representation of a country's overall economic situation, hence, for many is the suddenness of the crisis and unprecedented exposure to volatility, risk, and uncertainty first time in the past seventy years. Further, the ongoing sovereign debt conundrums shadowing the European Monetary Union nations have exacerbated this exposed feature of the CDS spread. Yet, CDS volatility may, in fact, be interpreted as either a drawback by effecting real part of the economy (interest rate) or as a potential strength by providing more liquidity into financial markets. This chapter attempts to analyze this relationship including also trends on stock returns in the analysis.

In general, it is quite conventional to use either spreads or prices in stock market analysis since both measures represent the changing dynamic of the credit default. As is pointed out in a number of papers (e.g.

Jacobs, Karagozoglu and Peluso, 2010; Revoltella, Mucci and Mihaljek, 2010), there has been positive correlation between the implied volatility price index and CDS spread/price. Since CDS in its valuation/pricing includes market sentiment, in the volatile periods this could have a bigger effect than fundamentally determined country risk. Therefore in this study we focus on the analysis of the CDS prices.

The chapter relies on spectral analysis method for most of empirical research. Defined by Hamilton (1994), spectral analysis determines importance of cycles of different frequencies accounting for the behavior of the analyzed series. Related, is the harmonic analysis as a type of spectral analysis (besides periodogram analysis), which involves estimating the amplitude and phase of a cycle that best fits the time-series data. In this paper we start with determination of the relationship amongst CDS, interest rate and market returns with the help of co-spectrum analysis, and then follow that with harmonic analysis of CDS (a univariate case).

The rest of this chapter is structured as follows. In the next section we discuss relevant literature on CDS and financial markets interactions. Relevant stylized facts and data are presented following the literature review. Section 4 deals with more theoretical aspects of the chosen methodological approach offering a brief review of the co-spectrum and harmonic analysis. Section 5 summarizes the main finding of this research. The chapter ends with a Conclusion, Reference List and Appendix.

Literature Review

As financial instruments, credit default swaps have been trading for a “relatively” short period of time, since mid-1990s. In these twenty or so years a large and diverse mix of research literature has emerged discussing accurate asset pricing, valuation and importance of the CDS in the financial markets and macroeconomy [e.g., Longstaff (2011) for additional references]. Interestingly, less research exists on the topic of sovereign CDS problems of default probabilities and country rating changes. This may be driven by a somewhat typical orthodox finance axiom of sovereign solvency, by which a sovereign borrower does not default. However, the past several years have witnessed a change in economists’ view of this postulate. The heightened uncertainty of the financial and real sectors interaction applies to both developed and emerging economies adding to the current macroeconomic instability (e.g. Gevorkyan and Gevorkyan, 2012a).

To facilitate the multidimensional aspect of our topic the discussion in this section is divided into two main subsections: 1) review of literature devoted to CDS and its significance in the current macroeconomic processes; 2) discussion of published work looking into application of spectral analysis to financial data, CDS specifically. The latter subsection also develops harmonic analysis concept as part of spectral analysis and its relevance in financial data research.

Sovereign CDS and its prominence in the literature

Most of published academic work reviewed for this project deals with the structure of the CDS itself; its importance in the valuations of the corporate bonds, or corporate probability of default. For example, Longstaff, Pan, Pedersen and Singleton (2011) looked at the sovereign CDS as the determination of the sovereign credit risk. The authors analyzed a wide range of countries (26 countries) establishing a certain rising trend in the sovereign CDS spreads. Running different time intervals regressions for country groups they found widespread commonality in the sovereign credit spreads in crisis (during the period of high volatility). According to Longstaff et al (2011) "the average (positive) correlation is about 39 percent for the 2000-2006 period and 73 percent for the 2007-2010 period". The authors also determined that during volatile periods, sovereign credit risk is mainly driven by global factors, rather than country specific fundamentals. Implementing Pan and Sengleton (2008) method, authors decomposed sovereign CDS spreads, dealing with risk premiums and default risk component. The main finding of this research is that only one third of the CDS spread is attributed to a risk premium, which is associated with probability of default.

In another paper Revoltella et al. (2010) attempted to create a model that would eliminate short term volatility shocks in CDS spreads by including into regression analysis *VIX* - a Chicago Board Options Exchange Market Volatility Index - and the probability of default derived by the rating agencies. Revoltella et al. (2010) analyzed country risk premium in order to determine the dynamics of the willingness to invest into the emerging countries by the banking sector. Running OLS regression, the authors noted, "a 1% increase in the probability of sovereign default is estimated to increase the corresponding CDS spread on average by 0.20%". The main conclusion is that CDS spread is quite dynamic and fast changing mechanism, which includes market sentiment and volatility, but not necessarily always provides an adequate picture related to the fundamental country risk premium.

Related is a curious clarification found in Gevorkyan and Gevorkyan (2012b), on a more applied level, if one adopts the view that CDS spread reflects the fundamental macroeconomic situation in a given country. In their work (part of a larger study on derivatives) the authors referred to empirical evidence suggesting growth in commodity derivative contracts trade and its relation to a country's social costs, via volatility in exchange rate. This primarily would be a problem for the export-oriented emerging economies, especially those specializing in the world's staple commodities (e.g. oil, sugar, wheat, rice, etc.). This is an important clarification in what follows below, as we primarily rely on financial markets analysis, rather than real-economy's trends. This is done purposely relying on assumption that specific trends in the financial markets may already reflect some of the changes in the real segment. This is emphasized in the complexity of the commodity derivatives market's operations.

Jacobs et al. (2010) looked at the relationship between the credit rating and the CDS spread. In the authors' opinion, there could be five elements that affect CDS spread, such as: a) market volatility, b) industry, c) leverage of the reference entity, d) the risk-free rate, and e) liquidity of the CDS contract. These variables were analyzed with applied regression analysis, suggesting the CDS spreads for the given company could be quite distinct from the credit ratings of that company. Jacobs et al. (2010) also illustrate that credit ratings don't necessarily show the realistic picture of the risk, and that the market prices change first.

Related to one country of interest in this chapter, Varga (2009) in his paper argued that CDS spread for Hungary represented the most reliable and full information about Hungarian Country Risk Premium. All new information was already captured by the CDS before bond market responded. The author also noticed that during 2008 crisis Hungarian CDS spread grew at a higher rate then was fundamentally justified. Another paper, by Gultekin-Karakas, Hisarciklilar and Ozturk (2011), attempted to analyze a pattern on the basis of which credit rating agencies made their sovereign country ratings. According to that model and econometric analysis, credit rating agencies were biased toward favor-able rating for developed countries regardless of the macroeconomic indicators. Such potential bias in the ratings would determine the availability and the cost of finance for the developing countries. This is an important finding to consider going forward. Some other representative research papers analyzed as part of this study and worth mentioning are Cossin and Hricko (2001), Houweling and Vorst (2001), Hull et al. (2003), Norden and Weber (2004). For brevity we omit a detailed discussion of each, though we rely on some motivation found in these papers for our project.

Spectral Analysis Literature

One should note that current literature on spectral (alternatively can be referred to as harmonic) analysis in the frequency domain for analyzing financial data is still emerging with more comprehensive work being produced every year. The method, however, is widely used in physics and only recently has been adopted by econometricians, in application to the financial and economic indicators as few authors devoted their research on this decomposition method (e.g. Artis, Clavel, Hoffmann and Nachane, 2007).

One of the early contributions was a paper by Wilson and Okunev (1999) that looked into the conceptual definitions of the spectral analysis and its application on the real estate and stock market. The authors analyzed the co-spectrum, defining coherence, phase and gain of the spectrum between those two indicators. They found the data to be cyclical. However the cycle in the real estate data, due to less noisiness, was not that obvious when compared with the financial assets markets. Co-spectral analysis has shown similar results, concluding that the study period was not sufficiently long to allow determining the true cycles by spectral analysis. Therefore, conduct a spectral analysis on the financial data would be more viable.

Beaubrun-Diant (2006) took a slightly different approach. The author analyzed spectral properties of asset pricing models comparing the results with the DSGE modeling. Beaubrun-Diant conducted the time domain research and compared it with the frequency domain, concluding that spectral evaluation confirmed some of the time domain results. On top of that, spectral analysis provided some results that were veiled in the time domain representation. In general, the literature on spectral analysis suggests that approach best can be applied to the financial data.

However, it also could be applied to the real economic indicators analysis with a large number of observations.

Harmonic Analysis Literature

Next, we briefly sketch a methodological context around harmonic analysis. Sandoval and De Paula Franca (2011) analyzed five years from 2006 to 2011 characterized by extremely high volatility and shocks in the economy. Their methodology relied on damped harmonic oscillations, which provided the parameter estimators describing the processes during crisis time. Eleven stock markets were analyzed with estimated parameters for each five shock periods. The results showed mixed picture, requiring more detailed further analysis. However, the general conclusion was that "some markets share some characteristics and differ in others like volatility after crash." Damped harmonic oscillators, in the authors' opinion, could be used to analyze further financial shocks or instabilities since current results show global financial markets as very interconnected especially during the crisis time.

A model by Ataullah and Tippet (2007) developed a centered return on the London Stock Exchange's FTSE All Share Index in the period from January 1st, 1994 through June 30th, 2006. The main objective was to replicate with the use of the harmonic analysis the hypothesis that there was a cycle in the stock market returns. On average a cycle would last six months. This hypothesis has commonly appeared in the finance literature especially on centered returns and their periodicity.

In their paper, Ataullah and Tippet (2007) argued that "the equity prices are compatible with that of a simple harmonic oscillator with Gaussian noise." Conducting a number of tests (Ljung-Box, Jarque-Bera, Likelihood ratio), the authors concluded that centered (abnormal) returns would potentially decline in the first six months of its period, but then gradually increase for the next year, following the period when returns start falling again for the six-month period and repeat the cycle over.

On a technical note, it is worth pointing out that the assumption that somebody makes regarding the historical market return (usually 5% or 15% per annum), determines whether or not there might be a period in the centered returns data. If the assumptions regarding historical and future market returns fall below 7%, then there is extremely little evidence of the period in the data. However, Ataullah and Tippet proved the hypothesis that was presented by Jegadeesh and Titman

(1993), regarding the periodicity of the centered returns with extraction of harmonic oscillations from stock returns data.

A paper by Artis et al. (2007), provides a comparison of five methods of estimation of the harmonic regression with the diverse data. Those five unique approaches are: 1) method based on the periodogram; 2) mixed spectrum method developed by Priestley; 3) autoregressive methods including the Prony method and Amplifies Harmonic method; 4) Pisarenko's Harmonic Decomposition Method; 5) Dynamic Harmonic Regression Method.

According to the paper's analytical review the first two methods are the frequency domain methods, whereas next two are regarded as time domain methods. Only the fifth method is considered in the literature to be a mix of time and frequency domain analysis of the data. Artis et al. (2007), also discuss the evaluation of the forecasting abilities of the tests, which they suggest to be done by the Hansen predictive ability test. Empirical illustration of the paper provides a comparison of the estimation of the harmonic coefficients obtained by the five methods, and comes to the conclusion that estimation of the cycles and periods are quite similar amongst different methods. In general, that paper may be considered as foundational for comparison of diverse estimation methods of harmonic regressions coefficients.

Overall, the range of literature on spectral/harmonic analysis is quite wide and is attributed to varying data sets with substantial number of observations. Quite a few recent papers tackle financial data analysis. In the next section we present some stylized facts and discuss financial data used in our research.

Stylized Facts and Data

Stylized Facts

Countries of the European Union (EU) and European Monetary Union (EMU) are undergoing one of the most challenging periods since the European Union (EU) and EMU creation. Depending on the exact short and medium term dynamic the process may potentially lead to economic and political restructuring of the entire union. Overall, the EU economy struggles to deepen the integration of its various members while the euro remains the dominant currency for pricing of real and financial sector assets. In the background of the sovereign debt crisis and global uncertainty, it is then informative to look at trends between the EMU member countries and standalone economies.

For our study we have selected a group of four countries that eventually are analyzed in two subgroups. France and Spain are in the first subgroup, representing countries that are part of the EU and EMU. The second subgroup consists of Poland and Hungary, the two countries that are members of the EU but with their own national currencies. With such set of countries one may derive few conclusions on potential effect of debt burden for common currency and "standalone" countries. Moreover this set of countries is chosen precisely to depict that two somewhat more macro sustainable countries (France and Poland), could potentially be compared with the two weaker economies (Spain and Hungary).

The European Union since its creation is assumed to be the union of the countries with similar macroeconomic indicators and stable economies (conditions for the entry in the EU). However, the main aspects of the current crisis deterioration are the unprecedented levels of debt to GDP ratios, in some countries (e.g. Greece) over 100 percent.

The goal of our research would not be to analyze the isolated extreme cases, such as Greece or Portugal in the context of the EU crisis. Both, we believe, present extreme event scenarios and can be solved primarily through political will. Alternatively, the ongoing research effort should also entail countries that could potentially represent other larger group of economies. For example, France currently is the one of the strongest economies in the EU and is the biggest creditor to the European Central Bank (ECB), after Germany. On the other hand, Spain is one of the weaker in the EMU with substantial level of debt to GDP and considered to be the biggest debtor of the ECB.

Since one of the primary issues of the crisis is the debt over GDP ratio, it would be sensible to analyze debt dynamics relying on CDS spread data. This spread is modeled on the main premise of existing link between CDS to a country's solvency. Other factors (market sentiment, liquidity, GDP growth, inflation, unemployment, exchange rate, and others) may have an effect on the change of the CDS as well. That sometimes could be quite significant. On the other hand, the increasing yield on government bonds (hereinafter, interest rate) would mean that it becomes costly for a country to borrow with every new period, turning away investors due to the solvency issues.

It is also considered, that market returns would play some role in the change of the CDS spreads. Therefore another series analyzed here is the return on the national stock markets. Figures 1 and 2 present the evolution of the five-year sovereign CDS, five-year interest rate on government bonds, and returns on the national stock markets for France and Spain respectively.

The second country subgroup consists of the members of the EU, but not part of the EMU, hence with own currency: Poland and Hungary. These are the standalone economies in the EU. From the macroeconomic indicators one can infer that Poland is relatively sustained economy compared to some of its neighbors. Hungary on the other hand, went through severe crisis with almost 80% capital outflow from the country (Gevorkyan and Gevorkyan, 2012a). Consistent with above definitions, Figures 3 and 4 present the comparison of the CDS and interest rate, as well as CDS with the market return for Poland and Hungary.

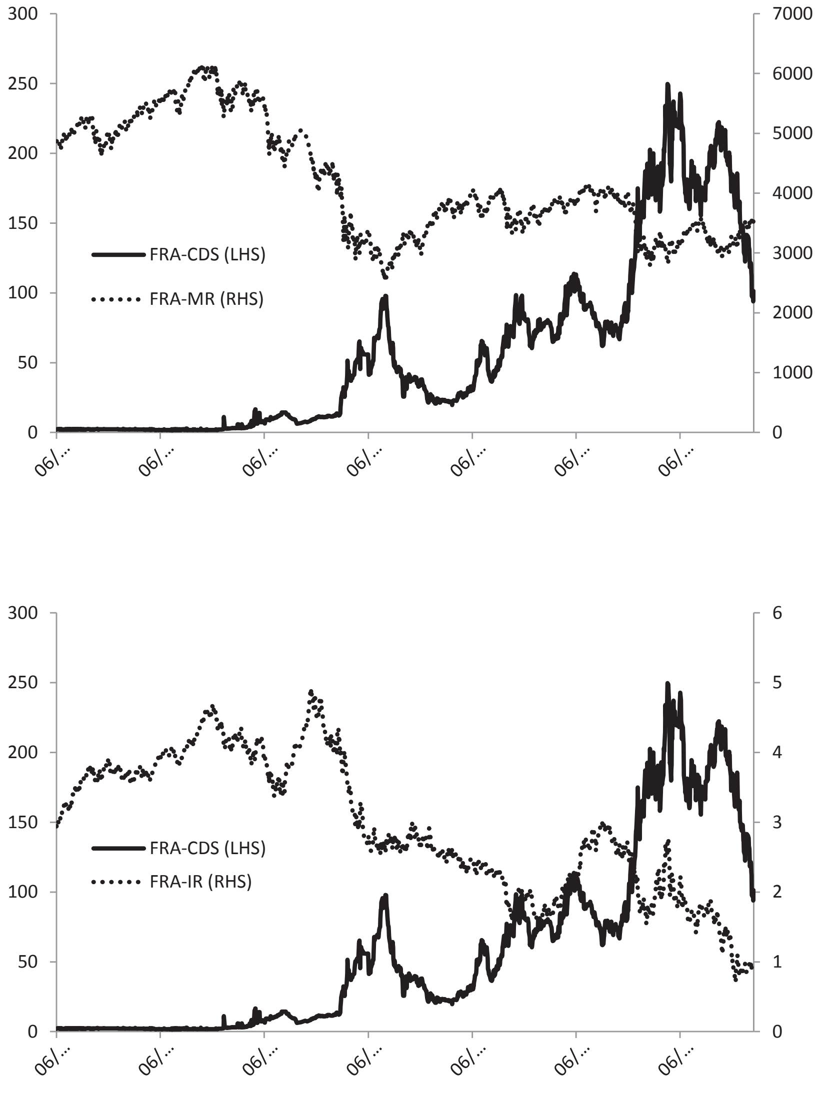

Figure 1. France CDS vs. MR and CDS vs. IR

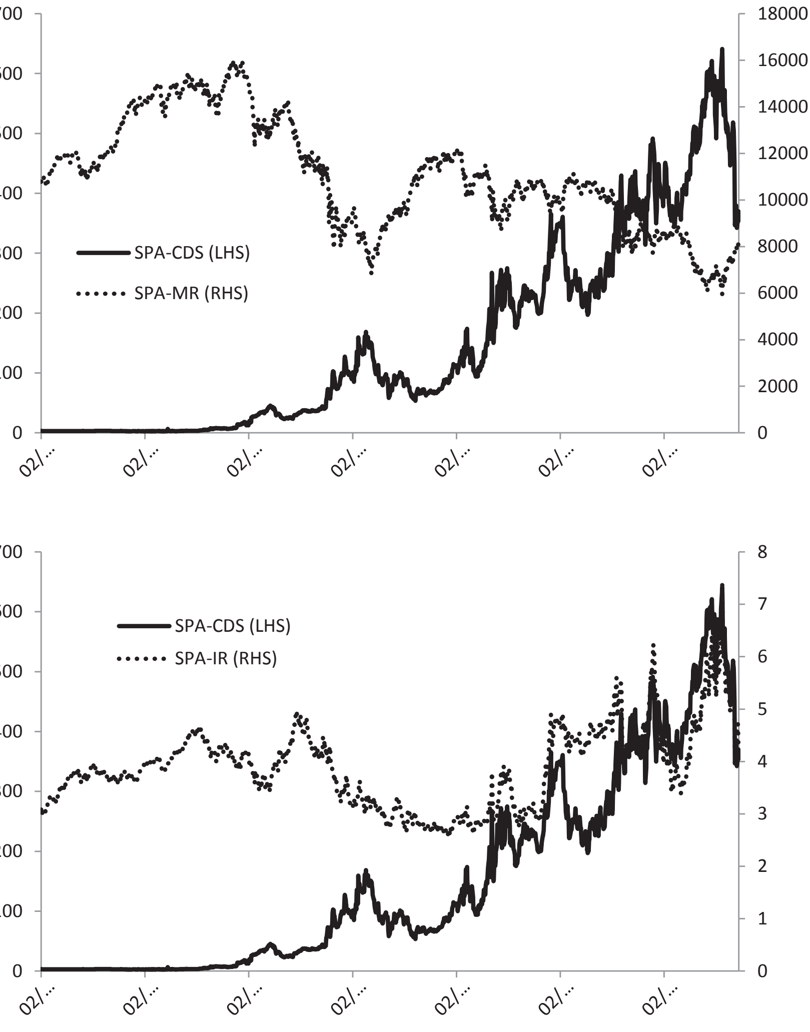

Figure 2. Spain CDS vs. MR and CDS vs. IR

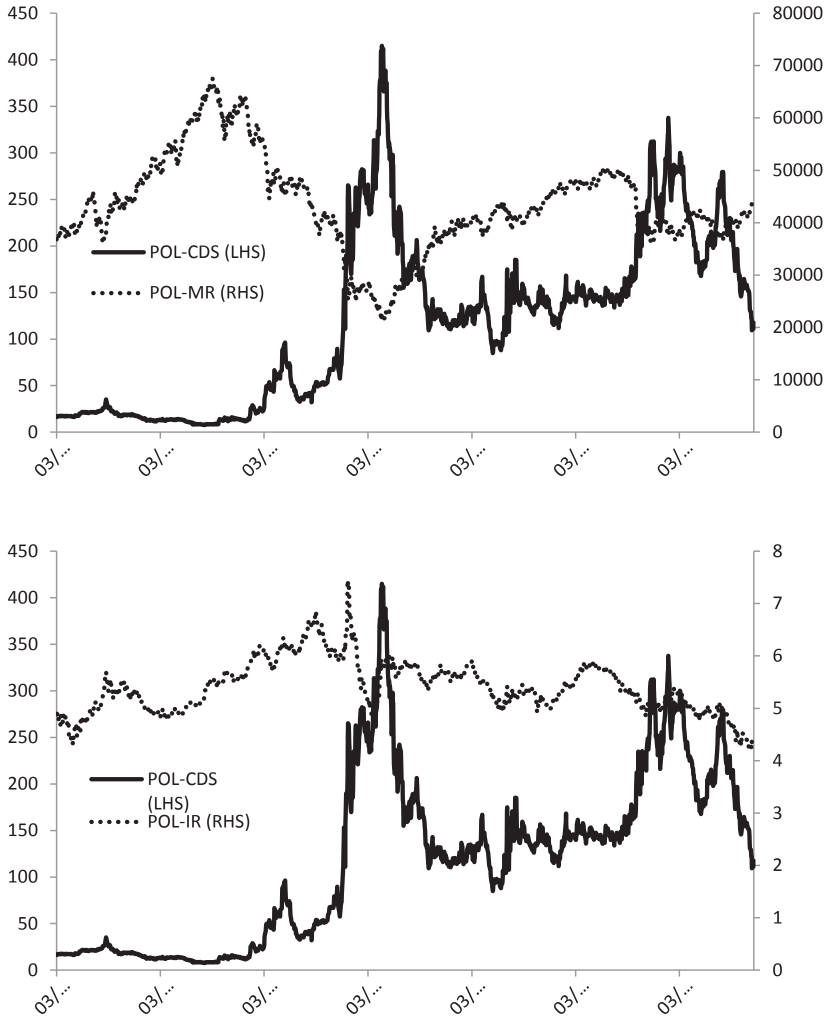

Figure 3. Poland CDS vs. MR and CDS vs. IR

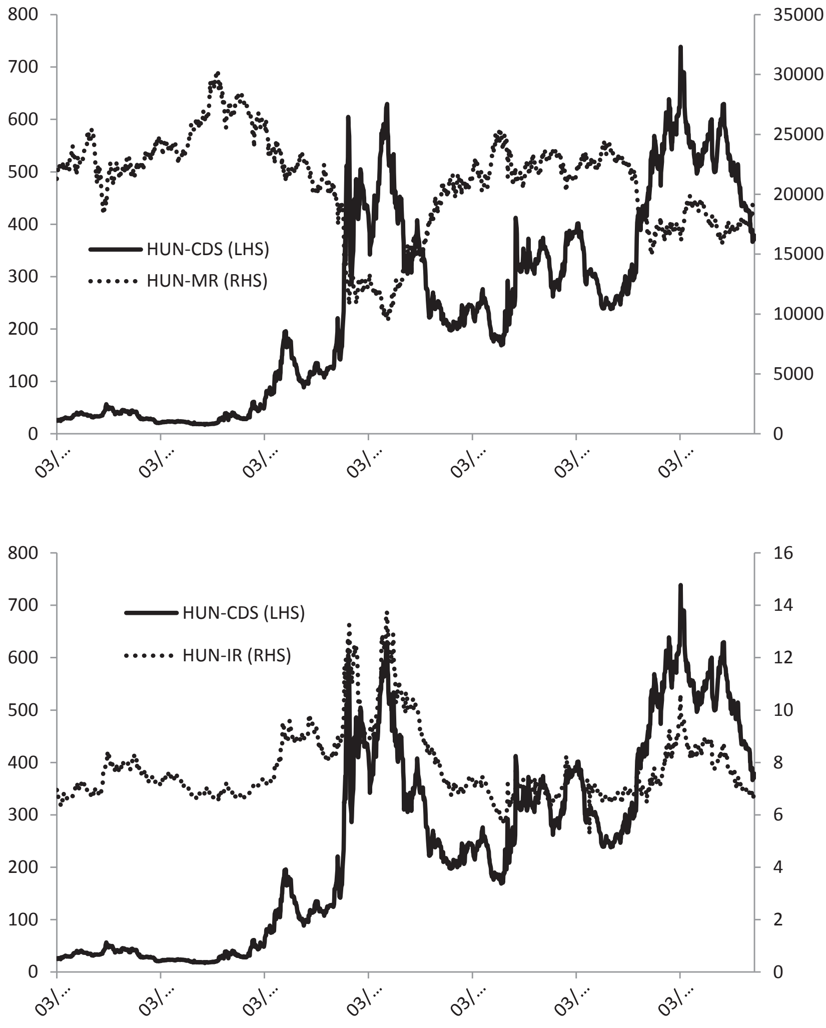

Figure 4. Hungary CDS vs. MR and CDS vs. IR

From Figures 2 and 4 one can infer that although the countries like Spain and Hungary are in the different subgroups (one is EMU the other is standalone country), they are quite similar in the analyzed series dynamics. On the other hand, looking at the trends in Figures 1 and 3, it is evident that France and Poland resemble similar patterns and present a stable path. A correlation analysis results for the given dataset in the time domain appears in Table 1.

Table 1
Correlations

	France	*Spain*	*Poland*	*Hungary*
CDS and IR	-0.7830	0.4735	-0.0215	0.4599
CDS and MR	-0.7128	-0.7732	-0.6783	-0.7398

From Table 1 it can be seen that Spain and Hungary exhibit strong significant positive correlation of CDS and interest rate (IR) fluctuations. This phenomenon would be researched further in the frequency domain analysis below. On the other hand, France and Poland show a strong negative correlation. At the same time CDS and market returns (MR) are negatively correlated.

While a number of other observations may be derived for each economy, the above discussion is sufficient to develop a relevant context for this research. We next look closely at the data and analyze it.

Researched Data and Its Analysis

The main component of the researched data is the five year sovereign CDS spread. A sovereign CDS spread represents fixed payments (compared to coupon payments in practitioner's literature) from the buyer of the swap (insurance) to the seller. Here in case of default of the third party the seller of the insurance guarantees repayment of loan's face value to the insurance buyer.

The second series that is analyzed in this work, as has been mentioned, is the five year interest rate on government bonds, which is referred to as the interest rate in this paper. Lastly, we look at the national stock market returns. It is important to note that for the analyzed set of countries stock market returns are similar and have high correlation with the European index (Eurostoxx), even when individual national markets are considered as in this paper. All data were obtained from Bloomberg terminals and adjusted for this project. Adjustment was needed due to differences in the equity and fixed income markets across countries. Therefore the missing days were substituted with the value of the previous day close.

The chosen analysis period is from January 1st, 2006 through September 20th, 2012, based on daily observations. This period matters for several reasons. First, previously data for sovereign CDS, since its inception, was private, available only to high-paying individual market participants. Starting in the mid-2000s this information became public, and, for example, in the US it became transparent with the Dodd-Frank Act introduced in 2010. Second, during the critical period of 2007-2009 sovereign CDS experienced the highest volatility and extraordinary expansion of the volume with highest rates of capital flows into these instruments since their creation. Such tremendous growth could be vividly seen especially for the European countries in absolute levels and average weekly volumes in Figure 5.

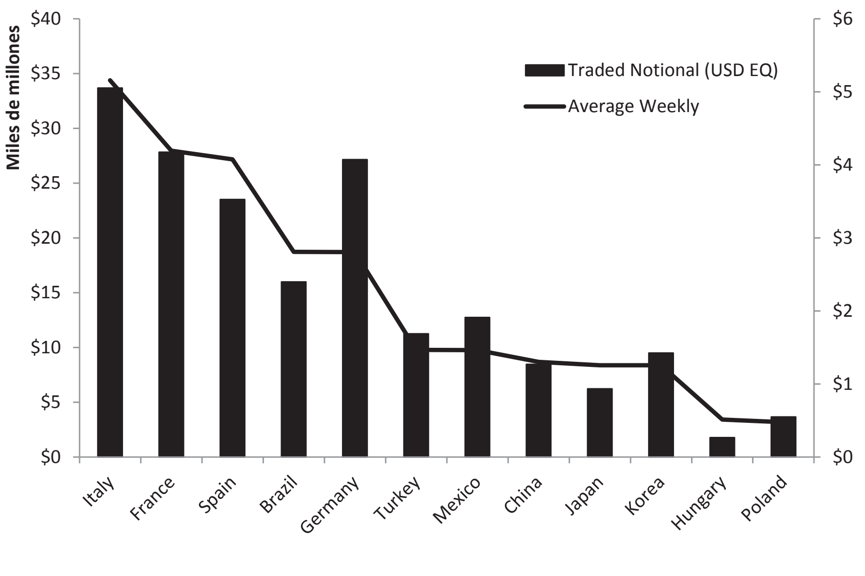

Figure 5. Net Sovereign CDS outstanding and average weekly traded for six months March – August, 2012 (USD EQ blns, Source: DTCC, 2013)

Initially we ran several standard tests on all data. It was found, that Augmented Dickey Fuller test and Phillips Perron test identified an I(1) process in all series for the four countries. The first difference was applied to the entire data set. Also, for the application of the harmonic regression, the five year sovereign CDS for every country was de-trended (calculations available via MATLAB file).

Analysis of the Sovereign CDS Dynamics

Spectral Analysis and Its Implications

Generally, most of the macroeconomic and financial data is represented in a time series format. This data is presented in the time domain and can be divided into long-, medium- and short-term categories. Separately, it could also be associated with three processes: the trend, business cycle and seasonality, respectively. The stylized facts section above provides a brief analysis of the data in the time domain. However the analysis could also be done in the frequency domain. In other words, the information shown in the time domain can also be extended in more detailed way in the frequency domain representation or spectral analysis.

One can transform data from time to frequency domains utilizing the Fourier transformation in the analysis of time series. Here the frequencies of the data can be analyzed with help of spectral density function, which is defined as the Fourier Transform of the autocovariance function, according to Hamilton (1994) and assumes the following form:

$$S_y(\omega) = \frac{1}{2\pi} g_Y\left(e^{-i\omega}\right) = \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \gamma_j \, e^{-i\omega j} \tag{1}$$

where, in equation [1], the real component of the cross spectrum, which is also known as the co-spectrum between X and Y is:

$$c_{YX}(\omega) = 2(\pi)^{-1} \sum_{k=-\infty}^{\infty} \gamma_{YX}^{(k)} \cos(\omega k) \tag{2}$$

and the imaginary component of the cross spectrum is known as the quadrature spectrum from X and Y is:

$$q_{YX}(\omega) = -2(\pi)^{-1} \sum_{k=-\infty}^{\infty} \gamma_{YX}^{(k)} \sin(\omega k) \tag{3}$$

In our research one of the centered methods for comparing frequencies and periods is the cross-spectral analysis, which is basically used to find the direction and magnitude of co-movements between two time series. According to Koompans (1995) this can be considered as a frequency domain equivalent of correlation analysis in time domain.

The analysis of the co-spectrum assumes that we estimate coherence, phase and gain. Determination of the co-spectrum, according to Hamilton (1994), is the combination of the real and imaginary parts of the spectrum, where cross spectrum is a cross covariance generating function:

$$s_{YX}(\omega) = c_{YX}(\omega) + i * q_{YX}(\omega) \tag{4}$$

The rate of relationship in the frequency domain between the two series can be identified by the statistics of the squared coherence, which is common referred to in literature (e.g., Koopmans, 1995) to the R^2 in the time domain. Coherence indicates (according to Hamilton, 1994) the proportion of the variance in one series at frequency ω that is accounted for by variation in the other series. Formally, it can be represented by the formula:

$$h_{YX}(\omega) = \frac{|c_{YX}(\omega)|^2 + |q_{YX}(\omega)|^2}{s_{YY}(\omega) s_{XX}(\omega)} \tag{5}$$

Also, we present the phase, which shows the lead of Y series over X series with the frequency ω. In other words, as defined by Koopmans (1995), the phase is a dimensionless parameter which measures the displacement of the sinusoid relative to the given time origin. The phase is restricted to the range $-\pi < \psi \leq \pi$. Therefore, Fishman (1969, p.65), formally defines the phase as:

$$\varphi(\omega) = tan^{-1}[-q_{YX}(\omega)/c_{YX}(\omega)] \tag{6}$$

The phase is also referred to as a time lag, which indicates the timing of peaks in the Y series relative to peaks in the X. As discussed by Warner (1998) the phase relationship between two time series can be estimated reliably if coherence is substantial, therefore, it would make sense to look at the phase when the coherence is relatively high. As defined by

Fishman (1969), gain tells how amplitude in X is multiplied in contributing to the amplitude of Y at frequency ω, and can be presented by the formula:

$$G(\omega) = \frac{(|c_{YX}(\omega)|^2 + |q_{YX}(\omega)|^2)^{1/2}}{s_{YX}(\omega)} \tag{7}$$

Therefore cross-spectral analysis results can be utilized in order to

make inferences about several kinds of different relations between the two series. If there is high coherence at some frequencies, then this might indicate, as pointed out by Warner (1998), a time lagged dependence between the two time series, thus the length of the time lag can be inferred from the phase spectrum. We switch now to the discussion of the harmonic analysis in general.

Harmonic Analysis of the sovereign CDS

The second empirical part of the paper is the presentation and estimation of harmonic regression with the determination of the harmonic coefficients. The concept of harmonic analysis in econometrics is presented in depth by several papers and manuscripts, for example: Warner (1998), Bloomfield (2000), Priestley (1981), Art is et al. (2007), Ataullah and Tippet (2007) and others.

As emphasized by Warner (1998), harmonic analysis can be used as one of the estimation methods in the frequency domain in the case when cycle length of the data is known. Estimation of harmonic analysis allows researcher to fit an entire set of different cycles or periods, assessing if any cycle provides a good fit of the analyzed data. However, a trend must be removed before estimation. As defined in Bloomfield (2000, p.39), "harmonic analysis represents the decomposition of a series into components each of which is repeated a whole number of times in the span of the data."

The formal representation of the harmonic regression can be presented as a summation of the sinusoidal and cosine functions where a_i, b_i and ω_i" are the unknown constant parameters and need to be estimated. An example of such harmonic regression is given by:

$$y_t = \sum_{i=1}^{k} \left(a_i sin\left(\frac{2\pi}{\tau_i}(t - t_0)\right) + b_i cos\left(\frac{2\pi}{\tau_i}(t - t_0)\right)\right) \qquad (8)$$

In regression [8] typically the number of harmonics k is assumed to be equal to 6 for consistency. According to Artis et al. (2007), the estimated coefficients a_i and b_i represent the harmonic representation in the frequency domain the data.

All in all, it should be noted that the harmonic analysis provides a method of fitting a cyclical component to a time series. According to Bloomfield (2000), if there are two or more cyclical components in the analyzed data, each one can be represented as an additional pair of sinusoidal and cosine terms. In our representation, we would plot the fitted estimation of the regression on the de- trended data, which provides a clear illustration of the features of the data that we are analyzing.

Main Findings

Co-spectrum of the Data

Cross-spectral analysis was performed on a pair of time series (sovereign CDS with stock market returns and sovereign CDS with interest rate) for each country. This helps assess whether the conclusion obtained on the time domain earlier can also be seen in the frequency domain. Estimates of the gain, coherence and phase for the two series for the ease of comparison for all four countries appear in Figures 6, 7, 8 and 9. Note that in all graphs the x - axis is cycles per observation. To convert this to frequency in cycles per day, we would need to divide the frequency shown on the x axis by Δt, in order to convert the cycles per observation into an estimate of the period. (Warner, 1998).

As can be noticed, in the presentation of the results, the coherence for Spain and Hungary is quite significant, which indicates a higher R^2 - exactly the same result was seen in the Figures 1 through 4. Estimated correlation on those graphs is very significant. The coherence amongst standalone countries is significant as well, especially for Hungary.

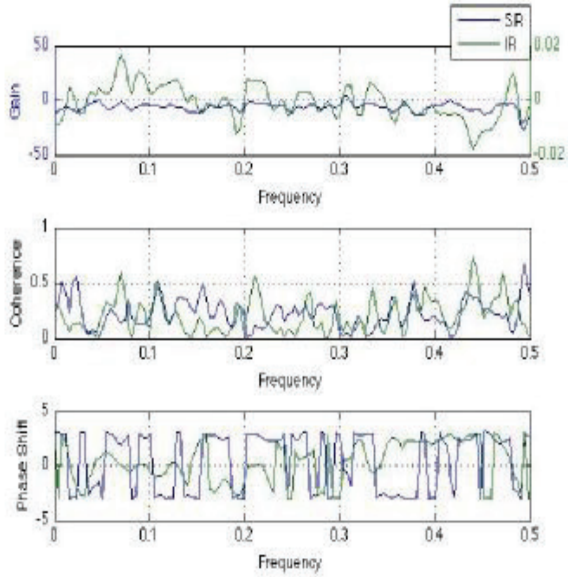

Figure 6. France

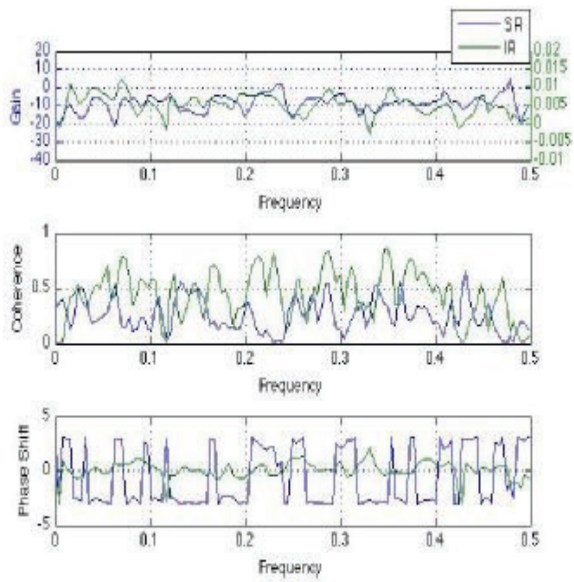

Figure 7. Spain

It should be noted that the national stock exchanges of all four economies reviewed here are highly correlated with the Eurostoxx index, therefore the results for this series are quite similar. We also estimate the time lag or phase relationship using examples of France and Spain. That can be done by looking at the phase spectrum of CDS and interest rate series. We are interested in the phase estimate for the highest frequency band of 0.441 for France and 0.349 for Spain. At these frequencies, the phase relationship was 3.12 and -0.015 respectively. Where the phase relationship for France is almost equal to π and for Spain is almost zero. Thus if we divide by 2π to convert radians to proportions of a cycle, this means that the peaks in the interest rates and CDS dynamics occurred almost exactly half a cycle apart. Therefore $a + \pi$ or a half of π is equivalent of saying that the dynamics in the CDS is a half cycle ahead, when the cycles are repeating regularly. For Spain, since the phase relationship is very close to zero, thus the lead or lag indicator cannot be determined, the assumption that those two series move contemporaneously.

For France (Figure 6) the coherence is not that significant, staying below 0.5 for the most period of time, whereas for Poland (Figure 8) the coherence rises above 0.5 level several times, with the peak being on the 0.22 frequency.

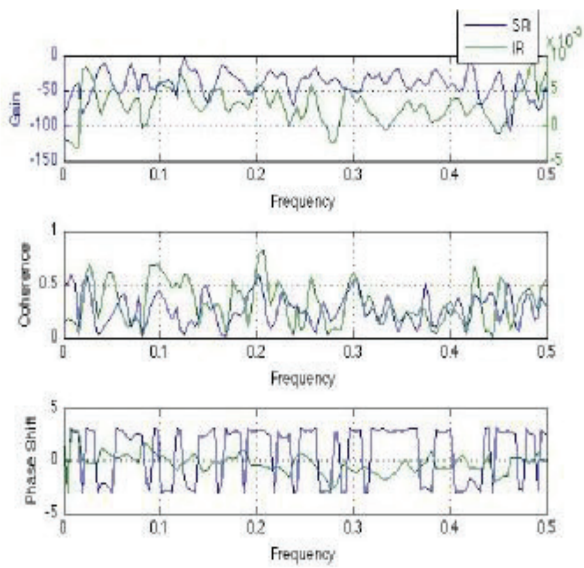

Figure 8. Poland

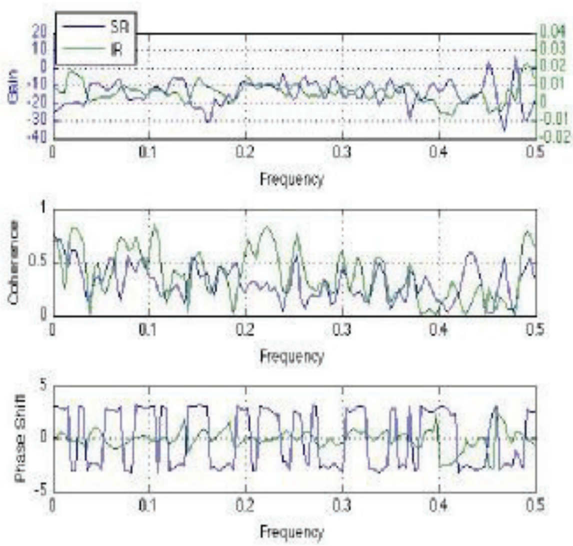

Figure 9. Hungary

These are quite interesting findings in the bivariate analysis of the two time series. Replication of the results of the time domain analysis in the frequency domain is quite consistent. Being dynamic and very sensitive to any changes the spread of Spain and Hungary would have contemporaneous effect with the interest rates.

Harmonic Analysis

Here we start by applying the Fast Fourier Transformation on de-trended data. Here this method picks up the periods for the harmonic fit, which have the highest power. Power spectral density describes how power of a signal or time series will be distributed over different frequencies. These estimates were completed utilizing the formula in the equation [7]. Figures 10 and 11 represent the power spectrum of the period.

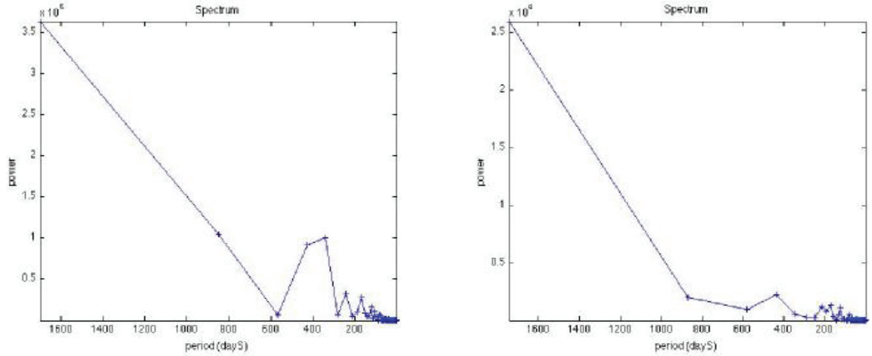

Figure 10. Power spectrum (France and Spain)

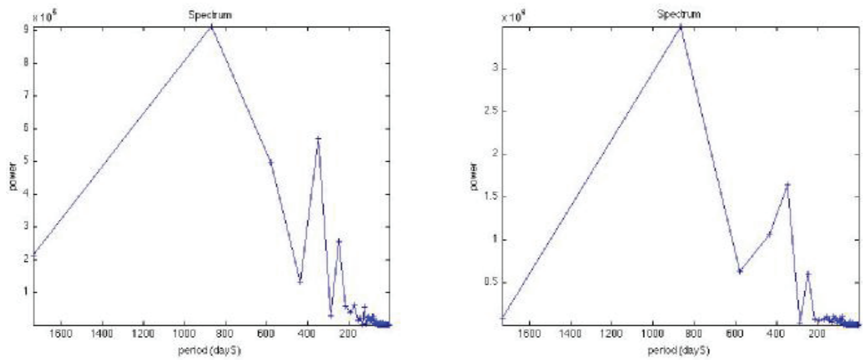

Figure 11. Power Spectrum (Poland and Hungary)

It can be seen that the peak in the power spectrum for Hungary and Poland, from Figure 11 is very close (around 900 days), whereas for Spain it is 840 days and for France it is 575 days the length of the period. Power spectrum for the stand alone countries has the same form and dynamics, which could serve as a characteristic for the stand alone countries.

Harmonic analysis provides a fitting of the sinusoidal and cosine functions onto the data, with the goal of determining the coefficients. Corresponding figures appear in the Appendix, where the number of "harmonics" k is known in our case (should not be estimated) and assumed to be equal to k=6. All of the estimates of the harmonic analysis were obtained utilizing equation (8).

Table 2 shows the coefficients a_i, b_i and ω_i for four countries. It can be observed, that these coefficients vary significantly in their values. This could be something to emphasize in a future subsequent research effort. A number of simulations were ran, in order to reduce the dispersion in the values of the coefficient for different “harmonics”. The presented results represent the “best estimate” of the coefficients that can be fitted on the de-trended data.

Table 2
Harmonic coefficients

	k=1	k=2	k=3	k=4	k=5	k=6
France	-0.0102	29.1028	10.2958	-9.3648	-9.9213	5.0891
	2.6102	-11.9034	12.1295	-10.8824	7.0225	1.5552
Spain	-0.0417	76.9072	5.8622	19.3875	-17.2504	-1.4409
	5.9848	-21.8251	-9.4497	-1.9570	-16.1180	11.3535
Poland	0.0113	40.5490	-18.3166	-29.5403	9.8630	-22.0561
	-21.5593	31.1845	16.4540	22.1877	-1.4773	-17.000
Hungary	-0.0058	79.6297	-49.8448	0.8044	-29.6006	13.4481
	-41.7044	35.8148	-49.5923	23.9689	34.4864	14.4311

Based on the above analysis we could conclude the length of the cycle of the CDS data for four countries. That information is presented in Table 3:

Table 3
Periodicity of the data

	France	*Spain*	*Poland*	*Hungary*
Cycle length per day	Hungary	109.38	136.72	58.59

The above discussion leads to a conclusion that the cycle length of the EMU countries is very similar, whereas for the standalone countries it varies and is not as consistent. That result can be attributed to a number of economic (e.g. debt sustainability, capital inflow/outflow, GDP growth, pegged exchange rate) and financial (e.g. high volatility of the CDS spread, liquidity of it, correlation of the stock market with other markets and its impact, etc.) factors that a country deals with on a daily basis.

Overall, the results present a mixed picture vis-à-vis monetary union and standalone distinction. Country specifics seem to matter. In other words, we find similar outcome of analysis of bivariate series looking at coherence and phase between CDS and market returns and CDS and interest rate in the case of Spain and Hungary. At the same time, France and Poland can be grouped separately based on the similar dynamic the series for these two countries exhibit.

In the univariate case, when we look only at the CDS dynamics (see the power spectrum and harmonic analysis above), the standalone countries (Hungary and Poland) and EMU members (France and Spain) break out of their grouping. Now, the so-called standalone correspond closer with each other more as is also the case for France and Spain. Clearly future research then should aim to properly account for country specifics while identifying common patterns (perhaps in an expanded sample) in the financial markets influences on external and macroeconomic indicators for standalone and monetary union-member economies.

Conclusion

The analysis presented in this paper in the frequency domain supports our proposition made in the beginning of the paper in the time domain analysis, regarding correlations between CDS and interest rates across standalone and monetary-union member economies. The frequency domain analysis has complemented and reconfirmed our initial knowledge with additional information. It is especially obvious for the countries with substantial high CDS spreads, due to the higher uncertainty.

However, the results of the power spectrum (as in Table 3) caution us that standalone countries and members of a monetary union such as EMU still should be treated somewhat differently. It is clearly seen though, that countries like Spain and Hungary, where there is a great uncertainty in the ability of a country to pay out its debt, eventually leads to the higher and unstable CDS spreads. Coherence and phase diagrams analysis support our hypothesis of high interactions between interest rates and CDS. Also, from the obtained harmonic coefficients, we see that for Spain and Hungary there is a wider range in values of those than for more stable countries, like France and Poland.

In conclusion, one can argue that standalone countries are in a different situation than monetary union members. Still, at the end of the day, the strength and direction of the CDS spread and interest rate dynamic relationship is determined by speculative interactions in the financial market and macroeconomic parameters of a given economy. Future research on a larger sample can help extend the analysis presented in this paper to a more general case.

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Appendix

Harmonical fitting on the de-trended data for the case of France, Spain, Poland and Hungary.

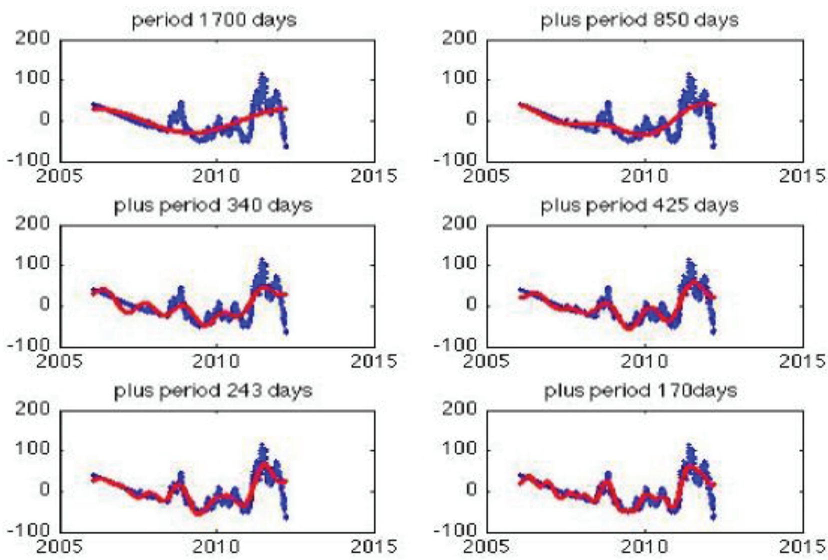

Figure 12. France

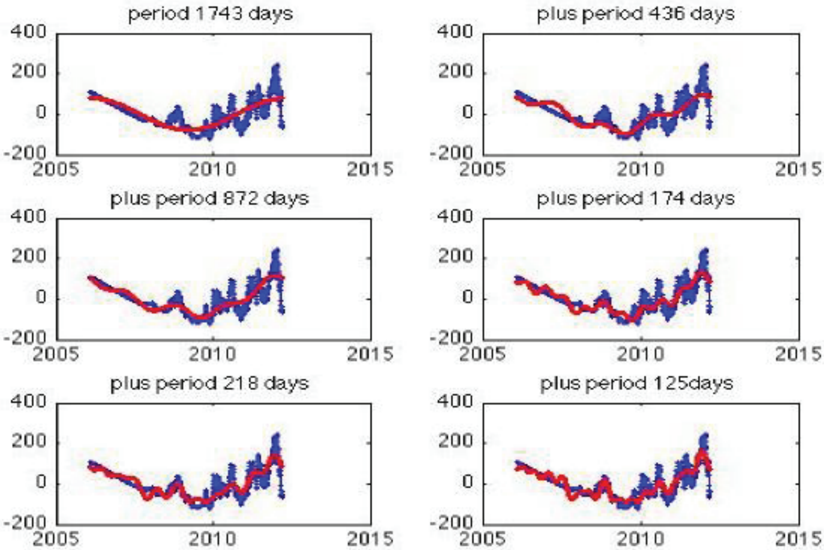

Figure 13. Spain

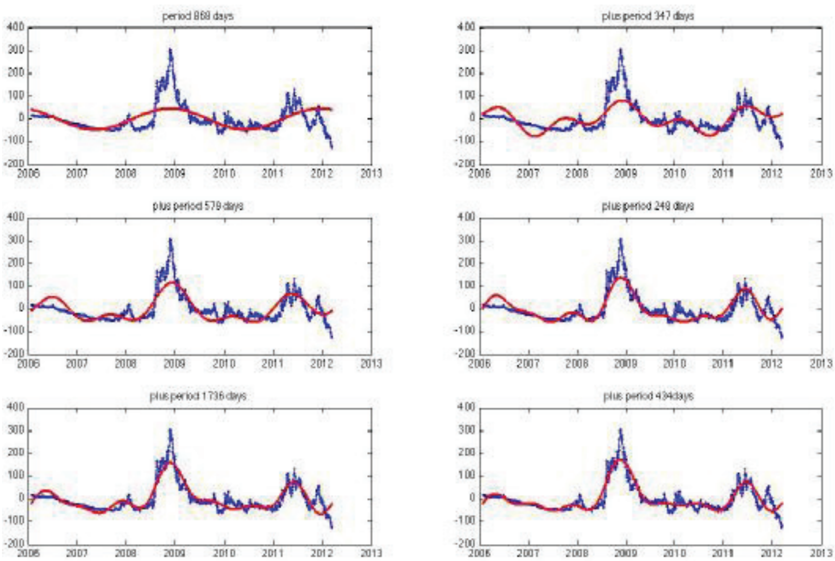

Figure 14. Poland

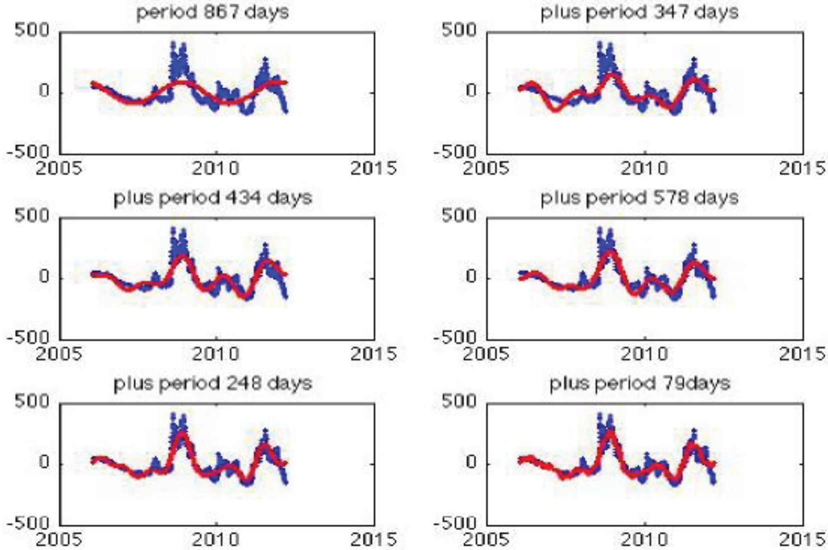

Figure 15. Hungary

CHAPTER 5
Impact of Free Cash Flow on Overinvestment: An Empirical Evidence of Chinese Listed Firms

Wei He
NyoNyo A. Kyaw

Introduction

Free cash flow and overinvestment have been extensively examined by many researchers due to its importance in financial management towards value maximization. The agency cost explanation to over-investment proposes that firms with a high level of free cash flow may overinvest in negative NPV projects, destroying the firm's value. While over-investment has been a problem cited for many U.S. listed companies, the evidence on Chinese listed companies remains unknown. China has grown tremendously over the past two decades and now became one of the largest economic powers. Unlike the U.S. public firms, Chinese listed companies generally have a unique ownership structure with an average of 64% non-tradable shares owned by state and state legal persons as of December 2004 (CSRC). Negotiable shares are owned by small individual shareholders, who exert only modest influence on company affairs and provide little monitoring of the management. In most state-controlled companies, the local government appoints board members and top management, who have no material interests or risks in the company. While the separation of ownership and control is generally accepted as an advantage of a corporation, the agency problem inherited in the ownership structure of Chinese listed companies may cause managers to make decisions against the objective of shareholders' wealth maximization.

Based on 5,296 firm-year observations of Chinese listed companies during the period from 2003 to 2008, we first investigate the relationship between free cash flows and over-investment following Richardson (2006). The second focus of the paper is to examine how ownership structure affects the relationship and the sensitivity of investment to free cash flows for Chinese firms. Since good corporate governance structure mitigates the agency costs associated with overinvestment, we study various share ownerships and ownership concentration as they are directly related to corporate control and monitoring over the firm's operation. If the concentrated ownership from state or institutional shareholders is effective in monitoring, then we would observe lower overinvestment-free cash flow sensitivity. We also investigate whether the sensitivity of overinvestment to free cash flow varies for financially constrained versus unconstrained firms and the valuation effect of firms with overinvestment. Our findings show a significantly positive relationship between free cash flows and over-investment. With minimal influence from the insiders, large block holders and mutual fund investors in Chinese corporations do not exert sufficient monitoring on corporate overinvestment. As expected, the financially unconstrained firms tend to overinvest and the financially constrained firms are more sensitive to free cash flows when making overinvestment decisions. Overinvesting Chinese firms destroy value.

Our paper contributes to the international evidence of investment decisions and agency theory in several ways. First, we investigate the sensitivity of over-investment to free cash flows for Chinese listed companies for a recent time period. Second, we study the unique ownership structure of Chinese firms as one of the key corporate governance mechanisms influencing the firm's agency cost resulted from the conflicts of interests among the stakeholders. We provide evidence that ownership structure affects corporate investment levels. Third, we enrich the agency theory by examining whether financially constrained and unconstrained firms respond differently to free cash flows. Fourth, our findings on stock valuation effects of overinvesting firms should benefit the investors in detecting and guarding against possible over-investment behaviors of listed companies to ensure investments are made towards value maximization. Fifth, our study contributes to the understanding of institutional investors and block holders and their roles played in corporate governance of listed companies in countries with weak investor protection like China. The remainder of the paper is organized as follows. Section II discusses the literature on over-investment-cash flow sensitivity and factors influencing the sensitivity. Section III describes the sample. Section IV explains research design. Section V reports the empirical results. Finally, Section VI provides concluding remarks.

Literature review

The prior research has documented a positive relationship between cash flows and investment. According to the free cash flow hypothesis of agency theory, the firms with high level of free cash flows may have more managerial discretion and incentives to over invest in negative net present value projects to maximize their personal benefits, rather than paying dividends, against the interests of the shareholders (Jensen, 1986). This would not happen if internal funds are unavailable or external funds are expensive. Underinvestment on the other hand refers to rejection of positive net present value projects due to the lack of financing. According to Myers and Majluf (1984) and Myers (1984), asymmetric information may lead to rejection of positive net present value projects due to high cost of external financing since the market is not well informed about the firm's financial strength at time of financing. Consequently, the adverse selection occurs when possible conflicts of interests between bond holders and shareholders and between existing shareholders and prospective shareholders become apparent. The cost of external financing would rise to a point where firms have to forego positive NPV projects when internal funds are unavailable, leading to underinvestment problem.

Overinvestment problem has been widely examined from a corporate governance perspective. Ownership structure as a corporate governance mechanism influences the agency problems derived from conflicts of interests between owners and managers. The generally accepted benefit of having insider ownership is to align interests of managers with those of shareholders (Opler, Pinkowitz, Stulz and Williamson, 1999; Ozkan and Ozkan, 2004; Pinkowitz, Stulz and Williamson, 2006; Chen, 2001). The converged interests mitigate the agency problems. However, with moderate to high insider stake, entrenchment is likely to occur, where entrenched managers may expropriate the rights of minority shareholder. Cho (1998) shows that the level of investment rises as insider ownership increases up to 7%, decreases as insider ownership rises from 7% to 38%, and remains unaffected by insider ownership beyond 38%. Hadlock (1998) finds inverted U-shaped relationship, indicating the benefits of insider ownership at lower ownership level and entrenchment or reversed relationship at the higher level, exacerbating the overinvestment problem.

Similarly both benefits and costs are associated with concentrated ownership. Concentrated ownership with large block holders implies monitoring and can serve to align the interests between the controlling and minority shareholders (Shleifer and Vishny, 1986, 1997; Kaplan and Minton, 1994; Lins, 2003). A higher concentration of ownership is expected to be associated with more control over managerial behavior, given the decrease in monitoring incentives when there is no controlling shareholder (Stiglitz, 1985). Gomes (2000) claims that higher ownership concentration is perceived as a commitment by the controlling shareholders for not expropriating the interest of minority shareholders. However, the extremely high ownership concentration may not necessarily indicate better shareholder protection. Instead, controlling shareholders have an incentive to exploit the minority shareholders by diverting resources at the expenses of the minority shareholders. (Morck, Yeung and Yu, 2000: Claessens, Djankov, Fan and Lang 2002; Fan and Wong, 2002). Entrenched controlling shareholders may engage in self-dealing transactions that hurts the minority shareholders' interests. La Porta et al. (1999) document that the concentration of ownership in the largest public companies is negatively related to investor protections, implying that small shareholders are unlikely to play a major role in countries that fail to protect their rights. La Porta, Lopez-de-Silanes, Schleifer and Vishny, (2002) also find the evidence of higher valuation of firms in the countries with better protection of minority shareholders.

The insider ownership and ownership concentration are found nonlinearly related to the firm's agency cost and value. (Morck, Shleifer and Vishny, 1988; McConnell and Servaes, 1990; Hadlock, 1998; Gedajlovic and Shapiro, 1998; Claessens and Djankov, 1999; Mitton, 2002). Hadlock (1998) examines how insider ownership affects the sensitivity of investment to cash flow. He offers two competing explanations to the overinvestment and underinvestment problems with evidence consistent with the underinvestment explanation. The findings are a non-linear influence on the firm's agency problems and non-linearly related to firms value. Therefore, higher levels of insider ownership and ownership concentration may not necessarily lead to value maximization. Instead due to greater managerial entrenchment and rent expropriation, the value may decrease. Claessens and Djankov (1999) find that blockholdings or concentrated ownership is associated with superior performance in privatized firms. Mitton (2002) reports that firms with high ownership concentration show better stock performance during the East Asian financial crisis.

While the ownership structure in the western economies is quite dispersed, stock ownership of Chinese listed companies is still concentrated in a few large shareholders such as state and state legal person shareholders even after several waves of privatization. The interests of minority shareholders are less protected. In addition, the state shares are non-tradable and can not realize capital gains like the tradable shares. Lee and Xiao (2004) and Lin and Su. (2008) find that firms with state control or higher ownership concentration are likely to engage in higher cash dividends to tunnel assets, consistent with the rent expropriation hypothesis. Other ways of deriving private benefits include related party transactions, which provide controlling shareholders with better access to valuable company assets (Jian and Wong, 2010). Evidence shows that the performance of Chinese firms is negatively related to ownership concentration (Qi, Wu and Zhang, 2000; Chen, 2001; Wei, Xie, and Zhang, 2005).

Further studies on sensitivity of overinvestment to free cash flows include the change of sensitivity in response to the change in firm's financial conditions. The evidence on the varying investment-cash flow sensitivity between financially constrained and unconstrained firms is mixed. Fazzari, Hubbard, and Petersen (1988) considered a firm financially constrained when external financing is too expensive and the firm has to use its internal funds to finance investment rather than pay dividends. They found that financially constrained firms have investments that are more sensitive to cash flows than financially unconstrained firms. Kaplan and Zingales (2000) find the opposite evidence when a different proxy for financial constraints is used, the access to external funds. Moyen (2004) reconciles the conflicting findings of Fazzari et al. (1988) and Kaplan and Zingales (2000) using two subsamples by different criteria for financial constraints.

The investment-cash flow sensitivity is investigated using financial models. Povel and Raith (2001) develop a one-period model in which investment is not observable by the market and find that the relation between investment and cash flow is U-shaped, and that more information asymmetry generally increases the cash flow sensitivity. Almeida and Campello (2002) impose credit constraints on investment and find that credit constrained firms exhibit higher sensitivity than those with free access to capital markets. The sensitivity of credit-constrained firms increases with their available collateral. Similarly, Dasgupta and Sengupta (2002) find that the relation between investment and cash flow is not monotonic using a two-period model with the assumption that investment is not observable by the market. Gomes (2000) and Alti (2003) provide mixed conclusion about the role of financing constraints in finding investment-cash flow sensitivities. Almeida and Campello (2002) and Boyle and Guthrie (2003) show that relatively unconstrained firms overinvest and the magnitude of overinvestment depends on the degree of financial constraints. Pawlina and Renneboog (2005) finds lower investment-cash flow sensitivity for financially unconstrained firms.

The question on whether overinvestment leads to value deterioration has been extensively studied. Several theories attempt to explain the negative investment and stock return relationship, commonly referred to as investment anomaly. The overinvestment-based explanation suggests that the stock market underreacts initially to overinvestment decisions and subsequently corrects itself resulting in lower stock returns. (Titman, Wei and Xie, 2004). The negative association between capital investments and future stock returns is stronger in firms with higher free cash flow and lower leverage. Titman, Wei and Xie (2004) interpret the evidence as investor under-reaction to the overinvestment behavior by managers with empire building incentives. The empire building managers may have an incentive to put the best spin on their investment opportunities as well as on their overall business when they make high capital investments, perhaps to justify their action. If investors fail to recognize the over investment behavior or are fooled by the rosy picture of firm performance, then the subsequent-period stock returns of firms that made excessive investment may deteriorate as overinvestment results in lower than expected performance.

Another explanation is related to stock mispricing. The stock returns are not correctly calculated or captured by the existing stock pricing models. Investors overreact to the good news signaled through increased investment leading to an overvaluation of company (Polk and Sapienza, 2009). Existing literature well documents market misevaluation on accruals (Sloan, 1996). Jensen (2005) and Polk and Sapienza (2009) argue that the managers of overvalued firms or firms with ample cash have incentives to overinvest and underinvest if they perceive undervaluation. Titman, Wei, and Xie (2010) contend that the abnormal investment-return relation cannot be fully explained through the equity misevaluation channel. Even after controlling for equity misevaluation firms with higher *unexpected* capital investment or asset growth subsequently earn significantly lower risk-adjusted returns. They further document that the investment anomaly is confined only to overinvesting firms and not found among underinvesting firms, consistent with the overinvestment explanation in their early research (Titman et al., 2004).

In this paper, we study overinvestment problems of Chinese listed firms and include different ownership variables and ownership concentration measures to investigate the net impact of ownership structure on investment decisions. Since the degree of conflicts of interests between shareholders and managers influences investment decision in response to free cash flows, we expect to observe ownership structure influences investment-free cash flow sensitivity. Our paper also looks into the valuation effects of Chinese overinvesting firm with the testable hypothesis that there is a negative relationship between investment and stock performance, especially for the overinvesting firms.

Samples

Our sample covers the Chinese listed companies for the period of 2003 to 2008. The financial statements and stock trading data are extracted from the well known CSMAR China stock financial statements database and CSMAR China stock market trading database (now part of WRDS) by GTA company. The corporate governance data are obtained from CSMAR shareholding database. Our sample consists of 5,296 firm-year observations after we exclude the finance firms from the sample. We start our sample from 2003 due to the availability of corporate governance data base as Chinese listed companies are required to disclose their ownership composition starting from 2003.

Research Design

We follow Richardson (2006) and use the accounting measures of free cash flow and overinvestment to offer an agency based explanation for why firms overinvest with free cash flows. Free cash flow is defined as cash flows that are beyond that is needed to maintain its current asset needs and to finance new investments. Overinvestment is defined as the investment expenditure beyond the required maintenance of current and new investments. We decompose total investment into required investment to maintain investment currently in place and new investment to keep up with the growth of the firm.

$$I_{TOTAL,t} = CAPEX_t + ACQUISITIONS_t + RD_t - SalePPE_t$$

Where $I_{TOTAL,t,}$ is the total investment, which equals to the sum of all outlays on capital expenditure $CAPEX_t$, acquisitions, $ACQUISITIONS_t$ and research and development, RD_t, less receipts from the sale of property, plant and equipment $SalePPE_t$.

$$I_{MAINTENANCE,t} = DEPRECIATION_t + AMORTIZATION_t$$

$I_{NEW,t} = I_{TOTAL,t} - I_{MAINTENANCE,t}$ [Note: $I_{NEW,t}$ is composed of $I^{*}_{NEW,t}$ and $I^{\varepsilon}_{NEW,t}$]

The proxy for required investment expenditure $I_{MAINTENANCE,t}$ is amortization and depreciation expenses. Amortization and depreciation is an estimate of the portion of total investment expenditure that is necessary to maintain plant, equipment and other operating assets. New investment expenditure, $I_{NEW,t}$, is further decomposed into over-investment in negative net present value projects and expected investment expenditure, where the latter varies with the firm's growth opportunities, financing constraints, industry affiliation and other factors.

Using $I_{NEW,t}$ as dependent variable, we run regression on lagged new investment and other firm characteristics to estimate the fitted value of new investment.

$$I_{NEW,t} = \alpha_0 + \alpha_1 Q_{t-1} + \alpha_2 Leverage_{t-1} + \alpha_3 Cash_{t-1} + \alpha_4 Age_{t-1} + \alpha_5 Size_{t-1} + \alpha_6 StockReturns_{t-1} + \alpha_7 I_{NEW,t-1} + \sum YearDummies + \sum IndustryDummies + I^{\varepsilon}_{NEW,t} \quad (1)$$

To control for firm characteristics, we include the following variables in the analysis.

Q_{t-1}, Tobin's Q is the proxy for growth opportunities, defined as the ratio of the market value of assets to the current replacement cost of those assets for year *t*-1.

$Leverage_{t-1}$, Leverage is the sum of book value of short-term debt and long-term debt divided by the sum of book value of total debt and total equity for year *t*-1.

$Cash_{t-1}$, Cash is calculated by the sum of cash and short-term investment like marketable securities divided by book value of total assets for year *t*-1.

Age_{t-1}, Age is the log of the number of years the firm has been listed on the stock exchange as of the beginning of the year.

$Size_{t-1}$, Size is the log of total assets measured at the beginning of the year.

$Stock\ Returns_{t-1}$, Stock return is the stock returns for the year prior to the investment year or the change in market value of the firm for year *t*-1.

$I_{NEW,t-1}$, is the new investment scaled by average total assets as of year *t*-1.

Year dummies are a vector of indicator variables to capture annual fixed effects.

Industry dummies are a vector of indicator variables to capture industry fixed effects.

The new investment expenditure, $I_{NEW,t}$, is expected to have positive relationship with cash balance, firm size, stock returns, and negative relationship with leverage, firm age, and growth opportunities in the previous year. Firms will reduce new investment when they experience difficulties of raising funds as indicated by shortage of cash, higher leverage, larger firm size and age. The new investment expenditure in the prior year is included to capture other firm characteristics not included in the model. We also include industry dummies to check for industry variables and year dummies to capture the fixed effects. Thus we derive our first hypothesis below.

Hypothesis 1: Investment is positively related to free cash flow.
The expected investment expenditure in new positive NPV projects is denoted by I^*NEW and abnormal (or unexpected) investment is denoted by $I^\varepsilon NEW$. The abnormal component of investment can be negative or positive. Negative (positive) values correspond to under-(over-)investment. The predicted value from the expectation model is I^*NEW and the residual value from the expectation model is $I^\varepsilon NEW$. The residual is my estimate of over-investment.

From above regression (1), we can derive fitted value $I^*_{NEW,t}$ and residuals $I^\varepsilon_{NEW,t}$ and calculate the following variables:

$$CF_{AIP} = CFO - I_{MAINTENANCE} + RD$$

Where CF_{AIP} is cash flow generated from assets in place and CFO is the cash flow from operations. Free cash flow on the other hand is determined by the formula below.

$$FCF = CF_{A/P} - I^*_{NEW} \tag{2}$$

We further examine the relationship between free cash flow and overinvestment using the regression decomposing the samples into sub-samples with positive and negative free cash flows.

$$I^\varepsilon_{NEW,t} = \alpha_0 + \alpha_1 FCF < 0_t + \alpha_2 FCF > 0_t + \varepsilon \tag{3}$$

Where FCF<0 is equal to FCF if that is less than zero and zero otherwise. FCF>0 is equal to FCF if that is greater than zero and zero otherwise. All investment and cash flow variables are scaled by total assets.

I^*_{NEW} and I^ε_{NEW} are the fitted value and residual value from equation (1).

The second focus of the paper is to test whether corporate governance structure of Chinese listed firms mitigates the agency problems associated with overinvestment. Both insider ownership and ownership concentration may have different implications on investment-cash flow sensitivity. If insider ownership works towards interest alignment between managers and shareholders and block holders exert substantial monitoring over corporate decisions, we should observe a decrease in agency cost therefore lower investment- free cash flow sensitivity. However, if managerial entrenchment and expropriation efforts dominate, then managers should overinvest whenever this is increasing free cash flows, thus the sensitivity would be higher.

Hypothesis 2 is as follows:
Chinese listed firms with higher insider ownership and ownership concentration exhibit lower overinvestment-free cash flow sensitivity.

We include the corporate governance variables including stock ownership by insiders, state shareholders, mutual fund shareholders, top 10 largest shareholders and Herfindahl index of top 10 shareholders. We run the regressions with continuous FCF variable as a sole determinant of over-investment and include the governance factors in the following regressions:

$$I^{\varepsilon}_{NEW} = \alpha_0 + \alpha_1 FCF + \sum \varphi GovernanceFactors + \sum \phi GovernanceFactors \; x \; FCF + \varepsilon \qquad (4)$$

Where governance factors are as follows:

- State ownership is the percentage of shares owned by state owners.
- Fund ownership is the percentage of shares owned by mutual fund investors.
- Insider ownership is the percentage of shares owned by executives.
- Top 10 ownership is the percentage of shares owned by top ten controlling shareholders.
- Herfindahl index 10 is the percentage shares owned by top 10 shareholders, percentage of shares owned by top 10 controlling shareholders.
- We expect a significantly positive coefficient for α_1 and negative coefficients for the interacted governance factors that lead to sound governance and positive coefficients for those that increase the agency cost of overinvestment.

The third focus of the paper is to examine whether financial constraints influence the firm's sensitivity of overinvestment to free cash flows. Following Fazzari et al. (1988), we use three financial constraints proxies: asset size, dividend payout ratio, and cash flow to capital. Firms with small asset size, low dividend payout ratios, and low cash flow to capital are considered more financially constrained than firms with large asset, high payout ratio and cash flow to capital ratios. We dropped KZ index and SA index as proxies for financial constraints since the estimated parameters in those indexes may not fit the Chinese listed companies. According to financial constraint hypothesis, firms with financial constraints indicated by high leverage and limited access to external financing should have greater sensitivity of investment to cash flows since leverage could potentially mitigate overinvestment problem as that restricts the free cash flows due to the financial obligations. On the other hand, the negative association should be stronger when firms have greater investment discretion such as greater free cash flows and lower leverage.

Hypothesis 3: Financially constrained firms exhibit greater sensitivity of overinvestment to free cash flows than financially unconstrained firms
We regress overinvestment on free cash flow and financial constraint indicators.

$$I^{\varepsilon}_{NEW} = \alpha_0 + \alpha_1 FCF + \sum \varphi FinancialConstraintFactors + \sum \phi FinancialConstraintFactors \times FCF + \varepsilon \quad (5)$$

The financial constraint factors are dummy variables in which 1 is given if dividend payout ratio is above median in the top 50% percentile and 0 is given otherwise. We do the same for cash flow to capital and size as measures of financial constraints. The interaction variables of financial constraint factors and free cash flows capture the degree of sensitivity of overinvestment to free cash flows for financially constrained firms.

Finally, we examine the valuation effect of overinvesting firms as a result of free cash flow. Since investment in negative net present value projects destroys firm value, we expect to find a negative relationship between firm value and overinvestment. We use Tobin's Q to represent the growth of firm value while controlling for size and firm value in the previous period to see how over investment affects the firm's value. We formulate the hypothesis as follows.

Hypothesis 4: Firm value is negatively related to overinvestment.

$$Q_t\ \alpha_0 + \alpha_1 I^{\varepsilon}_{NEW,t} + \alpha_2 I^{*}_{NEW,t-1} + \alpha_3 \text{Size}_{t-1} + \alpha_4 Q_{t-1} + \varepsilon \quad (6)$$

Empirical results

Free cash flows and overinvestment

This tables reports the descriptive statistics for investment expenditure variables, corporate governance variables and other corporate variables.

Investment expenditures

Table 1
Descriptive Statistics

Variable	*N*	*Mean*	*Std Dev*
CAPEX	5684	0.060	0.063
SalePPE	5389	0.005	0.015
RD	5705	0.000	0.003
SaleACQ	5705	0.002	0.016
Acquisitions	5705	0.002	0.015
Itotal	5379	0.054	0.064
Imaintain	5598	0.028	0.017
Inew	5296	0.026	0.063

Total investment, $I_{TOTAL,t} = CAPEX_t + ACQUISITIONS_t + RD_t - SalePPe_t - SaleACQ_t$

Where, CAPEX is the capital expenditure, ACQUISITIONS is the acquisition expenditures, RD is the research and development expenditures, SalePPE is the cash receipt from sales of property, plant and equipment, and SaleACQ is the cash receipt from sale of acquisitions. Investment required to maintain assets in place, $I_{MAINTENANCE,t} = DEPRECIATION_t + AMORTIZATION_t$ New Investment, $I_{NEW,t} = I_{TOTAL,t} - I_{MAINTENANCE,t}$ All investment expenditure variables are scaled by total assets.

Table 1 is a descriptive summary of investment expenditure variables and governance variables. The average total investment is 0.054 for the sample. The maintenance investment is 0.028 and the new investment is 0.026. All the investment measures are scaled by total assets. As shown in Table 1.2, the Chinese listed companies have an average 28.7% state ownership and 4.91% mutual fund ownership. The insider ownership of Chinese listed companies is minimal at 0.19%. The sample shows an average top 10 controlling shareholders' ownership of 56.86%. Another measure of the ownership concentration is Herfindahl index with an average of 0.1856, that is, the sum of squared ownership percentage shares controlled by each top 10 shareholder.

Table 1.2
Corporate governance variables

Variable	*N*	*Mean*	*Std Dev*
State Ownership	5705	0.286823	0.240417
Institutional Ownership	4260	4.907418	8.291682
Insider Ownership	5705	0.001866	0.024204
Top 10 Ownership	5701	56.85582	14.80911
Herfindahl Index	5701	0.185646	0.127537

State ownership is the percentage of shares owned by state and state agencies; Fund ownership is the percentage of shares owned by mutual funds; Insider Ownership is the percentage of shares owned by insiders; Top 10 ownership is the percentage shares owned by top 10 shareholders. Herfindahl Index is the percentage shares owned by top 10 shareholders, percentage of shares owned by top 10 controlling shareholders.

Control variables

Q: Tobin's Q – a measure of growth opportunities, calculated as (book value of total assets-book value of equity + market value of equity)/book value of total assets; Leverage is calculated as (Short-Term borrowings + Notes Payables + Long-Term Debt)/(Short-Term borrowings + Notes Payables + Long-Term Debt + Book value of Equity); Cash is the balance of cash and marketable securities scaled by total assets; Age is the logarithm of number of listed years; Size is the logarithm of total assets; Stock return is the stock returns for the year prior to the investment year or the change in market value of the firm for t-1. Cash flow or CF is calculated as (Cash Flow from Operations -(Depreciation + Amortization) + RD) scaled by total assets.

Table 1.3
Control variables

Variable	*N*	*Mean*	*Std Dev*
Q	5651	2.104843	1.618719
Leverage	5661	0.357808	0.261922
Cash	5705	0.183413	0.691988
Age	5704	2.182493	0.531626
Size	5726	21.33867	1.076149
Stock Returns	5726	0.544912	1.197289
CF	5598	0.023622	0.077250
Dividend Ratio	5369	0.369087	1.799110
CF/K	5594	0.032088	1.422295

Table 1.3 reports the mean values of control variables in determining corporate overinvestment. The sample firms are relatively young with an average age of 2.18 years since being listed. The average stock return for the year prior to the study period is 38.61% and mean Tobin's Q is 2.10, indicating a growing stock market. The sample firms have an average leverage of 35.78% and cash balance of 18.34%.

Total investment, $I_{TOTAL,t} = CAPEX_t + ACQUISITIONS_t + RD_t - SalePPe_t - SaleACQ_t$

Where, CAPEX is the capital expenditure, ACQUISITIONS is the acquisition expenditures, RD is the research and development expenditures, SalePPE is the cash receipt from sales of property, plant and equipment, and SaleACQ is the cash receipt from sale of acquisitions. Investment required to maintain assets in place, $I_{MAINTENANCE,t} = DEPRECIATION_t + AMORTIZATION_t$ New Investment, $I_{NEW,t} = I_{TOTAL,t} - I_{MAINTENANCE,t}$ All investment expenditure variables are scaled by total assets. State ownership is the percentage of shares owned by state and state agencies; Fund ownership is the percentage of shares owned by mutual funds; Insider Ownership is the percentage of shares owned by insiders; Top 10 ownership is the percentage shares owned by top 10 shareholders. Herfindahl Index is the percentage shares owned by top 10 shareholders, percentage of shares owned by top 10 controlling shareholders. Q: Tobin's Q – a measure of growth opportunities, calculated as (book value of total

Table 2
Comparison of Variables between Overinvesting and Underinvesting Firms

	Underinvesting Firms			*Overinvesting Firms*			*Mean Difference*
Variable	*N*	*Mean*	*Std Dev*	*N*	*Mean*	*Std Dev*	*t-statistics*
CAPEX	3100	0.033685	0.031793	2196	0.0956560	0.0741970	-41.44***
SalePPE	3100	0.007003	0.017782	2196	0.0028290	0.0078330	10.31***
RD	3100	0.000202	0.001501	2196	0.0004690	0.0037670	-3.56***
SaleACQ	3100	0.003299	0.020734	2196	0.0009430	0.0076160	5.09***
Acquisitions	3100	0.000627	0.005470	2196	0.0050690	0.0221620	-10.71***
Itotal	3100	0.024224	0.038054	2196	0.0958840	0.0692810	-48.23***
Imaintain	3100	0.029422	0.017332	2196	0.0263230	0.0150780	6.76***
Inew	3100	-0.005490	0.037494	2196	0.0694550	0.0646140	-53.17***
Q	3071	2.100144	1.669444	2172	2.0833460	1.4785660	0.38
Leverage	3075	0.350218	0.278045	2183	0.3782300	0.2251980	-3.89***
Cash	3100	0.170617	0.200192	2196	0.2019120	1.0819650	-1.57
Age	3098	2.196555	0.513401	2196	2.1998810	0.5320510	-0.23
Size	3100	21.374030	1.050576	2196	21.3683100	1.0795820	0.19
Stock Returns	3100	0.598659	1.253208	2196	0.5830360	1.1522530	0.46
CF	3100	0.017164	0.077685	2196	0.0338050	0.0749600	-7.79***
State Ownership	3093	0.290317	0.238690	2195	0.2832130	0.2384770	1.07
Institutional Ownership	2233	4.266193	7.582164	1710	6.1505070	9.3814420	-6.97***
Insider Ownership	3093	0.001550	0.020881	2195	0.0023410	0.0280180	-1.17
Top 10 Ownership	3095	56.455880	14.952610	2195	56.8568700	14.9212000	-0.96
Herfindahl Index	3095	0.185387	0.127660	2195	0.1849460	0.1284090	0.12
Dividend Ratio	2979	0.350128	1.881418	2077	0.3984460	1.6236510	-0.95
CF/K	3099	-0.000310	1.303199	2195	0.0689910	1.4887570	-1.80*

* significant at 10%; ** significant at 5%; *** significant at 1%

assets-book value of equity + market value of equity)/ book value of total assets; Leverage is calculated as (Short-Term borrowings + Notes Payables + Long-Term Debt)/(Short-Term borrowings + Notes Payables + Long-Term Debt + Book value of Equity); Cash is the balance of cash and marketable securities scaled by total assets; Age is the logarithm of number of listed years; Size is the logarithm of total assets; Stock return is the stock returns for the year prior to the investment year or the change in market value of the firm for t-1. Cash flow or CF is calculated as (Cash Flow from Operations-(Depreciation + Amortization) + RD) scaled by total assets. Dividend ratio is the dividend payout as a percentage of net income. CF/K is the ratio of operating cash flow to net fixed assets.

We break down the sample into overinvesting and underinvesting firms by the residual investment term $I^{\varepsilon}_{NEW,t}$ and compare their different characteristics as in Table 2. The overinvesting firms have significantly higher capital expenditure, research and development expenditure, acquisition expenditures than underinvesting firms. In addition, the total investment and new investment of overinvesting firms are significantly higher at the 1% level while the maintenance investments are significantly lower than underinvesting firms at the 1% level. As expected, overinvesting firms exhibit significantly higher cash flow balance and leverage ratio. However, the cash flow is not derived from the sales of property, plant and equipment or the sales of acquisitions as that is significantly below that of underinvesting firms. Regarding the ownership structure, the overinvesting firms exhibit similar percentage of state and insider ownership as well as top 10 shareholder ownership concentration except for the institutional ownership that is significantly higher compared to underinvesting firms.

Table 3 reports the determinants of new investment expenditures of Chinese listed companies. Consistent with our prediction, the new investment expenditure is positively related to firms' cash balance, size, and previous-year stock returns and new investment level and negatively related to firm leverage and age at the 1% level of significance. This enhances the U.S. evidence that Chinese listed companies will increase their new investment when they have higher cash balance, and good stock performance in the previous years and reduce their new investment when they are older with a high financial leverage. With industry and year dummies added, the results remain significant. However, Tobin's Q as a measure of growth opportunities is not significant in determining the new investment. As a robustness check, we use different measures of growth opportunities to examine the strength of the positive relationship between free cash flows and overinvestment, including market to book ratio, sales growth rate, price to earning ratios in addition to Tobin's Q and derive the same results.

Table 3
Determinants of Investment Expenditures

	Predicted Sign	New Investment (1)	New Investment (2)
Constant		-0.105***	-0.093***
		[0.020]	[0.020]
Qt-1	+	0.001	0.001
		[0.001]	[0.001]
Leveraget-1	–	-0.016***	-0.014***
		[0.003]	[0.003]
Casht-1	+	0.039***	0.043***
		[0.007]	[0.008]
Aget-1	–	-0.012***	-0.011***
		[0.002]	[0.002]
Sizet-1	+	0.007***	0.006***
		[0.001]	[0.001]
Stock Returnst-1	+	0.003***	0.003**
		[0.001]	[0.001]
Inew,t-1	+	0.458***	0.439***
		[0.018]	[0.018]
Year Indicators		No	Yes
Industry Indicators		No	Yes
R-squared		0.3	0.32

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

This table reports the determinants of investment expenditure.

$$I_{NEW,t} = \alpha_0 + \alpha_1 Q_{t-1} + \alpha_2 Leverage_{t-1} + \alpha_3 Cash_{t-1} + \alpha_4 Age_{t-1} + \alpha_5 Size_{t-1} + \alpha_6 StockReturns_{t-1} + \alpha_7 I_{NEW,t-1} + \sum YearDummies + \sum IndustryDummies + I^{\varepsilon}_{NEW,t}$$

New Investment, $I_{NEW,t} = I_{TOTAL,t} - I_{MAINTENANCE,t}$;

Total investment, $I_{TOTAL,t} = CAPEX_t + ACQUISITIONS_t + RD_t - SalePPe_t - SaleACQ_t$

Investment required to maintain assets in place, $I_{MAINTENANCE,t} = DEPRECIATION_t + AMORTIZATION_t$

Where CAPEX is the capital expenditure, ACQUISITIONS is the acquisition expenditures, RD is the research and development expenditures, SalePPE is the cash receipt from sales of property, plant and equipment, and SaleACQ is the cash receipt from sale of acquisitions. Q: Tobin's Q – a measure of growth opportunities, calculated as (book value of total assets-book value of equity + market value of equity)/ book value of total assets; Leverage is calculated as (Short-Term borrowings + Notes Payables + Long-Term Debt)/(Short-Term borrowings + Notes Payables + Long-Term Debt + Book value of Equity); Cash is the balance of cash and marketable securities scaled by total assets; Age is the logarithm of number of listed years; Size is the logarithm of total assets; Stock return is the stock returns for the year prior to the investment year or the change in market value of the firm for t-1. Cash flow or CF is calculated as (Cash Flow from Operations -(Depreciation + Amortization) + RD) scaled by total assets.

Table 4

Relationship between Overinvestment and Free Cash Flow

	Overinvestment	
Constant	0.002 [0.001]	0.002 [0.003]
Positive FCF	0.066*** [0.018]	0.065*** [0.018]
Negative FCF	0.123*** [0.018]	0.107*** [0.018]
Year Indicators	No	Yes
Industry Indicators	No	Yes
R-squared	0.02	0.02

Robust standard errors in brackets
"* significant at 10%; ** significant at 5%; *** significant at 1%"

This table shows the relationship between free cash flow and overinvestment using the regression below

$$I^{\varepsilon}_{NEW,t} = \alpha_0 + \alpha_1 FCF < 0_t + \alpha_2 FCF > 0_t + \varepsilon \cdot$$

Free cash flow is calculated as, $FCF = CF_{AIP} - I^{*}_{NEW}$, and $CF_{AIP} = CFO - I_{MAINTENANCE} + RD$

I^{*}_{NEW} and I^{ε}_{NEW} are the fitted value and residual value from:

$I_{NEW,\,t} = \alpha_0 + \alpha_1 Q_{t\text{-}1} + \alpha_2\, Leverage_{t\text{-}1} + \alpha_3 Cash_{t\text{-}1} + \alpha_4 Age_{t\text{-}1} + \alpha_5 Size_{t\text{-}1} + \alpha_6 StockReturns_{t\text{-}1} + \alpha_7 I_{NEW,t\text{-}1} + \sum YearDummies + \sum IndustryDummies + I^{\varepsilon}_{NEW,t}$

To avoid the potential mechanical relation between free cash flow and overinvestment as indicated in Richardson (2006), we further decompose new investment,, into expected and unexpected investment expenditure. Table 4 explains the sensitivity of the unexpected investment expenditure to the changes in firm's free cash flow. Consistent with the results in Table 3, the coefficients for positive FCF and negative FCF variables are both significantly positive at the 1% level indicating that Chinese listed companies tend to overinvest when free cash flow is positive and underinvest when free cash flow is negative.

Cash Flow Sensitivity of Over-investment with Governance Factors

This table examines the sensitivity of firm's over-investment on firm's free cash flows and how the governance factors influence such sensitivity. The analysis is done by

Overinvestment, $I^{\varepsilon}_{NEW} = \alpha_0 + \alpha_1 FCF + \sum \phi GovernanceFactors + \sum \varphi GovernanceFactors \times FCF + \varepsilon$

Free cash flow is calculated as, $FCF = CF_{AIP} - I^{*}_{NEW}$, and $CF_{AIP} = CFO - I_{MAINTENANCE} + RD$

I^{*}_{NEW} and I^{ε}_{NEW} are the fitted value and residual value from:

$I_{NEW,\,t} = \alpha_0 + \alpha_1 Q_{t\text{-}1} + \alpha_2\, Leverage_{t\text{-}1} + \alpha_3 Cash_{t\text{-}1} + \alpha_4 Age_{t\text{-}1} + \alpha_5 Size_{t\text{-}1} + \alpha_6 StockReturns_{t\text{-}1} + \alpha_7 I_{NEW,t\text{-}1} + \sum YearDummies + \sum IndustryDummies + I^{\varepsilon}_{NEW,t}$

Table 5.1
Without Industry and Year Indicators

	Overinvestment						
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Constant	0	-0.001	-0.002	0	-0.002*	-0.002*	-0.003**
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
FCF	0.095***	0.097***	0.083***	0.095***	0.092***	0.086***	0.084***
	[0.010]	[0.014]	[0.016]	[0.010]	[0.014]	[0.014]	[0.021]
State Ownership		0.002					-0.001
		[0.002]					[0.002]
FCF*State Ownership		-0.006					-0.013
		[0.020]					[0.026]
Institutional Ownership			0.009***				0.008***
			[0.002]				[0.002]
FCF*Institutional Ownership			0.008				0.007
			[0.022]				[0.022]
Top 10 ownership					0.005***		0.003
					[0.002]		[0.002]
FCF*Top 10 ownership					0.006		-0.009
					[0.021]		[0.029]
Herfindahl Index						0.004***	0.002
						[0.002]	[0.002]
FCF*Herfindahl Index						0.018	0.02
						[0.020]	[0.031]
Year Indicators	No	No	No	No	No	No	No
Industry Indicators	No	No	No	No	No	No	No
Observations	5296	5288	3943	5288	5290	5290	3943
R-squared	0.02	0.02	0.03	0.02	0.02	0.02	0.03

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5.2
With Industry and Year Indicators

	Overinvestment						
	(1)		*(2)*		*(3)*		*(4)*
Constant	0.001	0.001	-0.003	0.001	-0.001	-0.001	-0.004
	[0.003]	[0.003]	[0.004]	[0.003]	[0.003]	[0.003]	[0.004]
FCF	0.087***	0.091***	0.080***	0.087***	0.086***	0.082***	0.083***
	[0.011]	[0.014]	[0.016]	[0.011]	[0.014]	[0.014]	[0.021]
State Ownership		0					-0.002
		[0.002]					[0.002]
FCF*State		-0.009					-0.012
Ownership		[0.020]					[0.027]
Institutional			0.009***				0.009***
Ownership			[0.002]				[0.002]
FCF*Institutional			-0.003				-0.003
Ownership			[0.023]				[0.023]
Top 10 ownership					0.004**		0.002
					[0.002]		[0.002]
FCF*Top 10					0.001		-0.004
ownership					[0.021]		[0.029]
Herfindahl Index						0.003*	0.001
						[0.002]	[0.002]
FCF*Herfindahl						0.009	0.012
Index						[0.020]	[0.032]
Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5296	5288	3943	5288	5290	5290	3943
R-squared	0.02	0.02	0.02	0.02	0.02	0.02	0.03

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Corporate governance influence

To examine whether ownership structure has influence on firm's overinvestment according to agency cost explanation, we run regressions on ownership variables individually and also add ownership interaction variables as shown in Table 5. Mutual fund ownership, top 10 shareholder ownership and ownership concentration as measured by Herfindahl index are all found positively related to overinvestment at the 1% level of significance while insider ownership is insignificant. The implication is that the institutional investors of Chinese listed companies do not exert sufficient monitoring over corporate decisions towards reducing the agency costs of free cash flows. Consistent with managerial entrenchment hypothesis, the blockholders of Chinese listed companies do not exert sufficient monitoring on investment decisions instead the firms with high ownership concentration overinvest significantly than the counterpart. It is possible that the state shareholders remain dominating among blockholders and therefore the top 10 largest shareholders are not active shareholders as they are supposed to be as in the western economies. Unfortunately, none of the interaction variables are significant, indicating the firms with different ownership structures do not react differently to free cash flows when making investment decisions.

Financially constrained versus unconstrained Firms

We also examine the different characteristics between financially constrained and unconstrained firms as measured by dividend payout ratio, cash flow to capital ratio, and firm size. The three measures provide similar results as shown in Table 6. The financially constrained firms report significantly lower capital expenditure, total investment, new investment and residual investment than the financially unconstrained firms. But they do generate more cash from the sales of property, plant, and equipment as well as from acquisitions. Consistent with our predictions for financial constrained firms, they are smaller in size carrying higher financial leverage and lower cash balance, cash flow, and dividend ratio at the 1% level of significance. It is reasonable to conclude that the financial constrained firms have scarce resource to make new investment therefore possibly underinvest. Surprisingly, the financially constrained firms exhibit significantly higher stock returns and growth as measured by Tobin's Q at the 1% level of significance. The ownership structures between financially constrained firms and unconstrained firms are vastly different. The financially constrained firms have significantly lower state ownership, institutional ownership and top 10 shareholder concentration at the 1% level, but significantly higher insider ownership at the 10% level.

Characteristics Comparison between Financially Constrained and Financially Unconstrained Firms

Total investment, $I_{TOTAL,t} = CAPEX_t + ACQUISITIONS_t + RD_t - SalePPe_t - SaleACQ_t$

Where, CAPEX is the capital expenditure, ACQUISITIONS is the acquisition expenditures, RD is the research and development expenditures, SalePPE is the cash receipt from sales of property, plant and equipment, and SaleACQ is the cash receipt from sale of acquisitions. Investment required to maintain assets in place, $I_{MAINTENANCE,t} = DEPRECIATION_t + AMORTIZATION_t$ New Investment, $I_{NEW,t} = I_{TOTAL,t} - I_{MAINTENANCE,t}$ All investment expenditure variables are scaled by total assets. State ownership is the percentage of shares owned by state and state agencies; Fund ownership is the percentage of shares owned by mutual funds; Insider Ownership is the percentage of shares owned by insiders; Top 10 ownership is the percentage shares owned by top 10 shareholders. Herfindahl Index is the percentage shares owned by top 10 shareholders, percentage of shares owned by top 10 controlling shareholders. Q: Tobin's Q – a measure of growth opportunities, calculated as (book value of total assets-book value of equity + market value of equity)/ book value of total assets; Leverage is calculated as (Short-Term borrowings + Notes Payables + Long-Term Debt)/(Short-Term borrowings + Notes Payables + Long-Term Debt + Book value of Equity); Cash is the balance of cash and marketable securities scaled by total assets; Age is the logarithm of number of listed years; Size is the logarithm of total assets; Stock return is the stock returns for the year prior to the investment year or the change in market value of the firm for t-1. Cash flow or CF is calculated as (Cash Flow from Operations -(Depreciation + Amortization) + RD) scaled by total assets. Dividend ratio is the dividend payout as a percentage of net income. CF/K is the ratio of operating cash flow to net fixed assets.

Table 6.1

Dividend payout as a measure of level of financial constraint

Variables	*Dividend Ratio*						
	Low			*High*			*Mean Difference*
	N	*Mean*	*Std Dev*	*N*	*Mean*	*Std Dev*	*t-statistics*
CAPEX	2544	0.046756	0.054759	2807	0.06737	0.063127	-12.70***
SalePPE	2419	0.006476	0.017232	2698	0.004369	0.012199	5.09***
RD	2559	0.000339	0.002881	2809	0.000284	0.002492	0.74
SaleACQ	2559	0.003181	0.021588	2809	0.00159	0.010231	3.50***
Acquisitions	2559	0.002604	0.016725	2809	0.002367	0.013977	0.56
Itotal	2412	0.040054	0.059859	2697	0.062982	0.063793	-13.20***
Imaintain	2525	0.028116	0.016421	2780	0.028481	0.016681	-0.8
Inew	2386	0.011678	0.060021	2670	0.034194	0.060606	-13.25***
Ienew	2386	-0.00395	0.051125	2670	0.002836	0.049528	-4.79***
Q	2540	2.258767	1.736558	2803	1.87668	1.39686	8.90***
Leverage	2546	0.382674	0.305727	2793	0.347648	0.218742	4.84***
Cash	2560	0.152882	0.243867	2809	0.195871	0.944926	-2.24**
Age	2560	2.29409	0.38642	2809	2.235569	0.407521	5.39***
Size	2560	21.11211	1.016012	2809	21.54706	1.049678	-15.39***
Stock Returns	2560	0.698444	1.279946	2809	0.535445	1.112751	4.99***
CF	2525	0.010316	0.080952	2780	0.035997	0.071329	-12.28***
State Ownership	2560	0.25813	0.228447	2809	0.313769	0.241681	-8.65***
Institutional Ownership	1600	4.493534	8.393691	2382	5.481738	8.557286	-3.60***
Insider Ownership	2560	0.001621	0.021724	2809	0.000759	0.009649	1.91*
Top 10 Ownership	2560	54.14597	14.60485	2809	57.63649	14.30231	-8.84***
Herfindahl Index	2560	0.166504	0.120493	2809	0.197605	0.129687	-9.08***
Dividend Ratio	2560	-0.44067	1.83728	2809	1.107066	1.403159	-34.86***
CF/K	2521	-0.07667	1.584475	2780	0.113355	1.205296	-4.94***

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6.2

Ratio of cash flow to capital (CF/K) as a measure of level of financial constraint

Variables	*Cash Flow to Capital Ratio*						
	Low			*High*			*Mean Difference*
	N	*Mean*	*Std Dev*	*N*	*Mean*	*Std Dev*	*t-statistics*
CAPEX	2753	0.051657	0.055677	2826	0.067452	0.067336	-9.54***
SalePPE	2606	0.006242	0.016829	2696	0.004301	0.011952	4.85***
RD	2764	0.000216	0.001988	2830	0.000383	0.003121	-2.38**
SaleACQ	2764	0.002541	0.015606	2830	0.001989	0.017034	1.26
Acquisitions	2764	0.001941	0.013165	2830	0.002926	0.016757	-2.44**
Itotal	2600	0.044134	0.059388	2694	0.063477	0.066575	-11.14***
Imaintain	2764	0.028505	0.016832	2830	0.027529	0.01614	2.21**
Inew	2600	0.015361	0.05962	2694	0.035515	0.06374	-11.87***
Ienew	2600	-0.00609	0.049051	2694	0.005906	0.053582	-8.49***
Q	2740	1.991848	1.541077	2800	2.191202	1.645925	-4.65***
Leverage	2752	0.394488	0.281823	2802	0.323342	0.231293	10.29***
Cash	2764	0.14132	0.22297	2830	0.224634	0.954923	-4.47***
Age	2763	2.209851	0.494107	2829	2.168718	0.555188	2.92***
Size	2764	21.25399	1.05161	2830	21.42464	1.076314	-5.99***
Stock Returns	2764	0.522736	1.156298	2830	0.59106	1.244879	2.12**
CF	2764	-0.03143	0.055303	2830	0.077582	0.053408	-75.00***
State Ownership	2762	0.279238	0.233538	2824	0.292873	0.244787	-2.13**
Institutional Ownership	1918	3.083593	5.904606	2260	6.51475	9.65611	-13.56***
Insider Ownership	2762	0.001042	0.014768	2824	0.00274	0.031121	-2.59***
Top 10 Ownership	2763	55.54719	14.46087	2825	57.96531	15.05301	-6.12***
Herfindahl Index	2763	0.17727	0.122076	2825	0.192579	0.131681	-4.5***
Dividend Ratio	2629	0.3128	1.98641	2672	0.422007	1.574885	-2.23**
CF/K	2764	-0.47068	1.565649	2830	0.52313	1.056942	-27.88***

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6.3

Firm Size as a measure of level of financial constraint

Variables	*Firm Size*						
	Small			*Large*			*Mean Difference*
	N	*Mean*	*Std Dev*	*N*	*Mean*	*Std Dev*	*t-statistics*
CAPEX	2592	0.051536	0.058912	3092	0.067159	0.065105	-9.41^{***}
SalePPE	2397	0.006442	0.017315	2992	0.004275	0.011956	5.42^{***}
RD	2608	0.00029	0.002378	3097	0.000308	0.002805	-0.25
SaleACQ	2608	0.00286	0.02105	3097	0.001718	0.01051	2.65^{***}
Acquisitions	2608	0.002219	0.015543	3097	0.002616	0.014741	-0.99
Itotal	2390	0.043533	0.061134	2989	0.062824	0.065335	-11.07^{***}
Imaintain	2551	0.02698	0.015123	3047	0.028924	0.017603	-4.38^{***}
Inew	2347	0.015721	0.060976	2949	0.033437	0.062751	-10.33^{***}
Ienew	2347	-0.00105	0.051971	2949	0.000833	0.051588	-1.31
Q	2567	2.51306	1.950251	3084	1.765059	1.175607	17.77^{***}
Leverage	2600	0.317177	0.298197	3061	0.39232	0.22085	-10.87^{***}
Cash	2609	0.210642	1.005938	3096	0.160466	0.169307	2.73^{***}
Age	2609	2.132113	0.58644	3095	2.224963	0.476564	-6.60^{***}
Size	2617	20.467	0.593345	3109	22.0724	0.811543	-84.04^{***}
Stock Returns	2617	0.41124	1.17784	3109	0.657431	1.202137	-7.79^{***}
CF	2551	0.017736	0.079429	3047	0.02855	0.075036	-5.23^{***}
State Ownership	2609	0.244544	0.234789	3096	0.322452	0.239366	-12.35^{***}
Institutional Ownership	1659	3.48696	7.161126	2601	5.813432	8.821024	-9.01^{***}
Insider Ownership	2609	0.002816	0.031117	3096	0.001066	0.016197	2.72^{***}
Top 10 Ownership	2609	56.50731	13.35805	3092	57.14989	15.92726	-1.63^{*}
Herfindahl Index	2609	0.166485	0.112852	3092	0.201813	0.136668	-10.52^{***}
Dividend Ratio	2425	0.218092	2.084873	2944	0.493463	1.5131	-5.60^{***}
CF/K	2549	0.012407	1.479992	3045	0.048563	1.372161	-0.95

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7 reports the sensitivity of firm's over investment to free cash flows and how financial constraint factors influence such sensitivity. While firms with higher free cash flows are more likely to overinvest as evidenced by the significantly negative sign of free cash flow, the financially constrained firms do react differently from financially unconstrained firms. The significantly positive signs of dividend ratio and cash flow to capital indicate that financially unconstrained firms tend to overinvest, possibly due to their higher cash flow level. Financially constrained firms are more sensitive to free cash flows when making overinvestment decisions as captured by the interaction variables of free cash flows and financial constraint indicators. The explanation could be that financially constrained firms tend to underinvest or resist to overinvestment when they are lack of free cash flows and financially unconstrained firms are more likely to overinvest given their excessive cash flows. Size as a measure of financial constraint is insignificant though.

Table 7 examines the sensitivity of firm's over-investment on firm's free cash flows and how the financial constraint factors influence such sensitivity. The analysis is done by regressing overinvestment on free cash flow and financial constraint indicators.

$$I^{\varepsilon}_{NEW} = \alpha_0 + \alpha_1 FCF + \sum \varphi FinancialConstraintFactors + \sum \phi Financial\text{-}ConstraintFactors \ x \ FCF + \varepsilon$$

Free cash flow is calculated as, $FCF = CF_{AIP} - I^{*}_{NEW}$, and $CF_{AIP} = CFO - I_{MAINTENANCE} + RD$

I^{*}_{NEW} and I^{ε}_{NEW} are the fitted value and residual value from:

$$I_{NEW,\,t} = \alpha_0 + \alpha_1 Q_{t\text{-}1} + \alpha_2\, Leverage_{t\text{-}1} + \alpha_3 Cash_{t\text{-}1} + \alpha_4 Age_{t\text{-}1} + \alpha_5 Size_{t\text{-}1} + \alpha_6 StockReturns_{t\text{-}1} + \alpha_7 I_{NEW,t\text{-}1} + \sum YearDummies + \sum IndustryDummies + I^{\varepsilon}_{NEW,t}$$

Table 7
Cash Flow Sensitivity of Over-investment for Financially Constrained vs. Financially Unconstrained Firms

	Overinvestment							
	(1)	*(2)*	*(3)*	*(2)*	*(1)*	*(2)*	*(3)*	*(4)*
Constant	0	-0.004***	-0.002	-0.001	0.001	-0.003	-0.001	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.003]	[0.003]	[0.003]
FCF	0.095***	0.117***	0.092***	0.099***	0.087***	0.109***	0.076***	0.091***
	[0.010]	[0.016]	[0.018]	[0.016]	[0.011]	[0.016]	[0.019]	[0.016]
Dividend		0.007***				0.007***		
Ratio		[0.001]				[0.001]		
FCF *		-0.055***				-0.058***		
Dividend Ratio		[0.021]				[0.021]		
CF/K			0.005***				0.006***	
			[0.002]				[0.002]	
FCF * CF/K			-0.035				-0.028	
			[0.026]				[0.027]	
Size				0.002				0.002
				[0.002]				[0.002]
FCF' Size				-0.007				-0.008
				[0.021]				[0.021]
Year Indicators	No	No	No	No	Yes	Yes	Yes	Yes
Industry Indicators	No	No	No	No	Yes	Yes	Yes	Yes
R-squared	0.02	0.03	0.02	0.02	0.02	0.02	0.02	0.02

Robust standard errors in brackets, * significant at 10%; ** significant at 5%; *** significant at 1%

Valuation effect of overinvesting firms

Table 8 reports the result using Tobin' Q as the proxy for firm value regressed on the overinvestment and expected investment controlled for size and firm value for the previous year. We find a significantly negative relationship between firm value and overinvestment at the 1% level, consistent with the notion that overinvesting firms destroy value. The finding supports the investment anomaly that more investment leads to lower stock returns.

Table 8
Value Effect of Overinvestment

	Tobin's Q	
	(1)	*(2)*
Constant	4.330***	4.504***
	[0.396]	[0.404]
Ienew	-0.720***	-0.741***
	[0.279]	[0.278]
I*new	-1.725***	-1.779***
	[0.461]	[0.464]
Sizet-1	-0.166***	-0.169***
	[0.018]	[0.018]
Qt-1	0.607***	0.598***
	[0.026]	[0.026]
Year Indicators	No	Yes
Industry Indicators	No	Yes
R-squared	0.56	0.57

Value Effect of Overinvestment

This table reports how the level of overinvestment affects the firm's value as measured by Tobin's Q. $Q_t = \alpha_0 + \alpha_1 I^{\varepsilon}_{NEW,t-1} + \alpha_2 I^{*}_{NEW,t-1} + \alpha_3 Size_{t-1} + \alpha_4 Q_{t-1} + \varepsilon$. Q_t is Tobin's Q at year t. I^{*}_{NEW} and I^{ε}_{NEW} are the fitted value and residual value from:

$$I_{NEW,t} = \alpha_0 + \alpha_1 Q_{t-1} + \alpha_2 Leverage_{t-1} + \alpha_3 Cash_{t-1} + \alpha_4 Age_{t-1} + \alpha_5 Size_{t-1} + \alpha_6 StockReturns_{t-1} + \alpha_7 I_{NEW,t-1} + \sum YearDummies + \sum IndustryDummies + I^{\varepsilon}_{NEW,t}$$

Conclusions

Our findings provide strong support for free cash flow theory of overinvestment. Agency cost of free cash flows appears to be the main source of investment-cash flow sensitivity. The Chinese on the sensitivity of over-investment to free cash flows is consistent with that of the U.S. where over-investment is likely to exist in firms with the highest levels of free cash flows. While the insider ownership of Chinese listed companies is minimal, large block holders and mutual fund investors in China do not exert sufficient monitoring on corporate decisions towards mitigating overinvestment. As expected, the financially unconstrained firms tend to overinvest, possible due to their higher cash flow level, and the financially constrained firms are more sensitive to free cash flows when making overinvestment decisions. The valuation effect of overinvestment supports the U.S. evidence that overinvesting firms destroy value. Future research avenues include examining how ownership structure change over time influences overinvestment and why investment anomaly exists in China.

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Chapter 6
Oil Price Shocks and Business Cycles in Major OECD Economies

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1. Introduction

There exists a broad literature on the macroeconomic effects of oil price fluctuations. Given that crude oil is a basic input to production, the theory normally predicts that supply-side consequences of oil price hikes include a contraction in overall economic activity and inflationary pressures. In addition, aggregate demand is expected to fall in oil importing countries, and go up in oil exporting countries.

Existing empirical work has by and large confirmed the results found in the theoretical literature.[1] The first wave of empirical studies, which were carried out for the US economy, identified a linear negative link between oil prices and real activity. It was eventually found that by the mid-1980s such linear relationship began to lose significance. The reason was that the declines in oil prices occurred over the second half of the 1980s were found to have smaller positive effects on economic activity than predicted by linear models. Four leading non-linear approaches have been developed by Mork (1989), Lee, Ni and Ratti (1995), Hamilton (1996), and Hamilton (2003) with the aim of re-establishing

1. For a recent survey of the literature on the US, see Hamilton (2008). For evidence also on economies outside the US, see Jiménez-Rodríguez and Sánchez (2005) and the references therein

the negative relationship between increases in oil prices and real output developments. Mork's (1989) study found that the real effects of oil price increases are different from those of decreases, with oil price decreases not having a statistically significant impact on US economic activity. Three other non-linear models were later developed in the literature, namely: the scaled specification (Lee, Ni and Ratti, 1995), which takes the volatility of oil prices into account, the net specification (Hamilton, 1996), which considers the amount by which oil prices have gone up over the last year, and a variant of the latter (which we label net3) in which oil price changes are computed over the previous three years (Hamilton, 2003).

Among the theoretical explanations for a non-linear response of real activity to oil prices, the most widely accepted is Lilien's (1982) so-called *dispersion hypothesis* and its variants (see *e.g.* Loungani, 1986; Hamilton, 1988). The idea is that a change in oil prices induces an intersectoral reallocation of resources. A rise in oil prices leads to a contraction in sectors with high oil intensity in production, calling for a transfer of resources to other sectors. Given the short-run costs of reallocation of resources between sectors, oil shocks generate bigger output losses than expected simply from the direct effects. This also leads to a difference between the effect of oil price changes when they go up and when they go down.

The present paper extends the previous literature on oil price impacts by assessing the effects of oil shocks on both economic and inflation in the major developed countries during recession and expansion periods.[2] Specifically, we study the cases of France, Germany, Italy, the US, and the aggregate euro area economy, as well as the only oil exporting country in our sample, the UK.[3] Our aim is to shed light on the role of oil price shocks in business cycle fluctuations among major OECD countries. To do so, we use VAR models, which allow us to identify the exogenous component of oil prices as a driving force behind macroeco-

2. Unlike most studies carried out for OECD countries (see Mork, Olsen and Mysen, 1994; Cuñado and Pérez de Gracia, 2003; Jiménez-Rodríguez and Sánchez, 2005), which have been focused on real output effects of oil price shocks, we as Kilian (2008) carry out a balanced evaluation of oil shocks' effect on both economic activity and inflation.
3. Despite resorting to a wide variety of currently used structural models, we were not able to find a full set of economically meaningful results for Japan on the basis of widely available data sources explored.

nomic developments, and we consider the linear and the four leading non-linear specifications of oil prices described above.[4]

One important feature of our analysis of oil price shocks across different business cycles is that we do not assume that the causality goes only from oil prices to macroeconomic variables.[5] We allow oil prices to influence macroeconomic developments, and viceversa. In addition, the use of an identification strategy within a system of equations permits us to differentiate between the exogenous and the induced components of oil price behaviour. This is needed in order to assess the distinct role of oil price shocks in business cycles.

The rest of the chapter is organised as follows. Section 2 describes the methodology. Section 3 presents the empirical results. Section 4 concludes.

2. Methodology

We start by estimating a reduced form as given by a vector autoregression model of order p, or simply, VAR(p). More specifically, this system can be written as $y_t = Ax_t + \varepsilon_t$, where y_t is an $n \times 1$ vector of endogenous variables, x_t is an $np \times 1$ vector grouping all lagged terms of y_t up to order p, A is an $n \times np$ rectangular matrix, and ε_t is the $n \times 1$ generalisation of a white noise process with variance-covariance matrix Ω. To find the suitable lag length for the VAR, we use the Sims' (1980) modification of the likelihood ratio test.

The vector of endogenous variables used here includes the following set of variables: real GDP, real effective exchange rate (REER), real oil price, real wage, inflation, and real short- and long-term interest rates.

4. Unlike Kilian (2008), who analyses the role of oil shocks on the economy by using a direct measure of exogenous oil supply disruptions in an uniequational model, we perform a race competition between leading (linear and non-linear) specifications of oil prices proposed in the related literature within multivariate VAR models (which allow for interaction between oil prices and various macroeconomic variables). Blanchard and Galí (2009) also consider multivariate VAR models, although their focus is not on a deep examination of such econometric results themselves, but on motivating the development of a (policy-relevant) theoretical framework. On the latter, see also Sánchez (2008).
5. Barsky and Kilian (2004) provide evidence against assuming on a priori grounds the exogeneity of oil prices. We perform below relevant exogeneity tests before investigating the role of oil prices in dated business cycles.

Some variables (real GDP, REER, real oil price and real wage) are expressed in logs, while the remaining ones are simply defined in levels. Oil prices, real GDP and inflation are included since they are the main variables of interest of this study. The remaining variables in the model are added in order to capture the most important transmission channels through which oil prices may affect economic activity indirectly, in part by inducing changes in economic policies. Those channels include a variety of demand- and supply-side effects of oil prices operating via exchange rates, financial variables and the labour market.

Our common effective sample (excluding lags) is quarterly and runs from 1970:3 to 2005:4. Regarding data on individual countries, real GDP data is from IMF's International Financial Statistics (henceforth IFS) for all countries; CPI from OECD's Main Economic Indicators (henceforth MEI); interest rates from IFS except France (from Reuters); wages from MEI; and REER (based on CPI) from MEI except the UK (from Bank of International Settlements - hereafter BIS). Information on the euro area comes from the "synthetic" dataset described in Fagan, Henry and Mestre (2005), except for the REER (from BIS). Finally, we consider two measures of real oil prices. Given that, as we shall see below, the results are broadly robust across these definitions in the present context, we will use as the baseline measure the real oil price given by the ratio of the price of an internationally traded variety of crude (UK Brent) in US dollars to the US Producer Price Index (both from IFS). This measure has the advantage of being common, and thus very easy to compare, across countries. We also use an alternative, "national price" definition that converts US dollar oil prices into domestic currency (relevant bilateral exchange rates from IFS) and then deflates it using the corresponding domestic CPI.[6]

Before studying the effects of oil shocks on economic activity and inflation, we proceed to investigate the stochastic properties of the series considered in the model by analysing their order of integration on the basis of a series of unit root tests. Specifically, we perform the *DFGLS* and P_T tests of Elliott, Rothenberg and Stock (1996), and the $DFGLS_u$

6. Oil prices are used directly in the linear approach to VAR estimation, and are transformed - in ways discussed below - for their use in non-linear specifications. The choice of a readily available Producer Price Index for the denominator of our real oil price measure helps reduce the possibility that the identified oil shock mistakenly captures an inflation uncertainty component. The GDP deflator has the advantage of being more comprehensive, but it is also reported with a longer lag on top of being subject to larger revisions

and Q_T tests of Elliott (1999), as well as the Augmented Dickey-Fuller (ADF) test. Results of these formal tests are summarised in Tables 1.A-1.C for all economies. The vector of endogenous variables considered contains the first log-differences of four variables: real GDP, REER, real oil price (be it deflated by the US PPI or in national prices), and real wage, along with the levels of inflation, and real short- and long-term interest rates. From Tables 1.A-1.C, the growth rates of real GDP, real oil price, REER and the real wage appear to be stationary. The time series evidence for the remaining variables is less clear cut. Barring any model misspecification, we include in the model the levels of real interest rates and inflation as this enhances economic interpretability. Finally, in light of possible non-stationarity of the real interest rate measures, we have estimated another specification using the real interest rate variables in first differences.[7] Due to space constraints, we do not report these results, which are broadly consistent with those reported below using the real interest rate variables in levels.

We identify the VAR model by means of a Cholesky decomposition, which amounts to using exclusion restrictions on the contemporaneous impact of the structural shocks.[8] More specifically, we use the following recursive ordering for the variables in the system: real GDP, real oil price, inflation, real short-term interest rate, real long-term interest rate, real wage, and REER. This ordering presupposes that real GDP growth does not contemporaneously react on impact to the rest of the variables in the system. Oil prices are allowed to be immediately affected by unpredictable output developments, while being modelled as in turn having an immediate impact on wages, inflation, interest rates and the exchange rate.[9] It is worth noting that our focus is exclusively on short-

7. This is also done in Hochreiter, Korinek y Siklos 's (2003) structural VAR study
8. Formally, the structural form of the model can be expressed as $By_t = Cx_t + u_t$, where $u_t \equiv B\varepsilon_t$ is the vector of so-called structural form errors or more simply "shocks", B is an $n \times n$ matrix and $C \equiv BA$ is an $n \times np$ matrix. Under this scheme, B is assumed to be a lower triangular matrix with unit coefficients along the principal diagonal. The triangular factorisation of the positive definite symmetric matrix Ω is given by $\Omega = B^{-1}(B^{-1})'$. Without loss of generality, we assume that the variance-covariance matrix of the structural shocks is equal to the identity matrix.
9. As robustness checks, we have considered two additional orderings used by Jiménez-Rodríguez and Sánchez (2005). The first additional ordering only differs in that real oil prices have a contemporaneous impact on real output. The second additional ordering considered employs the following sequence: real short-term interest rate, real long-term interest rate, real GDP, real wage, REER, real oil price, and inflation. These checks yielded results (not shown) that were similar to those reported in this paper.

Table 1A
Unit-root tests

	Model with constant and trend					*Model with constant*					*Model without constant*	
	ADF	*DFGLS*	*PT*	*DFGLSU*	*QT*	*ADF*	*DFGLS*	*PT*	*DFGLSU*	*QT*	*ADF*	*DFGLS*
Real GDP in Levels												
EA	-2.93	-1.24	22.98	-2.29	7.14	-1.81	1.62	215.4	-0.49	57.98	4.48	4.48
FRA	-3.68**	-0.94	36.56	-2.25	11.66	-2.46	1.70	228.2	-0.82	79.22	3.02	3.02
GER	-2.35	-2.28	5.81*	-2.44	2.93*	-1.07	1.15	129.2	-0.73	59.77	2.48	2.48
ITA	-1.34	-0.37	48.88	-1.31	19.01	-3.29**	1.62	275.2	-1.30	116.1	4.06	4.06
UK	-2.23	-2.28	4.35**	-2.28	2.42**	0.17	1.77	206.5	-0.33	41.36	3.36	3.36
US	-3.71**	-3.73***	2.48***	-3.73***	1.24***	-0.26	2.04	295.4	-0.09	57.68	4.54	4.54
Real GDP in First Log-differences												
EA	-4.94***	-3.24**	4.91**	-4.46***	0.97***	-5.96***	-2.33**	3.24**	-5.81***	1.58***	-1.66*	-1.66*
FRA	-5.54***	-4.74***	2.92***	-5.41***	1.32***	-5.12***	-2.63***	2.67**	-5.09***	1.76***	-2.36**	-2.36**
GER	-4.04**	-2.21	20.3	-3.27**	5.59	-3.99***	-0.91	20.7	-3.70***	5.63*	-2.51**	-2.51**
ITA	-6.59***	-6.41***	0.04***	-6.77***	0.00***	-6.42***	-4.47***	0.79***	-6.43***	0.54***	-1.82*	-1.82*
UK	-4.07***	-2.55	12.30	-3.59**	1.56***	-4.06***	-1.36	10.34	-3.86***	0.82***	-2.25**	-2.25**
US	-5.26***	-4.65***	0.01***	-5.20***	0.23***	-5.28***	-3.50***	0.49***	-5.21***	0.24***	-1.89*	-1.89*
REER in Levels												
EA	-3.02	-2.96**	4.06**	-2.98*	2.25**	-2.60*	-2.61***	1.80***	-2.61*	3.61**	0.09	0.09
FRA	-4.08***	-3.99***	1.05***	-4.06***	0.53***	-2.04	-1.48	4.73	-2.05	4.97*	-0.34	-0.34
GER	-3.57**	-2.99**	4.13**	-3.41**	1.79***	-2.88*	-2.78***	1.26***	-2.88**	2.33***	-0.12	-0.12
ITA	-2.64	-2.01	10.53	-2.43	4.57	-2.72*	-1.35	6.99	-2.62*	5.00*	-0.46	-0.46
UK	-2.85	-2.58*	3.94***	-2.79	1.78***	-1.38	-1.09	7.50	-1.43	10.96	0.56	0.56
US	-2.91	-2.09	8.15	-2.63	3.26*	-3.02**	-1.21	8.28	-2.89***	4.44**	-0.45	-0.45
REER in First Log-differences												
EA	-5.69***	-5.68***	0.00***	-5.68***	0.00***	-5.69***	-5.71***	0.00***	-5.71***	0.00***	-5.71***	-5.71***
FRA	-5.88***	-5.91***	0.02***	-5.89***	0.01***	-4.53***	-4.55***	0.11***	-4.53***	0.20***	-4.52***	-4.52***
GER	-4.87***	-4.55***	0.25***	-4.76***	0.39***	-4.87***	-3.67***	0.17***	-4.89***	0.65***	-4.88***	-4.88***
ITA	-5.74***	-5.77***	1.71***	-5.76***	0.94***	-5.71***	-5.69***	0.48***	-5.73***	0.95***	-5.72***	-5.72***
UK	-4.13***	-4.14***	0.02***	-4.15***	0.01***	-4.12***	-3.88***	0.07***	-4.13***	0.01***	-4.08***	-4.08***
US	-3.90**	-3.86***	4.63**	-3.92***	2.46**	-3.83***	-3.82***	1.28***	-3.85***	2.56***	-3.83***	-3.83***
Real Oil Price in Level												
EA	-1.99	-1.68	16.80	-1.89	8.24	-1.67	-1.60	4.88	-1.68	9.10	-0.88	-0.88
FRA	-2.27	-1.67	18.44	-2.03	8.25	-2.23	-0.94	11.16	-2.21	8.55	-0.77	-0.77
GER	-2.18	-1.65	18.54	-1.97	8.45	-2.14	-0.99	10.47	-2.13	8.64	-1.74*	-1.74*
ITA	-2.27	-1.54	21.88	-1.97	9.42	-2.21	-0.84	13.23	-2.16	9.64	0.51	0.51
UK	-2.06	-1.23	27.99	-1.61	11.11	-1.77	-0.71	14.79	-1.71	10.62	-1.01	-1.01
US	-2.13	-1.21	29.38	-1.62	11.16	-2.60*	-0.51	18.79	-2.52*	10.32	0.67	0.67
Real Oil Price in First Log-differences												
EA	-10.9***	-10.9***	1.27***	-10.9***	0.69***	-10.9***	-10.9***	0.34***	-11.0***	0.70***	-11.0***	-11.0***
FRA	-6.56***	-6.57***	0.01***	-6.59***	0.00***	-6.60***	-6.46***	0.01***	-6.61***	0.00***	-6.58***	-6.58***
GER	-10.9***	-10.9***	1.28***	-10.9***	0.69***	-10.9***	-10.9***	0.34***	-10.9***	0.70***	-10.9***	-10.9***
ITA	-6.46***	-6.45***	0.03***	-6.49***	0.01***	-4.49***	-6.35***	0.02***	-6.50***	0.01***	-6.47***	-6.47***
UK	-6.54***	-6.48***	0.03***	-6.56***	0.00***	-6.57***	-6.22***	0.03***	-6.57***	0.00***	-6.56***	-6.56***
US	-6.52***	-6.43***	0.05***	-6.37***	0.03***	-6.54***	-6.40***	0.02***	-6.50***	0.02***	-6.48***	-6.48***

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Table 1B
Unit-root tests *(continued)*

	Model with constant and trend					*Model with constant*					*Model without constant*	
	ADF	DFGLS	PT	DFGLSU	QT	ADF	DFGLS	PT	DFGLSU	QT	ADF	DFGLS
CPI in Levels												
EA	-1.53	-1.23	6.93	-1.70	5.09	-3.11**	-0.31	14.29	-1.34	24.57	-3.32***	-3.32***
FRA	-2.17	-1.58	3.36***	-2.13	2.94*	-3.34**	-0.63	6.70	-1.85	24.05	0.30	0.30
GER	-2.35	-0.88	20.25	-1.49	8.42	-2.71*	0.58	71.10	-0.56	29.72	1.63	1.63
ITA	-2.58	-1.97	0.30***	-2.70	0.47***	-4.51***	-1.06	0.11***	-2.44	18.21	-0.17	-0.17
UK	-1.61	-0.67	24.46	-1.18	11.95	-3.20**	0.30	55.19	-1.07	37.53	0.69	0.69
US	-1.68	-0.84	28.27	-1.48	12.90	-3.60***	0.45	44.36	-0.98	22.91	1.84	1.84
CPI in First Log-differences												
EA	-3.03	-2.08	12.50	-2.67	4.83	-0.83	-0.82	10.30	-0.87	19.69	-0.82	-0.82
FRA	-2.73	-1.66	18.51	-2.26	7.17	-1.17	-1.20	7.35	-1.20	14.50	-0.97	-0.97
GER	-3.24*	-3.04**	2.57***	-3.23**	0.99***	-2.43	-2.29**	1.90***	-2.46*	3.34**	-1.63*	-1.63*
ITA	-3.85**	-1.45	20.20	-2.43	5.60	-1.21	-1.18	6.78	-1.23	12.04	-0.83	-0.83
UK	-3.88**	-3.04**	2.69***	-3.48**	0.78***	-1.87	-1.71	3.54*	-1.89	5.63	-1.25	-1.25
US	-4.23***	-3.50***	1.10***	-3.94***	0.29***	-2.72*	-2.69***	1.31***	-2.73**	2.40***	-1.05	-1.05
Real Wages in Levels												
EA	-2.88	-0.95	30.88	-1.29	13.35	-2.89**	0.37	106.9	-0.92	54.03	0.79	0.79
FRA	-3.88**	-1.67	15.65	-2.25	7.67	-1.98	0.30	59.44	-0.69	28.92	-2.15**	-2.15**
GER	-1.52	-0.97	16.34	-1.48	5.37	-1.68	0.55	115.5	-0.74	50.02	-2.31**	-2.31**
ITA	-3.45**	-0.79	33.63	-1.19	14.25	-4.09***	0.17	75.64	-1.45	46.13	-4.18***	-4.18***
UK	-2.19	-2.26	4.48**	-2.26	2.52**	-0.66	1.38	159.9	-0.40	51.95	-2.23**	-2.23**
US	-2.93	-2.09	9.34	-2.53	3.57	-1.74	-1.62*	4.03*	-1.75	6.39	-1.47	-1.47
Real Wages in First Log-differences												
EA	-3.02	-1.18	51.04	-2.01	14.22	-2.79*	0.50	130.4	-1.81	36.06	-2.87***	-2.87***
FRA	-1.87	-1.97	31.18	-1.92	17.05	-1.99	-1.35	15.06	-1.99	23.15	-1.92*	-1.92*
GER	-3.09	-2.77*	25.99	-2.94*	12.53	-2.74*	-1.10	18.43	-2.65*	17.39	-2.37**	-2.37**
ITA	-3.26*	-1.38	60.57	-2.27	15.79	-2.51	-0.03	75.99	-2.08	27.05	-2.41**	-2.41**
UK	-3.88**	-3.22**	15.09	-3.40**	5.84	-3.87***	-2.17**	9.94	-3.49***	5.18*	-2.40**	-2.40**
US	-4.34***	-4.35***	0.17***	-4.32***	0.11***	-4.38***	-4.37***	0.04***	-1.31	0.11***	-4.40***	-4.40***
Real Short-term Interest Rate in Levels												
EA	-0.42	-0.96	34.23	-0.93	18.84	-1.48	-1.49	5.06	-1.49	10.19	-1.28	-1.28
FRA	-1.52	-1.47	20.99	-1.55	10.41	-1.53	-1.35	6.42	-1.53	10.51	-1.29	-1.29
GER	-2.13	-2.42	13.09	-2.46	4.78	-2.37	-1.32	9.11	-2.38	4.35*	-1.18	-1.18
ITA	-2.31	-0.88	42.42	-1.66	15.69	-1.06	-0.97	10.66	-1.08	15.61	-0.64	-0.64
UK	-1.59	-1.66	22.39	-1.67	12.36	-1.60	-1.04	12.95	-1.56	16.72	-1.35	-1.35
US	-2.44	-2.49	5.63*	-2.49	3.06*	-2.48	-2.49**	1.56***	-2.49*	3.18***	-2.17**	-2.17**
Real Short-term Interest Rate in First Differences												
EA	-5.89***	-2.41	28.73	-3.56**	3.87	-5.71***	-1.39	18.28	-5.67***	5.95	-5.74***	-5.74***
FRA	-7.65***	-7.47***	0.62***	-7.39***	0.33***	-7.64***	-6.82***	0.00***	-7.58***	0.51***	-7.68***	-7.68***
GER	-7.39***	-4.37***	2.48***	-3.89***	0.79***	-7.10***	-6.00***	6.21	-6.01***	12.15	-7.14***	-7.14***
ITA	-4.94***	-4.32***	0.21***	-4.37***	0.07***	-7.10***	-7.12***	0.04***	-7.12***	0.08***	-7.12***	-7.12***
UK	-7.68***	-2.61*	45.20	-4.90***	0.24***	-7.69***	-1.22	26.89	-6.60***	14.56	-7.71***	-7.71***
US	-4.89***	-3.31***	14.87	-2.83	14.22	-4.90***	-4.75***	0.19***	-4.04***	1.83***	-4.91***	-4.91***

Table 1C
Unit-root tests *(continued)*

	Model with constant and trend					*Model with constant*					*Model without constant*	
	ADF	DFGLS	PT	DFGLSU	QT	ADF	DFGLS	PT	DFGLSU	QT	ADF	DFGLS
Real Long-term Interest Rate in Levels												
EA	-0.87	-1.10	24.90	-1.13	13.76	-1.13	-1.11	8.18	-1.13	15.96	-0.78	-0.78
FRA	-1.80	-1.76	14.34	-1.83	7.54	-1.69	-1.70*	4.19*	-1.70	8.54	-0.98	-0.98
GER	-1.47	-1.83	14.27	-1.79	7.69	-1.57	-1.27	5.75	-1.61	7.87	-0.77	-0.77
ITA	-1.95	-1.45	20.18	-1.83	9.10	-1.11	-1.19	6.66	-1.17	15.57	-0.84	-0.84
UK	-2.81	-2.84*	4.26**	-2.82	2.42**	-2.50	-2.02**	3.27*	-2.49*	3.88**	-1.88*	-1.88*
US	-2.92	-2.98**	2.87***	-2.98*	1.59***	-2.93**	-2.88***	0.91***	-2.94**	1.73***	-1.59	-1.59
Real Long-term Interest Rate in First Differences												
EA	-6.24***	-4.15***	0.80***	-5.03***	0.78***	-6.22***	-2.97***	3.36*	-6.24***	9.81	-6.24***	-6.24***
FRA	-4.20***	-3.81***	10.18	-3.94***	1.93***	-4.15***	-2.60***	16.61	-4.01***	1.46***	-4.17***	-4.17***
GER	-6.34***	-3.07***	26.71	-3.03*	12.36	-6.22***	-1.79*	18.14	-3.82***	4.17	-6.23***	-6.23***
ITA	-7.33***	-7.32***	1.62***	-7.36***	0.88***	-7.26***	-6.67***	0.49***	-7.27***	0.89***	-7.27***	-7.27***
UK	-7.35***	-2.90**	29.74	-5.21***	0.69***	-7.37***	-1.48	18.06	-6.66***	2.61***	-7.40***	-7.40***
US	-4.88***	-3.82***	3.25***	-3.35**	4.49	-4.89***	-4.91***	0.26***	-4.28***	0.31***	-4.91***	-4.91***

The sample is 1970:1-2005:4 for the variables in levels, and starts one quarter later for the variables in first differences. We use data-driven lag selection procedures for the Augmented Dickey-Fuller tests, taking 1.645 as the critical value used for significance of lagged terms and 8 as the maximum number of lags allowed in these procedures into account. The same number of lags is used in the other tests considered. We denote with one/two/three asterisks the rejection of the null hypothesis at the 10%/5%/1% significance levels.

Critical levels used for ADF test are the following:
- In the model with constant and trend: -4.05 (1%), -3.45 (5%) and -3.15 (10%).
- In the model with constant: -3.50 (1%), -2.89 (5%) and –2.58 (10%).
- In the model without constant: -2.59 (1%), -1.94 (5%) and –1.62 (10%).

Critical levels used for DFGLS test are the following:
- In the model with constant and trend: -3.48 (1%), -2.89 (5%) and –2.57 (10%).
- In the model with constant: -2.58 (1%), -1.95 (5%) and –1.62 (10%).
- In the model without constant: -2.58 (1%), -1.95 (5%) and –1.62 (10%).

Critical levels used for PT test are the following:
- In the model with constant and trend: 3.96 (1%), 5.62 (5%) and 6.89 (10%).
- In the model with constant: 1.99 (1%), 3.26 (5%) and 4.48 (10%).

Critical levels used for DFGLSu test are the following:
- In the model with constant and trend: -3.71 (1%), -3.17 (5%) and –2.91 (10%).
- In the model with constant: -3.28 (1%), -2.73 (5%) and –2.46 (10%).

Critical levels used for QT test are the following:
- In the model with constant and trend: 2.05 (1%), 2.85 (5%) and 3.44 (10%).
- In the model with constant: 3.06 (1%), 4.65 (5%) and 5.94 (10%).

run dynamics, neglecting the long-run considerations dealt with by the branch of the literature stretching back to Rasche and Tatom (1977, 1981), and more recently analysed by Carruth, Hooker and Oswald (1998), Hooker (2002) and Cologni and Manera (2008).

VAR models are estimated for both a linear specification and the four leading non-linear approaches in the literature. The latter are the following: i) Mork's (1989) asymmetric model; ii) Lee, Ni and Ratti's (1995) scaled model; iii) Hamilton's (1996) net oil model; and iv) Hamilton's (2003) net3 oil model. The asymmetric specification allocates positive realisations of the rate of change in the oil price to variable o_t^+, and the corresponding negative realisations to o_t^-. In the scaled approach, the relevant oil variable - standing for "scaled oil price increases" - is, $SOPI_t \equiv max\,(0, \hat{e}_t/\sqrt{\hat{h}_t})$ where $\hat{e}_t$ and $\hat{h}_t$ are, respectively, the estimates of the error and the conditional variance of oil prices from a AR(4)-GARCH(1,1) representation. The net oil model uses the "net oil price increase" variable, defined as the amount by which oil prices (in logs), p_t, exceed - if at all - the maximum value over the previous 4 periods (quarters); that is, $\text{NOPI}_t \equiv \max\{0, p_t - \max\{p_{t-1}, p_{t-2}, p_{t-3}, p_{t-4}\}\}$. Finally, the net3 specification considers the amount by which oil prices have gone up over the last 12 quarters, that is, three years. We label the corresponding oil price increase variable NOPI3_t.[10] In order to make the scaled, net and net3 specifications comparable to the remaining two models considered, the impulse responses to unit oil shocks are scaled down by the sample mean of the standard deviation $\sqrt{\hat{h}_t}$ (in the case of the scaled model) and the average effective number of quarters over which NOPI_t and NOPI3_t are calculated (for the net and net3 approaches, respectively).

3. Empirical results

This section reports all the empirical results of this paper. Subsection 3.1 reports a number of preliminary tests for significance, block exo-

10. We similarly construct scaled, net and net3 oil price decrease variables, that is, SOPD_t, NOPD_t and NOPD3_t, respectively. As we show in the next section, neither of the three are however found to have statistically significant macroeconomic effects in most of the cases.

geneity and model selection. Subsection 3.2 describes our results for accumulated responses of real GDP growth and inflation to oil price shocks. Subsection 3.3 describes our results for the corresponding variance decompositions. In subsections 3.2 and 3.3, we discuss impulse response and variance decomposition results with a focus on the preferred model, which turns out to be the scaled model in all countries. Subsection 3.2 reports results for the linear model (in which the real oil price is deflated by the US PPI) and two versions of the scaled model, which differ in the way oil prices are deflated: the baseline specification deflates oil prices by the US PPI while the alternative variant expresses real oil prices in terms of national prices. In subsection 3.3, we concentrate purely on results for the baseline and alternative specifications of the scaled model. Moreover, subsection 3.2 explores in some more detail a number of factors that could be responsible for our impulse response results, with an emphasis on those for which some concrete measure is more easily available, such as oil intensity and the degree of rigidity of product and labour markets. Finally, subsection 3.4 reports historical decompositions which are analysed with a focus on the impact of oil shocks across dated business cycles.

3.1. Testing for significance, exogeneity and model selection

In this subsection we start by investigating the significance of the relationship between oil prices and the other variables of the model.[11] We carry out two different types of tests for both linear and non-linear specifications for all economies. First, we test for the significance of the oil price variables under consideration for the VAR system as a whole, using the null hypothesis that all of the oil price coefficients are jointly zero in all equations of the system but its own equation (see Table 2). The likelihood ratio test is informative in that oil prices, in addition to their direct effect on real GDP and inflation, could well impact the latter two variables through the rest of the system. We find that the oil price variable in the linear model, as well as the positive changes in the asymmetric, scaled, net and net3 models, are all significant at the 5% significance level for the system in all of the economies, with the only exception of all five US

11. The tests reported in this subsection correspond to the baseline specification. These results are found to be broadly similar to those obtained for the alternative specification.

models. Moreover, the negative changes in the asymmetric, scaled, net and net3 models are not significant in most economies. These negative changes are only significant in the cases of the net and net3 specifications for France, and the net3 model for the euro area. The price decrease variable is subsequently eliminated from those asymmetric, scaled, net and net3 specifications in which it is not significant.

Our second group of significance tests consists of so-called tests of block exogeneity, which constitute multivariate Granger causality-type tests. We first test the null hypothesis that the oil price variable under consideration is not Granger-caused by the remaining variables of the system (see Table 3, line 1 for each country). We generally reject the null hypothesis at the 5% significance level. The exceptions to this are given by the linear models in all economies other than those for Germany, the UK and the US, as well as the asymmetric and scaled models for France. In addition, we test for whether a given oil price variable Granger-causes the remaining variables of the system (see Table 3, line 2 for each country), obtaining that we can reject the hypothesis that oil price variables do not Granger-cause the remaining variables of the system at the 5% significance level. The exceptions to this are all models for the US.[12] In sum, the block exogeneity tests show that the interaction between oil prices and macroeconomic variables is generally significant, with the direction of causality going in at least one direction in all economies and in both directions in most economies.

12. Even though the null hypothesis that oil prices do not Granger-cause other variables cannot be rejected by this particular test, we later in the paper provide evidence that oil shocks affect the US economy, which provides a more conclusive finding than the present Granger-causality tests.

Table 2
Likelihood ratio test

	Linear	*Asymmetric*		*Scaled*		*Net*		*Net3*	
	ot	*ot+*	*ot-*	*SOPIt*	*SOPDt*	*NOPIt*	*NOPDt*	*NOPI3t*	*NOPD3t*
Economies									
EA	0.00181***	0.00039***	0.11945	0.00010***	0.11866	0.00790***	0.50558	0.00046***	0.04397**
FRA	0.01771**	1.45E-06***	0.31072	5.18E-05***	0.50152	0.00147***	0.02791**	0.00018***	0.00182***
GER	1.42E-06***	1.57E-07***	0.56320	2.09E-06***	0.38442	2.95E-06***	0.42976	1.44E-06***	0.11297
ITA	6.85E-05***	1.50E-06***	0.55502	1.35E-06***	0.17589	2.81E-05***	0.67194	4.66E-07***	0.13034
UK	6.59E-11***	4.32E-10***	0.15710	4.75E-11***	0.18800	3.01E-12***	0.39915	1.28E-13***	0.32206
US	0.14189	0.05656*	0.93226	0.06222*	0.08132*	0.36160	0.13795	0.11537	0.10624

The entries are the p-values of the test statistics for the null hypothesis that all oil price coefficients are jointly zero in all equations of the system but its own equation (*i.e.* $D_2 = 0$ below). One/two/three asterisks denote a *p*-value from the asymptotic distribution below 10%/5%/1%.

The test statistic is constructed as follows. Let the *p*-th order VAR model be rewritten as follows:

$$y_{1t} = k_1 + D_1' x_{1t} + D_2' x_{2t} + \varepsilon_{1t}$$
$$o_t = k_2 + C_1' x_{1t} + C_2' x_{2t} + \varepsilon_{2t}$$

where y_{1t} is the vector of variables other than o_t, x_{1t} contains lags of y_{1t}, o_t represents the real oil price change, and x_{2t} contains lags of o_t.

The statistic for testing the null hypothesis $D_2 = 0$ is as follows:

$$2 \times [L(\theta_1) - L(\theta_2)] \overset{a}{\sim} \chi^2(rows(y_{1t}) \times p)$$

where $L(\theta_1)$ and $L(\theta_2)$ denote the value of the log likelihood function of the unrestricted and restricted models, respectively.

Table 3
Block-exogeneity test

		Linear	*Asymmetric*	*Scaled*	*Net*	*Net3*
	y_{1t} / *Null Hypotheses*	o_t	o_t^+	$SOPI_t$	$NOPI_t^a$	$NOPI3_t^a$
EA	$A_2 = 0$	0.05743*	0.00555***	0.00241***	0.00363***	0.01637**
	$B_1 = 0$	0.00243***	0.00079***	0.00058***	0.00256***	1.72E-05***
FRA	$A_2 = 0$	0.10866	0.08052*	0.05989*	0.01725**	0.01607**
	$B_1 = 0$	0.03243**	0.00359***	0.00243***	0.00029***	3.26E-06***
GER	$A_2 = 0$	1.86E-06***	4.86E-11***	7.37E-12***	2.78E-12***	1.51E-12***
	$B_1 = 0$	3.86E-06***	3.30E-08***	1.80E-07***	2.13E-07***	6.92E-07***
ITA	$A_2 = 0$	0.07864*	0.03619**	0.03098**	0.00956***	0.00416***
	$B_1 = 0$	8.38E-05***	5.43E-07***	4.77E-07***	1.22E-05***	2.35E-07***
UK	$A_2 = 0$	0.00117***	1.56E-06***	2.86E-06***	8.48E-20***	1.13E-08***
	$B_1 = 0$	2.16E-08***	3.76E-10***	3.26E-12***	1.20E-12***	6.06E-21***
US	$A_2 = 0$	0.00229***	0.00010***	4.64E-05***	1.06E-05***	4.28E-05***
	$B_1 = 0$	0.20491	0.23213	0.30427	0.39842	0.07886*

The entries are the p-values of the test statistics for the null hypotheses that $A_2 = 0$ and $B_1 = 0$. One/two/three asterisks denote a *p*-value from the asymptotic distribution below 10%/5%/1%.

The test statistic is constructed as follows. We categorise the variables of the VAR in two groups, as represented by the $(n_1 \times 1)$ vector y_{1t} and the $(n_2 \times 1)$ vector y_{2t}. We rewrite the *p*th-order VAR as follows:

$$y_{1t} = c_1 + A_1' x_{1t} + A_2' x_{2t} + \varepsilon_{1t} \qquad (1)$$

$$y_{2t} = c_2 + B_1' x_{1t} + B_2' x_{2t} + \varepsilon_2 \qquad (2)$$

where x_{1t} is an $(n_1 p \times 1)$ vector containing lags of y_{1t}, and x_{2t} is an $(n_2 p \times 1)$ vector containing lags of y_{2t}.

y_1 (y_2) is block-exogenous in the time series sense with respect to y_2 (y_1) when $A_2 = 0$ $(B_1 = 0)$ (See Hamilton, 1994).

The statistic for testing the null hypothesis $A_2 = 0$ is the following:

$$T \times \{\log |\Omega^*_{11}(0)| - \log |\Omega^*_{11}|\} \overset{a}{\sim} \chi^2(n_1 n_2 p)$$

where Ω^*_{11} is the variance-covariance matrix of the residuals from OLS estimation of *(1)* and $\Omega^*_{11}(0)$ that of the residuals from OLS estimation of *(1)* when $A_2 = 0$.

The test statistic for H_0: $B_1 = 0$ is derived analogously.

[a] We use both positive and negative oil price changes for the net and net3 specifications for France, and the net3 specification for the euro area, all of which are statistically significant.

For model selection purposes, we look at two selection criteria as given by the Akaike information criterion (AIC) and Schwarz Bayesian information criterion (BIC). Table 4 reports the AIC and BIC obtained from each econometric specification.[13] On the basis of these two criteria, we conclude that the scaled model turns out to be the best-performing in all economies.[14] This result suggests that it is important to consider not just whether oil prices increase or decline (and by how much), but also the environment in which the movements take place. An oil shock in a stable price environment is likely to have larger economic consequences than one in a volatile price environment. In this regard, the scaled model more specifically highlights the importance of controlling for the time-varying conditional variability of oil price shocks. The latter result is in conformity with that of Hamilton (2003), who points out that "the transformation proposed by Lee, Ni and Ratti (1995) seems to do the best job of the measures explored in this paper". In subsections 3.2 through 3.4, we describe the main results of the paper for the same economies analysed in the present subsection, concentrating on the preferred, scaled specifications in all cases.

3.2. Accumulated response functions

This subsection contains a discussion of the impact of oil price shocks on real GDP and inflation with a focus on the scaled model. Table 5 reports accumulated responses of real GDP growth and inflation to a 100% oil price shock for three specifications. The first specification corresponds to the linear model (panel A in Table 5), which we report for comparison purposes, while the remaining two are the baseline and alternative versions of the scaled model. As described above, in our baseline scaled model the vector of endogenous variables consists of the growth rates of three variables (real GDP, REER, and real wage), the SOPI variable, along with the levels of inflation, and real short- and long-term interest rates. The alternative scaled model differs from the previous one in that the real oil price is measured in national prices, as opposed to being deflated by US PPI.

13. On the basis of the Sims' (1980) modification of likelihood ratio test, the optimal lag length was found to be four for all models in all economies with the following exceptions: all specifications but the scaled one in Germany (the optimal lag is five) and all UK models (the optimal lag is eight).
14. The same result is obtained when we consider real oil prices in terms of national prices.

Table 4
Relative performance of the models

		Linear	*Asymmetric*	*Scaled*	*Net*	*Net3*
Economies						
EA	AIC	12.758	12.213	11.188	12.077	17.875
	BIC	17.064	16.519	15.494	16.383	23.475
FRA	AIC	13.943	13.363	12.349	19.529	18.816
	BIC	18.249	17.669	16.655	25.129	24.416
GER	AIC	15.122	14.456	13.542	14.285	14.225
	BIC	20.493	19.828	17.848	19.656	19.596
ITA	AIC	18.764	18.122	17.105	17.987	17.813
	BIC	23.069	22.428	21.411	22.293	22.119
UK	AIC	19.793	18.979	17.876	18.503	18.152
	BIC	28.422	27.608	26.505	27.133	26.780
US	AIC	14.787	14.243	13.257	14.088	13.965
	BIC	19.093	18.549	17.563	18.394	18.271

The results are based on a seven-variable VAR that excludes oil price decrease variables from all four non-linear models, namely, the asymmetric, scaled, net and net3 specifications, with the following exceptions: the euro area net3 model, and the French net and net3 models, in all of which oil price decrease variables are found to be statistically significant.

Table 5
Accumulated responses: Linear and scaled models

A) *Linear model, real oil prices deflated by US PPI*						
	Real GDP growth			*Inflation*		
Economies	*after 1 year*	*after 2 years*	*after 3 years*	*after 1 year*	*after 2 years*	*after 3 years*
EA	-0.2	-1.0	-0.6	1.8	1.7	1.7
FRA	-0.9	-1.9	-1.4	2.7	3.2	3.6
GER	-0.1	-0.5	-0.4	1.2	1.6	1.3
ITA	-0.7	-1.7	-0.9	3.7	4.0	5.0
UK	-0.4	-2.7	-3.4	2.0	3.7	3.9
US	-1.3	-2.9	-3.0	3.1	4.2	4.7

Table 5

Accumulated responses: Linear and scaled models (*continued*)

B) *Scaled model, real oil prices deflated by US PPI (baseline model)*						
	Real GDP growth			*Inflation*		
Economies	*after 1 year*	*after 2 years*	*after 3 years*	*after 1 year*	*after 2 years*	*after 3 years*
EA	-1.2	-2.1	-0.9	2.1	1.2	0.8
FRA	-1.8	-3.1	-2.2	3.8	4.5	5.1
GER	-1.8	-2.9	-1.6	1.1	1.1	0.4
ITA	-2.3	-4.1	-2.6	6.0	5.5	6.4
UK	0.1	-1.3	-1.3	3.2	5.6	5.5
US	-2.3	-3.7	-3.5	3.4	4.0	4.2
C) *Scaled model, real oil prices in national prices (alternative model)*						
	Real GDP growth			*Inflation*		
Economies	*after 1 year*	*after 2 years*	*after 3 years*	*after 1 year*	*after 2 years*	*after 3 years*
EA	-1.0	-2.1	-1.0	2.1	1.1	0.7
FRA	-1.7	-3.0	-2.2	3.1	3.4	3.7
GER	-1.6	-2.9	-2.0	1.4	1.3	0.7
ITA	-2.0	-3.4	-2.2	6.0	5.7	7.0
UK	0.2	-1.2	-1.1	3.0	5.1	4.8
US	-2.3	-3.7	-3.5	3.4	4.0	4.2

The entries refer to the accumulated responses attributed to a 100% oil price shock (in percentage). They can be interpreted as cumulated growth rates measuring the percentage difference in the level of the variable with and without the shock.

The accumulated responses of real GDP growth to a 100% oil price shock indicate that the overall pattern is similar, although there also are interesting country- and model-specific features. For net oil importing economies, a qualitatively robust feature of the two scaled models discussed here is that unexpected hikes in oil prices reduce real output and increase inflation, in line with the theoretical predictions. In the case of oil producer UK, the same results are obtained with the exception the first year, where real GDP growth expands slightly. The finding that UK economic activity eventually falls after an increase in oil prices is consistent with what was reported in Jiménez-Rodríguez and Sánchez (2005), who attribute such result to a Dutch disease-type effect.

The macroeconomic impacts of oil price shocks are found to gain momentum over time in some cases, while in others they peak at a certain time horizon, thereafter decreasing in intensity. A decaying pattern may be justified in terms of the gradual unwinding of the oil price hike. Moreover, it could well be that the increase in oil prices consists of a level effect whose magnitude is over time eroded by substitution effects. The latter include substitution of other inputs for oil in production as well as substitution of other types of goods for oil-related products in consumption. Yet another plausible explanation concerns expectational and confidence channels in which economic agents initially believe that oil price shocks will have a stronger macroeconomic impact than is later assessed to be the case.[15]

The comparison between the linear and scaled models shows that the latter approach tends to yield larger impacts of oil shocks on both real GDP and inflation, and in some cases considerably so. For the baseline version of the scaled model, after the second year the adverse real GDP impact is in the range of 1.3% to 4.1%, broadly in line with results for the alternative version of the scaled model. In contrast, also after two years, the fall in real GDP growth induced by the oil shock in the linear model ranges from 0.5% to 2.9%. With regard to inflation, it is raised by the oil price shock by 1.1% to 5.6% after two years under the baseline model. This range again aligns well with that obtained for our alternative specification.

The results in the previous paragraph imply that the preferred non-linear model yields larger effects of oil prices on real GDP growth and inflation. As described in the Introduction, empirical studies have previously uncovered similar effects for the case of real output. In this case, the theoretical literature has also produced rationalisations for non-linear effects of oil shocks, as in the work of Lilien's (1982) dispersion hypothesis and its later extensions. The finding of a non-linear link between oil price shocks and inflation is instead new. The amplification of both the negative effects on real activity and the inflationary effects - as found in this study - is consistent with a relative stability of nominal GDP. This overall result is however at odds with standard macroeconomic channels predicting a positive link between real output and prices. Such channels may involve aggregate demand effects on overall prices and the Phillips curve featuring a tradeoff between real output and in-

15. Overreactions of this type could affect both pricing and output decisions. This behaviour could in turn arise either because agents initially evaluate that oil price increases would be overly persistent, or because the shock is in the beginning expected to propagate too quickly or intensely across the economy.

flation. Further investigation may thus be needed to better understand this feature of the data from the standpoint of macroeconomic theory.

Taking a closer look, we note that there are also country-specific reactions to oil price shocks. With regard to the latter's adverse real impact in the baseline model, it is largest in the cases of Italy and the US. Moreover, as mentioned above, the UK's real GDP growth response is positive within the first year, then turning negative. These developments for the UK are in line with its status as an important oil producer, coupled with the eventual adverse Dutch disease-type effects previously documented by *e.g.* Jiménez-Rodríguez and Sánchez (2005). Among net oil importing economies, the euro area (and its largest countries other than Italy) appears to exhibit less of an adverse real impact of the oil shock. These results are broadly confirmed for the alternative version of the scaled model. Turning to inflation, after two years the two versions of the scaled model produce relatively small inflationary effects of oil shocks for Germany and the euro area, but relatively large ones for Italy, France, the US and the UK.

The impact of oil prices on euro area real GDP appears to be smaller than that of each of the grouping's three largest economies. In the case of inflation, the euro area is affected somewhat more intensely than Germany, but the former economy's response lies considerably below those of France and Italy. Among the possible explanations for these results, there is of course a possibility that the euro area model is misspecified, not least - as sometimes mentioned in the literature - in light of the fact that the euro area is a "synthetic" construct, and not a real entity, for most of the sample used here. However, it is also possible to rationalise the results in ways that do not involve model misspecification. For instance, as we shall see in subsection 3.4 for the three largest euro countries historical decompositions of individual member countries do not exactly coincide, and for most of the sample they appear to display different types of cross-country patterns. In this context, the euro area behaviour could fail to respond to shocks in a way that simply amounts to adding up the individual countries' reactions, as the latter may in different periods partly offset rather than compound each other.

In the rest of this subsection, we evaluate in some detail a number of factors that could help explain our impulse response results, with a focus on the effect of oil shocks on real GDP growth. In doing so, we concentrate on some structural features for which some concrete measure is easily available, such as oil intensity and the degree of rigidity of product and labour markets.

Looking at product and labour market rigidities can be deemed especially appropriate in light of the empirical superiority demonstrated by the scaled model. The reason is that structural rigidities should magnify the inter-sectoral adjustment costs in reaction to shocks (such as oil price disturbances), with such costs being a key ingredient to the dispersion hypothesis normally used to justify larger real output fluctuations as entailed by the scaled specification.[16]

Regarding product market rigidity indicators, OECD data for a relatively long period are available for the manufacturing sector. Figure 1 shows that the degree of product market flexibility is highest in the UK and the US, with the former country overtaking the latter during the first half of the 1990s. The euro area appears to be the most rigid economy concerning product markets. Among the three largest euro area economies, Germany appears to exhibit more rigid product markets than France or Italy. Turning to labour markets, the OECD reports information on employment legislation protection, which is available only since 1990. Table 6 shows that, according to this indicator, the euro area appears to also display the most rigid economy as far as its labour market is concerned. The UK and especially the US would exhibit the most flexible labour markets among the advanced economies analysed here. Among euro area countries, German and Italian labour markets have improved in flexibility since the beginning of the 1990s to overtake France since the end of that decade. Information obtained from the Fraser Institute permit us to double-check the OECD measures of product and labour market rigidities by means of the former institution's data on labour market and business regulations, respectively. As can be seen in Table 7, information from the Fraser Institute broadly corroborates that, overall, the euro area is a more rigid economy than the UK and US. Naturally, a number

16. The inter-sectoral adjustments highlighted by the dispersion hypothesis may help account for the higher inflationary effects of oil price shocks. The linear model, by not capturing such adjustments, should also miss out to deal with relevant relative price movements. Non-linear methods which are better suited to take sectoral adjustments into account could also implicitly allow for stronger inflationary pressures as arising from propagation mechanisms associated with relative price fluctuations. The presence of non-linear effects on inflation could also be partly rationalised in terms of the evidence of a stronger impact of oil price increases than of oil price decreases on gasoline prices (see Borenstein and Cameron, 1997; Huntington, 1998; Balke, Brown, and Yücel, 2002).

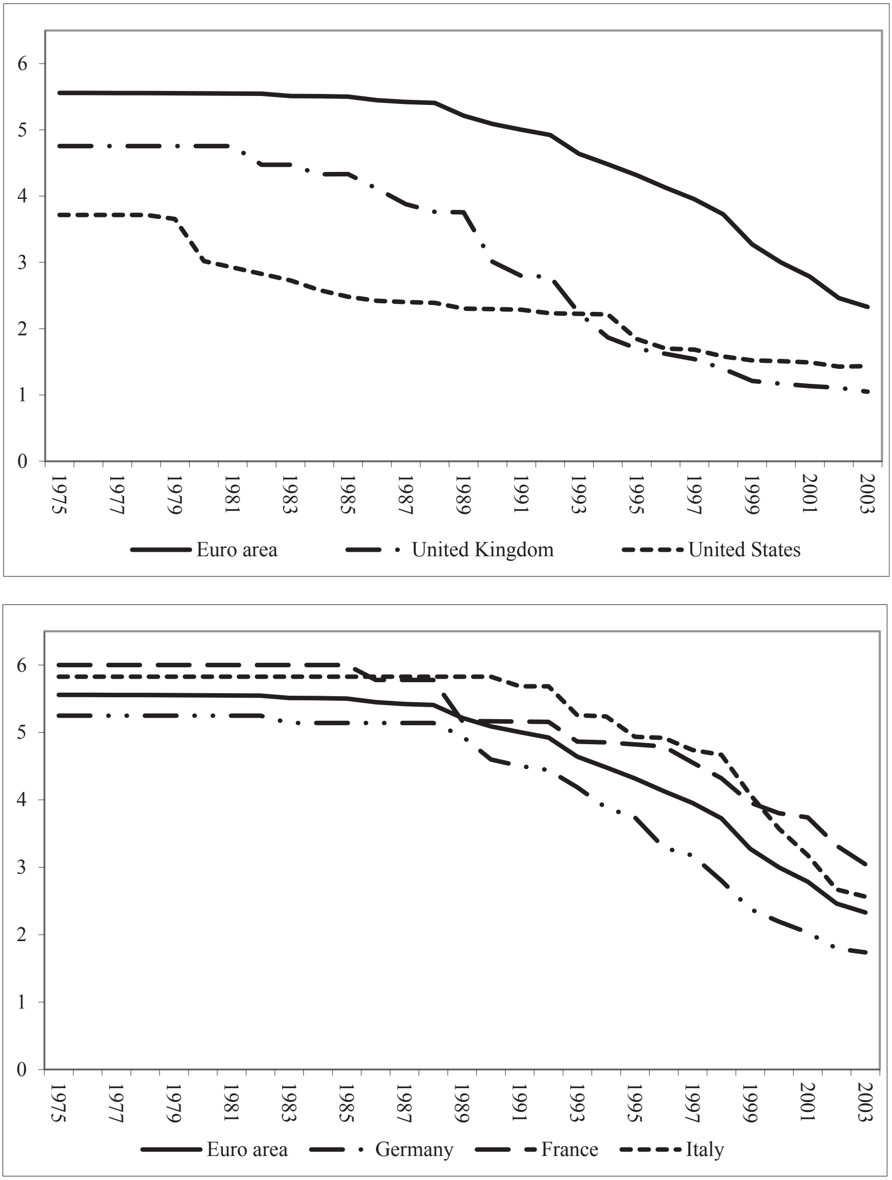
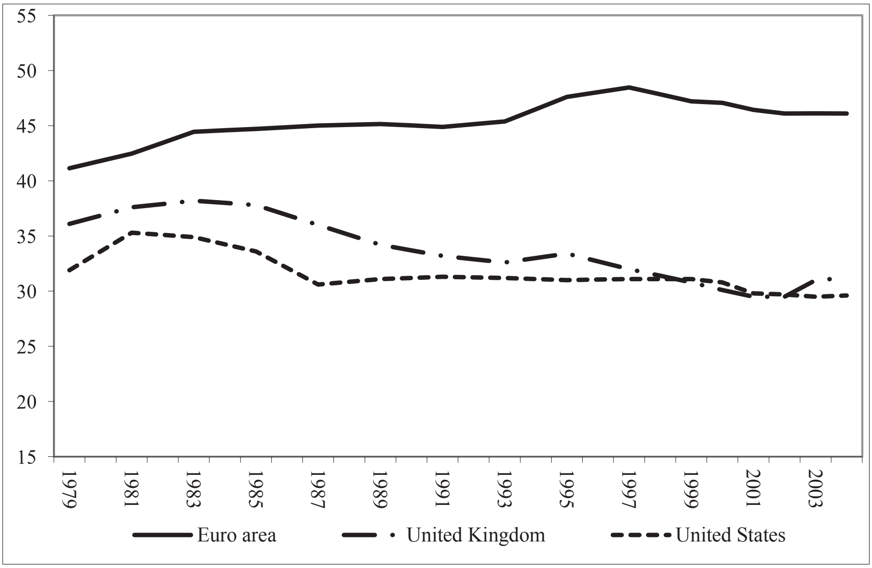


Figure 1. Index of product market regulation in the manufacturing sector
Scale 0-6 from least to most restrictive.
Source: OECD.
Note: The euro area data excludes Luxembourg and Slovenia.



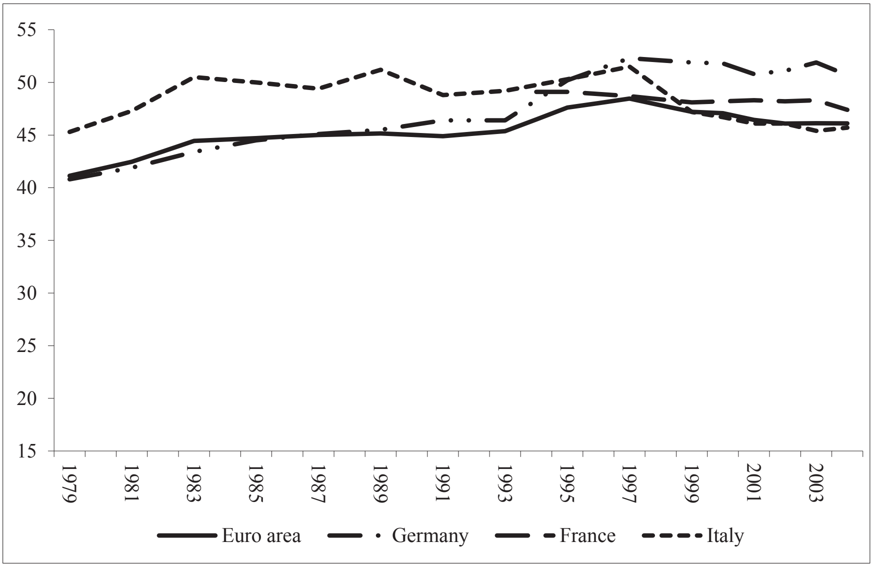


Figure 2. Tax wedges for single persons without children (67% of average earnings) as a percentage of labour costs.
Source: OECD.
Note: The euro area data exclude Slovenia and (up to 1993) France.

of other indicators are available to judge more specific aspects. These indicators, which are seldom available since the 1970s, may or may not confirm the rankings previously discussed for the most comprehensive data available. One important such indicator concerns tax wedges, measured as a percentage of labour costs. Figure 2 reports OECD data from the late 1970s. These data indicate that the euro area exhibits the highest tax-related labour costs in the group, with the UK and the US once more displaying the lowest degree of labour market rigidity.

Table 6
Overall strictness of employment protection legislation

	1990	*1998*	*2003*
Euro area[1]	3.2	2.7	2.4
France	2.7	3.0	3.0
Germany	3.2	2.5	2.2
Italy	3.6	2.7	1.9
United Kingdom	0.6	0.6	0.7
United Status	0.2	0.2	0.2

Source: OECD.
Note: This indicator corresponds to OECD's overall employment protection legislation (EPL) version 1.
The index ranges from 0 to 6 with higher values indicating more restrictive regulation.
1) Excluding Luxembourg and Slovenia.

Table 7
The Fraser Institute's 'Economic freedom of the world' index, 1970-2004

	Labour Market Regulations								*Business Regulations*		
	1970	*1975*	*1980*	*1985*	*1990*	*1995*	*2000*	*2004*	*1995*	*2000*	*2004*
Euro area[1]	3.4	3.7	3.7	3.7	3.8	3.7	4.0	4.8	6.1	7.3	6.0
France	3.4	4.0	3.9	3.8	3.8	3.4	5.0	5.7	6.1	7.3	6.3
Germany	3.3	3.3	3.3	3.3	3.5	3.6	2.9	3.3	7.0	7.8	6.1
Italy	3.7	3.8	4.1	4.1	4.2	3.5	3.5	5.5	4.4	6.3	5.7
United Kingdom	6.6	6.8	6.7	6.8	7.2	7.2	6.9	6.9	8.4	8.1	6.8
United States	4.3	7.8	7.7	7.7	7.7	7.5	7.2	7.9	8.2	8.3	6.9

Source: The Fraser Institute: Economic Freedom of the World, Annual Report, 2006.
Note: The index ranges from 0 to 10 with higher values indicating lower regulation. The index is calculated for 150 countries.
1) Euro area excluding Luxembourg and Slovenia.

The evidence about product and labour market rigidities documented in the previous paragraph does not seem to help much to understand the rankings observed for the real effects of oil price shocks under the scaled model. The finding that euro area countries are less flexible than the UK and US would be expected to imply that inter-sectoral adjustment costs are larger in the euro area, thereby magnifying real output losses in the latter grouping's countries compared to those taking place in the British and American economies. Admittedly, this is consistent with the result that British real GDP is less adversely affected by the disturbance than the euro area, but this could also be explained by factors such as the UK being a net oil exporter. Our impulse response findings however indicate that the US is worse hit by oil shocks than euro area countries and even more so compared with the UK. This is not in line with the US economy being more flexible than the euro area, while also being inconsistent with the evidence that the former country is at least as flexible as the UK.

Another indicator that could be used to interpret our impulse response results concerns oil intensity. In this regard, the direct macroeconomic effects of oil prices are expected to be correlated with the degree of intensity in oil use. The result that the US is most adversely affected by oil price shocks among the economies under study can be partly explained by the finding that it appears to be the least oil efficient as well (Figure 3). Additionally, the evidence that the UK displays the lowest oil intensity in our group is consistent with this country being the one where real output is least negatively affected by the shock. However, it also makes it more difficult to understand why the UK inflationary effects appear to be considerable. Among euro area countries, the larger real GDP and inflation impacts reported here for Italy compared to France could be in part rationalised in terms of the higher oil intensity found in the former economy (see also Barrell and Pomeranz, 2004). However, it is worth stressing that the difference in oil efficiency between these two countries is very small.[17]

17. Another source of data on oil intensity is given by OECD's latest input-output tables (for 2000). The results obtained from this source are broadly comparable with those cited in the text. For instance, the US appeared to be more inefficient in the use of oil than the UK (oil consumption amounted in 2000 for 2.4% and 1.9% of total output, respectively). France was more oil efficient than Italy (with the corresponding ratios being 2.1% and 2.4%, respectively). For completeness, 2000 values of oil consumption in Germany and the euro area as a whole represented 2.3% and 1.8% of total output, respectively.

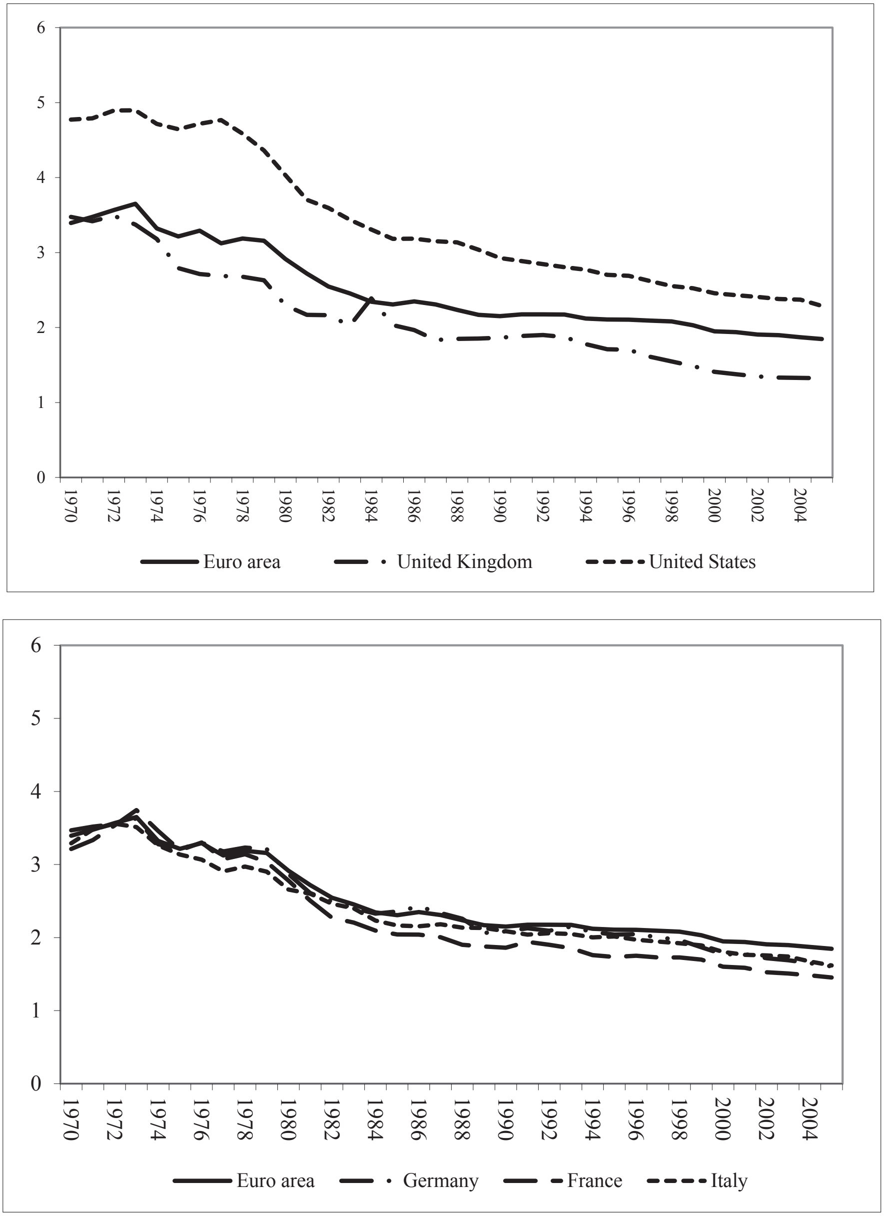


Figure 3. Oil intensity. Barrels per day per unit of output (1990 US$ converted at Geary Khamis PPPs)
Sources: British Petroleum and Groningen Growth & Development Centre.
Note: The euro area does not include Slovenia.

Finally, the effects of oil shocks on REER may also help understand what is behind the impulse response results reported earlier. As can be observed in Table 8, such disturbances tend to induce a real exchange rate depreciation in Germany and the euro area as a whole. Such depreciation would help mitigate the contraction entailed by unexpectedly higher oil prices. REER results are mixed for the euro area's two other large countries (France and Italy). In the US, there is evidence of a real exchange rate appreciation resulting from the oil price disturbance. This leaves relatively low oil efficiency as the most reasonable explanation (among those considered here) why the US is worse hit by oil shocks than the euro area as a whole. While the UK suffers from the largest real appreciation of all countries in the group, the concomitant smaller adverse effects on the country's real GDP could be rationalised in terms of other features previously discussed, such as its oil producer status, its efficiency in the use of oil and the considerable flexibility of its product and labour markets.

Table 8
Accumulated responses: Linear and scaled models

A) *Linear model, real oil prices deflated by US PPI*			
	Rate of change in REER		
Economies	*after 1 year*	*after 2 years*	*after 3 years*
EA	-5.4	-5.0	-3.6
FRA	-2.1	0.8	0.5
GER	-4.0	-3.3	-0.4
ITA	-1.5	-0.4	-1.0
UK	10.1	14.7	8.1
US	2.9	2.7	3.7
B) *Scaled model, real oil prices deflated by US PPI (baseline model)*			
	Rate of change in REER		
Economies	*after 1 year*	*after 2 years*	*after 3 years*
EA	-5.6	-5.3	-3.0
FRA	-2.3	1.9	1.2
GER	-5.6	-6.8	-5.7
ITA	1.1	1.7	-0.5
UK	18.1	26.4	18.0
US	1.9	0.6	1.2

Table 8

Accumulated responses: Linear and scaled models (*continued*)

C) *Scaled model, real oil prices in national prices (alternative model)*			
	Rate of change in REER		
Economies	*after 1 year*	*after 2 years*	*after 3 years*
EA	-9.4	-8.5	-6.5
FRA	-3.3	0.5	0.2
GER	-9.0	-9.9	-9.6
ITA	-2.2	-1.7	-3.7
UK	18.8	27.8	19.4
US	1.9	0.6	1.2

The entries refer to the accumulated responses attributed to a 100% oil price shock (in percentage). They can be interpreted as cumulated growth rates measuring the percentage difference in the level of the variable with and without the shock.

3.3. Variance decomposition analysis

Table 9 reports the variance decompositions of output and inflation due to oil price shocks under the preferred specification, *i.e.,* the scaled specification. For the baseline scaled model (Table 9, panel A), the results show that oil prices are a considerable source of variability in real GDP and inflation. The contribution of oil prices to output variability ranges in most of the cases from 5% to 10%. The contributions after the first year are slightly above that range in France and below it in Germany and the UK; in the US the corresponding contributions are below that same range within the first year. Overall, the role of oil prices in driving output appears to be smaller in the latter two countries than in the three euro area countries under study (except Germany). Moreover, the contribution of oil shocks to inflation normally ranges from 5% to 14%. The shares are smaller in the US and especially Germany than in the remaining economies. We find that, by and large, these results also hold for the alternative version of the scaled model (Table 9, panel B).

The related literature has focused on variance decompositions of real GDP for the US economy. In this regard, our findings align rather well with those of Jiménez-Rodríguez and Sánchez (2005) for this country. They also are by and large comparable with those found earlier in the literature for the US. On the low side of our range lie Brown and Yücel's (1999) estimates, while Bjornland's (2000) are on the high side of the range as she reports that oil price shocks explain 18% of US real GDP variance. In addition, our estimates for the contribution of oil shocks to real GDP variability are broadly similar to those reported for economies other than the US. In this regard, Jiménez-Rodríguez and Sánchez (2005) estimate variance decompositions for real GDP to range from 8% to 12% for the euro area and its three largest countries, as well as for the UK. These results are consistent with Bjornland's (2000) estimate for the UK, at 9%, and Germany, at 8%. In comparison with the former study, our results also broadly in line in the cases of France and Italy. In turn, relative to Jiménez-Rodríguez and Sánchez's (2005) and Bjornland's (2000) variance decompositions, our results are somewhat low for Germany and somewhat high for the UK.

Table 9

Forecast error variance decompositions

A) *Scaled model, real oil prices deflated by US PPI (baseline model)*						
	Real GDP growth			*Inflation*		
Economies	*after 1 year*	*after 2 years*	*after 3 years*	*after 1 year*	*after 2 years*	*after 3 years*
EA	5.3	7.4	8.3	8.8	6.1	5.1
FRA	8.0	10.6	11.0	17.0	11.6	9.6
GER	1.3	2.1	2.3	3.0	2.5	2.5
ITA	6.1	10.4	11.2	17.2	10.0	8.5
UK	2.5	3.5	4.1	7.3	13.1	9.9
US	4.1	5.6	5.5	10.2	6.6	5.5
B) *Scaled model, real oil prices in national prices (alternative model)*						
	Real GDP growth			*Inflation*		
Economies	*after 1 year*	*after 2 years*	*after 3 years*	*after 1 year*	*after 2 years*	*after 3 years*
EA	5.2	7.8	8.7	10.2	7.1	6.0
FRA	8.1	11.4	11.8	15.2	10.1	8.2
GER	1.3	2.5	2.6	4.6	3.7	3.7
ITA	6.2	9.9	10.6	20.4	11.8	10.2
UK	2.5	3.5	4.1	7.1	13.1	9.9
US	4.1	5.6	5.5	10.2	6.6	5.5

The entries refer to the fraction of each variable's variance attributed to oil price shocks (in percentage). The model used is given by the scaled specification.

3.4.Historical decomposition analysis

Here we consider the economic impact of oil prices both in periods where economies were in a recession and in those in which they were expanding. In relation to this periodisation, we perform historical decompositions showing the contribution of oil prices to real GDP over time. We take the dating of business cycles from the NBER for the US, the CEPR for the euro area, and Artis, Marcellino, and Proietti (2004) for the remaining economies. These dates are broadly consistent with a number of other studies conducted in recent years (see *e.g.* Artis, 2002; Artis, Krolzig and Toro, 2004; Krolzig and Toro, 2005). Table A.1 in the Appendix presents a description of dated business cycles.

Figures 4.A-4.F assess the role of oil prices in the determination of real output in terms of historical decompositions. The shaded areas correspond to the dated business cycles. We report the actual series and the contribution of oil price shocks to the forecast, both of them in percentage deviations from a 4-quarter-ahead base projection.[18]

Oil price surprises are seen to play an important role in driving real GDP in the recessions of the mid-1970s and early 1980s. During those years, oil price increases appear to induce a deceleration in economic activity in all economies considered, especially following the oil price hikes of 1973-74 and around the late 1970s-early 1980s. Indeed, oil prices have contributed to contractionary cycles at the end of the first half of the 1970s in all six economies here considered, and also - to a lesser extent - the euro area as a whole, France, the UK and the US in their second recession of the early 1980s. These two recessionary phases correspond to contractions 1 and 2 for these countries in Table A.1, respectively.[19] Finally, after the early 1980s the only periods in which the

18. Historical decompositions reported in Figures 4.A-4.F start in 1972:3 with the exception of the UK, where it starts one year later. In his study of German unemployment, Gottschalk (2005) uses the same approach but applied to an 8-quarter-ahead base projection instead. We also computed decompositions using different conditional forecasts, which tended to broadly corroborate our substantive results.
19. In the UK recession of the last part of the early 1970s, our measure of actual real GDP growth in Figure 4.E (which is in deviations from the base projection) exhibited considerable volatility, on average even being in positive territory. The base projection from our VAR model tends to overpredict the actual drop in output that took place in that episode, which explains why our positive deviations from the base projection are still consistent with the period being known to be recessionary.

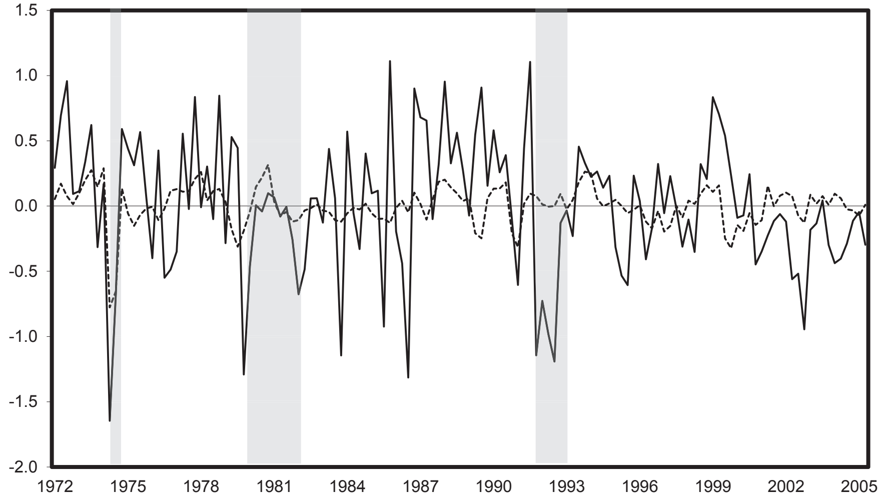


Figure 4.A. Euro area: Historical decompositions of real GDP growth under dated business cycles

—— Actual - - - Contribution of oil prices

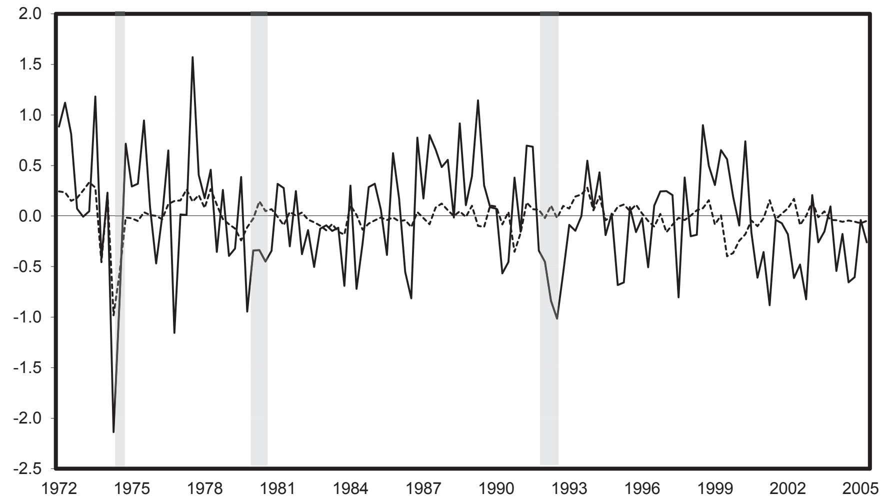


Figure 4.B. France: Historical decompositions of real GDP growth under dated business cycles

—— Actual - - - Contribution of oil prices

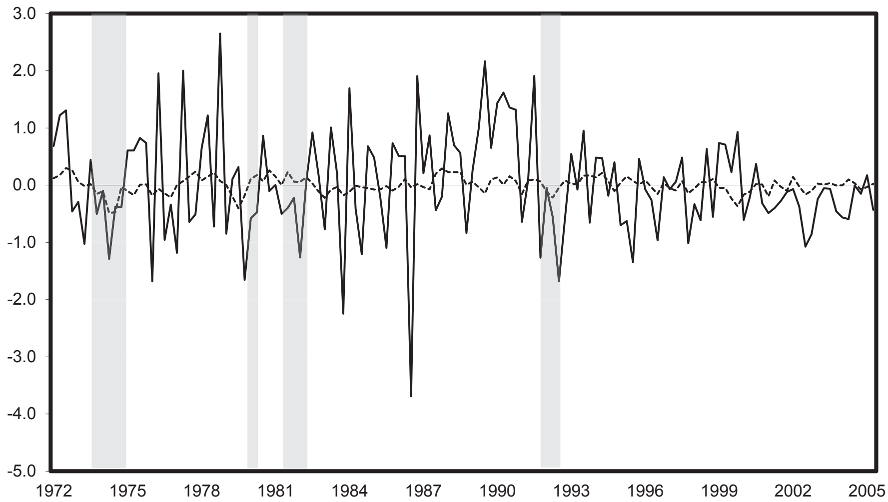


Figure 4.C. Germany: Historical decompositions of real GDP growth under dated business cycles

Actual - - - Contribution of oil prices

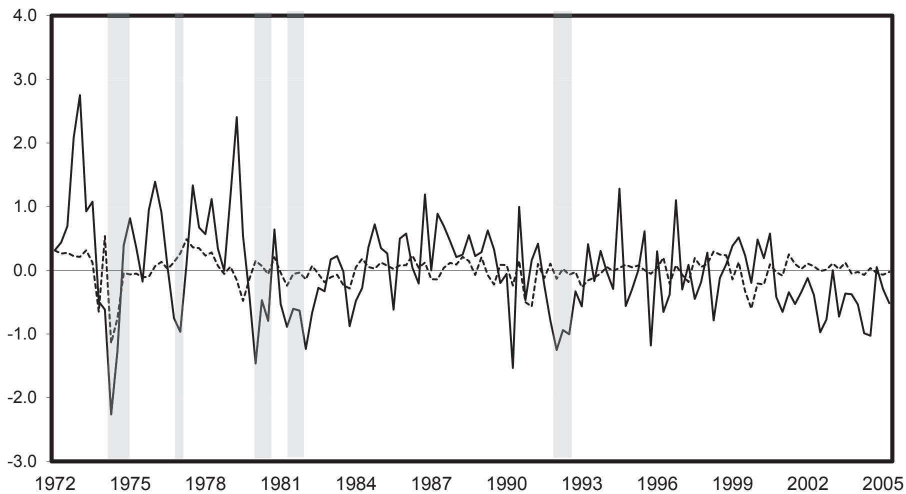


Figure 4.D. Italy: Historical decompositions of real GDP growth under dated business cycles

Actual - - - Contribution of oil prices

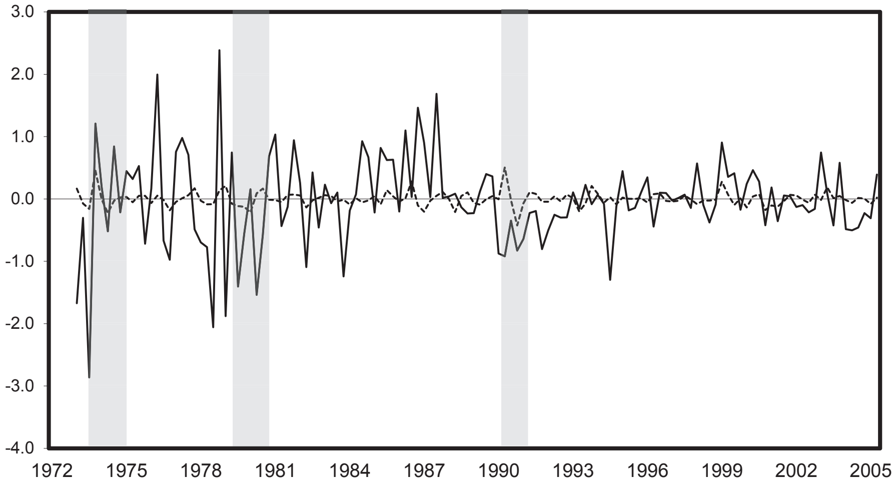


Figure 4.E. UK: Historical decompositions of real GDP growth under dated business cycles

—— Actual - - - Contribution of oil prices

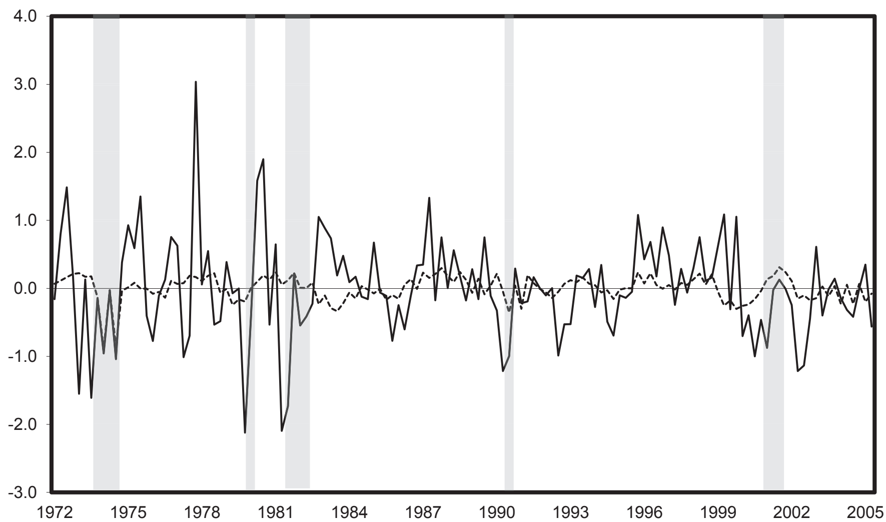


Figure 4.F. US: Historical decompositions of real GDP growth under dated business cycles

—— Actual - - - Contribution of oil prices real impact of oil prices can be detected - although in a more muted fashion than before - is during the recessions of 1990-1991 in the UK and US, and those of 1992-1993 in Germany and Italy.[20]

Conclusion

This paper adds to the literature by investigating the role of structurally identified oil price shocks in real GDP growth and inflation developments among major OECD countries. The empirical findings concerning the effects of oil shocks on business cycle fluctuations follow the expected pattern. Indeed, unexpected hikes in oil prices lead to lower real GDP growth and raise inflation in major oil importing OECD economies. Oil exporting UK behaves in a broadly similar fashion, except for a moderate expansion in real GDP within the first year after the shock. Historical decompositions reveal that oil shocks had a widespread impact on real activity during the recessions of the mid-1970s and early 1980s - a period characterised by very high oil prices never before witnessed. Starting with the oil price spike of 1990-1991 (which induced a recession within two years in all economies considered), oil shocks have exerted weaker effects on real GDP.

The present study confirms the existence of non-linear macroeconomic impacts of oil prices that are larger in magnitude than the ones obtained from a linear approach. One specific non-linear model, the so-called scaled specification, turns out to dominate all other standard approaches, including the linear one. The scaled model, by controlling for the time-varying conditional variability of oil prices, highlights the importance of considering not only the magnitude and direction of actual oil price changes, but also the context in which the latter occur. The same oil price movement will normally entail a larger macroeconomic impact in an environment of stable as opposed to volatile prices for the commodity.

20. We have also computed historical decompositions for inflation (not shown here, but available on request). These results indicate that oil price disturbances also had considerable consequences on inflation during the periods of high oil prices of the mid-1970s and early 1980s. Later periods of oil price hikes elicited smaller inflationary effects, even if still detectable around 1990-1991 and 2000-2001 - the latter period marking a rebound from the low oil price levels of the late 1990s.

Interestingly, amplified non-linear effects of oil price hikes are detected here for both real output and inflation. While comparable consequences on economic activity have been reported in previous studies, the result of a non-linear link between oil price shocks and inflation is new. The most widely accepted explanation for such non-linear effects on real output is given by the presence of inter-sectoral adjustment costs that aggravate the adverse impact of higher oil prices. The magnification of both negative real activity and positive inflation effects found here is consistent with a relative stability of nominal output. It however defies standard transmission mechanisms involving a positive association between real activity and inflation, as captured by aggregate demand effects on overall prices or the supply-side Phillips curve schedule. Further research is needed to better understand the reasons behind this empirical result.

Appendix: Dating of Business Cycles

This Appendix presents the dating of business cycle phases used in this paper, distinguishing between periods in which the OECD economies under study were in a recession and those in which they were expanding. The dating used here is taken from the NBER for the US; the CEPR for the euro area; and Artis, Marcellino and Proietti (2004) for the remaining economies (see Table A.1).[21]

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21. The periodisations reported by NBER and CEPR are available at http://www.nber.org and http://www.cepr.org, respectively.

León). The views expressed in this paper are those of the authors and do not necessarily reflect the position of the European Central Bank.

Table A.1

Business cycle expansions and contractions (1970:3 - 2005:4)

EA			*ITA*		
Cycles	*Expansion*	*Contraction*	*Cycles*	*Expansion*	*Contraction*
1	70:3 - 74:3	74:4 - 75:1	1	70:3 - 74:2	74:3 - 75:2
2	75:2 - 80:1	80:2 - 82:3	2	75:3 - 77:1	77:2 - 77:3
3	82:4 - 92:1	92:2 - 93:3	3	77:4 - 80:1	80:2 - 80:3
4	93:4 - 05:4		4	80:4 - 82:2	82:3 - 82:4
			5	83:1 - 92:1	92:2 - 93:1
			6	93:2 - 05:4	
FRA			*UK*		
Cycles	*Expansion*	*Contraction*	*Cycles*	*Expansion*	*Contraction*
1	70:3 - 74:3	74:4 - 75:1	1	70:3 - 73:3	73:4 - 75:2
2	75:2 - 80:1	80:2 - 81:1	2	75:3 - 79:2	79:3 - 81:1
3	81:2 - 92:1	92:2 - 93:1	3	81:2 - 90:2	90:3 - 91:3
4	93:2 - 05:4		4	91:4 - 05:4	
GER			*US*		
Cycles	*Expansion*	*Contraction*	*Cycles*	*Expansion*	*Contraction*
1	70:3 - 74:1	74:2 - 75:2	1		70:3 - 70:4
2	75:3 - 80:1	80:2 - 80:4	2	71:1 - 73:4	74:1 - 75:1
3	81:1 - 81:3	81:4 - 82:4	3	75:2 - 80:1	80:2 - 80:3
4	83:1 - 92:1	92:2 - 93:1	4	80:4 - 81:3	81:4 - 82:4
5	93:2 - 05:4		5	83:1 - 90:3	90:4 - 91:1
			6	91:2 - 01:1	01:2 - 01:4
			7	02:1 - 05:4	

Sources: CEPR (available at http://www.cepr.org) for the euro area; NBER (available at http://www.nber.org) for the US; and Artis, Marcellino and Proietti (2004) for the remaining economies.
Note: It is assumed that no recession has taken place since the final periods reported in the sources.

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Chapter 7
Long Memory Volatility and VaR for Long and Short Positions in the Mexican Stock Exchange

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1. Introduction

Long memory processes have received a great deal of attention in financial research during the last few decades since the concept was first identified by Mandelbrot (1965, 1971, 1972), Mandelbrot and Van Ness (1968), Mandelbrot and Wallis (1968, 1969), McLeod and Hipel (1978) among others. This phenomenon signals the persistence of autocorrelations in observed financial returns and volatility which is inconsistent with either an I(1) or an I (0) process, i.e. realizations of the series are time dependent so that distant returns and volatility influence future realizations. In addition to suggesting market inefficiency and predictability and hence the possibility of obtaining extraordinary returns, the presence of long memory has important implications for the pricing of derivatives, volatility prediction and for the implementation of risk analysis and management models requiring variance series. Thus, the presence of long memory in the returns and volatility of financial assets must be taken into consideration in its measurement. That is the case of Value at Risk (VaR); singling out the presence of long memory in financial assets series most likely yields more conservative and precise estimation in this kind of analysis.

Numerous models have been employed to determine the existence of long memory, both in the returns and volatility of stock markets. However, most studies have focused in the case of well developed markets. Additionally, many models previously applied to the case of emerging markets have not examined the presence of long memory on asset returns taking into account autoregressive fractionally integrated models and different distribution alternatives. This work overcomes such constraints. In order to analyze volatility and the persistence of long memory in the returns of the Mexican stock market, this work applies models from the ARCH family with autoregressive fractionally integrated moving average (ARFIMA) for the mean equation. Analyses presented are compared with models estimated under alternative assumptions of normal, student-t, and skewed student-t distributions of the error term.

Concerning risk, taking into account prevailing recommendations from regulatory authorities, derived from the Bassel Committee agreements, VaR has become the most applied model to assess potential losses from investment. However, there is potential tail risk in the use of VaR since conventional models neglect considering valuable information from the tails of a distribution of returns of financial series, which can convey to sizable losses or profits. For that reason using VaR to determine minimum capital requirements from banks or simply for investment decision making may lead to incorrect assessments, if a VaR model produces too many incorrect predictions due to the use of inappropriate distributions. In this regard, to identify more efficient alternatives for VaR analyses this work employs ARCH models with different distributions assumptions. Backtestig, which allows comparing actual profits and losses with VaR measures, is used to validate their efficiency. VaR estimates correspond to one day ahead investment horizon. Daily returns data for the period January 1983 to December 2009 period are used to carry out the corresponding econometric analysis.

The chapter is divided in four sections. Section II presents a review of recent literature, emphasizing long memory studies and derived VaR analysis research on about emerging markets. Section III presents the methodology. Section IV highlights the empirical application and results. The last section presents the conclusions.

2. Review of the Literature

There is a considerable amount of evidence about the presence of long memory in financial assets for the case of mature stock markets. However, while the evidence concerning stock returns is mixed, the evidence about volatility is strong. Lo (1991) tests the presence of long-run memory applying the range over standard deviation statistic (R/S) to daily, and monthly data from the Center for Research in Security Prices (CRSP) and the S&P Composite stock index. He finds no evidence of long-run dependence for any of the indexes over any sample over any sample period or sub-periods once short-range dependence is considered.

However, testing an extended R/S statistic robust to short-range dependence Lo finds long-run memory for at least two model specifications, using selected Montecarlo experiments. Cheung and Lai (1995), Yamasaki, Munchnik, Havlin, Bunde, and Stanley (2005), and Wang, Yamasaki, Havlin, and Stanley (2006) also do not find evidence of long memory in a sample of equities from the United States. Similarly, Lobato and Savin (1998) find that S&P returns have short memory, whereas squared returns power transformations of absolute returns appear to present long memory; they do not find evidence of long memory for the S&P index, using daily data for a sample for the period July 1962 to December 1994. Similarly, also examining the behavior of the S&P 500 with a large sample of 1,700 observations, Caporale and Gil-Alana (2004) find little evidence of fractional integration.

Finally, Huang and Yang (1999) investigate the NYSE and the NASDAQ stock indexes using intraday data. Employing Lo's modified R/S statistic their evidence reports the presence of long memory in both markets, Lillo and Farmer (2004) prove for the London stock market that the signs and order of its series comply with a long memory process.In the case of other developed countries, Andreano (2005) applying the Bolllerslev and Jubinski (1999) methodology finds evidence of long memory in the returns from the Milan stock market for a sample covering the period January 1999 to September 2004. Tolvi (2003) also reports evidence of long memory for the case of the Finnish market.

Finally, Gil-Alana (2006) demonstrates the presence of long memory for six developed markets: EOE (Amsterdam), DAX (Frankfurt, Hang Seng (Hong Kong), FTSE 100 (London), S&P 500 (New York), CAC 40 (Paris, Singapore All Shares, and the Nikkei (Japan). Barkoulas, Baun and Travlos (2000) find evidence of long memory in the

Greek stock market. The fractional differencing parameter is estimated employing the spectral regression method. Results show significant and robust evidence of positive long-term persistence.

As compared to benchmark linear models, the estimated fractional models provide improved out-of-sample forecasting accuracy for the Greek stock returns series over longer forecasting horizons. This confirms the conclusions reached by Ding, Granger and Engle(1993) assertion that both returns and volatility from financial markets are adequately portrayed by long memory processes. They find that not only there is substantially more correlation between absolute returns than returns themselves, but the power transformation of the absolute return also has quite high autocorrelation for long lags. Representative mixed evidence is presented by Sadique and Silvapulle (2001), Henry (2002) and Bilel and Nadhem (2009).

Sadique and Silvapulle present mixed results in their analyses of sample of six countries: Japan, Korea, Malaysia, Singapore, Australia, New Zeland and United States. Their results suggest that returns from the markets from Korea, Malaysia, Singapore and New Zeland, essentially emerging markets, show long-run dependency in returns. Henry investigates the presence of long memory using parametric and non parametric methodologies in a sample of nine international stock index returns. The results offer positive evidence of long memory in only the German, Japanese, South Korean, and Taiwanese markets. In turn, Bilel and Nadhem apply a test for fractionally integrated (FI) processes identified as Fractional Dickey-Fuller (FD-F) test. Additionally they apply the log-period gram regression and rescaled range analyses (R/S) to a wide range of G7 market stock returns. The authors find evidence find some evidence for positive long memory in 5 of the 7 series considered.

Concerning volatility recent financial literature generally confirms the presence of long memory. Conrad (2007) employs FIGARCH and HYGARCH models finding significant long memory effects in the volatility of the New York Stock Exchange (NYSE). Wright (2002) using Monte-Carlo simulations finds that the choice of volatility measure makes little difference to the log-period gram regression estimator if the data is Gaussian conditional on the volatility process.

However, if the data is conditionally leptokurtic, the log-period gram regression estimator using squared returns has a large downward bias; this is avoided by using other volatility measures. Employing U.S. stock return data obtained from the Center for Research in Security

Prices (CRSP), he finds that squared returns give much lower estimates of the long memory parameter than the alternative volatility measures, which is consistent with the simulation results. Wright suggest that researchers should avoid using the squared returns in the semi parametric estimation of long memory volatility dependencies.

Other studies worth mentioning are those by Crato and de Lima (1994), and Lux and Kaizoji (2007). Crato and de Lima examine persistence in the conditional variance of U.S. stock returns indexes. Results show evidence of long memory in high-frequency data suggesting that models of conditional heteroskedasticity should be made flexible enough to accommodate these empirical findings.

Finally, Lux y Kaizoji investigate the predictability of both volatility and volume for a large sample of Japanese stocks. They stress assessing the performance of long memory time series models vis-à-vis short-memory counterparts. The long memory models ARFIMA, FIGARCH and the multiracial model dominate over GARCH and ARMA models. Nonetheless, FIGARCH and ARMA also show many prediction failures, but the multiracial model is successful and practically always improves upon naïve forecasts provided by historical volatility. They also find that average parameter estimates for FIGARCH and ARFIMA models give better results than individually estimated models.

Deganniakis (2004) also investigates the presence of long memory volatility. He employs an asymmetric Autoregressive Conditional Heteroscedasticity (ARCH) model to capture the skewness and excess kurtosis, present in asset returns and the fractional integration of the conditional variance. The data set consists of the CAC40, DAX30, and FTS100 stock indexes for the period July 10, 1987 to June 30, 2003. The model takes into consideration both the fractional integration of the conditional variance as well as the skewed and leptokurtic conditional distribution of innovations.

The evidence shows that the FIAGARCH skewed T model generates improved one day ahead volatility predictions. Ma, Li, Zhao and Luo (2012) apply ARFIMA modeling to examine the distribution characteristics of realized volatility based on high frequency data of the Hushen200 index.The evidence confirms the superiority of the ARFIMA model vis-à-vis GARCH modeling. In turn, Cuñado, Gil-Alana, and Pérez de Gracia (2008) explore the behavior of the S&P index for the period August 1928 to December 2006. Their result suggests that the squared returns present long run memory. Returns also exhibit a similar behavior. Interestingly, their evidence also demonstrates that volatility is more persistent for declining markets that for increasing markets.

Similarly, Martens, VanDijk and de Poter (2004) develop a non linear ARFIMA model and apply it to realized volatilities of the S&P stock index and three exchange rates. The model produces improved forecasts that the linear ARFIMA model and from conventional time-series models based on daily returns, treating volatility as a latent variable. Finally, Fleming and Kirby (2011) use fractionally integrated time series to investigate the joint behavior of equity trade volume and volatility. The data include 20 stocks from the MMI for the January 4, 1993 to December 31, 2003 period. Using high frequency realized volatility, their evidence shows that both volume and volatility present long memory but reject the hypothesis that these series share a common order of fractional integration for a fifth of the firms in the sample. Furthermore, they find a strong correlation between the innovations to volume and volatility. Lastly, it is worth noting that strong evidence concerning the absence of long run memory in the volatility of stock returns is presented by Jacobsen (1996); applying the R/S statistic modified by Lo he concludes The Netherlands, Germany, United Kingdom, Italy, France, United States and Japan do not exhibit long memory in their volatility.

Recent research has also dealt with the benefits of determining the existence of long memory for risk analysis. Giot and Laurent (2001) model VaR for the daily returns of a sample that includes stock market indexes from five developed countries: CAC40 (France), DAX (Germany), NASDAQ (United States), Nikkei (Japan) and SMI (Switzerland). They also estimate the expected shortfall and the multiple average to measure VaR. Their APARCH model produces considerable improvements in VaR prediction for one day investment horizons for both the long and short positions. In a similar study So and Yu (2006) also examine the performance of several GARCH models, including two with fractional integration.

Their study considers return series from the NASDAQ index from United States and FTSE from the United Kingdom and proves that VaR estimations obtained with stationary and fractional integration are superior to those obtained with the Riskmetrics model at 99.0 percent confidence levels. Similarly, VaR analysis carried out by Kang and Yoon (2008) initially applying Riskmetrics reveals the importance of taking into account asymmetry and fat tails in the distribution of returns of corporate shares of three important firms listed in the South Korean stock markets. In line with this type of studies, analyzing the importance of skewness and kurtosis for determining VaR with greater precision Brooks and Pesard (2003) compare VaR estimates for the case of five Asian markets and the S&P 500 index. Models applied are Riskmetrics, semi-variance, GARCH, TGARCH, EGARCH and multivariate extensions of the GARCH models used.

Their results suggest that incorporating asymmetry generates better volatility predictions which in turn improves VaR estimations. Tu, Wong and Chang (2008) scrutinize the performance of VaR models that take into account skewness in the process of innovations. They apply the model APARCH based on the skewed t distribution; the study includes the markets from Hong Kong, Singapore, Australia, Korea Malaysia, Thailand, Philippines, Indonesia, China and Japan, albeit performance of this model is not satisfactory in all cases. A similar study by McMillan and Speigh (2007) examine daily return series for eight markets from the Asia-Pacific area, and in addition from the U.S. and U.K. markets to have a comparative frame of reference. Applying very restrictive levels of confidence, the authors find that the models that take into account long memory mitigate common under estimations from models that do not consider skewness and kurtosis in the distribution of financial series.

Analogously, Yoon and Khang (2007) investigate the relevance of skewed Student-t distributions in capturing Long memory volatility characteristics in the daily return series of the Nikkei 225 index and the Yen-U.S. dollar exchange rate. For this purpose they investigate the performance of two long memory value at risk models, FIGARCH and FIAGARCH VaR models with three different alternatives: the normal, student-t, and skewed Student –t distributions. Their evidence suggests that the skewed Student-t distribution produces more precise estimations than the other two models. Yoon and Kang conclude that accounting for skewness and excess kurtosis in the asset return distribution can provide suitable criteria for VaR model selection in the context of long memory volatility.

Finally, Ñiguez (2003) analyzes the relative performance for an ample range of Gaussian and Student-t short- and long-memory conditional heteroskedasticity models, including: GARCH, AGARCH, APARCH, EWMA, FIGARCH and FIAPARCH GAARCH and FIAGARCH models for volatility and VaR forecasting, using daily time series from the Spanish IBEX-35 index from July 1, 1987 to December 30, 2002. For the in-sample analysis Student-t FIGARCH offers a better fit than nested models; for the out-of sample volatility forecasting both performance. Concerning VaR estimations the Student-t FIAGARCH is the most recommendable.

In the case of emerging equity markets, consistent with their lower level of efficiency, in general, the presence of long memory is confirmed in most markets analyzed. Disario, Saraoglu, McCarthy, and Li. (2008) and Kasman and Torun (2007) show evidence about the existence of long memory in the returns and volatility in the Istanbul stock market. Nevertheless, applying parametric FIGARCH models and non parametric methods Kilic (2004) finds opposite evidence to what is generally reported for emerging markets, including the case of Turkey. His study reveals that daily returns are not characterized by long memory; however his study reveals that, similar to the case of developed markets, emerging markets present a dynamic long memory in the conditional variance, which can be adequately modeled by a FIGARCH model. Kurkmaz, Cevic and Özatac (2009) confirm these results. Using structural rupture tests for the variance and the model ARFIMA-FIGARCH they do not find evidence of long memory in the returns of the Istanbul market; but they did find evidence of long memory in the volatility of returns.

Additional research on emerging markets verify long memory in their equity markets. Contrary to Barkoulas, Baum, and Travlos (2000), previously reviewed, Vougas (2004) finds weak evidence concerning the presence of long memory in the Athens markets, applying an ARFIMA-GARCH model, estimated via maximum conditional likelihood. In relation to the emerging Asian capital markets, Cajueiro and Tabak (2004) show that the markets from Hong Kong, Singapore and China present long-run dependency in the returns from their stock markets, which has been confirmed for the case of China. Analyzing the stock market index for the Shenzhen market, Lu, Ito and Voges (2008) find significant evidence pointing out to the presence of long memory and lack of efficiency in this market.

Applying fractionally integrated models Cheong (2008) presents evidence of long memory in the absolute returns, squared returns, and the volatility from the stock market from Malaysia. In the case of India, Kumar (2004) proves the existence of long memory due to the presence of conditional heterokedasticity in the series. Kumar applies ARFIMA. GARCH models obtaining robust results. Similarly, Banerjee and Sahadeb (2006) find evidence of long memory in India analyzing return series SENSEX index. In his study the fractionally integrated GARCH model is the most appropriate to represent volatility.

Persistence of autocorrelation in the volatility of returns has also been defined for the case of emerging markets. Examining three markets from developing countries, Egypt (Assaf, 2004), Kwait (Assaf, 2006), and Tunisia (Bellalah, 2005), these authors apply a FIGARH model to determine long-run dependency in volatility. In all cases estimations yield a long memory parameter which is very significant. Jayasuyira (2009) finds long memory in the volatility in a wide sample of 23 emerging and frontier markets from various regions, covering the period January 2000 to October 2007. Applying an EGARCH fractional integration model, her evidence reveals long memory; however, no evidence of long memory is found for the most recent period analyzed.

Chung, Huang and Tseng (2008) using data from the Taiwan Stock Exchange they consider two realized volatility models, the 'heterogeneous autoregressive' (HAR) and 'mixed data sampling' (MIDAS) models to predict volatility. Their study also compares forecast accuracy in terms of the MSE (mean squared error) of different regressors to evaluate performance in the out-of-sample forecasting. The authors demonstrate that 'realized power variance' (RPV) is the best predictor for use in predicting future volatility for different prediction horizons, and significantly outperforms model based on 'realized variance' (RV); these results hold up for both the in-sample and out-of-sample forecasts.

Furthermore, investigating the Kuala Lumpur market for the period 1992 a 2002, Cajueiro and Tabak (2005) find long memory in the volatility of returns; they report a Hurst index of 0.628. Also for this market, Cheong, Hassan, and Zaadi (2007) prove with GARCH modeling the presence of asymmetry and long memory in the volatility of returns using daily returns for the period 1991-2005, subdividing also the series into four sub periods.

Tan, Cheong and Yeap (2010) also report long memory for the Kuala Lumpur stock exchange. Applying the model by Geweke and Porter-Hudak (1983) the authors find that during the 1985-2009 period during which took place several upward and downward periods, the persistence of long memory was longer during the periods previous to the 1997 crisis. Similarly, Battachairya and Battacharya (2012) examine the presence of long-memory in ten emerging stock markets (Hungary, China Brazil, Chile, Malaysia, Korea. Russia, Mexico, India, and Taiwan). They compute the Hurst-Mandelbrot's R/S statistic, Lo's extended R/S and semiparametric GPH statistic and Robinson´s Gewekw-Porter-Hudak modified statistic (1995). The evidence suggests the existence of long-memory in volatility and in absolute returns; random walk is also found all selected indexes. The study does not confirm the presence of Taylor's effect in the selected stock markets.

Long memory effects also impact VaR estimations in developing stock markets. Mighri, Mokni and Mansouri (2010) study the impact of asymmetric long memory volatility models on the accuracy of stock index return VaR estimations for a sample of six developed and emerging stock markets: S&P 500 of the US, CAC40 of France, NIKKEI225 of Japan, Kuala LumpurStock Exchange (KLSE) for Malaysia, Hang Seng Index (HSI) for Hong Kong, and Indice de Precios y Cotizaciones (IPC Mexico), covering the same period from January 2, 1997 to August 25, 2008. They measure and compare the performance of asymmetric FIEGARCH and FIAGARCH versus symmetric long memory models, with normal, Student-t and skewed Student-t distributions. Testing the results applying Kupiec's likehood ratio tests, the FIAPARCH (1,d,1) model with skewed Student-t innovations is more precise in in-sample VaR analysis for both long and short positions, than the other models. For out-of-sample VaR estimations the FIAPARCH (1.d,1) model with Student-t innovations provide more accurate estimates.

Yoon, Woo and Kang (2011) consider the relevance of the skewed Student-t distribution in capturing the long memory and asymmetry characteristics in the volatility of the Shanghai Stock Market. The data consists of daily closing prices for the January 4, 200 to March 31, 2011. Their analysis also examines the performance of in-sample and out-of-sample VaR employing the FIAGARCH model with normal, Student-t, and skewed Student-t distribution innovations. The evidence shows that accurate VaR estimations and margin levels are obtained applying the skewed Student-t FIAGARCH models for long and short trading positions.

Chin, Mohr Nor, and Isa (2009) analyze the asymmetric long memory volatility of Bursa Malaysia using daily data for the January 1, 2001 to November 30, 2005 period. The long memory characteristics of stock returns are examined by variance time plot, R/S statistic, and Whittle's estimator. The behavior of volatility is tested using GARCH and FIGARCH modelings. The evidence shows that asymmetric and long memory models exhibit better predictability. Concerning VaR, the asymmetric FIGARTCH shows the best estimations for in-sample forecasting evaluations and stronger out-of sample estimations than other models. Finally, Demireli (2009) models Istanbul Stock Exchange index returns using a number of symmetric and asymmetric conditional heteroscedasticity models GARCH IGARCH, GJR-GARCH, APARCH, FIGARCH and FIAPARCH long memory models.

The accuracy of one-day-ahead Value-at-risk (VaR) is tested applying the Kupiec-LR statistic under the normal, student-t, and skewed student-t distributions. The results of ARCH class models show the existence of both leverage effect in stock exchange and fractional integration in conditional volatilities, which emphasizes the use of FIAPARCH model for the Istanbul market. Similarly, the Kopek LR test based on in-sample and out-of-sample VaR confirms the superiority ofFIAPARCH model. The data consists of daily closing price of ISE-National 100 index for the period January 2, 2002 to April 17, 2009.

Among other recent works worth mentioning Angelidis and Degiannakis (2008) evaluate the performance of Symmetric and Asymmetric ARCH models in forecasting the one-day-ahead Value at Risk and the realized intravolatility of the General Athens Stock index as well as for a banking index. The data covers quotation data from May 8, 1994 to December 19, 2003. Results show that the most adequate method for the Bank index is the Symmetric model with normally distributed innovations; for the General index the asymmetric model is the most appropriate.

Further, the asymmetric model tracks closer the one-step-AHEAD intra-day realized volatility with conditional normally distributed innovations for the Bank index but with asymmetric and leptokurtic distributed innovations for the General index. Thupayagale (2010) evaluates the forecasting performance of a range of volatility models in Value-at-Risk estimation for the stock indexes of 10 emerging markets (Brazil, China, Egypt, India, Kenya, Nigeria, Russia, South Africa, and Turkey; additionally data for the United States (S&P 500) is included as a benchmark comparator. The data cover a span period from January 1, 1998 to January 31 2010.

The results suggest that models with long memory or asymmetric effects or both are important considerations in providing improved VaR estimates. Millan and Thupayagale (2012) examine the performance of a range of alternative volatility models in forecasting Value at Risk for the case of the South African stock market. Several GARCH models are applied, including a variety of asymmetric and long memory models. Their evidence suggests that models incorporating both asymmetric and long memory attributes generally outperform all other methods in estimating VaR across three stringent percentiles considered. These findings are similar to the volatility forecasting; the standard RiskMetrics model is consistently outperformed by all the GARCH-type models analyzed in the context of VaR modeling.

Their evidence also suggests the importance of using the stringent probability criteria prescribed by the Basle regulatory framework, and of employing out-of-sample forecast evaluation techniques for the selection of forecasting models that provide accurate VaR estimates. Finally, Gaio, Tabajara and de Lima (2012) compare the performance of conditional models in estimating Value-at-Risk (VaR) of stock market indexes, considered the presence of long dependence on their returns. They use daily closing prices related to the returns of six main indexes from the world's largest capital markets: S&P, Dow Jones, NASDAQ, NIKKEI, FTSE, and IBOVESPA.

Data are from January 1st, 2000, to January 1st, 2008. The results showed that the models that consider the long-term memory effect in the conditional volatility of index returns, specifically the FIAPARCH (1,d,1) model, showed the best fit and predictive performance to estimate market risk (Value-at-Risk), as shown by the Kupiec Failure Rate Test values. Results underlie the importance of long memory (symmetric and asymmetric) models to assess risk, particularly characterized by financial crisis.

In the case of the Latin American emerging stock markets, although there is a marked shortage of local research about long memory in these markets, some relevant research has been recently published. Cavalcante and Assaf (2005) examine the Brazilian stock market and conclude emphatically that volatility in these markets is characterized by the presence of long memory, while they find weak evidence about the existence of long memory in the returns series of this market. Cajueiro and Tabak (2005) assert that the presence of long memory in the time series from financial assets is a stylized fact.

Examining a sample of individual shares listed at the Brazilian stock market they find that specific variables from the firms explain, at least partially, long memory in this market. Lastly, Perez Perez (2009) evaluate the presence of long memory in the level, returns, and volatility in the Colombia stock market indexes and some high liquidity shares. He finds evidence of long memory in index returns and volatility for all the series which suggests that lack of efficiency in this market. The data includes daily quotations from July 5, 2002 to September 4, 2009. In a broader approach, Venegas Martínez and Islas Camargo (2005) present evidence of long memory in the markets from Argentina, Brazil, Chile, Mexico, and United States.

Research dealing with the Mexican Stock Market (MSM) is a growing and important area. Some pioneer studies account for the presence of long memory in this market. Islas-Camargo and Venegas-Martinez (2003) report long memory in the volatility of the Mexican Stock index applying a stochastic volatility model.

Additionally they show the negative impacts that can arise from this behavior on hedging of European options. Similarly, López-Herrera, Venegas-Martínez and Sánchez-Daza (2009) examine the existence of long memory in the returns of the MSM index; positive results are obtained employing different ARFI-GARCH volatility parameters. In turn, López-Herrera, Villagómez-Bahena and Venegas-Martínez (2011), apply FIGARCH modeling finding strong statically significant long memory in the conditional variance process; this both applying Gaussian and Student t specifications for the error terms. Finally, it is worth mentioning a recent work by López-Herrera, Ortiz and de Jesús (2012). They evaluate the capacity of the GARCH, IGARCH, GJR and APARCH models to estimate VaR in the presence of long memory in the returns square. In this respect, this chapter extends that work testing the capacity of models from the ARCH family in measuring VaR applying specifications modeling the effects of long memory in the conditional variance equation.

Summarizing, the existence of long memory in the returns and volatility of finalcial assets has important implications both for the valuation of assets, as well as for risk analysis. Alternative models have been advanced and applied, among them models using autoregressive fractional integration. Research has concentrated in the case of mature markets, albeit there is a growing trend to scrutinize these issues in emerging markets; in both cases results have been mixed. The impact of long memory is relevant for VaR analysis; ample financial literature also reports mixed results. In the case of emerging markets it is important to acknowledge that research dealing long memory processes and its applications is still a limited but growing area in financial research.

3. Methodology

The works by Granger (1980), Granger and Joyeux (1980) and Hosking (1981) advanced the notion of fractional integration, also named fractional differentiation to model time series stochastic process with long memory. These models, denominated ARFIMA (*autoregressive fractionally integrated moving average*) differ from the common stationary ARMA and ARIMA models in the lag function of the residuals; in the ARFIMA models this function is represented by $(1-L)^d$ where d is different from cero, as is in the ARMA stationary processes or else from 1, like in the case of integrated ARMA models, i.e. ARIMA or unit root processes. An ARFIMA (p,d,q) process is generated by:

$$\phi(L)(1-L)^d = \psi(L)\varepsilon_t, \tag{1}$$

where d is not an integer and

$$\left(1-L\right)^d = \sum_{j=0}^{\infty} b_j L^j \tag{2}$$

where $b_0 = 1$ and the nth j autoregressive coefficient b_j, is given by:

$$b_j = \frac{-d\Gamma(j-d)}{\Gamma(1-d)\Gamma(j+1)} = \frac{j-d-1}{j} b_{j-1}, \qquad j \geq 1. \tag{3}$$

A well known fact concerning the behavior of stock returns, as well as from other financial series, is their time varying volatility; additionally, large price positive changes are followed by large negative changes; similarly, small price changes are followed by small price changes; as a result, changes tend to cluster which derives in time dependency of returns. It has been also observed that the distribution of daily financial returns tend to show fat tails which is absent in the normal distribution. For that reason ARCH (autoregressive conditional heterokedasticity) models have been used extensively to analyze financial time series. The original ARCH model was developed by Engle (1982) and soon after Bollerslev (1986), advanced a generalized version, commonly known as GARCH model. In its original version the GARCH (p,q) model can be expressed as follows:

$$
\begin{aligned}
e_t &= z_t s_t \\
z_t &= i.i.d.N.(0,1) \\
\sigma_t^2 &= \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2
\end{aligned}
\tag{4}
$$

Similarly, GARCH models have also been extended to take into account long memory effects in the conditional variance. Three important fractional GARCH have been put forth by Chung (1999), Tse (1998), and Davidson (2004), expressed as follows:

FIGARCH (1,d_s,1) with Chung's (1999) specification:

$$\sigma_t^2 = \sigma^2 + \left\{1 - \left[1 - \beta\left(L\right)\right]^{-1} \phi\left(L\right)\left(1 - L\right)^d\right\}\left(\varepsilon_t^2 - \sigma^2\right).$$

FIAPARCH (1,d_s,1), presented by Tse (1998):

$$\sigma_t^\delta = \omega + \left\{1 - \left[1 - \beta\left(L\right)\right]^{-1} \phi\left(L\right)\left(1 - L\right)^d\right\}\left(\left|\varepsilon_t\right| - \gamma\varepsilon_t\right)^\delta.$$

HYGARCH (1,d_s,1) advanced by Davidson (2004):

$$\sigma_t^2 = \omega\left[1 - \beta\left(L\right)\right]^{-1} + \left\{1 - \left[1 - \beta\left(L\right)\right]^{-1} \phi\left(L\right)\left\{1 + \alpha\left[\left(1 - L\right)^d\right]\right\}\right\}\varepsilon_t^2,$$

Which nests the FIGARCH model when $a = 1$ (equally when $\log a = 0$). The process is stationary when $a < 1$ ($\log a < 0$), which contrasts with the FIGARCH model which tend to be highly non stationary.

Empirical Analysis

The data spans from the first stock market operating day from 1983 to the last operating day of 2009. Daily returns are simply computed as: $100^*(\ln P_t - \ln P_{t-1}) = r_t$. Realized volatilities were calculated using the ARCH models previously described, taking into account for the error three different distributions: normal, Student T and skewed Student T. For all case the mean equations were estimated using a fractionally integrated AR(2) model.

Results presented in Table 1 show that almost all values of the parameters estimated by the maximum likelihood method are highly significant, most of them at a one percent significance level. In particular stand out d_m y d_s, which are precisely the values estimated for the parameters accounting for long memory in the returns and volatility, respectively, of the Mexican market. The FIAPARCH model in the three specifications for the errors offers values slightly superior of the parameter for long memory in the returns while the HYGARCH model produces the largest estimated values for the long memory volatility parameters.

To test the benefits on Value at Risk analysis Kupiec's backtesting model (1995) is used. VaR calculations for Mexico's stock market index returns, for a one day ahead investment horizon, are obtained by in-sample application from G@ARH 4.2 (Laurent y Peters, 2006) in the Ox V5.0 matrix program developed by Doornik (2001; 2007). Table 2 summarizes the backtesting results, which allows evaluating the specified models based on the percentage of failures of violations observed in them for VaR estimations for one-day-ahead forecasts. Following Jorion (2006), representing the number of exceptions as x and the total number of observations as T, the failure rate can be defined as x/T. Ideally, this rate would reflect the selected confidence level. For instance, for a confidence level of 99 % a null hypothesis that the frequency of tail losses is equal to p = (1-c) = 1- 0.99 = 1%. Assuming that the model is correct the observed failure rate should act as an unbiased measure of p, and therefore converge to one percent as the sample size increases.

Table 1

Fractional Integration Mean and Volatily Parameters[1]

	Variable	*FIGARCH*	*FIAPARCH*	*HYGARCH*
Errors with gaussian distribution	*m*	0.2086***	0.1255***	0.2094***
	d_m	0.057422***	0.0861***	0.0572***
	j_1	0.1564***	0.1312***	0.1573***
	j_2	-0.0782***	-0.0837***	-0.0779***
	w	3.6884***	5.5977***	0.1733***
	d_s	0.4094***	0.4051***	0.4835***
	f	0.1456*	0.1528**	0.1569**
	b	0.3937***	0.4112***	0.4583***
	g		0.2670***	
	d		1.7606***	
	log(*a*)			-0.0431*
Errors with Student-t	*m*	0.1980***	0.1528***	0.1955***
	d_m	0.0786***	0.0921***	0.0781***
	j_1	0.1403***	0.1264***	0.1407***
	j_2	-0.0953***	-0.0953***	-0.0946***
	w	4.0267***	5.2716***	0.1506***
	d_s	0.4349***	0.4212***	0.6286***
	f	0.2470***	0.2074***	0.2237***
	b	0.5007***	0.4669***	0.6333***
	g		0.2425***	
	d		1.7876***	
	log(*a*)			-0.0525**
	g.l.	6.095***	6.5133***	5.9931***
Errors with skewed student-t	*m*	0.1961***	0.1499***	0.1959***
	d_m	0.0784***	0.0922***	0.0782***
	j_1	0.1402***	0.1263***	0.1407***
	j_2	-0.0954***	-0.0955***	-0.0946***
	w	4.0372***	5.2998***	0.1506***
	d_s	0.4351***	0.4214***	0.6287***
	f	0.2471***	0.2074***	0.2236***
	b	0.5009***	0.4669***	0.6334***
	g		0.2425***	
	d		1.7876***	
	log(*a*)			-0.0525**
	$x_{(\text{asimetría})}$	-0.0028	-0.004	0.0006
	g.l.	6.0981***	6.5177***	5.9922***

*, **, *** denote, respectively 10%, 5% y 1% significance levels.

1. Estimations were carried out using the G@rch software from Laurent and Peters (2006) in its academic version for Ox (Doornick 2001 y 2007).

Table 2
Kupiec's Tests

α(%)	5%		2.5%		1%		0.5%	
Positions	*Larga*	*Corta*	*Larga*	*Corta*	*Larga*	*Corta*	*Larga*	*Corta*
Percent	*a*	*1- a*	*a*	*1- a*	*a*	*1- a*	*a*	*1- a*
FIGARCH^{n}	0.299	3.45*	6.277**	0.877	36.99	0.433	45.84***	6.82***
FIGARCH^{t}	0.913	0.01	2.607	2.247	3.323*	3.93**	0.300	2.519
FIGARCH^{ts}	0.541	0.002	2.607	2.011	2.543	3.419*	0.300	2.519
FIAPARCH^{n}	4.608**	0.513	1.929	0.158	16.192***	6.825***	25.501***	4.636**
FIAPARCH^{t}	0.056	1.021	1.021	0.092	1.556	4.475**	0.002	1.467
FIAPARCH^{ts}	0.056	1.021	0.736	0.021	1.556	3.419*	0.002	1.467
HYGARCH^{n}	0.189	3.892	5.218**	0.382	33.422***	1.026	42.412***	8.48***
HYGARCH^{t}	0.811	0.143	1.351	2.247	0.801	2.948*	0.002	3.164*
HYGARCH^{ts}	0.811	0.143	1.351	2.247	0.801	2.948*	0.002	3.164*

^{n}, ^{t}, ^{ts} represent respectively the nornal, Student T, and skewed Student T especifications.
*,**,*** denote, respectively 10%, 5% and 1% significance levels.

Table 2 highlights the fact that VaR estimated for the long and short positions employing the FIGARCH with distribution *t* skew, FIAPARCH with student T, and skewed student t distributions as well as the HYGARCH model also with student t and skewed t distributions do not exceed expected failure rates or all confidence levels analyzed. Results for the Kupiec test for all specifications with normal distribution do not show an efficient performance for the long positioning in trade.

Results are less promising for the case of the short position for all estimated models. In general there is no specification of the estimated models in which can be observed that VaR does not exceed the expected failure rates for all specifications. Nonetheless, it can be observed in Table 2 that the FIGARCH model with skewed student t distribution exceeds only for the significance level of 10% the expected failure rate for a confidence level of 99%. The same situation takes place for the FIAPARCH model, with errors specified with the skewed student t distribution and for the, HYGARCH model both for the student t and skewed t distributions. In turn the FIGARCH model with student t distribution for the error exceed at 5% significance level the significance level of 99%. The FIAPARCH models with student t distribution of the errors exceeds at 5% The FIAPARCH model with student t distribution in the errors at the 5% level of significance exceeds the expected level of failures for a confidence level of 99%. Finally the HYGARCH model with student t distribution of errors surpasses expected proportion of failures at the 99.5% confidence level with a level of significance of 10%. Again, it can be observed that the models with gaussian error specifications do not show a better performance than other models applying other specifications.

Conclusions

This work has evaluated the performance of three models of the ARCH family in Value at Risk estimations for the Mexican Stock Index. The models used, FIGARCH, FIAPARCH and HYGARCH, allow capturing long memory conditional volatility effects. Three specifications were used for the error distributions, normal, Student *t,* and skewed Student-t. Their capacity to measure VaR, representing market risk was ascertained applying Kupiec's failure rate.

Evaluating their performance in VaR estimations for the long positions for a day-ahead forecast the most competitive models are the FIGARCH model with skewed Student t specification for the error; the FIAPARCH model using Student t and skewed Student t specifications; and the HYGARCH model also with Student t and skewed Student t distributions, also with Student t and skewed Student t specifications; their failure rate did not exceed for any significance level for any confidence level analyzed. Therefore, from the evidence there is no reason to prefer any of these models.

Nevertheless, although the models above mentioned above might appear as excellent candidates for widespread applications in VaR analysis it is worth noting that for short positioning in stock trading in the Mexican Stock Market no model that overcomes Kupiec' test was for all confidence levels. However, it is worth mentioning that the models FIGARCH with skewed Student t, FIAGARCH with a similar distribution, and HYGARCH with Student t and Skewed student t distribution exceeded the expected failure rate at the 99 percent confidence level, but only at the 10% level of significance.

This suggests that there is a possibility of selecting long memory specifications to determine the presence of long memory, both for returns and volatility to obtain accurate VaR estimates for the Mexican

Stock Market. Indeed, it appears to be adequate selecting any of the three models tested in this study, with skewed Student t distribution for the errors, It is also clear that it is not acceptable to calculate VaR in this market employing normal distribution specifications.

Summing up, the evidence of this study underlies the need of continuing assessing the performance of alternative VaR estimations related to other long memory models from the ARCH, as well as for the case of other models that aid identifying and measuring risk characteristic of financial series, particularly non linear models. It is also necessary complementing the evaluation of the models here presented in this chapter using other tests advanced to this effect.

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CHAPTER 8
Characterization of Non-Linear Time Series of Spare Parts Demand in Service Companies

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Introduction

Modern telecommunications services have been a catalyst for the development of nations: they represent an indispensable element for the proper functioning of companies and institutions and are part of everyday life for a large part of the inhabitants of this planet.

As Luna (2008) argues, the technology of traditional landlines has matured and become saturated, and this has been surpassed by the emergence of other technologies related to mobile phone services, broadband Internet and VoIP.

The supply of telecommunications services runs in parallel with scientific and technological development and with the increasingly demanding service level expected from customers, who demand a 99.9% availability of modern equipment to avoid interruptions in their daily activities.

To maintain the required reliability, phone operators (who offer landline, mobile telephony and Internet services) require total maintenance services for their telecommunications network, including on-site maintenance, remote maintenance, software updates, spare parts and repairs, among other services, that guarantee a high level of confidence in the services provided to their customers. However, this is not an easy task, and the risk of equipment failure is always latent.

The complexity of maintaining telecommunications services, the risk of their interruption and high maintenance costs have caused phone operators to subcontract telecommunications network maintenance services directly to the original equipment manufacturers (OEM), reducing their annual operating costs by 10 to 15% (O'Shea, 2006). This is a business opportunity for the OEM, representing an important source of income and an opportunity to acquire and retain customers and achieve a competitive advantage. However, the design and operation of the resources required for the OEM to offer maintenance services to phone operators involves various complexities, such as a large volume of information and materials, the life cycles of the products, management of the product catalogue, the operations and capacity of the repair centres, warehouse and transport management, the availability of technicians, customer service centres, investment budgets, contracts with customers with different levels of service, different information systems and fluctuations in demand as well as in transit and repair times.

Based on the diverse post-sales maintenance services offered by OEMs, this study presents a non-linear characterisation of the in-advance spare parts replacement service whose supply chain involves a process of intermittent demand.

In this service, the customer (or phone operator) requests in advance a unit from the OEM that should be delivered within the contracted time. Once the customer receives the unit, he or she returns the faulty unit to the OEM in the days following receipt. Once the OEM receives the faulty unit, it is sent to be fixed, and when it is sent back, it is once again stored in the OEM's warehouses to meet future customer demands. Concurrently with the delivery, and owing to the commitment of the OEM to make deliveries to the customer, a unit in working condition is moved from the distribution centre to the local warehouse from which the unit was first delivered to the customer. Figure 1 presents the flows and edges of the supply chain involved in the advanced spare parts replacement service. In this Figure, represents warehouse, for, represents the distribution centre and refers to the repair centre.

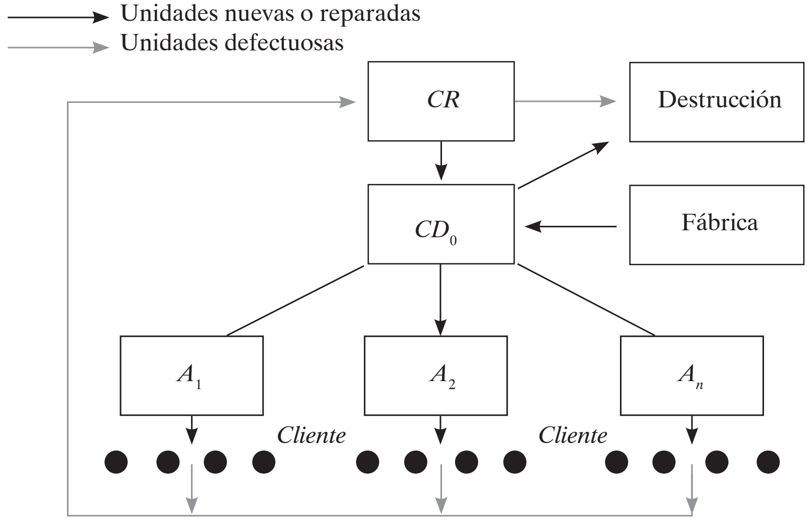

Figure 1. Post-sales spare parts service supply chain.

Figure 1 also includes factory and destruction links. The processes of buying material and/or destroying it are not included in the analysis because they take place only occasionally, whereas the process of repairing the units occurs continuously. The supply chain with a distribution centre shown in Figure 1 is also not considered; rather, a simplified version involving only a warehouse, the customer's location and a repair centre (Figure 2) is taken into account to simplify the process described above as explained below.

In this simplified process, the customer, in advance, requests a new or repaired unit from the OEM that should be delivered in the contracted time. Once the customer receives the unit, he or she returns the faulty unit to the OEM. Once the OEM receives the faulty unit, it is sent off by the OEM to be repaired, and once the unit is returned, it is once again stored in the OEM's warehouse to meet the future demands of the customer.

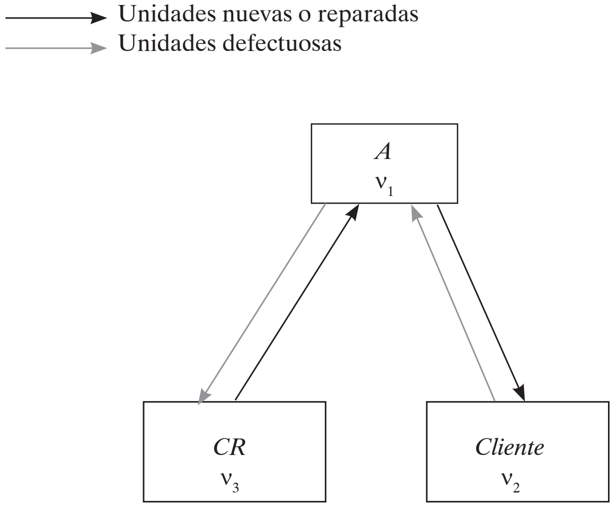

Figure 2. Simplified spare parts supply chain.

Bullwhip effect in supply chains

Procter and Gamble (P&G) executives examined the behaviour of orders in their diaper production supply chain and found that despite the fact that the demand for diapers is constant throughout the year, the variability (fluctuations) in the delivery orders within the supply chain increases as they progress through the supply chain. P&G called this phenomenon the "bullwhip effect" (Chung, Lu, Dewey and Galas,, 2003). The causes of this phenomenon have been enumerated in a number of studies (Lee, Padmanabhan and Whang, 1997; Zhang, 2004; Gilbert, 2006; Jakic and Rusjan, 2008). Some of the reasons include (i) demand forecasts; (ii) batch delivery orders; (iii) price fluctuations; (iv) the rationing of the product for customers by the factory and the creation orders that are in excess of demand; (v) long supply times and auto-correlated demand; and (vi) restocking policies.

The bullwhip effect cannot be eliminated (Helbing and Lämmer, 2004), which is why it is very important for it to be measured. One way of measuring the bullwhip effect is by quantifying the increase in variability (fluctuations) in orders that occurs in every step of the supply chain. This is important for verifying the nature of the relations among forecasting techniques, delivery times and increases in variability (Chen, Drezner Ryan and Simchi-Levi, 2000).

To characterise the time series of the fluctuations in the supply chain (as it progresses), this research applied the non-linear tools of complex networks and fractal theory (R/S analysis and visibility algorithm).

Complex networks

A network is any system that allows for an abstract mathematical representation in a graph whose nodes (vertices) identify the elements of the system and in which the set of connections between the nodes (arcs) represents the presence of a relation or interaction between the elements. Networks are described in a rigorous way by the mathematical language of graph theory (Bollobás, 1998).

This concept refers to those networks that have a more complex architecture than those generated from a uniform random graph with a certain number of nodes and arcs. Usually, hubs (extremely connected or concentrating nodes) play a determining role in the architecture of complex networks. In this sense, the great majority of networks in the real world are complex (Dorogovtsev, 2010).

To study complex networks, this section will establish the definitions of graph theory that were used throughout this research.

Definition 1. An indirect graph W is defined by the set of pairs $W = [V, J]$, where V is the set of vertices and J is the set of arcs.
An arc can be represented as a pair (i, j), where $i, j \in V$ are the vertices that bind this arc.

Definition 2. All vertices $j \in V$, such that there exists $(i, j) \in J$ are called i successors. All vertices $j \in V$, such that there exists $(j, i) \in J$ are called i predecessors.

Additionally, the functions $\Gamma^{+}, \Gamma^{-} : X \to \wp(X)$ (power set of X) are defined, where for $i \in V$ (Bollobás, 1998; Hernández, 1997),

$\Gamma^{+} = \{i\ successors\} = j \in V \mid (i,j) \in V$ and
$\Gamma^{-} = \{i\ predecessors\} = j \in V \mid (j,i) \in V$

Definition 3. Two vertices i and j are adjacent or neighbouring if they are joined by an arc.

Definition 4. The grade of vertex i (denoted by k), is defined as the number of arcs incident to i.

Definition 5. The path of vertex i to j, of a length l in W, is the ordered sequence of different vertices $i = j_0, j_1, ..., j_l$ satisfying $\{j_a, j_{a+1}\} \in E(W)$ for a=0,1,…, l-1.

Definition 6. Given two vertices $i, j \in E(W)$, the distance between i and j, denoted by $d(i, j)$, is the shortest distance from every path between i and j.

The study of very large networks has prompted the introduction of new definitions and statistical analyses for their study. Despite the size and complexity of these networks, they exhibit certain coherence. Chung and Lu (2006) and Chung (2010) note the following properties:

- *Small-world phenomenon*. This refers to the minimum number of arcs between vertices; it is also known in social networks as six degrees of separation (Watts and Strogatz, 1998). This phenomenon exhibits the following characteristics: (1) any pair of nodes is connected in the network by a short number of arcs, and (2) two nodes that share a neighbouring node are also very likely to be neighbouring. The first feature is measured by comparing the average shortest path $\bar{l}$ of equation (1) with a comparable path of a random graph: $\bar{l}/\overline{l_{GA}} \sim 1$.

$$\bar{l} = \frac{1}{N(N-1)} \sum_{ij} l_{ij} \tag{1}$$

where l_{ij} denotes the shortest path between nodes i and j. The second feature is measured by comparing the average coefficient of the cluster of equation (2) to a coefficient of a random graph, in obedience to $\bar{C}_{datos} \gg \bar{C}_{GA}$

$$\bar{C} = \frac{1}{N} \sum_i C(i) \tag{2}$$

where

$$C(i) = \frac{e_i}{k_i(k_i - 1)/2} \tag{3}$$

and e_i can be calculated in terms of the adjacent matrix X for the vertices i, j and l as

$$e_i = \frac{1}{2}\sum_{jl} x_{ij}x_{jl}x_{li} \tag{4}$$

Any pair of nodes is connected by the shortest small path and the combination of a high density of clusters constitutes what is commonly known as the small-world phenomenon (Watts and Strogates, 1998).

- *Distribution of the network degree as a power law*. This refers to those networks in which the distribution of the degree of the connected nodes acts as a power law $P(k) \sim k^{-\gamma}$.
- *Large*. The typical size of these networks is in the range of hundreds of thousands or even billions of nodes.

Scattered. Given the number of nodes N in a graph and the maximum number of arcs $\binom{N}{2}$, the density of a graph is the number of existing arcs divided by the maximum possible number of arcs (without allowing for arcs that connect the node with itself) is $D=E/N[((N-1))/2]$. A graph is scattered if $D \ll 1$ (Barrat, Barthélemy and Vespignani, 2008).

The scaling exponent γ of a graph that exhibits a power law in the distribution of the degrees of its nodes can have two different value ranges. Barabási and Albert (1999) found that $\gamma = 3$ and that these types of networks are the consequence of two generic mechanisms: (i) networks constantly expand through the addition of new vertices and (ii) the new vertices are added to the network by preferably connecting to those nodes that have a very high degree of connections with other nodes. This mechanism was called the preferential attachment scheme, which can be described as "the rich get richer" and produces graphs with power laws with values of γ ranging from 2 to ∞ (Dorogovtsev et al., 2000). Figure 3 demonstrates an example of the mechanism of preferential attachment in a network.

The range $1 < \gamma < 2$ is produced through the *Partial Duplication Model*, which is based on the duplication of genetic information in biological networks. The model is described as follows (Chung et al., 2003).

Take z_0 as a constant and W_{z0} as a graph in z_0 vertices. For $z > z_0$, W_z is constructed by the partial duplication of W_{z-1}, according to the following: a random vertex u, of W_{z-1} is selected, and a new vertex v is added to W_{z-1} such that, for each neighbour x of u, a new arc $v - x$ is added with a probability of p (Figure 4).

The exponent and the probability relate as follows:

$$p(\gamma - 1) = 1 - p^{\gamma-1} \qquad (5)$$

where the value of γ is between 1 and 2, the probability p is $0.5 < p < 0.56714329\ldots$ and equation (5) can be linearly approximated as:

$$\gamma \approx 9.45 - 14.9p \qquad (6)$$

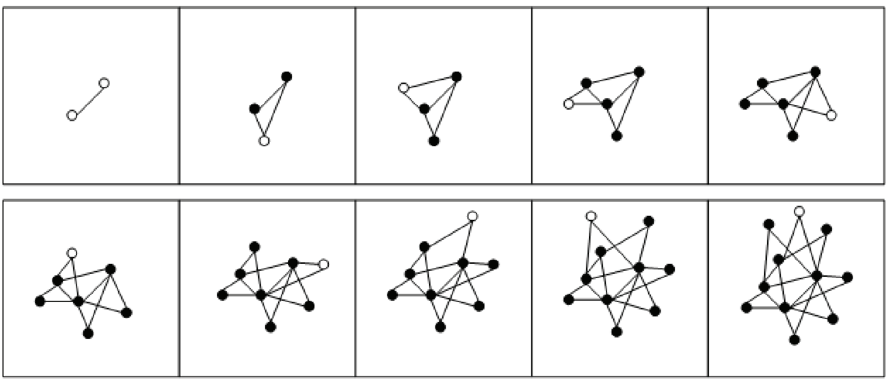

Figure 3. The emergence of a network according to the mechanism of preferential attachment.

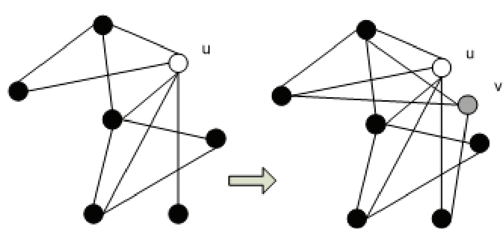

Figure 4. Sample diagram of the model of Partial Duplication.

Fractal theory

A fractal is an object or phenomenon whose structure persists in different scales, from the macroscopic to the microscopic. Fractals are sets whose Hausdorff dimensions are greater than their topological dimensions and are statistically self-similar objects (Mumford, Series and Wright, 2002).

Mandelbrot (2002; 2003) uses the term self-similar to refer to those fractals that are invariant under similarity transformations, which is to say that the scale factor transforming the fractal object is similar to the original, only larger or smaller. However, different fractal objects in nature or time series do not exhibit the behaviour of self-similar fractals because they present different transformations with different scales and lengths. Mandelbrot called these fractals self-affine.

Consider a finite set F in the d – Euclidean space. The position of each point in F is described by the vector $X = (x_1, x_2, \ldots, x_d)$. An affine transformation of the real scaling radii r_i $(0 < r_i < 1, i = 1,2, \ldots, d)$ takes each element of F from X position within an element of the set $r(F)$ with a position $R = (r_1 x_1, r_2 x_2, \ldots, r_d x_d)$. The set F is self-affine if this is a union of different subsets N consistent with $r(F)$. The set F is statistically self-affine if its subsets are statistically consistent with $r(F)$ (Balankin, 1997).

Definition 7 (Self-affine process). The standard definition of self-affinity indicates that a continuous time process $\mathrm{Y} = \{ \mathrm{Y(t)}, \mathrm{t} \geq 0\}$ is self-affine if the probability of the distribution of $\mathrm{Y} = \{\mathrm{Y(t)}\}$ has the same probability distribution as $\{\mathrm{a^H\, Y(at)}\}$ for $\mathrm{a} > 0$.

The parameter H takes values between 0 and 1 and is known as the self-affinity parameter or Hurst scaling exponent. This parameter measures the deployment of autocorrelation in the data of the phenomenon or complex system being studied (Gao, Cao, Tung and Hu, 2007):

- If $0 < H < 1/2$,, the process displays negative autocorrelations or anti-persistence.
- If $1/2 < H < 1$, the process displays positive autocorrelations or persistence. The higher the value of H, the more persistent the behaviour. Due to this property, time series demonstrate long-term dependency.

- If $H = 1/2$, it is said that the time series has no memory, which is to say that it has a completely random (or Brownian) behaviour.

In general, it is difficult to estimate the long-term memory with the scaling exponent H (Gao et al., 2007). In this paper, the value of H is estimated using Rescaled Range Analysis (R/S) and the Visibility Graph Algorithm. Other methods in the literature include the Variance-Time Plot, the Periodogram Method and α the estimator of a Power Law distribution, which can be found in Gao et al. (2007), Monte, Roca and Vilardell (2002) and Beran (1994), respectively.

Rescaled Range Analysis

Given a set of observations $\{X_k, k = 1, 2, \ldots, n\}$ with a sample mean of $\bar{X}(n)$ and a sample variance of $S^2(n)$, the statistic R/S is given by

$$\frac{R(n)}{S(n)} = \frac{1}{S(n)}[max(0, W_1, W_2, \ldots, W_n) - min(0, W_1, W_2, \ldots, W_n)] \quad (7)$$

where

$$W_k = \sum_{i=1}^{k}[X_i - \bar{X}(n)] \quad (8)$$

and the factor $S(n)$ is introduced for normalisation purposes. Therefore, $R(n)/S(n)$ essentially characterises the process range W_k. The expectation is that (Mandelbrot, 2003):

$$E\left[\frac{R(n)}{S(n)}\right] \propto n^H, n \to \infty \quad (9)$$

Thus, the value of H can be obtained through a linear regression on a sample time horizon

$$\log\left(E\left[\frac{R(n)}{S(n)}\right]\right) = \log(c) + H\log(n) \quad (10)$$

where $\log(c)$ is a constant that determines the point in which the line of equation (10) crosses the axis $\log(E[R(n)/S(n)])$.

Visibility Graph Algorithm

The algorithm of the visibility graph is a new method used to estimate the value of H by converting the fractional Brownian movement (fBm) into a self-scaling network,[1] according to the following criteria (Lacasa, et al., 2008; 2009): two arbitrary points of a time series (t_a, y_a) and (t_b, y_b) have a visibility and, as a consequence, are converted into two connected nodes in a determined graph, if any other point (t_c, y_c), where $t_a < t_b < t_c$ meets the following criteria:

$$y_c < y_a + (y_b - y_a)\frac{t_c - t_a}{t_b - t_a} \tag{11}$$

where t refers to the time and y is the value adopted by this point in time t. To illustrate the algorithm, Figure 5 presents an example for a given time series.

Lacasa *et al.* (2009) demonstrated that the degree of distribution of the nodes in graph $P(k)$, derived from a generic fBm, follows the power law, that is, $P(k) \sim k^{-\gamma}$, where the degree of node k is the number of nodes adjacent to it. The linear relation between the exponent γ of the distribution of the degrees, according to the power law of the visibility graph, and the exponent H, of the fBm series, is described as follows (Lacasa et al., 2009):

$$\gamma(H) = 3 - 2H \tag{12}$$

To estimate the scaling exponent γ, the logarithm of the vertex k degree is plotted against the logarithm of the number of vertices of the degree $k{:}m_k$. The resulting curve should approximate a straight line and the points should satisfy the following equation:[2]

$$\log(m_k) \approx a - \gamma \log(k) \tag{13}$$

1. In the same way, when applying this algorithm, periodic time series are converted into regular graphs and random time series are converted into random graphs (Lacasa et al., 2009).
2. See Clauset et al. (2009) to calculate the Hurst exponent with other techniques.

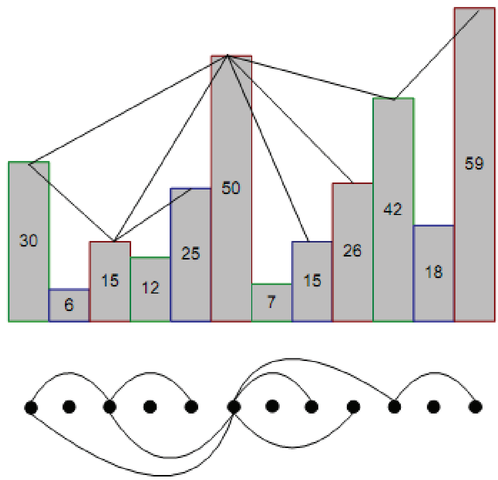

Figure 5. Example of the visibility graph algorithm.

The possibility of converting a time series into a graph allows for the use of quantitative tools of complex network analysis in understanding how variability (fluctuations) emerge in the process queues of the supply chain.

Non-linear Characterisation of Demand Time Series

For the non-linear characterisation of spare parts demand time series in telecommunications companies, we only had data visibility in four of the eight steps of the service process of advanced spare parts replacement: the demand $D(t)$, the faulty spare parts delivered by the customer to the OEM $ED(t)$, the units sent for repair $ER(t)$ and the repaired units returning to the OEM $RI(t)$. With these four time series, the process cycle is closed (those that are not present are intermediate steps) and its study is made possible. The demand time series includes one year of information for 4,217 units containing 548 unique codes (or spare part numbers). Unfortunately, not all units were collected from the customer for being faulty, nor were all of them already repaired. For this reason, only 3,617 units that completed the full cycle were considered for this analysis.

Figures 6 and 7 show the time series for each of the processes in the supply chain of a service company defined above: (a) demand, (b) faulty units delivered to the customer pending collection, (c) units sent for repair and (d) units collected by the OEM that returned from repair. The demand for the 3,617 units took place in a period of 365 days. The process of collecting the faulty units *ED*(*t*) and the process of sending them to be repaired *ER*(*t*) took place in a period of 434 days, and the process of units returning from repair to the OEM *RI*(*t*) took 464 days. Despite the fact that the quantity of units processed in each time series was constant, the number of days involved for each process increased at each subsequent step of the supply chain.

Table 1 shows the statistical calculation of the analysed time series. These statistics demonstrate an increase in the variability (fluctuations) between *ED* and *D* and between *ER* and *ED*, which confirms the emergence of the "bullwhip effect".

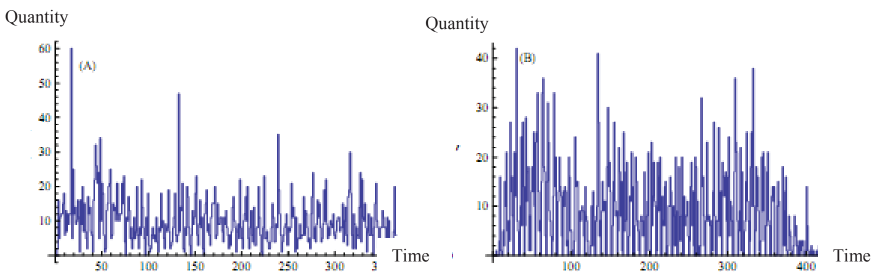

Figure 6. Time series of (a) demand and (b) faulty units pending collection from the customer.

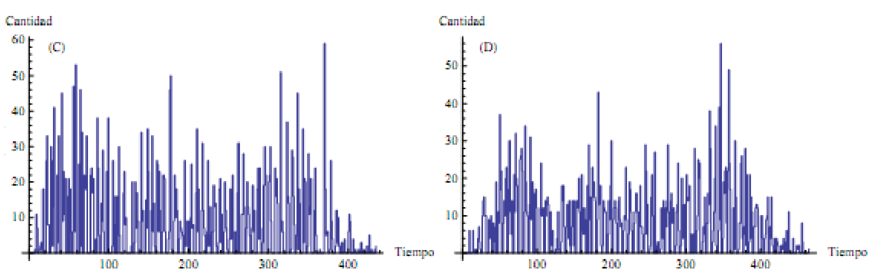

Figure 7. Time series of (c) units sent to be repaired and (d) units returning from repair to the OEM.

Table 1
Time series statistics

	D	*ED*	*ER*	*RI*
Promedio	9.9095	8.3341	8.3341	7.7952
Desv. Est.	7.0877	8.5929	11.468	9.1284
Varianza	50.23	73.83	131.51	83.3338

Graphical representation of demand dynamics

Consider the system in Figure 1 as a system of queues in which the servers are the elements or links of the supply chain and the inventory includes the objects that flow through it. Likewise, consider that in time $t = 0$, the system begins to operate without any work or service queue pending in any link. Finally, consider time to be a continuous variable. According to Figure 1, in process number one, a spare part i is requested for $i = 1, 2, 3, ..., n$ for the inventory of the link v_1 at time t_1^i; it reaches link v_2 at time t_2^i. The spare part is delivered in functioning (new or repaired) condition. Step two is the return of spare part i, in faulty condition, from link v_2 in time t_3^i; this spare part reaches link v_1 at time t_4^i. In step three, the link v_1 sends spare part i to be repaired at time t_5^i and it reaches link v_3 at time t_6^i. Finally, link v_3 returns the already-fixed spare part i to edge at time t_7^i, which reaches it at time t_8^i.

Note that

$$0 \leq t_1^i \leq t_2^i \leq t_3^i \leq t_4^i \leq t_5^i \leq t_6^i \leq t_7^i \leq t_8^i \tag{14}$$

and that this sequence will be followed each time a spare part i. However, it can be observed that the following is also met:

$$0 \leq t_1^1 \leq t_1^2 \leq t_1^3 \ldots \tag{15}$$

This can be graphically represented in a straight line, as presented in Figure 8.

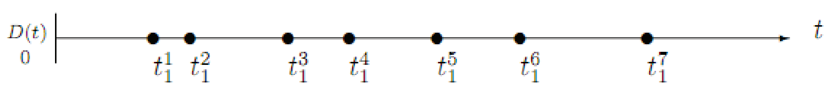

Figure 8. Representation of spare parts demand.

Likewise, as in the case of plotting spare parts demand in Figure 8, the following times can be plotted, which correspond to the passage of each spare part *i* through the entire supply chain. However, if the times experienced by each spare part t^n_i for $n=1,2, ..., 8$, are different, then it is possible that the previously indicated equality in equation (15) is not met.

Another more proper way of representing the entire supply chain is through graphs of the data accumulated to time *t* (Daganzo, 2003; 2004). The accumulated demand to time *t* in link v_1 is denoted by $D(t)$ and the quantity of delivered units accumulated to time *t* in link v_2 is denoted by $C(t)$. The accumulated faulty spare parts delivered to time *t* by link v_2 are denoted by $ED(t)$. The accumulated quantity of returned faulty units to time *t* that arrive to link v_1 is denoted by $RD(t)$. The accumulated volume of units sent to be repaired to time *t* by link v_1 is denoted as $ER(t)$ and their receipt in link v_3 is denoted by $RR(t)$. The accumulated repaired units to time *t* sent by link v_3 are denoted by $UR(t)$, those that are received are denoted by link v_1 and those that are already repaired are denoted by $RI(t)$ (see Figure 9).

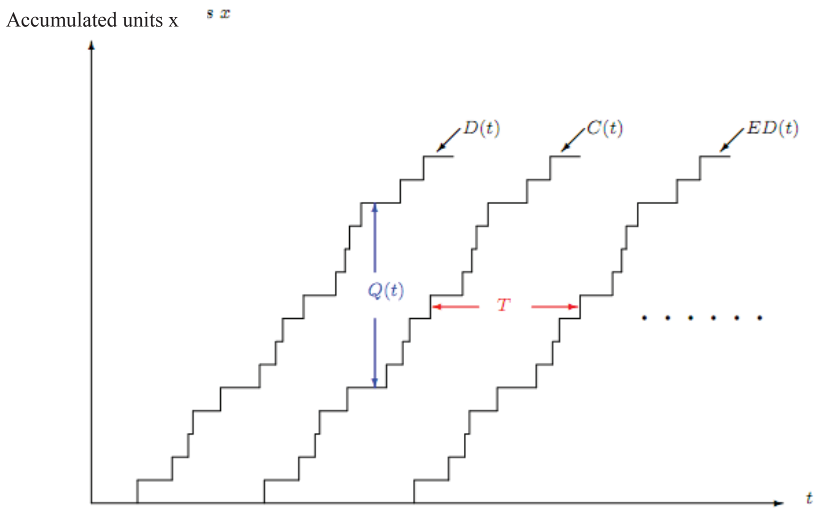

Figure 9. Graphic representation of accumulated demand, collection of faulty units and repair data.

In Figure 9, the vertical distance between two curves at any time represents the quantity of units that have entered a process and that have not yet left it; for example, the distance between curves $D(t)$ and $C(t)$ would represent the quantity of units requested by the customer and not yet delivered to him or her at time t. In general, this would be represented as follows:

$$Q_{kl}(t) = Curve_k(t) - Curve_l(t) \geq 0 \tag{16}$$

for $k > l$, where $k = 1,2,3, \ldots, n-1$ and $l = 2, 3, 4, \ldots, n$. Meanwhile, the horizontal distance between the two curves k and l corresponds to time T_i, which unit i takes from the moment it enters the process of $Curve_k\,(t)$ to the moment it reaches $Curve_l\,(t)$, for $i = 1,2,3, \ldots, n$.

When applying equation (16) in the four analysed time series, the time series of the supply chain queues are obtained (Figure 10).

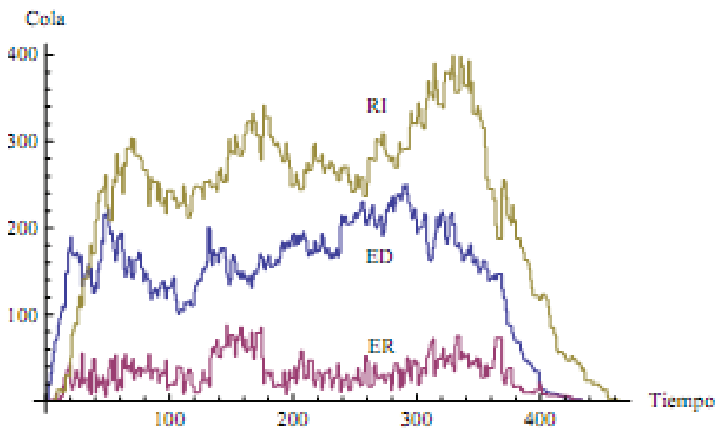

Figure 10. Unit queues in the supply chain of a service company.

Furthermore, to verify the impact that supply time has on the increase in the quantity and variability (fluctuations) of the queues generated in the supply chain, various time series are generated from the demand time series, taking into account the following complete process cycles: 1, 7, 14, 30, 60 and 90 days (Figure 11).

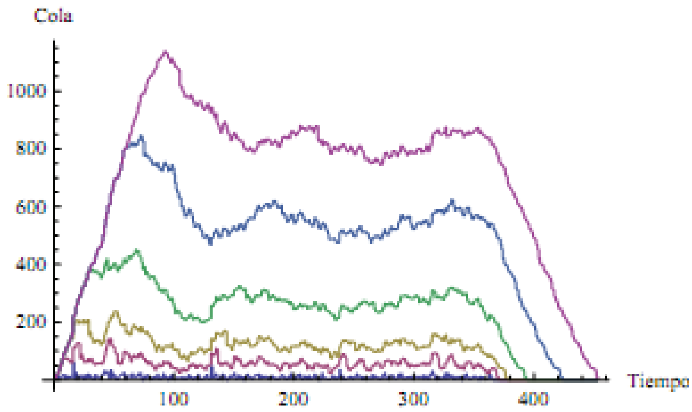

Figure 11. Unit queues in the supply chain for different delivery times.

Table 2 presents the statistical analysis of the time series of each queue. The queue corresponding to the process of units in repair *RI*(*t*) displays the greatest quantity and variability (fluctuation). This is followed by the process of faulty units pending collection from the customer *ED*(*t*) and, finally, by the process of collected faulty units to be sent for repair *ER*(*t*).

Table 2
Statistical calculations of the time series
of the unit queues in the supply chain

	Promedio	*Desv. Est.*	*Varianza*	*CV*
ED_{queue}	147.70	60.91	3710.57	0.41
ER_{queue}	32.48	19.49	379.94	0.60
RI_{queue}	223.42	105.03	11032.17	0.47
$L=1_{queue}$	9.90	7.08	50.23	0.71
$L=7_{queue}$	58.65	20.61	425.14	0.35
$L=14_{queue}$	124.72	37.12	1378.40	0.29
$L=30_{queue}$	266.90	81.89	6707.14	0.30
$L=60_{queue}$	504.49	178.05	31704.03	0.35
$L=90_{queue}$	710.62	273.52	74817.45	0.38

With regard to the impact of time of the complete service cycle of advance spare parts replacements, Table 2 shows how the coefficient of variation (CV) has the lowest dispersion when $L = 1$. However, this dispersion increases rapidly when complete cycle times are longer.

Characterisation of complex networks in time series

Each of the time series of the queues is converted into a graph by applying the Visibility Graph Algorithm. From here, equations corresponding to the theory of Complex Networks are applied to characterise the emergence of variability (fluctuations) in the supply chain queues. The networks can be observed in Figures 12 and 13. All calculations were performed with Network Workbench tool software (NWB Team, 2006).

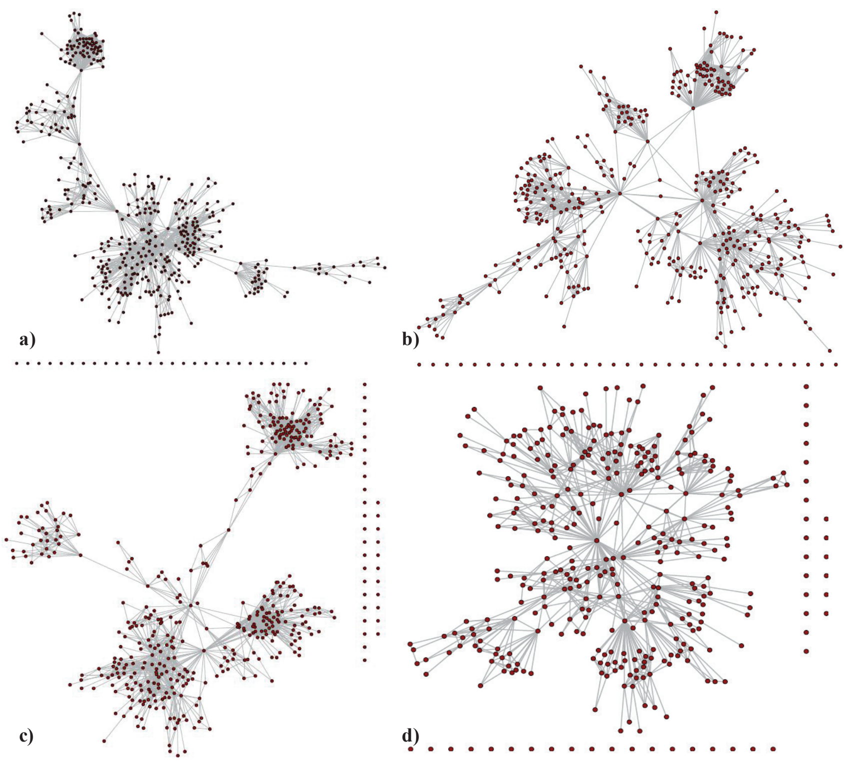

Figure 12. (a) Network corresponding to the queue of process ED(t). (b) Network corresponding to the queue of process ER(t). (c) Network corresponding to the queue of process RI(t). (d) Network corresponding to the queue if $L = 1$.

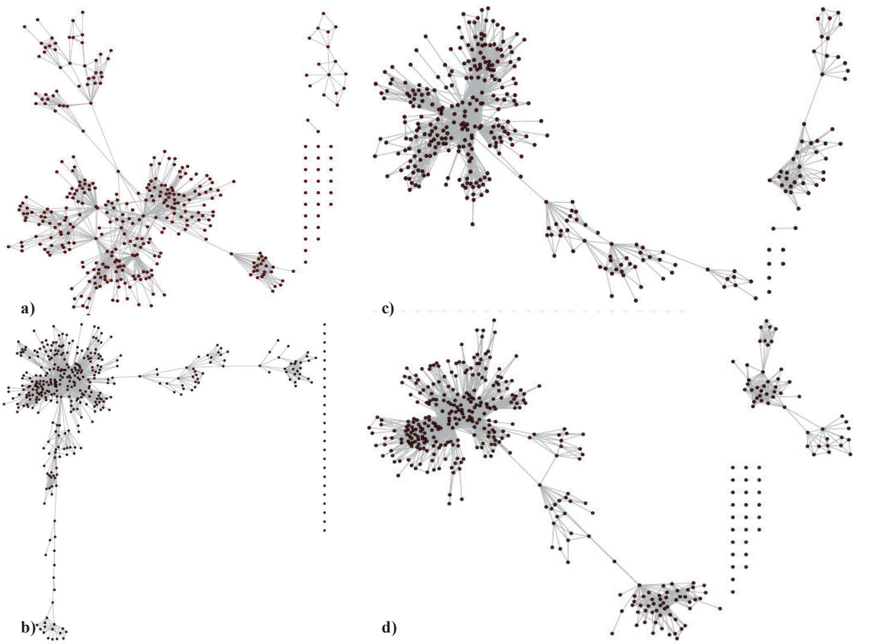

Figure 13. (a) Network corresponding to the queue if $L = 7$. (b) Network corresponding to the queue if $L = 4$. (c) Network corresponding to the queue if $L = 30$. (d) Network corresponding to the queue if $L = 60$.

All of the formed networks are dispersed because their density values satisfy $D \ll 1$ (Table 2), which is one of the characteristics of complex networks. To identify whether the networks experience the small-world phenomenon, random networks with the same number of nodes were constructed, taking into account that the probability of all of the nodes being connected is $p = \bar{k}/N$ (Newman, 2006). These two data points were introduced into the NWB tool to obtain the random networks. Because $\bar{C}_{data} \gg \bar{C}_{GA}$ in all cases and the shortest average path of the data is comparable with that of the random network $\bar{l}/\bar{l}_{GA} \sim 1$ (see Tables 3 and 4), it can be concluded that all of the networks are small-world.

The values of the dynamic scaling exponent γ shown in Tables 3 and 4 confirm that the degree distribution of the nodes is a power law. Because the values of γ are $1 < \gamma < 2$ in all cases, it can be confirmed that their variability (fluctuation) emerges through the model of Partial Duplication.

Table 3
Analysis of complex networks on the time series of queues

	Queue E	*Queue*	*Queue RI*
n	433	431	458
Archs	1795	1183	2220
Isolated nodes	27	31	33
Density	0.0191	0.30127	0.0212
Average clustering coefficient (data)	0.4875	0.5484	0.5261
Average clusterin coefficient (random graph)	0.0202	0.0138	0.0202
Average shortest path (data)	4.3325	4.0373	4.9235
g	1.2854	1.3069	1.0703
p	0.5479	0.5465	0.5623

Table 4
Analysis of networks with different cycle times

	L=1	*L=7*	*L=14*	*L=30*	*L=60*	*L=90*
n	365	370	377	393	423	453
Archs	838	1,265	1,442	2,026	2,390	2,467
Isolated nodes	40	26	26	25	26	26
Density	0.0126	0.0185	0.0203	0.0263	0.0267	0.0241
Average clustering coefficient (data)	0.5695	0.4675	0.4898	0.4742	0.4258	0.4518
Average clustering coefficient (random graph)	0.0177	0.0219	0.0238	0.0266	0.0253	0.0227
Average shortest path (data)	3.7439	4.0429	3.7606	4.7307	4.0064	2.9688
Average shortest path (random graph)	4.1832	3.3913	3.2262	2.8181	2.7629	2.8300
g	1.4251	1.3627	1.2309	1.1883	1.0673	1.1720
p	0.5385	0.5427	0.5516	0.5544	0.5625	0.5555

Fractal characterisation of time series

The values obtained after applying the methods mentioned above to determine the value of the Hurst exponent H are presented in Table 5. Consistency is exhibited for both the R/S and Visibility Graph Algorithm methods because the value of H is greater than 1/2 in both cases. Therefore, the analysed time series show positive correlations, which is to say that they display a persistent behaviour, which implies memory or dependency in the long term.

Table 5

Values of the Hurst exponent, H, of the queues

	H (R/S)	H (Alg. Visib. Gra.)
ED_{queue}	1.00	0.85
ER_{queue}	0.89	0.84
RI_{queue}	0.95	0.96
$L=1_{queue}$	0.74	0.78
$L=7_{queue}$	0.81	0.81
$L=14_{queue}$	0.89	0.88
$L=30_{queue}$	0.94	0.90
$L=60_{queue}$	0.89	0.96
$L=90_{queue}$	0.90	0.91

Conclusions

We demonstrate the emergence of the "bullwhip effect" in the supply chain of a telecommunications company that offers an advance replacement of spare parts service and whose supply chain involves intermittent demand. With respect to the variability (fluctuations) experienced by the queues of the supply chain of the service company analysed in this study, it becomes evident that they are slower when the cycle time is shorter.

However, the time series of the queues display positive correlations or persistence because the values of the Hurst exponent are greater than . This forms the basis for the (probabilistic) prediction of the demand for spare parts, which, in turn, would be the starting point for the construction of inventory models for companies with intermittent demand.

Finally, when converting the time series of the queues into graphs using the Visibility Graph Algorithm, the resulting networks demonstrated the small-world phenomenon and adjusted to the power law in the distribution of the degrees of their nodes with a value of . This result suggests that the variability (fluctuations) in the supply chain queues emerges according to the Partial Duplication model.

To conclude, the variability (fluctuations) of the supply chain queues of the service company increases when the values of the dynamic scaling exponents of and are close to one as a result of an increase in cycle time. Therefore, cycle time is an important factor for mitigating variability (fluctuations) in a complex system, which is the object of this study.

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CHAPTER 9
Predictability of Exchange Rate: A Comparison of Stochastic Simulation Models

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Francisco Venegas-Martínez

Introduction

The economic and financial literature concerning the prediction of the exchange rate can be grouped into two areas. The first of these is associated with monetary policy intervention in the exchange market, and the second one explores the possibilities for prediction and simulation of the exchange rate. Both issues are interrelated because when the exchange rate can be controlled by the monetary authority its prediction is highly possible in the short term, but the quality of this prediction depends on the models used to represent agents' expectations.

One of the most used methodologies for modeling future behavior of financial series is the Monte Carlo simulation. Through this technique, the price dynamics is represented by a specific stochastic process. Under this framework the key element in the simulation is the generation of random numbers from the probability distribution of the chosen generating process. The obtained realization by the process at each time is recursively calculated, that is, the basis to compute the current value is the value generated in the previous period. The simulated paths can be produced for any number of periods, and, often, the average path is the main outcome used to forecast.

One of the purposes of this paper is to contrast the performance of the Geometric Brownian Motion (GMB) and the Ornstein-Uhlenbeck (OU) processes, as models for estimating future changes in the exchange rate. In this regard, we will focus on the hypothesis that the lower the development of financial markets, the greater the central bank intervention in the foreign exchange market. The following exchange rates will be analyzed: U.S. Dollar/Mexican Peso (USD/MXN), U.S. Dollar/British Pound (USD/GBP), U.S. Dollar/Euro (USD/EUR), and U.S. Dollar/Yuan (USD/CNY).

This research is organized as follows: section 2 presents a brief review of the specialized literature concerning with the influence of monetary policy on the exchange rate, and the issue of the exchange rate predictability; section 3 lists the properties of the stochastic processes used in the analysis; section 4 provides a theoretical discussion of the Monte Carlo simulation of the exchange rate; and, finally, section 5 presents the conclusions of the research.

Monetary Policy and Exchange Rate

According to the criteria of orthodox monetary policy, the central bank main objective is to control inflation, and the main instrument is the benchmark interest rate (interbank rate). Many countries adopted these criteria, in the early nineties, when the use of the interest rate was a control variable as proposed by Taylor (1995). Since then, there are many possible representations of the Taylor's Rule. These include, for example, the gap between the observed and expected values of output, inflation, wages, and exchange rates.[1]

One of the main issues of monetary theory is that in countries with lower financial development and lower macroeconomic stability, there is a larger intervention by the central bank to control the exchange rate, because it is assumed that these controls amplify the effects of the interest rate; see, for instance, the contributions to the control of the exchange rate by the central bank in Ball (1999), McCallum and Nelson (1999), Svensson (2000), and Sideris (2008).

1. It should be emphasized that the rigorous application of the orthodox criteria requires the interest rate to be the only instrument of monetary policy.

Now then, regarding the studies on exchange rate modeling we mention that from Sutherland (2006), who examines the effects of the exchange rate fluctuations on the term structure interest rates. This author establishes the dynamics of the exchange rate as the specific Brownian motion:

$$S_t = \theta + \mu(t - \tilde{t}), t \geq \tilde{t},$$

where S_t, defines the exchange rate, θ expresses the size of a devaluation, μ is the expected rate of depreciation, and $\tilde{t}$ is the date when a crisis happens. Also, Domowitz and Hakkio (1985) investigated on the existence of the risk premium in the foreign exchange market. In their study, they assume that the supply of each currency is described as a stochastic process autoregressive of order one. Hakkio and Leiderman (1986) propose to model the forward exchange rate as the sum of two terms: the expected value of the variable in the short term, and a risk premium, the latter measured as the covariance between the forward rate and the usefulness of possessing foreign currency. Moreover, Bazdresch and Werner (2002) seek to explain the volatility of the rate Mexican Peso/U.S. Dollar between 1995 and 2001. The authors compare three possible predictive estimates of the exchange rate: the value of the forward exchange rate, autoregressive processes, and an alternative model in which they suggest to express the dynamics of the exchange rate by the equation

$$\Delta S_t = \mu_i + p_i \Delta S_{t-1} + \varepsilon_t^{\sigma_i}, i = 0,1,$$

where p_i denotes the probability of transition between two states, and μ_i and $\sigma_i > 0$ are given constants.

In financial literature there are several studies that show the convenience of representing the dynamics of asset prices by a Brownian process and a Poisson process. Among the first studies that precisely seek to explain the behavior of the exchange rate are: Ball and Torous (1985), Akgiray and Booth (1986), Khoury and Ghosh (1987), and Akgiray and Booth (1988). In all these cases, the authors demonstrate the benefits of representing the evolution of the exchange rate through the combination of a normally distributed process that presents a stable behavior, and a Poisson distribution to model the unexpected sudden jumps. This characterization of the exchange rate has been extended by other authors to different purposes; for example, Chang (2003) seeks a better accuracy in representation, so the author uses a bivariate function with Poisson jumps. More recently, Wang and Tong (2008) restate this representation of the exchange rate to incorporate stochastic volatility.

Among other works that suggest the possibility of exchange rate predictability are Preminger and Franck (2007) testing several methods as a linear autoregressive model and a neural network model for the Japanese Yen/U.S. Dollar (JPY/USD) rate and the British Pound/U.S. Dollar (GBP/USD). Furthermore, Guo and Savickas (2008) predict the exchange rate through variables as: the default premium, the term spread, the excess stock market return, aggregate stock market volatility, and the average idiosyncratic stock volatility. Finally, Wu and Hu (2009) find evidence to reject the random walk hypothesis as exchange-rate path, and instead they prove that real effects are indeed important in its definition.

Useful Stochastic Processes for Simulation Purposes

The Monte Carlo simulation method is widely used because, many times, it appropriately replicates the dynamics of relevant financial variables associated with the time series models. As a result of Monte Carlo method, a set of different possible paths is obtained and the average path represents the main outcome of the simulation. It should be noted that one of the main features of this method is that the best approaches are only for the short term, i.e., for a few time periods following the last observation; in the case of economic and financial time series this means that the best predictions are achieved only for a few days.

The stochastic processes best known and most used for the analysis of economic and financial series are the Geometric Brownian Motion (GBM) and the Ornstein-Uhlenbeck process (OU). The definition of the GBM is associated with notable researchers Bachelier (1990), Einstein (1956), and Wiener (1964). The GBM is defined as:

$$S_t = S_0 e^{X_t}, \quad X_t = \left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma W_t, \tag{1}$$

where S_t defines the exchange rate, μ is the trend parameter, $\sigma_i > 0$ is the volatility parameter, and W_t is the Brownian motion (a random normal variable with mean cero an variance t). Expression (1) is solution of the following stochastic differential equation of first order:

$$\mathrm{d}S_t = \mu S_t \mathrm{d}t + \sigma S_t \mathrm{d}W_t \qquad (2)$$

The properties of a GBM are:

a) $\{W_t : t \geq 0\}$ represents a Brownian Motion;
b) $S_t \sim$ lognormal $(S_0\, e^{\mu(t-s)}, e^{2\mu(t-s)} S_0^2 (e^{\sigma 2 (t-s)} - 1))$, $0 \leq s < t$;
c) When time goes to infinity, the mean and volatility scaled by time increase without limit.

In 1957, Paul Samuelson used the GBM stochastic differential equation to model the price of financial assets. Subsequently, Black and Scholes (1973) used the GBM for determining the price of a European option, and Merton (1973) also used it to obtain the price of a contingent claim and the discounted price of a zero coupon bond.

Another useful stochastic process is that from Uhlenbeck and Ornstein (1930). They proposed a process with mean reversion to represent the motion of a gas molecule, Vasicek (1970) establishes an equation to model the dynamics of the interest rate on short term, by defining:

$$dS_t = a(b - S_t)dt + \sigma dZ_t, \quad a, b > 0, \quad dZ_t \sim N(0, dt) \qquad (3)$$

The terms a and b are positive constants, the variable S_t fluctuates over time, around its long term average b; if $S_t > b$, then S_t is forced to decrease, while when $S_t < b$, then S_t tends to increase; the adjustment speed is determined by constant a. In this case,

$$S_t \sim N\left(b + \left((S_0 - b)e^{-a(t-s)}\right), \frac{\sigma^2}{2a}\left(1 - e^{-2a(t-s)}\right)\right), \text{ given } 0 \leq s < t$$

As noted S_t could be negative, and if $t \to \infty$, then the mean converges to b, and the volatility converges to $\sigma^2/2a$.

Monte Carlo Simulation

Monte Carlo method for simulation of stochastic processes involves the following stages:

a) First, random numbers are generated from a uniform distribution. These random numbers are transformed into standard normally distributed random numbers by using the Box-Muller transformation:

$$Z = \sqrt{-2lnU_1}\cos(2\pi U_2), \qquad Z_2 = \sqrt{-2lnU_1}\sin(2\pi U_2) \tag{4}$$

where U_1, U_2 are uniform random variables, and Z_1, Z_2 are standard normal random variables. Each series of random numbers provides a path of the stochastic process being simulated.

b) The standard normal random are substituted[2] into the discretization of (2) and (3) given by:

$$S_{t+dt} = S_t e^{\mu\Delta t} + S_t^2 e^{2\mu\Delta t + e^{\sigma^2\Delta t}} Z_t\ ,\ Z_t \sim N(0,1) \tag{5}$$

$$S_{t+\Delta t} = S_t\ e^{-\hat{a}\Delta t} + \hat{b}\left(1 - e^{-\hat{a}\Delta t}\right) + \ \sigma\sqrt{\frac{1}{2\hat{a}}(1 - e^{-2\hat{a}\Delta t})}Z_t,\ \ Z_t \sim N(0,1) \tag{6}$$

c) The parameters of equations (5) and (6) have to be estimated. In the case of the GBM, to determine the parameters, mean μ and variance σ^2, only requires descriptive statistics of the series. For the OU process, the definition of the parameters *a* and *b*, of the above equations, requires an Ordinary Least Squares (OLS) estimate from the observed series. Regression analysis generates β_0 and β_1 estimators, used as $\widehat{\beta_0} = \hat{a}\hat{b}$, $\widehat{\beta_1} = (1 - \hat{a})$, and therefore $\hat{a} = 1 - \widehat{\beta_1}$ and $\hat{b} = \widehat{\beta_0}/\hat{a}$. The estimated parameters for each exchange rate series are shown in Table 2.

d) Generate recursively paths of the stochastic process, and finally the average path is obtained.

2. This observation is very important, if we model the variation of the exchange rate, it is possible to obtain negative valuess, which is consistent with the stochastic models used here; if instead, the level of the exchange rate was modeling, the results could not be negative, and therefore would not be feasible using the processes GBM or OU.

Simulation Results

This research test GBM and OU models for the variation of the following exchanges rates: U.S. Dollar/Euro (USD/EUR), U.S. Dollar/British Pound (USD/GBP), U.S. Dollar/Yuan (USD/CNY), and U.S. Dollar/Mexican Peso (USD/MXN). All data were obtained from the Federal Reserve System of the United States. A first study of the series between 1999 and 2012 is presented in Table 1 and in Figure 1. In all cases is observed the increased volatility in the exchange rate occurred between 2008 and 2009. The rate USD/GBP was the most stable in the period under review; in fact it has the smallest variance. In contrast, the USD/MXN is the series that has greater dispersion between the highest and lower values. A special case is China, which kept artificially undervalued its currency against the dollar between 1997 and 2004 (around \$8.28 yuan per dollar), this perhaps in an effort to promote exports (this explain the low variance), in addition, according to official data from that country, in 2010, China international reserves became of 2.8473 billion, that is, almost 20% of U.S. GDP.

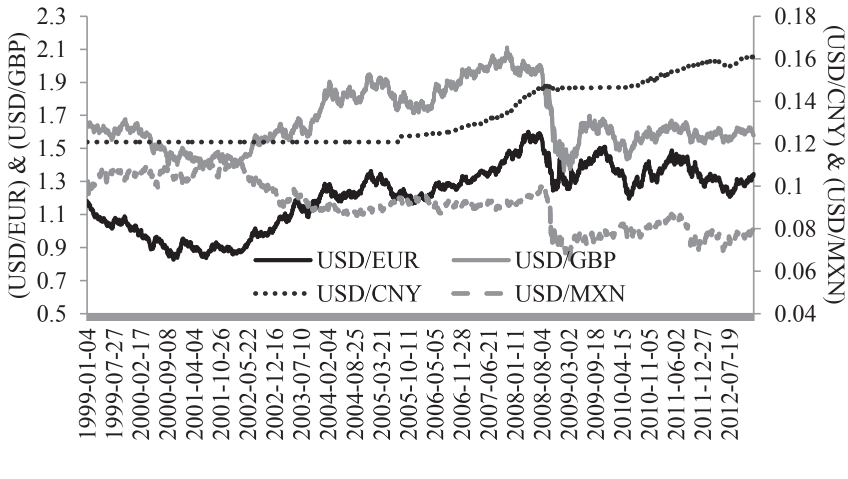

Figure 1. Exchanges rates (U.S. Dollar/Foreign Currency)

Table 1
Descriptive Statistics of Daily Variation of Exchange Rates

	USD/EUR	*USD/GBP*	*USD/CNY*	*USD/MXN*
Mean	0.00368	-0.00137	0.00808	-0.00724
Standard Deviation	0.65178	0.59992	0.08992	0.64559
Minimum	-3.00310	-4.96625	-0.98613	-8.11406
Maximum	4.62079	4.43486	2.01867	5.95996
Range	7.62389	9.40111	3.00479	14.07401

Table 2 shows the parameters used in forecasting. It is worth noting that these parameters were estimated considering the daily data of exchange rate between January 1999 and November 2012.

Table 2
Parameters estimated for MGB, and OU processes

Process	*USD/EUR*	*USD/GBP*	*USD/CNY*	*USD/MXN*
MGB	μ=0.002760 σ^2=0.427465	μ=-0.009709 σ^2=0.362491	μ=0.008141 σ^2=0.008096	μ=-0.007800 σ^2=0.419104
OU	a=0.996610 b=0.008613 1/2a=0.501700	a=0.979031 b=-0.000115 1/2a=0.510709	a=1.163694 b=0.007031 1/2a=0.429666	a=1.010211 b=-0.010147 1/2a=0.494945

To see which model provides a better fit to the observed data, the simulation results were compared for the last forty days in 2012 with the actual data, in each case were estimated both the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE). These results are showed in Table 3. The equations defining errors are

Root Mean Square Error:

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(X_t - Y_t)^2} \tag{7}$$

Mean Absolute Error:

$$\text{MAE} = \frac{1}{T}\sum_{t=1}^{T}|X_t - Y_t| \tag{8}$$

where X_t is the observed value, Y_t is the estimated value, and T is the number of observations.

Table 3
Estimated errors of the Monte Carlo Simulation

Process	*USD/EUR*	*USD/GBP*	*USD/CNY*	*USD/MXN*
GBM	RMSE=0.628355 MAE=0.499461	RMSE=0.641869 MAE=0.519187	RMSE=0.020234 MAE=0.014871	RMSE=0.570786 MAE=0.437205
OU	RMSE=1.538300 MAE=1.229950	RMSE=1.466694 MAE=1.127891	RMSE0.024489 MAE=0.0185542	RMSE=0.238536 MAE=0.119621

Note: RMSE, Root Mean Square Error; MAE, Mean Absolute Error.

Finally, the results shown in Table 3 suggest that for the USD/EUR and USD/GBP exchange rates, presumably the cases where there were less intervention in markets by the monetary authority, the best estimate is provided by the GBM; whereas in the cases of USD/CNY and USD/CAD, the best fit was provided the OU process.

Conclusions

This paper has focused on examining the predictability of the exchange rate of various currencies against the dollar, specifically were examined the cases of USD/EUR, USD/GBP, USD/CNY, and USD/MXN. The higher estimation errors are derived from the simulation of the variation of the dollar against European currencies; also in these cases the best adjustment comes from the GBM process. In contrast, for the USD/CNY and USD/CAD exchange rate variation, the estimation errors are lower, especially when the simulation is performed by the OU process. However, it is very important to note that the estimation results reveal the monetary authority intervention in the control of the exchange rate; precisely the smallest error was obtained for the USD/CNY variation, when it is known that the exchange rate has been controlled, or, the USD/MXN variation, although there is a floating regime, the bank of Mexico has made constant interventions in the exchange market, especially since 2003. It is also likely that the simulation results would improve considerably if it is considered only a limited horizon in the estimation of the parameters of the OU and GBM process. Between

2008 and 2009, a high volatility was observed in all cases (except for USD/CNY).

Finally, it is important to point out that the central bank intervention is a factor which must necessarily be considered in studies on the feasibility of forecasting exchange rate, because their validity could be questioned if it is exercised a control over the variable, which depends in turn on factors such as the purpose of controlling the inflation.

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Chapter 10
Financial Time Series: Stylized Facts for the Mexican Stock Exchange Index Compared to Developed Markets

Omar Rojas-Altamirano
Carlos Trejo-Pech

Introduction

It is widely agreed on that Mathematical Finance, and in particular the study of financial time series from a statistical point of view, started on March 29th, 1900 at La Sorbonne, Paris, when Louis Bachelier, Poincaré's student, presented his thesis *Théorie de la Spéculation,* c.f. (Bachelier, 1900). Bachelier introduced the theory of Brownian motion used for the modeling of price movements and the evaluation of contingent claims in financial markets (Courtault et al., 2000). In Bachelier's proposition, if P_t denotes the price of an asset, at period *t*, then $P_{t+1} = P_t + \varepsilon_t$ is the price of the asset at a future unit instance, assuming that $\varepsilon_t \sim N(\mu, \sigma^2)$. Such an asumption was, in fact, a preamb le of the Efficient Market Hypothesis developed much later by Fama (1965).

However, hidden in the chaos of this pure stochastic process, some patterns in the price movement were recognized by Osborne (1959). In particular, Osborne showed that from moment to moment the market price is much more likely to reverse itself than to continue on a trend. However, when a price moves in the same direction twice, it is much more likely to continue in that direction than if it had moved in such direction only once (Weatherall, 2013). Other behaviours, common to a wide variety of assets, have also been documented. For instance, the non-Gaussianity of returns -contradicting Bachelier's original assumption, as empirical distributions of price changes are usually too peaked to be relative to samples from Gaussian populations (Mandelbrot, 1963). From then on, sets of properties, common across many instruments, markets and time periods, have been observed and termed *stylized facts* (Cont, 2001).

Some of these stylized facts relate to the shape of the probability distribution function of returns. In particular, empirical studies report that the distributions are *leptokurtic* (more peaked and with fatter tails than those corresponding to the normal distribution) and *skewed*. Using a kernel density estimator, it can be shown that most distributions of returns can be adjusted by a fat-tail distribution, e.g. a Student's *t*-distribution with 3 to 5 degrees of freedom. On the other hand, as one increases the time-scale on which returns are measured, the distributions tend to Gaussianity. Another set of stylized facts can be derived from the *autocorrelation function* (ACF). For instance, the slow decay of the ACF in absolute returns, the absence of correlation after some time, and the formation of volatility clusters. Some of these stylized facts have been empirically confirmed on some indexes and exchange rates, see, e.g. (Franses and van Dijk, 2000) and (Zumbach, 2013). The case of the Belgrade Stock Market was treated in Miljković and Radović (2006). For a more exhaustive list of references, see Sewell (2011).

After observing the predominant stylized facts of returns of a given asset, and running some normality and linearity tests, one could be in a more comfortable position to chose a proper model, most of the times non-linear, for the empirical financial data at hand. We study some of these stylized facts exhibited by the Mexican Stock Exchange Index (IPC), and compare them to those of indexes from both developed and emerging markets (USA [S&P 500], UK [FTSE], JAPAN [NIKKEI 225], Brazil [IBOVESPA], and India [BSE]). Some authors have already focused their attention on the IPC, studying different, but related, empirical problems. Asymmetric ARCH models where used to model the daily returns of 30 stocks of the IPC by Lorenzo Valdéz and Ruíz Porras (2011), and by López Herrera (2004). These studies focused on volatility of returns. We believe this chapter will be of interest since it provides the stylized facts of the IPC returns time series. The knowledge of those facts could be helpful to determine better empirical models, most of the times nonlinear, to produce reliable forecasts.

Stylized Facts of Returns for the Mexican Stock Exchange Index

In this section we present some of the *stylized facts* exhibited by the IPC and compare them to those from other developed and emerging markets (USA [S&P 500], UK (FTSE), JAPAN [NIKKEI 225], Brazil [IBOVESPA], and India [BSE]). Daily-adjusted closing prices from January 1997 to December 2011 are used, see Figure 1.

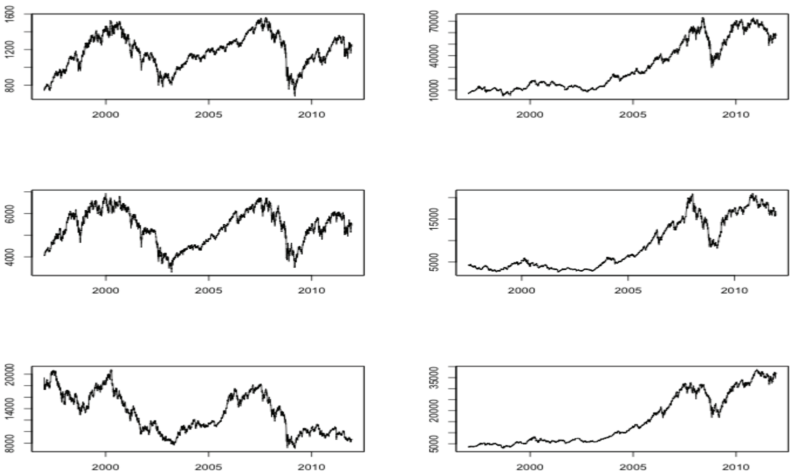

Figure 1. Daily observations on the level of the stock indexes of developed markets (left), from top to bottom USA (S&P 500), United Kingdom and Japan, and emerging markets (right), from top to bottom Brazil, India and Mexico from January 1997 to December 2011.

As can be observed from Figure 1, the time series of the stock indexes do not look very similar. However, as we will see in the next section, returns are in fact very similar.

From prices to returns

Most financial studies involve returns of assets instead of prices. According to Campbell et al. (1997), there are two main reasons for using returns. First, for average investors, returns represent a complete and scale-free summary of the investment opportunity. Second, return series are easier to handle than price series because the former have more attractive statistical properties.

Let P_t be the price of an asset at time t. The *simple return* is

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}},$$

from where

$$1 + R_t = \frac{P_t}{P_{t-1}}.$$

The natural logarithm of the above *gross return* in percentual terms, leads to the *continuously compounded percentual return*

$$r_t = 100 \cdot (p_t - p_{t-1}),$$

where $p_t = \ln(P_t)$ and $r_t = \ln(1 + R_t)$. We will focus our attention throughout the rest of this chapter, on the time series of returns (also called *percentual log-returns*) defined by $\{r_t\}$. Figure 2 plots the time series of returns for the different indexes under study.

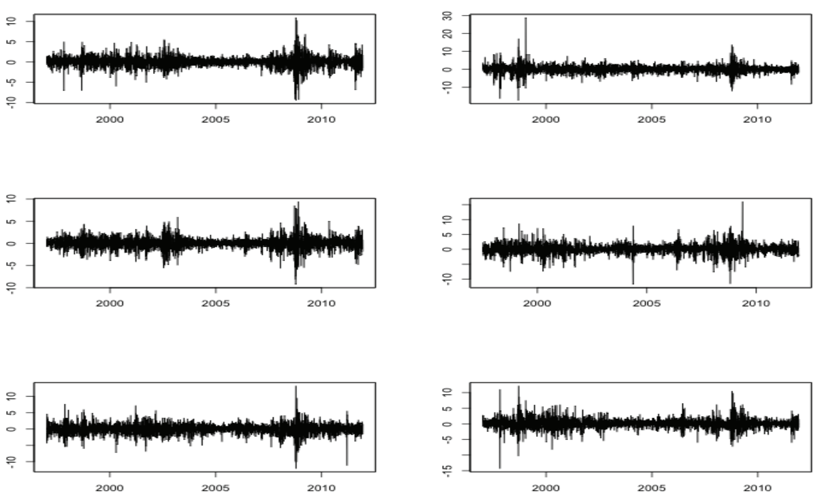

Figure 2. Time series of returns corresponding to stock indexes of developed markets (left), from top to bottom USA (S&P 500), United Kingdom and Japan, and emerging markets (right), from top to bottom Brazil, India and Mexico from January 1997 to December 2011.

Probability Density Function

A traditional assumption in financial mathematics, convenient to make statistical properties of returns tractable, is that $r_t \sim i.i.d.\ \ N(\mu, \sigma^2)$. However, as it has been known since Mandelbrot (1963), such assumption encounters difficulties when empirically tested. To illustrate, cf. to Figure 3, where the peak of the histogram is much higher than the corresponding to the normal distribution and it is slightly skewed to the right.

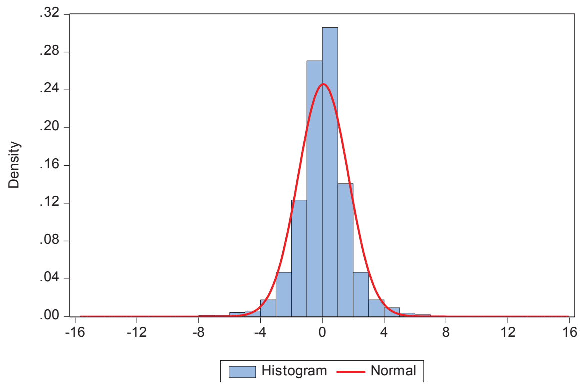

Figure 3. Histogram of daily returns of the IPC against the theoretical normal distribution

Summary statistics for daily index returns r_t from 1997 to 2011 are provided in Table 1. These statistics are used in the discussion of some stylized facts related to the probability density function of the series below.

Table 1
Summary statistics for stock index returns

Index	*Mean*	*Median*	*Min*	*Max*	*StdDev*	*Skewness*	*Kurtosis*
S&P 500	0.0137	0.0687	-9.4695	10.9571	1.3501	-0.2040	9.7826
FTSE	0.0077	0.0413	-9.2645	9.3842	1.2918	-0.1203	8.0672
NIKKEI	-0.0220	0.0037	-12.1110	13.2345	1.6048	-0.2861	8.5632
IBOVESPA	0.0570	0.1379	-17.2082	28.8324	2.2520	0.3184	15.3954
BSE	0.0365	0.1062	-11.8091	15.9899	1.7193	-0.0899	8.1902
IPC	0.0642	0.1073	-14.3144	12.1536	1.5955	0.0131	9.4692

Gain/loss asymmetry

The *skewness* $\hat{S}$ of r_t is a measure of the asymmetry of the distribution of r_t. The sample skewness can be estimated consistently by

$$\hat{S} = \frac{1}{n}\sum_{t=1}^{m}\frac{(r_t - \hat{\mu})^3}{\hat{\sigma}^3}.$$

Recall that all symmetric distributions, including the normal, have skewness equal to zero. With the exception of Mexico and Brazil, most indexes returns have negative skewness (Table 1). This might point into possible opportunities of investment in these developing markets, since negative (positive) skewness implies that the left (right) tail of the distribution is fatter than the right (left) tail, or that negative (positive) returns tend to occur more often than large positive (negative) returns (Franses and van Dijk, 2000).

Fat tails

A random variable is said to have *fat tails* if it exhibits more extreme outcomes than a normally distributed random variable with the same mean and variance (Danielsson, 2011). This implies that the market has more relatively large and small outcomes than one would expect under the normal distribution.

The *kurtosis* measures the degree of peakedness of a distribution relative to its tails. The sample kurtosis can be estimated by

$$\hat{K} = \frac{1}{n}\sum_{t=1}^{n}\frac{(r_t - \hat{\mu})^4}{\hat{\sigma}^4}.$$

High kurtosis generally means that most of the variance is due to infrequent extreme deviations than predicted by the normal distribution that has kurtosis equal to 3. Such leptokurtosis is a signal of fat tails. As seen in Table 1, all stock index returns have excess kurtosis, well above 3, which is evidence against normality.

The most commonly used graphical method for analyzing the tails of a distribution is the quantile-quantile (QQ) plot. QQ plots are used to assess whether a set of observations has a particular distribution. The QQ plots for the IPC returns against some theoretical distributions are shown in Figure 4.

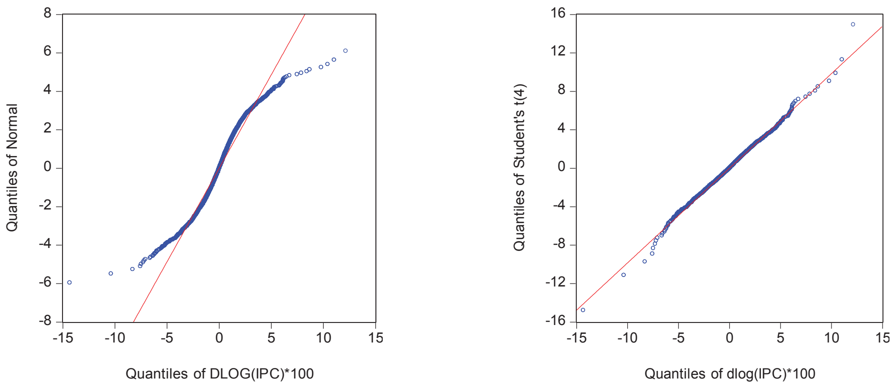

Figure 4. QQ plot of IPC returns against Normal (left) and Student t-distribution with 4 degrees of freedom (right)

Returns seem to have fatter tails to fit the normal distribution. To have a sense on how fat the tails are, the Student t-distribution is used as this is a distribution with fat tails, where the degrees of freedom indicate how fat the tails actually are. Figure 5 shows an almost perfect fit by the Student t-distribution to the kernel density of IPC returns.

The fact that the distribution of returns is fat-tailed has important financial implications, especially because it leads to a gross underestimation of risk, since the probability of observing extreme values is higher for fat-tail distributions compared to normal distributions. Alan Greenspan (1997) warned financial markets on this: "The biggest problems we now have with the whole evolution of risk is the fat-tail problem, which is really creating very large conceptual difficulties. Because as we all know, the assumption of normality enables us to drop off the huge amount of complexity in our equations. Because once you start putting in non-normality assumptions, which is unfortunately what characterizes the real world, then these issues become extremely difficult".

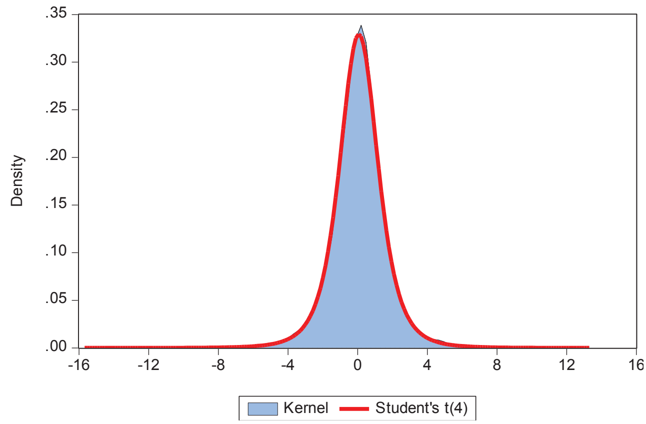

Figure 5. Kernel density of IPC returns against Student t-distribution with four degrees of freedom

Normality tests

Two of the most common tests for normality are the Kolmogorov-Smirnov and the Jarque-Bera. The Jarque-Bera (JB) test is given by the statistic

$$JB = \frac{\hat{S}^2}{6/T} + \frac{(\hat{K}-3)^2}{24/T},$$

which is asymptotically distributed as a χ^2 random variable with 2 degrees of freedom, where $\hat{S}$ is the sample skewness, $\hat{K}$ the sample kurtosis and T the sample size. One rejects H_0 of normality if the p-value of the JB statistic is less than the significance level (Jarque and Bera, 1987). JB statistics for all 6 stock index return series are: S&P 500 (7237.259), FTSE (4046.752), NIKKEI (4778.961), IBOVESPA (23730.45), BSE (4010.862) and IPC (6532.395). The p-values = 0.0000, for all, reject normality.

Agregational Gaussianity

As one increases the time scale over which returns are calculated, the distributions looks more and more like a normal distribution. In general, the shape of the distribution is not the same at different time scales

(Cont, 2001). Table 2 shows how the kurtosis and the value of the JB statistic decrease as the time scale increases. Daily, weekly and monthly returns all have a JB *p*-value that rejects normality; however, quarterly returns do not, as shown in Figure 6. In empirical research quarterly returns are seldom used.

Table 2
Summary statistics for IPC returns taken at different time scales from 1991 to 2011

Time scale	*Mean*	*Median*	*StdDev*	*Skewness*	*Kurtosis*	*JB*	*JB p-value*
Daily	0.0648	0.0800	1.6201	0.0201	8.3821	6075.06	0.0000
Weekly	0.3107	0.5727	3.6367	-0.2313	5.7106	330.83	0.0000
Monthly	1.3642	2.2857	7.6775	-0.8049	5.2890	78.6402	0.0000
Quarterly	4.0528	4.7035	12.9816	-0.0250	2.5772	0.6417	0.7255

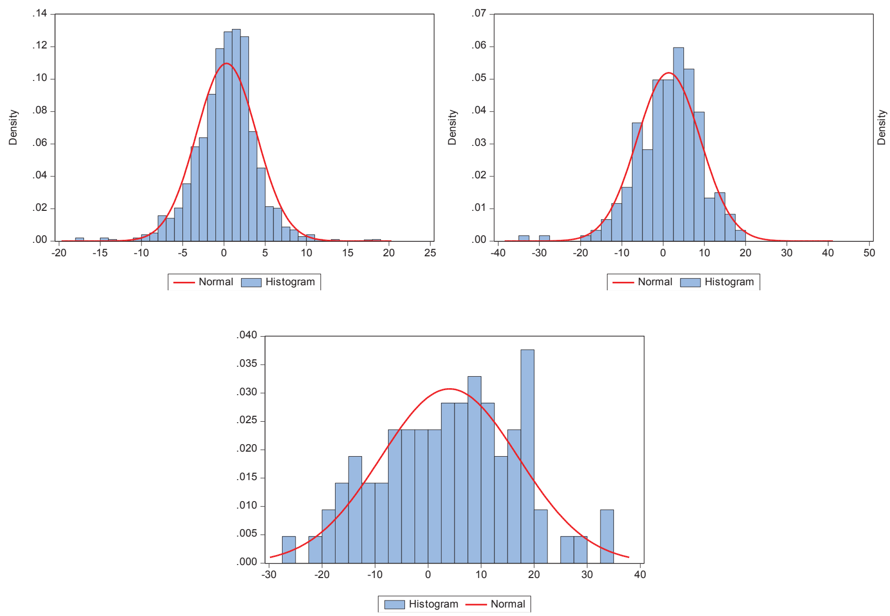

Figure 6. Histogram vs. theoretical normal distribution for IPC returns. Weekly (left), monthly (center) and quarterly (right).

Autocorrelation Function

The lag-k *autocorrelation function* (ACF) of a time series r_t is defined by

$$\rho_k = \frac{\gamma_k}{\gamma_0} = \frac{Cov(r_t, r_{t-k})}{Var(r_t)}.$$

The ACF measures how returns on a given day are correlated with returns on previous days. If such correlations are statistically significant, we have strong evidence for predictability.

Absence of linear autocorrelation

It is a well-known fact that price movements in liquid markets do not exhibit any significant linear autocorrelation (Cont, 2001). It is seen in Figure 7 how the autocorrelation function for the IPC series rapidly decays to zero after a lag (day). For more on the absence of significant linear autocorrelations in asset returns, cf. (Fama, 1965).

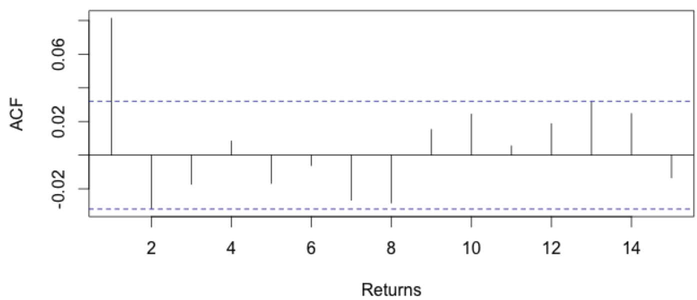

Figure 7. Autocorrelation plot of IPC returns, along with a 95% confidence interval, for the first 15 lags.

Volatility clusters

The most common measure of market uncertainty is volatility (the standard deviation of returns). A standard graphical method for exploring predictability in statistical data is the ACF plot. Figure 8, top panel, shows the ACF plot of IPC returns, along with a 95% confidence interval, from where it is evident that most autocorrelations lie within the interval. In contrast, middle panel and bottom panel of Figure 8 show the ACF plot of squared and absolute returns, respectively, where the ACF is significant even at long lags, providing strong evidence for the predictability of volatility, given the persistence of the autocorrelations. For various indices and stocks, it has been shown that the squared ACF of returns remains positive and decays slowly, remaining significantly positive over several days. This phenomenon is what is usually called the autoregressive conditional heteroscedasticity (ARCH) effect (Engle, 1995).

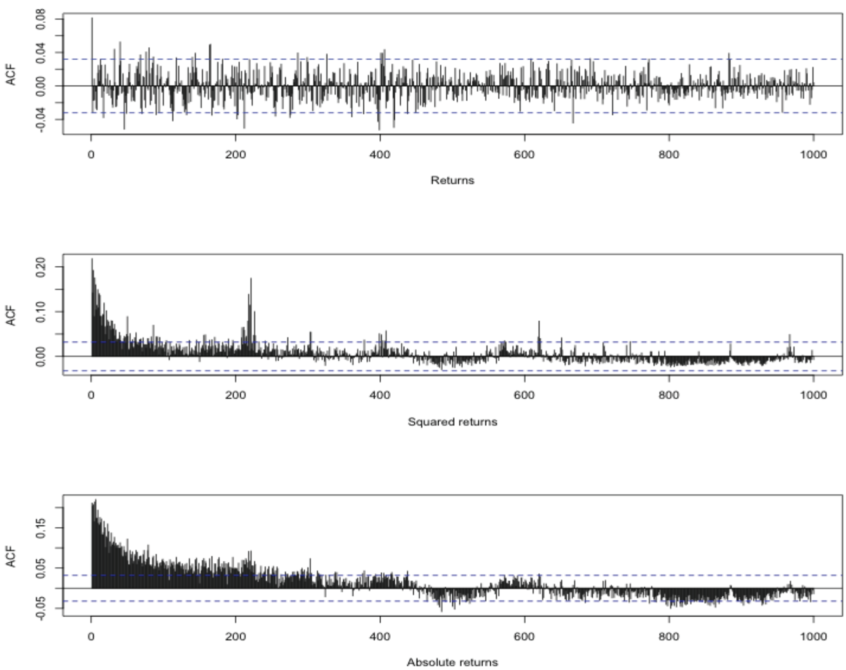

Figure 8. Autocorrelation plots of daily IPC returns 1997-2011 (top), squared returns (middle) and absolute returns (bottom). All the plots with a 95% confidence interval

The *Ljung-Box* (LB) test (Ljung and Box, 1978) is used to test the joint significance of autocorrelation coefficients over several lags. It is a Portmanteau statistical test for the null hypothesis $H_0 : \rho_1 = \cdots = \rho_m = 0$

against the alternative hypothesis $H_a : \rho_i \neq 0$ for some $i \in \{1,\ldots,m\}$. It is given by

$$LB(m) = T(T+2)\sum_{l=1}^{m} \frac{\hat{\rho}_l^2}{T-l} .$$

The decision rule is to reject H_0 if the *p*-value is less than or equal to the significance level.

We used the LB test using 21 lags (approximately the number of trading days on a given month) of daily IPC returns. We tested using the full sample size (3,746 observations), as well as the most recent 1,000 and 100 observations. We performed the test on returns, square returns and absolute returns.

Table 3
Ljung-Box test for daily IPC returns, squared returns and absolute returns, using 21 lags

Time series	*Sample size*	*Ljung-Box test*	*p-value*
IPC returns	3746	56.4024	4.403e-05
IPC returns	1000	51.0081	0.0002
IPC returns	100	29.1682	0.11
IPC squared returns	3746	1254.434	2.2e-16
IPC squared returns	1000	962.7398	2.2e-16
IPC squared returns	100	19.9187	0.5264
IPC absolute returns	3746	2317.262	2.2e-16
IPC absolute returns	1000	1268.726	2.2e-16
IPC absolute returns	100	30.6823	0.07911

Table 3 shows that there is significant return predictability for the full sample and the last 1,000 observations using returns, square returns and absolute returns. Using the last 100 observations, the data are independently distributed, i.e., no correlations amongst the observations. This does not imply a violation of market efficiency, since we would need to consider the risk free rate, adjust returns for risk, and include transaction costs (Danielsson, 2011). It is also shown how *p*-values for square and absolute returns are much smaller than for returns, suggesting how nonlinear functions of returns show significant positive autocorrelation or persistence. This is a quantitative sign of the stylized fact known as *volatility clustering*: large price variations are more likely to be followed by large price variations. Thus, returns do not follow a random walk (Campbell, Lo, and MacKinlay, 1997).

Volatility/return clusters

Another way to possibly characterize volatility and return clusters is by looking at lag plots of returns, i.e., scatterplots of r_t against r_{t-1}. A stylized fact that can be observed from such plots is that large returns tend to occur in clusters, i.e., it appears that relatively volatile periods characterized by large returns alternate with more stable periods in which returns remain small. Figure 9 shows the lag plots corresponding to returns of the S&P 500, the IBOVESPA, and the IPC index. From these plots, it is apparent the aforementioned stylized fact.

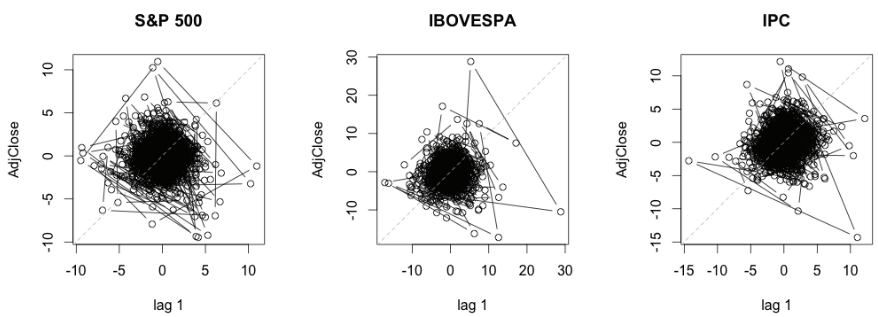

Figure 9. Lag plots of the returns on the S&P 500 (left), IBOVESPA (center) and IPC (right), on day *t*, against the return on day *t-1*

In order to concentrate on a partial route followed by the IPC return series, in Figure 10 we focus our attention on what appears to be the most volatile section of the lag plot from Figure 9 (right panel).

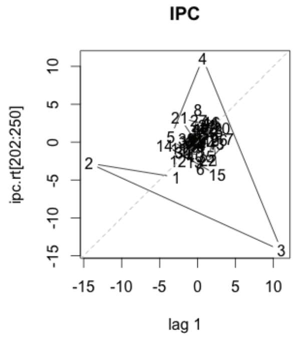

Figure 10. Lag plot of IPC returns corresponding to Oct 23rd, 1997 to Jan 5th, 1998

IPC returns start to deviate from the main cloud of zero returns at the point marked by 1, corresponding to Oct 23rd, 1997 with return (in percentual terms) of -4.64, moving to observation 2 (-2.77), then to the observation 3 (-14.31), to 4 (11.05), and finally going back to the cloud at observation 5 (with return 0.68), after 5 days. Another property of the stock return series that can be inferred from the lag plots presented is that periods of large volatility tend to be triggered by a large negative return.

Volatility modeling

Volatility clustering can be observed by modeling the conditional variance structure of the time series. The conditional variance of r_t, given the past values $r_{t-1}, r_{t-2}, \ldots$, measures the uncertainty in the deviation of r_t from its conditional mean. We have already mentioned how daily returns of stocks are often observed to have larger conditional variance following a period of violent price movement than a relatively stable period. The majority of volatility models in regular use belong to the generalized ARCH (GARCH) family of models. The first of these models was the ARCH model, proposed by Engle (1982), giving way to the GARCH model by Bollerslev (1986). Such models are based on using optimal exponential weighting of historical returns to forecast volatility.

Evidence for heteroscedasticity can be shown by performing a McLeod-Li test (plot of the p-values of the Box-Ljung statistic applied to squared returns), cf. (McLeod and Li, 1978). Figure 11 shows that the McLeod-Li test statistics are all significant at the 5% significance level and formally shows strong evidence for ARCH in this data.

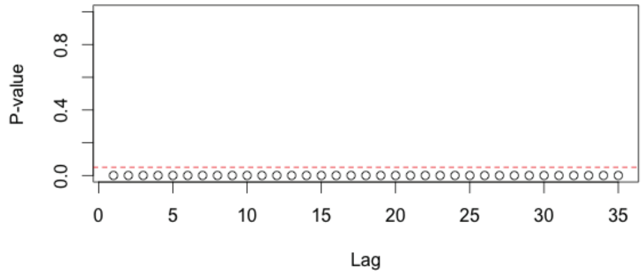

Figure 11. McLeod-Li test statistics for daily IPC returns

We fit a GARCH(1,1) model to the time series resulting from subtracting the mean from the IPC returns. For more on GARCH models, see, e.g. (Cryer and Chan, 2008). Figure 12 shows the conditional volatility of IPC returns. The full GARCH(1,1) estimation, likelihood and analysis of residuals is beyond the scope of the present work but is available from the authors upon request. A complete study of non-linearity tests using the GARCH(1,1) model applied to the IPC was recently published by Coronado Ramírez, Venegas-Martínez and Sandoval Mejía (2012).

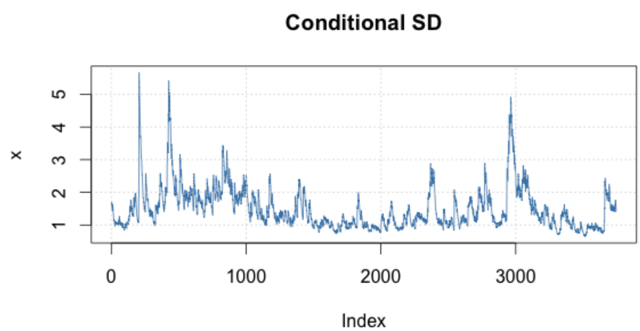

Figure 12. Conditional volatility of IPC returns

Finally, Figure 13 shows the normalized IPC return series with double positive and negative volatility superimposed.

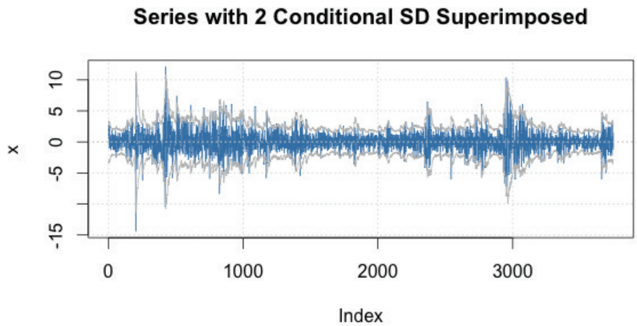

Figure 13. Normalized IPC return series with doubled positive and negative volatility superimposed

Conclusions

We have documented some stylized facts exhibited by the return time series of the Mexican Stock Exchange Market (IPC), and compared some of them to other return series, from both developed (USA, UK and Japan) and emerging (Brazil and India) markets. We showed how the probability density function of returns for these indexes is skewed and fat tailed. The skewness is negative, indicating that large market returns are usually negative. However, this was not the case for the IPC and IBOVESPA, implying possible investment opportunities in these emerging markets. Furthermore, fattails existed for all markets, with kurtosis far in excess of the corresponding to the normal distribution. Normality of the distribution of the IPC daily returns was rejected using graphical and analytical methods, finding that the kernel density of IPC daily returns was better fitted by a Student t-distribution with four degrees of freedom. However, as the time scale to measure returns is larger (e.g. quarterly), the distribution of IPC returns is better fitted by the normal distribution.

After this, we turned our attention to the autocorrelation function. We find that linear autocorrelations are insignificant after a few lags. However, nonlinear autocorrelations prevailed, which was evidence for the existence of volatility clusters. Such clusters were exhibited using graphical and analytical tools, as well as with the aid of a GARCH(1,1) model.

This study might be thought of as the tip of the iceberg concerning the modeling and forecasting of time series analysis of financial time series. It is helpful to get acquainted with the empirical data before looking for the appropriate models. This is the foundation for our work in progress on nonlinear modeling of financial assets returns, in particular applied to equities. We have focused our future research on threshold autoregressive (TAR) models, both self-exciting and Markov switching.

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CHAPTER 11
Geometric Brownian Motion and Efficient Markets in Mexico

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Calum G. Turvey

Introduction

This chapter tests the hypothesis that commodities prices follow a geometric Brownian motion (gBm). The assumption of gBm is essential for time series analysis and option pricing. Failure to meet this condition has several consequences: first, it implies that the time series is not stationary and that markets are not efficient (Rogers, 1997); second, pricing of derivatives on those commodities become biased (Cutland, Kopp and Willinger, 1995); third, as a consequence, hedging commodities with futures contracts will not be effective.

The method used here to test for gBm is based on a scaled variance ratio test to obtain the Hurst coefficient (H). Popular methods to estimate H in the financial literature are rescaled range analysis, R-S (Mandelbrot, 1972), and stochastic volatility models including GARCH/ARCH and fractional integrated GARCH (Wei and Leuthold, 1998; Jin and Frechette, 2004). Estimations for H are consistent for all methods.

A time series follows a gBm if its Hurst value is not significantly different from 0.5. If its H value is significantly different from 0.5, the time series follows a fractional Brownian motion (fBm). When the value of $H > 0.5$, the time series behaves as if it has long term memory, or positive autocorrelation. When $H < 0.5$, the time series is said to be ergodic, anti-persistent, or negatively autocorrelated.

A Hurst coefficient not different from 0.5 is a sufficient proof that its returns follow a Brownian motion. This method for testing stationarity through a gBm produces the same result than traditional tests for unit root. Non-stationary data can lead to biased results due to spurious correlations. In finance, we are interested in the return of a time series, which is what ultimately matters from an investor's point of view. Therefore, the stationarity condition is always tested on the data returns. One of the conditions for pricing derivatives using the Black-Scholes framework is that the asset prices follow a geometric Brownian motion for its results to be unbiased. A gBm series is not stationary, but its increments are. That is, if a series follows a GBM its returns are non-stationary (Tsay, 2005). Thus, by testing for GBM in a series we are also testing for stationarity in its returns.

Estimation of Hurst Coefficient using Variance Ratio

The Hurst coefficient is estimated by first assuming that our time series follow a geometric Brownian motion, with the following stochastic differential equation:

$$dS = \mu S dt + \sigma_s S dW^H \tag{1}$$

Where $dW^H = \varepsilon\sqrt{t^{2H}}$ is a Weiner process with $\varepsilon\sqrt{t^{2H}} \sim N(0,1)$, S, is the commodity spot price, σ_s the variance of the percentage change in price, μ its growth rate and $H \in (0,1)$ its Hurst exponent. The variance of a Brownian motion increases with time, such that at lag K, or Δt, is K times the variance of a single lag. The ratio of the variances of two time steps becomes the lag between them, that is, $\frac{\sigma_K^2}{\sigma_1^2} = K$, or $(\Delta t)^{2H}$. From this relationship we can run a regression of its log values to estimate H. The regression becomes $\left(\frac{\sigma_K^2}{\sigma_1^2}\right) = \alpha_0 + \alpha_1 \ln(K) + \varepsilon$, where $H = \frac{\alpha_1}{2}$. A Hurst exponent of 0.5 implies that [1] is a stationary process, if $H > 0.5$ the time series shows positive autocorrelation, and if $H < 0.5$ the process is negatively autocorrelated.

For the first 10 regressions we used the same number of lags (10), after that, the number of lags in the regressors corresponded to the value of K.

Confidence Intervals of Brownian Motion

Looking at the Hurst coefficient alone is not a reliable indicator of Brownian motion. A Hurst value different from 0.5 does not mean that the time series doesn't follow a Brownian motion. We observe only one realization of a time series, and in order to generate a confidence interval we need to simulate several random walks with $H = 0.5$ and measure the its deviation from its expected value of 0.5. If a time series lies between the simulated random walks, we can say, within a confidence interval, that our series is consistent with a Brownian motion.

In our analysis, we obtained the Hurst coefficients for each of our time series, and then compared them to the 90% confidence level estimated by Turvey (2007). The confidence level depends on a sample size, *N*, and the number of overlapping steps, . For the sample path we used the formula suggested by Weron (2002) of $K = \sqrt{N}$.

It is important to mention that since the confidence limits are approximations, at lower steps ($K < 10$) those values are not very stable. The confidence limit is valid at larger steps. Also, the confidence interval depends on the number of steps chosen. The larger *K*, the wider the confidence interval for a Brownian motion. That is, as the number of steps increases, there is a greater chance for the random walk to take extreme values that are different from $H = 0.5$. On top of that, as the sample size increases, the confidence interval converges to 0.5. This means that we should not look at the value of *H* alone, but rather look at the sample size, *N*, and step size, *K*, in order to have meaningful comparisons.

Data

We used data for three commodities (white corn, yellow corn, and sorghum) in 13 locations throughout Mexico, futures contracts for yellow and exchange rate MXP/USD. Local commodity prices in Mexico were obtained from Grupo Consultor de Mecados Agricolas, S.A. de C.V., a consulting company specialized in agricultural markets in Mexico, futures contract prices from the CME, and the exchange rate from the Mexican Central Bank (Banco de Mexico).

Data collection for grain prices in local markets in Mexico is very difficult; most of it is estimated by adding to the price in the US, transportation cost to the local market (basis). Cash prices were estimated by the consulting company for 13 locations nationwide for both varieties of corn, and a subset of 7 locations for sorghum. These prices are paid to the farmer at the elevator, which are greatly affected by the US corn price, exchange rate and transportation cost. Among the three commodities, yellow corn is the most commonly traded in a futures exchange. In Mexico, the nearby future contract price of yellow corn at the CME (CBOT before) is used as a reference for both white corn and sorghum subject to local demand and supply conditions.

The data obtained for the local prices in Mexico were available to us from July/ 18th/ 2003 to Dec/ 31st / 2007, for a total of 1,370 daily observations. In order to be consistent with this analysis we used the same time frame for the rest of the data. The sample path used to estimate the Hurst coefficient is 37.

Results

Table 1 shows the value of the Hurst coefficient for each crop and location at lag . This value is compared with its corresponding 90% confidence interval. The Hurst values that lay outside this confidence level are marked by an asterisk.

In general, every time series at each location has a Hurst value within the 90% interval. Only two locations, Culiacan and Mochis, both from the state of Sinaloa and both or yellow corn have the only values that lay outside the 90% level; however, they lay within the 95% level. For most locations, yellow corn has the lowest Hurst value, followed by white corn and sorghum with the highest value. Given the sample size and number of lags, the Hurst coefficient values at the 90% confidence level lies between 0.5529 and 0.4470; at 95% is between 0.5631 and 0.4368; and at 99% between 0.5832 and 0.4167.

Table 1
Estimated Hurst Coefficients of Local Prices.

Market	*Yellow Corn*	*White Corn*	*Sorghum*
Campeche, Camp.	0.4622	0.4558	
Tuxtla Gutierrez, Chis.	0.4586	0.4491	
Arriaga, Chis.	0.4573	0.4522	
Tapachula, Chis.	0.4557	0.4506	
Cihuahua, Chih.	0.4598	0.4617	
Toluca, Mex.	0.4567	0.4610	
Irapuato, Gto.	0.4637	0.4708	0.4862
Guadalajara, Jal.	0.4698	0.4731	0.4926
Morelia, Mich.	0.4625	0.4659	0.4942
Culiacan, Sin.	*0.4423	0.4612	0.4705
Mochis, Sin.	*0.4419	0.4639	0.4718
Victoria, Tamps.	0.4702	0.4691	0.5151
Matamoros, Tamps.	0.4685	0.4678	0.5116

The Hurst values for changes in local basis were estimated at three locations for simplicity: Guadalajara, Culiacan and Matamoros. Results are shown in Table 2. They were chosen because they represent major grain producing regions. The local basis for yellow corn at all locations has Hurst values below the 99% level. This is the only crop which basis has insignificant Hurst values. White corn and sorghum are within the 90% confidence interval, except for the local basis of sorghum at Matamoros, which is in the 95% level. We are not sure why the local basis for yellow corn show mean reverting values, it may be that its basis is comprised mostly of transportation costs, which are almost constant through time due to the rigidity of gas prices in Mexico; while local supply and demand conditions may have a stronger effect on local basis for white corn and sorghum, on top of transportation costs.

Table 2
Estimated Hurst Coefficients of Local Basis

Market	*Yellow Corn Basis*	*White Corn Basis*	*Sorghum Basis*
Guadalajara, Jal.	0.3820	0.4815	0.4878
Culiacan, Sin.	0.3887	0.4574	0.4605
Matamoros, Tamps.	0.4088	0.4922	0.4181

The behavior of time series data from futures markets is analyzed next. The prices form institutional markets have Hurst values within the 90% confidence level. Futures price of yellow corn has a value of 0.5031, and it stays about 0.5 throughout the whole time interval. This is a characteristic of perfect markets. It is assumed that futures markets and other institutional markets with many players are efficient. This can be seen by the consistency of the Hurst coefficient to stay near 0.5, which proves that it follows a geometric Brownian motion. Foreign exchange has an estimated Hurst coefficient of 0.4598 at lag 37, but by looking at its Hurst dynamics (in Figure 1), there is indication of mean reverting behavior at longer periods. It is evident that after lag 100 (about November, 2003), the Hurst value stays well below the 90% level. This may be the result of government policies regarding foreign exchange parity that tried to keep the foreign exchange value within a certain value. The Hurst coefficient shows this market intervention.

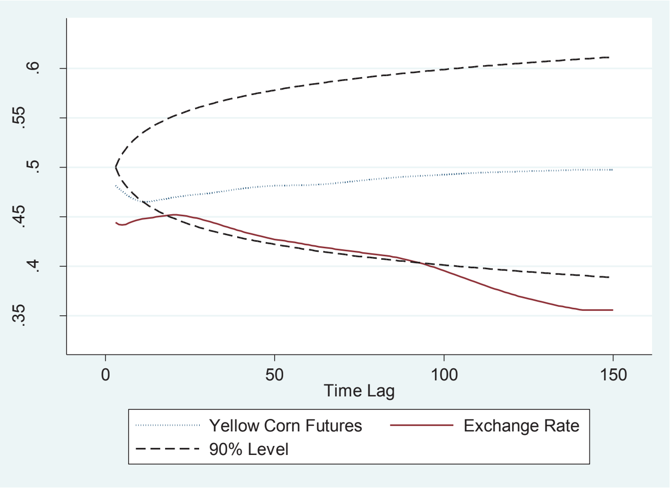

Fig. 1. Hurst Coefficient Dynamics for Yellow Corn Futures and Exchange Rate.

The Hurst coefficient dynamics for yellow corn at local markets are within the 90% level for higher lags. Since most of the variability in local prices come from the futures price, it is no surprise that local prices also follow a gBm. Similarly, prices for white corn and sorghum at local markets are within the 90% level. However, the dynamic is different for all three commodities. White corn tends to converge quickly towards H=0.5; and sorghum, even though all are within the limit, have three groups of locations that share very similar Hurst values. Again, this may be due to local market conditions and proximity to a port of entry. Figure 2, 3 and 4 show the dynamic for yellow corn, white corn and sorghum.

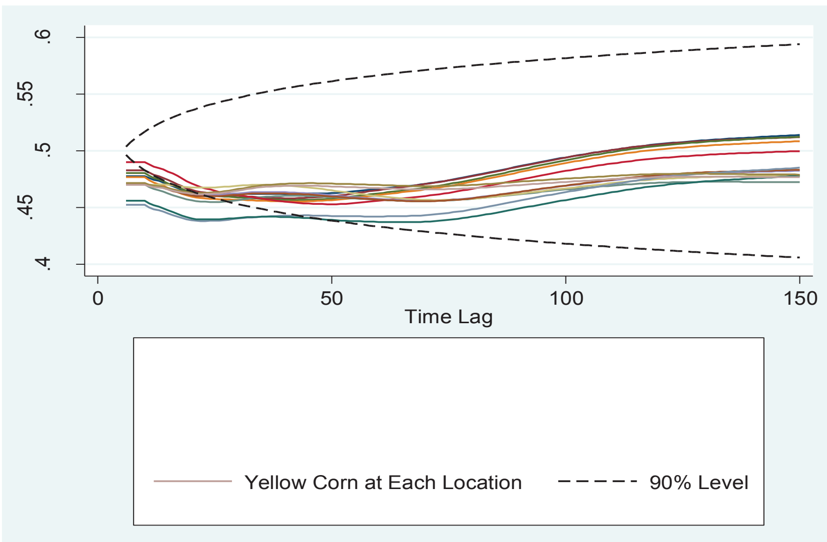

Fig. 2. Hurst Coefficient Dynamics for Yellow Corn at All Locations.

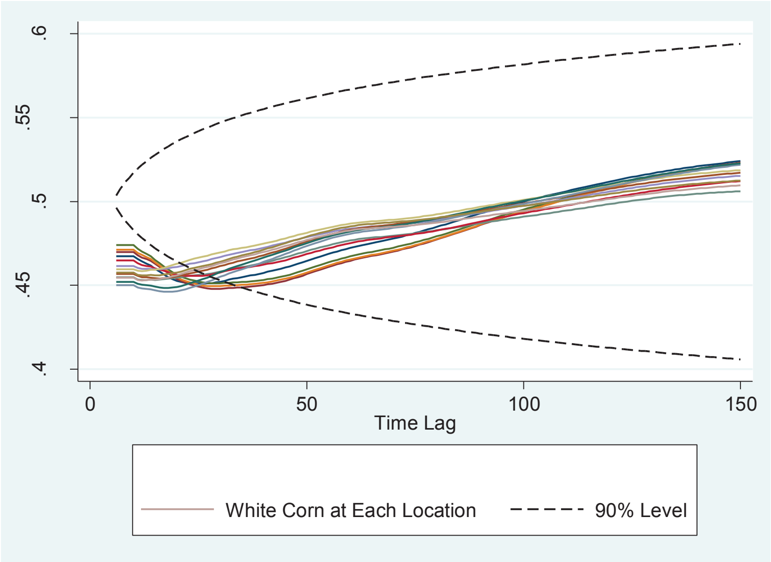

Fig. 3. Hurst Coefficient Dynamics for White Corn at All Locations.

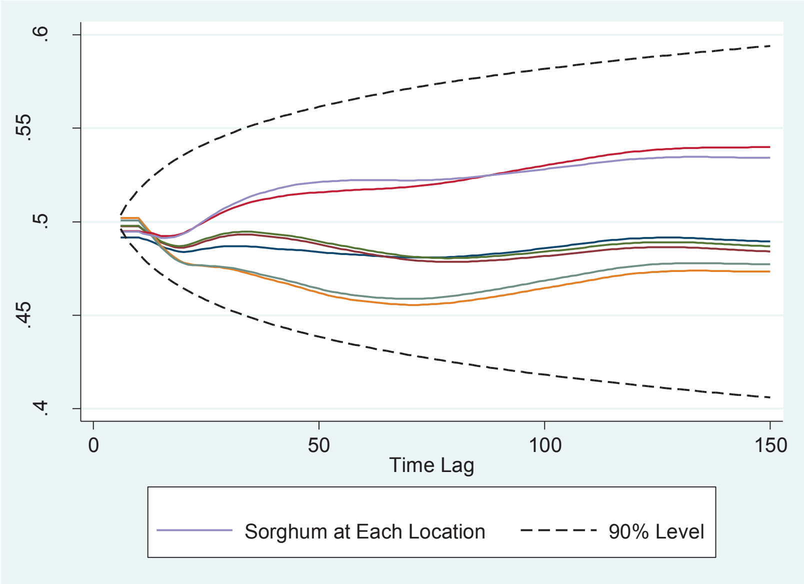

Fig. 4. Hurst Coefficient Dynamics for Sorghum at All Locations.

Conclusions

In this study we analyzed the price dynamics of three commodities at several local markets in Mexico, the exchange rate MXP/USD and the futures price of yellow corn at the CME. Our results have shown that local grain prices in Mexico are consistent with a geometric Brownian motion. However, futures prices for yellow corn have more consistent Hurst values at 0.5, which is expected from perfect markets. On the other hand, even though the exchange rate MXP/USD show consistency with a gBm for short lags, at lag 100 (November, 2003) its Hurst value quickly dropped below the 90% confidence level, and stayed well under it throughout the time frame. This is an indicator of market intervention, possibly by the government, to keep the currency within some limits.

To our knowledge, this is the first study of this type for Mexican grain prices and exchange rate.

Local prices are not affected significantly by the exchange rate dynamics, but rather by the futures market price at the CME. Since local prices follow a gBm, hedging strategies using futures and options are feasible.

This analysis can be expanded to other commodities and financial assets.

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