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How the U.S. Capital Markets Volatility Interacts With Economic Growth

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Empirical finance suggests that US capital markets' volatility has a negative relationship with economic growth. As the main focus is on the equity market volatility dynamics and less on other equally important asset types, in this paper we examine the dynamics between US money markets, government debt, corporate debt and equities volatilities, and a real GDP growth proxy, between 1963 and 2009. Results show that assets' volatility is essentially counter-cyclical of growth. However, this interaction changes when specific time subsamples are considered: in recessions, rising volatility leads the economic cycle, while in expansions its downward trend lags the business cycle.

Key Words: Business cycle; Causal relationship; Growth.
JEL Classification Numbers: C20, E32, G10.

1. INTRODUCTION

The year 2008 was characterized by unusual variations in asset prices leading to a period of extreme high volatility in global financial markets, amplified by Lehman Brothers's demise and its disruptive effects. The systemic degree of instability was reflected in the pattern of different historical and implied volatility return price measures of the main asset classes, including the less risky ones like government bonds, which exhibited a substantial rise to levels last seen during the 1980 decade.

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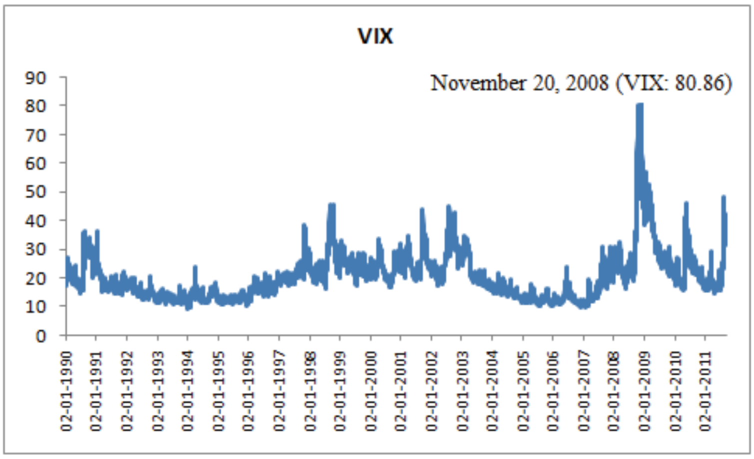
As one can see in figure 1, the Chicago Board Options Exchange (CBOE) Volatility Index (VIX), the most prominent indicator of investors' expectations on future market volatility, achieved its 80.86 greatest value in November 20, 2008. Recall that VIX values greater than 30 are generally associated with high volatility as a result of investors fear or uncertainty, while values below 20 generally correspond to less stressful, even complacent, times in the financial markets.

FIG. 1. Chicago Board Options Exchange (CBOE) Volatility Index (VIX)



The huge uncertainty related to those price movements froze economic decisions, leading to a large drop in aggregate outcomes and firms temporarily pausing their investments. Reported data confirms strong negative consequences in terms of growth in the United States and in several developed and emerging economies. According to Reinhart and Reinhart (2010), fully one-half of 182 countries posted outright declines in real GDP in 2009. In the U.S., the economy entered into a major recession, with quarterly real GDP growth figures being lower than -5%, on an annualised basis, and the unemployment rate rose dramatically to the highest level since 1982.

Historically, financial research has been more focused on the interaction between the capital markets returns and output, with famous references being Fama (1981), Fischer and Merton (1984) and Barro (1990). There is a broad consensus for the leading role of financial markets because expected returns are a forward looking variable, which incorporates expectations about future cash flows and discount rates. Barro and Ursúa (2009) find that, for a long-term history of 30 countries, stock market crashes have substantial predictive power for economic depressions.

However, for the markets' volatility link with the underlying macroeconomic fundamentals, not only there are less theoretical foundations but also studies in this field have mainly focused on the equity market volatility and its implications for economic growth. This way, it is crucial to test until what extent fluctuations in financial volatility, considering different asset classes, affect the rate of economic growth. Indeed, and irrespectively of the price pattern juncture, a regime of upward volatility might be negative to the performance of key economic measures over the long run.

In the case of equities, there are robust findings from Officer (1973) and Schwert (1989) that equity market volatility tends to increase dramatically during financial crises and in periods of recessions. Research from Campbell et al. (2001), Guo (2002), Bloom et al. (2009) and more recently from Raunig and Scharler (2011), show that stock market volatility is related to uncertainty about future cash-flows and, consequently, consumption and investment decisions might be negatively affected. Also Shim and Peter (2007), in line of Fisher (1933), find that distressed selling in capital markets, with rising volatility, generate a feedback mechanism that ultimately creates inertia for growth.

With respect to the government bond and money markets asset classes, Serna and Arribas (2008) show that implied volatilities of European short-term interest rates, have a strong negative relationship with the economic sentiment. Also, findings from Gerlach at al. (2006) and Hornstein and Uhlig (1999) show that there is a negative correlation between the evolution of government bond price returns volatilities and the path of economic growth.

Moreover, in terms of corporate bonds, Kounitis (2007) shows that credit spreads volatility rises with its level, complementing the majority of available studies like King et al. (2007), Tang and Yan (2008) and Gilchrist and Zakrajsek (2011) that suggest a direct relationship between wider credit yield spreads and higher default risk premia and lower growth.

Therefore, the aim of this study is to find an empirical long term relationship, for the United States, between capital markets volatility and the economic growth, considering other important financial assets, besides equities, like money markets, government debt and corporate and financial debt. Additionally, we also test the effect of volatility of the slope of the treasury yield curve on growth. It is also important to find if there is a persistence of a leading (or lagging) characteristic of volatility in its predictive power of economic growth, for each asset type. Finally, it also matters to investigate which are the potential changes in these dynamics when different time periods (e.g. decades) and economic regimes (official recessions, slowdowns and expansions) are explicitly considered in the empirical analysis.

A probable ubiquitous pattern in policies has been to assume external shocks to the economy, like changes in financial volatility, as generating temporary effects, when in fact they could translate into very persistent economic consequences. Given the potential cost of those misconceptions, in the future, fiscal and monetary authorities, along with financial industry regulators, might be prone to pursue different frameworks in order to take into account markets volatility regime changes and to minimise their effects on real activity.

The remaining sections are organised as follows. Next section describes the theoretical relation between asset prices volatility and economic growth. Section 3 describes the methodology behind the empirical study, namely, the GDP proxies, the volatility measures and the econometric methods. Section 4 encompasses all the results from the empirical research. Finally, in Section 5 the conclusions for the entire paper are presented.

2. FINANCIAL ASSETS VOLATILITY AND ECONOMIC GROWTH

At the macro level, cash flows for equities can be approximated by GDP, so that changes in the output volatility, everything else being equal, are related to changes in equity volatility. Uncertainty over economic conditions also affects real interest rates, expected inflation and risk premiums. According to Hamilton and Lin (1996), GDP volatility is relatively high during recessions and high financial volatility tends to be associated with weak economic conditions. Cochrane (2005) shows that volatility is also related to fluctuations in risk aversion, as investors tend to be more risk averse during recession periods, which should make volatility countercyclical. Another macro factor is the monetary policy expectations and decisions that affect volatility through its potential impact on real interest rates, inflation patterns and on the general pace of economic activity.

The firm-specific factors also determine the behaviour of volatility and, according to Campbell et al. (2001), there has been a rising trend and increased importance over the past several decades of idiosyncratic volatility. Two characteristics of firms have been found to be critical. Firstly, volatility is positively related to financial leverage and, secondly, is negatively correlated with the profitability of companies and positively with the uncertainty of the firm profitability (Wei and Zhang, 2006). This can also explain the negative correlation between stock returns and volatility observed by Bae et al. (2007). The effect of leverage and profitability predicts counter-cyclical variations in volatility because recessions are associated with higher debt/equity ratios and lower earnings. Consequently, when leverage increases, equity holders bear a greater share in the total cash flow risk of the firm and the volatility of equity returns increases accordingly.

Volatility is also affected by the structure of financial markets where the most important factors are: market liquidity and integration, financial innovation. The significant growth in risk transfer instruments may indirectly enhance markets liquidity and reduce volatility, in that allows investors to take or unwind exposures in a short period of time, without having to trade in the underlying securities market. In the same way, the opening of new derivatives markets should affect the availability of information about financial assets future cash flows. Options contracts can complete an otherwise incomplete market and can have a significant impact on the price behaviour of the underlying securities.

The evolving role of different types of investors and their degree of willingness to bear risk, in recent years, have also contributed to the behaviour of asset price volatility. Financial variability may be reduced by the rise in the fraction of securities controlled by informed agents holding well diversified portfolios (Avramov et al., 2006). However, volatility may be exacerbated in the short term by the investment decisions of asset managers if these are based either directly or indirectly on the decisions of others, like positive feedback trading or herding behaviour. Such effects can be worsened in bad times by the presence of large players (Pritsker, 2005). In the same vein, according to several authors (Campbell et al., 2001; Gompers and Metrick, 1999; Malkiel and Xu, 1999), institutional investors, notably pension funds and mutual funds, form a relatively homogeneous group whose sentiment may be influenced by a few common factors, suggesting that shocks to institutional sentiment might be important in explaining the increased idiosyncratic volatility of equity returns. Finally, and according to Rajan (2006), hedge funds tend to trade more frequently and it is quite possible that their actions, like increased selling in falling markets, can also potentially raise the level of volatility.

Several empirical studies confirm that U.S. equity markets volatility increases during recessions and decreases in periods of economic expansion. Classic and well-known contributions are from Officer (1973), finding robust evidence of a relationship between the stage of the business cycle and stock market volatility, in particular, stock market volatility is higher in recessions, and Schwert (1989) who suggests that equity market volatility tends to increase dramatically during financial crises and in periods of high geopolitical uncertainty (like the 1962 Cuban missile crisis). Guo (2002) points that a positive shock in equity market volatility may reduce future economic growth because it reflects uncertainty about future cash flows and discount rates; hence providing important information about future economic activity. According to Campbell et al. (2001) capital markets volatility is related to a structural change in the economy; structural changes consume resources, which depresses gross domestic product growth; similarly, if an increase in capital markets volatility raises the compensation that equity and bond holders demand for bearing systematic risk, than those expected higher returns lead to a higher cost of capital and debt, which will negatively affect investment and output. Furthermore, Raunig and Scharler (2011) explore the concept of the uncertainty hypothesis associated with stock market volatility and suggest, for the U.S., that higher stock market volatility, or more uncertainty, is to a non-eligible extent responsible for the decline in durable consumption and investment growth during recessions, although the direction of causality remains debatable. In the same vein, Bloom et al. (2009) demonstrate that rising uncertainty, also measured by equity market volatility, leads to large drops in employment and investment that ultimately will provoke a fall in productivity and in the business cycle.

In the case of money markets and government debt instruments, Serna and Arribas (2008) show that, using a looking forward measure of uncertainty about future economic activity like the 1-month and 1-year offer inter-bank rates implied volatilities, of Germany and UK derivative markets, there is a strong inverse relationship with the European economic sentiment for those two countries. Also, Gerlach et al. (2006) find that an increase in the output gap (a rise in real GDP relative to trend) is typically negatively correlated with government bond market volatility. Their results also show that there is a contemporaneous relationship, between the change in the output gap and the volatility of bond returns, in the post-WWII period. Hornstein and Uhlig (1999) state that the standard real business cycle models predict investment to be quite elastic with respect to interest rate volatility: the fluctuations in the real rate should lead to substantially larger swings in investments.

With respect to corporate and financial debt, the majority of studies have mainly focused on the relationship between the level of credit spreads and business activity. Recent analysis for the U.S. market, by Gilchrist and Zakrajsek (2011), shows that positive innovations in excess bond premia that are orthogonal to the current state of the economy may lead to a substantial decline in economic activity, via a reduction in the effective risk-bearing capacity of the financial sector and a consequent contraction in the supply of credit. Tang and Yan (2008), based on U.S. data, find that credit default swap spreads are decreasing in GDP growth rate and should be lower when investor sentiment is high and systematic jump risk is low. Also, research by King et al. (2007) suggests that widening corporate credit spreads embed crucial information about probability of future economic recession. In terms of spreads volatility behaviour, research by Kounitis (2007) points that credit spreads changes are an increasing function of their own volatility, implying that in a regime of higher excess premium, over risk-free rates, the volatility pattern should also be higher.

On a cross asset view, Shim and Peter (2007) develop the concept of distress selling and asset market feedback. This is a process of financial instability characterized by sequential events of distressed institutions selling assets, asset prices falling, cash flows and balance sheets deteriorating and more assets being sold into a falling market. The fall in the asset price decreases its mean and increases its volatility, introducing a negative skewness in the ex-post price distribution. Also, Campbell and Cochrane (1999) introduce the slow-moving habit concept, or time-varying subsistence level, in the consumer's utility function, and confirm the counter-cyclical nature of financial volatility. Their findings are that as consumption falls toward the habit, in a business cycle through, the curvature of the utility function rises, asset prices fall, expected returns rise and, consequently, returns volatility also rise.

3. METHODOLOGY

3.1. U.S. economic growth proxies

Firstly, in order to investigate the interaction between the low frequency data of real GDP growth, published on a quarterly basis, and financial volatility, available on a daily basis, it is imperative to consider a real GDP proxy of a higher frequency than quarterly releases. The reason is that by using only quarterly information of financial volatility, to investigate the dynamics with growth, would increase the probability of losing important information about the change in patterns of financial assets variability, namely the volatility clustering stylized fact of returns. At the same time, for not incurring in lost of accuracy, it is needed to consider a proxy that almost replicates real GDP growth.

At the same time, the objective was to find a type of data that not only encompasses the broader economic activity but also is coincident with the real GDP number and tracks different business cycles. Therefore, we considered three main indicators, released on a monthly basis, which could serve as potential proxies. The first one was the Chicago Fed National Activity Index (CFNAI), released by the Federal Reserve Bank of Chicago. It is a weighted average of 85 indicators of U.S. economic activity from four categories of data: 1) production and income; 2) employment, unemployment and hours; 3) personal consumption and housing; and 4) sales, orders and inventories. All these data series measure some aspect of overall macroeconomic activity. Consequently, the derived index provides a single summary measure of a factor common to the U.S. economic data. Each month, the index number reflects economic activity in the latest month.

The second measure considered was the Purchasing Managers Index (PMI), published by The Institute for Supply Management. The survey is done among 40,000 members engaged in the supply management and purchasing activities. It is a composite index of five sub-indicators, which are extracted through surveys on purchasing managers from around the United States, chosen for their geographic and industry importance. The five sub-indexes are production, new orders from customers, supplier deliveries, inventories and employment level. The PMI is a crucial sentiment reading, not only for manufacturing, but also for the overall economy. Although U.S. manufacturing is not the huge component of total gross domestic product, the industry sector is where recessions tend to begin and end. Moreover, its strengths arise from the timely release, always coming out on the first day of the month following the survey month and from being a good predictor of future GDP releases.

Thirdly, the Composite Index of Coincident Indicators (COI), from the Conference Board, that was first developed by the NBER (National Bureau of Economic Research) as making part of a set of indicators with the objective of tracking business cycles. The Composite Index comprises four cyclical economic data sets. The components were originally chosen because they exhibit strong correlation with the current economic cycle. The Conference Board considers the coincident components of a broad series that measures aggregate economic activity and thus the business cycle. The four components are: 1) employees on non-agricultural payrolls; 2) personal income less transfer payments; 3) index of industrial production and 4) manufacturing and trade sales. Historically, the cyclical turning points in COI have occurred at about the same time as those in aggregate economic activity.

In order to find if the economic indicators, described above, were able to be considered proxies for the U.S. real GDP year-over-year (YoY) growth rate, we ran standard OLS regressions (using EViews software) between those proxies (independent variables) and the real GDP growth rate (dependent variable) using quarterly data, which corresponds to the GDP release frequency. Three different types of metrics were considered for the explanatory variables: the quarter end level, the average quarter level and the YoY growth rate at the end of each quarter. If the monthly indicators are true proxy candidates for GDP, not only must exhibit significant correlation with growth but also the strongest fit must be contemporaneous and not too much leading or lagging. Consequently, for those three metrics of the indexes a contemporaneous regression and another with one quarter lag were run in order to measure the significance of the statistical relationship.

As the data samples should be equal for the proxy candidates, and due to the different times each indicator started to be released, the smallest time horizon begins in March 31, 1967, for the CFNAI. All the regressions were performed until March 31, 2009. Although the data considered in the tests performance is on a quarterly frequency, with the smallest sample consisting of 169 observations, it is reasonable to admit that the number of observations is enough to interpret the regression results with a degree of confidence. Heteroskedastic and autocorrelation consistent (HAC) Newey-West coefficients standard errors estimates were computed for all the regressions. The results point that all the estimated coefficients are statistically significant at 1% level, with the exception of the CFNAI YoY rate of change. Results are shown in Table 1.

TABLE 1.

U.S. real GDP proxies

R-squared from linear regression with US Real GDP Growth YoY			
	Proxies for GDP growth		
Proxies Measures	Coincident Indicator	Purchasing Managers Index	Chicago FED National Activity Index
Quarter end level	0.83	0.42	0.36
Quarter end level-1	0.62	0.59	0.56
Average quarter level	0.81	0.51	0.55
Average quarter level-1	0.50	0.60	0.68
Year-over-year change	0.82	0.27	0.05^{**}
Year-over-year change-1	0.62	0.35	0.29

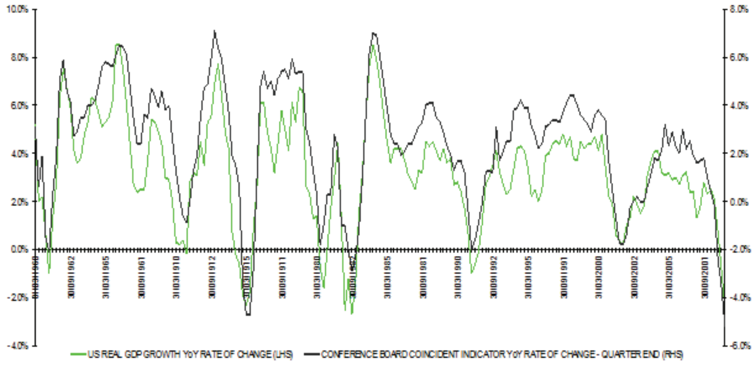
Note: This table reports R-squared from OLS regression between different measures of US economic growth proxies (independent variables) and US Real GDP Growth (dependent variable). Regressions are based on quarterly raw data available for each indicator. -1 represents one observation lag. Newey-West Standard Errors are computed. All the estimated coefficients are significant at 1% level, with the exception of **. All ending in the 1°Q 2009. Real GDP Growth from the Bureau of Economic Analysis begins in Feb/50. The Conference Board-Composite Index of Coincident Indicators begins in Jan/1959. The Purchasing Managers Index from the Institute for Supply Management Index begins in Jan/50. The Chicago Fed National Activity Index from the Federal Reserve Bank of Chicago begins in Mar/67. Source: Bloomberg.

The indicator for which the regression results are statistically more significant is COI. It has a higher coefficient of determination, compared to PMI and CFNAI, when the quarter end level ($R^2 = 0.83$) and year-over-year rate of change ($R^2 = 0.82$) metrics are contemporaneously considered. The same conclusions are also taken when the independent variables are lagged one quarter. In Figure 2, it is shown the high degree of correlation between the two variables. Not only persists in periods of growth acceleration but also in times where the economy enters in slowdown or recession periods. Thus, in this study the COI YoY growth rate is the variable of choice to be the monthly proxy for the GDP YoY growth rate, which is quarterly released.

3.2. U.S. capital markets

Although the U.S. capital markets have developed significantly in the last decades, in terms of its size and financial instruments complexity, we considered the asset classes that are the bulk of the U.S. capital market constituents and for which there is data available for an extended time span: equities, government debt, corporate and financial debt. Moreover, having

FIG. 2. Coincident Indicator and real GDP growth



in mind that capital markets by definition, following Mishkin (1998), are the ones in which longer-term debt (maturity of one year or more) and equity instruments are traded, we also decided to consider in the analysis the money markets class, given its crucial role for the economy.

In terms of the benchmarks selected for volatility calculations, we considered the S&P 500 (ex-dividend gains) for the equity market, which is an index computed by equity prices of 500 companies, ranked by market-capitalisation, listed on the New York Stock Exchange, the American Stock Exchange and the Over the Counter market. It constitutes a good proxy given the significant number of its constituents, the ample liquidity and the fact of being the underlying index for many derivatives instruments and benchmark for financial assets portfolios managed on a global scale. Furthermore, and according to White (1999), the S&P 500 is though to be a better index because it dominates other important U.S. measures, satisfying the most number of desirable properties of an equity index. Finally, it has an historical record that is as longer as the one available for the economic Coincident Indicator considered in the analysis.

In the case of government debt, we assumed the effect of 10yr yield changes in the level of an index, given a constant modified duration risk parameter. Typically the main maturity benchmarks considered by market investors are 2yr, 5yr, 10yr and 30yr. Following Estrella and Trubin (2006) we opted to choose the 10yr benchmark maturity as the reference for the government debt market. The main reasons were: (1) the data availability for the 10yr bucket is the longest one; (2) the 5yr maturity is highly correlated with the 10yr so there is no great loss of additional information; (3) the 30yr benchmark is a less traded point of the U.S. yield curve, highly influenced by supply and demand issues; and (4) the 2yr bucket, in spite of being more attached to short-term interest rates expectations than the longer ones, has much less historical data available; Furthermore, a proxy for monetary policy is considered in the money markets class.

For money markets (short-term debt up to one year maturity), and also in line with Estrella and Trubin (2006), our criteria was to consider a benchmark security, available on a long term historical horizon and on a continuous market-to-market basis, that is less subject to credit risk premium and essentially reflects short-term expectations of the Federal Funds Rate path. Thus, we considered the 3-month constant maturity treasury-bill benchmark. We assumed an index capitalised at the prevailing 3-month rate in the beginning of each month. No modified duration assumptions were made given the constant residual maturity of the benchmark treasury-bill.

Finally, in the corporate and financial debt class, that encompasses corporate and financial credit risk issuers, we also used the effect of the Average Rating Corporate Yield Index changes, from Moody's rating agency, in the level of an index, given a constant modified duration assumption. According to Bank for International Settlements (2000), Moody's rates almost all issuers in the U.S., regardless of whether a rating has been solicited by the issuer, and represents the highest coverage, given the total rated population by agencies, of both financial and corporate sectors. This way, and besides the availability of historical data for the time dimension considered in the analysis, the average rating index should constitute a better proxy for the U.S. overall credit risk.

3.3. Volatility measures

Analysts and financial markets participants estimate volatility in one of the two following ways. The first one is by computing the historical financial instrument volatility, using the standard deviation measure. Considering and the security prices in periods p_t and p_{t-1}, respectively, the variable of interest (r_t) is the compounding rate of change in price between two time periods, expressed as follows

$$r_t = 100 * \ln\left(\frac{p_t}{p_{t-1}}\right). \tag{1}$$

The second method is to estimate the financial instrument volatility using derivatives observed prices (like options). Volatility calculated using this approach is called implied volatility and it captures the expectation of financial markets about realised volatility, for any period in the future. Unlike historical volatility, implied volatility is the reflection of the realised volatility resulting from the Black-Scholes option pricing model, using the options premiums observed in the market.

Since capital markets are considered forward looking variables of the state of the economy the volatility measure to adopt, in order to investigate the interaction with economic growth, could be an estimation of implied volatility. However, there are important caveats. It has to be assumed that the option pricing model is correct and this type of models usually consider the volatility parameter constant over the option's life, which in turn makes more difficult to interpret an implied volatility output. Also, Ang et al. (2006) raise a concern about implied volatility measures because it combines both expected volatility and the volatility risk premium. Finally, there is only historical data available for implied volatility in some asset classes, like equities. In this case, the Chicago Board Options Exchange introduced the CBOE Volatility Index (VIX), which is the benchmark for U.S. equity market volatility, with quotes only existing from 1986.

With regard to the U.S. government bonds asset class, a reference index could be the Deutsche Bank U.S. Volatility Gamma Index (DGX), which consists of weighted averages of at-the-money swaptions premiums with the underlying swap maturity ranging from 3 months to 30 years. The historical data available of this index, which begins in 1994, is not enough to analyse the interaction of this gauge and different phases of U.S. business cycles. In addition to this, in the case of the corporate bond market it is even more difficult to find a measure of implied volatility, with a wide historical time-length and of general acceptance of market participants.

Since several asset classes are included in the analysis, and given the caveats of implied volatility explained above, the default measure used for all the asset classes is the historical volatility. Empirical analysis is also done with implied volatility in the case of equities.

Historical volatility for equities is estimated by computing the annualised standard deviation of the last twelve months rolling natural logarithm returns. In the fixed income space, the volatility calculations based on percentual changes is known as yield volatility, whereas the volatility on absolute yield changes is known as normalised volatility. For interest rates and yields, although there is no consensus on how volatility should be defined, according to Rieger et al. (2007), market participants should use a metric of normalised volatility. Thus, in this study we adopted the standard deviation of yield and interest rate absolute changes.

3.4. Econometric methodology

To investigate the dynamics between the U.S. capital markets and COI YoY, we estimated standard OLS regressions using EViews software. Not only were tested contemporaneous relations, but also 12 leads and lags (one year gap) of volatility of the different asset classes as the explanatory variable, against COI YoY.

Since heteroskedasticity is a common phenomenon in this type of statistical relationships, White's tests were performed in every estimated model, and the results were conclusive in terms of evidence of heteroskedasticity, meaning that it is not plausible to assume that the variance of the errors is constant. By the same way, we also tested whether the residual series from the estimated models were autocorrelated, via Breusch-Godfrey LM test, and, as in the case of heteroscedasticity, the residuals from the regressions appeared to be correlated. Consequently, the t-statistics of the original regressions were appropriately corrected using Newey-West modified heteroskedastic and autocorrelation consistent (HAC) standard error estimates. For the full-sample or sub-sample periods considered the regressions to estimate are:

$$COI\_YoY_t = \alpha + \beta * CM\_Vol_{t+i/-i} + u_t \quad (2)$$

$$COI\_YoY_t = \alpha + \beta * CM\_Vol_t + \delta \cdot D_{t+i/-i} + u_t \quad (3)$$

where COI_YoY is the natural log year-over-year returns of Conference Board Coincident Indicator; CM_Vol is the 12-month rolling historical annualised volatility of natural logarithm monthly returns of equities, or 12-month rolling historical annualised volatility of first differences of short-term yields, long-term government bond yields, corporate and financial bond yields and corporate and financial yield spreads; D is a dummy variable taking the value 1 or 0, to represent a particular observation either having or not a given property: NBER recession periods, uptrend and downtrend economic growth periods; δ represents a shift in the intercept of the regression line due to the presence of a given property; u is a iid Gaussian random variable distributed with mean 0 and variance σ^2; $+i/-i$ represents monthly leads/lags, up to 12, applied to the explanatory variables.

In this study, and according to equations (2) and (3), we assume that financial assets volatility drives the U.S. GDP growth but the economic growth can also drives volatility. Therefore, to acknowledge the direction of the relationship between economic growth and volatility, we computed the Granger causality test between the COI YoY returns and financial assets volatility. The test results point that for less than 30% of the estimated regressions, U.S. economic growth Granger-causes volatility and simultaneously volatility does not Granger-causes U.S. economic growth. Thus, based on this small percentage, it seems reasonable to admit that financial assets volatility drives the economic growth.

To conclude if the linear equations (2) and (3) miss some potentially important nonlinearities, we computed the Ramsey's (1969) RESET test for the lead/lag regression with the highest coefficient of determination (for each one of the financial assets under analysis). For most of the estimated regressions we do not reject the null. It means that the linear functional form is the correct one and nonlinearities do not play an important role in the relation between U.S. financial assets volatility and economic growth.

Due to this empirical result, linear regression models seem to be the most appropriate framework to describe the relationship between economic growth and volatility. With the same purpose, linear models had been also used by Fatas and Mihov (2006), Ramey and Ramey (1995), Aizenman and Marion (1993) and Kormendi and Meguire (1985).

4. EMPIRICAL STUDY

4.1. Data

The objective was to consider a large sample enough to encompass different business cycles, phases of expansions, slowdowns and recessions and also different stages of capital markets. All the economic and financial data was obtained through Bloomberg Data Base System. Given that the data availability of the financial and economic variables is not the same, we considered the beginning of the 10yr treasury yield series (the latest set of data to be available for the defined asset classes group) as the initial historical observation of the empirical analysis between U.S. financial volatility and growth.

The analysis, for all asset classes, starts in January 31, 1963 and ends in March 31, 2009, which results in 555 monthly data observations. However, the existing literature confirms a striking decline in the business cycle volatility since the early 1980s in most advanced economies, including the U.S., and across most industrial sectors and expenditure categories. Research done by Davis and Kahn (2008), Arias and Hansen (2006) and references therein, all identify that large and statistically significant permanent shift in the aggregate economic activity, beginning in 1984, and point to factors, between many others, that might have contributed to what is designated by the Great Moderation period like the decline and volatility reduction of inflation, the largely improvements in inventory management techniques or the stabilisation growth effects from improved monetary policy stance. Furthermore, not only those authors find a discrete break in the U.S. growth pattern around 1984 but also encourage a focus on distinct analysis before and after that reference year. This way, for money markets, government debt and corporate and financial debt classes, besides estimating the regression models using the raw data, we also considered two distinct periods in our exploration: the first one starting in January 31, 1963 and ending in December 31, 1984 and the second one from January 31, 1985 to March 31, 2009.

In the case of equities, and besides the overall sample, the analysis was also performed for two distinctive periods: (a) one that begins in January 1963 and finishes in September 1987 and (b) another from October 1988 to March 2009. From our point of view, the reason for this sample partition is that the equity market crash that occurred in October 1987, with the major equity indexes falling around 20% in one day, was essentially a financial phenomenon that provoked a huge spike in levels of realized and implied volatilities. Accordingly, Shiller (2005) argues that the crash apparently had nothing particularly to do with any fundamental factors other than that of the crash itself, but rather with a psychological feedback loop among the general investing public from price declines to selling and thus to further price declines. In fact, financial institutions in the United States survived with very few problems and the economy did not enter into any kind of recession. Thus, based on the method used by Campbell et al. (2001) to downweight the 1987 crash in their analysis of volatility trends, via replacement of those observations by the others largest in their sample, we opted to implement an ad hoc procedure of not including the 12-month observations period between October 1987 and September 1988 in the data set. The reason was that the substantial spike in realized volatility, due to the equity crash, did not completely faded away until September 1988.

Natural logarithmic returns were calculated for the GDP growth proxy and also for the equities historical volatility metric. In the case of short term rates, long term yields and corporate bonds yield spreads, volatility was computed based on the first absolute differences.

4.2. Equity Volatility

Table 2 shows the OLS estimation results for the raw data and for the two sub-samples analysed. Results show that the estimated coefficients are always negative, irrespectively of the leads and lags considered, up to 12. It is also evident that the more contemporaneous is the data, the R^2 and t-statistics (in absolute value) also tend to be higher. In the three time frames considered, the contemporaneous level and one lag applied to the explanatory variable generate the most significant results. It is also shown that, given the lead-lag results (with the lagging ones being more significant than the opposite leading ones) the volatility pattern shortly leads the rate of economic growth pattern. Consequently, it means that, besides the negative relationship that exists between U.S. equity volatility and economic growth, there is not a substantial time gap between higher volatility and the negative impact it has on the economic activity.

However, in terms of the three samples considered, results show significant differences. The R^2 and t-statistics obtained in the January 1963 — September 1987 regressions are the highest in all leads/lags applied to volatility. Given a contemporaneous relationship, 43% of the variability of economic growth (COI) is explained by the variability of S&P 500 returns historical volatility.

In the period of October, 1988 to March, 2009, results obtained are not so strong, given that less than 20% of the variability of economic growth is

TABLE 2.

Equity Historical Volatility

	Regression with US equity volatility		
Volatility lead (months)	31/Jan/1963-30/Sep/1987	31/Oct/1988-31/Mar/2009	31/Jan/1963-31/Mar/2009
+12 Lead	0.01	0.01	0.01
	-1.40^{***}	-0.76^{*}	-1.23^{*}
+11 Lead	0.02	0.02	0.01
	-1.84^{***}	-0.90^{*}	-1.54^{**}
+10 Lead	0.04	0.02	0.02
	-2.32^{***}	-1.06^{*}	-1.86^{**}
+9 Lead	0.07	0.03	0.04
	−2.83	-1.18^{*}	-2.15^{***}
+8 Lead	0.10	0.04	0.04
	−3.32	-1.36^{*}	-2.38^{***}
+7 Lead	0.13	0.05	0.05
	−3.85	-1.56^{*}	−2.62
+6 Lead	0.18	0.06	0.07
	−4.41	-1.81^{**}	−2.83
+5 Lead	0.23	0.08	0.08
	−5.05	−2.04	−2.99
+4 Lead	0.28	0.10	0.11
	−5.77	−2.27	−3.15
+3 Lead	0.33	0.12	0.13
	−6.55	−2.49	−3.29
+2 Lead	0.37	0.14	0.15
	−7.32	−2.70	−3.41
+1 Lead	0.41	0.16	0.17
	−8.12	−2.85	−3.52
Contemporaneous	0.43	0.18	0.18
	−8.77	−2.91	−3.59

explained by the variability of the volatility measure, when the relationship is contemporaneous or with one month volatility lag.

Furthermore, all the coefficients are statistically significant at 1% significance level in the regression based on the sample January 1963 - September 1987, when maximum 9 leads and lags are considered. In the period October 1988 - March 2009, beyond 7 lead months, estimated coefficients are not statistically significant and lead 6 is significant only at 10% level. Moreover, when time lags higher than ten months are considered, the estimates are statistically significant only at the 10% significance level. Finally, in

TABLE 2—*Continued*

	Regression with US equity volatility		
Volatility lead (months)	31/Jan/1963-30/Sep/1987	31/Oct/1988-31/Mar/2009	31/Jan/1963-31/Mar/2009
−1 Lag	0.44	0.17	0.18
	−9.04	−2.92	−3.59
−2 Lag	0.44	0.17	0.18
	−8.88	−2.96	−3.61
−3 Lag	0.41	0.16	0.16
	−8.30	−2.98	−3.59
−4 Lag	0.37	0.15	0.14
	−7.34	−2.98	−3.51
−5 Lag	0.31	0.13	0.12
	−6.17	−2.93	−3.36
−6 Lag	0.26	0.11	0.09
	−5.07	−2.75	−3.15
−7 Lag	0.20	0.10	0.08
	−4.12	−2.63	−2.93
−8 Lag	0.15	0.09	0.06
	−3.35	-2.49^{***}	−2.66
−9 Lag	0.11	0.08	0.04
	−2.73	-2.27^{***}	-2.37^{***}
−10 Lag	0.07	0.07	0.03
	-2.22^{***}	-2.05^{***}	-2.04^{***}
−11 Lag	0.05	0.06	0.02
	-1.78^{**}	-1.89^{**}	-1.72^{**}
−12 Lag	0.03	0.05	0.01
	-1.42^{*}	-1.73^{**}	-1.42^{*}

Note: This reports R-squared and t-statistics from OLS regressions between the Conference Board Coincident Indicator year-over-year rate of change (dependent variable) and leads and lags of U.S. equity realized volatility (independent variable). Newey-West Standard Errors are computed. T-statistics are in bold italic. The estimated coefficients are significant at 1% level, with the exception of: *** significant at 5% level; ** significant at 10% level; * not significant. Data frequency is on a monthly basis. Regressors are twelve leads and lags (1 year) of 12-month rolling annualised realized volatility of S&P 500 index monthly returns. The period between October 1987 and September 1988 is excluded from the raw data because the substancial spike in realized volatility, which was a function of the October 1987 equity market crash, was an equity market phenomenom without any major consequences for the US economy. The October 1987 crash effect in rolling realized volatility was completely faded away in October 1988. Source: Bloomberg.

the regressions where the raw data is considered, only the lead and lag 12 are not statistically significant.

Thus, it is possible to conclude that since January, 1963 equity volatility has been counter-cyclical of economic growth with a slight leading dependence. These results are similar to the ones obtained by Campbell et al. (2001), where market volatility is negatively correlated with GDP and tends to lead growth by three months, given quarterly observations. However, we also find that the countercyclical and predictive relationship is much stronger between January, 1963 and September, 1987 than in the subsequent time frame until March, 2009.

Analysis was also performed between implied volatility, measured by the VIX index, and COI YoY. The raw data available corresponds to the historical record of VIX, which dates back to January 1986. In the same vein, a sample partition is considered in order to avoid the equity market crash of October 1987. Similar methodology of lead-lags is adopted, with 12 leads and lags applied to the volatility measure. Furthermore, the rolling six-month average level of VIX is used instead of the original series levels because of its high noise pattern. Preliminary tests were done between different metrics of VIX and economic growth, and the rolling six-month average level showed the highest correlation.

Given the information of OLS regressions[1], it is possible to conclude that the smoothed VIX seems to be a better explanatory variable than historical volatility of economic growth, in the comparable sample between October 1988 and March 2009. In this period, 26% of the variability of COI YoY is explained by the variability of the VIX rolling six-month average level, with the estimated coefficients being always negative. Considering the raw data (January 1986 - March 2009), the correlation is not so high, given the R^2 of 0.16 with the VIX one month lagged. In the sub-sample regression all the estimated coefficients between lead 5 and lag 11 are statistically significant at 1% level. Leads 6, 7 and lag 12 are statistically significant at 5% level, and leads 10, 11 and 12 are not statistically significant. However, in the full-sample regression estimated coefficients of lags 1 to 8, contemporaneous level and leads 1 and 2 of the explanatory variable are the most statistically significant. Additionally, the results profile is similar in terms of the volatility lags being more significant in explaining economic growth than the equivalent leads. Also, there seems to be a contemporaneous, with a slight monthly lead, significant relationship of implied volatility and U.S. economic growth.

4.3. Money markets volatility

In terms of the full-sample data, OLS estimated regressions outputs show that the variability of volatility of 3-month bills explains, by 22%, the variability of COI YoY. The estimated coefficients are negative, meaning that when the interest rate volatility is higher the economy rate of change tends to slowdown. After 3 months lag periods applied to the explanatory variable, the R^2 is lower, meaning that the relationship is more contemporaneous than lagged. Conversely, when leads are considered for volatility, the

[1]The tables with the full regression results are not shown in the next subsections. The appearance is very similar to the one of Table 2 and we support our conclusions in the most important observed results. The full tables can be sent if requested by the reader.

correlation is lower when compared to the same distance lags. However, estimated coefficients are all statistically significant at 1% level until when maximum 10 leads-lags are considered.

Considering the first sub-period (1963-1984) the results obtained are much more significant than the ones for the raw data, with the coefficients being always negative. The R^2 values are substantially higher for all the analysis of contemporaneous, leads and lags of the short-interest rate volatility. At coincident and 1 lagged period of volatility, the R^2 values are the highest (0.56), and when other higher lags and leads are considered the coefficient of determination turns lower. Furthermore, the estimated coefficients are all statistically significant at 1% level in all leads-lags considered. Hence, in this period, and given the lower transparency of monetary policy, associated to the exogenous oil shocks that hit the U.S. economy, rising volatility of short-term rates and inflation premium happened when the economy entered into a downturn (as a consequence of the inflation shock).

For the second sub-sample data, that many authors call The Great Moderation (Bernanke, 2004), the estimated models show absence of correlation between short interest rates volatility and the economic cycle, with the highest R^2 at 6%. Moreover, the estimated coefficients are not statistically significant, irrespectively of the leads-lags applied to the volatility.

4.4. Government debt volatility

The profile of the estimated models is similar to the results obtained for the 3-month bills, with results being more significant in the period of January, 1963-December, 1984 ($R^2 = 0.33$ at the contemporaneous level), although less strong in all respects. For the entire sample, the R^2 obtained in the contemporaneous analysis is 0.18, and the same result is achieved in the first and second leads applied to the financial volatility variables. For higher gaps of leads and lags the significance of OLS regressions is reduced. Finally, in the period of the Great Moderation, the results obtained do not indicate linear dependency between yield volatility and COI YoY. All the estimated coefficients are not statistically significant, with the exception of when the 8-12 lags are considered for volatility. In this case the estimated coefficients are significant at 10% level, although the correspondent R^2 values are too small.

The results obtained for the U.S, and considering the sample partition, extend the ones obtained by Gerlach et al. (2006), which only find a significant and negative relationship between cross-country bond returns volatility and the global output gap after de World War II.

4.5. Yield curve volatility

Although there have been several empirical studies that confirm the predictive power of the yield curve slope on the changes in real output, like

Estrella and Hardouvelis (1991) and Estrella and Trubin (2006), the links between yield curve volatility and growth have remained largely unstudied. Thus, in our analysis we also try to find if there are meaningful effects of volatility changes of the yield curve, considering the spread between the 10yr government bond yield and the 3-month treasury-bill yield, on the growth proxy. Results from the estimated models using the volatility of the yield curve as the explanatory variable for economic growth seem statistically more significant than the ones obtained considering the individual maturity buckets. Regressions based on the full-sample (January, 1963 - March, 2009) show that the variability of curve changes volatility explains 29% of the variability of COI YoY, at the contemporaneous level. The results are marginally better when 2 lags in volatility are applied, with the R^2 value of 30% and t-statistics of the negative estimated coefficients at the highest absolute level for all lags-leads considered. Consequently, higher yield curve volatility leads the slowdown in the rate of change of the U.S. economy.

Considering the first sub-period (January, 1963 - December, 1984), although the R^2 values obtained are not higher than the ones from the estimated models using the 3-month rate, the results are still significant and the absolute value of t-statistics is higher. Once more, curve changes volatility leads, inversely, COI YoY, with the coefficient of determination being the highest at the contemporaneous level (0.42). Moreover, in all the 12 leads-lags applied the estimated coefficients are statistical significant at 1% level.

When the estimated models are based on the second sub-period (January, 1985 - March, 2009), output results are more significant than the single maturity volatility analysis. At the coincident level, the variability of COI YoY is explained in 11% by curve volatility, with a negative estimated coefficient. However, given the leads-lags estimated models, it is possible to see that the best results ($R^2 = 0.21$, estimated coefficient statistically significant at 1% level and highest absolute value t-statistic) are obtained when 5 lags are applied to volatility, meaning that curve volatility is leading economic growth, with the estimated coefficients still negative.

4.6. Credit markets volatility

In order to find the interaction between credit risk volatility and economic growth, two different approaches can be considered on the explanatory variable: the yield and the spread level vs. the risk-free rate.

The corporate bond yield, for a certain maturity (T) with rating (Z), can be calculated as

$$Yield_{Corporate,Z,T} = Yield_{Risk-Free,T} + Credit\_Risk\_Spread_{Z,T}. \qquad (4)$$

According to equation (4), volatility changes in the corporate bond yield can be function of the variability of its risk-free component, of the credit spread or from the two components simultaneously. This way, we estimated the models based on two different regressors (the composite corporate yield and the spread).

In terms of corporate bond yield, results obtained for the full-period (January, 1963 - March, 2009) show that the estimated coefficients are negative, for all leads-lags, and the relationship is stronger at the contemporaneous level, with the R^2 of 0.21 and statistically significant at 1% level. Additionally there is no substantial lead-lag effect of the financial variable in explaining COI YoY, as the higher are the gaps considered, less significant are the estimated models in terms of lower coefficients of determination and significance level. Consequently, the relationship is very contemporaneous meaning that a rise or fall in the historical volatility of the corporate bond yield does not anticipate a fall or rise in the rate of economic growth.

For the January, 1963 - December, 1984 period, results are more relevant, with higher R^2 and more statistically significant estimated coefficients for all leads-lags considered. Moreover, all the coefficients are negative and statistically significant at 1% level, with the exception of the 12 lag that is significant at 5% significance level.

In the second sub-sample (January, 1985 - March, 2009), the relationship is not statistically significant for most of lead and lags considered, meaning that there is no statistical evidence of linear interaction between credit volatility and growth.

When the spread of corporate bond yield is considered, the results from the estimated models exhibit a similar profile of the ones from the yield level volatility. Although the results are marginally less significant, they only reflect the interaction between the credit risk component of pricing of this asset class and economic growth. When the full-sample is considered, estimation results show that the relationship between the two variables is statistically significant at the contemporaneous level, with a coefficient of determination of 0.15. The estimated coefficients are negative, in all lead-lags of the explanatory variable, meaning that when the credit spread volatility shows a positive variation, the rate of economic growth tends to slow down. Furthermore, the estimated coefficients are all statistically significant at 1% level, with the exception of the 12^{th} lead and 9^{th} up to 11^{th} lag of credit spread volatility, that are significant at 10% level, and the 12th lags that is insignificant.

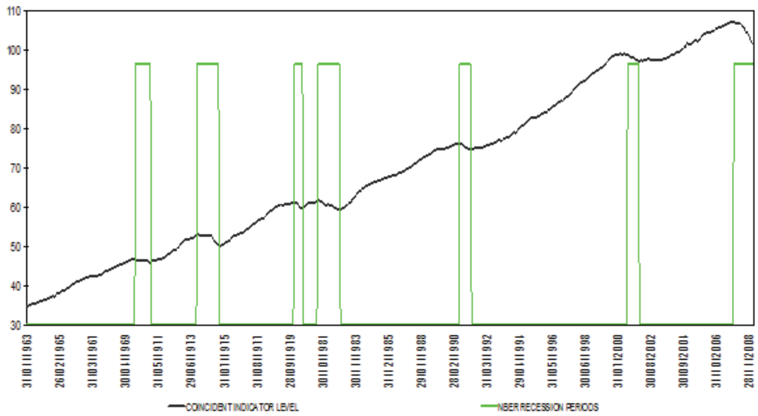
In the period of January, 1963 to December, 1984, as for the yield level, results are statistically more significant, with all leads-lags of volatility estimated coefficients statistically significant at 1% level. When both variables are coincident in time, 32% of the variability of COI YoY is explained by the variability of the credit spread volatility.

Finally, in the second sub-period, there is no statistical relationship between both variables (the exceptions are lags 11 and 12 that are statistically significant at 10% level). R^2 values are almost zero and the estimated coefficients from the regressions are most of all statistically insignificant.

4.7. Economic recessions, expansions and slowdowns

Besides testing the full interaction between economic growth and financial volatility, it was also important to perform the same tests in different regimes of the economic cycle, as a way to conclude if the relationship is more significant in a context of recession periods and of uptrend or downtrend in the rates of economic growth. The NBER is the national U.S. entity that officially determines the chronology of the beginning and ending dates of recessions. According to Figure 3, it is possible to see that in every recession period the level of COI always exhibits a break in the long-term upward trend.

FIG. 3. Coincident indicator level and NBER recessions (JAN 1963 — MAR 2009)



Note: Source: Bloomberg.

Furthermore, tests were also performed in downtrend periods of COI YoY, because not only all these periods coincide with an official recession but also, typically, downtrends start before the beginning of the recession period. Thus, we have considered the visible and significant periods of decrease in the year-over-year rate of economic growth. Finally, uptrend periods were also defined by the same rational as for downtrends. Tables 3, 4 and 5 include the official dates of recessions occurred in the full-sample, considered for the analysis, and also the downtrend and uptrend periods.

For all the three regimes of economic growth, we used dummy variables to characterize each monthly observation for being, or not, included in the

TABLE 3.

NBER Recessions

NBER - Business cycle reference dates		
Peak Date	Through Date	Peak to Through
December 1969	November 1970	11
November 1973	March 1975	16
January 1980	July 1980	6
July 1981	November 1982	16
July 1990	March 1991	8
March 2001	November 2001	8
December 2007	...	...

Note: This table reports all the official recession determined by the National Bureau of Economic Research (NBER), occurred in the full-sample analysis (January/1963 - March/2009). Peak to through is the contraction period measured in months. The determination that the last expansion ended in December 2007 is the most recent decision of the business cycle dating committee of NBER. Source: NBER

TABLE 4.

COI YoY Downtrends

COI YoY Downtrends		
Peak Date	Through Date	Peak to Through
October 1969	November 1970	13
November 1972	May 1975	30
January 1979	July 1980	18
July 1981	August 1982	13
May 1984	March 1986	22
January 1988	March 1991	38
April 2000	December 2001	20
August 2006	March 2009	31

Note: This table reports all the periods where there was a visible and significant downtrend in the year-over-year rate of change of the Conference Board Coincident Indicator (COI YoY), occurred in the full-sample analysis (January/1963 - March/2009). Peak to through is the downtrend period measured in months. Source: Bloomberg

period defined for the filtered analysis. By creating a new qualitative independent variable, the purpose was to find if the changes in the intercept of the simple model, generated by the coefficient of the binary variable (when assumes the value 1), would increase the significance of the relationship between economic growth and financial volatility. Thus, regression models, according to equation (3), were estimated for the full sample period and

TABLE 5.

COI YoY Uptrends

COI YoY Uptrends		
Through Date	Peak Date	Through to Peak
November 1970	November 1972	24
May 1975	April 1976	11
October 1982	March 1984	17
March 1991	January 1995	47
December 2001	December 2004	36

Note: This table reports all the periods where there was a visible and significant uptrend in the year-over-year rate of change of the Conference Board Coincident Indicator (COI YoY), occurred in the full-sample analysis (January/1963 - March/2009). Through to peak is the uptrend period measured in months. Source: Bloomberg.

for all the asset classes' volatilities, in the continuous independent variable. Following Schwert (1989), we also tested the models with i lags and leads ($i = 3, 6, 9, 12$) for the dummy variables. This methodology was justified by the fact that the outcomes of coincident economic variables, dictating recession, expansion or slowdown, usually happen after other leading economic and financial variables start to incorporate expectations about those states of the economy.

In the case of S&P 500 volatility (equity), the estimated regressions show that with the introduction of a dummy variable the three economic states considered improve the statistical results (Tables 6, 7 and 8). When recession periods are considered (Table 6) the adjusted R-square ($\overline{R}^2$, given the introduction of a new exogenous variable) obtained with the binary variable, at the contemporaneous level, improve to 0.36, from 0.18 in the original regression (Table 2). With lags applied to the dummy, the estimated coefficients are all negative and statistically significant at 1% level. Moreover the $\overline{R}^2$ values are higher, with the 6^{th} lag producing the highest adjusted value of 0.51. However, when leads are considered, not only the R^2 values decrease, but also the dummy estimated coefficients reduce its statistical significance.

In the case of a downtrend in growth regime (Table 7), the profile of results is similar, with dummy lags producing the best regression results (in the 9^{th} lag $\overline{R}^2$ achieves the highest value: 0.48). With leads applied to downtrends, the $\overline{R}^2$ values are lower than its corresponding lags, and the estimated coefficients for dummies are always positive (9^{th} and 12^{th} leads are also statistically significant at 1% level). When compared to the recession regime, results imply that in downward trend periods the

TABLE 6.

Equity Volatility and Coi YoY — NBER Recessions

Regression with S&P 500 volatility and NBER recessions (JAN/1963-MAR/2009)										
		Recession dummy variable: LEADS-LAGS								
Explanatory Variables	Regression Statistics	−12	−9	−6	−3	0	+3	+6	+9	+12
S&P 500 Volatility	Estimated Coefficient	−0.15	−0.11	−0.10	−0.11	−0.15	−0.18	−0.18	−0.19	−0.18
(Continuous Variable)	T-Statistics	−3.21	−2.80	−2.56	−2.63	−2.99	−3.25	−3.33	−3.38	−3.36
	P-Value	0.0014	0.0052	0.0109	0.0088	0.0029	0.0012	0.0009	0.0008	0.0008
NBER Recession	Estimated Coefficient	−0.03	−0.04	−0.04	−0.04	−0.03	−0.02	−0.01	0.00	0.00
(Dummy Variable)	T-Statistics	−5.15	−8.90	−10.36	−8.93	−6.03	−3.84	−2.21	−0.95	0.19
	P-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0274	0.3415	0.8480
	R-Squared	0.3349	0.4658	0.5130	0.4720	0.3626	0.2495	0.1944	0.1787	0.1771
	Adjusted R-Squared	0.3324	0.4638	0.5112	0.4701	0.3602	0.2468	0.1915	0.1757	0.1741

Note: This reports output statistics from OLS regression between the Conference Board Coincident Indicator log returns (dependent variable) and S&P 500 log returns volatility and leads and lags of NBER Recessions. S&P 500 volatility consists of 12-month rolling annualised historical volatility of log returns. NBER Recessions is the qualitative binary variable assuming: 1 - if the observation is in a recession period; 0 - if not. Newey-West standard errors are computed. Data frequency is on a monthly basis. NBER recession periods: Dec/69-Nov/70; Nov/73-Mar/75; Jan/80-Jul/90; Jul/81-Nov/82; Jul/90-Mar/91; Mar/01-Nov/01; and Dec/07-... . Sources: Bloomberg, NBER.

quality of the regression adjustment is lower. Additionally, given that the highest $\overline{R}^2$ in downtrends is obtained at the 9^{th} lag, in comparison with the 6^{th} lag during recessions, when an economic downtrend period is eminent, volatility starts to rise before than it does in recession environments.

Finally, in the case of uptrend scenarios (Table 8), volatility interacts better with growth when leads are applied to the dummy independent variable. The corresponding estimated coefficients are negative, statistically significant at 1% level and the better fit is achieved at the 9^{th} lead, with the $\overline{R}^2$ being 0.47.

By this, equity volatility tends to increase well in advance before the real recession or downtrend are in place and tends to lag the economic recovery, lowering its level when the uptrend in growth is already taking its course. These findings deviate from the ones obtained by Schwert (1989), where equity volatility tends to rise after fail or panic crises (which usually occur during economic recessions), and by Campbell et al. (2001), where correlation between market volatility and growth is negative during recessions but decreases in absolute value when volatility is lagged.

The three economic regimes improve the results from the original regressions, when the 3-month yield volatility is considered[2] (money markets

[2]In order to reduce the dimension of the paper, other tables with full regression results are not shown. However, the main results from those tables are pointed in the text.

TABLE 7.

Equity Volatility and Coi YoY — Downtrends

Regression with capital S&P 500 volatility and COI YoY Downtrends (JAN/1963-MAR/2009)										
		COI YoY Downtrends dummy variable: LEADS-LAGS								
Explanatory Variables	Regression Statistics	−12	−9	−6	−3	0	+3	+6	+9	+12
S&P 500 Volatility	Estimated Coefficient	−0.12	−0.13	−0.14	−0.16	−0.19	−0.19	−0.19	−0.19	−0.19
(Continuous Variable)	T-Statistics	−2.94	−3.18	−3.09	−3.14	−3.35	−3.52	−3.61	−3.76	−3.86
	P-Value	0.0034	0.0016	0.0021	0.0018	0.0009	0.0005	0.0003	0.0002	0.0001
COI YoY Downtrends	Estimated Coefficient	−0.03	−0.03	−0.02	−0.02	−0.01	0.00	0.01	0.01	0.01
(Dummy Variable)	T-Statistics	−7.58	−8.04	−6.55	−4.57	−2.12	0.36	1.87	3.14	3.64
	P-Value	0.0000	0.0000	0.0000	0.0000	0.0341	0.7165	0.0624	0.0018	0.0003
	R-Squared	0.4458	0.4811	0.4151	0.3187	0.2261	0.1832	0.1987	0.2436	0.2681
	Adjusted R-Squared	0.4438	0.4792	0.4130	0.3162	0.2261	0.1802	0.1958	0.2408	0.2654

Note: This table reports output statistics from OLS regression between the Conference Board Coincident Indicator log returns (COI YoY) (dependent variable) and S&P 500 log returns volatility and leads and lags of COI YoY Downtrends. S&P 500 volatility consists of 12-month rolling annualised historical volatility of S&P 500 returns. COI YoY Downtrends is the qualitility binary variable assuming: 1 - if the observation is in a downtrend peroid; 0 - if not. Newey-West standard errors are computed. Data frequency is on a monthly basis. COI YoY downtrend periods: 31/Oct/69-30/Nov/70; 30/Nov/72-31/May/75; 31/Jan/79-31/Jul/80; 31/Jul/81-31/Aug/82; 31/May/84-31/Mar/86; 31/Jan/88-31/May/91; 30/Apr/00-31/Dec/01 and 31/Aug/06-31/May/09. Sources: Bloomberg.

TABLE 8.

Equity Volatility and Coi YoY — Uptrends

Regression with capital S&P 500 volatility and COI YoY Uptrends (JAN/1963-MAR/2009)										
		COI YoY Uptrends dummy variable: LEADS-LAGS								
Explanatory Variables	Regression Statistics	−12	−9	−6	−3	0	+3	+6	+9	+12
S&P 500 Volatility	Estimated Coefficient	−0.19	−0.19	−0.20	−0.21	−0.20	−0.17	−0.14	−0.12	−0.12
(Continuous Variable)	T-Statistics	−3.24	−3.41	−3.62	−3.77	−3.82	−3.66	−3.35	−2.98	−2.64
	P-Value	0.0013	0.0007	0.0003	0.0002	0.0002	0.0003	0.0009	0.0003	0.0086
COI YoY Uptrends	Estimated Coefficient	0.01	0.01	0.00	−0.01	−0.01	−0.02	−0.03	−0.03	−0.03
(Dummy Variable)	T-Statistics	1.44	1.28	0.20	−1.35	−3.28	−5.64	−7.45	−8.64	−8.39
	P-Value	0.1509	0.2000	0.8427	0.1781	0.0011	0.0000	0.0000	0.0000	0.0000
	R-Squared	0.2133	0.2116	0.2025	0.2107	0.2539	0.3404	0.4264	0.4729	0.4645
	Adjusted R-Squared	0.2104	0.2087	0.1996	0.2078	0.2512	0.3380	0.4243	0.4709	0.4625

Note: This table reports output statistics from OLS regression between the Conference Board Coincident Indicator log returns (COI YoY) (dependent variable) and S&P 500 log returns volatility and leads and lags of COI YoY Uptrends. S&P 500 volatility consists of 12-month rolling annualised historical volatility of S&P 500 returns. COI YoY Uptrends is the qualitility binary variable assuming: 1 - if the observation is in a uptrend peroid; 0 - if not. Newey-West standard errors are computed. Data frequency is on a monthly basis. COI YoY uptrend periods: 30/Nov/70-30/Nov/72; 31/May/75-30/Apr/76; 31/Oct/82-31/Mar/84; 31/Mar/91-31/Jan/95; 31/Dec/01-31/Dec/04. Sources: Bloomberg.

volatility). The results for recessions and downtrends show that with lags applied to the dummy variable, the $\overline{R}^2$ values are higher and the estimated coefficients are negative and statistically significant at 1% level. However, the highest $\overline{R}^2$ is achieved for different lags. In recessions, the highest value (0.48) is obtained at lag 6 and in downtrends it is lag 9 that produces the higher $\overline{R}^2$ (0.45).

In the case of dummy leads, for recession periods the goodness-of-fit is not improved, as the results obtained, for leads 3, 6, 9 and 12 show lower $\overline{R}^2$ than in the original regression. However, in downtrend periods, leads 9 and 12 improve the results from the simple model, with $\overline{R}^2$ of 0.32 and 0.34, respectively, and the positive estimated coefficients for the dummy variable are statistically significant at 1% level. This way, in recessions and downtrends, not only the inverse relationship between 3-month yield volatility and COI YoY is improved but also volatility tends to rise in advance to the opposite pattern in economic growth. Moreover, volatility also tends to rise with a substantial lag (leads 9 and 12) to the economic downtrend.

In uptrend periods, results are improved when leads are considered for the dummy variable. The contemporaneous level and leads (3, 6, 9 and 12) result in substantially higher $\overline{R}^2$ values than the ones resulting from the original model, with the highest adjusted value (0.55) occurring at lead 9. The estimated coefficients of the uptrend dummy variable are all negative and statistically significant at 1% level. Thus, 3 month yield volatility tends to drift lower after the economic expansion is confirmed, by the uptrend in the year-over-year rate of economic growth.

In terms of long term government debt bond yields volatility, the inclusion of dummy variables reflecting recessions and downtrends generates an improvement in the goodness-of-fit of the original estimated model. In case of recessions, the adjusted R-squared is 0.34 for the contemporaneous level, much higher than the one obtained in the original model (0.18). When considering lags 3 to 9 months, the adjustment gets even more significant, with the 6^{th} lag in recession periods showing a $\overline{R}^2$ of 0.52. The results for the leads are less significant with the $\overline{R}^2$ values being substantially lower. All the estimated coefficients for the dummy variable are negative, with the exception of the 12^{th} lead, and statistically significant at 1% level, with the exception of the 6^{th} and 12^{th} leads. In downtrend scenarios, the profile is similar. However, at the coincident dummy level, the goodness-of-fit is lower than the one from recessions ($\overline{R}^2 = 0.21$) but yet higher than the original model. With lags applied to the downtrend dummy variable, statistical results are improved with higher $\overline{R}^2$ values, and the estimated coefficient of dummy variables being significant at 1% level. If in recessions the best fit is achieved at the 6^{th} lag, in case of downtrend periods the 10yr volatility and economic growth inverse relationship is best improved ($\overline{R}^2 = 0.46$)

when 9 lags are considered. When the model is estimated with leads for downtrend periods, the fit is much lower and the dummy estimated coefficients being positive imply an upward adjustment in the intercept of the original regression. However, some of them are not statistically significant.

In the uptrend regime, once again financial volatility is laggard of economic growth, with the 9^{th} and 12^{th} leads for the binary variable producing the highest $\overline{R}^2$ values, of 0.49 and 0.48 respectively. At the coincident level of the dummy variable, statistical results are similar to the ones obtained in the downtrend regime, and when lags are considered the statistical significance is also lower. Only the 12^{th} lag for the dummy variable generates an estimated coefficient that is statistically significant at 1% level.

Once more, in the case of 10yr yield, rising financial volatility leads the rate of economic growth, both in recessions and downturns. Additionally, in environments of economic recovery or expansions the reduction in 10yr yield volatility tends to be laggard.

The results for corporate and financial debt volatility, and using the average Moody?s yield spread as the proxy, also show an improvement when the three economic states are considered via the new independent dummy variable. In recessions, results with the dummy variable being coincident substantially improve the ones obtained in the original model. The new $\overline{R}^2$ value, of 0.31, compares with 0.15 in the simple regression. In the estimated regressions with lags for recessions, $\overline{R}^2$ are higher and all the estimated coefficients are statistically significant at 1% level. The best fit is at lag 6, with the adjusted R-squared reaching 0.50. In the case of leads, the adjusted measure, with the exception of lead 3, is lower than the original model and, thus, not incorporating new valuable recession information.

In downtrends, the contemporaneous regression shows a much lower $\overline{R}^2$ value (0.17) when compared to the recession regime results. In the same vein, the goodness-of-fit is better with lags, than leads, applied to growth downtrends. All the estimated coefficients for downtrends lags are negative with p-values lower than 1%. The highest $\overline{R}^2$ (0.44) is obtained at the 9^{th} lag applied to the dummy variable. For leads in downtrends, results are less significant and only lead 9 and 12 produce significant results and $\overline{R}^2$ values slightly higher than the ones in the original regression.

Finally, in uptrend contexts, the inclusion of a binary variable also increases the significance of the original regression, with a $\overline{R}^2$ value of 0.20, and when leads are considered the most statistically significant fits are obtained. Leads 9 and 12 generate the highest absolute t-statistics values for the dummy variable and the highest adjusted R-square, of 0.46 and 0.45, respectively. With the introduction of lags, the significance of regressions results is always lower than the ones resulting from the contemporaneous levels.

Hence, a rise in corporate and credit spreads volatility also lead recessions and downturns, but a falling trend in variability will lag the economy uptrend rate of growth.

5. CONCLUSION

This study aims to find an empirical relationship between capital markets volatility and the rate of real economic growth, for the U.S.. In this vein, the empirical study focused on how to measure the interaction between individual markets (or asset classes) volatilities and growth, considering a long time span enough to encompass different economic and capital markets cycles. The period considered for all the analysis was from January 31, 1963 to March 31, 2009.

An important restriction was that economic data is of low frequency, with the release of the U.S. real GDP being on a quarterly basis. Given the high frequency of financial data (e.g. daily), trying to establish a quantitative relationship based on quarterly observations would raise the probability of loosing valuable information in terms of markets volatility patterns. By this, we had to look for other economic indicators, released on a monthly basis, which should be strongly and contemporaneously correlated with GDP growth. The indicator that best fitted the criteria was the Conference Board Coincident Indicator.

In terms of volatility metrics, we considered the 12-month rolling historical calculation, given the lack of availability of implied volatility measures for the asset classes considered (with the exception of equities).

Then, for each market not only were performed standard OLS regressions based on the entire period, but also sample partitions were considered, given structural economic and financial changing regimes, or specific events within asset classes, occurring in the full-sample.

In the case of equities volatility, we found a statistically significant negative relationship with growth with a slightly leading effect of volatility. Thus, results imply that an upward trend in equity volatility has a small lead in the slowdown of the year-over-year rate of economic growth. For the entire period and sub-periods analysed (January, 1963 - September, 1987 and October, 1988 - March, 2009) the relationship is more significant when the sample from January, 1963 to September, 1987 is considered.

For the money, government bond and corporate and financial bond markets volatilities, OLS results show a strong contemporaneous, and negative, significant relationship with economic growth, until December, 1984. Thereafter, with the emergence of the Great Moderation and Gradualism of monetary policy regimes, the volatility of interest rates structurally lost cyclicality and, consequently, also explanatory power of economic growth, from January, 1985 onwards. However, the results for the entire period show a statistically significant relationship implying that volatilities of these markets are negatively correlated with growth. Regressions were also performed considering the volatility of the U.S. yield curve changes, and results obtained were statistically more significant. In the period of January, 1985 to March, 2009 the yield curve variability had explanatory power of economic growth.

When considering economic states of official recessions, economic downtrends and uptrends, regression results are improved, showing a highly explanatory power of individual assets volatilities in growth. In fact, financial volatility tends to rise in advance of the beginning of a recession, or an economic slowdown, (leading) and typically enters into a downward trend after the beginning of an economic expansion period (lagging). In other words, this filtered analysis shows that rising financial volatility could be a trigger of economic downturns and, when it is falling, could be a consequence of economic expansions.

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