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Latin American Equities, Volatility Regimes, and the US Economic Policy Uncertainty

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Abstract

We investigate how the volatility of the iShares Latin America 40 ETF (ILF) responds to key economic and market sentiment indicators associated with economic uncertainty. Specifically, we explore the regime-dependent nature of ILF volatility in relation to Economic Policy Uncertainty (EPU), U.S. Economic Uncertainty (ECU), Global Economic Policy Uncertainty (GEPU), and implied risk, as captured by the Chicago Board Options Exchange's VIX (CBOE VIX), from 2001 to 2023. Our findings highlight that the connection between market volatility and economic/market sentiment is influenced by distinct volatility regimes. Utilizing a two-covariate GARCH-MIDAS (GM) model, a regime-switching Markov Chain (MSR) model, and quantile regressions (QR), we reveal that the impact of sentiment on realized volatility varies depending on the prevailing volatility regime, reflecting investors' differing responses to market uncertainty. Additionally, our results show a significant linkage between ILF's short and long-term volatility and economic uncertainty/sentiment indicators, suggesting that these factors shape ILF volatility across different market conditions and quantiles of the volatility distribution. Overall, our findings indicate that investor sentiment and economic uncertainty extend beyond their domestic origins, influencing volatility patterns in U.S., global, and Latin American markets.

JEL classification: G12, G14, G38.

Keywords: Volatility, GARCH-MIDAS, VIX, Economic policy uncertainty, Global economic policy uncertainty, Quantile regression, Regime switching Markov Chain regression.

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1. Introduction

Behavioral finance literature (e.g., Baker and Wurgler (2006, 2007)) holds that investors are often irrationally driven by excessive unjustifiable pessimism or optimism, rather than fundamental factors. Thus, asset price dynamics may also be explained by investor psychology, contrary to the thesis of efficient markets (Fama (1965)). This paper addresses issues regarding the role of investor sensitivity in Latin American equity markets to the US and Global indicators of policy and equity market uncertainties. We examine the short-term volatility or the persistence of long-term volatility by analyzing the short- and long-term volatilities in the popular Standard & Poors Ishares Latin America 40 ETF (ILF), which is comprised of equities from Mexico, Brazil, Chile and others. They are active in all sectors of several Latin American economies with roughly 35 percent in technology, 25 percent in financial, and 17 percent in consumer cyclical sectors, respectively.

Chile, Brazil, and Mexico are all important trading partners for the United States, especially in Latin America. In 2023, these countries accounted for 40% of the US's total trade with Latin America. In 2023, the US exported $37.9 billion in goods and services to Brazil, and imported $36.9 billion. The US is Brazil's second-largest trading partner, while Mexico is the US's largest trading partner.

The understanding of the equity market volatility is critical in financial modeling (e.g., in portfolio optimization), the assessment of risk (e.g., in stress testing), and in derivatives pricing. For instance, in futures contracts, volatility is considered a source of contango and backwardation (e.g., Robe and Wallen (2016), Beckmann and Czudaj (2014) and Alizadeh and Nomikos (2011). However, evidence shows that the accurate quantitative assessment of equity market volatility is challenging. The evidence shows that equity price dynamics follow nonlinear processes (e.g., Peters (1994), Eve et al. (1997), Adrangi et al. (2015), Adrangi et al. (2001))) tend to cluster and are time varying (e.g., Bollerslev (1988)), and that co-movements across asset classes tend to increase in periods of distress (e.g., Ang and Chen (2002) and Ang and Bekaert (2015)). Our study extends this literature by examining the role that investor sentiment might play in nonlinear volatility dynamics.

We investigate the association of the volatility in ILF with variables that reflect sentiments and uncertainties surrounding markets and economic policies in the US, and the global economic policy uncertainty from 2001 to 2023. Baker et al. (2012a, 2012b, 2016, 2021, 2019) have created several indices that capture economic or financial uncertainty, Twitter-derived measures of economic uncertainty (TEU), and others that quantify uncertainties in the US and Global markets.

Economic uncertainty in this research is captured via the Economic Policy Uncertainty index (EPU, Baker 2012b), which measures uncertainty on economic policy risks, the CBOE VIX (expected volatility measure from S&P 500 options), and global economic policy uncertainty. The EPU has been extensively used in the literature to proxy lack of consensus on economic policy. Therefore, it is also a measure of sentiment relating to economic uncertainty. The VIX is widely known as the “fear index” as it is known to rise at times when stress is indicated and fall when markets are bullish (e.g., Whaley (2009)). It is one of our sentiment indicators for the stock market. The global economic policy uncertainty index (GEPU, Davis (2016)) is designed to reflect the economic policy broadly. uncertainties for 16 economies. The GEPU Index is a GDP-weighted average of national EPU indices for 16 countries that account for two-thirds of global output.

Economic uncertainties refer to the unpredictability of economic conditions, which can arise due to various factors, such as changes in government policies, geopolitical tensions, global economic shocks, and natural disasters. Such uncertainties can have a significant impact on the enterprise value of firms, which is the market value of a company's total equity and debt.

The relationship between economic uncertainty and firm value is rooted in economic theory. Early investigations into the influence of economic uncertainty on corporate behavior trace their origins back to the groundbreaking work of Sandmo (1971). Following Galbraith's work, 'The Age of Uncertainty,' in 1977, numerous significant events, covered extensively in both the media and academic circles, underscored the pivotal role of uncertainty in the economic and financial realm. Building upon this foundation, subsequent scholars, including Flacco and Kroetch (1986), Fooladi and Kayhani (1990, 1991), and Adrangi and Raffiee (1999a), Adrangi et al. (1999b, 2024a), Golchin and Rekabdar (2024) have delved into diverse facets of how firms respond to uncertainty. These researchers have undertaken comprehensive theoretical inquiries to unravel the intricate ways in which firms may adjust their production processes, pricing strategies, and profit-seeking activities in the face of market risks and uncertainties.

Further pioneering work by Bernanke (1983), Pindyck (1991), and Dixit (1989) and Dixit and Pindyck (1994) lead to the theory of investment under uncertainty. This theory suggests that heightened uncertainty leads to delayed investment decisions, which may affect a firm's value.

While there is unanimous agreement on the importance of uncertainty, a single, universally accepted definition of the term remains elusive. Furthermore, it wasn't until relatively recently that scholars began to empirically investigate the role of uncertainty in the economy and financial markets. Recent developments in the measurement of economic and economic policy uncertainties were spearheaded by the work of Baker et al. (2012a, 2016) and Golchin and Riahi (2021) which has played a pivotal role in quantifying and analyzing economic and economic policy uncertainties. Their research has provided indices that provide valuable insights into the dynamics of economic uncertainty, helping policymakers, economists, and investors better understand the intricacies of these critical factors.

As asserted by Baker et al. (2016), in the aftermath of the 2008 global financial crisis, uncertainty surrounding government policies reached its zenith. This was primarily due to the uncertainty businesses and households faced concerning the government's future stance on regulatory frameworks, spending, taxation, monetary policies, and healthcare. The authors contend that this policy uncertainty significantly hindered the recovery from the recession, as businesses and households delayed their decisions regarding investment and consumption expenditures.

Attention to sentiment and uncertainty indicators have led researchers to quantify various aspects of uncertainty. Manela and Moreira (2017) introduced a monthly news-driven metric called NVIX, while Davis et al. (2019) and Baker et al. (2006, 2007, 2012a, 2012b, 2016, 2019, 2021) developed several indices designed to capture economic and financial uncertainties. They also devised Twitter-based measurements of economic uncertainty (TEU) and other tools for quantifying market uncertainties.

We estimate a two-covariate GARCH-MIDAS model, which has been proven superior to other variations of GARCH frameworks in terms of its predictive power as well as its ability to simultaneously deliver the short- and long-term predictions of volatility. Short- and long term volatilities are examined across regimes. The low frequency variables that determine the long-term volatility of ILF are the US industrial production and the US national financial condition index (NFCI). Edwards et al. (2001), among others shows that contagion in equity markets mainly spreads from the large economies like the US to other economies through trade connections or financial channels.

Our paper relies on a two-step methodology because the estimation of GARCH-MIDAS models becomes complicated or impossible with additional variables. We deploy Markov switching and quantile regressions (MSR and QR, respectively), suitable to delineate the association of volatility with uncertainty indicators during the low- and high-volatility periods.

Our findings indicate that sentiment and uncertainty indicators significantly influence both short- and long-term volatilities across high- and low-volatility regimes. These indicators play a crucial role in linking market uncertainties to fluctuations in ILF volatility, highlighting the importance of VIX, EPU, and GEPU in shaping ILF's risk dynamics. This is particularly noteworthy because volatility clustering and persistence are often regarded as purely statistical phenomena, lacking a clear economic explanation. By demonstrating the significance of investor sentiment and uncertainty in driving these patterns, our results offer an intuitive and fundamental perspective on market behavior.

Overall, our results support the effectiveness of the GARCH-MIDAS approach in capturing the dynamics of ILF volatility. The finding that economic uncertainty indicators such as EPU, GEPU, and VIX influence volatility under both high- and low-volatility regimes aligns with economic intuition. Extreme volatility often emerges suddenly and unpredictably, making shifts in sentiment a key driver of market fluctuations. For example, growing expectations of monetary tightening can trigger a spike in ILF volatility, regardless of whether the market is experiencing relative calm or heightened turbulence.

Our paper contributes to the literature in two important ways: (i) We analyze, jointly, how short-term and long-term components of volatility are linked with market sentiment and economic uncertainty. (ii) We improve the Su et al. (2019) model by first deriving the short- and long-term ILF volatility measures from a two-covariate GARCH-MIDAS model. In the second step, we include three market uncertainty trackers in the Markov switching and Quantile regressions, thus, avoiding possible specification errors that precious research possibly suffered from. These uncertainty trackers have been shown by researchers to be significantly associated with short- and long-term volatility is asset returns (see Pan et al. (2017, 2021), Su et al. (2017, 2018, 2019), Adrangi et al. (2019, 2021, 2023a, 2023b, 2024a, 2024b, 2024c, 2025a, 2025b,2025c), among others).

The rest of the paper is structured as follows: Section 2 provides a brief review of the literature on sentiment indicators and an overview of the GARCH-MIDAS methodology employed in this study. Section 3 details the data and their sources, while Section 4 outlines the methodologies used. Section 5 presents and discusses the empirical results, and finally, Section 6 summarizes the findings and offers concluding remarks.

2. Literature review of EPU and GARCH-MIDAS

The section provides a brief review of literature on the EPU and other uncertainty indicators that we deploy in this study. It also summarizes some the pertinent studies that use GARCH-MIDAS framework for equity returns volatility.

2.1 Literature on Economic Policy Uncertainty

There is a growing interest in sentiment and uncertainty indicators. Manela and Moreira (2017) created a monthly news-based indicator (NVIX). Baker et al. (2012a, 2012b, 2016, 2021, 2019) have created several indices that capture economic or financial uncertainty, Twitter-derived measures of economic uncertainty (TEU), global economic policy uncertainty index (GPECU), and China economic policy uncertainty index (GPUCH), and others that quantify uncertainties in the market.

Such indictors have been recently deployed, especially as they pertain to volatility of various asset classes (e.g., Pan et al. (2017), Su et al. (2017, 2018,2019), Altig et al. (2020), Krol (2014), Dutta et al. (2021), Jiang et al. (2019), Xu et al. (2021), Pan et al. (2021), Lindblad (2017), Adrangi et al. (2023a, 2023b, 2025a,2024a,2024b. 2024c, 2025b,2025c), Li et al. (2020), Zhang et al. (2019), Adam et al. (2022), Kyriazis, et al. (2025), Sun & Li (2025), among others). Researchers have studied the association of various indices of economic, market, financial, and policy uncertainties with equity and commodity markets of the of the US and the world.

Baker et al. (2012b) develop the EPU to capture uncertainty about fiscal and monetary policies. Baker et al. (2012a) examine the EPU in context of the 2009 recession and to isolate the reasons behind a slow recovery in the post-recession years. They find the EPU index fluctuates over time and shows extraordinary high levels of EPU over the period of 2008 through 2012, reaching its maximum in August 2011. Furthermore, they document that policy uncertainties account for the large fraction of the overall economic uncertainty during the study period. They find that rising economic policy uncertainty foreshadows slows output, employment and investment. They conclude with some confidence that high levels of policy uncertainty are associated with weaker economic growth.

Al-Thaqeb & Algharabali (2019) review the findings of some research regarding EPU's associations with financial markets and firms' behavior. Overall, the results from previous studies indicate that firms turn conservative at times of high EPU (Colak et al.(2017), Jens, (2017), Kelly et al. (2016)). Therefore, firms reduce capital investment (Gulen & Ion, (2015)), launch fewer initial public offerings (Colak et al., 2017), curtail mergers and acquisitions (Bonaime et al. (2018), Nguyen & Phan, (2017)), reduce dividend payments (Panousi & Papanikolaou (2012), Walkup (2016)), and retain cash (Demir & Ersan (2017), Im et al.(2017), Phan et al. (2019)).

Therefore, the EPU appears to proxy uncertainty as it relates not just to economic policy per se, but also to corporate performance and ultimately to stock market volatility. Each of the following studies indicates an association between EPU and volatility.

Liu and Zhang (2015) investigate the association of economic policy uncertainty (EPU) with realized stock market volatility. Using five-minute high frequency data for realized volatility, they show lagging EPU is significantly related to contemporaneous volatility. These findings support those in Antonakakis et al. (2013) that a rise in policy uncertainty increases equity market return uncertainty and that including EPU in volatility models improves their predictive power regardless of the model specification. Arouri et al. (2016) study the effect of economic policy uncertainty (EPU) on the US stock market. Their regression findings reveal that a rise in EPU reduces stock returns and especially during extreme volatility periods.

Many papers also study EPU with the possibility that it captures international contagion risks. Tsai (2017) explores the role of the economic policy uncertainty (EPU) in China, Japan, Europe, and the *United States* on the contagion risk of investments in 22 equity markets worldwide. *The results show* the EPU in Europe and China influence volatility in Asian and European markets, respectively. They attribute the association of various EPU indices with the interdependence of equity markets. Choi and Hammoudeh (2010) conditional correlations (DCCs) among several assets including crude oil and S&P500 in a regime switching context. Chang (2022) deploys Markov-switching regressions to analyze synchronous and asynchronous volatility association between the U.S. and Japanese stock markets by including EPU index. The results show that this association switches from synchronous to asynchronous patterns and the EPU contagion to equity volatility is mainly happening in the US markets. Wen et al. (2019) investigate the association of macroeconomic variables in China with the US EPU index also find some relationship. Other scholars have been interested in the contagion from EPU to crude oil prices (Sahrif at al. (2020), exchange rates (Krol (2014), real time economic uncertainty indices (Altig et al. (2020), bond markets (Liow et al. (2018)), to name a few.

2.2 Literature on GARCH-MIDAS and related applications

In this section, we summarize some of the literature on methods that we deploy in the current study – namely GARCH-MIDAS, quantile regressions (QR), and Markov Switching regressions (MS). Most of our review is focused on applications, though the major intention is also to show the continued development and repurposing of the GARCH framework to the GARCH-MIDAS frameworks. The studies most pertinent to our paper are Su (2017) and Pan (2021), both of which we build upon.

Efforts to improve volatility measurement and forecasts by enhancing existing GARCH and other econometric models are ongoing. Among pioneering work is that of Ding and Granger (1996) and Engle and Lee (1999). Inspired by their seminal work, researchers have taken steps that show improvements in volatility estimation of GARCH models.

For instance, Javaheri et al. (2004) propose a GARCH (1,1) model combined with a convexity condition to investigate hedging of volatility swaps. Awartani and Corradi (2005) estimate the out-of-sample volatility predictive ability of several GARCH model variations and find that, for one-step-ahead and longer horizon forecasts, the asymmetric GARCH models are superior to GARCH (1,1). Liu and Hung (2010) conduct superior performance ability tests to compare various GARCH formulations. They find that the GJR-GARCH model achieves the most accurate volatility forecasts for the S&P 500, closely followed by the EGARCH model. Hajizadeh et al. (2012) propose hybrid models based on EGARCH and artificial neural networks to enhance the performance of the EGARCH model in forecasting the volatility of the S&P 500 index. Their hybrid model opens the door to other innovative approaches for estimating volatility forecasts of various financial assets. Carnero et al. (2012) suggest robust methodology alternatives to improve GARCH volatility estimates and possibly correct for the upward estimation bias. Adrangi et al. (2015) estimate bivariate vector autoregressive EGARCH models to estimate volatility and examine volatility spillovers across crude oil and equity markets.

The latest approach to improve the performance of GARCH models in the past decade has been tapping into data with varying frequencies. The pioneering effort in this direction by Engle et al. (2013) gave rise to a mixed frequency data sampling method combined with generalized autoregressive conditional heteroskedasticity-mixed-data sampling (GARCH-MIDAS) modeling. Following Engle et al. (2013), Asgharian et al. (2013), Conrad and Loch (2015), Lindblad (2017), Amendola et al. (2017, 2019), Pan et al. (2017, 2021), Conrad et al. (2018), and Borup and Jakobsen (2019) have employed the model in their research. These researchers show that including the available low-frequency macroeconomic variables in forecasting the volatility of financial assets in high frequencies improves volatility estimates and forecasts. A recent work by Amado et al. (2019) provides a survey on multiplicative component GARCH-MIDAS model performance and applications.

Pan et al. (2017) deploy a regime switching univariate GARCH-MIDAS model to investigate the association between WTI and Brent crude oil spot price volatility and market fundamentals. Importantly, regime-switching GARCH-MIDAS models produce superior forecasts of crude oil volatility. Fang et al. (2018) employ a two-covariate GARCH-MIDAS model and find that changes in the investor confidence in the US spills into the G7 equity markets. Zhu et al. (2019) consider equity market volatility (EMV) indices based on the text-counts of newspaper articles including several keywords related to US economy or stock market volatility. They deploy uni-covariate GARCH-MIDAS to examine the daily volatility in S&P 500, NYSE Composite, NASDAQ Composite, and DJIA. Conrad et al. (2018) deploy a GARCH-MIDAS approach to derive the long- and short-term volatility components of cryptocurrencies.

Of particular interest to this study, Su et al. (2019) investigate the role of uncertainty in short-and long-term volatilities of equities in nine economies. They deploy a two-variable GARCH-MIDAS model, decomposing the conditional variance into short-term and long-term components. The short-term component corresponds to daily volatility. For the long-term component they estimate a linear function for low frequency measures of uncertainty. They consider three measures of US market uncertainties, namely EPU, FU, and NVIX. EPU is constructed from the three types of underlying components. One component quantifies newspaper coverage of policy-related economic uncertainty. The second component reflects the number of federal tax code provisions set to expire in the next 10 years. The third component uses the disagreement among economic forecasters as a proxy for uncertainty. FU, proposed by Ludvigson et al. (2021), measures a common component in the time-varying volatilities of h-step ahead forecast errors across a large number of financial indicators.

The estimation results in Su et al. (2019) show that EPU is positively associated with the industrialized countries' equity market volatility. Considering forecasting power, higher NVIX surprisingly leads to lower volatility. FU fails to add to and predictive power of the model especially for the long-term stock market volatility. Their results, though mixed, adds to the literature regarding the crucial role of the uncertainty indices in the volatility of equity markets. Su et al. (2019) do not include all three indicators of uncertainty in their two-covariate GARCH-MIDAS model possibly to avoid complex estimation problems. However, their GARCH-MIDAS model may also suffer from misspecification as it is limited to two out of three uncertainty trackers. The possible misspecification may also jeopardize the accuracy of the model predictive power are result in spurious findings.

Pan et al. (2021) propose a set of uni-variate GARCH-MIDAS models for value at risk (VaR) and expected shortfall. They obtain the parameters of the proposed models by minimizing the loss function suggested by Fissler and Ziegel (2016). Their data sets consist of daily returns of S&P 500, monthly values of industrial production (IP) and producer price index (PPI). Their proposed GARCH-MIDAS models show that macroeconomic uncertainty plays an important role in affecting the long-term volatility component. The main shortcoming of Pan et al. (2021) model maybe that proposed GARCH-MIDAS models are univariate. They only account for each volatility measure one at a time which raises the risk of models being misspecified. They do not show how their models may perform relative to bivariate or other GARCH-MIDAS models.

Several studies have used quantile regressions to estimate the link between volatility and sentiment indicators. Dutta et al. (2021) use quantile regressions to examine the association between news-based equity market volatility (EMV) and crude oil volatility. Their quantile regressions on monthly data indicate a significant but asymmetric effect of EMV trackers on the oil market volatility during periods of high oil volatility but not when the oil market is less volatile. XU et al. (2021) deploy a quantile regression-based uni-variate GARCH-MIDAS (QR-GM) model to predict value-at-risk (VaR) of daily spot and futures returns for crude oil. Their findings suggest that GM and QR-GARCH-MIDAS models are powerful tools to study the impact of the low-frequency variables on the quantile of high-frequency dependent variables. The main drawback of this research is that it includes a single covariate, GEPU in its GM.

Conrad and Kleen (2020) demonstrate that the multiplicative GARCH-MIDAS outperforms the heterogeneous autoregression (HAR) of Corsi (2009), the realized GARCH of Hansen et al. (2012), the high-frequency–based volatility (HEAVY) of Shephard and Sheppard (2010); and the MS-GARCH. They conclude that the multiplicative component structure of the GARCH-MIDAS model may be the source of its superior performance over other GARCH model variations. The indications of the superior performance of the GARCH-MIDAS method motivates its deployment in the current study.

The extensive literature on the subject of volatility estimation and methodologies to investigate volatility drivers points to interest among investors, policy makers, fund managers, and speculators regarding the subject. Our paper is a continuation of the previous stream of papers on the subject. Prior to this paper, Fang et al. (2018) and Su et. al. (2019) have also deployed a two-variable GARCH- MIDAS model to investigate the association of market uncertainties with equity market volatility. However, as suggested by Conrad and Kleen (2020) "GARCH-MIDAS models that include more than two variables in the long-term component are difficult to estimate because the likelihood is relatively insensitive with respect to changes in the weighting parameters." Based on our experience, GARCH-MIDAS models that include more than two covariates to model the long-term volatility are impossible to estimate. That is the main reason that almost all GARCH-MIADS models estimated in previous research are uni-variate and therefore, misspecified. Su et al. (2017) resort to including permutations of the pairs of measures of uncertainty in their GM models. This approach while making estimation possible, is incomplete as several uncertainty measures are needed. Our paper adds to the literature by including economic fundamentals in the GARCH-MIDAS model, and uncertainty measures in QR and MS regressions in a complementary second step. This methodology allows us to investigate the association of several variables with market volatility in a two-step manner.

3. Data

We sample data between November 21, 2007 and December 31, 2021 to derive volatility estimates in ILF. Monthly data on the national financial confidence index (NFCI) and US industrial production are taken from the Federal Reserve Bank of St. Louis (FRED).

The daily data for the iShares Latin America 40 ETF (ILF) over the same period are sourced from Yahoo Finance. ILF is chosen for analysis because it tracks the investment performance of the S&P Asia 50, which comprises 50 of the largest Asian equities across key sectors of major Asian economies, including Samsung, Alibaba, and Taiwan Semiconductor, among others. The fund allocates at least 80% of its assets to the component securities of its index or similar securities, with the flexibility to invest up to 20% in futures, options, swap contracts, cash, and cash equivalents. Daily index values for the VIX and the U.S. Economic Policy Uncertainty (EPU) index are obtained from Bloomberg and the Federal Reserve Economic Data (FRED) database, respectively. Additionally, the monthly purchasing power parity (PPP)-adjusted Global Economic Policy Uncertainty (GEPU) index is sourced from FRED.

The daily news-based EPU index is constructed using the archives of Access World News's News Bank service. This global database stores archives of thousands of newspapers and other news sources. The EPU index is based on more than a thousand US newspapers, ranging from large national papers, such as *USA Today*, to small local ones. The index is computed by determining the number of newspaper articles that contain the words *economy*, *uncertainty*, *legislation*, *deficit*, *regulation*, *Federal Reserve*, or *White House*. This number is then normalized by the total number of newspaper articles. The EPU index is updated daily for the current and past months.

We also include the daily index of the leading indicator of implied market volatility, the VIX. The Chicago Board Options Exchange (CBOE) introduced the first volatility index in 1993, which was known as the VXO. It was based on implied volatilities from at-the-money options on the S&P 100 index, using a methodology proposed by Whaley (1993). The CBOE used an alternative methodology in 2003 to calculate the VIX as a weighted sum of out-of-money option prices for all S&P 500 strikes in real time. Whaley (2009) discusses the public and media interest in the value of the VIX as a measure of volatility and explains the origin and purpose of creating the VIX and its role in explaining the state of the economy and equity markets.

The VIX is intended to measure the expected price fluctuations in the S&P 500 index options over the next 30 days. Market participants have used the VIX and its predecessor, the VOX, to gauge the market sentiment in the US and around the world. We use the VIX as an indicator of the future financial market risk because the financial press quotes the VIX volatility index as a gauge of investor fear. Governmental agencies and central banks use the VIX to assess risk in financial markets. Previous research has shown that, though far from perfect, the VIX does have some forecasting power. Moreover, a strong association exists between the VIX and contemporaneous price dynamics: positive shocks to the VIX are associated with declining markets and vice versa. It follows, therefore, that an elevated VIX portends weaker prices in the future. In that sense, the VIX captures both, fear and price dynamics – a high VIX indicates fear associated with market declines (e.g., Whaley (2009)).

Baker et al. (2016) developed the Global Economic Policy Uncertainty (GEPU) index as a measure of uncertainty in economic policy across various countries. This index is designed to capture fluctuations in economic policy uncertainty that can influence economic decisions, financial markets, and overall economic activity.

To create the GEPU index, Baker et al. (2016) computed the EPU index for 20 major economies of the world. Each national EPU Index is subsequently renormalized to a mean of 100 from 1997 to 2015.

The aggregation is done by taking a weighted average of the EPU indices of several large economies, with the weights reflecting each country's relative economic importance based on GDP. The more economically significant a country is, the more weight its EPU index has in the global measure. The countries included in the GEPU are:

- Americas: Australia, Brazil, Canada, Chile, Mexico, United States
- Europe: France, Germany, Greece, Italy, Spain, United Kingdom
- Asia: China, India, Japan, South Korea
- Other: Ireland, Netherlands, Russia, Sweden

4. Methodology

Methodology of this paper closely follows Adrangi et al. (2023a, 2023b, 2025a). However, we explain the methodology for the benefit of the readers of the present research. As in Adrangi (2023a, 2023b, 2025a) we deploy the multiplicative GARCH-MIDAS methodology to derive the short- and long-term volatility estimates. Daily ILF return series and monthly NCFI and industrial production are the high- and low-frequency series included in the GARCH-MIDAS estimation of short- and long-run volatilities in ILF (STV, and LTV, respectively). Other researchers, for example, Engle et al. (2013) use monthly industrial production growth and monthly inflation as explanatory variables.

Having derived estimates for STV and LTV, we estimate Markov switching and quantile regressions too investigate the association of the dependent variable (i.e., STV or LTV) and the explanatory variables under changing volatility regimes and in several quantiles. Equation (1) is the implicit regression model.

$$\text{ILF volatility} = f(\text{EPU, GEPU,VIX}) \quad (1)$$

Before testing the association of ILF Volatility with the potential explanatory variables, we examine the STV and LTV of the ILF for possible structural breaks. These structural breaks may be a sing of regime changes latent in the data. Volatility in ILF in the short-and long-term will plausibly vary during these regime changes. The Markov switching regression are well equipped to account for the changes in the state of volatility. Markov switching regression show the manner of transition of these relationships from one regime to another. Similarly, quantile regressions appropriately examine the association of uncertainty indices with volatility at low to high quantiles of the volatility of ILF. Furthermore, it is necessary to test each time series for stationarity. Visual inspection shows that the ILF volatilities appears stationary with possibly structural breaks, whereas the VIX and others exhibit structural breaks and appear not to be stationary. The structural break in these variables may share common roots. Therefore, we test the volatilities of the ILF, the focus of this study, for structural breaks.

We apply Bai and Perron's (2003) test of structural breaks and examine the stationarity of the series under study by deploying the augmented Dickey–Fuller (ADF; Dickey and Fuller (1979)) and the Phillips–Perron (PP; Phillips and Perron (1988)) tests.

Bollerslev (1986) proposed the GARCH model to better capture the volatility clustering evidenced in financial markets. In financial markets, volatility demonstrates temporal heteroscedasticity. Volatility clustering exists for prices and rates of return. Periods of low volatility can follow periods of high volatility and vice versa.

In this study, we use a class of component GARCH based on MIDAS regression models, which were introduced by Ghysels et al. (2004, 2016). MIDAS methodology offers a framework to incorporate variables of different frequencies to obtain multi-horizon volatility. We estimate the GARCH-MIDAS model to derive the short- and long-term real volatility in the daily returns of the ILE. We follow Adrangi et al. (2023a, 2023b, 2025a) in the deployment of this methodology. However, we briefly explain the methodology in this section. The MIDAS regression model is expressed as equation (2):

$$y_{t+k} = \alpha_0 + \alpha_1 x^m{}_t + \varepsilon_t^m, \tag{2}$$

where y_{t+k} is the *k* step-ahead value of the dependent variable at time *t* with the highest frequency, $x^m{}_t$ may be a vector of independent variables at time *t* and *m* is the frequency matching that of y, ε_t^m is the random innovation at time *t* with *m* frequency, and α_0, α_1 are the intercept and a conformable vector of model coefficients. The expressions for ε_t and its variance in GARCH (1,1) specification are:

$\varepsilon_t = (\varepsilon_{t-j})\sqrt{\sigma_{\varepsilon,t}{}^2}$ and $\sigma^2_{\varepsilon,t} = f(\varepsilon_{t-1}, \sigma^2_{t-1})$, for GARCH (1,1) specification.

Following Engle et al. (2013), Ghysels et al. (2016), and Conrad and Kleen (2020), we combine the high-frequency daily data with low-frequency monthly data in the GARCH-MIDAS model. To this end, the GARCH-MIDAS model includes monthly values of the NFCI and industrial production variables in the US. The conditional variance of innovations is decomposed into short- and long-term volatility components multiplicatively as:

$$\sigma^2_{\varepsilon,t} = h_{i,t}\tau_t, \tag{3}$$

where *h* and *τ* capture the short-term volatility of the high-frequency data and the long-term volatility, respectively, given by equations (4) and (6).

The short-term component of GARCH-MIDAS in equation (3) is taken from Engle et al. (2013) which uses the GARCH process of Bollerslev (1986).

The short-term component of GARCH-MIDAS in this paper is taken from Engle et al. (2013) which uses the GARCH process of Bollerslev (1986). It is designed to capture daily volatility clustering and is a mean-reverting unit-variance GJR-GARCH(1,1) process as in equation (4) .

$$h_{i,t} = (1-\alpha-\gamma/2-\beta) + (\alpha+\gamma\,|_{\varepsilon_{i-1,t}<0})\frac{\varepsilon^2_{t-1}}{\tau_t} + \beta h_{i-1,t}. \tag{4}$$

Equation (5) is the basis for the long-term volatility for which the realized volatility is smoothed over K periods, and will be expanded by adding low frequency covariates.

$$\tau_t = m + \theta \sum_{k=1}^{K} \phi_k(w_1, w_2) x_{t-k}, \tag{5}$$

The long-term component is constant across days and changes at lower frequency, consistent with low frequency series in the GARCH-MIDAS model, which in this paper is bi-monthly, similar to Conrad and Kleen (2020) specification.

The weighting scheme in equation (5) is given by

$$\phi_k(w_1, w_2) = \frac{(k/K)^{w_1 - 1}(1 - k/K)^{w_2 - 1}}{\sum_{j=1}^{K} (j/K)^{w_1 - 1} \sum_{j=1}^{K} (1 - j/K)^{w_2 - 1}},$$

Where

$$\sum_{k}^{K} \phi_k(w_1, w_2) = 1.$$

The weighting scheme in (7) generates hump-shaped or convex weights. As w_1 is restricted to 1 (see su et al. (2017), Fang (2018), Conrad and Kleen (2020), the weighting scheme guarantees a decay pattern where the rate of decaying is determined by parameter W_2. The restricted weighting scheme boils down to

$$\phi_k(w_2) = \frac{(1 - k/K)^{w_2 - 1}}{\sum_{j=1}^{K} (1 - j/K)^{w_2 - 1}}.$$

Regime Switching Markov Regression (RSMR) are explained in most econometrics textbooks. Adrangi et al. (2023a, 2023b, 2025a) offer a cogent summary of the methodology. In this section we briefly explain the methodology without attempting a complete textbook treatment of the methodology. In a regime switching framework, a random variable *y* may depend on a discrete latent state variable that is not observable. This regression model is appropriate when one believes that there are multiple regimes present in the data-generating process. The structural breaks in the ILF STV and LTV raise the possibility of the regie switches during the sample period. At any time *t*, the process could be in state s_t. The switching model allows for a different regression model for each regime. The conditional mean of y_t in regime *m*, given a vector of switching regressors *x* and coefficients β_m and nonswitching vectors of regressors z_t and coefficients ϕ, is given by equation (8).

$$\mu_t^{(m)} = x_t{}'\beta_m + z_t{}'\phi. \tag{6}$$

Assuming that the regression error ε_t is independently and identically distributed (iid) and its variance may be regime dependent, the regime switching regression model may be expressed by equation (7).

$$y_t = x_t{}'\beta_m + z_t{}'\phi + \sigma_m \varepsilon_t. \tag{7}$$

Regime probabilities may be assumed to be a function of a vector of exogenous variables and parameters. The multinomial logit expression of the regime probabilities is given by equation (8).

$$P(s_t = m \mid \Omega_{t-1}, \psi) = p_m(E_{t-1}, \psi) = \frac{\exp(E'_{t-1}, \psi_m)}{\sum_{j=1}^{M} \exp(E'_{t-1}, \psi_j)} \tag{8}$$

In equation (8),
m is a given regime,
p_m is the regime probabilities,
Ω_{t-1} is the information set at time *t*-1,
E_{t-1} is the vector of exogenous observable variables, and
ψ represents model coefficients.

A variation of equation (8) is a first-order Markov process where the probability of being in a regime depends on the previous state. Therefore, the transition probabilities are given by equation (9).

$$p(s_t = j \mid s_{t-1} = i) = p_{ij}^t\,. \tag{9}$$

The transition matrix for *M* regimes may be written as equation (10),

$$p(t) = \begin{pmatrix} p_{11}^t & \cdots & a^t{}_{1M} \\ \vdots & \ddots & \vdots \\ a^t{}_{M1} & \cdots & a^t{}_{Mn} \end{pmatrix}. \tag{10}$$

The extreme movements and structural breaks in the STV and LTV series are potentially asymmetric. Market participants and investors are not only sensitive to the smoothed association of the VIX and EPU with ILF volatility; they are also interested in the impact of extreme up-and-down movements of the VIX and EPU and their association with ILF volatility. Structural breaks may be one source of extreme fluctuations in volatility.

Quantile regressions (QR) are the proper tools for capturing and explaining the asymmetric dependence between the dependent and explanatory variables. QR models are nonlinear (see e.g., Galvao et al. 2020) and robust in the presence of extreme events and asymmetric dependence when the assumption of linearity may not be appropriate (see Geraci 2019; Yu et al. 2003). They are superior to OLS estimates because they allow coefficient estimates to vary with the distribution of the dependent variable, thus, accurately modeling the relationship between the explanatory variables and the dependent variable. The following is a brief explanation of QR. A more comprehensive treatment of this methodology is beyond the scope of this research. The treatment of QR in this paper follows Adrangi et al. (2023a, 2023b, 2025a) closely.
Suppose that we have a random variable *Y* (ILF volatility) with probability distribution function

$F(y) = \text{Prob}(Y \leq y)$

so that, for $0 < \tau < 1$, the τth quantile of *Y* may be defined as the smallest *y* satisfying $F(y) \geq \tau$:

$$Q(\tau) = \inf \{ y : F(y) \geq \tau \}.$$

The empirical quantile may be expressed as an optimization problem as:

$$Q_n(\tau) = \arg\min \left\{ \sum_i \rho_\tau (Y_i - \omega) \right\},$$

where $\rho_\tau(w) = w(\tau - 1(w < 0))$, which asymmetrically assigns weights to positive and negative values in the estimation process.

The extension of this methodology that allows for regressors *X* is the quantile regression. We assume a linear specification for the conditional quantile of the dependent variable ILF given values for the vector of explanatory variables *X* such that:

$$Q(\tau \mid X_i, \beta(\tau)) = X_i^{'}\beta(\tau) \tag{11}$$

where in equation (11) $\beta(\tau)$ is the vector of coefficients associated with the τ th quantile.

Then, the conditional quantile regression estimator can be shown to be:

$$\beta_n(\tau) = \arg m\text{in}_{\beta(\tau)} \left\{ \sum_i \rho_\tau (Y_i - X_i^{'}\beta(\tau) \right\}.$$

The quantile regression estimator is derived as the solution to a linear programming problem. We use a modified version of the Koenker and D'Orey (1987) version of the Barrodale and Roberts (1973) simplex algorithm.

We deploy the Powell (1986) kernel method based on residuals of the estimated model as

$$\hat{H} = 1/n \sum b_n^{-1} K(\vartheta(\tau)/b_n X_i X_i^{'},$$

where *K* is a kernel function that integrates to 1 and b_n is a kernel bandwidth. For bandwidth specification, we employ a method suggested by Hall and Sheather (1988) and a kernel bandwidth suggested by Koenker and Ng (2005). Koenker and Machado (1999) define a pseudo R-squared for the goodness-of-fit statistic for quantile regression that is analogous to the R-squared from conventional regression analysis.

5. Empirical Findings

5.1 Structural Breaks and Stationarity

Figures 1 and 2 present the grpah of STV and LTV, respectively. The time seris plots suggest that there are posibilities of structural breaks and LTV could be non-stationary. The Bai–Perron test signals four structural breaks in the short- and long-term volatility in the ILF that occurred on several occasions. The break dates in the STV do not coincide with those of the LTV and could be due to many events.

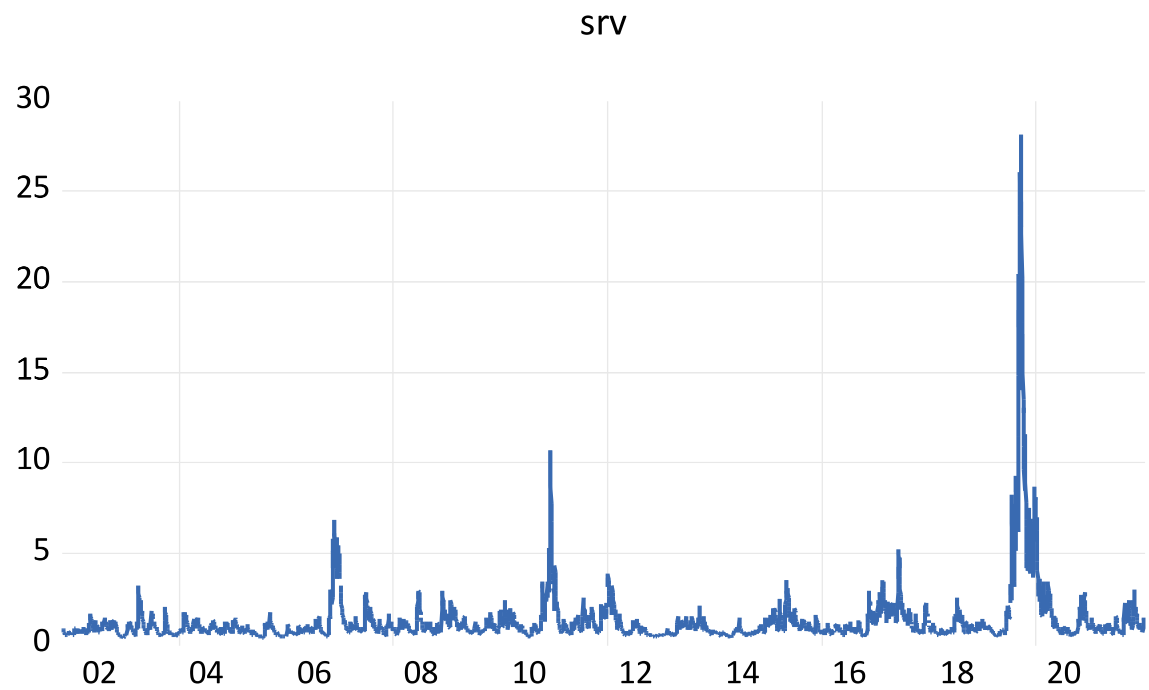

Figure 1: Short-term volatility of ILF, GARCH-MIGAS Model

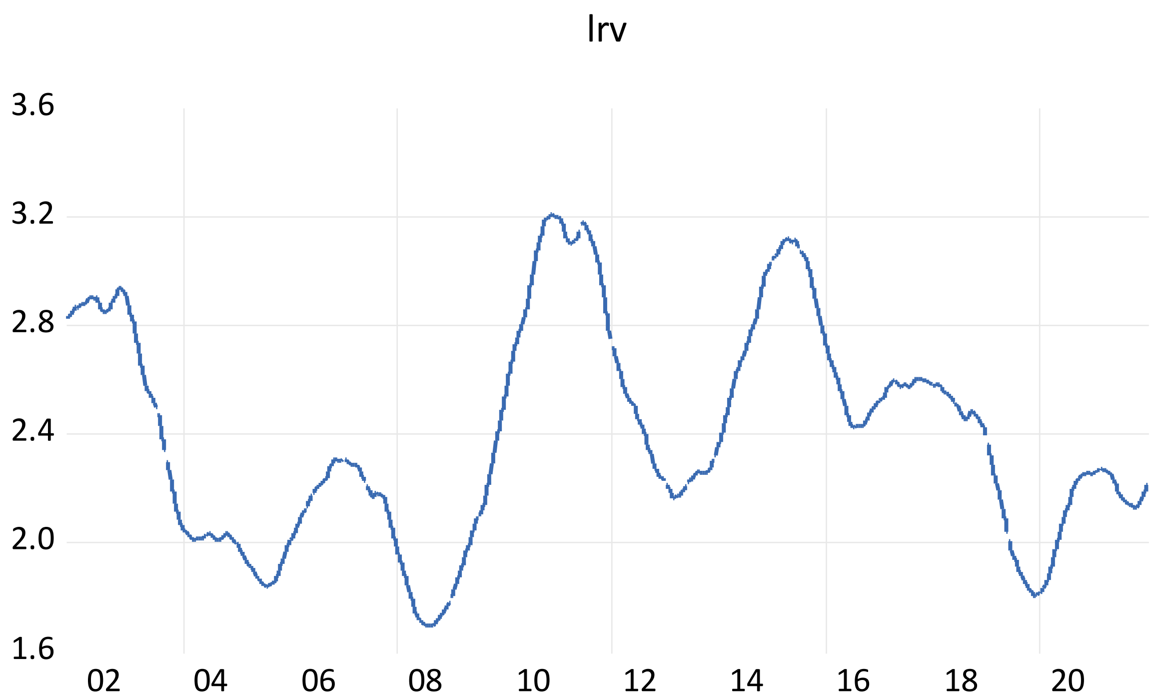

Figure 2: Long-term volatility of ILF, GARCH-MIGAS Model

The year 2012 witnessed geopolitical and economic upheavals and possibly impacted global equity markets immediately or with some time lag is it usually is the case. For instance, wars in Syria and Afghanistan continued to rage. The European Union announced that it was imposing oil embargo on Iran. These without a doubt shocked the crude oil markets for a few months before a new equilibrium was achieved. Similarly, world equity markets absorbed other shocks from ISIS success in Iraq which continued to threaten crude oil supplies from that country. Taliban were also expanding their operations with destabilizing political and economic effects in the entire region.

Breaks in 2014 were possibly related to failed nuclear negotiations with Iran, crude oil price crash, faltering EU economies. Similarly, 2016 was market by significant economic and geopolitical evens. The Trans-Pacific Partnership (TPP) was unraveling under the administration of the US President Donald Trump. This had taken seven years of hard negotiations and was the largest regional trade pact for the US and its trading partners in East Asia in history. The eleven nations who had joined the US in this treaty, were forced to rethink the future of their trade with the US and possibly entering negotiations with the second largest economy of the world, china. Britain and Whales voted to leave the EU while Scotland and Ireland opposed this move. Markets expected the Brexit saga to continue and the fallouts on UK EU economies remained uncertain. North Korea also intensified it missile tests in response to the US saber rattling. Effects of these events on world trade, security, and economies were unsettling.

Among the events of 2019 that fueled market with uncertainty and rocked the investment world are nuclear impasse between the US and North Korea, the Brexit are the most salient. These evens cast pall on global trade, fueled inflation worries, and contributed to risk and uncertainty for equity markets of the world. The year 2021 was gripped with the COVID19-related supply chain disruptions, as well as domestic and global economic events. Fears of persistent inflation kept equity and commodity markets volatile.

The graphs of the short- and long-term ILF volatility and the uncertainty indicies under study, suggests possible mean and covariance stationarity in some cases. Therefore, we conduct formal statistical tests. Table 1, Panel B presents the statistical evidence of the behavior of these series. As shown, all variables under study are found to be stationary, employing the ADF tests with the inclusion of the break points.

Table 1: Break Points in ILF Volatility, Diagnostics and Summary 10/29/2001-12/31/2023

Panel A: Bai Perron Test of Structural Breaks					
	STV	LTV		STV	LTV
Break Test	Scaled F	Scaled F	F Critical Value*	Dates	Dates
1	11.87[a]	21.80[a]	11.47	11/26/2007	6/30/2005
2	22.28[a]	69.54[a]	12.95	12/07/2010	9/28/2010
3	16.47[a]	17.29[a]	14.03	4/21/2015	10/07/2013
4	16.97	18.62	14.85	5/20/2020	10/19/2021
*Bai-Perron (Econometric Journal, 2003) critical values.					
Diagnostics and Summary 10/29/2001-12/31/2023.					
Panel B: Levels					
	EPU	GEPU	VIX	STV	LTV
ADF with Break	-35.459[a]	-4.966[a]	-8.443[b]	-11.708[a]	-4.871[b]
Panel C: Summary descriptive statistics for model variables. All variables are in level					
Mean	106.924	140.511	19.541	1.244	2.396
Stand Dev	89.500	73.018	8.950	1.687	0.396
Skewness	1.683	1.385	2.349	7.989	0.307
Kurtosis	7.728	4.744	11.176	89.306	2.146
J-B	7136.217[a]	2271.513[a]	18820.98[a]	163164.00[a]	234.555[a]

Notes: Bai and Perron (2003) (Econometric Journal), critical values. The null hypotheses for ADF is that a series is nonstationary. Intercepts were included in the PP tests. The ADF test is performed with breakpoint possibility and includes both a trend and an intercept. a represents significance at 1percent level. 10/29/2001-12/31/2023.

5.2 Markov Switching Regression Results

Table 2 shows the coefficient estimates of the GARCH-MIDAS model that produce the short-term and long-term volatility components of the realized volatility in ILF in equations (5) and (6), respectively. The estimated β of 0.872 is statistically significant which confirms strong persistence in the short-term volatility component. Other researchers, e.g., Su et al. (2017) find similar results in their research. The statistically significant α and Υ coefficients in equation (5) confirm the validity of equation (4) in the GARCH-MIDAS estimation. The θ coefficients represent the changes in the long-term volatility stemming from the lagged effects of the industrial production and NFCI, respectively. The coefficient θ is statistically significant and negative, indicating that a rise in the US industrial production reduces the long-term volatility in ILF. Given that most major Latin American economies are the US trading partners, it is plausible that the upticks in the US industrial production would have a calming effect in these economies leading to drops in the volatility in their equity markets. The rise in NCFI and the long-term volatility are positively associated as shown by the θ_2. However, this coefficient is statistically insignificant. These findings suggest that the forty Latin American top companies exhibit sensitivity to the US economy. Trade with the US is a significant opportunity for the significant players among the Latin American companies like Petróleo Brasileiro S.A, América Móvil, S.A.B, Grupo México, S.A.B., among others.

Table 2: ILF GARCH -MIDAS coefficient Estimates with two covariates, change in the US industrial production and NFCI. 10/29/2001-12/31/2023

μ	0.025
	(0.021)
α	0.035[a]
	(0.010)
β	0.872[a]
	(0.019)
ϒ	0.112[a]
	(0.022)
m	0.962 [a]
	(0.116)
θ	-0.437[b]
	(0.175)
w2	3.770 [c]
	(2.094)
θ_2	0.209
	(0.238)
w2_2	2.078
	(5.302)

Note: [a ,b,c] significant at 1, 5, and 10 percent levels.

Table 3 presents the estimation results of the MSR. Examining the STV, we find that it rises in response to VIX, GEPU and EPU during high volatility regime (1). Thus, investors in ILF are focused on the policy changes in the US and world economies. However, the US economic uncertainty changes do not elevate the volatility in ILF. The responses of STV remain robust under low volatility regime (regime 2) despite the mix responses to VIX. The interpretation is that under conditions of high and low market volatility ILF investors are desensitized to any marginal changes uncertainties under study.

The US ECU, the global policy uncertainties, and VIX raise long-term volatility in ILF across under the low (regime 2). Thus, under low volatility regime, ILFinvestors are behaving cautiously. This is plausible as investors may expect the low volatility to continue and are surprised by changes in the global and the US policy uncertainties as well as the VIX movements. We also interpret these findings as ILF investors' long-term concerns are focused on market conditions in the US contained in VIX and EPU and GEPU. These findings are supporting the notion that long-term investors in the blue Latin American equities are sensitive to policy changes in the US and Globally. These observations also emphasize the economic and financial market contagion between the US and Latin American equity markets.

We also conclude that the attitude of market participants regarding the VIX and the EPU is dependent on the volatility regime and varies asymmetrically in the long-run but not so in the short-run. Lin and Zhang (2015), Su et al. (2019), Tsai (2017) and Chang (2022) also find a positive association between EPU and volatility in equity markets.

Table 3. Markov Switching Estimation of Equation (1)

	Regime	C	ECU	EPU	GEPU	VIX	LN(σ)
STV	Regime 1	7.371[a]	-0.002	-0.009[a]	0.024[a]	-1.119[a]	1.879[a]
		(0.970)	(0.003)	(0.004)	(0.004)	(0.033)	(0.028)
STV	Regime 2	1.393[a]	-0.0003[c]	0.001[a]	0.002[a]	0.0151[a]	-0.175
		(0.047)	(0.00016)	(0.0002)	(0.0002)	(0.0016)	(0.019)
LTV	Regime 1	8.765[a]	-0.002	--0.019[a]	0.026[a]	-1.122[a]	1.833[a]
		(1.147)	(0.004)	(0.004)	(0.004)	(0.042)	(0.030)
LTV	Regime 2	1.423[a]	-5.59E-05	0.001[a]	0.003[a]	0.0131[a]	-0.158[a]
		(0.046)	(0.00016)	(0.0002)	(0.0002)	(0.0016)	(0.015)

Notes: Significance indicates nonstationary. a,c represent significance at 1 and 10 percent levels. Numbers in parentheses are root mean squared errors (RMSE). STV and LTV represent short- and long-run volatilities in ILF from GARCH-MIDAS model. 10/29/2001-12/31/2023.

In summary, our findings highlight the crucial role of sentiment and uncertainty indicators in explaining both short- and long-term ILF volatility across different market regimes. Investors in ILF appear to be particularly sensitive to uncertainties arising from U.S. economic policies, U.S. equity markets, and global economic policies, regardless of the prevailing volatility regime. This is especially significant because volatility clustering and persistence are often viewed as purely statistical characteristics of financial markets, lacking a clear intuitive explanation. By demonstrating the influence of investor sentiment and uncertainty, our results offer a more intuitive understanding of these volatility patterns. The magnitudes of the coefficients may be indicating that variables may not be a strong driver of regime shifts or that the differences between regimes may not be substantial.

Table 4 summarizes the transition probabilities from low to high volatility regimes for both short- and long-term volatilities in the ILF. It appears that the probability of transitioning from high (regime 1) and low volatility (regime 2) to high volatility regimes are low whether examining the short-or long-term volatilities. On the contrary, the transition probability from high and low volatility regimes to low volatility regime in Latin America is above 80 percent. The ILF experiences shorter duration in high volatility regime 1 than low volatility regime 2. These observations are the sign of highly erratic equity market in Latin America. Thus, investors in Latin American ILF ETF would benefit from taking a long-term approach and avoid attempts to time the market. Furthermore, investing for the long haul is the appropriate strategy because derivatives and other hedging instruments are not well-developed in Latin American equity markets.

Table 4: Volatility Transition summary: Constant Markov transition probabilities and expected durations

	STV		LTV	
	Regime1	Regime2	Regime1	Regime2
Regime 1	0.143	0.856	0.116	0.884
Regime 2	0.143	0.856	0.116	0.884
Constant expected	1.169	6.990	1.131	8.644

Notes: STV and LTV represent short- and long-run volatilities in ILF from GARCH-MIDAS model. 10/29/2001-12/31/2023.

Figures 3 and 4 plot the predicted one-step transition probabilities of being in low- and high-volatility regimes for the short- and long-term volatilities. The constant transition probabilities and the expected duration of each regime for both volatility cases are presented in Table 4. It is evident that the low-volatility regimes are expected to last longer than the high-volatility regime. Therefore, policy uncertainties and the VIX will be less critical for longer periods than not. Thus, ILF investors may concentrate and plan for uncertainties in EPU, GEPU and VIX during the low volatility regimes.

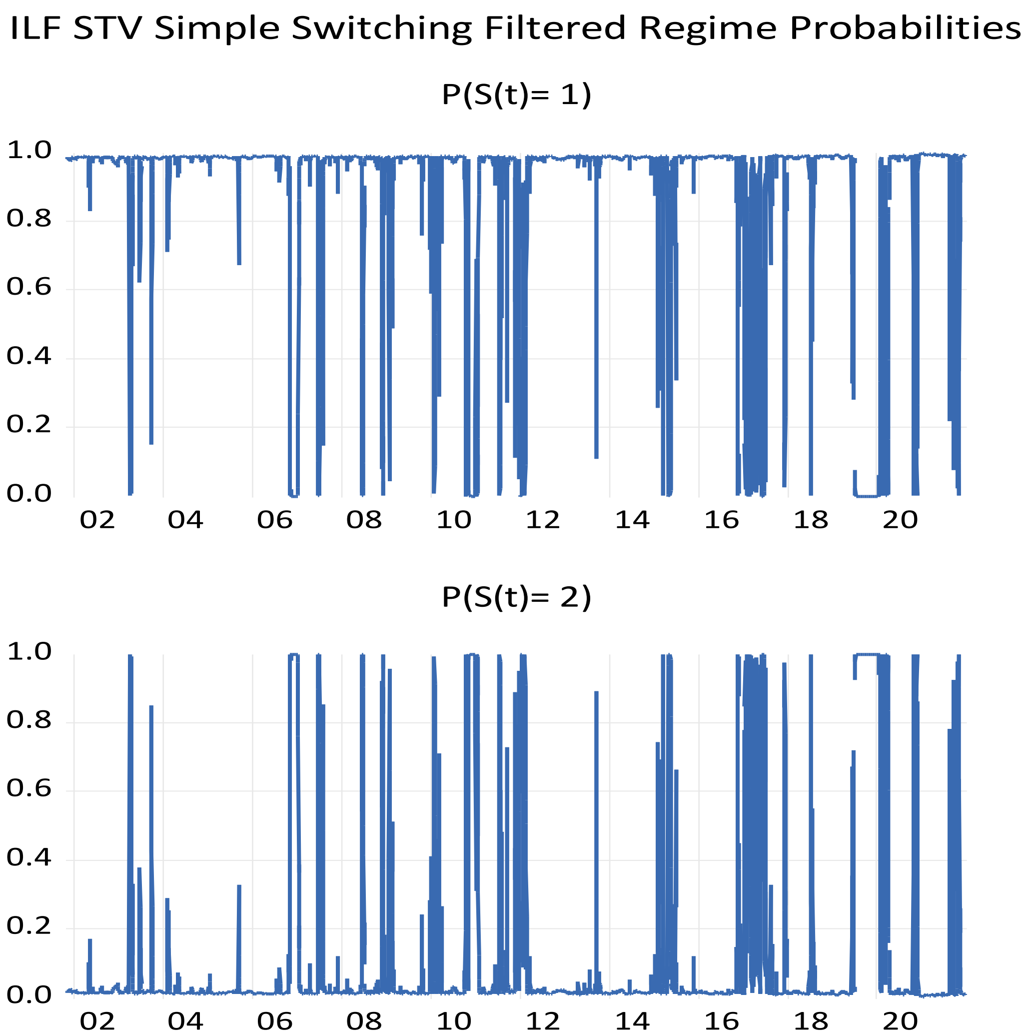

Figure 3: Markov switching transition probabilities for short-term ILF volatility. 10/29/2001-12/31/2023

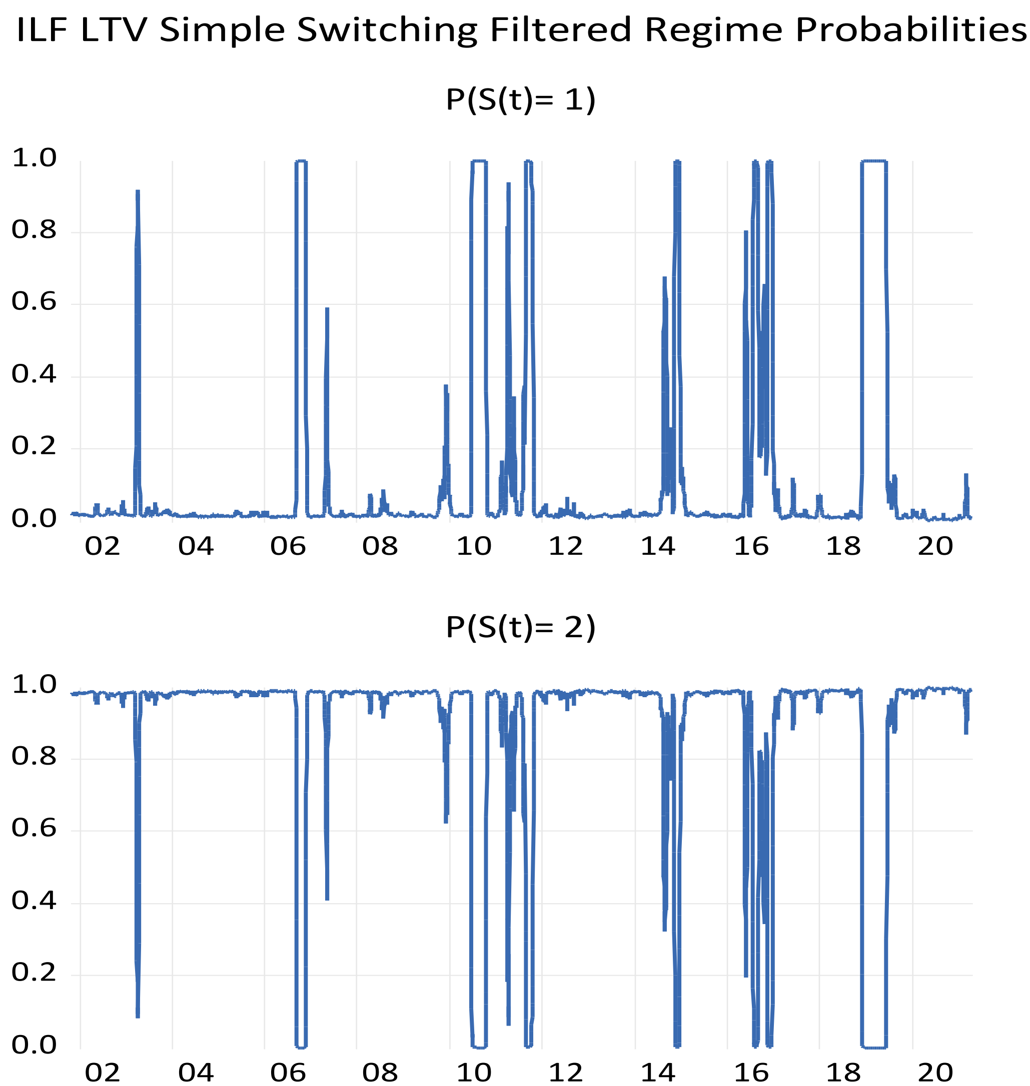

Figure 4: Markov switching transition probabilities for long-term ILF volatility. 10/29/2001-12/31/2023

5.3 Quantile Regression Results

The QR estimation results of equation (1) are presented in Tables 5 and 6 for the short- and long-term volatility of the ILF, respectively. The Lagrange Multiplier test for ARCH effects in Table 1 show the presence of ARCH effects in the STV but not LTV. The QR estimates remain robust and reliable in the presence of ARCH effects. Thus, the QR estimates of the coefficients at various quantiles of distribution of the ILF volatility are better suited to capture the relationship among the variables in the presence of heteroscedasticity and at extreme levels of the volatility distribution as well as the conditional median.

Consistent with the MSR findings, the US EPU, and various policy uncertainties raise the short-term volatility in ILF at most quantiles. For instance, in most quantiles, the associations of the STV with these measures of uncertainty are statistically significant and have the expected positive sign. However, STV is not sensitive to VIX in several quantiles. This may change in other sample as it has been well documented that contagion among equity markets is common and investors in Latin American equities may put more weight on the US or global policy uncertainties. There is research in support of this phenomenon. Edwards et al. (1995) analyze media coverage of issues in the context of elections. They estimate logit models of public opinion polls and time series regression of the relationship between salient issues and presidential approval. They confirm that the public perception of salient issues varies over time. Judging by the coefficient signs and statistical significance, the US economic policy and the global economic policy uncertainties are crucial in the minds of ILF investors in the short-run and when they rise they raise volatility in this ETF.

The OLS estimation results, which predict the association of the variables based on the conditional mean of the ILF volatility for both the STV and the LTV, may be misleading. For instance, Tables 5 and 6, the OLS estimation results do not corroborate the QR estimates.

Turning to the LTV, QR estimate results indicate that LTV in ILF is consistently responsive to the GEPU as well as VIX in all quantiles and to the EPU in most quantiles and rise in response to them. However, the association between the LTV and ECU is erratic and statistically unstable. In summary, our findings lend support to contagion effects from the US economy and confirm that economic uncertainties in the US markets play a significant role for investors in the major Latin American firms. Furthermore, long-term volatilities in ILF react to equity market conditions in the US and global economic policy uncertainties.

The OLS estimation results corroborate the LTV positive reactions to the GEPU and VIX. However, the conditional mean of the long-term volatility in ILF is not sensitive the US economic policy uncertainties. This finding reinforces the need to investigate the volatility of ILF in various quantiles.

The main take away is that STV and LTV react to policy uncertainties as well as equity markets uncertainties in the US, represented by EPU and VIX. However, movements in STV and LTV are sensitive to the saliency of global or regional events in the minds of investors. For instance, if investors are focused on the US economy, then economic policy uncertainties in the US raise volatilities either in the short-term or long-term or both. Global economic policies in almost all quantiles appear to raise STV and LTV.

Table 5: Quantile Regression Estimation of Equation (1), Short-Term Volatility of ILF

	Quantile	**C**	**ECU**	**EPU**	**GEPU**	**VIX**	**PsR2**	**QLR**
STV	1st Q	0.845[a]	-0.0002	0.0008[a]	0.0008[a]	0.0066[a]	0.012	103.134
STV		(0.037)	(0.0001)	(0.0001)	(0.0001)	(0.0012)		
STV	3rd Q	1.140[a]	-0.0003[a]	0.0009[a]	0.0013[a]	0.011[a]	0.011	128.12
STV		(0.047)	(0.0001)	(0.0002)	(0.0002)	(0.002)		
STV	5th Q	1.315[a]	-0.0002	0.0008[a]	0.003[a]	0.012[a]	0.016	179.130
STV		(0.069)	(0.0002)	(0.0003)	(0.0005)	(0.003)		
STV	7th Q	1.490[a]	-0.0001	0.001[b]	0.008[a]	0.002	0.033	328.653
STV		(0.089)	(0.0003)	(0.0005)	(0.0005)	(0.001)		
STV	9th Q	2.574[a]	-0.0007	-0.0009	0.027[a]	-0.0477[a]	0.063	259.207
STV		(0.301)	(0.0005)	(0.0016)	(0.002)	(0.0046)		
STV	OLS	2.284[a]	-0.0002	-0.0004	0.0092[a]	-0. 030[a]	0.042	55.115
STV		(0.165)	(0.0005)			(0.0007)	(0.0007)	(0.005)

Notes: a represents significance at 1percent level. The values of R-sq and F statistics for the OLS estimates and pseudo R-sq and quasi-likelihood ratio functions are in the last two columns. Huber sandwich standard errors and covariances. Method of Epanechnikov kernel, and Hall–Sheather residuals bandwidth (bw = 0.020127). STV and LTV represent short- and long-run volatilities in ILF from GARCH-MIDAS model. 10/29/2001-12/31/2023.

Table 6: Quantile Regression Estimation of Equation (1), Long-Term Volatility of ILF

	Quantile	C	ECU	EPU	GEPU	VIX	PsR2	QLR
STV	1st Q	0.918[a]	-0.0002	0.0008[a]	0.001[a]	0.0064[a]	0.015	121.348
STV		(0.041)	(0.0001)	(0.0001)	(0.0002)	(0.0009)		
STV	3rd Q	1.108[a]	-0.0001[a]	0.001[a]	0.0015[a]	0.013[a]	0.017	203.580
STV		(0.047)	(0.0001)	(0.0002)	(0.0001)	(0.002)		
STV	5th Q	1.352[a]	1.3E-05	0.0008[a]	0.004[a]	0.008[a]	0.021	256.360
STV		(0.058)	(0.0002)	(0.0002)	(0.0004)	(0.0025)		
STV	7th Q	1.466[a]	7.6E-05	0.001[a]	0.009[a]	0.0003[a]	0.042	465.318
STV		(0.075)	(0.0003)	(0.0004)	(0.0006)	(0.002)		
STV	9th Q	2.752[a]	-0.0005	-0.0004	0.023[a]	-0.053[a]	0.073	380.558
STV		(0.291)	(0.0004)	(0.0009)	(0.003)	(0.003)		
STV	OLS	2.360[a]	-0.4.0E-05	-0.0008	0.0093[a]	-0.033[a]	0.049	65.815
STV		(0.154)	(0.0005)	(0.0006)	(0.0006)	(0.005)		

Notes: a and b represent significance at 1percent level. The values of R-sq and likelihood ratio functions for the OLS estimates and pseudo R-sq and quasi-likelihood ratio functions are in the last two columns. Huber sandwich standard errors and covariances. Method of Epanechnikov kernel, and Hall–Sheather residuals bandwidth (bw = 0.044558). STV and LTV represent short- and long-run volatilities in ILF from GARCH-MIDAS model. 10/29/2001-12/31/2023.

While the small coefficient sizes indicate that uncertainty indices play a limited role in ILF's volatility, these associations remain statistically significant. Small coefficients do not necessarily mean the variable is unimportant—statistical significance matters. Furthermore, two critical measurement considerations possibly contribute to the small magnitude of the coefficients. First, the measurement of uncertainty, and second, omitted variables. We discuss these as follows.

The seminal work of Baker et al. (2012) paved the way for empirical studies on uncertainty by introducing uncertainty indices. However, these indices are not flawless and may evolve with advancements in AI. For instance, the U.S. Economic Policy Uncertainty (EPU) Index by Baker et al. (2012) is currently constructed using three primary components, each comprising distinct elements that contribute to the overall index. The following is a brief discussion of the EPU components.

1. News-Based Component

Derived from articles in 10 major U.S. newspapers, including *The Wall Street Journal*, *The New York Times*, and *USA Today*. Articles must contain terms related to *economy*, *policy*, and *uncertainty*.

2. Tax Code Expiration Component

Based on the number of federal tax provisions set to expire in future years. Baker et al. track hundreds of tax provisions that impact policy uncertainty.

3. Forecast Disagreement Component

Uses forecasts from the Survey of Professional Forecasters (SPF). Tracks dispersion in GDP and inflation forecasts to measure policy-related economic uncertainty.

Each component plays a role in shaping the index, with the news-based measure serving as the primary driver. While the number of articles or tax provisions included fluctuates over time, these elements form the foundation of the EPU Index. Although not exhaustive, the index captures a broad spectrum of issues that contribute to economic uncertainty. However, some sources of uncertainty inevitably remain unaccounted for. It is a well-established fact that uncertainties disrupt financial markets. For instance, in the last two weeks of March 2025, the S&P 500 declined by over 10%, while ILF experienced only a minor correction, suggesting that it is less sensitive to both U.S. and Global Economic Policy Uncertainty Economic Policy Uncertainty. The small coefficient observed in our regression results further supports this finding. Our research highlights ILF's limited responsiveness to many of the uncertainty indices included in the model. A key reason for this could be the relatively small presence of Latin American equity markets, which account for only 1 to 2 percent of global equity markets and are far less integrated into the broader global financial system.

Secondly, other factors, such as financial and managerial variables, undoubtedly influence ILF's volatility. However, accounting for the financial and managerial characteristics of forty companies that make up ILF would be impractical and beyond the scope and the objective of this study.

Figures 5and 6 show the coefficient evolution process through quantiles for the STV and LTV, and their 95 percent confidence intervals, respectively. They show the responses of the short and long-term volatilities in every quantile to each measure of uncertainty holding all else constant. Figure 5 shows that the association of STV with GEPU is positive, rises over time, and statistically significant in most quantiles. The conclusion is that Latin American equities are sensitive to global economic shocks because these economies have become closely integrated with major world economies through significant trade.

For instance, major companies included in ILF ETF are from Mexico and other countries in Latin America, notably Brazil, Argentina and Chile. These economies are trading partners of Europe, US, and China. For instance, Mexico and Brazil are often the second and the ninth largest importers from the US. IFL STV is relatively less sensitive to VIX and EPU as indicated by the roughly steady coefficients in almost all quantiles. It is not surprising that STV in ILF is moderately sensitive to the US EPU.

ILF STV responses to shocks to VIX are mostly positive and statistically significant, indicating that ILF is influenced by the US equity market risks. However, the same is not true of the US economic uncertainties, which may be that equity markets of Latin America are not necessarily focused on the US economic uncertainties in the short-run. This observation supports the findings of the MSR and QR estimates and shows that these associations are dynamic and that coefficient signs and statistical significance are regime and quantile dependent.

Figure 6 confirms that LTV of ILF is positively and statistically significantly associated with EPU, VIX and GEPU at least for some quantiles. Therefore, short-term and long-term volatilities in ILF respond similarly to the US and Global market policy uncertainties. This finding is plausible as firms' and investors' short-term and long-term strategies in response to global and the US economies are expected to be similar. The findings of quantile regressions are generally in support of the conclusions derived from Markov Switching regressions indicating that reactions of volatilities in ILF to various measures of uncertainties in question are dynamic and sensitive to volatility regimes.

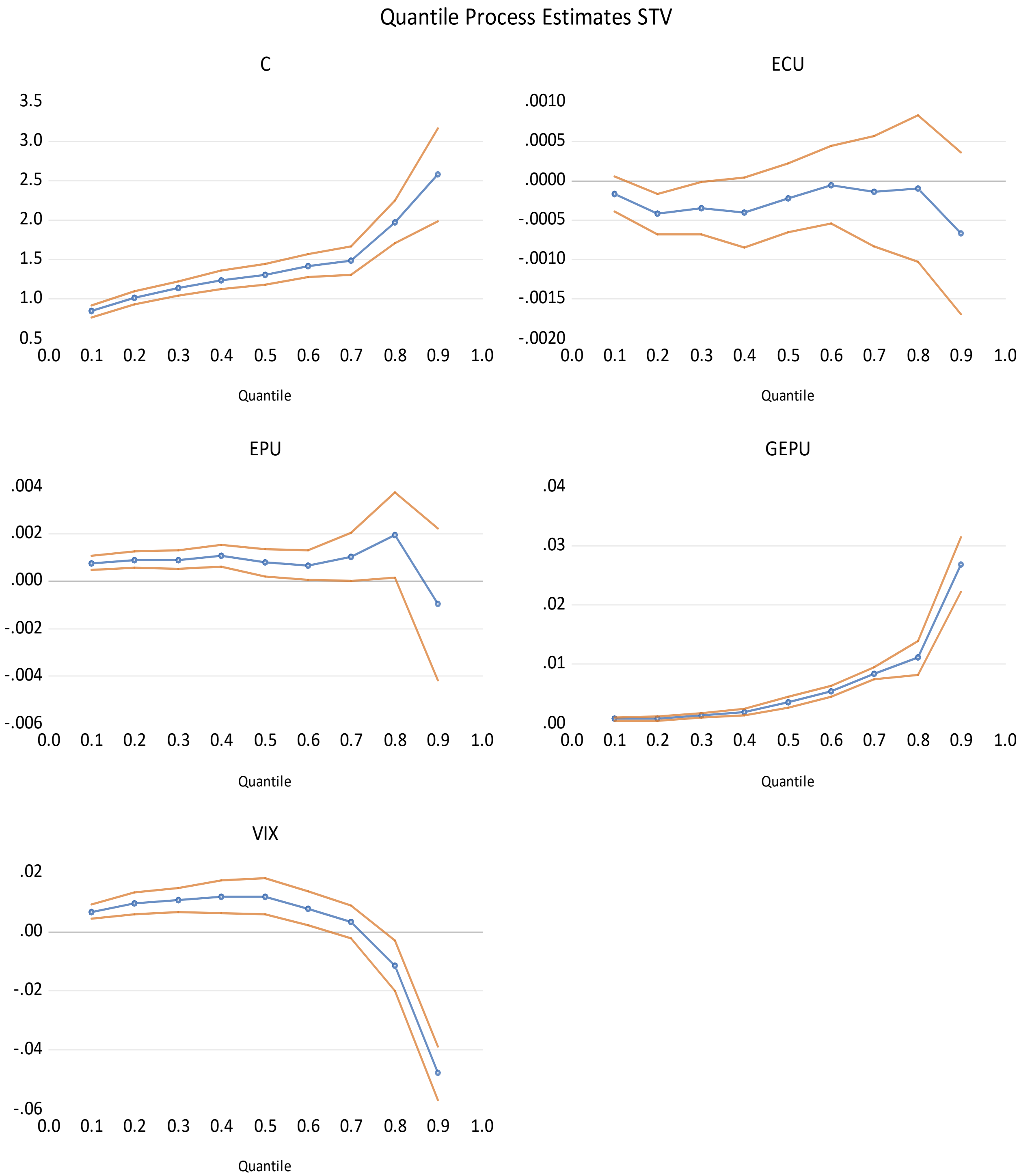

Figure 5: Coefficient estimate process for STV regressions through quantiles. 10/29/2001-12/31/2023

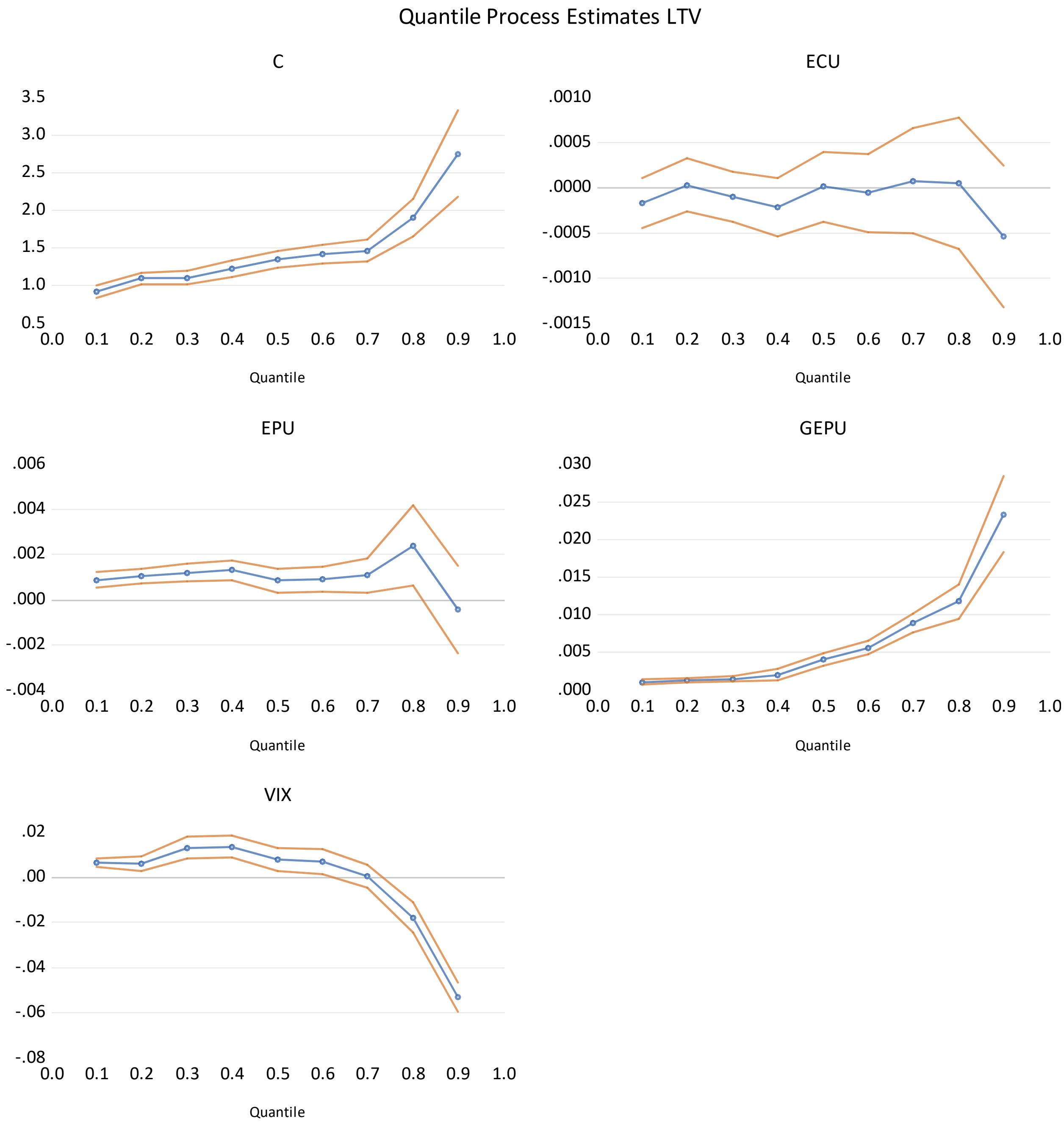

Figure 6: Coefficient estimate process for LTV regressions through quantiles. 10/29/2001-12/31/2023

6. Summary and Implications

This study examines the relationship between Latin American market volatility—represented by the ILF ETF—and key economic and financial fundamentals, along with uncertainty indicators related to market conditions and U.S. and global economic policies. Specifically, we analyze how these uncertainties collectively influence both short- and long-term ILF volatility dynamics.

The United States maintains strong trade relationships with major Latin American economies, with exports and imports playing a crucial role in the economic ties between the regions. U.S. exports to Latin America include a diverse range of goods, including machinery, automobiles, refined petroleum products, agricultural commodities, and pharmaceuticals. Countries such as Mexico, Brazil, Chile, and Colombia are among the top destinations for U.S. exports, with Mexico being the largest trade partner due to its geographic proximity and integration through the USMCA (United States-Mexico-Canada Agreement). The U.S. exports large quantities of corn, soybeans, and meat to Latin America, capitalizing on the region's demand for high-quality agricultural products. Additionally, industrial goods such as aircraft, medical equipment, and chemicals also constitute a significant portion of U.S. exports to Latin American economies. On the import side, the U.S. relies on Latin America for a variety of essential goods, including crude oil, minerals, electronics, and agricultural products such as coffee, fruits, and sugar. Mexico remains the largest supplier of goods to the U.S., exporting automobiles, electronics, and machinery due to its integrated supply chains with American manufacturers. Brazil and Argentina are major suppliers of agricultural commodities like soybeans and beef, while Chile and Peru provide copper and other minerals essential for U.S. industries. The trade relationships between the U.S. and Latin America are influenced by trade agreements, economic policies, and geopolitical factors. While trade partnerships remain robust, challenges such as tariffs, supply chain disruptions, and economic uncertainties continue to shape the dynamics of U.S.-Latin American trade.

Using data from 2001 to 2023, we estimate ILF volatility through a two-covariate GARCH-MIDAS model, which is recognized for its superior predictive accuracy and ability to capture both short- and long-term volatility components simultaneously. We further investigate the responsiveness of these volatility estimates to U.S. and global economic policy uncertainty, as well as implied risk measured by the CBOE VIX, across different market regimes. By employing Markov switching and quantile regression techniques, we effectively assess how volatility interacts with uncertainty indicators during periods of high and low market turbulence and across various points in the volatility distribution, particularly in the presence of structural breaks.

Our findings from MSR and QR indicate that the relationship between ILF volatility and uncertainty varies little across high- and low-volatility market regimes. Notably, in both regimes, ILF volatility is influenced by uncertainties arising from government policies and broader market risks. These results reinforce the effectiveness of MSR and QR methodologies, as they remain robust in capturing the link between ILF volatility and uncertainty despite structural breaks in short- and long-term volatility and shifts in economic conditions. The observation that indicators like EPU, GEPU, and VIX impact ILF volatilities across two regimes aligns with expectations. Significant volatility events often stem from prevailing market or economic sentiment, leading to sharp fluctuations when uncertainty rises. Moreover, even in periods of market stability, shifts in sentiment and uncertainty can trigger substantial investor reactions, further underscoring their relevance in volatility analysis.

Volatility is a fundamental factor in options and derivative pricing models and significantly influences futures contract pricing through contango and backwardation. Our study offers valuable insights for investors, speculators, and market participants by shedding light on ILF's volatility dynamics. By understanding these patterns, market participants can develop effective hedging strategies using options and futures contracts. Additionally, our findings indicate that fluctuations in EPU, GEPU, and VIX provide useful signals for planning such strategies in the U.S. equity markets. Furthermore, we demonstrate that while short- and long-term volatility, VIX, EPU, and GEPU exhibit stationarity, they also experience structural breaks over time. This suggests that their relationship with ILF volatility is likely to remain stable and informative for future market analysis.

The economic uncertainties triggered by the tariff policies introduced by the Trump administration in early 2025, along with the resulting shifts in both domestic and global economic policies, reinforce the findings of our study. Our research demonstrates that equity market volatilities in the short- and long-run are heightened by domestic and global economic and policy uncertainty. These real-world developments serve as timely validation of our empirical results, highlighting the sensitivity of the equity markets to unpredictable policy environments.

We make two key contributions to the literature. First, we confirm that sentiment and economic uncertainty play a crucial role in long-run volatility. Our findings highlight the need for incorporating behavioral finance metrics into statistical models of volatility, particularly when explaining patterns such as volatility clustering and persistence. Second, we employ a more robust GARCH-MIDAS framework, integrated with Markov switching and quantile regressions. This approach effectively captures regime-dependent volatility dynamics in ILF, demonstrating the importance of considering structural shifts when modeling market fluctuations.

Given that ILF is sensitive to economic and policy uncertainties in both the U.S. and Latin America, monitoring key indicators like the VIX, economic policy uncertainty, and global economic policy uncertainty can help investors anticipate market swings and adjust their hedging positions accordingly.

U.S. investors in the iShares Latin America 40 ETF can hedge their exposure to volatility using various risk management strategies. One common approach is utilizing options and futures contracts to offset potential losses. For instance, investors can purchase put options on ILF to protect against downside risk or use VIX futures to hedge against broader market volatility. Additionally, diversifying their portfolio by including assets with low correlation to Latin American markets—such as U.S. Treasuries or gold—can help mitigate risks. Another effective strategy is employing stop-loss orders to limit potential drawdowns in times of heightened volatility.

Declarations

Authors declare no funding or conflict of interest. Data for the research are available upon request.

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References

Adam, N., Sidek, N. Z. M., & Sharif, A. (2022). The impact of global economic policy uncertainty and volatility on stock markets: Evidence from Islamic countries. Asian Economic and Financial Review, 12(1), 15.

Adrangi, B., & Raffiee, K. (1999a). On total price uncertainty and the behavior of a competitive firm. The American Economist, 43(2), 59-65.

Adrangi, B., Chatrath, A., & Raffiee, K. (1999b). Volatility characteristics and persistence in Latin American emerging markets. International Journal of Business, *4*(1), 20-37.

Adrangi, B., Chatrath, A., Hatamerad, S. & Raffiee, K. (2025a). Equity Markets Volatility, Regime Dependence and Economic Uncertainty: The Case of Pacific Basin. Bulletin of Applied Economics, Bulletin of Applied Economics, 2025, 12(1), 75-105. https://doi.org/10.47260/bae/1215

Adrangi, B., Hatamerad, S., Kolay, M., & Raffiee, K (2025b). Economic and Policy Uncertainties and Firm Value: The Case of Consumer Durable Goods. Journal of Theoretical Accounting Research, Forthcoming.

Adrangi, B., Chatrath, A., Kolay, M., & Raffiee, K (2025c). Economic and Policy Uncertainties and Firm Value in The Oil and Gas Industry. Journal of Theoretical Accounting Research, Forthcoming.

Adrangi, B., Chatrath, A., & Raffiee, K. (2023a). S&P 500 volatility, volatility regimes, and economic uncertainty. Bulletin of Economic Research, 75(4), 1362-1387.

Adrangi, B., & Hamilton, E. (2023b). Market concentration and performance: The case of the US airline industry. The Journal of Theoretical Accounting Research, 18(3), 54-78.

Adrangi, B., Chatrath, A., Maitra, D., & Sengupta, A. (2024a). Is the Influence of Oil Shocks on Economic Policy Uncertainty Fading?. American Business Review, 27(2), 5.

Adrangi, B., Chatrath, A., Madhuparna K., & Raffiee, K. (2024b). Enterprise Value, and economic uncertainty: The Case of US Air Carriers. Journal of Theoretical Accounting Research, 20(1), 123-175.

Adrangi, B., Chatrath, A., Raffiee, K. (2024c). U.S. Diesel Fuel Price Volatility and Economic Policy Uncertainty. Oil, Gas & Energy Quarterly 72 (3), 533-566.

Adrangi, B., Chatrath, A., Macri, J., & Raffiee, K. (2021). Dynamics of crude oil price shocks and major Latin American Equity Markets: A study in time and frequency domains. *Bulletin of Economic Research*, *73*(3), 432-455.

Adrangi, B., Chatrath, A., Macri, J., & Raffiee, K. (2019). Dynamic responses of major equity markets to the US fear index. *Journal of Risk and Financial Management*, *12*(4), 156.

Adrangi, B., Chatrath, A., Macri, J., & Raffiee, K. (2015). Crude oil price volatility spillovers into major equity markets. Journal of Energy Markets, 8(1), 77-95.

Adrangi, B., Chatrath, A., Dhanda, K. K., & Raffiee, K. (2001). Chaos in oil prices? Evidence from futures markets. Energy Economics, 23(4), 405-425.

Alizadeh, A. H., & Nomikos, N. K. (2011). Dynamics of the term structure and volatility of shipping freight rates. Journal of Transport Economics and Policy (JTEP), 45(1), 105-128.

Al-Thaqeb, S. A., & Algharabali, B. G. (2019). Economic policy uncertainty: A literature review. The Journal of Economic Asymmetries, 20, e00133.

Altig, D., Baker, S., Barrero, J. M., Bloom, N., Bunn, P., Chen, S., & Thwaites, G. (2020). Economic uncertainty before and during the COVID-19 pandemic. Journal of Public Economics, 191, 104274.

Amado, C., Silvennoinen, A., & Teräsvirta, T. (2019). Models with multiplicative decomposition of conditional variances and correlations. Financial mathematics, volatility and covariance modelling, 2, 217-260.

Amendola, A., Candila, V., & Scognamillo, A. (2017). On the influence of US monetary policy on crude oil price volatility. Empirical Economics, 52(1), 155-178.

Amendola, A., Candila, V., & Gallo, G. M. (2019). On the asymmetric impact of macro–variables on volatility. Economic Modelling, 76, 135-152.

Ang, A., Bekaert, G. (2015). International Asset Allocation With Regime Shifts. The Review of Financial Studies, 15, 1137–1187.

Ang, A., Chen, J. (2002). Asymmetric correlations of equity portfolios. Journal of Financial Economics, 63, 443–494.

Antonakakis, N., Chatziantoniou, I., Filis, G., (2013). Dynamic co-movements of stock market returns, implied volatility and policy uncertainty. Economics Letters, 120, 87-92.

Arouri, M., Estay, C., Rault, C., & Roubaud, D. (2016). Economic policy uncertainty and stock markets: Long-run evidence from the US. Finance Research Letters, 18, 136-141.

Asgharian, H., Hou, A. J., & Javed, F. (2013). The importance of the macroeconomic variables in forecasting stock return variance:A GARCH-MIDAS approach. Journal of Forecasting, 32(7), 600-612.

Awartani, B. M., & Corradi, V. (2005). Predicting the volatility of the S&P-500 stock index via GARCH models: the role of asymmetries. International Journal of Forecasting, 21(1), 167-183.

Bai, J., & Perron, P. (2003). Critical values for multiple structural change tests. The Econometrics Journal, 6(1), 72-78.

Baker, S. R., Bloom, N., Davis, S. J., & Kost, K. J. (2019). Policy news and stock market volatility (No. w25720). National Bureau of Economic Research.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. The Quarterly Journal of Economics, 131(4), 1593-1636.

Baker, S. R., Bloom, N., & Davis, S. J. (2012a). Has economic policy uncertainty hampered the recovery?. Becker Friedman Institute for Research In Economics Working Paper, (2012-003).

Baker, Scott, Bloom, Nicholas and Davis, Steven J. (2012b), "Measuring Economic Policy Uncertainty," University of Chicago and Stanford University. Available at www.policyuncertainty.com

Baker, S. R., Bloom, N., Davis, S. J., & Renault, T. (2021). Twitter-derived measures of economic uncertainty. Available online: PolicyUncertainty. com (accessed on 15 June 2022).

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. The journal of Finance, 61(4), 1645-1680.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. Journal of economic perspectives, 21(2), 129-152.

Ball, C. A., & Roma, A. (1994). Stochastic volatility option pricing. Journal of Financial and Quantitative Analysis, 29(4), 589-607.

Barrodale, I., & Roberts, F. D. (1973). An improved algorithm for discrete l_1 linear approximation. SIAM Journal on Numerical Analysis, 10(5), 839-848.

Beckmann, J., & Czudaj, R. (2014). Non-linearities in the relationship of agricultural futures prices. European Review of Agricultural Economics, 41(1), 1-23.

Bekaert, G., Ehrmann, M., Fratzscher, M., & Mehl, A. (2014). The global crisis and equity market contagion. The Journal of Finance, 69(6), 2597-2649.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. The Quarterly Journal of Economics, 98(1), 85-106.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307-327.

Bollerslev, T., Engle, R. F., & Wooldridge, J. M. (1988). A capital asset pricing model with time-varying covariances. Journal of political Economy, 96(1), 116-131.

Bonaime, A., Gulen, H., & Ion, M. (2018). Does policy uncertainty affect mergers and acquisitions? Journal of Financial Economics Forthcoming, 129(3), 531–558.

Borup, D., & Jakobsen, J. S. (2019). Capturing volatility persistence: a dynamically complete realized EGARCH-MIDAS model. Quantitative Finance, 19(11), 1839-1855.

Carnero, M. A., Peña, D., & Ruiz, E. (2012). Estimating GARCH volatility in the presence of outliers. Economics Letters, 114(1), 86-90.

Chang, K. L. (2022). Do economic policy uncertainty indices matter in joint volatility cycles between US and Japanese stock markets?. Finance Research Letters, 47, 102579.

Choi K, Hammoudeh S. (2010). Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment. Energy Pol 2010; 38: 4388 e99.

Colak, G., Durnev, A., & Qian, Y. (2017). Political uncertainty and IPO activity: Evidence from U.S. gubernatorial elections. Journal of Financial and Quantitative Analysis,1–42.

Conrad, C., & Loch, K. (2015). Anticipating long-term stock market volatility. Journal of Applied Econometrics, 30(7), 1090-1114.

Conrad, C., Custovic, A., & Ghysels, E. (2018). Long-and short-term cryptocurrency volatility components: A GARCH-MIDAS analysis. Journal of Risk and Financial Management, 11(2), 23.

Conrad, C., & Kleen, O. (2020). Two are better than one: Volatility forecasting using multiplicative component GARCH-MIDAS models. Journal of Applied Econometrics, 35(1), 19-45.

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. Journal of Financial Econometrics, 7(2), 174-196.

Davis, S. J. (2016). An index of global economic policy uncertainty (No. w22740). National Bureau of Economic Research.

Davis, S. J., Liu, D., & Sheng, X. S. (2019). Economic policy uncertainty in China since 1949: The view from mainland newspapers. In Fourth Annual IMF-Atlanta Fed Research Workshop on China's Economy Atlanta (Vol. 19, pp. 1-37).

Demir, E., & Ersan, O. (2017). Economic policy uncertainty and cash holdings: Evidence from BRIC countries. Emerging Markets Review, 33, 189–200.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366a), 427-431.

Ding, Z., & Granger, C. W. (1996). Modeling volatility persistence of speculative returns: a new

Dixit, A. K., & Pindyck, R. S. (1994). Investment under uncertainty. Princeton university press.

Ding, Z., & Granger, C. W. (1996). Modeling volatility persistence of speculative returns: a new approach. Journal of Econometrics, 73(1), 185-215.

Dutta, A., Bouri, E., & Saeed, T. (2021). News-based equity market uncertainty and crude oil volatility. Energy, 222, 119930.

Edwards III, G. C., Mitchell, W., & Welch, R. (1995). Explaining presidential approval: The significance of issue salience. American Journal of Political Science, 108-134.

Edwards, S., & Susmel, R. (2001). Volatility dependence and contagion in emerging equity markets. Journal of Development Economics, 66(2), 505-532.

Engle R. F, and Lee, G, (1999). A permanent and transitory component model of stock return volatility R. Engle, H. White (Eds.), Cointegration, Causality, and Forecasting: A Festschrift in Honor of Clive W.J. Granger, Oxford University Press, New York (1999), pp. 475-497

Engle, R. F., Ghysels, E., & Sohn, B. (2013). Stock market volatility and macroeconomic fundamentals. Review of Economics and Statistics, 95(3), 776-797.

Eve, R. A., Eve, R. A., Horsfall, S., & Lee, M. E. (Eds.). (1997). Chaos, complexity, and sociology: Myths, models, and theories. Sage.

Fama, E. F. (1965). The behavior of stock-market prices. The journal of Business, 38(1), 34-105.

Fang, L., Qian, Y., Chen, Y., & Yu, H. (2018). How does stock market volatility react to NVIX? Evidence from developed countries. Physica A: Statistical Mechanics and its Applications, 505, 490-499.

Fissler, T. and Ziegel, J.F. (2016). Higher order elicitability and Osband's principle. Ann. Stat., 2016, 44(4), 1680–1707.

Flacco, P. R., & Kroetch, B. G. (1986). Adjustment to Production Uncertainty and the Theory of the Firm. Economic Inquiry, 24(3), 485-495.

Fooladi, I., & Kayhani, N. (1991). Random Cost Functions and Production Decisions. Eastern Economic Journal, 17(2), 199-202.

Fooladi, I., & Kayhani, N. (1990). Profit tax and output level under uncertainty. Atlantic Economic Journal, 18(1), 27.

Galvao, A. F., Gu, J., & Volgushev, S. (2020). On the unbiased asymptotic normality of quantile regression with fixed effects. Journal of Econometrics, 218(1), 178-215.

Geraci, M. (2019). Modelling and estimation of nonlinear quantile regression with clustered data. Computational Statistics & Data Analysis, 136, 30-46.

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2004). The MIDAS touch: Mixed data sampling regression models.

Ghysels E. , Virmantas Kvedaras, V., Vaidotas Zemlys, V. (2016). Mixed Frequency Data Sampling Regression Models: The R Package midasr. Journal of Statistical Software, 72(4). doi: 10.18637/jss.v072.i04.

Golchin, B., and B. Rekabdar. (2024). Anomaly Detection in Time Series Data Using Reinforcement Learning, Variational Autoencoder, and Active Learning. Conference on AI, Science, Engineering, and Technology (AIxSET), Laguna Hills, CA, USA. 1-8, doi: 10.1109/AIxSET62544.2024.00007. https://ieeexplore.ieee.org/abstract/document/10770963

Golchin, B., and N. Riahi. (2021). Emotion detection in twitter messages using combination of long-short-term memory and convolutional deep neural networks. International Conference on Computer and Knowledge Engineering (ICCKE), World Academy of Science, Engineering and Technology International Journal of Computer and Information Engineering Vol:15, No:9.

Gulen, H., & Ion, M. (2015). Policy uncertainty and corporate investment. Review of Financial Studies, 29(3), 523–564.
Hajizadeh, E., Seifi, A., Zarandi, M. F., & Turksen, I. B. (2012). A hybrid modeling approach for forecasting the volatility of S&P 500 index return. Expert Systems with Applications, 39(1), 431-436.
Hansen, P. R., Huang, Z., & Shek, H. H. (2012). Realized GARCH: a joint model for returns and realized measures of volatility. Journal of Applied Econometrics, 27(6), 877-906.
Hall, P., & Sheather, S. J. (1988). On the distribution of a studentized quantile. Journal of the Royal Statistical Society: Series B (Methodological), 50(3), 381-391.
Hendricks, W., & Koenker, R. (1992). Hierarchical spline models for conditional quantiles and the demand for electricity. Journal of the American statistical Association, 87(417), 58-68.
Im, H. J., Park, H., & Zhao, G. (2017). Uncertainty and the value of cash holdings. Economics Letters, 155, 43–48.
Javaheri, A., Wilmott, P., & Haug, E. G. (2004). GARCH and volatility swaps. Quantitative Finance, 4(5), 589-595.
Jens, C. E. (2017). Political uncertainty and investment: Causal evidence from US gubernatorial elections. Journal of Financial Economics, 124(3), 563–579.
Jiang, Y., Zhu, Z., Tian, G., & Nie, H. (2019). Determinants of within and cross-country economic policy uncertainty spillovers: Evidence from US and China. Finance Research Letters, 31(2019), 195–206.
Kelly, B., P_astor, L., & Veronesi, P. (2016). The price of political uncertainty: Theory and evidence from the option market. The Journal of Finance, 71(5), 2417–2480.
Koenker, R., & Machado, J. A. (1999). Goodness of fit and related inference processes for quantile regression. Journal of the American Statistical Association, 94(448), 1296-1310.
Koenker, R. W., & d'Orey, V. (1987). Algorithm AS 229: Computing regression quantiles. Applied statistics, 383-393.
Koenker, R., & Ng, P. (2005). A Frisch-Newton algorithm for sparse quantile regression. Acta Mathematicae Applicatae Sinica, 21(2), 225-236.
Krol, R. (2014). Economic policy uncertainty and exchange rate volatility. International Finance, 17(2), 241-256.
Kyriazis, N. A., Papadamou, S., & Koulis, A. (2025). The nexus of monetary, regulatory and national security policy uncertainties with S&P500: lessons of stock market crashes. Journal of Financial Economic Policy, Forthcoming.
Li, T., Ma, F., Zhang, X., & Zhang, Y. (2020). Economic policy uncertainty and the Chinese stock market volatility: Novel evidence. Economic Modelling, 87, 24-33.
Lindblad, A. (2017). Sentiment indicators and macroeconomic data as drivers for low-frequency stock market volatility.
Liow, K. H., Liao, W. C., & Huang, Y. (2018). Dynamics of international spillovers and interaction: Evidence from financial market stress and economic policy uncertainty. Economic Modelling, 68, 96-116.
Liu, H. C., & Hung, J. C. (2010). Forecasting S&P-100 stock index volatility: The role of volatility asymmetry and distributional assumption in GARCH models. Expert Systems with Applications, 37(7), 4928-4934.
Liu, L., & Zhang, T. (2015). Economic policy uncertainty and stock market volatility. Finance Research Letters, 15, 99-105.
Ludvigson, S. C., Ma, S., & Ng, S. (2021). Uncertainty and business cycles: exogenous impulse or endogenous response?. American Economic Journal: Macroeconomics, 13(4), 369-410.
Manela, A., & Moreira, A. (2017). News implied volatility and disaster concerns. Journal of Financial Economics, 123(1), 137-162.
Nguyen, N. H., & Phan, H. V. (2017). Policy uncertainty and mergers and acquisitions. Journal of Financial and Quantitative Analysis, 52(2), 613–644.

Pan, Z., Y.Wang, and L. Liu (2021). Macroeconomic uncertainty and expected shortfall (and value at risk): a new dynamic semiparametric model. Quantitative Finance, 1–15.
Pan, Z., Wang, Y., Wu, C., & Yin, L. (2017). Oil price volatility and macroeconomic fundamentals: A regime switching GARCH-MIDAS model. Journal of Empirical Finance, 43, 130-142.
Panousi, V., & Papanikolaou, D. (2012). Investment, idiosyncratic risk, and ownership. Journal of Finance, 67(3), 1113–1148.
Pindyck, R. S. (1991). Irreversibility, uncertainty, and investment. NBER, Working paper 3307.
Perron, P., & Phillips, P. C. (1987). Does GNP have a unit root?: A re-evaluation. Economics Letters, 23(2), 139-145.
Peters, E. E. (1994). Fractal market analysis: applying chaos theory to investment and economics (Vol. 24). John Wiley & Sons.
Phan, H. V., Nguyen, N. H., Nguyen, H. T., & Hegde, S. (2019). Policy uncertainty and firm cash holdings. Journal of Business Research, 95, 71–82.
Powell, J. L. (1986). Censored regression quantiles. Journal of Econometrics, 32(1), 143-155.
Robe, M. A., & Wallen, J. (2016). Fundamentals, derivatives market information and oil price volatility. Journal of Futures Markets, 36(4), 317-344.
Sandmo, A. (1971). On the theory of the competitive firm under price uncertainty. The American Economic Review, 61(1), 65-73.
Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. International Review of Financial Analysis, 70, 101496.
Shephard, N., & Sheppard, K. (2010). Realising the future: forecasting with high-frequency-based volatility (HEAVY) models. Journal of Applied Econometrics, 25(2), 197-231.
Su, Z., Fang, T., and Yin, L. (2019). Understanding Stock Market Volatility: What is the Role of U.S. Uncertainty? North American Journal of Economics and Finance 48, 582-590.
Su, Z., Lu, M., & Yin, L. (2018). Oil prices and news-based uncertainty: novel evidence. Energy Economics, 72, 331-340.
Su, Z., Fang, T., & Yin, L. (2017). The role of news-based implied volatility among US financial markets. Economics Letters, 157, 24-27.
Sun, Z., & Li, J. (2025). The impact of economic policy uncertainty on household portfolios effectiveness: Evidence from China. Finance Research Letters, 78, 107215, https://doi.org/10.1016/j.frl.2025.107215.
Tsai, I. C. (2017). The source of global stock market risk: A viewpoint of economic policy uncertainty. Economic Modelling, 60, 122-131.
Walkup, B. (2016). The impact of uncertainty on payout policy. Managerial Finance, 42(11), 1054–1072.
Wen, F., Xiao, Y., & Wu, H. (2019). The effects of foreign uncertainty shocks on China's macro-economy: Empirical evidence from a nonlinear ARDL model. Physica A: Statistical Mechanics and its Applications, 532, 121879.
Whaley, R. E. (1993). Derivatives on market volatility: Hedging tools long overdue. The journal of Derivatives, 1(1), 71-84.
Whaley, R. E. (2009). Understanding the VIX. The Journal of Portfolio Management, 35(3), 98-105.
Xu, Y., X. Wang, and H. Liu (2021). Quantile-based GARCH-MIDAS: Estimating value-at-risk using mixed-frequency information. Finance Research Letters.
Yu, K., Lu, Z., & Stander, J. (2003). Quantile regression: applications and current research areas. Journal of the Royal Statistical Society: Series D (The Statistician), 52(3), 331-350.
Zhang, D., Lei, L., Ji, Q., & Kutan, A. M. (2019). Economic policy uncertainty in the US and China and their impact on the global markets. Economic Modelling, 79, 47-56.
Zhu, S., Liu, Q., Wang, Y., Wei, Y., & Wei, G. (2019). Which fear index matters for predicting US stock market volatilities: Text-counts or option based measurement?. Physica A: Statistical Mechanics and its Applications, 536, 122567.