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Economic Policy Uncertainty and Fluctuations in Monthly IPO Volume: Evidence from the US

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Abstract: *This research examines the dynamic relationship between economic policy uncertainty (EPU) and initial public offering (IPO) volume in the United States from 1990 to 2020. Employing time-series econometric methods, we find that EPU has a significant negative effect on IPO activities. According to impulse responses, the number of IPOs significantly reacts to the innovations on EPU within the next 1 to 4 months and approaches the new equilibrium in 6 to 8 months. However, EPU does not contribute to forecast error variance decompositions of the number of IPOs. Our empirical results also show that the number of IPOs switches between low-mean/high-variance and high-mean/low-variance regimes. The results have some useful implications for timing IPOs in terms of economic policy uncertainty.*

Keywords: Economic Policy Uncertainty, IPOs, VAR, Impulse-responses, Regime Change

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1. Introduction

Initial public offerings (IPOs) are a critical aspect of financial markets, serving as a primary mechanism for companies to raise capital. According to IPO data compiled by J. Ritter, the United States experienced seven distinct IPO waves from 1990 to 2020, each varying in duration from 2 to 14 months, with a median duration of 3 months. The peak number of IPOs recorded in a single month reached 76, and during the most active periods, the average number of IPOs stood at 52. However, following August 2000, the market observed a significant decline, with the average number of monthly IPOs plummeting from 34 during the 1990-2000 period to just 9 from 2001 to 2019.

During these intervals, the level of economic policy uncertainty (EPU) in the United States has also seen notable fluctuations. Data from Baker et al. (2016) indicates that the average EPU index rose from approximately 97 for the 1990-2000 period to 137 for the 2001-2020 period. Correlations between IPO volumes and EPU during these times were found to be around -36% and -55%, respectively. Interestingly, 2020 emerged as a landmark year for the US IPO market, largely influenced by the COVID-19 pandemic, with the correlation between IPOs and EPU declining to -17%. These observations suggest that variations in IPO numbers are sensitive to changes in EPU over time.

EPU encompasses uncertainties surrounding fiscal, regulatory, and monetary policies (Baker et al., 2016). When policy actions are perceived as attempts by economic agents to shape a new future, they can have profound implications for investors and firms alike. As one of the primary objectives of an IPO is capital

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raising, companies' expectations will inevitably be shaped by anticipated changes in economic policy, leading to potential capital supply shocks. Consequently, EPU can significantly influence firms' decisions to go public, particularly through its impact on stock market dynamics and the broader macroeconomic environment. During recessionary periods, when information asymmetries between firms and investors are pronounced, companies may alter their financing strategies. As uncertainty rises, macroeconomic instability is likely to follow, often resulting in delays in firms' public offerings to raise capital. Investors, becoming more risk-averse, may shift their preferences towards safer assets, potentially reducing their willingness to fund new public offerings during periods of heightened uncertainty. Therefore, increased economic policy uncertainty can lead to unfavorable market conditions, creating a weaker IPO landscape. This paper posits that EPU is a significant macroeconomic driver influencing IPO frequency, as fluctuations in policy uncertainty directly affect firms' public offering and capital-raising strategies.

A growing body of literature addresses the broader implications of policy uncertainty on several macroeconomic and financial dimensions, including economic growth (Ghirelli et al., 2019; Sahinoz & Cosar, 2018), export performance (Aslan & Acikgoz, 2021), investor sentiment (Qi et al., 2022), and dynamics within global markets (Zhang et al., 2019). Given this landscape, it is essential for both investors and companies planning IPOs to understand how EPU affects the IPO market, the duration of its impacts, and the degree to which it influences decisions to go public. While previous studies have explored various macroeconomic drivers of IPO volume fluctuations (Angelini & Foglia, 2018; Erel et al., 2012; Tran & Jeon, 2011), this paper aims to specifically investigate the impact of EPU on IPO activity.

The primary objectives of this paper are twofold. First, it seeks to examine the dynamic impact of EPU on IPO activities while controlling for various macroeconomic and stock market indicators. Second, the study aims to explore the causality and impulse response mechanisms between shocks in EPU and IPO volume. Additionally, this research investigates potential regime changes in the number of IPOs over time, particularly in light of the diminished number of IPOs in the US economy since the 1990s, especially following the enactment of the Sarbanes-Oxley Act of 2002.

To achieve these objectives, we utilized a vector autoregressive (VAR) model to facilitate a comprehensive analysis of the dynamic interactions among multiple time series related to monthly IPO activities in the US, covering the period from January 1990 to December 2020. Our findings demonstrated a negative impact of EPU on IPO activities, aligning with the conclusions drawn by Chan et al. (2021), found that EPU increases the cost of raising equity capital, especially in weaker economic conditions, as reflected by a significant rise in price discounts for seasoned equity offerings. Boulton (2022) provided robust evidence that elevated EPU correlates with increased underpricing1 in IPOs across 22 countries from 1998 to 2018, indicating that uncertainty may deter investors or lead to cautious pricing strategies. Similarly, Gupta et al. (2021) emphasized that factors influencing pre-market and post-market underpricing differ, with EPU positively impacting investor subscription rates and issue expenses, while also influencing pre-market underpricing significantly. Their findings suggest that EPU encapsulates publicly available information, aligning with the semi-strong form of the Efficient Market Hypothesis.

This paper differs from these studies and contributes to the literature in two significant ways. First, it extends the analysis of macroeconomic factors affecting IPO market fluctuations by integrating economic policy uncertainty (EPU) over the 1990 to 2020 period. Second, it introduces an innovative application of a regime-switching model to the US IPO market, providing new insights into how IPO market fluctuations are influenced by regime shifts. The findings suggest that while EPU does influence these regime changes, its influence is relatively modest compared to other macroeconomic variables.

The structure of this paper is organized into six sections. The second section elucidates the mechanism through which economic policy uncertainty affects IPO activities by detailing the employed model. The third section outlines the methodology applied in the research. The fourth section presents the data utilized, accompanied by descriptive analysis. The fifth section discusses the empirical findings, and the final section concludes the paper.

2. Literature and Hypothesis Development

The theoretical literature about policy uncertainty and its impacts are pioneered by Rodrik (1991), Higgs (1997), Hassett and Metcalf (1999), Pastor and Veronesi (2012, 2013), Born and Pfeifer (2014), and Baker et al. (2016). These articles define policy uncertainty as uncertainty about the fiscal and monetary policy of the government, and they use calibration methods and econometric approaches to study the effect of policy uncertainty from both micro and macro perspectives. According to Rodrik (191) in terms of investments and economic growth, establishing policy stability and sustainability are likely to bring greater payoffs than focusing on economic liberalization and getting prices right. Higgs (1997) connects the insufficiency of private investments in the late 1940s in the US to a pervasive uncertainty, arising from the character of the federal government, among investors related to the security of their property rights in their capital. Hassett and Metcalf (1999) take tax policy as a key source of uncertainty about the cost of capital to US firms. The authors highlight the two-sided effect of policy uncertainty on investments: it may discourage investment, and it may also increase investment because firms always have the option to decide when to invest. Born and Pfeifer (2014) state that the uncertainty surrounding the future policy staggers economic activity by prompting a wait-and-see approach.

Pastor and Veronesi (2012, 2013) consider two types of policy uncertainty; uncertainty about whether the current government policy (political uncertainty) will be amended and uncertainty about whether a new government policy will have on the profitability of the private sector (impact uncertainty). Governments are motivated by both economic and non-economic objectives and since their non-economic objectives are unknown to investors, they do not fully anticipate whether the policy change will occur. If a policy change occurs, the agents replace their posterior beliefs. Pastor and Veronesi (2012) argue returns to positive government announcements are smaller than returns to negative government announcements because negative ones contain a bigger element of surprise. However, political uncertainty could have a positive impact if the government reacts properly to unexpected shocks (Pastor & Veronesi, 2013). Conversely, political uncertainty could have a negative impact when it is not fully diversifiable. These cited studies commonly investigated the effects of policy uncertainty on investments and the aggregate economy, and mainly highlighted its depressing effect on investments. Investments and financing decisions are vital for firms in maintaining their operational functionality and enabling their growth. For investors, it is important to be compensated for the risk of an investment. Therefore, it is necessary to understand how both firms and investors react to such uncertainties within the context of IPOs on an aggregate level. Even though economic policy uncertainty is an exogenous factor for firms and investors (Nagar et al., 2019; Pastor & Veronesi, 2012), it can be claimed that firms and investors generally factor it into their investment decisions, thereby endogenizing it.

Discussions in Pastor and Veronesi (2012, 2013) can be extended to the IPO market. They argue that policy changes cause stock returns to become more volatile and more correlated across firms when the economy is weak. In other words, firms' cost of capital increases in higher policy uncertainty times. This may discourage some firms from going public because expecting a better offer price can be a higher priority than immediately receiving capital from conducting an IPO during such periods (Çolak et al., 2017). As stated by Ibbotson et al. (1994) among others, IPO pricing is a difficult issue because, on the one hand, a low price does not provide the issuer with the expected complete benefit in raising capital. On the other hand, if the price is too high, the investor might receive a lower return and would reject the offer. Increases in the cost of capital, especially for newly established firms due to increases in policy uncertainty may prevent firms from going public or make them delay their process for going public. Therefore, one might expect that the number of firms going public would decrease during the higher uncertainty times. Therefore, we propose the following hypothesis:

H1: During periods with increasing EPU, the number of firms going public reduces.

However, as previously noted, policy uncertainty may increase in investments if economic actors anticipate policy changes. As a result, EPU may not have a detrimental impact on the IPO market as expected. Moreover, since the IPO market introduces issuing firm's insiders to investors, the role of underwriters between them is crucial, and firms might hire high-reputation underwriters during uncertain times instead of postponing their issuance to decrease information asymmetry and thus lower underpricing (Carter & Manaster, 1990; Megginson & Weiss, 1991). Nevertheless, this does not have to mean that all firms in the market would act in the same way, due to firm-specific conditions. Therefore, we test whether the level of IPO activities is affected by EPU.

Policy changes are not exogenous, as they are shaped by various economic factors (Pastor & Veronesi, 2012). The relationship between economic policy uncertainty and initial public offering activity may be affected by the macroeconomic environment. Market conditions, such as stock market returns and volatility, along with macroeconomic indicators like inflation rates, interest rates, and shifts in monetary policy, can all influence IPO activity. On one hand, real economic activity can directly impact IPO dynamics, as it reflects the overall health of the economy. Conversely, an increase in IPO activity may signal a robust economy, prompting more companies to pursue public offerings to raise capital. Additionally, inflation and price instability significantly affect the profitability of firms and investor sentiment. As inflation rises, the real value of assets declines, potentially deterring investors from financing new offerings and hindering companies from going public (Omran & Pointon, 2001).

The interest rate is another key macroeconomic factor in making investment decisions for both companies and investors. Higher interest rates may hinder enterprises' operational functionality and growth, causing investors to diversify their existing portfolios rather than invest in new issues (Ameer, 2012; Brau et al., 2003). As a result, rising inflation and interest rates will reduce the number of companies seeking to go public. Indeed, the interaction between economic growth, inflation, and interest rates will have an impact on the IPO market by influencing firm and investor decisions. As a result, understanding the interconnected relationship between the macroeconomic climate of the economy and the IPO market via EPU is essential. When it comes to determining when to go public, stock market performance outweighs other macroeconomic criteria. Entrepreneurs aim to take advantage of a stronger stock market to take their company public, attracting investors looking for larger profits. When the market is volatile, firms choose to remain private to prevent their newly listed equities fall in value (Angelini & Foglia, 2018; Gleason et al., 2008; Tran & Jeon, 2011). When all these aspects are considered, it is worthwhile to investigate the impact of uncertainty emerging from economic policy expectations and policy changes on the IPO market.

As discussed in the Introduction section, the IPO market may exhibit cyclical patterns characterized by fluctuations in the number of IPOs over time. These variations consist of periods with high IPO activity followed by phases of lower activity. Such shifts in IPO activity can be attributed to changes in market conditions, economic factors, investor sentiment, and regulatory developments. During optimistic market conditions, characterized by high activity periods, there is an increase in IPOs. Conversely, during cautious or risk-averse times, when activity is low, the number of IPOs tends to decrease. Additionally, the state of the economy plays a role, as periods of economic growth and stability encourage companies to go public, leading to higher IPO figures. In contrast, during economic downturns or uncertain times, IPO activity may decline. Moreover, endogenous factors within the IPO market itself, such as the success of prior IPOs and overall stock market performance, create feedback loops influencing firms' decisions to go public.

In the US economy, there has been a significant decrease in the average annual number of firms going public, especially compared to pre-2000 levels. The implementation of the Sarbanes-Oxley Act in 2002 played a significant role in this decline. Consequently, one aspect of the second hypothesis posits that the data-generating process for the number of IPOs has changed over time. Furthermore, the study indicates that EPU has contributed to this regime change, in conjunction with other influencing factors discussed earlier. Accordingly, we present the following two hypothesis:

H2a: The data-generating process for the number of IPOs has changed over time.

H2b: EPU has contributed to this regime change, along with other influencing factors.

3. Methodology

This paper uses time series methods to analyze the dynamic impact of EPU on IPO fluctuations. Firstly, unit-root tests for each of the variables are performed to confirm that the regressions are not spurious.2 Secondly, estimated ordinary least squares (OLS) regressions are used as benchmark regressions with the stationary values of the series. Thirdly, impulse responses and forecast error variance decompositions are estimated by using vector autoregression (VAR) modelling. Finally, an examination was conducted to determine whether there was a regime change in monthly IPO fluctuations over time, and whether EPU played a role in influencing this change.

The following presents a summary of the estimation methods utilized in this study.

VAR Modeling

In a VAR model, all of the variables in the system are endogenous and are defined as a linear function of the lagged values of all of the variables in it, each with its own lagged values. The vector autoregression with nine variables (see Table 1 below for complete information and abbreviations) can be expressed in the following way:

$$\mathrm{y}_t = \mathrm{c} + \sum_{i=1}^{p} \mathrm{A}_i\, \mathrm{y}_{t-i} + \sum_{j=1}^{4} \mathrm{B}_i\, \mathrm{x}_{jt} + \mathrm{u}_t \qquad (1)$$

where there is a maximum of *p* lags on the endogenous variables. $\mathrm{c}' = (c_1, c_2, \cdots, c_9)$ is a 1×9 vector of constants. $\mathrm{A}_1, \mathrm{A}_2, \cdots \mathrm{A}_p$ is a set of $n \times n$ matrix of coefficients of endogenous variables. B_i is a 1×4 vector of binary variables coefficients used in OLS benchmark regressions. $\mathrm{u}_t' = (u_{1,t}, u_{2,t}, \cdots, u_{9,t})$ is a 1×9 zero mean vector of errors or innovations with 9×9 error covariance matrix.

Results from VAR analysis are sensitive to the choice of lag length and the number of variables used, and there is no consensus on what the selection mechanism should be for both. In this paper, we determine the number of lags by using several information criteria (AIC, SIC, final prediction error) with a detailed inspection of the residual correlation structure, including cross-correlations. Interpretation of higher order of VAR models is problematic because it increases the number of coefficients, and they will be imprecisely estimated and highly intercorrelated (Mills, 2019). This will lead to obtaining statistically not significant VAR coefficients. Vector moving average representations of VAR models (VMA) are used to estimate impulse-response functions and variance decompositions and to interpret the information coming from these VAR coefficients. However, the impulse-responses and variance decompositions depend on the order of the variables in the system. Due to the complication of a 9-variable system, the variables are ordered by using generalized impulse-responses developed by Pesaran and Shin (1997).

Markov Regime-Switching Modeling

Markov regime-switching (MRS) models are a class of econometric models used to capture the presence of multiple regimes or states in time series data. Unlike traditional linear models, which assume a constant relationship between variables over time, regime-switching models allow for shifts in the underlying dynamics of the data, often associated with changes in economic conditions, market regimes, or policy interventions.

In a MRS model, the time series data is assumed to be generated by a hidden or unobservable Markov chain. This Markov chain governs the transition probabilities between different regimes or states. Each regime represents a distinct state of the system, characterized by different parameters or relationships between variables.

A regime dependent MRS model that fits the AR(*p*) process in both regimes is generally defined as follows:

$$y_t = \begin{cases} \phi_{0,1} + \phi_{1,1} y_{t-1} + \cdots + \phi_{1,1} y_{t-p} + \varepsilon_t & \text{for } s_t = 1 \\ \phi_{0,2} + \phi_{1,2} y_{t-1} + \cdots + \phi_{1,2} y_{t-p} + \varepsilon_t & \text{for } s_t = 2 \end{cases} \qquad (2)$$

where s_t is an unknown regime variable. The probability that s_t is equal to 1 (*i* in general) or 2 (*j* in general) is expressed below.

$$\Pr(s_t = j | s_{t-1} = i) = p_{ij}$$

where p_{ij} is an element of a Markov transition matrix. All elements of this matrix are nonnegative and each column (it can also be row depending on the expression) sums to 1. This model is generalized to a multivariate model as given below.

$$y_t = c_{r_t} + \mathrm{x}_t \alpha + \mathrm{z}_t \beta_{r_t} + u_r \quad (3)$$

Equation (3) represents the log of the number of IPOs (y_t) as a function of regime-dependent intercept (c_r), a vector of exogenous variables with regime-invariant coefficients (x_t), and another vector of exogenous variables with regime-dependent coefficients (z_t) denoted by β_{r_t}. In a Markov regime switching model, the state variable represents the unobserved or latent regimes that dictate the behavior of the observed variables in the model. It is typically not directly observable; it is inferred from the observed data. It indicates which regime the system is currently in at a given point in time. The error term u_r follows an independent and identically distributed (i.i.d.) distribution with a mean of zero and regime-dependent variance σ_r^2. Both x_t and z_t may include lagged observations of y_t.

The transitions between regimes in the model follow a Markov chain, where movement from one regime to another is governed by specific probabilistic rules. The probability of being in a particular regime is solely determined by the previous regime. Inferences on the unobserved regime variable (r_t) are made based on conditional parameter estimates. Filtered probabilities (probability of being in a regime at period *t* given all observations up to period *t*) or smoothed probabilities (probability of being in a regime at period *t* given the entire sample) are computed as part of the analysis.

4. Data and Descriptive Analysis

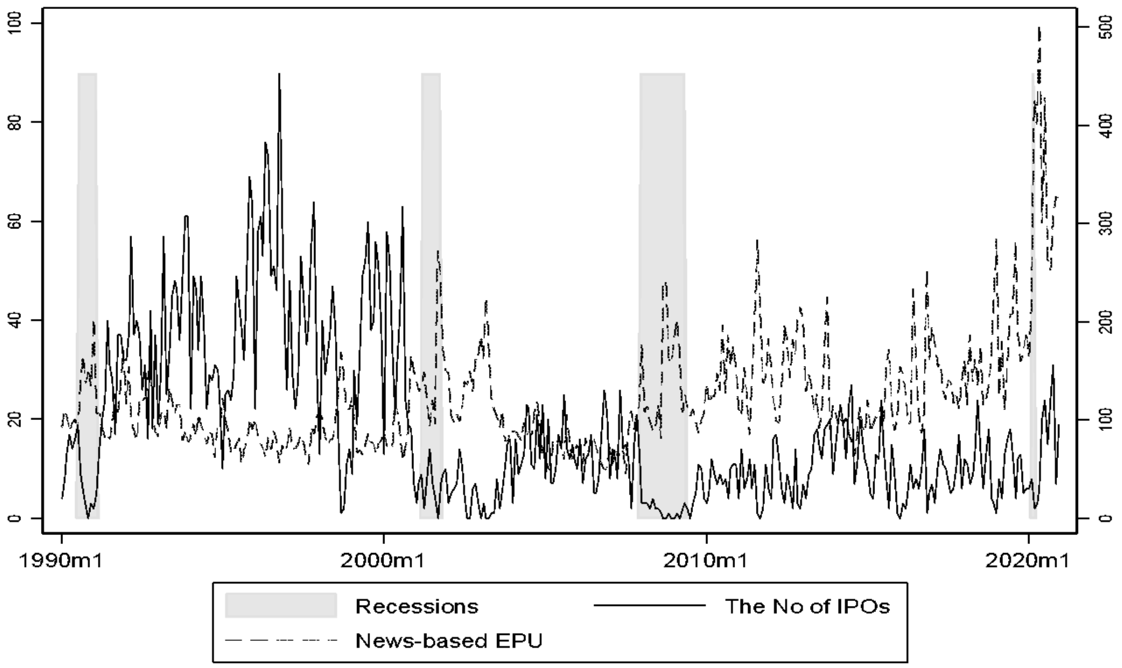
This paper uses three data sources for the period of 1990-2020: the IPO database of J. Ritter (the number of IPOs per month or IPO volume), the website of Baker et al. (2016) (EPU indexes), and the Federal Reserve Economic Data from the Federal Reserve Bank of St. Louis (macroeconomic time series except the 10-year US Treasury Bill yield and market liquidity). Based on newspaper coverage frequency, Baker et al. (2016) build indices of policy-related economic uncertainty. They try to seize uncertainty about who will make economic policy decisions, which policies will be implemented, when they will be implemented, and what the economic implications of those policies are. The monthly economic policy uncertainty (EPU) index for the United States relies on ten nationwide leading newspapers starting from 1985 and counts the following trio of terms to measure the policy uncertainty: “uncertainty” or “uncertain”; “economic” or “economy” with the one of following policy terms: “Congress,” “deficit,” “Federal Reserve,” “legislation,” “regulation,” or “White House”. Thus, an article published in those newspapers must contain terms in all three categories belonging to uncertainty, the economy, and policy (Baker et al., 2016: 1599). This index is mainly a weighted index based on the ratio of articles containing at least one of these selected words to the total number of articles published in the same month by each of the 10 newspapers. They also produce another EPU index that is a combined version of the news-based EPU index with the number of federal tax code provisions set to expire and economic forecasters’ disagreement (the three-component EPU index). Table 1 presents details on the variables, including their abbreviations and sources.

Table 1. Variables and their Data Sources

Variable	Abbreviation	Source
The Number of IPOs*	*ipo*	Monthly Number of IPOs and the average first-day return in "The Market's Problems with the Pricing of Initial Public Offerings," Journal of Applied Corporate Finance, 1994, 66-74. the IPO database of J. Ritter; https://site.warrington.ufl.edu/ritter/ipo-data/
Economic Policy Uncertainty Indexes	*epu*	https://www.policyuncertainty.com/
The Industrial Production Index	*ipi*	Federal Reserve Economic Data of Federal Reserve Bank of St. Louis.
The Consumer Price Index	*cpi*	Federal Reserve Economic Data of Federal Reserve Bank of St. Louis.
The Effective Federal Funds Rate	*fundr*	Federal Reserve Economic Data of Federal Reserve Bank of St. Louis.
The 10-year US Treasury Bill Yield	*tb10year*	US Department of Treasury
The Standard & Poor's 500 Index	*spx*	Federal Reserve Economic Data of Federal Reserve Bank of St. Louis.
The CBOE Volatility Index (VIX)	*volat*	Federal Reserve Economic Data of Federal Reserve Bank of St. Louis.
Market Liquidity	*mliquidity*	https://finance.wharton.upenn.edu/~stambaug/liq_data_1962_2020.txt

* The IPO data has been updated based on J. Ritter's 1994 article. Penny stocks, units, closed-end funds, etc. are excluded. All series except market liquidity are in their logarithms and they are seasonally adjusted if necessary. The "*l*variable" represents the logarithm of the variable, while "*dl*variable" is used to denote the first difference of the logged values of that variable.

Figure 1. Time Plot of the Number of IPOs and the Economic Policy Uncertainty Index with NBER Recession Periods



Note: *The y-axis on the left indicates the number of IPOs, while the y-axis on the right shows the economic policy uncertainty index.*
Sources: https://finance.wharton.upenn.edu/~stambaug/liq_data_1962_2020.txt (Access Date: October 26, 2021) and https://www.policyuncertainty.com/ (Access Date: September 27, 2021)

Figure 1 and Table 2 together presents time plots of news-based economic policy uncertainty, the number of IPOs, and their summary statistics. This figure also shows the US recession periods determined by the National Bureau of Economic Research (NBER). The EPU index and the number of IPOs appear to move in different directions over time. The opposite movement directions between the number of IPOs and EPU indexes are more obvious during recessions and can be visualized in Table 1.

As shown in Table 2, from years 1990-2020, an average of 18 companies went public every month. This average is 34 firms for the boom periods (1998:09-2000:08) and approximately 4 in the recession months. The number of firms that went public is more volatile in the boom periods changing between 1 and 63. The EPU indexes take positive values implying that the higher the value is, the greater the uncertainty is. The two EPU indices have lower averages during the boom periods compared to other periods and have the strongest absolute connections with the number of IPOs. Policy uncertainty is higher in recession months, as expected. EPU is also more volatile throughout these months. Increases in EPU reduce the number of companies going public, according to correlation coefficients.

Table 2. Summary statistics of the Number of IPOs and Economic Policy Uncertainty Indexes

Series	*n*	mean	sd	min	max	correlation
Period	*from September 1998 to August 2000 (the boom period)*					
The Number of IPOs	24	34.042	19.103	1	63	-
The News-based EPU index	24	90.620	27.601	58.906	169.037	-0.86***
The Three-component EPU Index	24	82.417	15.062	62.712	123.962	-0.80***
Period	*The NBER recession periods*					
The Number of IPOs	36	4.028	4.365	0	19	-
The News-based EPU index	36	154.995	68.867	81.163	425.779	-0.33*
The Three-component EPU Index	36	138.310	40.474	84.289	283.147	-0.40*
Period	*from January 1990 to December 2020*					
The Number of IPOs	372	18.097	16.689	0	90	-
The News-based EPU index	372	122.823	60.054	44.783	503.963	-0.50***
The Three-component EPU Index	372	112.703	41.77193	57.202	350.460	-0.37***

Authors' calculations from J. Ritter's data available at https://site.warrington.ufl.edu/ritter/ipo-data/ and Baker et al. (2016)'s data available at https://www.policyuncertainty.com.
The EPU index for the United States is based on searches of ten national newspapers for the following keywords and variants: "economic" or "economy"; "Congress", "deficit", "Federal Reserve", "legislation", "regulatory" or "White House", and "uncertain" or "uncertainty".
The three-component EPU index adds the number of federal tax code provisions set to expire and disagreement among economic forecasters and the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters.
Correlations are based on the logged values of the number of IPOs to logged values of EPU indexes. *** $p < 0.01$, ** $p < 0.05$ and * $p < 0.10$

5. Empirical Findings

By following the most relevant literature and Tran and Jeon (2011), the vector autoregression (VAR) model includes the industrial production index (IPI) as a proxy for real economic activity; the S&P500 index as a measure for stock market performance; market volatility as a proxy for investment risk; market liquidity[3] as a measure of stock investors' willingness to commit resources to market. Inflation and the effective Federal funds rate are indicators of the Federal Reserve's (FED) monetary policy stance. Finally, the model includes the 10-year US Treasury Bill (TB) yield as a proxy for long-term financing costs in the debt market and information captured in the yield curve. As the variable of interest, the news-based economic policy uncertainty index of Baker et al. (2016) is used in the estimations. As a robustness check, the analysis was repeated with the use of the other EPU index shown in Table 1.

Correlations and OLS Benchmark Regressions

Before discussing the results of OLS regressions, cross-correlations between the number of IPOs and the other variables as well as pairwise correlations among the control variables are reported in Table 3. The table summarizes lead-lag relations between the variables and the number of IPOs up to 8 months. As noted in Watson and Stock (1999), a large positive correlation at $k = 0$ implies that the two series are moving in the same direction (co-movement), whereas a large negative correlation at $k = 0$ suggests that they are moving in the opposite direction (countermovement). A maximum correlation of $-k$ lags implies that the series tends to lag the number of IPOs by k months, whereas a maximum correlation of $+k$ shows that the series tends to lead the number of IPOs by k months. The EPU indices and stock market volatility move in opposite directions with the number of IPOs, and the direction of the correlation is consistent across all lags. The co-movement variables for the number of IPOs are growth rates of IPI and the 10-year US TB yield, monthly stock market return and market liquidity. They tend to lag the number of IPOs by 1 month and 3 months respectively, while inflation and the growth rate of effective Fed funds rate tends to lead it by 1 month.

Correlation coefficients given in Table 4, show that the EPU indexes are negatively related to all variables except for the stock market volatility indicator. The growth rate of IPI has a positive and significant correlation with inflation, the growth rate of effective Fed funds rate, and the growth rate of the 10-year TB rate. Stock market volatility is negatively related to IPI growth rate, inflation, and two interest rates. Market liquidity is negatively related to stock market volatility and positively related to the stock market return. In conclusion, correlations reveal that EPU and IPO activities are dynamically linked, with macroeconomic factors contributing to this dynamic relationship.

We also examine the relationship between economic policy uncertainty, IPO activity, and other factors over time with the OLS regressions. A general expression for OLS analysis is given in Equation (4).

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 X_t + \mathrm{M}_{jt}\beta + \mathrm{Z}_{kt}\gamma + u_t \tag{4}$$

X_t is economic policy uncertainty, M_j is a vector of macroeconomic variables ($j = 1, \ldots, 4$) and Z_t is a vector of stock market indicators ($k = 1, 2, 3$). Y_t and Y_{t-1} denote the log of the number of IPOs in the current month and the log of the number of IPOs in the previous month.

OLS estimates findings, shown in Table 5, suggest that EPU has a negative and considerable contemporaneous impact on IPO activity. When macro indicators and stock market variables are controlled, its marginal influence shrinks in magnitude. The number of IPOs is negatively affected by the stock market volatility, which has a larger contemporaneous effect than EPU. A 1% increase in economic activities or economic growth significantly increases the number of IPOs by about 0.08% on average. Increases in monthly stock market returns contemporaneously insignificantly decrease the number of IPOs. The cross-correlations between stock market return (*dlspx*) and the log of IPO (*lipoı)* are almost positive at the ± 8 time window, that is why we observe this collinearity between stock market return and the VIX index (*lvolat*).

According to OLS estimates, increases in the growth rate of effective Fed funds rate have a minor but significant negative impact on the number of IPOs. The growth rate of 10-year TB rate (*dltb10year*), inflation (*dlcpi*), and market liquidity (*mliquidity*) have no significant contemporaneous impact on IPO activity during 1990-2020. As expected, the number of IPOs increased in the boom periods (about 27%) and decreased in the recession months (about 30%).

Table 3. Cross-Correlations with the Number of IPOs (%)

	$corr(X_{t\pm8}, Y)$																
lags	**-8**	**-7**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
lepu (news based)	-37***	-37***	-38***	-38***	-37***	-38***	-41***	-44***	**-50*****	-44***	-39***	-34***	-32***	-30***	-27***	-23***	-24***
lepu (3 component)	-29***	-32***	-32***	-34***	-34***	-36***	-39***	-44***	**-50*****	-44***	-38***	-33***	-30***	-30***	-26***	-23***	-25***
dlipi	10	6	10	15**	13**	16**	20**	25***	**27*****	**27****	22**	21**	18**	10	15**	18**	14**
dlcpi	11*	12*	11*	12*	12*	11*	13*	**18*****	17***	13**	11*	6	5	2	2	6	6
dlfundr	8	5	8	10*	9	11*	13**	**18*****	17**	13**	8	9	10*	4	6	12*	8
dltb10year	-3	-3	-5	2	-1	0	5	9	**15****	15**	9	5	6	2	0	7	5
lvolat	-16**	-20**	-23***	-26***	-27***	-28***	-33***	-38***	**-45*****	-43***	-38***	-32***	-29***	-28***	-28***	-27***	-29***
dlspx	-2	0	1	6	7	1	-2	3	11*	**27*****	26***	21***	20**	20**	16*	14*	16*
mliquidity	-1	-2	1	5	7*	10*	11**	12**	17**	21***	20**	**23*****	15**	18**	22**	20**	19**

Correlations are reported as percentages. *Y* represents the number of IPOs, and *X* represents the other series. ***, ** and * shows that the cross-correlation coefficient is significant at the 1%, 5% and 10% significance levels, respectively.

Table 4. Pairwise Correlations (%)

	lepu (news based)	*lepu (3 component)*	*dlipi*	*dlcpi*	*dlfundr*	*dltb10year*	*lvolat*	*dlspx*	*mliquidity*
lepu (news based)	1								
lepu (3 component)	92.8***	1							
dlipi	-17.3***	-15.4***	1						
dlcpi	-15.2**	-13.4**	21.5***	1					
dlfundr	-20.7***	-20.5***	67.5***	33.5***	1				
dltb10year	-21.6***	-19.9***	27.9***	27.9***	31.6***	1			
lvolat	41.7***	43.1***	-18.1***	-19.4***	-31.7***	-23.9***	1		
dlspx	-7.9	-5.8	-4.0	1.8	-3.2	14.4**	-23.9***	1	
mliquidity	-10.3*	-7.8	8.7	2.3	9.7	15.5**	-36.1***	21.0***	1

Correlations are reported as percentages. ***, ** and * shows that the pairwise correlation coefficient is significant at the 1%, 5% and 10% significance levels, respectively.

For the period after Sarbanes-Oxley, the number of IPOs decreased by about 40% on average. The number of IPOs in 2020 is about 90% more than the number of IPOs in the other periods. Overall, the results of the OLS estimation show that EPU, economic growth, and stock market volatility are important factors in determining the number of IPOs.

Table 5. The OLS Benchmark Regressions

	(1) $lipo_t$	(2) $lipo_t$	(3) $lipo_t$	(4) $lipo_t$	(5) $lipo_t$	(6) $lipo_t$	(7) $lipo_t$	(8) $lipo_t$
$lipo_{t-1}$	0.545***	0.539***	0.538***	0.540***	0.544***	0.467***	0.465***	0.464***
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.048)	(0.047)	(0.047)
$lepu_t$	-0.573***	-0.567***	-0.565***	-0.564***	-0.545***	-0.407***	-0.407***	-0.406***
	(0.097)	(0.097)	(0.097)	(0.097)	(0.100)	(0.103)	(0.104)	(0.106)
$dlipi_t$		0.041**	0.039**	0.059	0.053	0.085***	0.084***	0.084**
		(0.018)	(0.019)	(0.038)	(0.038)	(0.037)	(0.037)	(0.037)
$dlcpi_t$			0.047	0.072	0.035	-0.013	-0.014	-0.015
			(0.104)	(0.108)	(0.111)	(0.108)	(0.108)	(0.109)
$dlfundr_t$				-0.002	-0.002	-0.004***	-0.004*	-0.004*
				(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
$dltb10year_t$					0.007	0.004	0.004	0.004
					(0.005)	(0.004)	(0.004)	(0.005)
$lvolat_t$						-0.639***	-0.649***	-0.656***
						(0.116)	(0.123)	(0.127)
$dlspx_t$							-0.002	-0.002
							(0.007)	(0.007)
$mliquidity_t$								-0.101
								(0.539)
boom	-0.030	-0.027	-0.027	-0.024	-0.027	0.234**	0.239***	0.240***
	(0.116)	(0.116)	(0.116)	(0.116)	(0.116)	(0.117)	(0.116)	(0.118)
nber	-0.576***	-0.542***	-0.545***	-0.546***	-0.539***	-0.344***	-0.351***	-0.350***
	(0.108)	(0.107)	(0.108)	(0.108)	(0.107)	(0.116)	(0.117)	(0.117)
covid	0.815***	0.821***	0.822***	0.786***	0.790***	0.888***	0.895***	0.897***
	(0.180)	(0.172)	(0.171)	(0.176)	(0.177)	(0.177)	(0.177)	(0.176)
sox	-0.383***	-0.381***	-0.381***	-0.371***	-0.374***	-0.483***	-0.486***	-0.487***
	(0.079)	(0.079)	(0.079)	(0.080)	(0.079)	(0.074)	(0.073)	(0.072)
Constant	4.118***	4.094***	4.079***	4.056***	3.966***	5.391***	5.430***	5.448***
	(0.525)	(0.524)	(0.523)	(0.519)	(0.537)	(0.542)	(0.560)	(0.538)
R^2	0.734	0.736	0.736	0.737	0.739	0.763	0.763	0.763
Adjusted R^2	0.730	0.731	0.730	0.730	0.731	0.756	0.755	0.754
F-stat.	186.9	169.4	147.9	133.4	138.4	125.1	114.6	104.8
rmse	0.507	0.506	0.506	0.507	0.505	0.482	0.483	0.483
AIC	555.77	555.19	556.99	558.19	557.24	523.31	525.18	527.12
BIC	583.18	586.52	592.24	597.35	600.32	570.30	576.09	587.95

(.) shows Newey-West standard errors. ***, ** and * shows that the individual coefficient is significant at the 1%, 5% and 10% significance levels, respectively. *boom* takes a value of 1 in 1998:09-2000:08. *nber* is equal to 1 in NBER recessions months. The *sox* dummy is equal to 1 for the months after Sarbanes–Oxley, which was implemented on 29 August 2002. The *covid* dummy takes a value of 1 for the year 2020. *rmse* stands for root mean squared error. AIC and SIC are Akaike and Bayesian Information criteria, respectively.

Results of VAR Analysis

After finding correlations between IPO activities and economic policy uncertainty, we explore the possibility of the effect of such uncertainty on the number of IPOs using the VAR. Due to the non-stationary properties of some variables used in modelling IPO activities over time, it is necessary to control whether there is/are the long-run relationship among them. However, the monthly number of IPOs between 1990-2020, the dependent variable, is found to be a stationary series in its levels, so we employ VAR analysis.[4]

According to the information criteria, the appropriate number of lags is found to be 1 or 2. Based on the serial correlations in the residuals and cross-correlations among the residuals of each equation in the VAR model, we estimate the VAR(1) model.[5] The estimated VAR(1) model satisfies the stability condition. The results of the Granger causality tests are summarized in Table 6. Response of the number of IPOs to innovations in EPU is pictured in Figure 2. Finally, the forecast error of variance decompositions of the number of IPOs are given in Table 7.

Table 6. Granger Causality Test Results

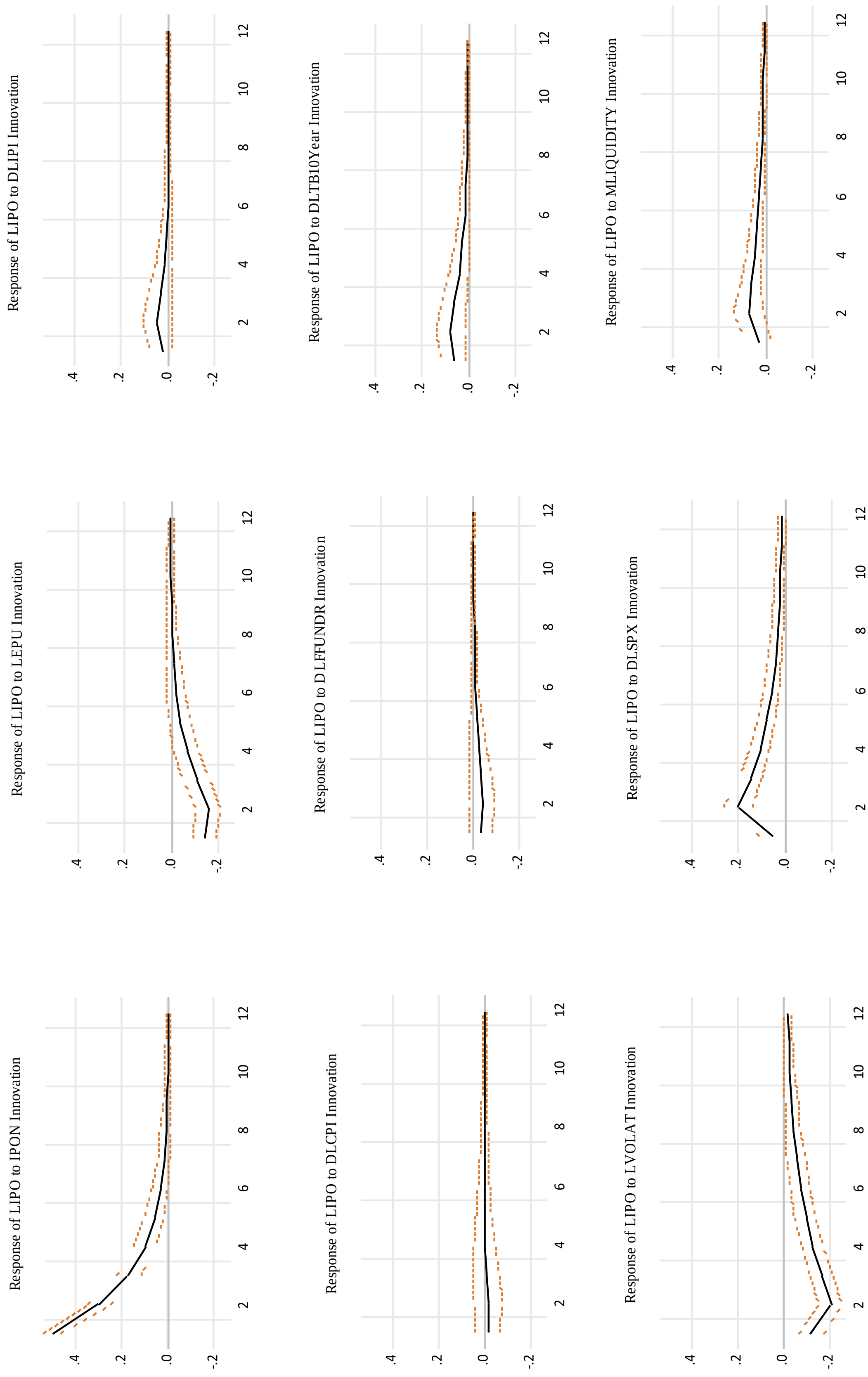
X → Y	***lipo***	***lepu***	***dlipi***	***dlcpi***	***dlffundr***	***dltb10year***	***lvolat***	***dlspx***	***mliquidity***
lipo	-	0.06	2.59	0.07	0.47	1.09	0.20	0.08	0.07
lepu	2.22	-	0.90	1.22	0.04	1.10	3.44^{*}	1.80	6.41^{**}
dlipi	8.94^{***}	3.29^{*}	-	0.39	0.51	1.72	1.51	3.99^{**}	1.75
dlcpi	0.27	0.69	1.22	-	0.97	9.21^{***}	0.004	0.25	0.007
dlfundr	4.94^{**}	1.20	0.63	0.14	-	1.36	2.24	3.46^{*}	0.04
dltb10year	0.004	0.005	38.58^{***}	1.12	31.98^{***}	-	0.90	0.16	0.37
lvolat	15.60^{***}	1.27	1.35	0.16	0.73	0.09	-	1.20	17.21^{***}
dlspx	21.96^{***}	12.69^{***}	9.67^{***}	16.48^{***}	18.87^{***}	12.45^{***}	13.16^{***}	-	2.77^{*}
mliquidity	0.03	0.31	1.61	0.01	0.51	3.64^{*}	0.17	0.43	-

[a] Authors' calculations from the VAR(1) model. The boom, the recession and the COVID-19 months as well as level change after 2001 are controlled. *F*-statistic in this table shows whether there is a causality from a variable in the row to a variable in the column. ***, ** and * shows that the null hypothesis of *X* is not Granger cause of *Y* can be rejected at 1%, 5% and 10% significance levels.

According to Granger (1969), EPU is said to Granger-cause the number of IPOs if the inclusion of lagged values of EPU significantly contributes to the explanation of the number of IPOs in a regression of the number of IPOs on its own past values and all other relevant information. Even if EPU is not a Granger cause the number of IPO, *F*-statistics suggest that it causes stock market volatility (*dlspx*) and market liquidity (*mliquidity*). The monthly growth rate of industrial production (as a proxy for economic growth) and stock market return both Granger-cause EPU at the same time. During the analysis period, there is a bidirectional causation between economic growth and stock market return. The growth rates of industrial production (*dlipi*) and the effective Federal funds rate (*dlfundr*), stock market performance (*dlspx*), and stock market volatility (*lvolat*) are the Granger cause of the number of IPOs. The number of IPOs seems to be the most endogenous variable. Economic growth (*dlipi*) influences the number of IPOs, EPU, and stock market returns (*dlspx*).

While a lagged value of the log of EPU does not contribute to the explanation of the log of the number of IPOs, it contributes to the explanation of the stock market volatility and stock market liquidity. The proxy (the VIX index) used for stock market volatility refers to uncertainty about equity returns, so it shows expectations (a 30-day look-ahead period) about the future of the publicly traded firms. Our results show that EPU has an indirect causality on the number of IPOs by explaining changes in stock market volatility at the 10% significance level. Market liquidity is the monthly aggregate liquidity measure, which is a cross-section average of individual-stock liquidity measures defined by Pastor and Stambaugh (2003). It uses daily returns and volumes of the stocks. This confirms the existence of Granger causality from stock market volatility to liquidity.

Figure 2. Generalized Impulse-Response Functions



Note: ±2 standard error bounds shown as dashed lines.

Among the macroeconomic variables, the growth rates of the 10-year Treasury bond rate (*dltb10year*), effective Federal Funds rate (*dlfundr*), and industrial production (*dlipi*) appear to be endogenous. Based on the test statistics, monthly stock market returns and the growth rate of the 10-year Treasury bond yield play a significant role in explaining economic growth during the 1990-2020 period. Stock market returns also influence economic policy uncertainty (EPU), inflation, the Federal Funds rate, the 10-year Treasury bond growth rate, and market volatility. Inflation acts as a Granger cause for long-term financing costs in the debt market and affects the information embedded in the yield curve, making inflation one of the most exogenous variables. Among stock market indicators, stock market returns seem to be the most exogenous, as they explain changes in all variables and are influenced only by economic growth. This suggests that both the IPO market and macroeconomic factors are largely driven by stock market performance, aligning with findings in the existing literature (Lee, 1992; Tran & Jeon, 2011). While stock market volatility explains variations in the number of IPOs and market liquidity, its own changes are driven by EPU and stock market returns. Overall, the causal relationships among macroeconomic indicators are multidirectional, supporting the use of generalized impulse response analysis.

Figure 2 depicts responses of the number of IPOs to EPU and the other macro and stock market variables of the system up to 15 months. Response of the number of IPOs to an innovation itself significantly vanishes within more than one year. Even though the response of the number of IPOs to an innovation in EPU is about to complete within 10 to 15 months, responses are statistically significant in the first four months. One might interpret that a firm willing to go public might delay its action by approximately 1 to 4 months due to the shocks that increase the EPU which supports the first hypothesis of the paper. An innovation rising market volatility decreases the number of IPOs within the next seven months after a shock. The system approaches an equilibrium in 15 months. Responses of the number of IPOs to the market volatility (*lvolat*) are deeper than the responses to the economic policy uncertainty (*lepu*). It especially significantly affects IPO activity in the second month after a shock that increases the volatility in the stock market.

Response of the number of IPOs to an innovation in the economic growth is insignificantly positive and close to zero in the first five months. This result is compatible with the Granger causality test result that shows there is one-way causal relation from the number of IPOs to economic growth if the significance level is taken as 1% or 5%. This might be interpreted as economic growth leading to the IPO activity. Even though there is a one-way causality from the growth rate of the Fed fund rate to the number of IPOs, responses of IPO activity to the shocks on it are only significantly negative in the first months.

There are significant positive effects of stock market return on the IPO activities in the US economy. These effects are higher in the 3^{rd} and 4^{th} months. This result implies that a good performance in the financial market encourages the firms to go public. The system erases the effects of innovations that increase stock market returns after 10 months. A similar but slightly lower positive response is also observed for market liquidity. Innovations on the inflation rate negatively affect IPO activities especially in the 2^{nd} and 4^{th} months. The system reacts to inflation shocks and goes to equilibrium after 6 months. The response of IPO to an innovation in the growth rate of 10-year TB rate is complete within 4 months with a positive and significant reaction.

According to Table 7, the variance decomposition results show that 100% of IPOs' forecast error variance can be clarified by the current IPO in the first period, and the percentage at the end of the twelfth period is 78.62%. At the end of the twelfth period, innovations to stock market volatility explain approximately 13% of the variation in IPO activities. Only around 2.6% of the variation can be attributed to economic policy uncertainty. Monthly stock market return explains changes in IPO activity by around 4%.

Table 7. Variance Decompositions for the Number of IPOs

Month	***lipo***	***lepu***	***dlipi***	***dlcpi***	***dlffundr***	***dltb10year***	***lvolat***	***dlspx***	***mliquidity***
1	100.000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	89.7984	1.6932	0.2634	0.0238	0.5036	0.2451	4.6200	2.8469	0.0055
3	84.9858	2.4030	0.3618	0.0229	0.8623	0.4452	7.4381	3.4502	0.0307
4	82.4298	2.6393	0.3647	0.0229	0.9770	0.5617	9.3441	3.6224	0.0382
5	80.9565	2.6943	0.3565	0.0250	1.0050	0.6183	10.6357	3.6666	0.0421
6	80.0658	2.6913	0.3519	0.0266	1.0073	0.6459	11.4965	3.6703	0.0444
7	79.5103	2.6765	0.3507	0.0273	1.0036	0.6602	12.0626	3.6629	0.0459
8	79.1568	2.6641	0.3512	0.0275	0.9997	0.6680	12.4317	3.6542	0.0469
9	78.9290	2.6566	0.3524	0.0275	0.9969	0.6723	12.6709	3.6468	0.0476
10	78.7812	2.6530	0.3536	0.0275	0.9950	0.6748	12.8256	3.6413	0.0480
11	78.6848	2.6519	0.3547	0.0275	0.9938	0.6762	12.9254	3.6374	0.0483
12	78.6219	2.6521	0.3556	0.0275	0.9931	0.6771	12.9897	3.6347	0.0485

Robustness check of VAR Results

One might think that both EPU and VIX indexes can be used interchangeably. The VIX index of CBOE is 30-day option-implied volatility in the Standard and Poor's 500 index measuring economic uncertainty. Baker et al. (2016) discussed conceptual differences between these two indexes. Firstly, the VIX reflects implied volatility for the next 30-day period, while the EPU index has no time limit. Secondly, the VIX covers only the uncertainty about equity returns and the EPU index reveals policy uncertainty, and not just for equity returns. Thirdly, the VIX covers only the publicly traded large firms. Therefore, the EPU and the VIX indexes are not used interchangeably in the estimations. However, we follow two strategies to check whether the results are robust or not. First, we estimate the 9-variable VAR system by using the other EPU indexes of Baker at al. (2016). Second, we investigate the effect of EPU on the IPO activity with and without the VIX index in the system.

Following the same estimation procedure, the VAR(1) model estimations with the three-component EPU index imply that the results are robust and irrespective of using either the news-based index or the three-component index. Estimates are also repeated by eliminating market volatility (the VIX index) from the system. The number of lags for the VAR model is selected as either 1 or 3 by the information criteria. While correlations among the residuals of the equations show there might be misspecification for the VAR(1) model, this misspecification is not observed in the residuals of VAR(3) model. According to impulse responses obtained by utilizing the VAR(3) model, shocks that increase economic policy uncertainty significantly decrease the number of IPOs in the first 4 months as given in Figure 2. Even though variance decompositions confirm the results reported in Table 5 for the EPU index, eliminating the market volatility from the model increases the explanatory power of stock market returns and market liquidity in the changes of the number of IPOs. This means that the results obtained for EPU are stable and they support the result for one-way causality from stock market returns to market volatility. It should be noted that the Granger causality result almost remains the same for the rest of the variables.[6]

The VIX index is the most used proxy for overall economic uncertainty (Baker et al., 2016). Therefore, we omit the EPU index from the model and repeated the VAR analysis. The results show that responses of the number of IPOs to the shocks in the VIX index are significantly negative in the first 7 months. This index also explains 13% of the error forecast variances of the number of IPOs on average. The results also show that the existence of the VIX index collects the effect of other stock market indicators on the IPO market. Both the EPU index and the VIX index are involved in the model. Its extra effect is shared by the EPU and market returns. The OLS estimations show that the marginal contribution of the VIX index is higher than the marginal contribution of the EPU index. In terms of the direction, impulse responses show no different reaction of the number IPOs to the shocks to either index. However, the IPO market's reaction to policy uncertainties is shorter than its reaction to market volatility shocks.

The findings of this paper can be compared to those of Tran and Jeon (2011) and Angelini and Foglia (2018). Both look at the macroeconomic factors that influence a firm's decision to go public. The first paper is concerned with the US market, whereas the second is concerned with the UK market. First, these two papers examine the cointegration between the number of IPOs and macroeconomic variables due to the non-stationary features of the series in their analysis periods. Therefore, their interpretations are based on vector autoregressive error correction models (VECM).[7] According to Tran and Jeon (2011), the stock market return, industrial production growth rate, inflation, market volatility, and liquidity Granger-cause the number of IPOs during 1970-2005. According to Angelini and Foglia (2018), stock market volatility, the growth rate of industrial production and the 10-year interest rate have a causal relationship with the number of IPOs in the UK market for the period of 1996 to 2016. Consistent with these two papers, our paper shows that stock market volatility is the Granger cause of the number of IPOs.

According to these two studies, the S&P500 return, and the Fed funds rate's growth rate play the most prominent roles in explaining the variation in the forecast error of the number of IPOs in the US market, but stock market volatility and economic growth explain the forecast error variance in the UK market. The response of the number of IPOs to macroeconomic shocks takes place mostly during the first 3 months after the shocks arrive in the US market. Responses are mostly completed within the period of 6 months to 1 year in the US; however, the effects of the innovations are not wiped out for more than a year in the UK market.

According to our findings, the effect of stock market volatility can be overstated, especially in impulse response research, if economic policy uncertainty is not handled in these types of models for IPO activities. Our results reveal that the number of IPOs reacts negatively to EPU and volatility shocks; however, the system wipes out the disequilibrium faster after an EPU shock than after a volatility shock.

Results of Markov Regime Switching Modeling

Non-linear nature of MRS models requires testing the linearity. We performed the BDS test following the methodology of Broock et al. (1996), along with the RESET test to determine if a non-linear model provides a more suitable fit for the number of IPOs over time. Applying the BDS test involves analyzing the correlation integrals of the IPO series directly, whereas the RESET test necessitates estimating an AR(p) model for the number of IPOs. The test results reported in Table A.2 (in Appendix) show that non-linear models can capture the fluctuations in the number of IPOs.

Therefore, Table 8 reports MRS estimation results. We assume that there are two regimes. High IPO months change with less fluctuation than low IPO months, as mentioned in the introduction: low-mean/high-variance (*regime 1*) and high-mean/low-variance (*regime 2*).

Table 8. Markov-regime Switching Model Estimates

Variables	**(1)** $lipo_t$	**(2)** $lipo_t$	**(3)** $lipo_t$	**(4)** $lipo_t$	**(5)** $lipo_t$	**(6)** $lipo_t$
	Regime 1: low-mean/high variance					
constant	2.074^{***}	2.087^{***}	-0.139	0.616^{***}	3.043^{***}	2.518^{***}
$lipo_{t-1}$			0.977^{***}	0.588^{***}	0.734^{***}	0.524^{***}
$lipo_{t-2}$				0.114^{*}	0.138^{*}	0.197^{***}
$lepu_t$					-0.630^{***}	-0.226^{***}
$dlipi_t$						0.102^{***}
dlcpi	0.088					0.084
$dlfundr_t$						-0.004^{*}
dltb10year						0.003
lvix						-0.243^{**}
dlspx						0.016^{**}
mliquidity						-0.029
variance	0.682	0.781	0.511	0.599		0.424

Table 8. Markov-regime Switching Model Estimates (Continue)

Variables	(1) *lipo_t*	(2) *lipo_t*	(3) *lipo_t*	(4) *lipo_t*	(5) *lipo_t*	(6) *lipo_t*
	Regime 2: high-mean/low variance					
constant	3.585***	3.613***	1.454***	1.646***	1.394***	4.952***
$lipo_{t-1}$			0.581***	0.333***	0.412***	0.516**
$lipo_{t-2}$				0.216***	0.243***	0.168
$lepu_t$					-0.043	-0.406***
$dlipi_t$						0.109
dlcpi						0.084
$dlfundr_t$						-0.007***
lvix						-1.133***
dlspx						-0.047***
mliquidity						-0.380
variance	0.682	0.340	0.288	0.269		0.183
	Transition probabilities					
p_{11}	0.991	0.993	0.585	*0.991*	0.562	0.088
p_{21}	0.022	0.021	0.881	*0.023*	0.487	0.074
	Testing the equality of selected coefficients across regimes					
constant	370.79***	683.43***	138.55***	11.970***	4.760**	2.41
$lipo_{t-1}$	-	-	15.78***	5.032**	10.290***	0.000
$lipo_{t-2}$	-	-	-	1.060	1.110	0.05
variance	-	99.46***	50.02***	85.46***	8.920***	11.79***
	Model Selection Criteria					
AIC	2.193	1.992	1.582	*1.503*	1.469	1.526
HQIC	2.214	2.017	1.615	*1.545*	1.519	1.635
SBIC	2.245	2.055	1.666	*1.609*	1.596	1.801

***, ** and * shows that the individual coefficient is significant at the 1%, 5% and 10% significance levels, respectively. *** and ** also show chi-squared test statistics reject the null of the selected coefficients are equal across regimes at the 1% and 5% significance levels, respectively. AIC, HQIC and SBIC are Akaike, Hannan-Quinn and Schwarz Bayesian information criteria, respectively.

Model (1) assumes that regime change occurs only in its intercepts with the same variance. Models (2) and (4) assume that the marginal effect of the number of IPOs on itself changes between these two regimes. Model (5) extends this assumption for the coefficients of EPU. Model (6) adds macro-economic factors, and stock market indicators to the model. In other words, Model (5) and Model (6) imply that if there is a regime change in the number of IPOs whether these factors will have an impact on it by switching across regimes or not.[8] Details can be found in Hamilton (1989 and 1994) and Kim and Nelson (1999).

According to Model (1), the expected number of IPOs per month is 8 in regime 1 and 36 in regime 2 with the same variance. Model 2 produces these values as 8 for regime 1 and 37 for regime 2. When the regime is low-mean/high-variance, these two models yield a probability of 99.1% of staying in the low-mean/high-variance regime. Based on the model selection criteria, we select the number of lagged terms of the number of IPOs as 2. A 1% rise in the number of IPOs in the previous month raises the number of IPOs in the current month by 0.59% in the low-mean regime and 0.33% in the high-mean regime, according to Model 4. In the low-mean regime, the effect of the number of IPOs in the previous two months is less than the one in the high-mean regime. These findings supports hypothesis 2a that posits the data-generating process for the number of IPOs has changed over time.

We test the equality of constants, variances, and the coefficients of lagged values of the number of IPOs across regimes reported in Table 7. Constants, the expected values of the number of IPOs, and variances are not similar across the regimes, according to the test results. There is no evidence that the coefficient of the two-lag term of the number of IPOs varies between regimes.

Estimates obtained with Model (5) show that a 1% increase in EPU index significantly decreases the number of IPOs by 0.63% in low-mean period. Its negative effect is insignificantly very small high mean regime. This supports the hypothesis 2b that is “EPU has contributed to this regime change”. Effect of EPU on the number of IPOs when the macro and stock market variables are added to the model is significantly -0.23% in low-mean/high-variance regime and -0.41% in high-mean/low-variance regime, respectively (Model 6). When the estimations are repeated with the three-component EPU index, we obtain similar results except the marginal effect of EPU is found to be not significant in high-mean/low-variance regime.[9]

According to estimates of Model (6), the marginal effect of stock market volatility was significantly negative. The marginal effect of the growth rate of the industrial production index is similar in these two regimes but it is insignificant in high-mean regime. Growth rate of the effective Fed funds rate has a smaller significant negative effect on the number of IPOs under two regimes. A 1% rise in stock market return increases the number of IPOs by 0.02% in the low-mean regime whereas decreases it by 0.05% in the high-mean regime. A similar result is obtained when the VIX index is excluded from the model. Estimations show that inflation, 10-year TB rate, and stock market volatility do not significantly explain changes in the number of IPOs in low-mean and high mean regimes. According to Model (6), the expected number of IPOs after controlling the other factors is the same but the variances differ across regimes.

All variables in a VAR system are considered endogenous. The results of the Granger causality test indicate that causality relationships are multidirectional, implying that one or more macro variables or stock market indicators (such as the growth rates of industrial production index, effective Fed fund rate, stock market return, and volatility) could be endogenous. To address this, we apply a multivariate Markov regime-switching model that incorporates lagged values (first, second, and third lags) of these endogenous variables, as well as lagged values of exogenous variables. Despite the estimation results of Model (6) showing minimal changes, it is crucial to exercise caution in their interpretation due to the presence of these endogenous explanatory variables in the model.

Among these models three information criteria both Model (4) and Model (5) have a better performance than the other models. The one-step predictions, the predicted number of IPOs obtained by using smoothed probabilities, and the residuals obtained by using filtered probabilities are also examined. Model 4 has a better fit in terms of prediction performance. Therefore, Model 4 is selected to obtain the expected duration of the process in a given regime. The expected durations given in Table 9 show that, average time the number of IPOs spends in a low-mean/high-variance and high-mean/low-variance regimes are 122 and 42 months, respectively. In other words, low-mean/high-variance regime persists for about 122 months and high-mean/low-variance regime persists for about 42 months.

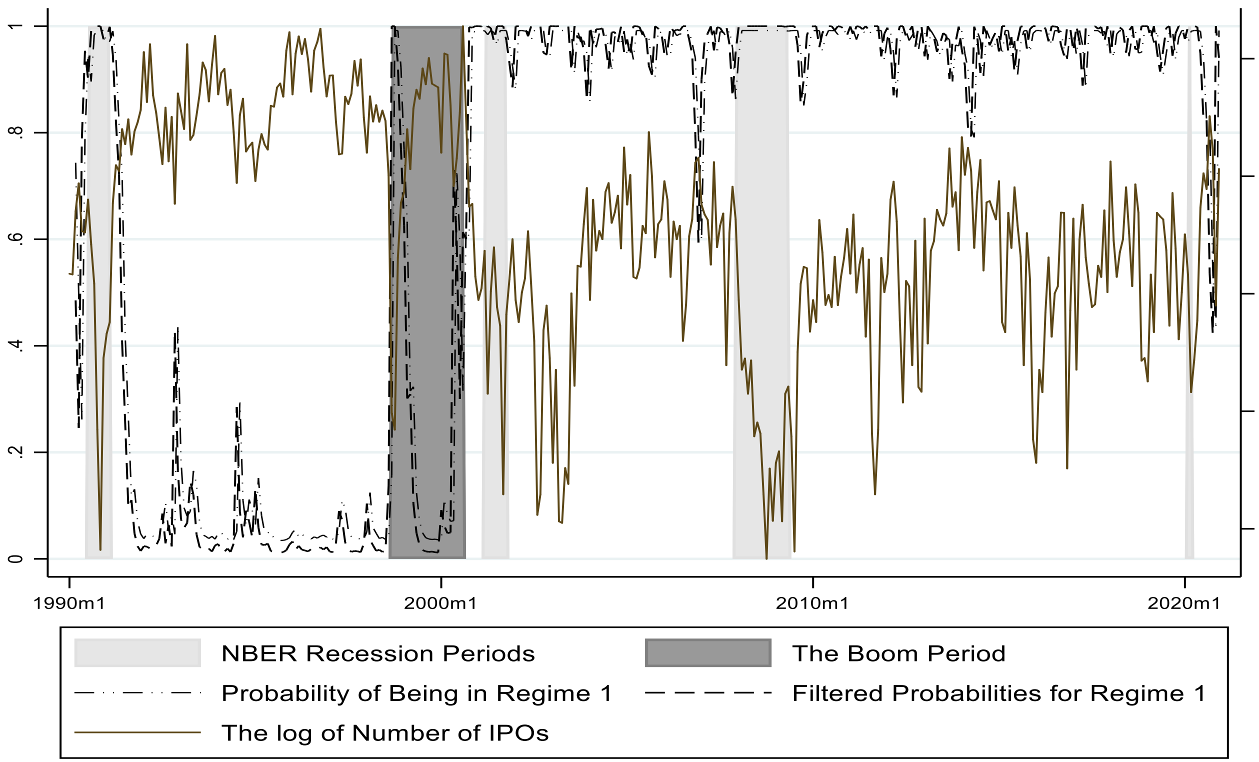
Table 1. Expected duration

	Estimate*	Std. Err.	[95% Conf. Interval]	
Regime 1	122.135	89.440	29.496	515.936
Regime 2	42.131	27.113	12.300	150.720

* shows the average length of low-mean/high-variance periods and high-mean/low-variance periods for the U.S. IPO market.

Figure 3 shows the natural logarithm of the number of IPOs (solid line) over time with the probability of being in the low-mean/high-variance regime (dashed-dotted line) and filtered probabilities (dashed line). The boom period (dark grey) and NBER recession months are shaded (light grey). The likelihood of being in the low-mean/high-variance regime during 1990:07-1991:02 period, the sample's first recession phase, is very close to 1. This can be seen in other recession months as well. The IPO market is in a high-mean/low-variance regime during the boom period, from 1998:09 to 2000:08. The low-mean/high-variance regime persists in the US IPO market following the boom period, as shown in the graph. During the global financial crisis and the COVID-19 pandemic, the probability of being in this regime shifted from low-mean/high-variance to high-mean/low-variance regime. The filtered probabilities also show almost the same pattern.

Figure 3. Probability of being in Low-mean/High-variance Regime with Filtered Probabilities



Note: The *y*-axis on the left indicates probabilities, while the *y*-axis on the right shows the logarithm of number of IPOs.
Being in Regime 1 indicates the probability of the IPO market being in a low-mean/high variance regime. The filtered probabilities for Regime 1 represent the probabilities of the IPO market being in such a regime, obtained by utilizing all of the available observations in the dataset.

6. Conclusion

Both economic policy uncertainty and macroeconomic conditions, as well as the stock market feed each other. As the IPO market is not independent from uncertainties arising from economic policy changes, this paper aimed to connect changes in the number of IPOs over time to changes in economic policy uncertainty after controlling the other factors. When taking into consideration the specific case of the US, which has the strongest IPO market, even though it is a free market economy in consumer goods and business services, the government imposes regulations to protect the good of all. As a result, understanding how firms react to uncertainty coming from changes in economic policies and regulations on the IPO market would be beneficial. With the increasing popularity of economic policy uncertainty indexes of Baker et al. (2016), investigating the possible effects of policy uncertainties at macro and microeconomic perspective will lead to expand the related empirical literature. This paper contributes to the IPO literature by examining the impact of economic policy uncertainty within the aspects of macroeconomics.

According to findings of the paper, the EPU has a detrimental effect on IPO activities. It affects the number of firms going public in the current period even though going public is a process generally taking 4 to 8 months. The IPO market responses to shocks to the EPU particularly during the first four months. When the relationship between the number of IPOs and the EPU index is evaluated over time with the use of VAR analysis, it is shown that the IPO market has a large reaction to uncertainty shocks in the coming first month.

Empirical findings also reveal that the predicted number of IPOs varies across low-mean or low-IPO and high-mean or high-IPO regimes that confirms the first leg of the second hypothesis. Even though the evidence of the contribution of the EPU to this regime change is limited, this paper shows that EPU is an important factor in going public when the IPO market is in low-mean/high variance regime.

The negative effect of economic policy uncertainty (EPU) on IPO fluctuations has significant policy implications for both firms and investors. Firms should strategically time their IPOs, implement risk management strategies, and seek regulatory support during uncertain economic policy periods. Policymakers can encourage firms by providing stability and incentives, simplifying regulations, and promoting transparent communication with investors. On the investor side, diversification, a long-term perspective, and access to reliable information are key to navigating IPO fluctuations driven by economic policy uncertainty. Policymakers should prioritize investor education and supportive policies to foster confidence during uncertain economic times, ensuring a stable and conducive IPO market environment.

The study's findings are specific to the US economy, which has its unique characteristics and regulatory environment. EPU and its impact on IPO activities may vary across different countries or regions with distinct economic and political conditions. Therefore, while the results provide valuable insights and implications for the US context, generalizing these findings to other economies may require further research and consideration of specific local factors.

The paper's possible limitations include potential endogeneity, and the period covered. To improve future research, cross-country analyses, sector-specific studies, and longitudinal research can provide a more comprehensive understanding of the impact of EPU on IPO fluctuations.

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End Notes

1. *Underpricing in the IPO (Initial Public Offering) market refers to the phenomenon where the offering price of a company's shares, set before they are listed on a stock exchange, is lower than the price at which the shares trade in the public market on the first day of trading. This difference results in a positive first-day return for investors who buy shares at the IPO price.*
2. *The integration order of the series is determined by using the Augmented Dickey-Fuller of Dickey and Fuller (1979, 1981), the generalized least squares detrended Dickey-Fuller (DF-GLS) test of Elliot, Rothenberg, and Stock (1996). To check the effect of structural changes on the unit root test results, we also use the tests developed by Zivot and Adrews (1992). The results show that the number of IPOs, the EPU index, market volatility, and market liquidity do not have unit roots in their levels. The industrial production index, the consumer price index, effective Fed funds rate, S&P500 index, and 10-year TB rate are found to be stationary in their first-differenced versions. All calculations and estimations are done with the use of stationary values of the series.*
3. *Market liquidity is based on Pastor and Stambaugh (2003) and is available at https://finance.wharton.upenn.edu/~stambaug/liq_data_1962_2020.txt (Access Date: 26 October 2020).*
4. *The reasoning behind using the VAR analysis is explained according to Engle and Granger's (1987) cointegration definition, "If all elements of the vector y_t are I(d) and there exists a cointegrating vector such that $b'y_t \sim I(d-b)$ for any $b > 0$, the vector process is said to be cointegrated, CI(d,b)." This definition requires d to be greater than 0. Furthermore, all variables must be integrated in the same order (d). Because there is no I(2) variable in the model, multicointegration cannot be tested. However, it is possible to determine if the I(1) variables in this model are cointegrated with each other. If they are, an I(0) component will be produced. In this scenario, our I(0) variables cannot be cointegrated with this I(0) component(s), since the definition of cointegration is violated.*
5. *Even though cross-correlations show that residuals of the nine equations are mostly not correlated in lagged terms, residuals of the economic growth and the growth rate of effective Fed funds rate equations, and the EPU index and VIX index equations are found to be contemporaneously correlated (about 50%). Therefore, we also estimate the VAR(1) model by putting short-run constraints on these variables. Responses of the number IPOs to an innovation on EPU index remain the same.*
6. *The results are available upon request from the corresponding author.*
7. *According to research on the Pakistani IPO market, macroeconomic factors with foreign direct investment and stock market performance also influence variations in the number of IPOs (Mehmood et al., 2021).*
8. *All variables in the system are endogenous in VAR modeling. The findings of the Granger causality test reveal that causality relationships are multidirectional. This means that one or more macro-variables or stock market indicators (the growth rates of industrial production index and effective Fed fund rate, stock market return and volatility) could be endogenous. We apply a multivariate Markov regime-switching model with lagged values (first, second, and third lags) of these variables. While the estimation results of Model 5 remain largely unchanged, it is essential to interpret them cautiously due to the presence of endogeneity.*
9. *We conduct the estimation using the smooth transition VAR to examine the impact of EPU on IPO fluctuations. However, the results reveal that the coefficient of EPU is insignificantly negative in both regimes.*

References

Ameer, R. (2012). Macro-economic factors and initial public offerings (IPOs) in Malaysia. *Asian Academy of Management Journal of Accounting and Finance*, *8*(8), 41-67.

Angelini, E., & Foglia, M. (2018). The relationship between IPO and macroeconomics factors: An empirical analysis from UK market. *Annals of Economics and Finance*, *19*(1), 319-336.

Aslan, Ç., & Acikgoz, S. (2023). Analysis of global economic policy uncertainty and export flows for emerging markets with panel VAR modeling. *International Journal of Emerging Markets*, *18*(9), 2790-2815. https://doi.org/10.1108/IJOEM-12-2020-1570

Baker, M., & Wurgler, J. (2002). Market timing and capital structure. *Journal of Finance*, *57*(1), 1-32. https://doi.org/10.1111/1540-6261.00414

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593-1636. https://doi.org/10.1093/qje/qjw024

Born, B., & Pfeifer, J. (2014). Policy risk and the business cycle. *Journal of Monetary Economics*, *67*, 68-85. https://doi.org/10.1016/j.jmoneco.2014.07.012

Boulton, T. J. (2022). Economic policy uncertainty and international IPO underpricing. *Journal of International Financial Markets, Institutions and Money*, *81*, 101689. https://doi.org/10.1016/j.intfin.2022.101689

Brau, J. C., Francis, B., & Kohers, N. (2003). The choice of IPO versus takeover: Empirical evidence. *Journal of Business*, *76*(4), 583-612. https://doi.org/10.1086/377032

Broock, W. A., Scheinkman, J. A., Dechert, W. D., & LeBaron, B. (1996). A test for independence based on the correlation dimension. *Econometric Reviews*, *15*(3), 197-235. https://doi.org/10.1080/07474939608800353

Chan, Y. C., Saffar, W., & John Wei, K. C. (2021). How economic policy uncertainty affects the cost of raising equity capital: Evidence from seasoned equity offerings. *Journal of Financial Stability*, *53.* https://doi.org/10.1016/j.jfs.2020.100841

Çolak, G., Durnev, A., & Qian, Y. (2017). Political uncertainty and IPO Activity: Evidence from U.S. gubernatorial elections. *Journal of Financial and Quantitative Analysis*, *52*(6), 2523-2564. https://doi.org/10.1017/S0022109017000862

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*, 427-431. https://doi.org/10.2307/2286348

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, *49*, 1057-1072. https://doi.org/10.2307/1912517

Elliott, G., Rothenberg, J., & Stock, J. H. (1996). Efficient tests for an autoregressive unit root. *Econometrica*, *64*, 813-836. https://doi.org/10.2307/2171846

Engle, R. F., & Granger, C. W. J. (1987). Co-Integration and error correction: representation, estimation, and testing. *Econometrica*, *55*(2), 251-276. https://doi.org/10.2307/1913236

Erel, I., Julio, B., Kim, W. N., & Weisbach, M. S. (2012). Macroeconomic conditions and capital raising. *The Review of Financial Studies*, *25*(2), 341-376. https://doi.org/10.1093/rfs/hhr085

Ghirelli, C., Pérez, J. J., & Urtasun, A. (2019). A new economic policy uncertainty index for Spain. *Economics Letters*, *182*, 64-67. https://doi.org/10.1016/j.econlet.2019.05.021

Gleason, K., Johnston, J., & Madura, J. (2008). What factors drive IPO aftermarket risk? *Applied Financial Economics*, *18*(13), 1099-1110. https://doi.org/10.1080/09603100701466062

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, *37*(3), 424-438. https://doi.org/10.2307/1912791

Gupta, V., Singh, S., & Yadav, S. S. (2023). Disaggregated IPO returns, economic uncertainty and the long-run performance of SME IPOs. *International Journal of Emerging Markets*, *18*(10), 3847-3867. https://doi.org/10.1108/IJOEM-09-2020-1098

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, *57*(2), 357-384. https://doi.org/10.2307/1912559

Hamilton, J. D. (1994). *Time series analysis*. Princeton University Press.

Hasset, K. A., & Metcalf, G. E. (1999). Investment with uncertain tax policy: Does random tax policy discourage investment? *Economic Journal*, *109*(457), 372-393. https://doi.org/10.1111/1468-0297.00453

Higgs, R. (1997). Regime uncertainty: Why the Great Depression lasted so long and why prosperity resumed after the War. *Independent Review*, *1*, 561-590. http://www.jstor.org/stable/24560785

Ibbotson, R. G., Sindelar, J. L., & Ritter, J. R. (1994). The market's problems with the pricing of initial public offerings. *Journal of Applied Corporate Finance*, 66-74. https://doi.org/10.1111/j.1745-6622.1994.tb00395.x

Kim, C. J., & Nelson, C. R. (1999). *State-space models with regime switching: Classical and Gibbs-sampling approaches with applications*. The MIT Press.

Lee, B. (1992). Causal relationships among stock returns, interest rates, real activity, and inflation. *Journal of Finance*, *47*, 1591-603. https://doi.org/10.2307/2328955

Loughran, T., Ritter, J. R., & Rydqvist, K. (1994). Initial public offerings: International insights. *The Pacific-Basin Finance Journal*, *2*, 165-199. https://doi.org/10.1016/0927-538X(94)90016-7

Mehmood, W., Mohd-Rashid, R., Ong, C. Z., & Abbas, Y. A. (2021). Factors driving IPO variability: Evidence from Pakistan Stock Exchange. *Journal of Economics, Finance and Administrative Science*, *26*(52), 300-316. https://doi.org/10.1108/JEFAS-04-2021-0036

Mills, T.C. (2019). *Applied time series analysis: A practical guide to modeling and forecasting*. Academic Press.

Nagar, V., Schoenfeld, J., & Wellman, L. (2019). The effect of economic policy uncertainty on investor information asymmetry and management disclosures. *Journal of Accounting and Economics*, *67*(1), 36-57. https://doi.org/10.1016/j.jacceco.2018.08.011

Omran, M., & Pointon, J. (2001). Does the inflation rate affect the performance of the stock market? The case of Egypt. *Emerging Markets Review*, *2*(3), 263-279. https://doi.org/10.1016/S1566-0141(01)00020-6

Pagano, M., Panetta, F., & Zingales, L. (1998). Why do companies go public? An empirical analysis. *Journal of Finance*, *53*, 27-64. https://www.jstor.org/stable/117434

Pastor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, *111*(3), 642-685. https://doi.org/10.1086/374184

Pastor, L., & Veronesi, P. (2005). Rational IPO waves. *Journal of Finance*, *60*(4), 1713-1757. https://doi.org/10.1111/j.1540-6261.2005.00778.x

Pastor, L., & Veronesi, P. (2012). Uncertainty about government policy and stock prices. *Journal of Finance*, *67*, 1219-1264. https://doi.org/10.1111/j.1540-6261.2012.01746.x

Pastor, L., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics*, 110, 520-545. https://doi.org/10.1016/j.jfineco.2013.08.007

Pesaran, M. H., & Shin, Y. (1997). Generalized impulse response analysis in linear multivariate models. *Economics Letter*, *58*, 17-29. https://doi.org/10.1016/S0165-1765(97)00214-0

Qi, X. Z., Ning, Z., & Qin, M. (2022). Economic policy uncertainty, investor sentiment and financial stability: An empirical study based on the time varying parameter-vector autoregression model. *Journal of Economic Interaction and Coordination*, *17*, 779-799. https://doi.org/10.1007/s11403-021-00342-5

Rodrik, D. (1991). Policy uncertainty and private investment in developing countries. *Journal of Development Economics, 36*(2), 229-242. https://doi.org/10.1016/0304-3878(91)90034-S

Sahinoz, S., & Cosar, E. E. (2018). Economic policy uncertainty and economic activity in Turkey. *Applied Economics Letters*, *25*(21), 1517-1520. https://doi.org/10.1080/13504851.2018.1430321

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica*, *48*(1), 1-48. https://doi.org/10.2307/1912017

Tran, A. L., & Jeon, B. M. (2011). The dynamic impact of macroeconomic factors on initial public offerings: Evidence from time-series analysis. *Applied Economics 43*(23), 3187-3201. https://doi.org/10.1080/00036840903493267

Watson M., & Stock, J. (1999). Business cycle fluctuations in U.S. macroeconomic time series. In J. Taylor, and M. Woodford (Eds.), *Handbook of macroeconomics* (pp. 3-64). Elsevier.

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 Modeling*, *79*, 47-56. https://doi.org/10.1016/j.econmod.2018.09.028

Zivot, E., & Andrews, D. W. K. (1992). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business and Economic Statistics*, *10*(3), 251-270. https://doi.org/10.2307/1391541

Appendix

Table A1. Linearity Tests

The Test	$lipo_t$	
The BDS Test	Dimension	*z*-stat.
	2	27.743*
	3	30.432*
	4	33.141*
	5	36.605*
	6	41.220*
The RESET Test	*k*	*F*-stat.
	2	87.810*
	3	88.465*
	4	93.448*

Notes:

1. The BDS test operates by comparing the observed cross-correlations with those expected under the assumption of linearity. If the observed cross-correlations significantly deviate from the expected values (rejecting the null hypothesis), it suggests the presence of nonlinear behavior in the data.
2. The dimension refers to the number of lags or delays used to calculate the cross-correlations between data points.
3. For the RESET test, AR(2) had the best fit according to both AIC and SIC. *k* shows the power of the fitted IPO values used in the test regression. The null hypothesis for the RESET is the model's functional form is correctly specified, and there are no omitted variables or misspecifications.
4. * shows that the null hypothesis can be rejected at 1% significance level.