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How Economic Policy Uncertainty Affects the Cost of Raising Equity Capital: Evidence from Seasoned Equity Offerings*

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Abstract
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JEL Classification: G24; G32; G38
Keywords: Economic policy uncertainty; Seasoned equity offerings; SEO discounts

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Abstract

Economic policy uncertainty (EPU) increases the cost of raising equity capital, especially when the economy is weak. A one standard deviation increase in the EPU index developed by Baker, Bloom, and Davis (2016) is associated with a 43 basis point increase in the price discount of seasoned equity offerings (SEOs) during the 2000-2014 period. The cross-sectional analysis shows that the EPU effect on SEO discounts is stronger for firms with greater dependence on government spending, less informative stock price, or a smaller EPU beta. Moreover, there are fewer SEO activities in periods when there is a high degree of policy uncertainty.

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1. Introduction

A number of very surprising political events were witnessed in recent years. For example, the world's major media and popular polls were way off on their predictions even before the votes were counted in Britain's referendum on leaving the European Union (popularly known as Brexit). As documented in various theoretical studies (e.g., Bernanke (1983), Bloom, Bond, and van Reenen (2007), and Bloom (2009)), the increase in uncertainty of government policy associated with these political events will exert a significantly negative effect on the real economy, including declines in employment and output. Anecdotal evidence also indicates that businesses pay attention to policy uncertainty when making corporate finance decisions. For example, in 2019 the IPO sentiment radar proposed by the consulting firm EY contains factors like "implications from global trade tensions", "US election", "monetary policy", and "Brexit". EY suggests that pre-IPO companies should analyze how these factors may affect their business and valuations and be more flexible in timing and pricing.

It is important to understand how policy uncertainty affects managers' investment and financing decisions, which are important for a country's long-run economic growth. Baker, Bloom, and Davis (2016) develop an economic policy uncertainty (EPU) index and find that changes in that index have a negative effect on contemporaneous quarterly capital expenditures for firms that are sensitive to policy uncertainty. Gulen and Ion (2016) document a negative effect of the average level of the EPU index in a given quarter on corporate capital expenditures in the following eight quarters, particularly for firms with irreversible investment. Economic policy uncertainty also has a negative effect on mergers and acquisitions (M&As), another important form of corporate investment. Bonaime, Gulen, and Ion (2018) show that an increase in the EPU index leads to a decrease in acquisition likelihood and aggregate deal volume and value. Similarly, Nguyen and

Phan (2017) find that increases in the EPU index lead to a decrease in the probability and deal value of M&As and an increase in time it takes to complete the deals.[1]

In this paper, we focus on the other side of corporate investment: corporate financing. In a related study, Çolak, Durnev, and Qian (2017) examine the effect of political uncertainty on firms' financing decisions in the context of initial public offerings (IPOs).[2] They find that there are fewer IPOs originating from a state when it is scheduled to have a gubernatorial election, and the offering price-to-value ratio is lower during election years than during nonelection years. While Çolak, Durnev, and Qian (2017) provide the insightful empirical evidence on the relation between state-level political uncertainty and the IPO decision of young and largely localized private firms, it is also important to understand the extent to which policy uncertainty within the whole country affects the financing decisions of the wider set of seasoned public firms.

To address this important research question, we examine the effects of EPU on seasoned equity offerings (SEOs). In terms of raising capital through equity issuance, the funds collected by firms from SEOs are slightly larger than that from IPOs. During 2001 to 2014, the aggregate proceeds collected by U.S. firms from IPOs equal $396 billion whereas those from SEOs are $458 billion.[3] For public companies, SEO represents an important and repeated channel for raising outside capital for their operation and investment. While a private firm can only conduct one IPO

[1] There are also studies documenting that economic policy uncertainty affects firms' capital structure. Datta, Doan, and Iskandar-Datta (2019) show that high policy uncertainty leads firms to shorten debt maturity. Using a broad range of uncertainty measures including the EPU index and its sub-indices, Çolak, Gungoraydinoglu, and Öztekin (2018) show that uncertainty dramatically slows down firms' adjustment toward their optimal capital structure.

[2] Although they are similar and related, there are some differences between economic policy uncertainty and political uncertainty. According to Baker, Bloom, and Davis (2016), economic policy uncertainty refers to who will make economic policy decision, what economic policy actions will be taken and when, and the economic effects of policy actions or inactions. On the other hand, political uncertainty is typically associated with specific political events such as presidential elections and gubernatorial elections. While elections may be sources of uncertainty, they do not tell us how much policy uncertainty changes during these elections (Gulen and Ion (2016)).

[3] The value of aggregate proceeds from IPOs and SEOs are collected from Professor Jay Ritter's website https://site.warrington.ufl.edu/ritter/ipo-data/ and compiled by the authors from the SDC New Issues database, respectively.

during its entire lifetime, there is no limit on the number of SEOs for public firms as long as there is an adequate market demand for the new shares. The importance of SEO to corporate financing is also supported by the finding of DeAngelo, DeAngelo, and Stulz (2010) that most issuers would have run out of cash by the year after the SEO had they not received the offer proceeds.

We study the impact of EPU on SEO activity from the perspective of pricing and volume of new issues. During the SEO process, the offering prices of new shares are often established shortly before the offering day. When setting an offering price, underwriters have to take into account the uncertainty and information asymmetry faced by the issuing firms and potential outside investors. As such, new SEO shares are often offered at a discount relative to the prevailing market price. If underwriters and investors factor in economic policy uncertainty to the SEO pricing process, the required SEO discount will increase with an increase in uncertainty and information asymmetry. Further, underwriters and investors will demand more protection on the potential fall in stock price in the aftermarket and require a higher SEO discount.

The EPU index is a weighted average measure consisted of three components: news events, tax code changes, and monetary and fiscal policy forecast dispersions. It is noted that in our setting, the EPU index provides further advantages over gubernatorial elections as it reflects economic policy uncertainty more directly. First, the EPU index is designed to reflect policy uncertainty related to the national economic environment, whereas gubernatorial elections are state specific and their effects on the aggregate economy are relatively less obvious. Second, the EPU index is a monthly measure which tracks the fluctuation of economic policy uncertainty over a shorter horizon compared with gubernatorial elections which occur once every several years. As the SEO pricing and offering process react to continuously changing environments, this renders the EPU index a more suitable uncertainty measure to address our research question.

Using SEO data from a 30-year period between 1985 and 2014, we find that EPU exerts a directly negative effect on the pricing of SEO shares. The effect is stronger during the second half of our sample period (2000-2014), where a one standard deviation increase in the EPU index is associated with a 43 basis point increase in SEO discounts. In addition, the EPU effect is stronger when the economy is weaker. These results are consistent with the prediction of Pástor and Veronesi's (2013) model, which shows that a higher degree of policy uncertainty is associated with a higher market risk premium, particularly when the economy is weak. Our results are robust after correcting various endogeneity concerns in our analysis.

We conduct cross-sectional analysis to investigate which types of firms suffer more from an increase in policy uncertainty. Consistent with the results of Baker, Bloom, and Davis (2016), Gulen and Ion (2016) and Çolak, Durnev, and Qian (2017) on corporate investment and IPO decisions, we find that policy uncertainty exerts stronger negative effects on firms which are more dependent on government contracts for their revenues. Our result indicates that these firms have to offer larger discounts in their SEO shares when there is a rise in EPU. What is more, we also find that stock price informativeness and sensitivity of stock returns to EPU also play a role in the effects of policy uncertainty. In particular, firms with less informative stock prices, as proxied by a low level of analyst coverage or a high degree of idiosyncratic volatility, together with firms with stock returns more negatively correlated with the increase in the EPU index tend to have higher SEO discounts during periods of greater policy uncertainty. Furthermore, we also document an adverse effect of EPU on the volume of SEOs as there are fewer offerings in periods with a high degree of EPU.[4]

[4] Jens (2017) also finds that firms delay equity issuance in the context of starting an investment project financed by an SEO before gubernatorial elections.

Our study makes several contributions to the growing literature on how policy uncertainty affects corporate decisions. We are the first to provide a comprehensive study on how EPU affects the cost of raising outside equity capital by public firms. We argue and find that increasing EPU creates more price uncertainty and information asymmetry faced by underwriters and outside investors, which, in turn, leads to an increase in SEO discounts. While Çolak, Durnev, and Qian (2017) use the level of offer price relative to the fair value (price-to-value (P/V) ratio) to reflect the cost of capital in IPOs, our use of SEO discounts is a more direct measure of cost of capital as compared to P/V ratio since V is not directly observable and has to be inferred from industry peers' price multiples. As a comparison, SEO discounts represent the directly observable cost to the issuers as a proportion of own firm's market value. In addition, our finding that stock price informativeness and sensitivity of stock returns to EPU also play a role in affecting the cost of capital has not been documented in any previous studies on the effects of policy uncertainty.

Our paper also contributes to the SEO literature by showing the factors that affect the cross-sectional and time-series differences in the effect of EPU on SEO discounts. Building on the existing SEO studies (e.g., Corwin (2003) and Mola and Loughran (2004)) that focus on the firm-specific determinants of discounts, we identify a new economy-wide factor that plays an important role in the pricing of SEO shares. Besides, we also provide further evidence on the market timing of SEOs (e.g., DeAngelo, DeAngelo, and Stulz (2010) and Lin and Wu (2013)). While Lin and Wu (2013) document that firms tend to issue SEOs when liquidity risk declines to the point where investors have the least concern of risk, we show that there are fewer SEO activities in periods when there is a high degree of economic policy uncertainty. As such, managers also care the negative impact from the economy-wide policy uncertainty when making their SEO decisions.

Lastly, we also add to the studies of how economic policy uncertainty affects firms' cost of external financing. Consistent with the existing findings that increases in EPU lead to increases in interest rate on bank loans (Ashraf and Shen (2019)) and corporate bond spreads (Kaviani, Kryzanowski, Maleki, and Savor (2020) and Waisman, Ye, and Zhu (2015)), we show that high EPU also adversely affects the cost of raising equity capital by seasoned firms and how such negative effect varies with the business cycles.

The rest of the paper is organized as follows. We develop hypotheses in Section 2. Section 3 describes the sample and data. Section 4 examines how economic policy uncertainty affects SEO discounts. Section 5 provides further cross-sectional analysis and Section 6 tests whether the level of SEO activities is affected by policy uncertainty. Section 7 addresses the potential endogeneity concerns in our analysis. Section 8 concludes.

2. Hypothesis development

Government policy makers can contribute to the uncertainty of fiscal, regulatory, or monetary policy. In general, the effect of policy uncertainty refers to the likelihood of economic policy differing in the next period and how it will affect macro- and firm-level activities. Theoretical analyses from Bernanke (1983), Bloom, Bond, and van Reenen (2007), and Bloom (2009) show that significant increases in uncertainty brought about by government policy changes after such major shocks as the 1997 Asian financial crisis, September 11 terrorist attacks, and 2007-2008 global financial crisis exerted a significantly negative effect on the real economy, including declines in employment and output.

Policy uncertainty also influences the financial markets. Pástor and Veronesi (2012) develop an asset-pricing model that analyzes the effect of government policy changes on asset prices.[5] The model predicts that stock returns are generally negative and more volatile during the announcements of policy changes. The magnitude of negative returns is positively associated with the level of uncertainty caused by government policy. Pástor and Veronesi (2013) extend their earlier model and show that political uncertainty commands a risk premium, which they call the political risk premium. They argue that political events affect investors' beliefs about which policy a government may adopt in the future and that investors care about the uncertainty associated with the outcomes of policy events. The market risk premium is higher when policy uncertainty is higher.[6]

A major determinant of SEO discounts is uncertainty and asymmetric information.[7] While policy uncertainty depresses an issuer's prevailing stock price due to a higher cost of capital, insiders of the issuer may know more about the impact of policy uncertainty on the intrinsic value of the firm than outsiders. Therefore, greater policy uncertainty will increase the magnitude of information asymmetry between the firm's insiders and outsiders and this will lead to higher discounts. Further, underwriters and outside investors must take into consideration any further

[5] According to Pástor and Veronesi (2012), policy changes are government actions that can change the economic environment. Two types of uncertainty are caused by policymaking. The first, political uncertainty, concerns whether the current government policy will change. The second, impact uncertainty, concerns the impact that a new government policy will exert on the profitability of the private sector.

[6] Several studies have provided empirical evidence supporting the predictions of the Pástor and Veronesi (2012; 2013) models. See, for example, Chan and Wei (1996), Pástor and Veronesi (2013), Brogaard and Detzel (2015), Kelly, Pástor, and Veronesi (2016), Liu, Shu, and Wei (2017), and Bali, Brown, and Tang (2017).

[7] Corwin (2003) provides a summary of the determinants of SEO discounts which include uncertainty and asymmetric information (e.g., Parsons and Raviv (1985)), price pressure (e.g., Corwin (2003)), manipulative trading and pre-offer price changes (e.g., Gerard and Nanda (1993)), transaction costs (e.g., Loderer, Sheehan, and Kadlec (1991)), and underwriter pricing practices (e.g., Mola and Loughran (2004)). Among the above determinants, the ones that are most relevant to our study are price uncertainty and asymmetric information.

price decrease that may occur prior to the completion of the offering and in the aftermarket.[8] Therefore, during periods of high policy uncertainty, underwriters and potential investors would demand more compensation when facing greater price uncertainty and ask for higher SEO discounts. Based on the above arguments, we develop our first hypothesis as follows.

H1. *SEO discounts are positively related to the level of policy uncertainty*.

Pástor and Veronesi (2013) show that a policy is more likely to be adopted if it has a stronger perceived effect on corporate profitability or is less uncertain. According to the decision rule for the optimal government policy choice as derived from their model, a policy change is more likely in weaker economic conditions when the current policy is perceived as harmful. Under weak economic conditions, investors are more uncertain about which new policies will be adopted by the government, and they respond more strongly to political signals. The implication is that the political risk premium is state-dependent and grows larger during the time of economic weakness. As a result, the compensation to underwriters and outside investors due to policy uncertainty should be higher under weaker economic conditions. This leads to our second hypothesis.

H2. *The positive relation between SEO discounts and the level of policy uncertainty is stronger in a weaker economy*.

There are reasons to believe that firms are not equally affected by policy uncertainty. We therefore expect cross-sectional differences in the effect of policy uncertainty on SEO discounts. First, previous studies have shown that the effects of such uncertainty are positively related to firms' dependence on government spending. Baker, Bloom, and Davis (2016), for example, find that firms with greater exposure to government purchases experience reduced investment rates and employment growth when policy uncertainty rises. Gulen and Ion (2016) demonstrate that the

[8] Underwriters have to care about price uncertainty since they may need to engage in price stabilization activities in the early aftermarket.

negative effect of EPU on capital investment is stronger for firms that are more dependent on government spending. Çolak, Durnev, and Qian (2017) show that the dampening effect of elections on IPO activity is stronger for firms in industries that rely more on government contracts.[9] Holding everything else constant, the same level of policy uncertainty should translate to a greater cash flow and stock price uncertainty for SEO issuers that are more dependent on government contracts for their revenues. Applying these arguments to the pricing of SEO shares gives our third hypothesis.

H3. *The positive relation between SEO discounts and the level of policy uncertainty is stronger for firms that are more dependent on government spending*.

Bowen, Chen, and Cheng (2008) and Chan and Chan (2014) use analyst coverage and idiosyncratic volatility as a proxy for stock price informativeness and show that lower analyst coverage or greater idiosyncratic volatility increases the level of information asymmetry among investors and raises the SEO discounts. As it is more difficult for outside investors to assess the effects of policy uncertainty on the stock prices of firms with less informative stock prices, investors have to demand greater compensation when buying SEO shares in face of such uncertainty. Therefore, our fourth hypothesis is as follows.

H4. *The positive relation between SEO discounts and the level of policy uncertainty is stronger for firms with less informative stock prices*.

Bali, Brown, and Tang (2017) document the role of a stock exposure to economic uncertainty in the cross-sectional pricing of individual stocks. They estimate a stock's economic uncertainty beta by regressing its excess returns on an economic uncertainty index developed by Jurado,

[9] Belo and Yu (2013) show that the U.S. federal government capital investment in the public sector is positively associated with risk premiums at both the aggregate and firm levels. The findings are opposite to those reported by Titman, Wei, and Xie (2004) in the cross section of the private sector's listed firms that firms with higher capital investment earn lower future returns. Moreover, Belo, Gala, and Li (2013) further document that firms with higher exposure to government spending experience higher future cash flows and stock returns during Democratic presidencies but opposite during Republican presidencies.

Ludvigson, and Ng (2015) and various risk factors. They find a significantly negative relation between the economic uncertainty beta and future stock returns. It is because the returns of stocks with a negative uncertainty beta are negatively correlated with increases in economic uncertainty, and uncertainty-averse investors demand a higher risk premium to hold those stocks. At the same time, stocks with a highly positive uncertainty beta perform relatively better during the periods of high economic uncertainty, and therefore investors are willing to accept lower returns and pay higher prices for those stocks. Based on their finding, we measure a stock's exposure to policy uncertainty by an EPU beta, which is estimated from the following regression model:

$$ExRet_{i,t} = \alpha + \beta_i^{EPU} EPU_t + \beta_i^{MKT} MKT_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{UMD} UMD_t + \epsilon_{i,t}, \quad (1)$$

where $ExRet_{i,t}$ is firm *i*'s stock return minus the risk-free rate in month *t*; EPU_t is the value of the EPU index from Baker, Bloom, and Davis (2016) in month *t* divided by 100; and MKT_t, SMB_t, HML_t and UMD_t are the market, size, book-to-market, and momentum factors in month *t*, respectively.[10,11]

According to Eq. (1), issuing firms with a high EPU beta (i.e., β_i^{EPU}) provide investors better ability to hedge against policy uncertainty. That is, stocks with a higher EPU beta perform relatively better than lower EPU beta stocks during high EPU periods. This suggests that investors are willing to accept a higher offer price or a lower SEO discount for higher EPU beta stocks during periods of high uncertainty. In other words, the SEO discounts for stocks with a lower EPU beta should be relatively higher during high EPU periods. This leads to our fifth hypothesis.

[10] These factors are retrieved from Professor Kenneth French's website.

[11] Bonaime, Gulen, and Ion (2018) also used a similar method to estimate the EPU beta (which they call the stock return sensitivity to policy uncertainty) for each Fama-French 48 industry and find that the negative relation between policy uncertainty and the likelihood of announcing an acquisition is stronger for firms with stock prices more sensitive to policy uncertainty.

H5. *The positive relation between SEO discounts and the level of policy uncertainty is stronger for firms with a lower EPU beta.*

Finally, in addition to affecting the pricing process, policy uncertainty should also affect the level of corporate financing activities. For example, Çolak, Durnev, and Qian (2017) find that firms delay their IPOs because the cost of capital increases around gubernatorial elections. We therefore hypothesize that policy uncertainty also has a negative effect on the volume of SEOs. As a result, there are fewer offerings surrounding the periods of high policy uncertainty. Our final hypothesis is thus stated as follows.

H6. *The number of SEOs are negatively associated with the level of policy uncertainty*.

3. Data, variable construction, and descriptive statistics

In this section, we explain our data collection and the construction of the variables used in our empirical analysis. We also present the offering and firm characteristics of our sample SEOs and descriptive statistics of the EPU index.

3.1. The data

We gather data on SEOs from the SDC Platinum's New Issues database of Thomson Reuters. Similar to previous SEO studies, we restrict our sample by requiring the SEOs (excluding unit offers and rights offers) to be issued by U.S. firms that are covered by the Center for Research in Security Prices (CRSP) database and listed on the NYSE, Amex, or NASDAQ. For inclusion, the offers should include at least some primary shares, have an offer price of at least $3 and no more than $400, and have an offer date within 365 days of the filing date. We begin our sample period in January 1985, which is the earliest month for which the EPU index is available. We use a 30-year investigation period that ends in December 2014. Overall, 7,200 SEOs from the SDC database fulfill our filtering criteria. We then delete 522 SEOs for which the estimates of idiosyncratic volatility are unavailable, as described in Section 3.2. In addition, we remove 57 SEOs with a relative offer size larger than 100% and 21 outliers whose absolute SEO discount value is greater than 50%. Our final sample consists of 6,600 SEOs issued by 3,985 distinct firms.

We collect data from several databases to construct the variables for our analysis. The SDC database provides such offering-specific information as the filing date, offering date, offer price, and number of shares offered, whereas the CRSP database provides issuer-specific information, including stock prices and returns, trading volume, listing exchanges, and Standard Industrial Classification (SIC) codes. We collect the SEO firms' accounting information from the Compustat database, and analyst coverage information from the I/B/E/S Unadjusted Detail History file.

The SDC database may not provide the correct offer date, as some offers occur after the close of trading. Hence, following Corwin (2003), we set the day following the SDC offer date as the correct offer date if we find the trading volume on the day following the SDC offer date to be more than twice the volume on the SDC offer date and more than twice the average daily volume over the 250 trading days prior to it. Of the 6,600 SEO observations in our final sample, 3,359 (50.89% of total observations) have been corrected using this adjustment method. This adjustment ratio is similar to that in Corwin (2003), who revises 51.5% of the offering date from the SDC database for SEOs issued between 1992 and 1998.[12]

We use the monthly EPU index developed by Baker, Bloom, and Davis (2016) as our measure of policy uncertainty. The EPU index is a weighted average measure consisted of three components: news events, tax code changes, and monetary and fiscal policy forecast dispersions.[13]

[12] Corwin (2003) reports that his correction method is able to accurately identify about 96-100% of the correct offer dates for a random sample of 200 SEOs issued between 1991 and 1998.

[13] To extend the measure over time and across countries, the EPU indexes contains the news component alone. The EPU measure used in our study contains all three components, which is similar to earlier versions of Baker, Bloom,

The first component measures news reports pertaining to economic policy uncertainty identified through an automated search of the 10 largest newspapers in the U.S. The second component estimates tax-related uncertainty on an annual basis using data from the Congressional Budget Office. Each year, the index is a measure of the discounted value of the revenue effects on all tax provisions set to expire during the subsequent 10 years. Finally, the third component captures forecaster disagreement about future monetary and fiscal policies, taken from the Survey of Professional Forecasters provided by the Federal Reserve Board of Philadelphia. This component takes into account the interquartile range of Consumer Price Index (CPI) forecasts and the interquartile range of the forecasts of purchases of goods and services by federal, state, and local governments. We collect the EPU index data from the website developed by Baker, Bloom, and Davis (www.policyuncertainty.com).

3.2. Construction of the control variables

When analyzing the effects of EPU on SEO discounts, there is a need to control for other factors that may affect the pricing of SEO shares. We follow the SEO discount regression model adopted by Corwin (2003), supplemented by Mola and Loughran (2004), Bowen, Chen, and Cheng (2008), and Chan and Chan (2014), in selecting our control variables. Those variables are described as follows.

One of the main reasons for firms to issue SEO shares at a discount is information asymmetry between firm insiders and outside investors. As outsiders are uncertain about the true value of the firm, issuers have to provide a discount to induce less informed outside investors to buy the newly

and Davis (2016). The three-component EPU measure is commonly used in the literature, including in Pástor and Veronesi (2013), Gulen and Ion (2016), and Nguyen and Phan (2017), among others.

issued shares. Bowen, Chen, and Cheng (2008) demonstrate that information asymmetry can be mitigated by analyst activity. We therefore include analyst coverage (*Analyst*) as a control variable. *Analyst* is the number of unique analysts issuing earnings forecasts as covered in the I/B/E/S dataset over the 12 months ending one month before the offer date. Similar to previous studies, we set *Analyst* to zero if the issuing firm is not covered by the I/B/E/S dataset.

Chan and Chan (2014) find a significantly negative relation between SEO discounts and stock return synchronicity measured by the R-squared of the market model. They argue that an increase in stock return synchronicity represents a better information environment or less information asymmetry for the issuing firm. As stock return synchronicity reflects the degree of systematic volatility relative to idiosyncratic volatility, we use both volatility measures as control variables. Following Chan and Chan (2014), we estimate the following daily return regression for each SEO over the 12 months ending one month before the offer.

$$Ret_{i,t} = \alpha_i + \beta_{1,i} Ret_{M,t} + \beta_{2,i} Ret_{M,t-1} + \beta_{3,i} Ret_{I,t} + \beta_{4,i} Ret_{I,t-1} + \epsilon_{i,t}, \tag{2}$$

where $Ret_{i,t}$ is firm *i*'s return on day *t*; $Ret_{M,t}$ is the return on the CRSP value-weighted market portfolio on day *t*; and $Ret_{I,t}$ is firm *i*'s industry return on day *t*. $Ret_{I,t}$ is the value-weighted return of all firms in the CRSP dataset with the same two-digit SIC code as firm *i*, but with the return of firm *i* excluded. Idiosyncratic volatility (*IVOL*) is calculated as the standard deviation of the residuals ($\epsilon_{i,t}$) in Eq. (2) and systematic volatility (*SVOL*) is the square root of the difference between total variance and residual variance in Eq. (2). To ensure that both volatility measures are reliable and not distorted by firms with few industry peers, we exclude SEOs with fewer than 100 observations in estimating Eq. (2) and firms with fewer than five industry peers. Based on the findings of Chan and Chan (2014), we use *IVOL* as our measure of stock price informativeness.

We expect that firms with a higher *IVOL* value have more severe information asymmetry and have to offer a higher SEO discount.

We also need to control for offering- and firm-specific factors as follows: (1) *Price*: the closing price of the issuing firm on the day prior to the offer. (2) *Size*: firm size, defined as the closing price on the day prior to the offer times the total number of shares outstanding prior to the offer. (3) *Relsize*: relative offer size, defined as the number of offered shares divided by the total number of outstanding shares prior to the offer. (4) *CAR positive*: a *CAR* dummy variable that equals one if *CAR* is positive and zero otherwise, where *CAR* is the cumulative stock returns adjusted by CRSP value-weighted market returns over the five days prior to the offer. (5) *CAR negative*: a *CAR* dummy variable that equals one if *CAR* is negative and zero otherwise. (6) *Tick<1/4*: a dummy variable that equals one (zero otherwise) if the decimal portion of the closing price on the day prior to the offer is not an increment of 25 cents and the issues are offered before the exchange in which the firm is listed completes decimalization. (7) *Cluster*: a dummy variable that equals one (zero otherwise) if the offer price is set at a whole dollar value. (8) *Rule10b-21*: a dummy variable that equals one (zero otherwise) if the issue is offered after the Securities and Exchange Commission (SEC) implemented Rule 10b-21 on August 25, 1988. (9) *NASDAQ*: a dummy variable that equals one if the firm is listed on NASDAQ at the time of the offer, and zero if it is listed on the NYSE or Amex. These variables are used to control for the underwriters' price-setting effect (through *Price*, *Tick<1/4*, *Cluster*, and *NASDAQ*), firm size effect (through *SIZE*), price pressure effect (through *Relsize*), and investors' price manipulation effect (through *CAR positive*, *CAR negative*, and *Rule10b-21*) on SEO discounts.[14]

[14] The underwriters' price-setting hypothesis states that underwriters tend to set the offer price at whole integers and avoid odd eighths (Mola and Loughran (2004)). Further, underwriters are also likely to set the offer price at the closing bid quote for NASDAQ firms and at the closing transaction price for NYSE firms (Corwin (2003)). Together, these factors imply that SEO discounts should be high when *Price* is low or when *Tick<1/4*, *Cluster*, and *NASDAQ* take a

3.3. Descriptive statistics

Table 1 presents the offering and firm characteristics of our sample SEOs and descriptive statistics of the EPU index.[15] As shown in Panel A, SEO discounts, where a discount is measured as minus one times the percentage price change from the pre-offer day closing price to the offer price, average 2.84% during the whole sample period. This indicates that the cost of raising new equity capital through SEOs is economically significant.[16] The sample firms have an average stock price of $24.75 and average market capitalization of $1,449 million at the time of offering. On average, the number of offered shares equals 20% of the total number of outstanding shares prior to the offer, and the proceeds raised from the offering equals $134 million. *Analyst* coverage has a mean value of 7.3 and a median value of 5, with our data indicating that 13.82% of the sample SEO firms have no analyst coverage. The other price informativeness measure, *IVOL*, has a mean value of 3.031%. Compared with the mean value of total volatility *TVOL* (3.333%), *IVOL* comprises a major portion of total volatility. Return on equity (*ROE*), defined as a firm's average earnings before extraordinary items scaled by the lagged book value of equity during the 12 fiscal quarters before the offer, has a mean value of -0.415% and a median value of 2.405%. The low mean value relative to the median indicates the presence of poorly performing firms that greatly

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value of one. The firm size effect assumes that small firms are likely to be associated with greater uncertainty, and the price pressure effect argues that the offer price has to be lower for larger-sized offers. Therefore, SEO discounts are negatively related to *Size* and positively related to *Relsize*. Finally, the stock prices of SEO firms may be subject to manipulative trading because investors have an incentive to depress offer prices through short selling prior to the offers (Gerard and Nanda (1993)). In addition, price manipulation will render the market price of an issuing firm less informative, leading to a larger SEO discount. As a result, SEO discounts are expected to be larger following a large *CAR*. Such manipulative trading became less significant after the implementation of SEC Rule 10b-21, which prohibits investors from covering a short position with stocks purchased from a new offering. It is also noted that Rule 10b-21 has been replaced by Rule 105 by the SEC in April 1997.

[15] To eliminate outliers, the values of *ROE, ROE volatility*, *CFO, CFO volatility*, *M/B, DGS* and *EPU beta* are winsorized at the 1% and 99% levels.

[16] It should be noted that not all SEOs are issued at a discount. In our sample, 5.26% of the offerings have an offering price higher than the pre-offer day closing price, and 21.42% have an offering price equal to it.

dilute *ROE* in the overall sample. *ROE volatility*, defined as the standard deviation of *ROE* during the 12 fiscal quarters before the offer, has a mean value of 15.227% and a median value of 2.701%, indicating that some of sample firms exhibit an extremely volatile ROE.

(Insert Table 1 about here)

Panel B of Table 1 reports the descriptive statistics of the monthly EPU index. To gauge the fluctuations in EPU, we partition our 30-year investigation period into six 5-year sub-periods. It shows a much larger swing in the EPU index during the later sub-periods relative to the earlier ones. During each of the 5-year periods between 1985 and 1999, the ranges of the EPU index (i.e., the differences between the maximum and minimum) are all smaller than 100. In contrast, in the three 5-year periods between 2000 and 2014, the lowest and highest range values are 121 and 173, respectively. Further, the largest mean EPU value is recorded in the final 5-year period. These findings indicate that the economy has faced greater fluctuations in policy uncertainty in recent years. Accordingly, we expect that the effects of policy uncertainty to be more pronounced in the second half of our sample period.

4. Empirical results from the effects of economic policy uncertainty on SEO discounts

4.1. Univariate analysis on SEO discounts

We begin our empirical analysis by presenting the time-series pattern and univariate analysis of SEO discounts. Previous studies document a steady increase in SEO discounts in recent years (e.g., Chan and Chan (2014)). That upward trend is confirmed when we partition the whole sample period into six 5-year periods and calculate the average SEO discount for each period. Our data show an average SEO discount of 1.144% during the 1985-1989 period, with that figure increasing to 4.285% during the 2010-2014 period. In contrast to this upward discount trend, we observe an inverted U-shaped time-series pattern in SEO activities, with more offerings taking place during the 1990-2004 period relative to the earlier or later periods.

(Insert Table 2 about here)

Consistent with previous studies (Bowen, Chen, and Cheng (2008), and Chan and Chan (2014)), we find that SEO discounts are negatively related to stock price informativeness, proxied by analyst coverage and idiosyncratic volatility. The SEO firms are separated into three groups: zero analyst coverage (Analyst Group 1), low analyst coverage (Analyst Group 2, comprising firms covered by one to four analysts), and high analyst coverage (Analyst Group 3, comprising firms covered by more than four analysts). As reported in Panel B of Table 2, we consistently find that SEO discounts increase monotonically from Analyst Group 3 to Analyst Group 1. Similarly, when we divide the SEO sample into terciles according to idiosyncratic volatility, as shown in Panel C of Table 2, the SEO discounts for firms in the largest *IVOL* tercile are always larger than those in the smallest *IVOL* tercile. The negative relation between SEO discounts and the two measures of price informativeness is consistently observed in all 5-year sub-periods and in the whole sample period.

Panel D of Table 2 shows the relation between SEO discounts and policy uncertainty. We first classify the monthly EPU measure during the whole 30-year sample period into terciles, and calculate the average SEO discount in each EPU tercile for each 5-year period and for the whole sample period. We find that the average SEO discount in the highest EPU tercile is larger than that in the lowest for the majority of the 5-year periods and for the whole period. In addition, the difference in SEO discounts between the highest and lowest EPU terciles is statistically significant at the 1% level for both the last two 5-year periods and the full 30-year period. Furthermore, it is notable that the SEO discount difference between the highest and lowest EPU terciles reached as high as 2.88% during the 2005-2009 period. This univariate analysis is consistent with the prediction of **H1** that the pricing of SEO shares is adversely affected by EPU, particularly during periods of greater uncertainty, such as in the more recent years of our period of investigation.

Figure 1 shows the patterns of the 3-month moving averages of SEO discounts and the EPU index over the 30-year period. As can be seen from the figure, the two series display similar movement, with their co-movement much more obvious after the mid-1990s. This figure confirms the univariate analysis result showing that SEO discounts react to EPU, and greater policy uncertainty exerting a detrimental effect on the pricing of SEO shares.

(Insert Figure 1 about here)

4.2. Regression analysis of the EPU effect on SEO discounts

In this section, we perform the following cross-sectional baseline regression to test our hypothesis:

$$\begin{aligned} SEO\ discount_{i,t} = \alpha_i + \beta_1 \ln(EPU_{i,t}) + \beta_2 \ln(1 + Analyst_{i,t-1}) \\ + \beta_3 ln(IVOL_{i,t-1}) + \beta_4 Controls_{i,t-1} + \epsilon_{i,t}, \end{aligned} \tag{3}$$

where $SEO\ discount_{i,t}$ is SEO discount for issuing firm *i* in time *t* and $EPU_{i,t}$ the corresponding EPU index; $Analyst_{i,t}$ is the number of analysts covering the firm and $IVOL_{i,t}$ is idiosyncratic volatility. $Controls_{i,t-1}$ is a vector of control variables discussed Section 3.2. The regression is estimated with year and industry fixed effects based on the definitions of Fama and French's 12 industry portfolios.[17] We use standard errors adjusted for clustering by firm and month in testing the statistical significance of the parameter estimates. **H1** predicts that β_1 is positive.

[17] We are not able to estimate the model with firm fixed effect since on average a firm has only 1.66 seasoned equity offerings in our whole sample period. Our use of industry fixed effect is similar to the study of Bonaime, Gulen, and Ion (2018).

Column (1) of Table 3 reports the ordinary least squares (OLS) regression results for the whole 30-year sample period. We find a negative relation between SEO discounts and the measures of stock price informativeness of the issuing firms. The estimated coefficient on *ln*(1+*Analyst*) is negative while that on *ln*(*IVOL*) is positive. Both are statistically significant at the 1% level. In addition, the effects of other offering- and firm-specific variables on SEO discounts are consistent with those found in previous studies. To be specific, the SEO discounts are higher for low-priced firms, NASDAQ firms, and firms that offer more shares relative to the number of shares outstanding or offers that are priced at the whole dollar value. However, it is surprising to observe a positive association between SEO discounts and *Size*, as outside investors should perceive less uncertainty concerning larger-sized firms and thus require smaller discounts.[18] More importantly, we find that the estimated coefficient on *ln*(*EPU*) is positive and statistically significant at the 5% level, which is consistent with the prediction of **H1** that EPU exerts an adverse effect on SEO discounts after controlling for all other factors determining the pricing of SEO shares.

(Insert Table 3 about here)

In addition to the OLS method, we follow Altinkilic and Hansen (2003) and estimate the SEO discount regression using the Tobit approach. In the Tobit regressions, the SEO discounts are set to zero for SEOs with negative discounts. As our explanatory variables are used to explain SEO discounts, the advantage of the Tobit approach is that it requires no explanation of why some SEOs are issued at an offer price higher than the prevailing market price. The Tobit regression results for the full sample are reported in Column (2) of Table 3. The signs of all of the estimated coefficients remain unchanged, and most of the statistical significance levels are similar to those

[18] This result may stem from the high degree of correlation between *Size* and *Price*.

in the OLS regression. In addition, *Size* becomes statistically insignificant, and *Tick<1/4* positively significant. Thus, compared with the OLS regression results, the Tobit regression results are more consistent with our prediction of the determinants of SEO discounts. Furthermore, the estimated coefficient on *ln*(*EPU*) is larger, with a *t*-statistic of 2.84, which is highly significant at the 1% level. As the Tobit method provides better estimation results than the OLS method, we report only the Tobit results in our subsequent analysis.

In addition to the statistical significance of the EPU effect, we are also interested in its economic significance. Based on the estimated coefficient on *ln*(*EPU*) reported in Column (2) of Table 3 and the standard deviation of EPU reported in Panel B of Table 1, a one standard deviation increase in EPU from its mean value causes a 30 basis point ((*ln*(140.27) – *ln*(107.65)) × 1.139) increase in SEO discounts. This magnitude is considered economically significant, given that SEO discounts average 284 basis points during our 30-year sample period.

We also divide the whole sample period into earlier and later 15-year sub-periods and compare the difference between them, with the results reported in Columns (3) and (4) of Table 3. Although the estimation results of other control variables are qualitatively similar in the two periods, we find that the estimated coefficient on *ln*(*EPU*) is statistically insignificant during the 1985-1999 period, but highly statistically significant at the 1% level (*t*-statistic = 3.10) during the 2000-2014 period. The coefficient in the later period suggests that a one standard deviation increase in EPU from its mean value is associated with a 43 basis point ((*ln*(152.86) – *ln*(114.34)) × 1.485) increase in SEO discounts.[19] These sub-period regression results are consistent with the univariate analysis presented in Panel D of Table 2, showing that EPU's effects on SEO discounts

[19] The mean and standard deviation of the EPU index equals 114.34 and 38.52, respectively, during the 2000-2014 period.

are statistically significant only in the later part of our sample period. Nevertheless, we still find that economic policy uncertainty affects the pricing of SEO shares in the earlier part of the period when we take into account the interaction effect between EPU and firm dependence on government spending, stock price informativeness, or the EPU beta, which is discussed further in Section 5.[20]

4.3. The effect of economic conditions

As discussed earlier, the political uncertainty models proposed by Pástor and Veronesi (2012, 2013) predict a larger political risk premium in weak economic conditions. To test **H2**, which posits that the positive relation between SEO discounts and the level of EPU is stronger when the economy is in a bad state, we interact *ln*(*EPU*) with variables indicating the state of the economy and include them in our baseline regression model. We use two variables to reflect economic conditions: *Recession* and −*CFNAI*. *Recession* is a dummy variable that equals one (zero otherwise) for the recession months identified by the National Bureau of Economic Research (NBER), whereas −*CFNAI* is minus one times the Chicago Fed National Activity Index (CFNAI), which is a weighted average of 85 monthly indicators of national economic activity. We reverse the sign on the latter variable such that a higher −*CFNAI* value indicates poorer economic conditions.

Column (1) of Table 4 indicates that the coefficient on *ln*(*EPU*) × *Recession* (i.e., 1.000) has a positive sign and have a similar magnitude of the coefficient on *ln*(*EPU*) (i.e., 0.917), which is consistent with the prediction of **H2**. However, it has a *t*-statistic of 0.96, which is not statistically significant. The main reason for the lack of statistical significance is the variable's small cross-sectional variation; it takes a value of zero in 6,149 of the 6,600 observations. In contrast, in

[20] To benchmark with Baker, Bloom, and Davis (2016), we also re-estimate the four regressions reported in Table 3 with the EPU index constructed from the news component alone, and the results remain qualitatively unchanged.

Column (2) of Table 4, the estimated coefficients on both $ln(EPU)$ and $ln(EPU) \times -CFNAI$ are positive and statistically significant at the 5% level or better. This result indicates that the negative effect of EPU on SEO discounts applies to both good and poor economic conditions. Moreover, the effect is stronger when the economic state is poorer, a finding consistent with the predictions of both **H1** and **H2**.

(Insert Table 4 about here)

4.4. Do changes in EPU matter?

In addition to the level of EPU, changes in EPU can also affect economic behavior. Baker, Bloom, and Davis (2016) find that a firm's investment decisions are affected by changes in the EPU index. Based on their vector autoregressive (VAR) analysis of aggregate economic activity, they suggest that an upward EPU innovation corresponds to an unforeseen policy uncertainty shock that causes the worsening of macroeconomic performance through the real options effect, the cost-of-capital effect, or other mechanisms. Brogaard and Detzel (2015) find that the first difference in the EPU index is significantly and negatively correlated with the excess return on the market. Given that EPU is relatively persistent, innovation in EPU should provide an important piece of information to investors.[21] Therefore, we also investigate whether changes in EPU have any effects on the SEO discounts.

We estimate the effect of the change in EPU on SEO discounts by modifying the regression model reported in Table 3, replacing $ln(EPU)$ with $\Delta ln(EPU)$, where $\Delta ln(EPU_t)$ equals $ln(EPU_t)$ minus $ln(EPU_{t\text{-}1})$ and EPU_t equals the EPU in month t. From our unreported analysis, the estimated coefficient on $\Delta ln(EPU)$ is 1.008 and statistically significant at the 1% level, which suggests that innovations in EPU also adversely affect SEO pricing, which is consistent with our first hypothesis.

[21] Brogaard and Detzel (2015) report that the EPU index has a first autoregressive coefficient of 0.77.

As we are more interested in determining how SEO discounts react to high levels of EPU rather than to economic policy uncertainty shocks, we focus only on the effects of a high level of EPU in our remaining analysis. This empirical design is also in line with other EPU studies such as those of Pástor and Veronesi (2013) and Gulen and Ion (2016).

5. Cross-sectional analysis

In Section 2, we hypothesize that there are three sources of cross-sectional heterogeneity in the effects of policy uncertainty on SEO discounts. We test these hypotheses as follows.

5.1. Interaction with dependence on government spending

To test **H3**, we interact *ln*(*EPU*) with the dummy variables that indicate firms with greater dependence on government spending and interact them with *ln*(*EPU*). More specifically, we add the interaction terms of *ln*(*EPU*) × *DGS tercile 2* and *ln*(*EPU*) × *DGS tercile 3* to the regression. *DGS tercile 2* (*3*) is a dummy variable that equals one if the dependence on government spending (*DGS*) variable for an offering firm belongs to the middle (top) tercile of the *DGS* distribution of all of the sample firms and zero otherwise. If the EPU effect is stronger for firms that are more dependent on government spending, these interaction terms should be positively significant. To avoid omitted-variable bias, we also include *DGS* as an additional explanatory variable in our regression model.

To construct the *DGS* variable, we follow Gulen and Ion (2016) and Belo, Gala, and Li (2013) and rely on Benchmark Input-Output (I-O) Accounts table published by the Bureau of Economic Analysis (BEA) to estimate the percentage of industry sales to government entities. We calculate *DGS* by the ratio x_i/y_i, where x_i denotes the total direct or indirect input from industry i necessary to meet government demand and y_i denotes industry i's total output. Industry-level government spending is calculated from the industry-by-commodity table in the I-O accounts as follows:

$$x_i = \sum_j a_{i,j}\, g_j,$$

where $a_{i,j}$ is the value of the input from industry i necessary to produce \$1 of industry j's output, and g_j is the value of the output from industry j that is sold directly to the government at the federal, state, or local level. Given that I-O accounts commence in 1982 and are updated every five years, we update our measure accordingly. Following Gulen and Ion (2016), we rely on the BEA concordance tables to merge our government spending dependence proxy with our data on three-digit SIC codes (before 2002) or North America Industry Classification System (NAICS) codes. If several industry codes in the I-O accounts match the same three-digit SIC or NAICS codes, we calculate a weighted average of industry dependencies on government spending, with the weights being a function of total industry outputs (see also Gulen and Ion (2016)). Out of our total 6,600 SEO observations, we are able to match the dependence on government spending data for 6,568. We winsorize the *DGS* variable at the 1% and 99% levels to eliminate outliers.

The regression results are presented in Panel A of Table 5. For brevity, we report only the coefficients related to the *ln*(*EPU*) variables. For the whole-period regression reported in Column (1), the coefficient estimates on *ln*(*EPU*) and the two *ln*(*EPU*) interaction variables are positively significant at the 10% level or better. Furthermore, the magnitude of the estimated coefficient on *ln*(*EPU*) × *DGS tercile 3* is larger than that on *ln*(*EPU*) × *DGS tercile 2*. The regression results for the two sub-periods are similar to those for the whole period, and with mostly larger coefficient estimates but weaker statistical significance. These results suggest that increasing policy uncertainty exerts a negative effect on the pricing of SEO shares for the issuing firms, and the effect is stronger for firms whose sales are more dependent on government contracts, thus supporting the prediction of **H3**.

(Insert Table 5 about here)

5.2. Interaction with stock price informativeness

In this sub-section, we test **H4**. Following Bowen, Chen, and Cheng (2008) and Chan and Chan (2014), we use analyst coverage and idiosyncratic volatility as proxies for stock price informativeness. We have two regression model specifications. In the first, we add the interaction terms of *ln*(*EPU*) × *Analyst group 1* and *ln*(*EPU*) × *Analyst group 2* to our baseline regression model. *Analyst group 1* (*2*) is a dummy variable that equals one if the offering firm has zero analyst coverage (is covered by one to four analysts) and zero otherwise. In the second specification, we add the interaction terms of *ln*(*EPU*) × *IVOL tercile 2* and *ln*(*EPU*) × *IVOL tercile 3*. *IVOL tercile 2* (*3*) is a dummy variable that equals one if the idiosyncratic volatility of the offering firm belongs to the middle (top) tercile of the *IVOL* distribution of all sample firms and zero otherwise.

The regression results are presented in Panels B and C of Table 5. The estimated coefficient on *ln*(*EPU*) is positive and statistically significant in both specifications for the whole-period regression, indicating that EPU exerts an adverse effect on SEO discounts even for the group of firms with the most informative stock prices. In addition, the coefficients on *ln*(*EPU*) × *Analyst group 1* and *ln*(*EPU*) × *Analyst group 2* are both positive and statistically significant, and the former is the larger of the two. These results show that EPU has the strongest effect on firms without any analyst coverage, with the EPU effect weakening with an increase in analyst coverage. In Panel C, the coefficient on *ln*(*EPU*) × *IVOL tercile 3* is also positively significant, showing that the group of firms with the greatest degree of idiosyncratic volatility also suffers the most from policy uncertainty. The results of the 2000-2014 sub-period regressions are similar to those of the whole-period regressions. For the 1985-1999 sub-period, the coefficient on *ln*(*EPU*) is statistically insignificant in both specifications. However, in Panel B we find that the coefficients on *ln*(*EPU*) × *Analyst group 1* and *ln*(*EPU*) × *Analyst group 2* are both positively significant. Moreover, the estimated coefficient on *ln*(*EPU*) × *Analyst group 1* is larger than that on *ln*(*EPU*) × *Analyst group 2*. The findings show that the EPU effect is still evident during the 1985-1999 sub-period, although it applies only to the firms that are more vulnerable to policy uncertainty.

In summary, the results in Panels B and C of Table 5 support **H4**, which asserts that less informative stock prices strengthen the detrimental effect of EPU on SEO discounts.

5.3. Interaction with EPU beta

To test **H5**, we use Eq. (1) to estimate the EPU beta for each offering based on data form the past 60 months before the offering month. We lose 898 SEOs due to the reason that we can estimate the regression only for those offerings starting in January 1990, as EPU data have been available only since 1985. Another 1,728 SEO observations are lost owing to our requirement that at least 30 monthly observations be used in the estimation to ensure a reliable estimate of *EPU beta*. We thus have 3,974 usable SEO observations for our analysis. To eliminate outliers, we winsorize *EPU beta* at the 1% and 99% levels.

Similar to the analysis presented in the previous sub-sections, we add *EPU beta* and the interaction terms of *ln*(*EPU*) × *EPU beta tercile 2* and *ln*(*EPU*) × *EPU beta tercile 3* to our baseline regression model. *EPU beta tercile 2* (*3*) is a dummy variable that equals one if the *EPU beta* of the offering firm belongs to the middle (top) tercile of the *EPU beta* distribution of all sample firms and zero otherwise. As shown in Panel D of Table 5, the estimated coefficient on *ln*(*EPU*) is positively significant, and the estimates on the two interaction terms are negatively significant in the whole-period regression. Furthermore, the absolute magnitude of the estimate on *ln*(*EPU*) × *EPU beta tercile 3* is larger than that on *ln*(*EPU*) × *EPU beta tercile 2*. These results indicate that the detrimental effect of policy uncertainty is mitigated when the offering firm has a larger *EPU beta*. The sub-period regression results also concur with these findings, particularly for the most recent sub-period. Overall, our findings are consistent with **H5**, which posits that SEO discounts are lower for stocks with a high and positive EPU beta because such stocks are able to hedge against increases in policy uncertainty.

6. The effects of economic policy uncertainty on the volume of SEOs

During the SEO process, the setting of an offering price is largely determined by underwriters and investors' assessment of firm value. The above findings reflect the way in which economic policy uncertainty affects the compensation of uncertainty required by a firm's outsiders. In this section, we examine whether economic policy uncertainty also affects the decision making of issuing-firms' insiders and their underwriters. We do so by testing whether the level of SEO activities is affected by such uncertainty.

We run a regression with the number of SEOs offered in month *t* as the dependent variable and *ln*(*EPU*) in months *t* and *t*-1 (i.e., *ln*($EPU_{t\text{-}1}$)) as the explanatory variables. As shown in Column (1) of Table 6, the coefficient on *ln*(*EPU*) is negatively significant at the 10% level, providing evidence that SEO activities in a given month are negatively related to economic policy uncertainty in the same month. In Column (2), we add the year fixed effect and the month fixed effect, and find that the coefficients on *ln*(*EPU*) and *ln*($EPU_{t\text{-}1}$) both become negatively significant at the 5% level. The large increase in the R^2 value after adding the year and month fixed effects also indicates that there is a time effect on the SEO activities. In Column (3), we further add the contemporaneous and lagged market returns and national economic activity (*CFNAI*) to control for the effects of market movement and macroeconomic conditions. Again, the coefficient on $ln(EPU_{t-1})$ continues to bear a negative and statistically significant value. In sum, the results of Table 6 support the proposition of **H6** that there are fewer SEO activities in periods when there is a high degree of economic policy uncertainty.

(Insert Table 6 about here)

7. Endogeneity issues

In this section, we address three potential endogeneity concerns in our analysis as follows.

7.1. Omission of variables on other economic uncertainty

The EPU index developed by Baker, Bloom, and Davis (2016) may not be a purely policy-related economic uncertainty measure, as it may also capture the effects of general economic uncertainty. As policy uncertainty is likely to increase in periods of considerable economic uncertainty, our regression results may be driven by uncertainty arising from sources other than economic policy such that there are omitted variables in our regression model. To address this first endogeneity issue, we follow Gulen and Ion (2016) to include the following four economic uncertainty measures as additional controls. (1) *JLN uncertainty*: a monthly comprehensive measure of uncertainty constructed by Jurado, Ludvigson, and Ng (2015), which aggregates individual uncertainty from 132 macroeconomic series and 147 financial time series. (2) *GDP forecast dispersion*: the cross-sectional coefficient of variation in forecasts of nominal GDP one year ahead from the Philadelphia Federal Reserve Bank's biannual Livingston Survey.[22] (3) *Stock return standard deviation*: the monthly cross-sectional standard deviation of individual firms'

[22] This variable is measured every June and December, and the value is used for six months until the next set of new data is available.

stock returns. (4) *Profit growth standard deviation*: the cross-sectional standard deviation of firm-level profit growth defined as a quarter-on-quarter change in net profits divided by average sales.[23]

We calculate *Stock return standard deviation* from the firms covered by CRSP, and *Profit growth standard deviation* from those covered by Compustat. To ensure that the two measures are not distorted by bias from newly listed firms, we restrict the sample to firms with at least 240 monthly observations from 1985 to 2014 in the CRSP monthly stock file and to firms with at least 60 quarterly observations over the same period in Compustat. It should be noted that *JLN uncertainty* is an aggregate uncertainty measure, and the other three measures are used to reflect uncertainty about future economic growth, uncertainty perceived by the equity market, and uncertainty about firms' future profitability, respectively.

The estimation results with the addition of the four economic uncertainty variables are presented in Column (1) of Table 7. The result indicates that the estimated coefficients on *ln*(*EPU*) and *ln*(*JLN uncertainty*) are both positive and statistically significant at the 5% level, whereas those on the three other uncertainty measures are statistically insignificant. These results suggest that the aggregate uncertainty arising from the macroeconomic and financial environment and the uncertainty from economic policy exert the adverse effect on the pricing of SEO shares. However, SEO discounts are not affected by uncertainty from the equity market or uncertainty about economic growth or profitability. In addition, the estimated coefficient on *ln*(*EPU*) is smaller than that reported in Column (2) of Table 3, suggesting that part of the effect from *ln*(*EPU*) on SEO discounts is captured by *ln*(*JLN uncertainty*).[24] Overall, the evidence confirms that our empirical

[23] Quarterly data on each firm are used for the three months starting from the month of the data date.

[24] According to the coefficient estimates of *ln*(*EPU*) and *ln*(*JLN uncertainty*) reported in Column (1) of Table 7, a one standard deviation increase in *EPU* and *JLN uncertainty* from their mean values will cause the SEO discount to increase by 23 and 48 basis points, respectively. The strong effect of *JLN uncertainty* is likely related to its high degree of correlation with the state of the economy and the financial market condition. All of the recession months within our 30-year sample period have larger than average *JLN uncertainty* values. In addition, *JLN uncertainty* and *-CFNAI*

results that the negative effect of EPU on SEO discounts are robust to controlling for other sources of uncertainty associated with the economic environment and the financial market.

(Insert Table 7 about here)

7.2. Selection bias

Since EPU may affect the timing of SEOs, it is possible that not all firms are affected similarly by EPU. For example, firms with financial constraints or poor financial performance may be eager to obtain outside capital and they are less able to delay the offering process during periods of high EPU. Since weak performing firms have to offer higher SEO discounts, the positive coefficient on *ln*(*EPU*) in our SEO discount regressions can be due to the high proportion of offerings conducted by weak performing firms in the high EPU period rather than to the direct effect from economic policy uncertainty. As a result, not controlling for differences in financial performance would lead to a positive selection bias, which may bias in favor of our findings. However, one may argue that good performing firms are more likely to conduct SEOs during the high EPU period since they suffer less from economic policy uncertainty. This will bias our estimates downwards and make the estimates less statistically significant. At the end, it is an empirical issue.

To address this selection bias, we control for firms' financial performance in our regression model. We use four financial performance measures: *ROE*, *ROE volatility*, *CFO*, and *CFO volatility*. *ROE* (*CFO*) is a firm's earnings before extraordinary items (net cash flow from operating activities) scaled by the lagged book value of equity (total assets) during the 12 fiscal quarters before the offer. Out of our 6,600 sample SEOs, we are only able to compile the *ROE* and *ROE*

have a correlation coefficient of 0.669, whereas the correlation between *EPU* and −*CFNAI* equals 0.342. If the influence of uncertainty on SEO discounts is stronger under weak economic conditions, then the strong correlation between *JLN uncertainty* and the state of the economy will produce a relatively large estimated coefficient on *ln*(*JLN uncertainty*) in our regression model.

volatility (*CFO* and *CFO volatility*) variables for 5,629 (4,868) observations from the Compustat database. Moreover, *CFO* and *CFO volatility* are only available starting from November 1988. All financial performance variables are winsorized at the 1% and 99% levels to eliminate outliers.

The results are presented in Columns (2) to (5) of Table 7. As expected, *ROE* and *CFO* have negative estimated coefficients, and *ROE volatility* and *CFO volatility* have positive estimated coefficients. All estimated coefficients except that on *ROE volatility* are statistically significant at the 5% level or better. More importantly, we find that the coefficient on *ln*(*EPU*) continues to be positively significant in all four regressions and the estimated magnitudes are comparable to those presented in earlier tables.

There is also another possibility of selection bias that firms conducting SEOs during high EPU periods are in urgent needs of cash to finance their M&A activities and therefore are willing to offer higher SEO discounts rather than waiting till the uncertainty becomes less.[25] To address this issue, we run a logistic regression of acquisition likelihood on policy uncertainty. The dependent variable is a dummy variable that equals one if the issuing firm has at least one M&A activity within 12 months after the SEO, and zero otherwise. The explanatory variables include *ln*(*EPU*), *ln*(*Size*), *ROE*, *CFO*, *M/B*, and industry dummies. We run this regression for the later 15-year sub-period in which policy uncertainty have the stronger negative effect on the pricing of SEO shares. From our unreported analysis, we find that the coefficient estimates on *ln*(*Size*) and *CFO* are positive and highly statistically significant, and the coefficient on *ln*(*EPU*) is negative and statistically significant at the 1% level. This result is consistent with Bonaime, Gulen, and Ion (2018) and Nguyen and Phan (2017) that higher policy uncertainty is associated with a lower likelihood of being an acquirer. Therefore, our earlier findings that policy uncertainty brings higher

[25] We thank an anonymous referee for pointing this out.

SEO discounts should not be caused by the selection bias that the SEO firms are those acquiring firms which are in need of cash and willing to accept a lower offer price.

7.3. The endogeneity concern of the EPU index

Finally, we address the endogeneity concern that the *ln*(*EPU*) variable is not truly exogenous in our regression model. Following Bonaime, Gulen, and Ion (2018), we use the monthly Partisan Conflict Index (PCI) as our instrument variable (Azzimonti (2019)).[26] This index tracks the degree of political disagreement among U.S. politicians at the federal level by conducting keyword searches on major newspapers. The PCI is able to satisfy both the relevance and exclusion conditions for the selection of a valid instrument as it is positively associated with policy uncertainty and should influence SEO discounts only through its effects from EPU.[27]

We estimate the first-stage monthly regression by regressing *ln*(*EPU*) on *ln*(*PCI*), the four economic uncertainty measures used in Column (1) of Table 7, together with the monthly averages of firm-specific control variables. We then replace *ln*(*EPU*) in our original SEO discount regression by *ln*(*EPU_IV*), where *ln*(*EPU_IV*) is the predicted value of *ln*(*EPU*) from the first-stage regression. Under the above specification, *ln*(*EPU_IV*) should reflect the exogenous variation in the EPU index. As reported in Column (6) of Table 7, the coefficient estimate on *ln*(*EPU_IV*) is positive and statistically significant at the 5% level. Moreover, it has an estimated magnitude of 1.200, which is similar in magnitude to that of *ln*(*EPU*) from the baseline regression as shown in Column (2) of Table 3. We therefore conclude that our earlier empirical results remain unchanged under the instrumental variable analysis.

[26] We obtain the Partisan Conflict Index from the website of Federal Reserve Bank of Philadelphia.

[27] See Azzimonti (2014) for the discussion on the similarities and differences between the EPU index and the PCI. Azzimonti (2014) finds that the correlation between the two indices is about 0.5.

Overall, the results from Table 7 confirm that our findings on the negative effect of economic policy uncertainty on SEO discounts are robust even after adjusting for various potential endogeneity issues.

8. Conclusion

In this paper, we examine the effect of economic policy uncertainty on the financing cost of raising external equity capital. In contrast to the study of Çolak, Durnev, and Qian (2017) on the IPO decision of private firms, we investigate how policy uncertainty affects the prices and volume of SEOs made by public firms. We use the EPU index constructed by Baker, Bloom, and Davis (2016) as our measure of economic policy uncertainty. We find that higher EPU is associated with higher SEO discounts, especially when the economy is weak. During the second half of our sample period (2000-2014) which corresponds to a high level and volatility of the EPU index, a one standard deviation increase in the EPU index raises the SEO discount by 43 basis points.

Cross-sectional analysis further shows that the EPU effect on SEO discounts is more pronounced for firms with less informative stock prices, greater dependence on government spending, and smaller EPU beta. Our results remain robust to controlling for other sources of macroeconomic and financial uncertainty and to correcting for potential endogeneity issues. Moreover, we show that economic policy uncertainty reduces the volume of SEOs.

Overall, our results appear to be consistent with the implications of the models developed by Pástor and Veronesi (2012; 2013) that a higher EPU level leads to a higher risk premium, particularly for firms that are more sensitive to economic policy uncertainty and when the economy is weak. Our paper contributes to the growing literature on the real effects of economic policy uncertainty. While most studies focus on corporate investment and the input and output of corporate production, our paper examines the other side of corporate investment and production, namely the corporate financing side. We indeed find that economic policy uncertainty not only affects the financing cost of raising external equity capital by seasoned public firms but also the activities.

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Appendix A: Definitions of variables

Variable	Definition
Panel A: Variables on offering and firm characteristics	
SEO discount	The percentage price change from the pre-offer day closing price to the offer price times minus one.
Analyst	The number of unique analysts issuing earnings forecasts as covered in the I/B/E/S dataset over the 12 months ending one month before the offer.
Analyst group i	Dummy variable that equals one (zero otherwise) if *Analyst* equals zero (*i*=1), one to four (*i*=2), and five or above (*i*=3), respectively.
IVOL	The idiosyncratic volatility of a stock which is defined as the standard deviation of the error term variance in Eq. (2) estimated with daily returns over the 12 months ending one month before the offer.
IVOL tercile i	Dummy variable that equals one (zero otherwise) if the *IVOL* of the offering firm belongs to the bottom (*i*=1), middle (*i*=2) or top (*i*=3) tercile of the *IVOL* distribution of all sample firms in the respective period.
SVOL	The systematic volatility of a stock, which is the square root of the difference between the total variance and the error term variance in Eq. (2), estimated with daily returns over the 12 months ending one month before the offer.
TVOL	The total volatility of a stock which is defined as the standard deviation of daily returns during the 12 months ending one month before the offer.
Price	The closing price of the stock on the day prior to the offer.
Size	Firm size defined as the closing price on the day prior to the offer times the total number of shares outstanding prior to the offer.
Relsize	Relative offer size defined as the number of offered shares divided by the total number of outstanding shares prior to the offer.
Proceeds	The offer price times the number of shares offered.
CAR positive	Equals *CAR* if *CAR* is positive and zero otherwise where *CAR* is the cumulative stock returns adjusted by the CRSP value-weighted market returns over the five days prior to the offer.
CAR negative	Equals *CAR* if *CAR* is negative and zero otherwise.
Tick<1/4	Dummy variable that equals one (zero otherwise) if the decimal portion of the closing price on the day prior to the offer is not an increment of 25 cents and the issues are offered before the exchange in which the firm is listed completes decimalization.
Cluster	Dummy variable that equals one (zero otherwise) if the offer price is set at a whole dollar value.
Rule10b-21	Dummy variable that equals one (zero otherwise) if the issue is offered after Rule 10b-21 becomes effective on August 25, 1988.
NASDAQ	Dummy variable that equals one if the firm is listed on the NASDAQ at the time of the offer and zero if the firm is listed on the NYSE or Amex.
ROE	The average of return on equity defined as earnings before extraordinary items scaled by lagged book value of equity during the 12 fiscal quarters

	before the offer. The values are winsorized at the 1% and 99% levels to eliminate outliers.
ROE volatility	The standard deviation of *ROE* during the 12 fiscal quarters before the offer. The values are winsorized at the 1% and 99% levels to eliminate outliers.
CFO	The average of scaled cash flow defined as net cash flow from operating activities scaled by total assets during the 12 fiscal quarters before the offer. The values are winsorized at the 1% and 99% levels to eliminate outliers.
CFO volatility	The standard deviation of *CFO* during the 12 fiscal quarters before the offer. The values are winsorized at the 1% and 99% levels to eliminate outliers.
M/B	Market to book ratio measured by the market value of equity divided by book value of equity calculated from the most recent quarterly report prior to the offer. The values are winsorized at the 1% and 99% levels to eliminate outliers.
DGS	Dependence on government spending calculated by dividing total or indirect input necessary to meet government demand by the firm's total output. The values are winsorized at the 1% and 99% levels to eliminate outliers.
DGS tercile i	Dummy variable that equals one (zero otherwise) if the *DGS* of the offering firm belongs to the bottom (i=1), middle (i=2) or top (i=3) tercile of the *DGS* distribution of all sample firms in the respective period.
EPU beta	The coefficient estimate of β^{EPU} from Eq. (1) of a stock estimated over the 60 months before the offer. The values are winsorized at the 1% and 99% levels to eliminate outliers.
EPU beta tercile i	Dummy variable that equals one (zero otherwise) if the *EPU beta* of the offering firm belongs to the bottom (i=1), middle (i=2) or top (i=3) tercile of the *EPU beta* distribution of all sample firms in the respective period.
Panel B: Variables on uncertainty and economic conditions	
EPU	The monthly economic policy uncertainty index compiled by Baker, Bloom, and Davis (2016) based on (i) the searches of newspaper articles containing terms regarding economic policy uncertainty, (ii) data from the Congressional Budget Office on the present value of future scheduled tax code expirations, and (iii) data from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecaster about economic forecaster disagreement on consumer price index, purchase of goods and services by state and local governments, and purchases of goods and services by the federal government. The index is collected from www.policyuncertainty.com.
ln(*EPU_IV*)	The predicted value of *ln*(*EPU*) from the first-stage instrumental variable analysis by regressing *ln*(*EPU*) on *ln*(*PCI*), *JLN uncertainty*, *GDP forecast dispersion*, *Stock return standard deviation*, *Profit growth standard deviation*, and the monthly *averages* of the firm-specific

	control variables used in the SEO discount regression. PCI is the Partisan Conflict Index developed by Azzimonti (2014).
JLN uncertainty	The monthly aggregate uncertainty measure compiled by Jurado, Ludvigson, and Ng (2015).
GDP forecast dispersion	The cross-sectional coefficient of variation of forecasts of nominal GDP one year ahead from the Philadelphia Federal Reserve Bank's biannual Livingston Survey. The variable is measured every June and December and the value is used for 6 months until the next new data are available.
Stock return standard deviation	The monthly cross-sectional standard deviation of individual firms' stock returns. The sample is restricted to firms with at least 240 monthly observations over 1985 to 2014 in the CRSP monthly stock file.
Profit growth standard deviation	The cross-sectional standard deviation of firm-level profit growth defined as quarter-on-quarter change in net profit divided by average sales. The sample is restricted to firms with at least 60 quarterly observations over 1985 to 2014 in the Compustat database. The quarterly data of each firm are used for 3 months starting from the month of the data date.
Recession	Dummy variable that equals one (zero otherwise) for the recession months identified by the National Bureau of Economic Research (NBER).
CFNAI	The Chicago Fed National Activity Index, which is a weighted average of 85 monthly indicators of national economic activity.

Table 1. Descriptive statistics

The SEO sample consists of 6,600 seasoned equity offerings (SEOs) issued by firms listed on the NYSE, Amex, and NASDAQ between 1985 and 2014. Definitions of variables are provided in Appendix A. *ROE*, *CFO*, *M/B*, *DGS*, and *EPU beta* data are available for 5,629, 4,868, 6,415, 6,568, and 3,974 observations only, respectively. Panel A provides SEO offering and firm characteristics, while Panel B the summary statistics of the economic policy uncertainty (EPU) index.

Panel A: SEO offering and firm characteristics

	Mean	Std. dev.	5^{th} pctl.	25^{th} pctl.	Median	75^{th} pctl.	95^{th} pctl.
SEO discount (%)	2.840	4.310	-0.029	0.000	1.700	4.000	10.555
Analyst	7.293	7.687	0.000	2.000	5.000	10.000	23.000
IVOL (%)	3.031	1.717	0.953	1.794	2.794	3.844	6.006
SVOL (%)	1.165	1.045	0.242	0.532	0.885	1.402	3.206
TVOL (%)	3.333	1.865	1.120	2.009	3.033	4.163	6.701
Price ($)	24.746	18.819	6.000	13.000	20.750	30.684	57.000
Size ($m)	1,448.858	6,796.839	38.114	138.464	353.893	984.495	5,053.315
Relsize (%)	20.934	14.857	4.034	10.619	17.592	27.175	49.103
Proceeds ($m)	134.281	477.826	9.482	28.401	59.919	122.744	411.938
ROE (%)	-0.415	14.602	-21.435	-0.330	2.405	4.093	8.810
ROE volatility (%)	15.227	53.508	0.396	1.180	2.701	6.659	58.293
CFO	-0.013	0.119	-0.278	-0.028	0.022	0.049	0.106
CFO volatility	0.067	0.075	0.008	0.023	0.044	0.079	0.210
M/B	4.378	6.384	0.712	1.473	2.623	5.199	14.814
DGS	0.107	0.103	0.002	0.039	0.084	0.143	0.302
EPU beta	-0.001	0.115	-0.193	-0.047	0.004	0.048	0.179

Panel B: Summary statistics of the EPU index

	1985-1989	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	1985-2014
Mean	114.14	108.99	79.74	103.38	99.07	140.55	107.65
Standard deviation	20.23	21.12	12.03	23.53	36.79	39.21	32.62
Minimum	74.84	76.50	61.16	66.58	57.20	71.26	57.20
Maximum	160.20	175.66	123.96	188.06	189.92	245.13	245.13
Range	86.36	99.16	62.80	121.48	132.71	173.86	187.92

Table 2. Univariate analysis of SEO discounts

This table reports the average SEO discount (in %) which is defined as minus one times the percentage price change from the pre-offer day closing price to the offer price. Analyst (*IVOL*) is the number of analysts covering a firm (stock return idiosyncratic volatility). The classification of terciles of EPU is based on the distribution of the EPU index over the whole sample period. The higher the group number, the higher the associated value of the variable. Definitions of variables are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on the *t*-statistics used to test the difference in average discounts between different groups of firms.

	1985-1989	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014	1985-2014
Panel A							
All offers	1.144	2.253	2.884	3.022	3.886	4.285	2.840
Panel B: Sorted by analyst coverage							
Analyst Group 1	1.998	3.646	3.953	4.225	4.058	8.722	3.614
Analyst Group 2	1.203	2.859	3.439	4.030	4.092	5.168	3.379
Analyst Group 3	0.643	1.439	1.879	2.393	3.785	3.657	2.320
Group 1 – Group 3	1.356***	2.208***	2.075***	1.832***	0.273	5.064***	1.294***
Panel C: Sorted by idiosyncratic volatility							
IVOL Tercile 1	0.792	0.805	1.543	1.710	2.322	2.732	1.590
IVOL Tercile 2	1.282	1.960	2.524	2.888	3.351	4.889	2.599
IVOL Tercile 3	1.905	3.867	4.102	3.872	5.987	6.539	4.332
Tercile 3 – Tercile 1	1.113***	3.062***	2.559***	2.162***	3.665***	3.807***	2.742***
Panel D: Sorted by EPU							
EPU Tercile 1	1.070	2.685	2.881	3.098	2.753	2.860	2.841
EPU Tercile 2	1.160	2.159	2.864	3.025	3.002	3.732	2.437
EPU Tercile 3	1.142	2.163	4.035	2.837	5.633	4.654	3.226
Tercile 3 – Tercile 1	0.072	-0.522	1.154	-0.262	2.880***	1.794***	0.385***
No. of observations	898	1,335	1,686	1,035	837	809	6,600

Table 3. The effect of economic policy uncertainty on SEO discounts

This table presents the regression results of the effect of economic policy uncertainty on SEO discounts based on SEOs issued by firms listed on the NYSE, Amex, and NASDAQ between 1985 and 2014. The dependent variable is the SEO discount, which is minus one times the percentage price change from the pre-offer day closing price to the offer price. EPU is the EPU index developed by Baker, Bloom, and Davis (2016). Definitions of other explanatory variables are provided in Appendix A. The regressions are estimated using the ordinary least squares (OLS) method and the Tobit method. In the Tobit regressions, the SEO discount is set to zero for SEOs with a negative discount. The *t*-statistics are reported in parentheses based on standard errors adjusted for clustering by firm and month. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Whole sample period	(2) Whole sample period	(3) 1985-1999	(4) 2000-2014
Regression method	OLS	Tobit	Tobit	Tobit
Intercept	-0.332	-4.472**	-3.809	-0.946
	(-0.18)	(-2.09)	(-1.07)	(-0.36)
ln(*EPU*)	0.734**	1.139***	0.789	1.485***
	(2.09)	(2.84)	(1.19)	(3.10)
ln(1+*Analyst*)	-0.512***	-0.747***	-0.665***	-0.719***
	(-6.46)	(-7.65)	(-5.12)	(-4.57)
ln(*IVOL*)	0.676***	0.937***	1.614***	0.624**
	(4.07)	(4.48)	(4.61)	(2.43)
ln(*SVOL*)	0.295**	0.457***	-0.093	0.764***
	(2.45)	(3.45)	(-0.50)	(3.79)
ln(*Price*)	-1.245***	-1.384***	-1.639***	-1.219***
	(-8.94)	(-8.88)	(-5.83)	(-6.59)
ln(*Size*)	0.184*	0.135	0.252	0.042
	(1.69)	(1.09)	(1.32)	(0.25)
Relsize	0.017***	0.015**	0.013	0.014
	(2.73)	(2.40)	(1.64)	(1.37)
CAR positive	0.036**	0.047***	0.080***	0.038**
	(2.43)	(3.01)	(3.92)	(2.12)
CAR negative	0.030**	0.053***	0.027	0.075***
	(2.24)	(3.57)	(1.29)	(3.64)
Tick<1/4	0.160	0.413***	0.407***	0.558
	(1.50)	(2.93)	(2.58)	(1.23)
Cluster	1.146***	1.519***	1.241***	1.863***
	(9.74)	(11.87)	(7.57)	(9.46)
Rule10b-21	0.123	-0.083	-0.205	
	(0.35)	(-0.05)	(-0.12)	
NASDAQ	0.546***	1.008***	0.987***	1.019***
	(3.93)	(5.46)	(3.69)	(3.70)
Year fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
R^2	0.186			
Log likelihood		-15,190	-8,247	-6,897
No. of observations	6,600	6,600	3,919	2,681

Table 4. Economic conditions and the effect of economic policy uncertainty on SEO discounts

This table presents the regression results of how economic conditions affect the effects of economic policy uncertainty on SEO discounts based on SEOs issued by firms listed on the NYSE, Amex, and NASDAQ between 1985 and 2014. The dependent variable is the SEO discount, which is minus one times the percentage price change from the pre-offer day closing price to the offer price. *Recession* is a dummy variable that equals one if it is a recession months identified by NBER; *-CFNAI* is minus one times the Chicago Fed National Activity index. Definitions of other explanatory variables are provided in Appendix A. The regressions are estimated using the Tobit regression method with the SEO discount set to zero for SEO with a negative discount. The *t*-statistics are reported in parentheses based on standard errors adjusted for clustering by firm and month. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Intercept	-3.431	-3.502
	(-1.54)	(-1.58)
ln(*EPU*)	0.917**	0.939**
	(2.14)	(2.19)
ln(*EPU*) × *Recession*	1.000	
	(0.96)	
Recession	-4.260	
	(-0.85)	
ln(*EPU*) × *-CFNAI*		0.811***
		(2.71)
-CFNAI		-3.772***
		(-2.66)
ln(1+*Analyst*)	-0.745***	-0.741***
	(-7.64)	(-7.62)
ln(*IVOL*)	0.962***	0.953***
	(4.61)	(4.57)
ln(*SVOL*)	0.445***	0.455***
	(3.33)	(3.41)
ln(*Price*)	-1.380***	-1.381***
	(-8.87)	(-8.86)
ln(*Size*)	0.133	0.131
	(1.07)	(1.05)
Relsize	0.015**	0.015**
	(2.41)	(2.42)
CAR positive	0.046***	0.046***
	(3.01)	(2.99)
CAR negative	0.053***	0.053***
	(3.61)	(3.65)
Tick<1/4	0.416***	0.411***
	(2.94)	(2.91)
Cluster	1.514***	1.519***
	(11.82)	(11.84)
Rule10b-21	-0.771	-0.055
	(-0.05)	(-0.03)
NASDAQ	1.008***	1.003***
	(5.45)	(5.42)
Year fixed effect	Yes	Yes
Industry fixed effect	Yes	Yes
Log likelihood	-15,188	-15,186
No. of observations	6,600	6,600

Table 5. The cross-sectional variation in the effect of economic policy uncertainty on SEO discounts: Dependence on government spending, stock price informativeness, and EPU beta

This table presents the regression results of how dependence on government spending (measured by *DGS*), stock price informativeness, and EPU beta affect the effects of economic policy uncertainty on SEO discounts based on SEOs issued by firms listed on the NYSE, Amex, and NASDAQ between 1985 and 2014. The dependent variable is SEO discount. Stock price informativeness is proxied by analyst coverage and idiosyncratic volatility. The control variables are the same as those in Table 3. Definitions of the explanatory variables are provided in Appendix A. The regressions are estimated using the Tobit regression method with the SEO discount set to zero for SEO with a negative discount. For brevity, we report only the coefficients related to EPU. The *t*-statistics are reported in parentheses based on standard errors adjusted for clustering by firm and month. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Whole sample period	(2) 1985-1999	(3) 2000-2014
Panel A: Interaction with dependence on government spending			
ln(*EPU*)	1.075***	0.646	1.434***
	(2.63)	(0.95)	(3.03)
ln(*EPU*) × *DGS tercile 2*	0.094**	0.153**	0.114**
	(2.27)	(2.33)	(2.13)
ln(*EPU*) × *DGS tercile 3*	0.134*	0.168	0.150
	(1.91)	(1.64)	(1.53)
Controls	Yes	Yes	Yes
No. of observations	6,568	3,901	2,667
Panel B: Interaction with analyst coverage			
ln(*EPU*)	1.032**	0.690	1.366***
	(2.54)	(1.02)	(2.84)
ln(*EPU*) × *Analyst group 1*	0.408***	0.344***	0.578***
	(4.21)	(2.90)	(3.48)
ln(*EPU*) × *Analyst group 2*	0.175***	0.116*	0.246***
	(3.85)	(1.90)	(3.77)
Controls	Yes	Yes	Yes
No. of observations	6,600	3,919	2,681
Panel C: Interaction with idiosyncratic volatility			
ln(*EPU*)	1.103***	0.811	1.436***
	(2.73)	(1.21)	(3.03)
ln(*EPU*) × *IVOL tercile 2*	0.010	-0.090	0.083
	(0.22)	(-1.52)	(1.30)
ln(*EPU*) × *IVOL tercile 3*	0.176***	0.050	0.216*
	(2.57)	(0.54)	(1.92)
Controls	Yes	Yes	Yes
No. of observations	6,600	3,919	2,681
Panel D: Interaction with EPU beta			
ln(*EPU*)	1.087**	1.171	1.086*
	(2.08)	(1.15)	(1.92)
ln(*EPU*) × *EPU beta tercile 2*	-0.109**	-0.175**	-0.078
	(-2.23)	(-1.97)	(-1.27)
ln(*EPU*) × *EPU beta tercile 3*	-0.147**	-0.124	-0.172**
	(-2.25)	(-1.01)	(-2.41)
Controls	Yes	Yes	Yes
No. of observations	3,974	1,914	2,060

Table 6. The effects of economic policy uncertainty on the volume of SEOs

This table presents the regression results of the effects of economic policy uncertainty on the volume of SEOs. The dependent variable is the number of SEOs offered in month *t*; and the explanatory variables include EPU in month *t* and month *t*-1, the market return as measured by the value-weighted return on the CRSP market index (in %) in month *t* and month *t*-1, and *CFNAI* which is the Chicago Fed National Activity Index in month *t* and month *t*-1. The regressions are estimated with ordinary least squares (OLS) method and the *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Intercept	65.715***	100.990***	71.266***
	(6.58)	(5.99)	(3.92)
ln(*EPU*)	-7.550*	-8.450**	-4.907
	(-1.89)	(-2.49)	(-1.39)
ln($EPU_{t\text{-}1}$)	-2.663	-8.720**	-6.308*
	(-0.67)	(-2.54)	(-1.80)
Market return			-0.047
			(-0.45)
Market return$_{t\text{-}1}$			0.257**
			(2.46)
CFNAI			1.576*
			(1.92)
$CFNAI_{t\text{-}1}$			1.659**
			(2.09)
Year fixed effect	No	Yes	Yes
Month fixed effect	No	Yes	Yes
R^2	0.061	0.567	0.589
No. of observations	359	359	359

Table 7. Addressing the endogeneity concerns on the effects of EPU on SEO discounts

This table presents the regression results of the effects of EPU on SEO discounts controlling for the effects of various uncertainty measures (Column (1)) and firms' financial performance (Columns (2)-(5)), as well as the use of an instrument variable (Column (6)) to measure EPU. The dependent variable is the SEO discount. *JLN uncertainty* is monthly aggregate uncertainty measure compiled by Jurado, Ludvigson, and Ng (2015). *GDP forecast dispersion* is cross-sectional coefficient of variation of forecasts of nominal GDP one year ahead. *Stock return standard deviation* is the monthly cross-sectional standard deviation of individual firms' stock returns. *Profit growth standard deviation* is cross-sectional standard deviation of firm-level quarter-to-quarter profit growth. *ln*(*EPU_IV*) is the predicted value of *ln*(*EPU*) from the first-stage instrumental variable analysis by regressing *ln*(*EPU*) on *ln*(*PCI*) (i.e., logarithm of the Partisan Conflict Index), the four economic uncertainty measures used in Column (1) of this table, together with the monthly averages of the firm-specific control variables. Definitions of other explanatory variables are provided in Appendix A. All regressions are estimated using the Tobit regression method with the SEO discount set to zero for SEO with a negative discount. The *t*-statistics are reported in parentheses based on standard errors adjusted for clustering by firm and month. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-1.184	-3.542	-3.583	-2.402	-2.613	-4.834
	(-0.43)	(-1.49)	(-1.51)	(-1.04)	(-1.13)	(-1.60)
ln(*EPU*)	0.880**	0.867**	0.872**	0.902**	0.923**	
	(2.15)	(1.98)	(2.00)	(2.02)	(2.06)	
ln(*EPU_IV*)						1.200**
						(2.03)
ln(*JLN uncertainty*)	9.574**					
	(2.53)					
ln(*GDP forecast dispersion*)	0.154					
	(0.94)					
ln(*Stock return standard deviation*)	-0.304					
	(-0.65)					
ln(*Profit growth standard deviation*)	-0.032					
	(-0.43)					
ROE		-0.013***				
		(-2.60)				
ROE volatility			0.001			
			(0.55)			
CFO				-3.052***		
				(-3.74)		
CFO volatility					3.449**	
					(2.55)	
ln(1+*Analyst*)	-0.751***	-0.822***	-0.828***	-0.903***	-0.923***	-0.755***
	(-7.65)	(-7.70)	(-7.76)	(-8.30)	(-8.44)	(-7.74)
ln(*IVOL*)	0.966***	0.904***	0.952***	0.610***	0.633***	0.943***
	(4.62)	(3.82)	(3.99)	(2.69)	(2.73)	(4.53)
ln(*SVOL*)	0.429***	0.583***	0.574***	0.616***	0.623***	0.442***
	(3.21)	(4.00)	(3.95)	(4.25)	(4.34)	(3.32)
ln(*Price*)	-1.378***	-1.242***	-1.273***	-1.354***	-1.429***	-1.373***
	(-8.82)	(-7.47)	(-7.78)	(-7.81)	(-8.30)	(-8.81)
ln(*Size*)	0.140	0.177	0.182	0.169	0.188	0.145
	(1.13)	(1.31)	(1.34)	(1.23)	(1.36)	(1.17)
Relsize	0.015**	0.023***	0.022***	0.021***	0.020***	0.015**
	(2.45)	(3.11)	(3.05)	(2.77)	(2.73)	(2.50)
CAR positive	0.047***	0.042**	0.043**	0.039**	0.041**	0.047***
	(3.04)	(2.53)	(2.58)	(2.46)	(2.45)	(3.02)
CAR negative	0.054***	0.055***	0.055***	0.055***	0.053***	0.053***
	(3.67)	(3.43)	(3.41)	(3.31)	(3.26)	(3.57)
Tick<1/4	0.422***	0.374**	0.378**	0.325*	0.339*	0.416***

	(2.99)	(2.31)	(2.34)	(1.76)	(1.84)	(2.94)
Cluster	1.513***	1.478***	1.485***	1.511***	1.522***	1.517***
	(11.81)	(10.36)	(10.41)	(10.25)	(10.29)	(11.86)
Rule10b-21	-0.041	0.933	1.027			0.004
	(-0.02)	(0.56)	(0.61)			(0.00)
NASDAQ	1.010***	1.037***	1.042***	1.130***	1.157***	1.022***
	(5.47)	(5.19)	(5.20)	(5.50)	(5.67)	(5.52)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	-15,187	-12,973	-12,977	-11,910	-11,915	-15,192
No. of observations	6,600	5,629	5,629	4,868	4,868	6,600

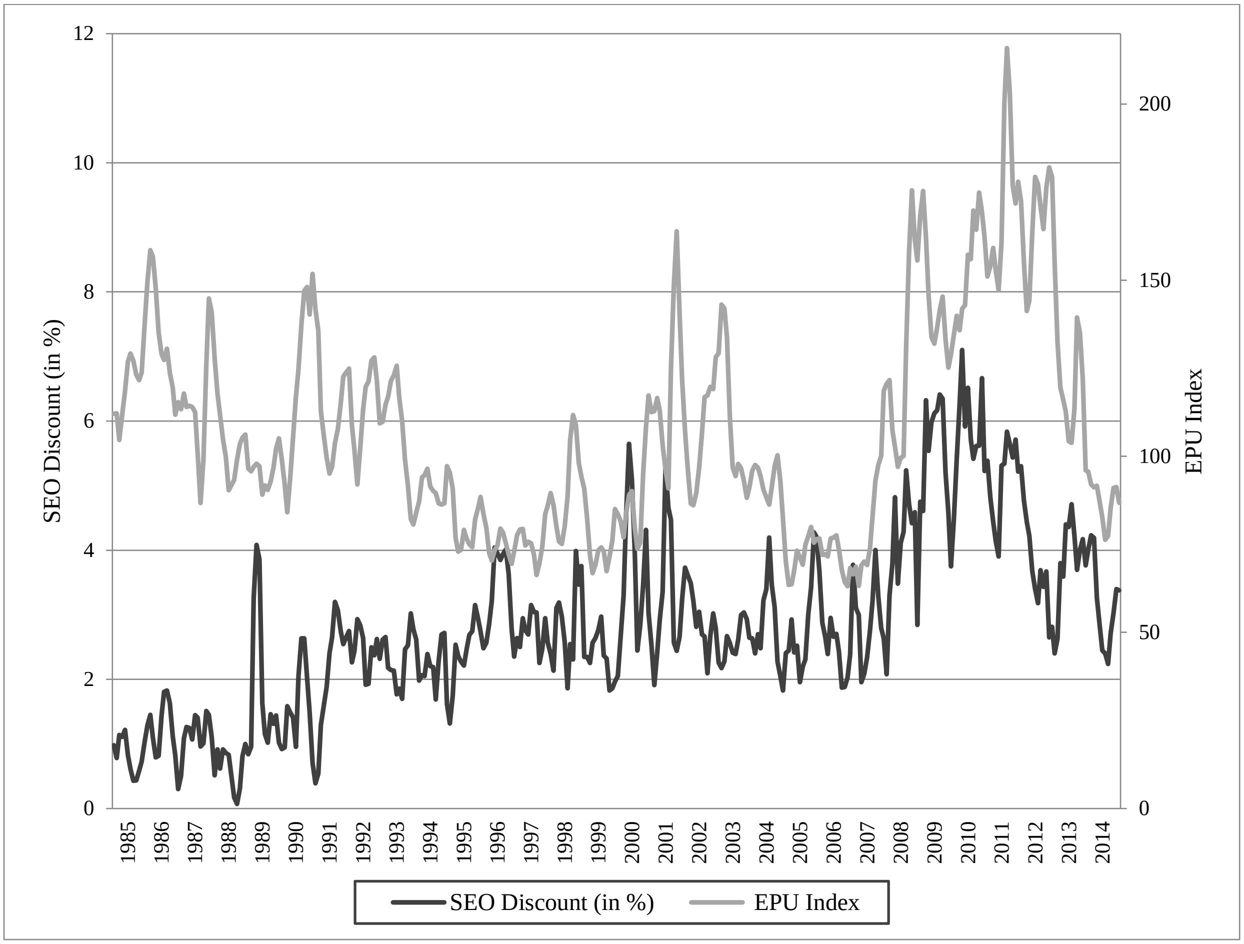

Figure 1. The time-series patterns of SEO discounts and the EPU index. This figure shows the time-series papers of the 3-month moving average of SEO discounts and the EPU index developed by Baker, Bloom, and Davis (2016).