Journal of Accounting and Economics 67 (2019) 36–57

Contents lists available at ScienceDirect

Journal of Accounting and Economics

journal homepage: www.elsevier.com/locate/jae

The effect of economic policy uncertainty on investor information asymmetry and management disclosures☆

Venky Nagar[a], Jordan Schoenfeld[b], Laura Wellman[*,c]

[a] *Ross School of Business, University of Michigan, 701 Tappan Avenue, Ann Arbor, MI 48109, United States*
[b] *McDonough School of Business, Georgetown University, 37th and O Streets, Washington, DC 20057, United States*
[c] *Smeal College of Business, Pennsylvania State University, 210 Business Building, University Park, PA 16802, United States*

ARTICLE INFO

Keywords:
Corporate disclosure
Economic policy uncertainty
Information asymmetry

JEL classification:
D80
E61
E65
G12
G14
G18
L50

ABSTRACT

Investor uncertainty about firm value drives investors' information collection and trading activities, as well as managers' disclosure choices. This study examines an important source of uncertainty that likely cannot be influenced by most managers and investors: uncertainty about government economic policy. We find that this uncertainty is associated with increased bid-ask spreads and decreased stock price reactions to earnings surprises. Managers respond to this uncertainty by increasing their voluntary disclosures, but these disclosures only partly mitigate the bid-ask spread increase. We conclude that government economic policy uncertainty is an important component of firms' information environments and managers' voluntary disclosure decisions.

1. Introduction

Investor uncertainty about firm value is a key driver of many investor and managerial activities (Verrecchia, 2001). Some investors collect private information about firm value before trading, thus inducing information asymmetry and illiquidity in the pricing process (e.g., wider bid-ask spreads). Managers react to such information asymmetry by supplying their own disclosures. However, testing these mechanisms is hampered by the possibility that investors and managers are self-interested agents who can first alter the uncertainty about firm value for their own benefit and then make their trading and disclosure choices accordingly (e.g., Core, 2001; Joos, 2000). This study therefore analyzes an uncertainty that likely cannot be significantly influenced by most individual

☆ We appreciate the helpful suggestions from John Core (the editor), Daniel Taylor (the referee), Nick Bloom, Steve Davis, Beverly Walther, and workshop participants at Baruch College, BYU, Georgetown University, INSEAD, Northwestern University, Pennsylvania State University, Temple University, the University of Hong Kong, the University of Michigan, the University of Utah, and the University of Texas at Austin. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

* Corresponding author.
E-mail addresses: venky@umich.edu (V. Nagar), jordan.schoenfeld@georgetown.edu (J. Schoenfeld), laura.wellman@psu.edu (L. Wellman).

https://doi.org/10.1016/j.jacceco.2018.08.011
Received 24 April 2017; Received in revised form 13 August 2018; Accepted 16 August 2018
Available online 21 August 2018
0165-4101/ © 2018 Elsevier B.V. All rights reserved.

investors and managers: uncertainty about government economic policy or "economic policy uncertainty" (EPU). Asset-pricing studies model EPU as investors' and managers' uncertainty over government action that is largely outside their control, but strongly contributes to uncertainty about firm value (Pastor and Veronesi, 2012; 2013). We examine how EPU affects information asymmetry among investors and how managers react through their voluntary disclosure choices.[1]

We first estimate a model regressing measures of information asymmetry such as bid-ask spreads on a measure of EPU. Theoretically, the direction of this relation is ambiguous because EPU could complement or substitute for investors' private information collection activities. Any effect of EPU on information asymmetry could be further exacerbated or ameliorated by the firm's earnings disclosures, which could also complement or substitute for investors' private information collection (Kim and Verrecchia, 1994).[2] We therefore also examine how investors' reaction to earnings changes with EPU. Finally, managers may supply additional voluntary disclosure if information asymmetry among investors increases (e.g., Coller and Yohn, 1997; Guay et al., 2016). We therefore examine managers' voluntary disclosure response to EPU and recursively estimate the extent to which these disclosures affect information asymmetry. These additional analyses enable us to better interpret our initial empirical model of EPU and information asymmetry.

Our main proxy for EPU is the EPU index of Baker et al. (2016). The EPU index measures uncertainty about economic policy using textual analysis of policy-related news articles in various media. This index has found widespread acceptance in the economics and finance literatures.[3] One advantage of the EPU index is that it is a daily measure that can be linked to contemporaneous measures of investor information asymmetry, earnings announcement returns, and voluntary disclosure. We measure information asymmetry among a firm's investors using percent DTAQ quoted percent bid-ask spreads and Amihud illiquidity—with appropriate fixed effects and controls.[4] We measure managers' disclosure response to EPU using the frequency of management forecasts and voluntary 8-K filings.

Our sample includes approximately 7000 U.S. public companies from 2003 to 2016. In the first analysis, we test how EPU affects information asymmetry, as proxied for by DTAQ quoted percent bid-ask spreads and Amihud illiquidity. We control for firm-year-fixed effects, the equity uncertainty (EU) index from Baker et al. (2016), and other relevant variables.[5] The firm-year-fixed effects control for a number of alternative explanations, including persistent firm-specific factors (such as industry membership) and time-varying, firm-year-specific factors (such as firm size and risk) that might affect spreads and Amihud. These fixed effects also mean that the coefficient on the EPU index reflects the effect of abnormal EPU, i.e., the current EPU's deviation from its corresponding time-series mean.

We use both market-level and firm-level tests and find that increased EPU is significantly associated with a contemporaneous increase in spreads and Amihud illiquidity. We use prior studies to show in Section 4.2 that the magnitudes of these relations are economically significant. We also perform cross-sectional tests and find, among other results, that the EPU-spread and EPU-Amihud relations are more pronounced for firms that are more exposed to EPU. These findings collectively suggest that increased EPU increases investor information asymmetry.

In the second analysis, we build on our empirical model of EPU and information asymmetry by testing how EPU affects investors' response to earnings surprises. We find decreased quarterly earnings announcement returns for the same earnings surprise during periods of increased EPU. To further link this result to the first analysis, we assess whether this finding is associated with a firm's expected liquidity risk, which is determined in part by information asymmetry in the market for firm shares (Pastor and Stambaugh, 2003).[6] We find that for the same EPU and earnings surprise, announcement returns decrease more in firms that are more exposed to liquidity risk. Taken together, these findings suggest that increased EPU decreases the weight investors place on earnings in valuing the firm, and that mandatory disclosures such as earnings are affected by increased information asymmetry due to EPU. These findings support our initial EPU and information asymmetry results and also raise the question of whether voluntary disclosures can overcome the negative effect of EPU on information asymmetry.

In the third analysis, we test whether managers respond to EPU by changing their provision of voluntary disclosure. Using market-level and firm-level tests with firm-year-fixed effects, we find that the average EPU level for a given year-quarter is positively associated with the frequency of management forecasts and voluntary 8-K filings in the following quarter. These findings suggest that EPU is an important component of managers' voluntary disclosure decisions.

To assess whether these additional disclosures mitigate the adverse effect of EPU on information asymmetry among investors, we link them to information asymmetry using a recursive structural equations model (or path model). We find that these additional disclosures only partly offset the increase in information asymmetry due to EPU. EPU thus appears to increase information asymmetry

[1] The importance of EPU is also evident in practice. Minutes of the Federal Reserve's Open Market Committee meeting in March, 2018 mention uncertainties associated with trade and tax policies as downside risks for the U.S. economy. In 2013, Moody's Chief Economist Mark Zandi commented on the negative corporate impact of uncertainty created by Washington (Novack, 2013). Other examples are listed in Pastor and Veronesi (2012). Note that it is always possible that a particular investor or manager has sway over some economic policies, but our assumption is that this effect is unlikely to be pervasive over our sample of approximately 7000 firms.

[2] Section 2 elaborates on these theoretical arguments.

[3] See http://www.policyuncertainty.com/ for details. We describe the salient features of the EPU index further in Section 3.

[4] As described in Section 3, we take steps to ensure that we capture the information asymmetry component of these measures, and we account for skewness and autocorrelation in all of our measures.

[5] Baker et al. (2016, p. 1614) find that the EPU index is correlated with general market uncertainty and advise researchers to use the EU index (our findings are similar when we control for the VIX).

[6] We use a firm's exposure to liquidity risk because a firm's liquidity itself changes during earnings announcements (Kim and Verrecchia, 1994).

among investors in a way that managers cannot fully mitigate. This result supports our initial finding that EPU is associated with increased bid-ask spreads and Amihud illiquidity.

To summarize, we find consistent evidence across a variety of empirical specifications that EPU decreases the quality of firms' information environments. Our evidence also suggests that managers respond to increased EPU by increasing their provision of voluntary disclosure. However, these additional disclosures only partly offset the information asymmetry created by EPU. Since it is unlikely that EPU is systematically influenced by the average firm, we have confidence in attributing causality to these large-sample firm-level findings.

Our focus on information asymmetry among investors and EPU complements research on how firms' information environments are impacted by uncertainty created by firm-specific factors such as the unexpected departure of analysts or complexity of financial statements (e.g., Balakrishnan et al., 2014; Guay et al., 2016). We also complement Pastor and Veronesi (2012, 2013), who find that EPU affects stock price volatility and risk premia but assume a representative-investor economy of firms in which all investors have exactly the same information. Our evidence linking EPU and information asymmetry suggests this is not the case: EPU increases information asymmetry among investors of a given firm, which firm disclosures do not fully compensate for.[7] This result supports Gao and Huang's (2016) and Jagolinzer et al.'s (2018) finding that certain sophisticated traders profit from government policy uncertainty. Furthermore, Bird et al. (2017) and Boone et al. (2017) examine managers' disclosure behavior during political elections for firms in battleground states, but they do not perform several of our analyses, nor do they analyze EPU, which may or may not arise in an election, or may persist even after its outcome.

Our study may also inform policymakers. The U.S. government increasingly relies on temporary or provisional laws that likely contribute to policy uncertainty (Fagan and Bilgel, 2015; Viswanathan, 2007). Our findings linking EPU to information asymmetry may therefore help policymakers to better understand the implications of policy stability on stock market liquidity.

The remainder of this study is organized as follows. Section 2 motivates our hypotheses in light of prior studies. Section 3 describes our data. Section 4 provides our empirical results. Section 5 concludes.

2. Hypothesis development

The importance of EPU at the firm level is well established (e.g., Baker et al., 2014; 2016). In particular, Pastor and Veronesi (2012) build a model where the government stochastically changes its economic policy based only on aggregate economic conditions, and each individual firm considers the uncertainty of government policy as exogenous to its own activities and market value when computing its reaction function (see their Eq. (1)). Their model suggests that we can consider EPU as an exogenous source of uncertainty for any specific firm.

Pastor and Veronesi (2012, 2013) only consider the case of identically informed representative investors, but we can conceptually expand their setting to the case where uncertainty prompts private information collection by some investors whose subsequent trading activity induces information asymmetry in the pricing process, as measured by bid-ask spreads or other market-based metrics (Verrecchia, 2001). There is considerable indirect evidence for such acquisition of private information. Gao and Huang (2016) find that hedge funds with lobbyist ties earn abnormal profits on policy-sensitive stocks. Christensen et al. (2017) find that analyst recommendations issued by politically connected brokerage houses are more profitable than those of non-connected brokers. Bradley et al. (2018) find that the clients of analysts with private access to policy research trade more aggressively in stocks for which policy research is available. Jagolinzer et al. (2018) suggest that access to politicians increases managers' and directors' trading profits.

On the other hand, there are several reasons EPU may not systematically affect information asymmetry. Information asymmetry in the U.S. may already be so low as to render negligible any information effect of EPU (e.g., Leuz and Verrecchia, 2000). That is, we are in effect back to the identically informed investor models of Pastor and Veronesi (2012, 2013). As yet another possibility, EPU could trigger additional disclosures from management that increase the precision of public information relative to investors' private information, in which case EPU could decrease or have no net effect on information asymmetry.

Consequently, the above arguments suggest that the general equilibrium association between EPU and information asymmetry is ambiguous, leading to our first hypothesis, stated in the null:

H1: EPU is not associated with information asymmetry among investors.

In addition, Pastor and Veronesi (2012, Section V) argue that different firms have different exposures to EPU and thus are impacted differently by EPU. This suggests a natural cross-sectional extension of H1, stated in the null:

Cross-Sectional H1: The association between EPU and information asymmetry among investors is not affected by a firm's exposure to EPU.

To the extent that EPU increases information asymmetry in H1, this could increase uninformed traders' losses resulting from trade with informed traders, thereby driving uninformed traders to trade less frequently or exit the market (Chordia et al., 2008). If these uninformed traders previously provided liquidity to informed traders, informed traders may now trade less in response to the release of new public information such as earnings disclosures. In this case, we would expect increased EPU to decrease investors' reaction to public earnings disclosures. We would also expect this result if EPU decreases the relative informativeness or precision of earnings disclosures, thereby decreasing the weight investors place on earnings in valuing the firm.

Conversely, earnings disclosures could decrease information asymmetry and uncertainty among investors and thus offset the

[7] Baker et al. (2016) also indicate that EPU is associated with return volatility, which is known to be associated with spreads (Chordia et al., 2005, p. 88). But this does not imply that EPU is associated with spreads. We therefore test this association while controlling for return volatility.

aforesaid effects. Some investors may also respond to EPU and earnings disclosures by increasing their information acquisition activities and trading more aggressively (Kim and Verrecchia, 1994). In this case, we would expect increased EPU to increase investors' reaction to earnings disclosures. Using the earnings surprise to proxy for the earnings release, these considerations lead to our second hypothesis, stated in the null:

H2: EPU is not associated with investors' reaction to earnings surprises.

For H1 and H2, we assume that EPU cannot be significantly influenced by the average management team in our large firm-level sample. However, managers may attempt to mitigate any adverse effect of EPU on investor information asymmetry through voluntary disclosures that help investors to better understand the firm (Baker et al., 2016, Section IV.C; Verrecchia, 1990). These additional voluntary disclosures may substitute for investors' private information acquisition activities, thereby reducing any information asymmetry among investors resulting from EPU. Managers may prefer this outcome to the extent that decreased information asymmetry decreases investors' trading costs or the cost of equity capital for the firm (e.g., Balakrishnan et al., 2014; Lang and Maffett, 2011). In addition, managers are compensated on stock price and may want investors to better understand and react more forcefully to subsequent positive earnings surprises (e.g., Nagar et al., 2003).[8]

At the same time, other studies find that management disclosures may increase investors' private information acquisition activities, thereby increasing adverse selection among investors (e.g., Kim and Verrecchia, 1994). In such situations, managers may not provide additional voluntary disclosures. Another possibility is that the benefit of additional disclosure may not exceed its cost to the firm or managers' private cost of disclosure (e.g., Bernard, 2016). Managers may also believe that EPU will soon reverse itself (e.g., Graham et al., 2005), or they may not be concerned about improving the firm's information environment for other reasons. Again, in these cases, managers may not respond to EPU through additional voluntary disclosure. These considerations lead to our last hypothesis, stated in the null:

H3: EPU is not associated with managers' provision of voluntary disclosure.

Our argument thus far follows the setting of Pastor and Veronesi (2012), who model investor uncertainty about a single policy decision that the government will undertake on a pre-specified future date (see their Eq. (2)). The empirical reality, however, is an overlapping set of such uncertainties facing a heterogeneous set of firms and investors. We do not make specific dynamic multiperiod predictions but instead use fixed effects to control for time-series variation in EPU, employ various EPU lead-lags, and check if our results vary with firms' (ex-post) exposure to EPU.

3. Data and sample

Our sample includes the entire NYSE daily TAQ (DTAQ) database from September 10, 2003 to December 31, 2016. We focus on firms headquartered in the U.S. since our primary measure of EPU pertains to the U.S. This reduces the DTAQ universe by about 25% . We also link each DTAQ firm to CRSP data using the linking table provided by DTAQ. We remove observations with missing data and impose no other survival criteria except where noted. Our final sample comprises nearly 7000 firms and 15 million daily observations of spreads and Amihud. The Appendix defines all of our variables and their sources.

Our first proxy for information asymmetry among investors is the percent quoted bid-ask spread. We follow Holden and Jacobsen (2014) and use the DTAQ database to compute daily percent quoted bid-ask spreads for each firm-day over our sample period. Fong et al. (2017) and Holden and Jacobsen (2014) suggest that this is the best measure of spreads among various alternatives—including the CRSP spread—because it incorporates all quotes on a given day. We compute percent quoted spreads as follows:

$$Percent\ \ Quoted\ \ Spreads_{it} = 100 \times \frac{Ask_{it} - Bid_{it}}{(Ask_{it} + Bid_{it})\,/\,2}, \tag{1}$$

where subscript i represents each firm, and subscript t represents each day. Ask_{it} is the National Best Ask, and Bid_{it} is the National Best Bid, where both variables are time weighted during trading hours for each day according to the procedure described in Holden and Jacobsen (2014). To ensure that we compute this measure accurately, we vet and implement the code provided by Holden and Jacobsen (2014).[9]

We recognize that spreads are comprised of several components, including (1) the cost of trading with better informed investors, (2) the cost of holding stock in inventory, and (3) order-processing costs (Foucault et al., 2013, p. 80). Foucault et al. (2013, Section 3.4) emphasize that (3) order-processing costs are driven primarily by trading technology, settlement fees, and the competitiveness of dealer markets, all of which are relatively stable from year to year. On the other hand, Foucault et al. (2013, Section 3.2.2) emphasize that information asymmetry in trade drives both (1) and (2) from above. That is, unanticipated trading losses and losses on inventory both increase for market makers when they trade with better informed investors, as in the model of Glosten and Milgrom (1985). Thus, (3) is relatively stable over time and (1) and (2) vary based on information asymmetry in trade. Therefore, prior studies often use fixed effects to isolate the information asymmetry component of spreads (e.g., Guay et al., 2016; Lang et al., 2012; Schoenfeld, 2017). We follow this approach and use firm-year-fixed effects to control for (3) in our firm-level spread regressions and year-fixed effects in our market-level regressions. We also control for several other determinants of spreads, including contemporaneous return volatility, turnover, dollar trading volume, and stock price (e.g., Holden et al., 2013). Our approach of including an extensive set of

[8] The above arguments assume that managers understand the nature of their firm's exposure to EPU.

[9] Our results are qualitatively similar when we use CRSP percent spreads and effective spreads. The latter is expected given that Holden and Jacobsen (2014, p. 293) find that quoted spreads and effective spreads are correlated at about 0.99. Figs. 1 and 2 of Chordia et al. (2001) also show that quoted spreads and effective spreads move in tight lockstep with each other.

fixed effects and additional controls creates a measure of abnormal spreads that isolates the information asymmetry component of spreads (e.g., Bushee et al., 2010; Leuz and Verrecchia, 2000).[10]

We also include a second proxy for information asymmetry, Amihud illiquidity, which measures the sensitivity of stock price to dollar trading volume (e.g., Amiram et al., 2016; Guay et al., 2016; Lang and Maffett, 2011; Schoenfeld, 2017). Following Amihud (2002), we compute daily Amihud illiquidity as follows:

$$Amihud_{it} = 10^6 \times \frac{|Return_{it}|}{Dollar\ \ Trade\ \ Volume_{it}}, \tag{2}$$

where $Return_{it}$ and $Dollar\ Trade\ Volume_{it}$ represent firm *i*'s stock return and dollar trading volume, respectively, on day *t* from CRSP. We again use firm-year-fixed effects in our firm-level regressions, year-fixed effects in our market-level regressions, and several relevant controls in both sets of regressions. We treat the residual Amihud after fixed effects and controls as another proxy for information asymmetry in trade.

We perform several robustness checks for bid-ask spreads. Chordia et al. (2008, p. 252) find that errors in the TAQ and CRSP databases have decreased considerably over time; nonetheless, we mitigate the influence of outliers by winsorizing spreads and Amihud from the top at the 1% level. We also find qualitatively similar results when we winsorize from the top at the 5% level, when we do not winsorize, and when we log transform one plus spreads and one plus Amihud. To address the concern raised by Lang and Maffett (2011, p. 114) that the Amihud measure is "naturally skewed," we follow their approach and ensure that our inferences are qualitatively similar when we use Amihud decile rankings and a modified Amihud that deflates dollar trading volume by market value of equity. We also find qualitatively similar results using decile rankings for spreads. Finally, in our market-level analyses, both spreads and Amihud are market-value weighted on the day of observation. Our use of value weights for the market-level tests follows Chordia et al. (2005), though we find similar results for equal weights as well. We perform both daily analyses and monthly analyses where we average each measure over the observation month.[11]

Our main proxy for EPU is the EPU index developed by Baker et al. (2016). The EPU index is constructed daily based on the number of news articles that contain the terms *economic* or *economy; uncertain* or *uncertainty*; and one or more of *Congress, deficit, Federal Reserve, legislation, regulation*, and *White House*.[12] Baker et al. (2016, p. 1593) note that both computational and human readings validate that the EPU index proxies for movements in EPU. The index spikes near tight presidential elections, the failure of Lehman Brothers, the 2011 debt ceiling dispute, and other major economic policy events. Using firm-level data, Baker et al. (2016) find that the EPU index is associated with reduced investment and employment in policy-sensitive sectors like defense, health care, finance, and infrastructure construction. At the macro level, the EPU index foreshadows drops in investment, output, and employment in the U.S.

Baker et al. (2016, p. 1614) find that the EPU index could be correlated with general market uncertainty; we do as they advise and control for the equity uncertainty (EU) index. The EU index is constructed daily based on the number of news articles that contain the terms *uncertainty* or *uncertain*, the terms *economic* or *economy*, and one or more of the following terms: *equity market, equity price, stock market*, or *stock price*.[13] In our monthly and quarterly analyses, we compute the average of both the EPU and EU indices over the observation month and quarter, respectively.

As part of our tests of H1, we perform a cross-sectional analysis of the association between information asymmetry and the EPU index based on several EPU-related firm-level attributes (Pastor and Veronesi, 2012, Section V). The first attribute is the sensitivity of a firm's returns to the EPU index. We use a firm-level EPU returns beta (Policy $Beta_i$), which we compute by first running firm-level regressions of monthly excess returns on the monthly EPU index over our sample period as follows:

$$r_{it} = \beta_i^0 + \beta_i^E EPU_t + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + \epsilon_{it}, \tag{3}$$

where *r* is firm *i*'s excess return, *MKT* is the excess return on a market index, and *SMB* and *HML* are long-short return spreads constructed on sorts of market capitalization and book-to-market ratio (Fama and French, 1993). Note that we run this regression at the firm level, not the portfolio level, to ensure that we can directly link each firm to its respective β_i^E. We are not interested in whether the EPU index is a priced factor; we only want to measure how sensitive a firm's return is to the EPU index.

One potential concern with Eq. (3) is that the betas could be biased due to non-synchronous trading. To address this, we follow Dimson (1979) and recompute the EPU betas after including all of the factors in Eq. (3) in both their contemporaneous (*t*) and prior month's lagged (t_{-1}) forms (for a total of eight factors). We then sum the contemporaneous EPU beta and the lagged EPU beta to create an alternative beta. Our cross-sectional inferences using this alternative beta are similar to the original beta in terms of sign, magnitude, and significance. More importantly, the EPU beta is not the only variable we use to measure a firm's exposure to EPU. We discuss our other measures below.

[10] Daily market microstructure analyses raise concerns such as bid-ask bounce and non-synchronous trading. However, as Campbell et al. (1996, p. 129) and Chordia et al. (2008) note, these concerns are more relevant for higher moments of intraday returns (e.g., autocorrelation, cross-correlation, variance), which we are not analyzing.

[11] The number of observations in our regressions vary slightly due to data availability. For example, on occasion CRSP does not provide trading volume; for these days we cannot compute Amihud illiquidity. Nonetheless, our results are not sensitive to requiring each firm-day, firm-month, or firm-quarter (depending on the test) to have both spread and Amihud illiquidity data. Our recursive estimates in Table 8 are also not impacted by these data availability issues.

[12] See http://www.policyuncertainty.com/us_daily.html.

[13] See http://www.policyuncertainty.com/equity_uncert.html. We also find qualitatively similar results when we use the VIX and squared VIX in place of the EU index (Baker et al., 2016, p. 1614; Drechsler, 2013).

Our next cross-sectional test of H1 uses a firm's international exposure, which might affect a firm's exposure to domestic U.S. EPU (e.g., Boutchkova et al., 2012). For example, firms with less U.S. exposure might be insulated from EPU in the U.S., which is our setting. Specifically, we use an indicator variable that equals one if a firm has foreign-subsidiary revenue in any year during our sample period (zero otherwise), derived from Compustat income statement data. We also use the average number of foreign trade words in a firm's 10-Ks over our sample period using the Baker et al. (2016) foreign trade dictionary. This dictionary includes *import tariffs, import duty, import barrier, government subsidies, government subsidy, WTO, World Trade Organization, trade treaty, trade agreement, trade policy, trade act, Doha Round, Uruguay Round, GATT*, and *dumping*. As with foreign-subsidiary revenue, foreign trade words in the 10-K may represent a firm's international exposure, which may affect its exposure to domestic U.S. EPU.

We also consider a firm's lobbying expenditures as a cross-sectional test of H1. These expenditures could represent a firm's effort to manage EPU or a firm's exposure to EPU (e.g., Gao and Huang, 2016; Hochberg et al., 2009). We hand collect lobbying data from the Center for Responsive Politics (CRP) and compute the average number of dollars a firm spends per year on lobbying over our sample period.[14] We also include a text-derived firm-level EPU measure computed using the average number of EPU words in a firm's 10-Ks over our sample period.[15] Note that both lobbying dollars and 10-K EPU words could proxy for a firm's exposure to EPU or effort put by managers towards mitigating EPU (e.g., Adelino and Dinc, 2014). We therefore do not have directional expectations for these measures.

We compute all of the above firm-level measures as their average values for each firm over our full sample period. The reason is that many of these measures are relatively firm invariant or can be computed only over yearly intervals. As a result, we cannot use these measures to perform meaningful within-firm-year analyses. However, one advantage of this approach is that we can perform an array of cross-sectional tests of H1, for which we can include firm-year-fixed effects.

H2 tests whether EPU affects investors' reaction to earnings surprises. For a given firm-quarter, we follow Lys and Sohn (1990) and measure the earnings surprise using I/B/E/S actual earnings minus the analyst consensus mean earnings forecast at day − 1, scaled by stock price at day − 1, where day 0 is the quarterly earnings announcement date. Our returns measure is the [−1, + 1 day] abnormal return, computed as firm return minus contemporaneous value-weighted market return.[16]

As we discuss further in Section 4.3, our interest in earnings announcement returns is two-fold: (1) we ask whether EPU affects investors' reaction to earnings surprises, and (2) we ask whether this effect is more pronounced for firms with high exposure to expected liquidity risk. To facilitate (2), we follow the research design in Kelly and Ljungqvist (2012, Section 3.4) and Pastor and Stambaugh (2003) and compute a firm's exposure to liquidity risk. We use exposure to liquidity risk as opposed to actual liquidity because liquidity changes endogenously during earnings announcements (e.g., Kim and Verrecchia, 1994; Sadka, 2011), and we want to measure a firm's steady-state exposure to liquidity risk.

We measure a firm's exposure to liquidity risk using a firm's β_i^L from Section 3 of Pastor and Stambaugh (2003). Following Chordia et al. (2014), we compute β_i^L by running the following regression for each firm using monthly returns data over our full sample period:

$$r_{it} = \beta_i^0 + \beta_i^L L_t + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + \epsilon_{it}, \tag{4}$$

where L is the Pastor and Stambaugh (2003, Eq. (8)) innovation in liquidity measure, r is firm i's excess return, MKT is the excess return on a market index, and SMB and HML are long-short return spreads constructed on sorts of market capitalization and book-to-market ratio.[17] We run this regression at the firm level, not the portfolio level, because we want to directly link each firm to its respective β_i^L, and we are not interested in constructing portfolios for trading. We also compute an alternative Dimson (1979) beta using the same procedure we described for the EPU beta in Eq. (3). Once again, the results are virtually identical to our original liquidity beta.

Our final hypothesis, H3, tests managers' voluntary disclosure response to EPU. These disclosures can take several forms. Managers may explain their firm's exposure to EPU, or they may explain their strategies to mitigate such exposure. Managers may also increase disclosure around firm operations and strategies unrelated to EPU, thus mitigating information asymmetry by allowing investors to better understand the firm overall. Guay et al. (2016, p. 237) likewise argue that when addressing uncertainty, managers need not disclose "verbiage that is directly tied to the source of increased uncertainty."

We use the quarterly frequency of management forecasts and various 8-K items as our disclosure metrics (e.g., Balakrishnan et al., 2014; Guay et al., 2016). We use quarterly frequencies because changing disclosure policy is costly (due to proprietary costs, setting up investor expectations, etc.), and therefore managers may take a longer term perspective before deciding to respond with changes to their disclosures. Forecasts are well-suited for our setting because they incorporate many of the financial variables that prior studies have linked to EPU, including future capital expenditures, research and development (which affects earnings), revenue, and earnings (e.g., Baker et al., 2016; Gulen and Ion, 2016; Wellman, 2017). We follow Guay et al. (2016) and Schoenfeld (2017) and do not distinguish between good and bad news disclosures, as the type of the news is more relevant when managers are trying to raise or lower their stock price. Our focus is information asymmetry, which depends not so much on the type of news, but on whether this

[14] Lobbying reports are filed with the Secretary of the Senate's Office of Public Records and are available by calendar year beginning in 1998. The CRP maintains the lobbying data, which we manually match to Compustat by company name.

[15] These terms are similar to those used for the EPU index and include *economic, economy, uncertain, uncertainty, Congress, deficit, Federal Reserve, legislation, regulation*, and *White House*.

[16] We use analyst forecasts because they are likely to better incorporate the impact of EPU on earnings compared to past earnings (Amiram et al., 2016). We find qualitatively similar results when we use the consensus median analyst earnings forecasts, for both positive and negative earnings surprises, and when we use the [- 5, + 5 days] window (Johnson and So, 2018).

[17] We obtain the innovation in liquidity measure from http://faculty.chicagobooth.edu/lubos.pastor/research/.

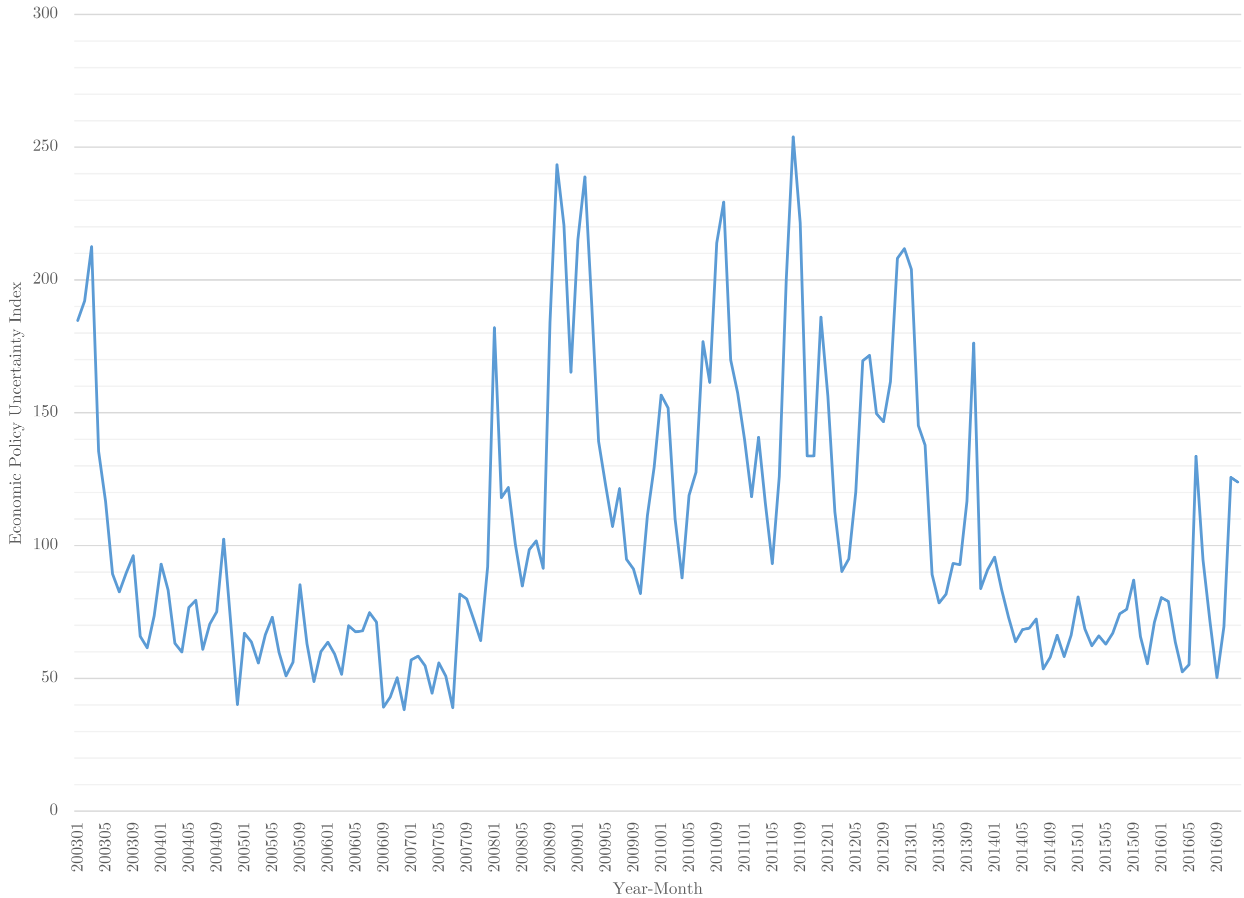

Fig. 1. The economic policy uncertainty index charted from 2003 to 2016. This figure plots the Baker et al. (2016) economic policy uncertainty index averaged by year-month. The index is provided on a daily basis at http://www.policyuncertainty.com/. The source for news articles is Newsbank, which covers U.S.-based media ranging from large national media like *USA Today* to small local media. See Baker et al. (2016) for more details.

news is withheld or released (e.g., Billings et al., 2015; Bozanic et al., 2018). We recognize that our frequency count approach masks some disclosure details, but it has the advantage of being tractable.

We obtain management forecasts from I/B/E/S, which covers all public U.S. companies. Similar to Balakrishnan et al. (2014), I/B/E/S confirmed for us that its forecast data do not have the coverage gaps that were identified in First Call, which was discontinued in 2012 (Chuk et al., 2013). We therefore follow Balakrishnan et al. (2014) and Guay et al. (2016) and treat no forecasts in I/B/E/S as evidence of non-forecasting firms.[18]

For our second disclosure proxy, we count 8-K filings labeled as items 2, 7, 8, or 9, which are often filed voluntarily and include management forecasts, non-mandated financial statements and exhibits, and other disclosures such as press releases (Cooper et al., 2017; Lerman and Livnat, 2010). Lerman and Livnat (2010, Table 1) show that item 2 includes results of operations and financial conditions, discussion of off-balance-sheet items, and impairments; item 7 includes Regulation FD disclosures; item 8 is other events; and item 9 is financial statements and exhibits.

Finally, in our market-level analysis, each disclosure measure is weighted by a firm's market-value weight on the disclosure date, aggregated into one daily measure of disclosure, and then aggregated into one quarterly measure of disclosure. This ensures that our disclosures are weighted in the same way as market-value-weighted spreads and Amihud, although our results are similar for equal weights.

4. Empirical results

4.1. Univariate statistics

During our sample period, the EPU index ranges from a low of 0.382 during December, 2012, to a high of 2.539 during August, 2011. As Fig. 1 shows, other periods of relatively high EPU include national election cycles and the financial crisis. Table 1, Panel A

[18] Nonetheless, non-forecasting firms rarely change their forecasting practices (Balakrishnan et al., 2014, Section III.D).

Table 1

Descriptive statistics for the market-level measures from 2003 to 2016. Value-weighted (VW) measures are weighted by market capitalization at day *t*. The column "AR(1) ρ w/ yr. F.E." in Panel A is the autocorrelation coefficient with year-fixed effects (i.e., within year). For display purposes, we divide the EPU and EU indices by 100 throughout the paper. Index *t* represents the observation day or year-quarter. All variables are defined in the Appendix.

Panel A: Descriptive statistics of the uncertainty, market-level information asymmetry, and market-level disclosure variables

Variable	N	Mean	σ	P25	P50	P75	AR(1) ρ	AR(1) ρ w/ yr. F.E.
Daily measures of uncertainty								
EPU Index$_t$	3351	0.978	0.666	0.510	0.803	1.262	0.55	0.34
EU Index$_t$	3351	0.469	0.679	0.121	0.259	0.542	0.45	0.40
Daily measures for information asymmetry tests								
VW Percent Quoted Spread$_t$	3351	0.092	0.088	0.071	0.080	0.093	0.07	0.04
VW Amihud Illiquidity$_t$	3351	0.027	0.057	0.009	0.013	0.026	0.18	0.12
Squared VW Returns$_t$	3351	0.000	0.001	0.000	0.000	0.000	0.22	0.13
Log of Total Trading Volume$_t$	3351	22.538	0.337	22.322	22.551	22.750	0.85	0.59
Log of Total Dollar Trading Volume$_t$	3351	26.028	0.390	25.841	26.113	26.278	0.88	0.57
Log of Total Market Value$_t$	3351	30.635	0.257	30.454	30.615	30.851	0.99	0.98
Quarterly measures for disclosure tests								
Log of VW Guidance$_t$	56	0.1292	0.1410	0.0000	0.0000	0.0000	0.78	0.21
Log of VW 8-Ks$_t$	56	0.1468	0.1501	0.0000	0.0000	0.0000	0.71	0.17

Panel B: Correlation matrix of the daily uncertainty and market-level information asymmetry variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) EPU Index$_t$	1.00							
(2) EU Index$_t$	0.40***	1.00						
(3) VW Percent Quoted Spread$_t$	0.08***	0.11***	1.00					
(4) VW Amihud Illiquidity$_t$	0.22***	0.14***	0.19***	1.00				
(5) Squared VW Returns$_t$	0.27***	0.36***	0.09***	0.16***	1.00			
(6) Log of Total Trading Volume$_t$	0.39***	0.20***	− 0. 18***	0.21***	0.32***	1.00		
(7) Log of Total Dollar Trading Volume$_t$	0.24***	0.12***	− 0. 23***	0.11***	0.21***	0.87***	1.00	
(8) Log of Total Market Value$_t$	− 0. 25***	− 0. 19***	− 0. 15***	− 0. 15***	− 0. 22***	−0.01	0.43***	1.00

provides the distributions of market-level spreads and Amihud, and Table 2, Panel A provides the distributions of firm-level spreads and Amihud. In relating our DTAQ descriptive statistics to those of other studies, we note that WRDS only recently began offering DTAQ data and accompanying computing power to manipulate DTAQ on a large scale. For example, as recently as 2014 it was prohibitively costly to perform large-scale studies using DTAQ, as evidenced by Holden and Jacobsen's (2014) decision to focus on a random sample of 100 firms over three months in 2008. Perhaps as a consequence of these computing costs, Holden and Jacobsen (2014) is the only study we are aware of that uses firm-day DTAQ percent quoted spreads. We therefore attempt to compare our descriptive statistics to theirs.[19]

Holden and Jacobsen (2014, Table1, Panel B) report a mean percent quoted spread of 0.399% , whereas our mean value is 0.904% . Our median spread value is much lower at 0.275% , but Holden and Jacobsen (2014) do not report their median values. The difference in means is likely due to our using the full DTAQ database over a significantly longer time horizon than that of Holden and Jacobsen (2014). Our mean values also weight small firms and large firms equally. Since smaller firms have wider spreads and outnumber larger firms (Chordia et al., 2008), the larger mean spread in our sample is what we would expect. Indeed, in Table 1, Panel A, the mean value of our value-weighted percent spread is much lower at 0.092% . In sum, we have confidence that our spread measure accurately reflects the full DTAQ database in part because we implement Holden and Jacobsen's (2014) DTAQ code, which we vetted for accuracy, and also because Holden and Jacobsen (2014) limit their sample to 100 firms over three months in 2008, which suggests that their descriptive statistics do not represent the full DTAQ database.

By contrast, Amihud illiquidity is widely used in the literature, and we find that our firm-level mean Amihud value compares well to those in prior studies. For example, Lang and Maffett (2011, Table 2) use a global sample of firms and report a mean Amihud value of 0.35. The original Amihud (2002, Table 1) paper reports a mean value of 0.34 using firm-level yearly averages from 1963 to 1996. Our daily firm-level mean Amihud value (which will vary more than its yearly average) in Table 2, Panel B is 0.43. Several studies report lower values of Amihud illiquidity because they use its log transformation (e.g., Balakrishnan et al., 2014). All of our findings are qualitatively similar when we use the natural log of one plus Amihud illiquidity (likewise for spreads).

Table 1, Panel B and Table 2, Panel B indicate that, as expected, percent quoted spreads and Amihud illiquidity are positively correlated. We also find positive correlations among the EPU index, spreads, and Amihud, which is preliminary evidence that

[19] Recall from fn. 9 that our inferences are similar when we use the CRSP percent spread. However, Holden and Jacobsen (2014) suggest that the CRSP spread can occasionally yield inferences that differ from those generated by the DTAQ spread, and they advise researchers to use the DTAQ spread.

Table 2
Descriptive statistics for the firm-level measures from 2003 to 2016. The number of observations in Panel A vary according to data availability in DTAQ and CRSP. Additional descriptive statistics for the EPU and EU indices are in Fig. 1 and Table 1. For display purposes, we multiply $|\text{Policy Beta}|_i$ by 1,000. Index i represents each firm, and index t represents the observation day or year-quarter. All variables are defined in the Appendix.

Panel A: Descriptive statistics of the firm-level information asymmetry, earnings surprise, and disclosure variables.

Variable	N	Mean	σ	P25	P50	P75
Daily measures for information asymmetry tests						
Quoted Percent Spread$_{it}$	15,127,411	0.904	1.722	0.121	0.275	0.784
Amihud Illiquidity$_{it}$	14,775,942	0.427	2.019	0.001	0.005	0.043
Squared Returns$_{it}$	15,031,782	0.001	0.112	0.000	0.000	0.001
Turnover$_{it}$	15,034,786	0.008	0.028	0.002	0.004	0.009
Log of Dollar Trading Volume$_{it}$	15,034,775	14.027	3.397	12.253	14.344	16.338
Log of Stock Price$_{it}$	15,034,807	2.734	1.001	2.117	2.779	3.419
Quarterly measures for earnings surprise tests						
Earnings Surprise$_{it}$	198,414	−0.001	0.019	−0.001	0.000	0.003
Returns $[-1, +1 \text{ day}]_{it}$	198,414	0.000	0.092	−0.039	−0.001	0.038
Quarterly measures for disclosure tests						
Log of Guidance$_{it}$	243,843	0.483	0.683	0.000	0.000	0.000
Log of 8-Ks$_{it}$	243,843	0.553	0.729	0.000	0.000	0.000
Returns$_{it}$	243,843	0.045	0.328	−0.097	0.010	−0.112
ROA$_{it}$	243,843	0.001	0.276	−0.034	0.024	0.082
Market to Book$_{it}$	243,843	1.879	1.902	1.099	1.274	2.289
Leverage$_{it}$	243,843	0.259	0.210	0.035	0.148	0.377
Analyst Following$_{it}$	243,843	4.107	5.179	1.000	2.000	5.000
Institutional Ownership$_{it}$	243,843	0.594	0.331	0.227	0.545	0.716

Panel B: Correlation matrix of the uncertainty, firm-level information asymmetry, and selected firm-level variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) EPU Index$_t$	1.00							
(2) EU Index$_t$	0.40***	1.00						
(3) Percent Quoted Spread$_{it}$	0.09***	0.06***	1.00					
(4) Amihud Illiquidity$_{it}$	0.08***	0.04***	0.60***	1.00				
(5) Squared Returns$_{it}$	0.01***	0.01***	0.01***	0.01***	1.00			
(6) Turnover$_{it}$	0.01***	0.01***	−0.08***	−0.05***	0.06***	1.00		
(7) Log of Dollar Trading Volume$_{it}$	−0.02***	−0.01***	−0.61***	−0.45***	−0.00***	0.21***	1.00	
(8) Log of Stock Price$_{it}$	−0.10***	−0.05***	−0.43***	−0.27***	−0.01***	0.03***	0.62***	1.00

Panel C: Descriptive Statistics of the Static Firm-Level Variables

Variable	N	Mean	σ	P25	P50	P75
$|\text{Policy Beta}|_i \times 1,000$	6,897	0.011	0.023	0.003	0.007	0.014
Log of Market Value$_i$	6,897	19.820	1.811	18.522	19.682	21.000
Foreign Income$_i$	6,897	0.287	0.453	0.000	0.000	1.000
Log of Trade Words$_i$	6,897	0.074	0.283	0.000	0.000	0.000
Log Lobbying Dollars$_i$	6,897	2.552	5.051	0.000	0.000	0.000
Log of EPU Words$_i$	6,897	2.120	2.005	0.000	3.1381	3.958

Panel D: Correlation Matrix of the Static Firm-Level Variables

	(1)	(2)	(3)	(4)	(5)	(6)
(1) $|\text{Policy Beta}|_i$	1.00					
(2) Log of Market Value$_i$	−0.15***	1.00				
(3) Foreign Income$_i$	−0.07***	0.21***	1.00			
(4) Log of Trade Words$_i$	−0.00	0.07***	0.07***	1.00		
(5) Log Lobbying Dollars$_i$	−0.10***	0.37***	0.12***	0.07***	1.00	
(6) Log of EPU Words$_i$	0.00	0.25***	−0.02*	0.07***	0.07***	1.00

increased EPU is associated with increased information asymmetry. Table 2, Panel B also shows that turnover, trading volume, and stock price are negatively correlated with spreads and Amihud, which is consistent with prior literature (Holden et al., 2013).

Table 2, Panel C shows that our firm-level sample includes 6897 firms, whose median market value is about $325.2 million. About 29% of firms have foreign income. Table 2, Panel D indicates that market value is correlated with several of the firm-level variables, underscoring the importance of using firm-year-fixed effects to control for firm-specific factors that might vary by year.

4.2. EPU index and information asymmetry among investors

H1 represents the average general equilibrium effect of EPU on information asymmetry among investors. We assume that investors react quickly to EPU and therefore test H1 by linking the EPU index to contemporaneous percent spreads and Amihud illiquidity, which are our proxies for information asymmetry among investors. We recognize that the effect of EPU on information asymmetry can vary both cross-sectionally and temporally. The effect may be stronger for certain firms, and may be weaker if managers and investors can anticipate future EPU and take steps to reduce its impact via disclosures, information collection, and other activities. We therefore conduct several cross-sectional tests, explicitly test for disclosure effects in H2 and H3, and use a variety of fixed effects, controls, and clustered standard errors in all of our tests. These fixed effects help to eliminate in our dependent and independent variables both firm-specific effects and time trends in the data due to factors such as technological advances in trading. All of our variables must be interpreted not in levels but as deviations from fixed-effect averages. In particular, we are measuring not the effect of total EPU but the effect of abnormal or deviations from a time-adjusted EPU. A similar interpretation also applies to spreads and Amihud illiquidity.

We first study this association at the monthly level using spreads and Amihud measured at both the value-weighted-market level and the firm level.[20] Our use of monthly intervals mitigates concerns that the findings from our daily tests are driven by spurious short-term correlations in the data. Our use of value weights follows Chordia et al. (2005), though our inferences are similar for equal weights as well. For the market-level regressions, we control for return volatility, several measures of trading volume, and market size to account for market growth and declines. For the firm-level regressions, we control for stock price, return volatility, and several measures of trading volume.

In our market-level analyses, we cluster by time period or use heteroscedasticity-robust standard errors. At the firm-level, we allow the error terms to be correlated both within a firm and across all firms for a given time period (Gow et al., 2010). The tables denote the fixed effects and clusters.

In addition, the Dickey-Fuller test rejects the null hypothesis of a unit root in all of our market-level variables. We also find Durbin-Watson test statistics of over two for all of our regressions, which suggests that the Newey–West approach is inappropriate for our analysis. Fig. 1 also shows that there is no apparent time trend in the EPU index.[21]

In Tables 3 and 4, we regress our information asymmetry measures on contemporaneous EPU based on the following specifications, the first of which represents the value-weighted market-level regression, and the second of which represents the firm-level regression:

$$Information\ \ Asymmetry_t = \phi_0 + \phi_1 EPU_t + \boldsymbol{\Phi} Controls_t + \zeta_t \tag{5}$$

$$Information\ \ Asymmetry_{it} = \omega_0 + \omega_1 EPU_t + \boldsymbol{\Omega} Controls_t + \varphi_{it}, \tag{6}$$

where *Information Asymmetry* stands for the information asymmetry proxies, index i represents the firm, index t represents the month or day depending on the test, and $\boldsymbol{\Phi}$ and $\boldsymbol{\Omega}$ represent vectors of control variables, which for the firm-level regressions include firm-level attributes, market-level attributes (i.e., the EU index), and firm-year-fixed effects. Tables 3 and 4 denote the control variables.

In Table 3, we regress monthly market-level averages of value-weighted spreads and Amihud on the contemporaneous EPU index average for the same month and controls. Table 3, columns 1 and 2 show that the coefficient on the EPU index is positive and significant for both value-weighted percent quoted spreads and value-weighted Amihud (1% level). A one standard deviation increase in the monthly EPU index is associated with a 0.013 increase in value-weighted percent spreads and a 0.019 increase in Amihud, respectively. These findings obtain after we control for year-fixed effects and the equity uncertainty (EU) index.[22]

Pastor and Veronesi (2012, 2013) argue that the government responds to market-level activity; we therefore turn to individual firms, which in their model treat EPU as exogenous. That is, we recognize that the positive association between EPU and market-wide information asymmetry may result from government economic policy responding to a few large firms. If this is the case, we would not expect to find consistent results for our firm-level analyses that treat our 7000 firms equally. Moreover, to the extent the government aims to reduce market-wide information asymmetry, we would expect the government to reduce EPU when information asymmetry is high. This would attenuate the positive association between EPU and market-wide information asymmetry and bias against finding the results in Table 3. Firm-level tests also facilitate cross-sectional analyses that can further strengthen our inferences from the market-level tests.[23]

At the firm level, Table 3, columns 3 and 4 show that the EPU index is positive and significant for both spreads and Amihud (1% level). Note that this is a within-firm-year analysis where the monthly EPU regressor is the deviation from the average EPU for that year. A one standard deviation increase in the monthly EPU index is associated with a 0.083 increase in firm-level percent spreads and a 0.062 increase in firm-level Amihud. These findings represent meaningful changes given our sample average firm-level spread of 0.908 (0.083/0.908 = 9.2%) and Amihud of 0.496 (0.062/0.496 = 12.5%). The magnitudes also increase from Columns 1 and 2,

[20] Section 3 describes the weighting procedure for the market-level tests.

[21] Nonetheless, we find qualitatively similar results using the Newey-West approach and Prais-Winsten regressions (Chordia et al., 2001, p. 518).

[22] We use the EPU and EU indices in their level forms, but these findings are qualitatively similar for the log transformation of one plus the indices. We also follow Lang and Maffett (2011, p. 114) and ensure that our results for Amihud are qualitatively similar when we use Amihud decile rankings and an Amihud measure that deflates dollar trading volume by market value of equity. Our results are also qualitatively similar when we use the natural log of one plus spreads and one plus Amihud.

[23] Chordia et al. (2014, p. 45) also advise using firm-level tests to reduce sensitivity to grouping procedures.

Table 3

The effect of economic policy uncertainty on information asymmetry using monthly data from 2003 to 2016. This table uses the monthly average value of all variables. Value-weighted (VW) measures are weighted by market capitalization each day and then averaged by month. The EPU Index stands for the economic policy uncertainty index, the EU Index stands for the equity uncertainty index, and S.D. stands for standard deviation. We find Durbin-Watson test statistics of over two for all of our regressions, which indicates that standard errors clustered across time are appropriate for our analysis (see Section 4.2). Robust standard errors correct for heteroscedasticity. When two parameters are separated by a comma in the "S.E. Clustering" row, this implies two-way clustering. YM stands for year-month. Index i represents each firm, and index t represents the observation month. All variables are defined in the Appendix. T-statistics are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Monthly data			
	Value-weighted market level		Equal-weighted firm level	
	VW percent quoted Spread$_t$	VW amihud Illiquidity$_t$	Percent quoted Spread$_{it}$	Amihud Illiquidity$_{it}$
	(1)	(2)	(3)	(4)
EPU Index$_t$	0.0134***	0.0194***	0.0846***	0.0633***
	(2.70)	(3.05)	(3.40)	(2.73)
S.D. of VW Returns$_t$	3.5163***	0.6650		
	(4.02)	(1.02)		
Log of Total Trading Volume$_t$	0.0368	−0.0502		
	(0.91)	(−1.26)		
Log of Total Dollar Trading Volume$_t$	−0.0824**	0.0547		
	(−2.15)	(1.45)		
Log of Total Market Value$_t$	0.0583	−0.1619***		
	(1.25)	(-3.53)		
S.D. of Returns$_{it}$			5.9828***	5.6810***
			(6.76)	(6.32)
Turnover$_{it}$			−1.0949***	1.3220***
			(-3.25)	(3.56)
Log of Dollar Trading Volume$_{it}$			−0.3132***	−0.5469***
			(-12.63)	(-14.85)
Log of Stock Price$_{it}$			−0.1878***	0.1500***
			(-4.82)	(5.80)
EU Index$_t$	−0.0064	−0.0109	0.0595**	0.0474**
	(−0.77)	(−1.38)	(2.20)	(2.37)
Fixed Effects	Year	Year	Firm-Year	Firm-Year
S.E. Clustering	Robust	Robust	Firm, YM	Firm, YM
Observations	160	160	720,535	720,506
R^2	0.64	0.69	0.91	0.87

though one concern is that the same EPU regressor repeats for every firm.[24]

The control variables are also associated with spreads and Amihud in the expected directions, although one should be cautious when interpreting the coefficients on the controls due to the possibility of a mechanical relation among some of the controls and Amihud. We also find qualitatively similar results with firm-year-quarter-fixed effects, with firm-year-month-fixed effects, and with no fixed effects. Overall, these findings suggest that increased EPU increases information asymmetry among investors.

Investors in capital markets are likely to react to EPU quickly, presumably in less than a month. Therefore, in Table 4, Panels A and B, we use daily data of the EPU index, spreads, Amihud, and controls. In Table 4, Panel A, our main coefficients of interest appear in Columns 1 and 4. At the daily market level, Table 4, Columns 1 and 4 show that the coefficient on the contemporaneous EPU index is positive and significant for both value-weighted spreads and Amihud (1% level), respectively, after controlling for year-fixed effects and the EU index. A one standard deviation increase in the daily EPU index is associated with a 0.0040 increase in value-weighted percent spreads and a 0.0038 increase in value-weighted Amihud. To the extent investors take longer than a day to react to EPU, we expect and find lower magnitudes in this table relative to those in Table 3, which uses monthly intervals. Still, these results represent meaningful changes given our sample mean daily value-weighted percent spread of 0.092 (0.0040/0.092 = 4.3%) and Amihud of 0.027 (0.0038/0.027 = 14.1%).

At the daily firm level, Table 4, Panel B, Columns 1 and 4 show that the coefficient on the EPU index is positive and significant for spreads and Amihud, after controlling for firm-year-fixed effects and the EU index (1% level). A one standard deviation increase in the daily EPU index is associated with a 0.058 increase in percent spreads and a 0.047 increase in Amihud (1% level). These findings again represent meaningful changes given our sample average percent spread of 0.904 and Amihud of 0.427.

To put these findings into the context of other studies, Bushee et al. (2010, p. 14) report that percent spreads decrease by 0.11 (or about three percent of their mean value) for a one standard deviation increase in their abnormal press coverage measure. Our one standard deviation increase in EPU translates to about a 0.058 increase in percent spreads and a 0.047 increase in Amihud. Compared to their respective mean values, these findings translate to about a 6.4% increase in spreads (0.058/0.904) and an 11.0% increase in

[24] The EU index is positive and significant for both spreads and Amihud, but at smaller economic magnitudes relative to the EPU index.

Table 4

The effect of economic policy uncertainty on information asymmetry using daily data from 2003 to 2016. Panels A and B of this table use the daily value of all variables at the market level and firm level, respectively. Value-weighted (VW) measures are weighted by market capitalization each day and then aggregated by day. The EPU Index stands for the economic policy uncertainty index, and the EU Index stands for the equity uncertainty index. We find Durbin-Watson test statistics of over two for all of our regressions, which indicates that standard errors clustered across time are appropriate for our analysis (see Section 4.2). Bolded coefficients represent our primary coefficients of interest. When two parameters are separated by a comma in the "S.E. Clustering" row, this implies two-way clustering. Index *i* represents each firm, and index *t* represents the observation day. All variables are defined in the Appendix. T-statistics are in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 4, Panel A: Daily data at the value-weighted market level

	VW percent quoted Spread$_t$			VW amihud Illiquidity$_t$		
	(1)	(2)	(3)	(4)	(5)	(6)
EPU Index$_{t-5}$		0.0001			0.0001	
		(0.16)			(1.16)	
EPU Index$_{t-4}$		0.0001**			−0.0000	
		(2.14)			(−0.01)	
EPU Index$_{t-3}$		0.0000			0.0000	
		(0.19)			(0.22)	
EPU Index$_{t-2}$		−0.0001			0.0001**	
		(−0.06)			(2.09)	
EPU Index$_{t-1}$		−0.0000			0.0001	
		(−0.25)			(0.44)	
EPU Index$_t$	**0.0041*****	0.0070	0.0001	**0.0039*****	0.0012	0.0026
	(2.84)	(0.25)	(0.02)	**(2.80)**	(0.40)	(1.25)
EPU Index$_{t+1}$			0.0041			−0.0001
			(1.13)			(−0.06)
EPU Index$_{t+2}$			0.0033			0.0015**
			(0.97)			(2.38)
EPU Index$_{t+3}$			0.0025			0.0023
			(0.73)			(1.14)
EPU Index$_{t+4}$			0.0034			−0.0017
			(0.98)			(−0.83)
EPU Index$_{t+5}$			0.0103**			0.0006
			(2.12)			(0.33)
Squared VW Returns$_t$	12.1165***	11.6890***	11.9113***	2.6020***	2.4210***	2.1533***
	(3.77)	(5.17)	(3.69)	(15.24)	(14.15)	(16.02)
Log of Total Trading Volume$_t$	−0.1976***	−0.1925***	−0.1874***	−0.0562***	−0.0522***	−0.0524***
	(-5.86)	(-4.13)	(-6.45)	(-3.00)	(−2.68)	(−2.79)
Log of Total Dollar Trading Volume$_t$	0.0181	0.0147	0.0083	0.0412**	0.0372**	0.0375**
	(0.68)	(0.56)	(0.31)	(2.38)	(2.14)	(2.16)
Log of Total Market Value$_t$	−0.2866***	−0.2700***	−0.2659***	−0.2054***	−0.1929***	−0.1973***
	(-10.22)	(-9.36)	(-9.21)	(-11.25)	(-10.26)	(-10.49)
EU Index$_t$	0.0035	0.0023	0.0019	0.0007	0.0001	0.0001
	(1.45)	(0.98)	(0.74)	(0.47)	(0.10)	(0.15)
Fixed Effects	Year	Year	Year	Year	Year	Year
S.E. Clustering	Year-Quarter	Year-Quarter	Year-Quarter	Year-Quarter	Year-Quarter	Year-Quarter
Observations	3351	3351	3351	3351	3351	3351
R^2	0.20	0.21	0.21	0.18	0.18	0.19

Table 4, Panel B: Daily Data at the Equal-Weighted Firm Level

	Percent Quoted Spread$_{it}$			Amihud Illiquidity$_{it}$		
	(1)	(2)	(3)	(4)	(5)	(6)
EPU Index$_{t-5}$		0.0193**			0.0184***e	
		(2.21)			(3.31)	
EPU Index$_{t-4}$		0.0282***			0.0072	
		(2.80)			(1.20)	
EPU Index$_{t-3}$		0.0516*			0.0166**	
		(1.88)			(2.78)	
EPU Index$_{t-2}$		0.0196			0.0166***	
		(1.48)			(3.03)	
EPU Index$_{t-1}$		0.0089			0.0237***	
		(0.92)			(3.26)	
EPU Index$_t$	**0.0598*****	0.0188*	0.0200**	**0.0479*****	0.0189***	0.0299***
	(6.37)	(1.69)	(2.21)	**(7.24)**	(3.38)	(5.28)
EPU Index$_{t+1}$			0.0224*			0.0090

(*continued on next page*)

Table 4 (*continued*)

	Table 4, Panel B: Daily Data at the Equal-Weighted Firm Level					
	Percent Quoted Spread$_{it}$			Amihud Illiquidity$_{it}$		
	(1)	(2)	(3)	(4)	(5)	(6)
			(1.88)			(1.48)
EPU Index$_{t+2}$			0.0251**			0.0162**
			(2.35)			(2.56)
EPU Index$_{t+3}$			0.0159			0.0152**
			(1.25)			(2.54)
EPU Index $_{t+4}$			0.0173			0.0036
			(1.54)			(0.68)
EPU Index$_{t+5}$			0.0419**			0.0130**
			(2.12)			(2.42)
Squared Returns$_{it}$	0.0578*	0.0564*	0.0568*	0.1150***	0.1142***	0.1121***
	(1.69)	(1.78)	(1.66)	(21.50)	(22.54)	(20.60)
Turnover$_{it}$	0.0004	−0.0075	−0.0104	5.1262***	5.1153***	5.2833***
	(0.02)	(−0.37)	(−0.50)	(14.09)	(15.07)	(17.13)
Log of Dollar Trading Volume$_{it}$	−0.1212***	−0.1209***	−0.1208***	−0.7663***	−0.7671***	−0.7675***
	(-12.91)	(-14.12)	(-13.28)	(-58.02)	(-59.47)	(-57.80)
Log of Stock Price$_{it}$	−0.6134***	−0.5808***	−0.5889***	0.2634***	0.2839***	0.2761***
	(-11.02)	(-11.88)	(-10.33)	(20.06)	(33.66)	(31.29)
EU Index$_t$	0.0442***	0.0312***	0.0284***	0.0401***	0.0411***	0.0415***
	(6.40)	(4.88)	(4.11)	(4.76)	(4.22)	(4.49)
Fixed Effects	Firm-Year	Firm-Year	Firm-Year	Firm-Year	Firm-Year	Firm-Year
S.E. Clustering	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day	Firm, Day
Observations	15,030,286	15,030,286	15,030,286	14,775,942	14,775,942	14,775,942
R^2	0.74	0.74	0.74	0.64	0.64	0.64

Amihud (0.047/0.427). Also, Balakrishnan et al. (2014, p. 2249) find that firms that lose one analyst see their Amihud increase by 0.024 on average, or about half the effect of a one standard deviation change in EPU on Amihud.

One advantage of using daily data is that we can study how long it takes EPU to enter into the news (and thus the EPU index), as well as how long it takes investors to process this information. In Table 4, Panels A and B, we include five-day lags and leads of the EPU index.[25] Table 1, Panel A indicates that the daily EPU autocorrelation coefficient is 0.34 with year-fixed effects, so multicollinearity is not a severe problem. The two main results of note are that (1) all the significant EPU index coefficients are positive, implying that increased EPU increases information asymmetry, and (2) the contemporaneous EPU index is highly significant in the firm-level regressions. Significant positive lags suggest that non-synchronous trading may cause news to be reflected later in spreads and Amihud at some firms; significant positive leads suggest that the EPU index could be capturing news with some delay relative to investors (Campbell et al., 1996, p. 84). The contemporaneous EPU index regressor, though significant in the firm-level regressions, is often insignificant in the market-level regressions, suggesting that its significance when used without lags and leads represents EPU not just on the day of observation, but also a few days before and after. In any event, we interpret the current day EPU index as an amalgamation of a few days' lags and leads, which does not impair our inferences.[26]

To further ensure that our results are not driven by spurious factors, we also perform a placebo test whereby we lag the EPU index by a year and replicate all the regressions above (untabulated). We find no significance for the lagged EPU index, which gives us added confidence that contemporaneous EPU affects information asymmetry.

We next turn to cross-sectional variation in H1 by allowing the coefficient on the EPU index to change with relevant firm-level attributes. We add several EPU index interaction terms at once and also include the EPU and EU indices as main effects. We do not include the interacting factors as main effects since they are firm-invariant and subsumed by the firm-year-fixed effects (see Section 3).

We first test whether variation in firm-specific exposure to EPU changes the relation between EPU, spreads, and Amihud. To do this, we compute a beta for each firm's stock return sensitivity to EPU as described in Section 3. We use the absolute value of the beta coefficient because both positive and negative coefficients suggest that a firm's return is sensitive to EPU, and because we do not have a clear expectation about whether a given firm will be negatively or positively affected by EPU over time.[27] Thus, a higher absolute value of the policy beta suggests that a firm is more sensitive to EPU. Table 5 indicates that firms with higher policy betas experience larger increases in spreads and Amihud for the same increase in EPU (1% level). This finding suggests that these firms are more sensitive to EPU.

One concern with any beta is its potential bias due to non-synchronous trading. However, we find similar results (untabulated) using the Dimson beta described in Section 3. We also use other measures of exposure to EPU. Our second interaction term incorporates firm size. It is well established that larger firms, which potentially operate in a richer information environment, are easier for investors to value (e.g., Fama and French, 1995). This implies that the magnitude of the relation between the EPU index and

[25] Note that the EPU index spans from 1985 to current day, so we can include EPU index leads and lags without losing any observations.
[26] Recall that Durbin-Watson tests indicate that EPU index autocorrelation is not causing us to overstate significance in the regressions.
[27] Our use of absolute values follows Addoum and Kumar (2016, p. 3473), who examine trading strategies around changes in political regimes.

Table 5
The effect of economic policy uncertainty on information asymmetry with firm attributes from 2003 to 2016. The interacted variables with subscript i are firm-invariant and vary only in the cross-section, which means that they are collinear with the fixed effects. The interaction coefficients therefore represent across-firm, not within-firm, results. We include the main effect for the EPU and the EU indices. When two parameters are separated by a comma in the "S.E. Clustering" row, this implies two-way clustering. YM stands for year-month. Index i represents each firm, and index t represents the observation day or month. All variables are defined in the Appendix. T-statistics are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Equal-weighted firm-level percent quoted Spread$_{it}$		Equal-weighted firm-level amihud Illiquidity$_{it}$	
	Monthly	Daily	Monthly	Daily
	(1)	(2)	(3)	(4)
EPU Index$_t$	0.09096***	1.01544***	0.07382***	0.76042***
	(2.78)	(6.45)	(3.22)	(8.26)
EPU Index$_t$ × |Policy Beta|$_i$	1.32994***	0.74213***	1.32994***	0.79769***
	(4.99)	(5.49)	(5.02)	(7.50)
EPU Index$_t$ × Log of Market Value$_i$	−0.00308***	−0.05176***	−0.00308***	−0.03853***
	(-4.83)	(-12.91)	(-4.32)	(-10.93)
EPU Index$_t$ × Foreign Income$_i$	−0.00025**	−0.00009	−0.00005**	−0.00011**
	(−2.81)	(−1.11)	(−2.10)	(−2.47)
EPU Index$_t$ × Log of Trade Words$_i$	−0.00033**	−0.00021**	−0.00024***	−0.00016***
	(−2.36)	(−2.50)	(-3.44)	(-6.15)
EPU Index$_t$ × Log of Lobbying Dollars$_i$	−0.00005**	−0.00001***	−0.00002**	−0.00001***
	(−2.41)	(-6.24)	(−2.53)	(-6.97)
EPU Index$_t$ × Log of EPU Words$_i$	0.00011***	0.00018***	0.00010***	0.00013***
	(4.41)	(5.88)	(3.51)	(6.02)
S.D. of Returns$_{it}$	5.79942***		5.66338***	
	(8.84)		(6.27)	
Squared Returns$_{it}$		0.05687***		0.11436***
		(19.74)		(21.19)
Turnover$_{it}$	−1.04416***	0.01331	1.34107***	5.12961***
	(-3.24)	(0.65)	(3.58)	(14.90)
Log of Dollar Trading Volume$_{it}$	−0.30834***	−0.12055***	−0.54760***	−0.76518***
	(-16.67)	(-12.93)	(-12.99)	(-49.31)
Log of Stock Price$_{it}$	−0.22584***	−0.61564***	0.16731***	0.26106***
	(-5.14)	(-11.09)	(5.61)	(29.88)
EU Index$_t$	0.05757**	0.04024***	0.09049	0.02722***
	(2.59)	(4.45)	(1.45)	(4.49)
Fixed Effects	Firm-Year	Firm-Year	Firm-Year	Firm-Year
Two-Way S.E. Clustering	Firm, YM	Firm, Day	Firm, YM	Firm, Day
Observations	720,535	15,030,286	720,506	14,775,942
R^2	0.91	0.75	0.87	0.55

information asymmetry might decrease in firm size. Accordingly, in Table 5, we interact the EPU index with firm size (log of market value of equity) and find a significant negative coefficient on the interaction term for spreads and Amihud. This implies that for a given increase in the EPU index, information asymmetry increases less in larger firms (1% level). Larger firms thus appear to be less sensitive to the information asymmetry created by EPU.

Our third and fourth interaction terms test whether international exposure decreases a firm's exposure to U.S. EPU, which is what the EPU index represents. Firms with international exposure are likely affected by the economic policies of all the countries they operate in. To the extent that this diversifies a firm's exposure to U.S. EPU, these firms may experience an attenuated relation between the EPU index and information asymmetry.

We use two measures to proxy for a firm's international exposure as described in Section 3. Table 5 shows that most of the interaction effects for the EPU index and the foreign income indicator are significantly negative for spreads and Amihud, as are the interaction effects for the EPU index and 10-K foreign trade words. Firms with international exposure thus appear to be less sensitive to U.S. EPU.

Our fourth and fifth interaction terms incorporate firm lobbying and EPU-related disclosures in the 10-K as described in Section 3. The literature is mixed on whether a firm's lobbying activities proxy for a firm's exposure to policy or a firm's ability to decrease its sensitivity to policy (e.g., Adelino and Dinc, 2014; Christensen et al., 2017, p. 92). Table 5 shows that the interaction of the EPU index and lobbying is significantly negative for spreads and Amihud, and the interaction of the EPU index and 10-K EPU words is significantly positive for spreads and Amihud. Managers' investment in lobbying thus appears to partly mitigate information asymmetry due to EPU, whereas 10-K EPU words appear to proxy for the firm's exposure to EPU.

In sum, our evidence suggests that EPU increases information asymmetry and more so for firms with more exposure to EPU.[28] An

[28] In additional untabulated analyses, we use a natural experiment and find results that are qualitatively similar to those in Table 4. Specifically, we use a difference-in-differences analysis of spreads and Amihud for health-care versus other firms as various Affordable Care Act laws were enacted by the government. These laws plausibly decreased EPU for health-care firms but not for other firms.

Table 6
The effect of economic policy uncertainty on the stock price reaction to earnings surprises from 2003 to 2016. For a given firm *i* quarter, we measure earnings surprises as actual earnings minus the analyst consensus mean earnings forecast at $t = -1$ scaled by stock price at $t = -1$, where $t = 0$ is the earnings announcement date (Lys and Sohn, 1990). The EPU and EU indices are averaged over year-quarter q prior to the earnings announcement date. Returns are firm returns minus the value-weighted market return from CRSP. To estimate the effect of EPU on the stock price reaction to earnings surprises through liquidity, we follow Section 3 of Pastor and Stambaugh (2003) and run the following regression for each firm using monthly data over our sample period: $r_{it} = \beta_i^0 + \beta_i^L L_t + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + \epsilon_{it}$, where L is the Pastor and Stambaugh (2003) innovation in liquidity measure, r is firm i's excess return, MKT is the excess return on a market index, and SMB and HML are long-short return spreads constructed on sorts of market capitalization and book-to-market ratio. Since a firm's exposure to expected liquidity risk is increasing in β_i^L, we set an indicator variable equal to one if a firm is in the top quintile of β_i^L (zero otherwise) and interact this with the EPU index and the earnings surprise. We interpret this three-way interaction term as the effect of EPU on investors' reaction to earnings surprises through liquidity (see Section 4.3). All variables are defined in the Appendix. T-statistics are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	(1)	(2)	(3)
	Returns $[-1, +1 \text{ day}]_{it}$	Returns $[-1, +1 \text{ day}]_{it}$	Returns $[-1, +1 \text{ day}]_{it}$
Earnings Surprise$_{it}$	1.0078***	1.2239***	1.2124***
	(25.50)	(13.09)	(14.72)
EPU Index$_q$		−0.0019	−0.0022
		(−0.54)	(−0.64)
EPU Index$_q$ × Earnings Surprise$_{it}$		−0.1776***	−1.3110***
		(-3.37)	(-4.53)
EPU Index$_q$ × Earnings Surprise$_{it}$ × Top β_i^L Quintile$_i$			−0.0635***
			(−2.70)
EPU Index$_q$ × Earnings Surprise$_{it}$ × Log of Market Value$_{it}$			0.1010***
			(4.11)
EPU Index$_q$ × Earnings Surprise$_{it}$ × BTM$_{it}$			0.0003***
			(2.97)
EU Index$_q$		−0.0046	−0.0047
		(−1.61)	(−1.59)
Fixed Effects	Firm-Year	Firm-Year	Firm-Year
S.E. Clustering	Year-Quarter	Year-Quarter	Year-Quarter
Observations	198,414	198,414	198,414
R^2	0.32	0.33	0.33

interesting observation in Table 4, Panel B is that the firm-level coefficients of current EPU are significant but drop in magnitude once lagged EPUs are included (a similar effect obtains when we include lagged EPU in Table 3, Panel B). One potential non-statistical explanation for the attenuated information asymmetry effect of current EPU is that managers may have already made disclosures in response to past EPU levels, which are now acting as disclosure proxies in the regression. We next examine investors' reaction to earnings and managers' voluntary disclosures.

4.3. EPU index and earnings surprises

This section tests H2 by measuring investors' response to earnings surprises as defined in Section 3. In Table 6, we regress earnings announcement returns on prior-quarter EPU based on the following specification:

$$Returns\ [-1,\ +1\ day]_{it} = \gamma_0 + \gamma_1 EPU_{t\text{-}1} + \boldsymbol{\Gamma} Controls_t + \xi_{it}, \tag{7}$$

where index i represents the firm, index t represents the quarterly earnings announcement date, and $\boldsymbol{\Gamma}$ represents a vector of control variables, which include firm-level attributes, market-level attributes (i.e., the EU index), and firm-year-fixed effects. Table 6 denotes the control variables.

As in the previous section, we use firm-year-fixed effect regressions to account for firm-invariant factors, such as industry membership. Table 6, Column 1 shows that, consistent with prior research, earnings surprises are significantly positively associated with $[-1, +1$ day] abnormal returns. Table 6, Column 2 further shows that the interaction of earnings surprises and the EPU index is significantly negatively associated with $[-1, +1$ day] abnormal returns. This finding is consistent with the idea that EPU decreases the weight investors place on earnings in valuing the firm.

Building on the prior result, we next test whether EPU affects investors' reaction to earnings surprises through expected liquidity risk. Our motivation is that liquidity risk is determined in part by information asymmetry in the market for firm shares, which the prior section shows is associated with EPU. EPU and liquidity risk thus might interact. We include a firm's exposure to expected liquidity risk as proxied for by β_i^L, which we compute following the procedure described in Section 3. Our use of the firm's exposure to liquidity risk as opposed to its actual liquidity (which changes endogenously around earnings announcements) follows the research design in Kelly and Ljungqvist (2012, Section 3.4).

Since a firm's exposure to expected liquidity risk is increasing in β_i^L, we set an indicator variable equal to one if a firm is in the top quintile of β_i^L (zero otherwise) and interact this with the EPU index and the earnings surprise.[29] We also follow Kelly and Ljungqvist (2012) and include interaction terms for a firm's log of market value of equity and book-to-market ratio.

In Table 6, Column 3, we find a negative coefficient on the three-way interaction term for the EPU index, earnings surprises, and the β_i^L quintile indicator (1% level). The interpretation is that for the same level of earnings surprise, investors in firms with relatively high liquidity risk exposure react less during periods of increased EPU. This finding suggests that EPU has a liquidity channel for investors' reaction to earnings surprises. As expected, we also find that the three-way interaction terms with log of market value of equity and book-to-market are positive and significant, which is consistent with there being fewer informational frictions for larger and relatively mature firms (Fama and French, 1993).[30]

The triple-interaction results in Table 6, Column 3 also obtain in a sample that requires each firm to have at least five years of monthly returns data in CRSP. This requirement further ensures that each firm's β_i^L is precisely estimated in Eq. (4) of Section 3. In fact, if the precision of β_i^L increases for these firms, we should find a stronger triple-interaction effect. As expected, in this untabulated test we find that the coefficient on the three-way interaction term for the EPU index, the earnings surprise, and the β_i^L quintile indicator increases in magnitude by about 21% (-0.0635 to -0.0767 in levels; 1% level). This occurs despite the fact that imposing the five-year data requirement decreases the sample size by about 18% .

In sum, we find that investors react less to earnings surprises during periods of increased EPU, especially for firms with higher liquidity risk. This result reinforces the association between EPU and information asymmetry that we document in Tables 3 and 4.

4.4. EPU index and voluntary disclosure

We next examine H3 by testing managers' disclosure response to EPU. Changing disclosure policy is costly (due to proprietary costs, setting up investor expectations, etc.); so managers are likely to have a longer term perspective on EPU before deciding to respond with changes to their voluntary disclosures. We therefore regress the frequency of management forecasts and voluntary 8-K filings in a given quarter on the average EPU index from the prior quarter. We perform this analysis at the market level and the firm level. At the firm level, we use firm-year-fixed effects and include control variables that are known to be associated with management forecasts and 8-K filings. These variables include firm size, return volatility, measures of trading activity, stock returns, market to book, leverage, analyst following, and institutional ownership (e.g., Beyer et al., 2010).[31] However, since this analysis is within firm-year, we do not expect to observe large effects for the control variables.

To ensure that the market-level regressions are consistent with and comparable to our spread and Amihud regressions, for a given day we weight each forecast by the market-value weight of the firm on that day and then aggregate all the value-weighted disclosures into a quarterly measure (similar to our quarterly value-weighted spread and Amihud measures). We perform the same procedure for the count of voluntary 8-K filings.

In Table 7, we regress current-quarter disclosure on prior-quarter EPU based on the following specifications, the first of which represents the value-weighted market-level regression, and the second of which represents the firm-level regression:

$$Disclosure_t = \delta_0 + \delta_1 EPU_{t\text{-}1} + \boldsymbol{Y} Controls_{t\text{-}1} + \epsilon_t \tag{8}$$

$$Disclosure_{it} = \kappa_0 + \kappa_1 EPU_{t\text{-}1} + \theta Controls_{t\text{-}1} + \tau_{it}, \tag{9}$$

where *Disclosure* stands for the disclosure proxies, index *i* represents the firm, index *t* represents the year-quarter, and $\boldsymbol{\Upsilon}$ and $\boldsymbol{\theta}$ represent vectors of control variables, which for the firm-level regressions include firm-level attributes, market-level attributes (i.e., the EU index), and firm-year-fixed effects. Table 7 denotes the control variables.

In Table 7, columns 1 and 2, we find positive and significant coefficients on the EPU index, which suggests that managers respond to past EPU trends by increasing disclosure. A one standard deviation increase in prior-quarter EPU is associated with a 7.05% increase in value-weighted management forecasts (5% level) and a 5.19% increase in value-weighted 8-K disclosures (10% level) in the current quarter. In equal-weighted levels, the management forecast result translates to about 385 additional management forecasts in the market per quarter, which is significant given that about 7232 management forecasts are released to the market in an average quarter in our sample.[32] Note that these results are statistically significant despite relatively low statistical power of 56 observations. We next turn to firm-level tests to increase statistical power.

In Table 7, columns 3 and 4, we use firm-year-fixed effect regressions and again find positive and significant coefficients on the

[29] We follow prior studies by using β_i^L in a quantile form as opposed to its raw form (e.g., Pastor and Stambaugh, 2003). We also check and find that β_i^L in our sample is negatively correlated with the betas for HML and MKT, as in Pastor and Stambaugh (2003, Table 3, Panel B). However, the correlation with the SMB beta is positive, perhaps because we use a more recent sample than Pastor and Stambaugh (2003).

[30] We do not have two-way interactions for these risk factors; we assume that the firm-year-fixed effects are adequate. We also replicate the above findings using the Dimson beta described in Section 3 (untabulated).

[31] The within-firm-year design lets us proxy for firm size using stock price (consistent with the information asymmetry regressions), though our inferences are unchanged if we include log of market value of equity and log of total assets.

[32] We also find similar results for equal-weighted management forecasts and 8-Ks (untabulated). To approximate all of the quarterly magnitudes for disclosure, we use the standard deviation of the EPU index as averaged by quarter over our sample period, which is 0.456. Following Balakrishnan et al. (2014, Table 5), we validate our disclosure findings using Poisson count models and find that forecast frequency and 8-Ks continue to be significantly positively associated with the EPU index. Both of the disclosure measures are also significantly positively associated with market volatility, but at lower economic magnitudes. By contrast, the EU index is not significantly different from zero in these tests.

Table 7

The effect of economic policy uncertainty on voluntary disclosure from 2003 to 2016. This table analyzes the effect of EPU on voluntary disclosure using data measured at quarterly intervals. We measure EPU and the other independent variables in the prior quarter (t_{-1}) because it takes time for managers to change disclosure in response to EPU. The value-weighted (VW) measures are weighted by market capitalization each day, then aggregated by day, and then averaged over the quarter. Index *i* represents each firm, and index *t* represents each year-quarter (YQ). Robust standard errors correct for heteroscedasticity. When two parameters are separated by a comma in the "S.E. Clustering" row, this implies two-way clustering. All variables are defined in the Appendix. T-statistics are in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Quarterly data			
	Value-weighted market level		Equal-weighted firm level	
	(1)	(2)	(3)	(4)
	Log of VW Forecasts$_t$	Log of VW 8-Ks$_t$	Log of Forecasts$_{it}$	Log of 8-Ks$_{it}$
EPU Index$_{t\text{-}1}$	0.1545**	0.1139*	0.0560***	0.0618***
	(2.17)	(2.03)	(3.49)	(3.07)
S.D. of VW Returns$_{t\text{-}1}$	18.8554*	20.1009**		
	(1.82)	(1.95)		
Log of Total Trading Volume$_{t\text{-}1}$	−0.5969	−0.8177		
	(−1.16)	(−1.00)		
Log of Total Dollar Trading Volume$_{t\text{-}1}$	−0.1271	−0.1531		
	(−0.21)	(−0.55)		
Log of Total Market Value$_{t\text{-}1}$	−0.4004	−0.4608		
	(−0.59)	(−0.61)		
S.D. of Returns$_{it\text{-}1}$			15.8320***	17.2192***
			(3.05)	(3.71)
Turnover$_{it\text{-}1}$			0.9310	0.8533
			(0.73)	(0.30)
Log of Dollar Trading Volume$_{it\text{-}1}$			−0.0304	0.0020
			(−0.20)	(0.13)
Log of Stock Price$_{it\text{-}1}$			0.1002*	0.1242**
			(1.72)	(2.15)
Returns$_{it\text{-}1}$			−0.8212**	−0.7939**
			(−2.28)	(−2.36)
ROA$_{it\text{-}1}$			0.4173***	0.4019***
			(4.64)	(4.42)
Market to Book$_{it\text{-}1}$			0.8192**	0.9020*
			(2.36)	(1.85)
Leverage$_{it\text{-}1}$			0.2079	0.1548
			(1.08)	(0.97)
Analyst Following$_{it\text{-}1}$			0.0041***	0.0029**
			(3.29)	(2.40)
Institutional Ownership$_{it\text{-}1}$			0.0028***	0.0033**
			(2.82)	(2.35)
EU Index$_{t\text{-}1}$	−0.01519	−0.01052	−0.0030	−0.0017
	(−1.61)	(−1.54)	(−1.19)	(−1.10)
Fixed Effects	-	-	Firm-Year	Firm-Year
S.E. Clustering	Robust	Robust	Firm, YQ	Firm, YQ
Observations	56	56	243,843	243,843
R^2	0.58	0.54	0.68	0.65

EPU index. A one standard deviation increase in prior-quarter EPU is associated with a 2.55% increase in management forecasts (1% level) and a 2.82% increase in 8-K disclosures (1% level) in the current quarter. In levels, these findings translate to about one extra forecast and 8-K each quarter. Decomposing the forecast result by forecast type, we find significant positive associations between EPU and future forecasts of capital expenditures, EPS, and sales (but not the other forecast types), which suggests that these forecasts are driving this result (untabulated).

Consistent with prior research, forecasts and 8-Ks are also significantly associated with return volatility, stock price, returns, ROA, market to book, analyst following, and institutional ownership. Note that by including firms with zero forecasts and voluntary 8-K filings over the sample period, our disclosure results are likely lower-bound estimates relative to firms that disclose frequently. For example, we have many small firms with zero disclosures that have equal weight in the regressions. Managers of these firms rarely change their disclosure practices and will not respond to EPU with disclosure as often (Balakrishnan et al., 2014, Section III.D). By contrast, the value-weighted market-level results are driven by proportionally larger firms that tend to forecast more frequently (Anilowski et al., 2007, p. 45). Nonetheless, the market-level and firm-level findings are internally consistent and suggest that managers increase disclosure in response to increased EPU.

We also check whether our cross-sectional findings from Section 4.2 occur for forecasts and 8-Ks. For example, managers of firms

Table 8

Economic policy uncertainty, voluntary disclosure, and information asymmetry from 2003 to 2016. This table analyzes the effect of disclosure on information symmetry using data measured at quarterly intervals. We estimate the effect of disclosure on information asymmetry by first regressing guidance on the EPU index and controls in Table 7. In this table, we then recursively regress spreads and Amihud on guidance, the EPU index, and controls. We account for the determinants of information asymmetry and disclosure by including contemporaneous control variables (similar to those in Table 4) and lagged control variables (similar to those in Table 7), respectively. We compute the indirect effect of EPU (through disclosure) on spreads and Amihud by multiplying the guidance and 8-K coefficients in Columns 1 through 4 by their corresponding EPU index coefficient in Table 7, Columns 3 and 4. Due to the small number of observations at the year-quarter market level, we only perform this analysis at the year-quarter firm level. We run separate regressions for forecasts and 8-Ks because these variables represent the same construct and are highly correlated. We describe this recursive estimation procedure further and interpret the results in Section 4.4. Index *i* represents each firm, and index *t* represents each year-quarter (YQ). When two parameters are separated by a comma in the "S.E. Clustering" row, this implies two-way clustering. All variables are defined in the Appendix. T-statistics are in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	Quarterly data			
	Equal-weighted firm level			
	Forecasts		8-K Filings	
	(1)	(2)	(3)	(4)
	Percent Spread$_{it}$	Amihud$_{it}$	Percent Spread$_{it}$	Amihud$_{it}$
EPU Index$_t$	0.0763***	0.0497***	0.0730***	0.0468***
	(3.02)	(3.60)	(2.89)	(3.65)
Log of Forecasts$_{it}$	−0.0128***	−0.0094***		
	(-3.46)	(-3.57)		
Log of 8-Ks$_{it}$			−0.0091***	−0.0083***
			(−2.82)	(-3.04)
S.D. of Returns$_{it}$	3.0112***	3.4401***	2.8978***	3.3016***
	(3.98)	(3.11)	(3.43)	(3.29)
Turnover$_{it}$	−1.2039***	0.8391***	−1.2531***	0.9208***
	(−2.88)	(2.90)	(-3.12)	(2.91)
Log of Dollar Trading Volume$_{it}$	−0.3841***	−0.4117***	−0.3655***	−0.4205***
	(-9.75)	(-9.51)	(-10.06)	(-8.97)
Log of Stock Price$_{it}$	0.1001***	0.1583***	0.0998***	0.1441***
	(5.43)	(4.12)	(5.49)	(4.03)
EU Index$_t$	0.02290*	0.0360**	0.0225**	0.0363**
	(2.01)	(2.39)	(2.11)	(2.30)
Lagged (t_{-1}) EPU, EU, and Firm-Level Controls from Table 7	Yes	Yes	Yes	Yes
Fixed Effects	Firm-Year	Firm-Year	Firm-Year	Firm-Year
S.E. Clustering	Firm, YQ	Firm, YQ	Firm, YQ	Firm, YQ
Observations	240,617	237,110	240,617	237,110
R^2	0.91	0.89	0.87	0.85
Indirect effect of EPU (through disclosure) on information asymmetry				
Log of Forecasts$_{it}$ *coeff.* × EPU Index$_{t\text{-}1}$ *coeff.* from Table 7, Column 3	−0.0007***	−0.0005***		
	(-3.94)	(−2.77)		
Log of 8-Ks$_{it}$ *coeff.* × EPU Index$_{t\text{-}1}$ *coeff.* from Table 7, Column 4			−0.0005**	−0.0005**
			(−2.36)	(−2.21)

exposed to EPU might invest in lobbying in part to gain access to additional information about pending policy. Such managers may make more EPU-driven disclosures. We run the regressions in Table 7, columns 3 and 4 with all the EPU index interaction terms from Table 5. We find positive significance for forecasts and 8-Ks for the policy beta and market-value interaction terms, but not for the other interaction terms. These findings are consistent with the idea that managers of firms more exposed to EPU and larger firms disclose more in response to increased EPU.

We next test whether managers' disclosures decrease information asymmetry by linking management forecasts and 8-K filings to spreads and Amihud. To do this, we follow Schoenfeld (2017, Section 4.5) and build a recursive structural equations model (or path model) of EPU, disclosure, and information asymmetry (Greene, 2002, p. 397). We use firm-level data to maximize the statistical power of this analysis.

The recursive model involves three steps. First, we empirically model disclosure as a function of EPU and controls (see Eq. (10)). Second, we empirically model information asymmetry (spreads and Amihud) as a function of disclosure, EPU, and controls (see Eq. (11)). Third, we use the results from the first two steps to compute the indirect effect of EPU on information asymmetry, i.e., the extent to which disclosure offsets (or does not offset) increased information asymmetry due to EPU. The exclusion restriction is that the error terms are uncorrelated in Eqs. (10) and (11), which implies that there is no factor that affects both disclosure and information asymmetry that is not accounted for by the firm-year-fixed effects or the control variables. Similar to asserting the exogeneity of an instrument, the exclusion restriction is untestable (Roberts and Whited, 2013). The equations for this procedure are as follows:

$$Disclosure_{it} = \alpha_0 + \alpha_1 EPU_{t\text{-}1} + \theta Controls_{t\text{-}1} + \varepsilon_{it} \tag{10}$$

$$IA_{it} = \beta_0 + \beta_1 EPU_t + \beta_2 Disclosure_{it} + \pi Controls_t + \beta_3 EPU_{t\text{-}1} + \theta Controls_{t\text{-}1} + \nu_{it}, \tag{11}$$

where *Disclosure* stands for the disclosure proxies, *IA* stands for the information asymmetry proxies, index *i* represents the firm, index *t* represents the year-quarter, and $\boldsymbol{\theta}$ and π represent vectors of firm-level and market-level (i.e., the EU index) control variables, which include firm-year-fixed effects throughout. Tables 7 and 8 denote the control variables. Note that since β_2's value in Eq. (11) depends on ε_{it} in Eq. (10), we must include in Eq. (11) the full Eq. (10) of $EPU_{t\text{-}1}$ and $\theta Controls_{t\text{-}1}$.

We recognize that, despite its controls and fixed effects, our quarterly recursive model only summarily captures the timing choices of disclosure. For example, managers may time disclosures strategically, considering factors such as mandatory disclosures and strategic investments to mitigate EPU exposure (Wellman, 2017). Managers may also respond to EPU through other disclosure channels or unmeasured activities. A justification for our parsimonious model is our aforesaid finding that there is mixed cross-sectional variation in disclosure patterns; however, we shortly discuss a cross-sectional test of our recursive model.

We expect that disclosure will impact information asymmetry relatively quickly in an active market. Thus, in Table 8, Columns 1 and 2, we regress quarterly firm-level spreads and Amihud illiquidity on contemporaneous quarterly firm-level forecasts and the EPU index with firm-year-fixed effects and controls.[33] As noted above, we include the full set of lagged regressors from Table 7, as well as contemporaneous controls for Amihud and spreads.

To compute the indirect effect of EPU (through forecasts) on spreads and Amihud, we multiply the forecast regressor coefficients in Table 8, Columns 1 and 2 by the EPU index regressor coefficient in Table 7, Column 3. The resulting negative products of -0.0007 for spreads (0.056×-0.0128; 1% level) and -0.0005 for Amihud (0.056×-0.0094; 1% level) signify that the indirect effect is present in our sample.[34] This finding implies that the additional forecasts associated with increased EPU decrease spreads and Amihud, partly offsetting the adverse information asymmetry consequences of increased EPU.

Notwithstanding the presence of lagged EPU as a regressor, current EPU is still associated with increased spreads and Amihud illiquidity, as evidenced by the significant positive coefficient on the EPU index in Columns 1 and 2 of Table 8. In fact, the extent to which management forecasts offset the increase in spreads and Amihud due to EPU amounts to about a 1% offset for both spreads and Amihud. This finding suggests that, on average, managers cannot fully offset the negative effect of EPU on their firm's information asymmetry at the quarterly level.[35]

More importantly, the magnitude of the offset is likely a lower bound because we have many small firms in our sample with forecast frequencies of zero, which implies that these firms do not attempt to mitigate the adverse information asymmetry effect of EPU through disclosure. That is, among larger firms and firms that release forecasts, the magnitude of the offset may be different. Indeed, when we run the recursive analysis only on firms in the top quartile of market value in our sample, we find that the offset increases in magnitude. We also find that the offset increases in magnitude when we run the recursive analysis only on firms that release forecasts. Still, the magnitudes in these additional analyses suggest that management forecasts cannot fully undo the adverse information asymmetry effect of EPU.

We then perform the same procedure for 8-K filings. Note that we run separate regressions in Table 8 for forecasts and 8-Ks because these variables proxy for the same construct and are highly correlated. In Table 8, Columns 3 and 4, we find that 8-Ks are also negatively associated with spreads and Amihud (1% level). We multiply the 8-K coefficients in Table 8 by the EPU index coefficient in Table 7, Column 4 and find that the offset (i.e., the indirect effect) is again significant for both spreads and Amihud (5% level for both). However, as Table 8 shows, the magnitudes of the offsets for 8-Ks are smaller relative to those for forecasts. Nonetheless, our findings in Table 8 are internally consistent and suggest that managers release forecasts and 8-Ks that mitigate some but not all of the adverse information asymmetry effect of EPU. This finding further validates the general equilibrium relation between EPU, spreads, and Amihud illiquidity that we document in Table 4.

5. Conclusion

The starting point of many asset-pricing models is investor uncertainty about firm value. This uncertainty often drives actions such as an investor's decision to collect private information and trade on it, an investor's use of private information to evaluate and trade on earnings releases, a market maker's decision to price protect though higher spreads, and a manager's decision to release voluntary disclosures. These decisions all interact with each other and determine how investor uncertainty about firm value affects liquidity and other stock price properties (Verrecchia, 2001).

Empirically, however, the challenge in testing these mechanisms is isolating a measure of investor uncertainty that cannot be significantly influenced by the actors above (e.g., Core, 2001; Joos, 2000). Recent theoretical models such as Pastor and Veronesi (2012, 2013) suggest that government economic policy uncertainty (EPU) is a strong candidate for this purpose. This uncertainty is driven by government actions that are likely outside the control of most individual managers and investors but nevertheless plausibly have a significant impact on most firms and investors.

In this study, we use the Baker et al. (2016) EPU index and find that increased EPU is associated with increased bid-ask spreads

[33] Note that if information asymmetry is high in the current quarter, managers may increase their forecasting frequency, which could result in positive associations between spreads, Amihud, and forecasts. This would bias against our results (Balakrishnan et al., 2014, p. 2271).

[34] We use the delta method to compute standard errors for these products (Krull and MacKinnon, 2001; Sobel, 1987).

[35] Similarly, managerial disclosures cannot fully offset the illiquidity effect of losing an analyst (Balakrishnan et al., 2014).

and Amihud illiquidity, especially for firms that have high EPU exposure. Investors also react less strongly to earnings surprises in periods of increased EPU, especially for firms with high liquidity risk. Managers try to reduce information asymmetry due to EPU with additional voluntary disclosures, but their disclosures are not enough, and a strong positive association between EPU and information asymmetry remains. Collectively, our evidence is consistent with the idea that EPU increases information asymmetry among investors and that managers respond to EPU with increased voluntary disclosure.

Our findings contribute to the ongoing research on the financial market implications of EPU. To further analyze this issue, one could conceivably extend our study to the information environments of other asset classes (e.g., Chordia et al., 2005; Hu et al., 2013), the actions of other economic agents such as stock and credit analysts, and managers' strategic timing of disclosures.

Appendix: Variable definitions for U.S. DTAQ firms from 2003 to 2016

Index i represents each firm, and index t represents the observation day, month, or quarter, depending on the test. VW stands for value weighted, CRP stands for the Center for Responsive Politics, and TR stands for Thomson Reuters. For our monthly and quarterly tests, we average the relevant measures over the observation month and quarterly, respectively. For the market-level tests, we value weight spreads, Amihud, and each guidance disclosure based on firm market capitalization on the observation day. See Section 3 for more details on all the variables.

Variable	Definition	Source
Uncertainty indices		
Economic Policy Uncertainty (EPU) index$_t$	Daily index based on the number of news articles that contain the EPU terms defined in Section 3	Baker et al. (2016)
Equity Uncertainty (EU) index$_t$	Daily index based on the number of news articles that contain the EU terms defined in Section 3	Baker et al. (2016)
Information asymmetry proxies as computed daily		
Percent Quoted Spreads$_{it}$	$\left[100 \times \frac{\text{Ask}_{it} - \text{Bid}_{it}}{(\text{Ask}_{it} + \text{Bid}_{it})/2}\right]$, time weighted as in Holden and Jacobsen (2014)	DTAQ
Amihud Illiquidity$_{it}$	$\left[10^6 \times \frac{\lvert\text{Return}_{it}\rvert}{\text{Dollar Trading Volume}_{it}}\right]$, as in Amihud (2002)	CRSP
Disclosure proxies		
Earnings Surprise$_{it}$	Actual earnings minus the analyst consensus mean earnings forecast at $t = -1$ scaled by stock price at $t = -1$, where $t = 0$ is the quarterly earnings announcement date	I/B/E/S
Log of VW Forecasts$_t$	$ln\,[1+ \sum_i$ Frequency of management forecasts$_{it}$], where t is the quarter and each forecast is VW	I/B/E/S
Log of Forecasts$_{it}$	$ln\,[1+$ Frequency of management forecasts$_{it}$], where t is the quarter	I/B/E/S
Log of VW 8-Ks$_t$	$ln\,[1+ \sum_i$ Frequency of 8-K items 2, 7, 8, or 9$_{it}$], where t is the quarter and each 8-K is VW	SEC
Log of 8-Ks$_{it}$	$ln\,[1+$ Frequency of 8-K items 2, 7, 8, or 9$_{it}$], where t is the quarter	SEC
Firm-level static variables		
|Policy Beta|$_i$	$\lvert\beta_i^E\rvert$ from the regression $r_{it} = \beta_i^0 + \beta_i^E EPU_t + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + \epsilon_{it}$, which we run monthly by firm over sample period (see Eq. (3))	CRSP, Baker et al. (2016)
Log of Market Value$_i$	$ln\,[1 + [\text{Price}_{it} \times \text{shares outstanding}_{it}]]$, averaged over sample period	CRSP
Log of Foreign Income$_i$	1 if firm had revenue in a foreign income over sample period, 0 otherwise	Compustat
Log of Trade Words$_i$	$ln\,[1+$ Average foreign trade words in firm's 10-Ks over sample period] (see Section 3 for dictionary)	SEC EDGAR
Log Lobbying Dollars$_i$	$ln\,[1+$ Firm's annual lobbying expenditures averaged over sample period]	CRP
Log of EPU Words$_i$	$ln\,[1+$ Average EPU words in firm's 10-Ks over sample period] (see Section 3 for dictionary)	SEC EDGAR
Liquidity Risk Exposure (β_i^L)	β_i^L of the regression $r_{it} = \beta_i^0 + \beta_i^L L_t + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + \epsilon_{it}$, which we run monthly by firm over sample period (see Eq. (4))	CRSP, Pastor and Stambaugh (2003)
Control variables		
S.D. of VW Returns$_t$	Standard deviation of value-weighted-index returns in month t (monthly tests only)	CRSP
S.D. of Returns$_{it}$	Standard deviation of returns for firm i in month t (monthly tests only)	CRSP

Squared VW Returns$_t$	Value-weighted-index return$_t$ ×value-weighted-index return$_t$ (daily tests only)	CRSP
Squared Returns$_{it}$	Return$_{it}$ ×return$_{it}$ (daily tests only)	CRSP
Log of Total Trading Volume$_t$	$ln\,[1+ \sum_i$ Trading volume$_{it}$]	CRSP
Log of Trading Volume$_{it}$	$ln\,[1+$ Trading volume$_{it}$]	CRSP
Log of Total Dollar Trading Volume$_t$	$ln\,[1+ \sum_i$ [Trading volume$_{it}$ × stock price$_{it}$]]	CRSP
Log of Dollar Trading Volume$_{it}$	$ln\,[1+$ (Trading volume$_{it}$ × stock price$_{it}$)]	CRSP
Log of Total Market Value$_t$	$ln\,[1+ \sum_i$ [Shares outstanding$_{it}$ × stock price$_{it}$]]	CRSP
Log of Stock Price$_{it}$	$ln\,[1+$ Stock price$_{it}$]	CRSP
Returns$_{it}$	$[\exp[\sum_{d=s}^{d=-1} \ln(1 + r_{id})] - 1]$, where $d = 0$ is the first day of year-quarter t, and $d = s$ is the first day of year-quarter t_{-1}	CRSP
Market to Book$_{it}$	Market value of equity$_{it}$/book value of equity$_{it}$, where t is the quarter	Compustat
ROA$_{it}$	Net income$_{it}$/total assets$_{it}$, where t is the quarter	Compustat
Leverage$_{it}$	Total debt$_{it}$/total assets$_{it}$, where t is the quarter	Compustat
Analyst Following$_{it}$	Average number of analysts with earnings forecasts for firm i over quarter t	I/B/E/S
Institutional Ownership$_{it}$	Institutional ownership for firm i at the end of quarter t from 13F filings	TR

Note: The monthly and quarterly analyses use the daily market-based variables averaged over the month and quarter, respectively.

References

Addoum, J.M., Kumar, A., 2016. Political sentiment and predictable returns. Rev. Financ. Stud. 29 (12), 3471–3518.
Adelino, M., Dinc, I.S., 2014. Corporate distress and lobbying: evidence from the stimulus act. J. Financ. Econ. 114 (2), 256–272.
Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Mkt.s 5 (1), 31–56. https://doi.org/10.1016/S1386-4181(01)00024-6.
Amiram, D., Owens, E., Rozenbaum, O., 2016. Do information releases increase or decrease information asymmetry? New evidence from analyst forecast announcements. J. Account. Econ. 62 (1), 121–138.
Anilowski, C., Feng, M., Skinner, D., 2007. Does earnings guidance affect market returns? The nature and information content of aggregate earnings guidance. J. Account. Econ. 44 (1), 36–63.
Baker, S., Bloom, N., Canes-Wrone, B., Davis, S., Rodden, J., 2014. Why has US policy uncertainty risen since 1960? Am. Econ. Rev. 104 (5), 56–60.
Baker, S., Bloom, N., Davis, S., 2016. Measuring economic policy uncertainty. Q. J. Econ. 131 (4), 1593–1636.
Balakrishnan, K., Billings, M., Kelly, B., Ljungqvist, A., 2014. Shaping liquidity: on the causal effects of disclosure and liquidity. J. Finance 69, 2237–2278.
Bernard, D., 2016. Is the risk of product market predation a cost of disclosure? J. Account. Econ. 62 (2), 305–325.
Beyer, A., Cohen, D., Lys, T., Walther, B., 2010. The financial reporting environment: review of the recent literature. J. Account. Econ. 50, 296–343.
Billings, M.B., Jennings, R., Lev, B., 2015. On guidance and volatility. J. Account. Econ. 60 (2), 161–180. https://doi.org/10.1016/j.jacceco.2015.07.008.
Bird, A., Karolyi, S., Ruchti, T., 2017. Political Uncertainty and Corporate Transparency.Political Uncertainty and Corporate Transparency. Working Paper
Boone, A., Kim, A., White, J., 2017. Political Uncertainty and Firm Disclosure.Political Uncertainty and Firm Disclosure. Working Paper
Boutchkova, M., Doshi, H., Durnev, A., Molchanov, A., 2012. Precarious politics and return volatility. Rev. Financ. Stud. 25 (4), 1111–1154.
Bozanic, Z., Roulstone, D.T., Buskirk, A.V., 2018. Management earnings forecasts and other forward-looking statements. J. Account. Econ. 65 (1), 1–20.
Bradley, D., Gokkaya, S., Liu, X., Michaely, R., 2018. Is Washington Policy Research Valuable to Capital Markets?. Working Paper
Bushee, B., Core, J., Guay, W., Hamm, S., 2010. The role of the business press as an information intermediary. J. Account. Res. 48 (1), 1–19.
Campbell, J., Lo, A., MacKinlay, A.C., 1996. The Econometrics of Financial Markets. Princeton University Press.
Chordia, T., Roll, R., Subrahmanyam, A., 2001. Market liquidity and trading activity. J. Finance 56 (2), 501–530. https://doi.org/10.1111/0022-1082.00335.
Chordia, T., Roll, R., Subrahmanyam, A., 2008. Liquidity and market efficiency. J. Financ. Econ. 87 (2), 249–268.
Chordia, T., Sarkar, A., Subrahmanyam, A., 2005. An empirical analysis of stock and bond market liquidity. Rev. Financ. Stud. 18 (1), 85–129. https://doi.org/10.1093/rfs/hhi010.
Chordia, T., Subrahmanyam, A., Tong, Q., 2014. Have capital market anomalies attenuated in the recent era of high liquidity and trading activity? J. Account. Econ. 58 (1), 41–58. https://doi.org/10.1016/j.jacceco.2014.06.001.
Christensen, D., Mikhail, M., Walther, B., Wellman, L., 2017. From k street to wall street: political connections and stock recommendations. Account. Rev. 92 (3), 87–112.
Chuk, E., Matsumoto, D., Miller, G., 2013. Assessing methods of identifying management forecasts: CIG vs. researcher collected. J. Account. Econ. 55 (1), 23–42.
Coller, M., Yohn, T.L., 1997. Management forecasts and information asymmetry: an examination of bid-Ask spreads. J. Account. Res. 35 (2), 181–191.
Cooper, M., He, J., Plumlee, M., 2017. Measuring Disclosure Using 8K Filings.Measuring Disclosure Using 8K Filings. Working Paper
Core, J., 2001. A review of the empirical disclosure literature: discussion. J. Account. Econ. 31 (1), 441–456. https://doi.org/10.1016/S0165-4101(01)00036-2.
Dimson, E., 1979. Risk measurement when shares are subject to infrequent trading. J. Financ. Econ. 7 (2), 197–226.
Drechsler, I., 2013. Uncertainty, time-varying fear, and asset prices. J. Finance 68 (5), 1843–1889. https://doi.org/10.1111/jofi.12068.
Fagan, F., Bilgel, F., 2015. Sunsets and federal lawmaking: evidence from the 110th congress. Int. Rev. Law Econ. 41, 1–6.
Fama, E., French, K., 1995. Size and book-to-market factors in earnings and returns. J. Finance 50 (1), 131–155.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33 (1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5.
Fong, K.Y.L., Holden, C.W., Trzcinka, C.A., 2017. What are the best liquidity proxies for global research? Rev. Finance 21 (4), 1355–1401.
Foucault, T., Pagano, M., Roell, A., 2013. Market Liquidity: Theory, Evidence, and Policy. Oxford University Press.
Gao, M., Huang, J., 2016. Capitalizing on capitol hill: informed trading by hedge fund managers. J. Financ. Econ. 121 (3), 521–545.
Glosten, L., Milgrom, P., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. J. Financ. Econ. 14 (1), 71–100.
Gow, I.D., Ormazabal, G., Taylor, D.J., 2010. Correcting for cross sectional and time series dependence in accounting research. The Accounting Review 85 (2), 483–512.
Graham, J., Harvey, C., Rajgopal, S., 2005. The economic implications of corporate financial reporting. J. Account. Econ. 40 (1–3), 3–73.
Greene, W.H., 2002. Econometric Analysis, 5. Pearson Education, Inc., Upper Saddle River, NJ.

Guay, W., Samuels, D., Taylor, D.J., 2016. Guiding through the fog: financial statement complexity and voluntary disclosure. J. Account. Econ. 62 (2), 234–269.
Gulen, H., Ion, M., 2016. Policy uncertainty and corporate investment. Rev. Financ. Stud. 29 (3), 523–564.
Hochberg, Y., Sapienza, P., Vissing-Jorgensen, A., 2009. A lobbying approach to evaluating the Sarbanes-Oxley act of 2002. J. Account. Res. 47 (2), 519–583.
Holden, C., Jacobsen, S., 2014. Liquidity measurement problems in fast, competitive markets: expensive and cheap solutions. J. Finance 69 (4), 1747–1785.
Holden, C., Jacobsen, S., Subrahmanyam, A., 2013. The empirical analysis of liquidity. Found. Trends Finance 8 (4), 263–365. https://doi.org/10.1561/0500000044.
Hu, G., Pan, J., Wang, J., 2013. Noise as information for illiquidity. J. Finance 68 (6), 2341–2382.
Jagolinzer, A., Larcker, D., Ormazabal, G., Taylor, D.J., 2018. Political Connections and the Informativeness of Insider Trades.Political Connections and the Informativeness of Insider Trades. Working Paper
Johnson, T.L., So, E.C., 2018. Asymmetric trading costs prior to earnings announcements: implications for price discovery and returns. J. Account. Res. 56 (1), 217–263.
Joos, P., 2000. Discussion of the economic consequences of increased disclosure. J. Account. Res. 38 (2000), 125–136.
Kelly, B., Ljungqvist, A., 2012. Testing asymmetric-Information asset pricing models. Rev. Financ. Stud. 25 (5), 1366–1413.
Kim, O., Verrecchia, R., 1994. Market liquidity and volume around earnings announcements. J. Account. Econ. 17, 41–67.
Krull, J., MacKinnon, D., 2001. Multilevel modeling of individual and group level mediated effects. Multivariate Behav. Res. 36 (2), 249–277. https://doi.org/10.1207/S15327906MBR3602_06.
Lang, M., Lins, K., Maffett, M., 2012. Transparency, liquidity, and valuation: international evidence on when transparency matters most. J. Account. Res. 50 (3), 729–774.
Lang, M., Maffett, M., 2011. Transparency and liquidity uncertainty in crisis periods. J. Account. Econ. 52 (2–3), 101–125.
Lerman, A., Livnat, J., 2010. The new form 8-k disclosures. Rev. Account. Stud. 15, 752–778.
Leuz, C., Verrecchia, R., 2000. The economic consequences of increased disclosure. J. Account. Res. 38 (2000), 91–124.
Lys, T., Sohn, S., 1990. The association between revisions of financial Analysts' earnings forecasts and security-Price changes. J. Account. Econ. 13, 341–363.
Nagar, V., Nanda, D., Wysocki, P., 2003. Discretionary disclosure and stock-based incentives. J. Account. Econ. 34, 283–309.
Novack, J., 2013. Political uncertainty will continue to stunt economic growth. Forbes. October 16
Pastor, L., Stambaugh, R., 2003. Liquidity risk and expected stock returns. J. Polit. Econ. 111 (3), 642–685.
Pastor, L., Veronesi, P., 2012. Uncertainty about government policy and stock prices. J. Finance 67 (4), 1219–1264.
Pastor, L., Veronesi, P., 2013. Political uncertainty and risk premia. J. Financ. Econ. 110 (3), 520–545.
Roberts, M., Whited, T., 2013. Endogeneity in empirical corporate finance. In: Constantinides, G.M., Harris, M., Stulz, R.M. (Eds.), Handbook of the Economics of Finance. Elsevier, pp. 493–572.
Sadka, R., 2011. Liquidity risk and accounting information. J. Account. Econ. 52 (2–3), 144–152. https://doi.org/10.1016/j.jacceco.2011.08.007.
Schoenfeld, J., 2017. The effect of voluntary disclosure on stock liquidity: new evidence from index funds. J. Account. Econ. 63 (1), 51–74.
Sobel, M., 1987. Direct and indirect effects in linear structural equation models. Sociol. Methods Res. 16 (1), 155–176. https://doi.org/10.1177/0049124187016001006.
Verrecchia, R., 1990. Information quality and discretionary disclosure. J. Account. Econ. 12 (4), 365–380. https://doi.org/10.1016/0165-4101(90)90021-U.
Verrecchia, R., 2001. Essays on disclosure. J. Account. Econ. 32, 97–180.
Viswanathan, M., 2007. Sunset provisions in the tax code: a critical evaluation and prescriptions for the future. NYU Law Rev. 82, 656–688.
Wellman, L., 2017. Mitigating political uncertainty. Rev. Account. Stud. 22, 217–250.