Gregoriou, A, Nguyen, NNQ, Nguyen, TT and Vu, N

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ABSTRACT

We posit that accounting reporting complexity includes two components – monetary reporting complexity (MRC) and textual reporting complexity (TRC). It is generally challenging to disentangle these components because they tend to increase with real business activities. Economic policy uncertainty (EPU) provides an ideal setting to overcome this challenge. Greater EPU reduces real business activities, suggesting a reduction in MRC. However, TRC can increase or decrease depending on disclosure incentives. Using monetary and textual eXtensible Business Reporting Language (XBRL) tags to measure MRC and TRC, respectively, we find that high EPU reduces MRC but increases TRC. These findings are robust to a series of robustness checks. Additional analyses show that [1] these relationships hold for all ten policy categories; [2] the reduction in five hard-to-reverse business activities drives the reduction in MRC; [3] the decrease in MRC drives the increase in TRC; [4] the simultaneous changes in MRC and TRC help reduce the increase in information asymmetry due to high EPU; and [5] these relationships are stronger for firms relying more on the government for their operations and weaker for firms with high political risk or proprietary risk. Collectively, these results suggest that, when facing greater uncertainty about future economic policies, firms tend to delay real economic activities and justify this reduction using textual disclosure. Our study makes several contributions to research on economic policy uncertainty and accounting reporting complexity.

Keywords: economic policy uncertainty; accounting reporting complexity; linguistic complexity; eXtensible Business Reporting Language; accounting concepts

JEL: E66, G18, M40

Data availability: Data are available from publicly available sources and from the authors upon request.

1. INTRODUCTION

The SEC broadly defines accounting reporting complexity (ARC) as the difficulty for "preparers to properly apply…U.S. GAAP…and communicate the economic substance of a transaction or event and the overall financial position and results of a company" (SEC, 2008). Prior research finds that accounting reports are increasingly complex, reducing their informativeness (Dyer et al., 2017; Lehavy et al., 2011; F. Li, 2008; Peterson, 2012; You & Zhang, 2009) and increasing the risk of misstatements (Filzen & Peterson, 2015; Hoitash & Hoitash, 2018). Given the negative consequences of heightened reporting complexity, it is important to understand its drivers.

Bertomeu and Marinovic (2016) classify accounting information into hard and soft, with hard (soft) information being objective (subjective). Accordingly, financial reports contain two types of information. Hard information refers to the reported monetary values (e.g., revenues and expenses) and soft information refers to the textual disclosure to discuss these values.[1] We thus view accounting reporting complexity as a function of both monetary reporting complexity (MRC) and textual reporting complexity (TRC),[2] with MRC capturing the complexity related to the reported numbers and TRC capturing the complexity related to the associated narratives.

Both MRC and TRC increase with real business activities.[3] Firms with more business activities need more accounting concepts to measure and report as well as to explain, justify, and discuss these activities. For example, firms report more monetary values when having a merger and acquisition (M&A) transaction, thus increasing MRC. Having an M&A transaction also requires longer texts to discuss this transaction. Therefore, all else equal, more business

[1] One may argue that the textual notes are also objective because they are based on accounting concepts. While this is true, it is likely that monetary values (e.g., recorded sales revenues) are more objective than the associated textual notes (e.g., discussion of sales revenue activities).
[2] Prior research also refers to textual reporting complexity as linguistic complexity and/or narrative complexity.
[3] Business activities include all real economic activities, regardless of their inclusion in operating, investing, or financing sections of the statement of cash flows.

activities lead to greater MRC and TRC. This makes it challenging to disentangle these two components of reporting complexity.

Economic policy uncertainty (EPU) is an ideal setting to examine the simultaneous changes in these two components of reporting complexity. EPU refers to the uncertainty arising from the passing of governmental economic policies (Bloom, 2014). It is well documented in prior research that firms facing high EPU tend to reduce hard-to-reverse activities such as investment, capital expenditures, borrowing, mergers and acquisitions, and hiring (Baker et al., 2016; Bloom, 2014; Gulen & Ion, 2016). Therefore, during periods of high EPU, there are fewer business activities. As such, MRC reduces because there are fewer monetary values to report. However, it is unclear how textual disclosure would change. On the one hand, *agency theory* (Jensen & Meckling, 1976), *voluntary disclosure theory* (Verrecchia, 1983), and *signaling theory* (Spence, 1973) predict that firms may need longer narratives to explain the reduced business activities or to discuss the impacts of EPU on the remaining activities. On the other hand, *voluntary disclosure theory* also predicts that firms may shorten their narratives because of proprietary concerns.[4] To the extent that longer texts are more complex, higher EPU may either increase or decrease TRC. Therefore, we expect a negative relationship between EPU and MRC and have no expectation for the relationship between EPU and TRC.

The recent development in eXtensible Business Reporting Language (XBRL) tags in 10-K reports allows us to empirically measure both components of ARC in the same setting. There are two types of XBRL tags – the *monetary* tags and the *text-block* tags. Each *monetary* XBRL tag links a monetary value to a relevant accounting concept. Following prior research (Burke & Gunny, 2022; Henry et al., 2023; Hoitash & Hoitash, 2018; Hwang et al., 2020), we measure MRC using the number of unique monetary XBRL tags in 10-Ks because more business activities mean more monetary values being reported, hence more monetary tags.

[4] Disclosing too much may allow competitors to take advantage of the focal firm's reduced business activities.

Meanwhile, each *text-block* XBRL tag links a disclosure note to a relevant accounting concept. Thus, text-block tags represent narratives associated with reported business activities. We measure TRC using the average length in word count of all text-block XBRL tags in the 10-Ks, with longer tags indicating more textual complexity.[5] Related to TRC is the literature on various textual properties of corporate disclosure such as length, readability, and tone or sentiment (Barth & Schipper, 2008; Bonsall et al., 2017; Burke & Gunny, 2022; Bushee et al., 2018; Chichernea et al., 2022; Jiang et al., 2022). While the MRC measure based on the number of unique monetary tags follows Hoitash and Hoitash (2018), the TRC measure based on the average length of the text-block tags is our innovation in this study.

We capture EPU using the news-based measure proposed by Baker et al. (2016). Because EPU is at the market level and MRC and TRC are at the firm level, EPU is likely to be an exogenous source of turbulence that exists outside the control of individual firms.[6] Using a sample of U.S.-incorporated firms from 2011 to 2019, we find that EPU is negatively associated with MRC and positively associated with TRC. These relationships are robust to various sensitivity checks including [1] isolating the policy-induced component of EPU, [2] performing a two-stage regression analysis using an instrumental variable for EPU, [3] incorporating presidential elections as external shocks to EPU, and [4] using the change specification. These robustness checks mitigate concerns of endogeneity and suggest causal relationships between EPU and both components of ARC.

We then provide several additional analyses to further understand these relationships. First, we document that these relationships hold for all ten categories of EPU ranging from

[5] All else equal, longer texts are more complex. Transparency is another textual property that is not necessarily correlated with length. Longer texts may or may not be more transparent depending on managerial incentives. We test for transparency later in this study using the information asymmetry tests. Another textual property is readability. However, we do not focus on readability because current measures of readability in extant research do not apply to text-block XBRL tags.

[6] While some firms can lobby the U.S. government to affect policy changes to a certain extent, we provide robustness checks later to show that this is unlikely to cause a reverse causality issue to our results. Additionally, research in corporate lobby in the U.S. shows mixed results regarding the ability of firms to successfully influence governmental policies (Cao et al., 2018).

monetary policies to sovereign debt policies. Second, we rely on a special feature of the monetary XBRL tags to categorize MRC into five hard-to-reverse activities. We then show that EPU reduces all five of them, which contributes considerably to the overall decrease in MRC.

Next, using a system of recursive equations, we show that high EPU reduces monetary complexity, which then increases textual complexity. We then show that while high EPU increases information asymmetry, the decrease in monetary complexity and the increase in textual complexity help mitigate this to a certain extent. The mitigating effect of the reduction in MRC on information asymmetry is consistent with prior findings that complex financial reports can hamper the information quality of the firms, and thus less complex reports can enhance the information quality. Meanwhile, the mitigating effect of the increase in TRC on information asymmetry suggests that the increased average length of the textual disclosure is mainly to inform rather than to obfuscate in the EPU setting. Thus, more complex texts are not necessarily uninformative, which extends our understanding about the relationship between complexity and informativeness in the textual analysis literature.

Finally, we triangulate the EPU-ARC relationships using three cross-sectional tests. We find that these relationships are stronger for firms that depend more on the government for their operations and weaker for firms more exposed to political risk. We also document that firms with higher proprietary risk tend to increase their textual disclosure to a lesser extent.

Collectively, these findings suggest that firms tend to delay hard-to-reverse activities when there is greater uncertainty about future economic policies. As a result, they report fewer monetary values, leading to lower reporting complexity related to real business activities. To justify this reduction in real activities, firms increase the average length of narratives in their 10-Ks, leading to more complex, yet more informative, textual disclosure.

2. LITERATURE REVIEW AND CONTRIBUTIONS

2.1. Contributions to the Literature on Economic Policy Uncertainty

Uncertainty refers to the inability of the economic agents to forecast the likelihood of future events (Gilboa et al., 2008; Hicks, 1980; Keynes, 1921; Knight, 1921; Lawson, 1985; LeRoy & Singell, 1987; Schumpeter, 1954). In our setting, it implies the inability of consumers, managers, and policymakers to forecast the future paths of economic indicators at the macro (e.g., GDP growth) and micro (e.g., firm-level growth) levels (Bloom, 2014). Bloom (2014) highlights that uncertainty at every level rises during recessions for every economy, with developing countries seeing a stronger rise than their developed counterparts.

In response to macroeconomic uncertainty, the government often passes policies to stabilize the economy.[7] However, this process introduces further uncertainties relating to who will set the new policies, which policies will be passed, when they will take effect, and how they will affect various aspects of the economy in the short and long terms (Baker et al., 2016). Policy uncertainty can also relate to the fact that higher macroeconomic uncertainty can make monetary and fiscal stabilization policies less effective (Bloom, 2014). Collectively, these uncertainties related to political matters are considered economic policy uncertainty (EPU).

Baker et al. (2016) derive a comprehensive measure of EPU based on newspaper coverage frequency that captures these policy uncertainties. They find that increases in EPU predict declines in investment, output, and employment in the U.S. and in 11 other major economies. They also observe that EPU in the U.S. has been increasing since the 1960s probably due to rising political polarization or the growing economic role of the U.S. government. Among the 11 policies underlying changes in EPU, fiscal policies, especially tax policies, and health care policies are the largest and the second-to-largest sources of EPU in recent years, respectively (Baker et al., 2016).

[7] Pástor & Veronesi (2013) argue that politicians tend to maintain the old policies until the need to set new ones arises during economic recessions.

EPU represents a salient macroeconomic factor that affects the operating environments of all firms. There is thus a growing literature documenting the effects of EPU on various firm-level characteristics (Baker et al., 2016; Bloom, 2014; Bonaime et al., 2018; Duong et al., 2020; Gulen & Ion, 2016; Nguyen & Phan, 2017). However, these studies mainly focus on specific settings such as capital expenditures, mergers and acquisitions, hiring, and borrowing, which limits the external validity of their results. We extend this literature by studying monetary reporting complexity as a *holistic* proxy for all forms of real corporate activities.

Reporting choices reflect firms' responses to the environment in which they operate. As such, it is important to consider macroeconomic factors such as EPU as potential determinants of firm-level reporting properties. However, only a few studies have addressed this frontier. They examine the effects of EPU on the frequency of management forecasts and voluntary 8-K filings (Nagar et al., 2019), accounting quality (El Ghoul et al., 2020), financial statement comparability (Dhole et al., 2021), and conditional conservatism (Dai & Ngo, 2021). Our paper extends this literature by documenting the effect of EPU on both components of reporting complexity, namely, monetary complexity and textual complexity.

2.2. Contributions to the Literature on Accounting Reporting Complexity

According to the SEC, accounting reporting complexity (ARC) refers to the difficulty for "preparers to properly apply…U.S. GAAP…and communicate the economic substance of a transaction or event and the overall financial position and results of a company" (SEC, 2008). In accounting research, ARC encompasses various aspects of reporting complexity, ranging from the number and variety of accounting concepts used in the financial reports to various textual properties of the reports such as length, redundancy, boilerplates, readability, and sentiment or tone (Barth & Schipper, 2008; Bonsall et al., 2017; Burke & Gunny, 2022; Bushee et al., 2018; Chichernea et al., 2022; Hoitash et al., 2021; Hoitash & Hoitash, 2018; Jiang et al., 2022). Prior research find that financial reports are increasingly complex, which leads to reduced informativeness of the financial disclosures (Dyer et al., 2017; Lehavy et al., 2011; F. Li, 2008; Peterson, 2012; You & Zhang, 2009) and the increase in the risk of financial misstatements (Filzen & Peterson, 2015; Hoitash & Hoitash, 2018).

At the core, each financial report includes a set of financial statements and disclosure notes to explain the numbers presented in these statements. As such, it may be easier to understand ARC by framing it as a function of two components: monetary reporting complexity (MRC) and textual reporting complexity (TRC). MRC refers to the number of unique monetary values reported in the financial statements, whereas TRC refers to the length of the disclosure notes associated with these statements.

More complex business transactions lead to more monetary values to be reported in the financial statements, which increases MRC. To explain this business complexity, firms need longer disclosure notes, thus increasing TRC. As the business world becomes increasingly complex, especially with the interconnected nature of economic activities due to globalization and international trades, business transactions become increasingly complex, making it increasingly challenging for preparers of financial reports to select and properly apply the correct accounting concepts for each business transaction. This explains, to a certain extent, the finding in prior research that financial reports are increasingly complex.

ARC is an important disclosure property because it affects the informativeness of the accounting reports. Changes in ARC can alter firms' information environment (Dyer et al., 2017; Lehavy et al., 2011; F. Li, 2008; Peterson, 2012; You & Zhang, 2009) and the risk of financial misstatements (Filzen & Peterson, 2015; Hoitash & Hoitash, 2018). Given the pervasive impact of reporting complexity on the informativeness of accounting disclosures, it is important to understand its determinants. While most studies focus on the consequences of reporting complexity, none has examined its determinants, especially those at the macro level. Our paper seeks to bridge this gap by documenting the effect of EPU on both the monetary and the textual components of reporting complexity. The setting of EPU is particularly useful as it allows us to isolate MRC from TRC through reduced real business activities, thus providing more insights into these two components of ARC.

2.3. Contributions to the Literature on XBRL-based Disclosure

To help preparers and users of financial reports process the complex information embedded in corporate filings, the SEC requires that all publicly traded firms in the U.S. file their 10-K reports in eXtensible Business Reporting Language (XBRL) format starting in 2011. Specifically, firms must assign an XBRL tag to each accounting item in both the financial statements and the supplemental notes in their 10-K reports. Each of these tags is then linked to a unique accounting concept approved by the FASB. These concepts relate to various accounting topics such as revenues, inventory, and raw materials.

Through the XBRL development that introduces an important source of machine-readable accounting information, the SEC seeks to facilitate standardized reporting and streamlined access to a vast amount of data, allowing for the efficient analyses and comparisons of financial data across firms and time. Some studies have document the increase in firms' information environment after the adoption of XBRL, measured by a decrease in reporting lags for 10-K and 10-Q filings (Du & Wu, 2018), and a decrease in post-earnings announcement drift (Efendi et al., 2014). Others use XBRL tags to construct novel measures of reporting complexity (Chychyla et al., 2019; Hoitash & Hoitash, 2018), and financial statement comparability (Caylor et al., 2019; Hoitash et al., 2018; Johnston & Zhang, 2021).[8]

There are two types of XBRL tags – the monetary tags and the text-block tags. The more business transactions a firm has, the more accounting concepts it needs to identify these transactions, and the more monetary tags there are in its 10-K report. Therefore, the number of monetary tags can capture the complexity of real business activities. Recent accounting

[8] Hoitash et al. (2021) provide a comprehensive review of the accounting research on XBRL.

research has taken advantage of these monetary XBRL tags (Burke & Gunny, 2022; Henry et al., 2023; Hoitash & Hoitash, 2018; Hwang et al., 2020). Focusing on the difficulty of applying a variety of accounting concepts, Hoitash and Hoitash (2018) measure reporting complexity based on the number of monetary tags in 10-K filings and document that more monetary tags are associated with greater likelihood of misstatements and material weakness disclosures, longer audit delay, and higher audit fees.

Using a closely related measure, Chychyla et al. (2019) find that firms seek to mitigate the adverse effects of reporting complexity by investing in accounting expertise. They find that reporting complexity is positively associated with the level of accounting expertise on the firms' board of directors and audit committee and that accounting expertise mitigates the negative outcomes of reporting complexity including internal control weaknesses, accounting restatements, and SEC comment letters.[9] We extend this literature by showing that high EPU can reduce the number of unique XBRL tags due to reduced economic activities.

While monetary tags are assigned to each reported numbers, *text-block* tags are assigned to each paragraph in the notes to the financial statements. Because these XBRL tags are standardized, they are not prone to the variety of language used by different firms to describe their notes. As such, text-block tags can objectively capture the length of each paragraph, an important textual attribute of reporting complexity. Despite the availability of text-block tags, prior studies primarily focus on monetary tags to examine reporting complexity. Among the few that rely on text-block tags are Ahn et al. (2020a, b). Ahn et al. (2020a) use text-block tags to identify fair value notes and find that following fair value comment letters, firms increase the length of their fair value disclosures. Ahn et al. (2020b) also use text-block tags to compute the words-to-numbers ratios of financial statement notes and observe that firms with higher

[9] Note that even though Hoitash and Hoitash (2018) and Chychyla et al. (2019) refer to their measures accounting reporting complexity, their measures capture monetary reporting complexity rather than textual reporting complexity.

ratios of words-to-numbers are less likely to receive comment letters from the SEC, suggesting that regulators favor textual disclosures that expand on numerical disclosures.

Our study is related to Ahn et al. (2020a, b) because we also use text-block tags to examine textual reporting complexity. However, our innovation is in the use of the average length of the text-block tags to measure the narrative complexity of the financial reports. By showing that EPU has different implications on two components of complexity of the financial reports captured by two types of XBRL tags, we demonstrate the usefulness of XBRL tags in financial accounting research.

3. HYPOTHESIS DEVELOPMENT

In this section, we develop predictions relating EPU to both MRC and TRC. Extensive prior research establishes that firms facing high EPU cannot reliably estimate their future paths given the information available to them, and consequently tend to hinder hard-to-reverse business decisions such as investment in long-term assets, hiring, and mergers and acquisitions (Baker et al., 2016; Bloom, 2014; Bonaime et al., 2018; Duong et al., 2020; Gulen & Ion, 2016; Nguyen & Phan, 2017). High EPU also decreases firms' borrowing because of higher financing costs and reduced access to bank loans (Bordo et al., 2016; Datta et al., 2019; Gungoraydinoglu et al., 2017; Kaviani et al., 2020; Pástor & Veronesi, 2013; Pham, 2019). Thus, high EPU reduces firms' real business activities, leading to fewer transactions to report and fewer accounting concepts to account for in their financial statements. For example, if firms do not have merger and acquisition (M&A) activities due to high EPU (Bonaime et al., 2018; Nguyen & Phan, 2017), they do not report the monetary values and the relevant accounting concepts related to these activities.[10] Therefore, high EPU can *decrease* monetary reporting complexity. We thus state our first hypothesis as follows:

Hypothesis 1: Economic policy uncertainty reduces monetary reporting complexity.

[10] Accounting concepts to account for M&A transactions relate to the measurement of acquired assets, liabilities, incomes, expenses, and cash flows, as well as fair value adjustments or goodwill.

If firms reduce their business activities in response to high EPU, they may need to justify this reduction to their shareholders. According to *agency theory* (Jensen & Meckling, 1976), managers (agents) run the firms on behalf of shareholders (principals), who continuously monitor managers' performance to protect themselves against information asymmetry. If heightened EPU makes it harder for shareholders to predict the future cash flows of the firms, similar to how it affects managers, shareholders may find it more challenging to monitor managers' performance during periods of high EPU. As such, they may perceive reduced business activities as managers' risk-aversion or attempt to hide poor results. Meanwhile, if shareholders are unaware of heightened EPU, they may perceive reduced business activities as managers' underinvestment or lack of adequate performance. Either way, high EPU can widen the information asymmetry between shareholders and managers.

Voluntary disclosure theory (Verrecchia, 1983) predicts that firms voluntarily disclose information when the benefits of doing so outweigh the costs. In the EPU setting, it is likely that managers have sufficient incentive to voluntarily disclose more information to alleviate information asymmetry that is widened during periods of high EPU. The incentive is particularly strong because managers can attribute the slow business to EPU that fluctuates outside of their control. Through voluntary disclosure, managers can justify their wait-and-see strategy, maintain their credibility and reduce monitoring costs for shareholders.

In the 10-K, managers can use the supplemental notes to elaborate on their reported accounting numbers. As such, the need to justify their slow business can increase the average length of these disclosure notes. Because narrative is essentially voluntary, this prediction is consistent with prior research showing that firms seek to mitigate information asymmetry through various channels of voluntary disclosure (Cheng et al., 2013; Cheng & Lo, 2006; Hirst et al., 2008; Lang & Lundholm, 2000; Skinner, 1994, 1997). Particularly relevant to our study is Nagar et al. (2019), which shows that high EPU can increase firms' voluntary disclosure through management forecast frequency and various 8-K items. If voluntary disclosure policies are consistent across firms' disclosure channels, the finding in Nagar et al. (2019) suggests an increase in textual note in 10-Ks during high EPU periods.[11] Therefore, EPU can increase TRC.

This prediction is also consistent with *signaling theory* (Spence, 1973), which suggests that superior firms tend to send costly signals to the market to differentiate themselves from inferior firms. When EPU is high, even superior firms may pause hard-to-reverse activities, but this is observationally similar to actions taken by inferior firms. As such, superior firms have incentives to increase voluntary disclosure to signal internal strength and confidence to differentiate themselves from inferior firms that cannot credibly do the same.

However, *voluntary disclosure theory* also considers the costs of disclosure. In our setting, one such cost is the leakage of proprietary information. A firm elaborating on various business activities that it pauses in response to high EPU may allow its competitors to extract sensitive information about its business such as supply chains, customer bases, and/or lending relationships. Moreover, highlighting the reduction in certain business activities may allow competitors to take strategic actions against the focal firm in these activities.[12] If so, firms with more proprietary concerns may reduce textual disclosure in response to high EPU, thus reducing the length of each text block in their 10-K reports. This is consistent with prior research finding that firms tend to reduce their voluntary disclosure while facing proprietary costs (Ellis et al., 2012; Imhof et al., 2018; Y. Li et al., 2018; Wang, 2007). Therefore, EPU can also reduce TRC.[13]

[11] Note that our study differs from Nagar et al. (2019) because we focus on the length of textual XBRL tags in 10-K filings rather than the frequency of management forecasts and 8-K items.
[12] For example, knowing that the focal firm reduces its activities, its competitors may increase their activities to outmatch the focal firm (Jiang et al., 2022).
[13] In our setting, we equate textual *length* to textual *complexity*, and thus longer (shorter) notes are more (less) complex. Length and transparency are two independent aspects of textual properties. Thus, in our setting, a longer (more complex) note can be either transparent or not. Similarly, a shorter (less complex) note can be either transparent or not. In a later test, we examine the implication of the changes in textual disclosure on information asymmetry to infer the change in transparency of these notes in response to the change in EPU.

Another complication in predicting the relationship between EPU and TRC relates to managerial incentives for textual disclosure – to inform or to obfuscate (Bushee et al., 2018; Jiang et al., 2022). The challenge here is that managerial intents can interact with textual complexity. If managers seek to inform, they can use either elaborated language in their textual disclosure, thus increasing the complexity of the texts, or simplified language, thus reducing such complexity. Meanwhile, if managers seek to obfuscate, they can either use overly complicated language and sentence structures, thus increasing textual complexity, or avoid discussing the reduction in real activities, thus reducing the textual complexity. Thus, more or less complex texts can be either transparent or not, depending on managerial intents. Along with the above discussion, this argument illustrates that the relationship between EPU and TRC is ex-ante unpredictable.[14] Therefore, we state our second hypothesis in the null form as follows.

Hypothesis 2: Economic policy uncertainty is not associated with textual reporting complexity.

4. RESEARCH DESIGN AND SAMPLE SELECTION

4.1. Measure of Economic Policy Uncertainty

To measure economic policy uncertainty, we compute the log of the annual average of the monthly EPU index developed by Baker et al. (2016). Baker et al. construct this monthly index using the weighted average of three measures: [1] the frequency of newspaper articles referencing policy uncertainty,[15] [2] the uncertainty in future changes in policy and federal tax

[14] In section 7.4, we conduct a market consequence test to examine the informativeness of the level of textual disclosure during periods of high EPU.

[15] This is a comprehensive measure of uncertainty based on textual analysis of ten large newspapers. Baker et al. count the articles containing terms related to economic and policy uncertainty, namely, “uncertain” or “uncertainty” and “economic” or “economy,” and at least one additional term such as “congress,” “legislation,” “White House,” “regulation,” “federal reserve,” or “deficit.” They scale the raw counts by the total number of articles in the same newspaper and month to control for the changes in volume over time of a given newspaper. Next, they normalize monthly scaled series of counts for each newspaper to have a unit standard deviation and then sum up the standardized values over newspapers in each month to obtain a multi-paper index. Finally, they obtain the average numbers across newspapers to have one representative index for each month.

code provisions,[16] and [3] the dispersion in economic forecasts concerning future inflation such as Consumer Price Index and future government spending.[17] We choose the Baker et al. (2016) index because it is a prominent measure of EPU in extant research.

4.2. Measure of Accounting Reporting Complexity

We measure the components of ARC using XBRL tags. First, we obtain all 10-K reports in XBRL format from the SEC. We choose 10-Ks over 10-Qs because firms report more XBRL tags in their 10-Ks and because 10-Ks are audited. These 10-Ks incorporate tags that link each accounting item (monetary tags) or each paragraph (text-block tags) to a corresponding concept in the FASB-approved U.S. GAAP taxonomy, which acts as a dictionary of universal concepts. The SEC requires that firms use the *taxonomy* tags whenever possible to facilitate comparability but allows firms to have customized (*extended*) tags to accommodate their unique situations. Thus, the taxonomy tags represent the component of the firms' business that is similar to that of the majority of other firms whereas the extended tags represent the unique business of each firm.[18] This distinction between the taxonomy tags and the extended tags applies to both monetary and text-block tags. Therefore, there are four types of XBRL tags: [1] taxonomy monetary tags, [2] extended monetary tags, [3] taxonomy text-block tags, and [4] extended text-block tags. We examine all four of them in different tests in this study.

For monetary reporting complexity, we follow Hoitash and Hoitash (2018) and count the number of *unique monetary* XBRL tags of each firm-year. Because 10-Ks present comparative financial statements, we remove prior years' tags reported in current year's statements to avoid over-counting the tags for each year. The natural log transformation of this count represents our measures of MRC. We assign the title *MRC* to all measures based on the

[16] This component captures taxation uncertainty for businesses and households based on lists of temporary federal tax code provisions compiled by the Congressional Budget Office (CBO).
[17] This component measures monetary policy uncertainty drawn from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. It measures dispersion from individual-level forecasts directly influenced by government policy, including the Consumer Price Index, Federal Expenditures, and State and Local Expenditures.
[18] Appendix A in Hoitash et al. (2021) provides an example of the XBRL tags in 10-K filings.

number of unique monetary tags. Specifically, we create *MRC_TAX* for the taxonomy monetary tags, and *MRC_EXT* for the extended monetary tags.[19]

For textual reporting complexity, we capture the average length of *unique text-block* tags of each firm-year. We also compute the natural log transformation of this metric to create our measures of TRC. We assign the title of *TRC* to all measures based on the average length of text-block tags. Specifically, we create *TRC_TAX* for the average length of the *taxonomy* text-block tags, and *TRC_EXT* for the average length of the *extended* text-block tags.

4.3. Model Specifications

To test H1 and H2, we run the following ordinary least square (OLS) regression.

$$ARC_{it} = \beta_0 + \beta_1\, EPU_t + CONTROLS_{it} + FE + \varepsilon_{it} \quad (1)$$

When testing MRC (TRC), ARC_{it} stands for MRC_{it}, MRC_TAX_{it}, and MRC_EXT_{it} (TRC_{it}, TRC_TAX_{it}, and TRC_EXT_{it}). EPU_t is the log transformation of the annual average of the monthly EPU index. To ensure that the associations between *EPU* and the ARC measures are not driven by correlated omitted variables, we include various controls at the firm and market levels ($CONTROLS_{it}$). Following previous studies (Chychyla et al., 2019; Doyle et al., 2007; Hoitash & Hoitash, 2018), we choose 17 firm-level controls and four macro-level controls. The 17 firm-level controls include [1] firm size (*SIZE*), [2] financial leverage (*LEV*), [3] return on assets (*ROA*), [4] market to book ratio (*MTB*), [5] acquisition (*ACQUISITION*), [6] restructuring charges (*RESTRUCTURE*), [7] foreign operations (*FOREIGN*), [8] accruals (*ACCRUAL*), [9] firm age (*AGE*), [10] bankruptcy risk (*DISTRESS*), [11] loss (*LOSS*), [12] frequency of loss (*LOSS_FRQ*), [13] volatility of cash flows (*STD_CF*), [14] volatility of sales (*STD_SALE*), [15] number of business segments (*BUS_SEGMENT*), [16] number of

[19] Hoitash & Hoitash (2018) validate this MRC measure using the number of monetary XBRL tags. They show that this approach produces strong indicators of reporting complexity, as evidenced by their strong predictability of poor financial reporting quality (greater probability of misstatements and internal control weakness, higher audit fees, and longer audit delays). Since its introduction in Hoitash & Hoitash (2018), this measure of reporting complexity has been widely applied in accounting research (Akamah & Shu, 2021; Brown et al., 2023; Burke et al., 2023; Cahan et al., 2022; Docimo et al., 2021; Hoitash et al., 2021; Seavey et al., 2022).

geographic segments (*GEO_SEGMENT*), and [17] Big Four auditor (*BIG4*). The four macro-level controls include [1] the macro uncertainty index (*MUINDEX*), [2] the GDP growth rate (*GDPGR*), [3] the unemployment rate (*UNEMRATE*), and [4] the returns on the S&P/Case-Shiller US National Home Price Index (*CSRET*). The Appendix presents detailed descriptions and data sources of all variables used in our study.

We incorporate fixed effects (*FE*) for firm and industry to control for time-invariant factors at these levels.[20] Following previous EPU studies (D'Mello & Toscano, 2020; Gulen & Ion, 2016; Nguyen & Phan, 2017; Phan et al., 2019), we do not control for year fixed effects because *EPU* affects all firms in a given year. In all regressions, standard errors are robust and clustered at the firm level (Petersen, 2009). Given H1 and H2, we expect *EPU* to be significantly negative under the MRC specifications but have no expectation for it under the TRC specifications.

4.4. Sample Selection

Our sample covers U.S.-incorporated firms in Compustat from 2011 to 2019. We start in 2011 because all U.S. firms must file their 10-Ks with the SEC in XBRL format starting in 2011. We stop in 2019 to avoid the effect of the COVID pandemic in 2020 on accounting reporting complexity. We remove firms that [1] are not incorporated in the U.S., [2] report their 10-Ks in non-US currency, [3] have names containing "holding," "holdings," "ADR," "partnership," "L.P.," and "LLP," [4] are financial institutions (SIC code 6000 – 6999) or utilities companies (SIC code 4900 – 4999), or [5] have missing variables used in our analyses. We winsorize all continuous variables at the 1st and 99th percentiles to mitigate the effects of outliers. Our baseline sample has 17,115 firm-year observations. Some tests are based on different sample sizes due to data limitations or specific requirements.

[20] We include fixed effects for industry to account for situations when firms changed their industries during our sample period.

5. EMPIRICAL RESULTS

5.1. Descriptive Statistics

Table 1, Panel A, presents descriptive statistics of the baseline variables. *MRC* has a mean (standard deviation) of 5.377 (0.388), similar to the equivalent measure in Hoitash and Hoitash (2018). Meanwhile, *TRC* has a mean (standard deviation) of 8.105 (0.366). The statistics of EPU are consistent with prior literature (Baker et al., 2016; Duong et al., 2020; Ng et al., 2020). The control variables have broadly similar statistics to those reported by Hoitash and Hoitash (2018) and Chychyla et al. (2019). For example, the mean values of financial leverage, return on assets, and market to book ratio are 0.242, -0.056, and 2.522, respectively. In our sample, over 60 percent of the firms do not have acquisition activities and restructuring charges, 64 percent of them do not have foreign operations, and 71.7 percent of them are audited by Big Four auditors.

The Pearson correlations between EPU_t and MRC_{it}, along with its taxonomy and extended components, are significantly negative (Table 1, Panel B). Meanwhile, the correlations between EPU_t and TRC_{it}, along with its taxonomy and extended components, are significantly positive. These correlations provide preliminary evidence that firms reduce their MRC but increase their TRC when EPU is high.

Figure 1 illustrates the movements of EPU with MRC and TRC over our sample period. Because EPU data are available at the monthly level from Baker et al. (2016), we prepare the graph at the monthly level to clearly show the fluctuation of this construct over time. Because MRC and TRC are at the firm-year level, we transform them into market-month level indices by computing their weighted averages at the firms' fiscal year ends, with the weight being each firm's concurrent market capitalization. Because each firm' fiscal year ends on a different month, this computation gives us aggregate indices for every month for both components of reporting complexity (*Agg_MRC* and *Agg_TRC*). We then merge the monthly market-level EPU with the monthly market-level indices of MRC and TRC and draw the graphs.[21]

Figure 1A (1B) shows the graph of monthly *EPU* and *Agg_MRC* (*Agg_TRC*). Accordingly, all constructs fluctuate considerably over time, with *Agg_MRC* (*Agg_TRC*) generally showing a negative (positive) comovement with monthly EPU. Because graphs only show the average comovement without considering all confounding factors, these figures provide preliminary evidence about the relationship among EPU, MRC, and TRC.

5.2. EPU, MRC, and TRC

We find that *EPU* is negatively associated with *MRC* and the relationships are statistically significant at the 1 percent level (Table 2, columns [1] and [2].[22] The coefficient estimate for *EPU* when all controls are included (column [2]) is 0.195, which is 2.19 and 2.43 times those of *SIZE* and *LEV*, respectively, and 96 percent that of *AGE*.[23] Dropping *EPU* from the model reduces adjusted R^2 by 0.5 percent while dropping *SIZE*, *AGE*, and *LEV* reduces it by 1.7 percent (untabulated). This means the explanatory power of *EPU* is approximately 29.4 percent that of *SIZE*, *AGE*, and *LEV* combined. These analyses suggest that *EPU* is an important predictor of *MRC* in both statistical and economic terms.[24]

EPU remains significantly negative for *MRC_TAX,* the GAAP-based taxonomy tags that are universal across firms (Table 2, columns [3] and [4]). EPU is significantly negative for *MRC_EXT,* the extended component of *MRC* (column [5]), but becomes insignificant when all controls are included (column [6]). Thus, the reduction in *MRC* in response to EPU is driven

[21] Note that the measures used in this graph are raw, whereas those in our final sample used for further regression analyses are log-transformed. This explains the differences in the measurement units.
[22] While the baseline results are based on the measures of *MRC* using *unique* monetary XBRL tags, our findings are robust to the *MRC* measures using *repeating* monetary XBRL tags (untabulated).
[23] Note that *SIZE*, *LEV*, and *AGE* are the most significant predictors of *MRC*.
[24] The estimated coefficients of the control variables are broadly similar to those reported by Hoitash and Hoitash (2018) and Chychyla et al. (2019).

by *MRC_TAX*, indicating that EPU affects the universal activities of a broad cross section of firms in the economy.

EPU is significantly positive at the 1 percent level for the average length of text-block tags (Table 2, columns [7] and [8]). With full controls, the coefficient estimate for *EPU* is 0.261, which is greater in absolute value than those of other firm-level determinants of *MRC*. The increase in *TRC* in response to *EPU* is driven by both the increase in *TRC_TAX* (column [10]) and the increase in *TRC_EXT* (column [12]).

The analyses so far suggest that when firms face high EPU, they pause their business activities to wait for more information that helps clear the uncertainty. This reduction leads to fewer monetary values and fewer relevant accounting concepts to be reported, and thus fewer unique monetary tags in the 10-K reports. To explain this, firms increase their textual disclosure, leading to longer notes in the 10-K reports. Overall, high EPU can simultaneously decrease business complexity and increase textual complexity.

6. ROBUSTNESS CHECKS

This section ensures that the baseline results are not driven by endogeneity concerns related to reverse causality, measurement errors, or correlated omitted variables.

6.1. First Endogeneity Test – Isolating the Policy-Induced Component of EPU

While we control for macroeconomic conditions in the main analyses, our *EPU* measure may capture all forms of economic uncertainty other than policy-related uncertainty due to the newspaper-based methodology used by Baker et al. (2016). To mitigate this, we isolate the policy-related component of *EPU* by following previous studies (D'Mello & Toscano, 2020; Kaviani et al., 2020; Ng et al., 2020) in using a two-stage regression analysis. In the first stage, we regress the U.S. *EPU* index on the Canada *EPU* index, which is derived by Baker et al. (2016) in the same manner as the U.S. *EPU* index, and other macro controls. This assumes that the Canada *EPU* index can capture the general economic uncertainties that may affect both the U.S. and Canada, which share similar economic conditions in North America. We compute the following model to estimate the first-stage regression.

$$EPU_t = \beta_0 + \beta_1\ EPU\_CAN_t + MAC\_CONTROLS_t + FE + \varepsilon_t \qquad (2)$$

In this equation, EPU_t is the *EPU* index for the U.S. and EPU_CAN_t is the *EPU* index for Canada. $MAC\_CONTROLS_t$ stands for the four macro-level controls used in equation (1). The residual value from this equation (EPU_R_t) captures the component of *EPU* that more closely reflects the economic uncertainty related to the U.S. government's policymaking. In the second stage, we re-estimate equation (1) using EPU_R_t as the independent variable. EPU_R_t is significantly negative at the 1 percent level for all components of *MRC* (Table 3, panel A, column [1] – [3]). Meanwhile, it is significant positive at the 1 percent level for all components of *TRC* (columns [4] – [6]). These results are consistent with the baseline results and thus mitigate the concerns of measurement errors.

6.2. Second Endogeneity Test – Instrumental Variable Regression

Next, we use an instrumental variable (IV) approach to address the concerns of correlated omitted variables. For this approach, we need an IV that affects accounting reporting complexity only through EPU. We select as our IV the Partisan-conflict index (Azzimonti, 2018), a newspaper-based measure of policy disagreements among lawmakers. Because these disagreements only affect EPU but not firm-level choices (e.g., accounting reporting complexity), the Partisan-conflict index is a common IV for EPU in prior research (Bonaime et al., 2018; D'Mello & Toscano, 2020; Gulen & Ion, 2016; Kaviani et al., 2020; Ng et al., 2020). In the first-stage regression, we run the following model.

$$EPU_t = \beta_0 + \beta_1\ PCONFLICT_t + CONTROLS_{it} + FE + \varepsilon_t \qquad (3)$$

PCONFLICT equals the natural log of the annual average of the Partisan-conflict index. Statistics from the first-stage regression – F-Statistic, Anderson-Rubin Wald Chi-Squared, and Wu-Hausman Chi-Squared – suggest that our IV survives the tests for weak identification, weak instrument, and endogeneity of the endogenous regressor, respectively (untabulated). In the second-stage regression, we re-run equation (1) using the instrumented *EPU* and find that it remains significantly negative at the 1 percent level for all *MRC* specifications (Table 3, Panel B, columns [1] – [3]) and remains significantly positive at the 1 percent level for both *TRC* and *TRC_TAX* (columns [4] and [5]). Overall, these findings are consistent with our baseline results and address the concern of correlated omitted variables.

6.3. Third Endogeneity Test – Exogenous Shock to EPU

Motivated by prior research (Duong et al., 2020; Julio & Yook, 2012; Kaviani et al., 2020), we consider presidential elections as exogenous shocks to *EPU*. First, the presidential elections are momentous events that increase uncertainty regarding all aspects of the economy, especially when the presidential races have tightened in recent years (Canes-Wrone & Park, 2012). Second, presidential elections are pre-established based on the national election cycles, meaning that firms cannot exert any influence on their timing. Third, presidential elections occur every four years, allowing us to compare the level of accounting reporting complexity in affected years with that in unaffected years.

For this test, we replace EPU_t in equation (1) with $ELECTION_{it}$, which equals one if the fiscal year t of firm i ends within 12 months of a presidential election and zero otherwise. We find that *ELECTION* is significantly negative at the 1 percent level for all *MRC* specifications (Table 3, Panel C, columns [1] – [3]), suggesting that firms have lower business complexity during presidential elections. Meanwhile, *ELECTION* is significantly positive at the 1 percent level for all *TRC* specifications (columns [4] – [6]), suggesting that firms have higher textual complexity during presidential elections. Because these elections represent clean exogenous shocks to *EPU*, these analyses address the concern of reverse causality.

6.4. Fourth Endogeneity Test – Change Specification

In the baseline analyses, we include fixed effects at the firm and industry levels to account for any time-invariant factors. To further address any remaining concern that unobserved characteristics may drive the EPU-ARC relationship, we re-run equation (1) in a change specification where we convert all variables to their respective changes from year t-1 to year t. We find that the change in *EPU* is significantly negative at the 1 percent level for all *MRC* specifications (Table 3, Panel D, columns [1] – [3]) and is significantly positive at the 1 percent level for all *TRC* specifications (columns [4] – [6]). These analyses indicate that unobserved characteristics at the micro or macro levels do not drive the relationships among *EPU*, *MRC*, and *TRC*, further mitigating the correlated omitted variable concerns. Overall, these extensive robustness checks provide more assurance about our baseline results.

7. ADDITIONAL ANALYSES

7.1. Specific Policies and Accounting Reporting Complexity

Baker et al. (2016) attribute fluctuations in EPU to ten categories of governmental policies. These categories include [1] monetary policy, [2] fiscal policy, [3] tax, [4] government spending, [5] health care, [6] national security, [7] entitlement programs, [8] regulation, [9] financial regulation, and [10] sovereign debt. Because these specific policies can directly affect firms' business activities, we expect each of these policies to affect firm-level accounting reporting complexity. We test this by replacing *EPU* in equation (1) with *EPU_P*, which stands for one of the 10 EPU indices related to these policies.[25] We find that firms have lower *MRC* (higher *TRC*) during times of high EPU related to all policies (Table 4). Thus, the baseline relationships between the EPU and both components of ARC (MRC and TRC) remain qualitatively the same when we examine the specific policies driving EPU.

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[25] Baker et al. (2016) derive these indices based on specific keywords in newspapers related to each policy.

7.2. Economic Channels of Monetary Reporting Complexity

Our baseline analyses suggest that high EPU induces firms to adopt a wait-and-see strategy for hard-to-reverse economic activities. To provide more direct evidence of these economic activities, we rely on a unique feature of the monetary XBRL tags to assign them to different categories. Specifically, we categorize MRC into five components related to [1] mergers and acquisitions (*MRC_MA*), [2] capital expenditures (*MRC_CAP*), [3] restructuring (*MRC_RES*), [4] borrowing (*MRC_BOR*), and [5] tax planning (*MRC_TP*).[26]

To test whether EPU reduces these activities and the extent to which their reduction contributes to the overall reduction in MRC, we follow Schoenfeld (2017) and Nagar et al. (2019) and use the following system of recursive structural equations.

$$MRC_{it} = \beta_0 + \beta_1\, EPU_t + CONTROLS_{it} + FE + \varepsilon_{it} \tag{4a}$$
$$MRC\_C_{it} = \beta_0 + \beta_1\, EPU_t + CONTROLS_{it} + FE + \varepsilon_{it} \tag{4b}$$
$$MRC_{it} = \beta_0 + \beta_1\, EPU_t + \beta_2\, MRC\_C_{it} + CONTROLS_{it} + FE + \varepsilon_{it} \tag{4c}$$

Equation (4a), which is equation (1) with a focus on *MRC*, establishes the overall effect of EPU on MRC. In equation (4b), *MRC_C* stands for the five components of MRC mentioned above. Equation (4c) is equation (4a) with the inclusion of *MRC_C*. While equation (4b) represents the direct effect of EPU on the components of MRC (*MRC_C*), equation (4c) quantifies both the direct effect of EPU on MRC and its indirect effect on MRC through each MRC component (*MRC_C*). The product of β_1 from model (4b) and β_2 from model (4c) represents the extent to which the change in the components of MRC due to EPU contributes to the change in the overall MRC.

The results for equation (4a) (Table 5, column [1]) are the same as the baseline results (Table 2, column [2]), i.e., EPU is significantly negative for the overall MRC. Columns [2], [4], [6], [8], and [10] present the results for equation (4b) when *MRC_C* stands for *MRC_MA*,

[26] For example, regarding *MRC_MA*, we use the following keywords to search for XBRL tags related to merger and acquisition (M&A): "merger", "acquisition", "acquired", "businesscombination." We then calculate *MRC_MA* in the same ways as *MRC.* The Appendix provides detailed keywords that we use to compute other economic components of *MRC*.

MRC_CAP, *MRC_RES*, *MRC_BOR*, and *MRC_TP*, respectively. Consistent with the baseline result, EPU is significantly negative for all five MRC components. Columns [3], [5], [7], [9], and [11] present the results for equation (4c) where *MRC_C* stands for the respective MRC components. In these columns, while EPU remains significantly negative, all MRC components are significantly positive. This is reasonable because each MRC component contributes positively to the overall MRC.

The products of β_1 (*EPU*) from model (4b) and β_2 (*MRC_C*) from model (4c) for all MRC components are -0.021 (-0.220 x 0.096), -0.005 (-0.065 x 0.076), -0.012 (-0.174 x 0.071), -0.088 (-0.611 x 0.144), and -0.079 (-0.194 x 0.410). We compute the standard errors of these products using the delta method following Nagar et al. (2019). The z-values for these components then become -5.068, -3.746, -5.136, -14.480, and -10.197, respectively, which are significant at the 1 percent level.

We interpret these results as follows. In the case of *MRC_MA*, high EPU reduces *MRC_MA* (β_1 = -0.220, column [2]), and this reduction reduces the overall MRC significantly (β_1 in column [2] x β_2 in column [3] = -0.220 x 0.096 = -0.021; p-value = 0.000). Because EPU still has a significant direct effect on MRC (β_1 = -0.174, column [3]), this indirect effect of EPU on MRC through *MRC_MA* accounts for 12.07 percent (-0.021 / -0.174, column [3]) of the direct effect of EPU on MRC. Applying this interpretation to the other MRC components, we find that the indirect effect of EPU on MRC through *MRC_CAP*, *MRC_RES*, *MRC_BOR*, and *MRC_TP* accounts for 2.63 percent (-0.005 / -0.190, column [5]), 6.56 percent (-0.012 / -0.183, column [7]), 82.24 percent (-0.088 / -0.107, column [9]) and 68.10 percent (-0.079 / -0.116, column [11]) of the direct effect of EPU on MRC, respectively.

Overall, these analyses show that all identifiable components of MRC reduce with EPU, and this reduction contributes significantly to the reduction of the overall MRC in response to high EPU. Among these components, borrowing and tax planning activities have the largest impacts on the overall reduction in MRC, followed by M&A, restructuring, and capital expenditure activities. Note that while these five components are identifiable based on the XBRL tags, firms have many more business activities that are not individually identifiable but can be captured in the overall measure of MRC. Therefore, these MRC components simply offer a glimpse into the change in the overall MRC in response to a change in EPU.[27]

7.3. The Mechanism among EPU, MRC, and TRC

Our hypothesis development and interpretation of the empirical results rely on the impact going from EPU to MRC and then to TRC. Specifically, high EPU hinders real business activities, which lowers MRC. To discuss this, firms disclose more, leading to higher TRC. To substantiate this interpretation, we again rely on the model of recursive structural equations as in the previous analyses. In this case, we test whether EPU affects TRC through MRC.[28]

$$TRC_{it} = \beta_0 + \beta_1\ EPU_t + CONTROLS_{it} + FE + \varepsilon_{it} \qquad (5a)$$
$$MRC_{it} = \beta_0 + \beta_1\ EPU_t + CONTROLS_{it} + FE + \varepsilon_{it} \qquad (5b)$$
$$TRC_{it} = \beta_0 + \beta_1\ EPU_t + \beta_2\ MRC_{it} + CONTROLS_{it} + FE + \varepsilon_{it} \qquad (5c)$$

These equations are based on equations (4a) – (4c), except that the dependent variable is *TRC* in equations (5a) and (5c) and *MRC* in equation (5b). Equation (5a) quantifies the overall effect of EPU on TRC, equation (5b) the direct effect of EPU on MRC, and equation (5c) both the direct effect of EPU on TRC and its indirect effect on TRC through MRC. The product of equation (5b)'s β_1 and equation (5c)'s β_2 represents the extent to which the change in MRC due to EPU contributes to the change in TRC.

Table 6 confirms that EPU reduces MRC and increases TRC (columns [1] and [2]). Importantly, when controlling for *MRC* (column [3]), *EPU* remains significantly positive for *TRC* while *MRC* is significantly negative. The product of equation (5b)'s β_1 (*EPU*) and

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[27] Also note that we do not examine the individual business components of TRC because text-block XBRL tags do not allow for the clear-cut categorization of economic activities like in the case of monetary XBRL tags.
[28] We do not test whether TRC leads to MRC because the goal of financial reporting is to record and communicate the actual business transactions. Therefore, it is more likely that the complexity of real business transactions (MRC) affects the complexity of textual disclosure in financial reports (TRC) than the other way around.

equation (5c)'s β_2 (*MRC*) is 0.117 (-0.195 x -0.598) and is significant at the 1 percent level, based on the standard errors using the delta method. This product represents the indirect effect of EPU on TRC through MRC and accounts for 80.42 percent (0.117 / 0.145) of the direct effect, which is economically significant. Therefore, EPU maintains a direct effect on TRC and a sizable indirect effect on TRC through MRC, suggesting that monetary reporting complexity is a strong mediator in the relationship between EPU and textual reporting complexity.

7.4. Market Consequence of Changes in Accounting Reporting Complexity

Prior research finds that higher reporting complexity increases information asymmetry. Thus, reduced MRC, which reflects the reduced complexity of real business activities, is likely to reduce information asymmetry. However, the effect of increased TRC on information asymmetry is ambiguous because longer texts can either inform or obfuscate (Bushee et al., 2018; Jiang et al., 2022). On the one hand, firms may want to increase their textual length to inform the market about reduced real activities. On the other hand, they may want to hide this by making the texts unnecessarily lengthy to increase shareholders' processing costs. To determine which incentive dominates on average, we test how increased TRC in response to high EPU affect information asymmetry. We thus test the effect of changes in both ARC components in response to high EPU on information asymmetry using the same system of recursive structural equations as in prior analyses.

$$IA_{it} = \beta_0 + \beta_1\, EPU_t + CONTROLS_{it} + FE + \varepsilon_{it} \tag{6a}$$
$$ARC_{it} = \beta_0 + \beta_1\, EPU_t + CONTROLS_{it} + FE + \varepsilon_{it} \tag{6b}$$
$$IA_{it} = \beta_0 + \beta_1\, EPU_t + \beta_2\, ARC_{it} + CONTROLS_{it} + FE + \varepsilon_{it} \tag{6c}$$

Nagar et al. (2019) find that high EPU increases information asymmetry and that management forecasts, a form of voluntary disclosures, help mitigate this to a certain extent. Equation (6a) seeks to replicate a finding in Nagar et al. (2019) that EPU increases information asymmetry at the daily level. In this equation, *IA* stands for daily bid-ask spread ($SPREAD_{it}$) while *CONTROLS* stands for its determinants, including [1] squared return (RET_{it}^2), [2] log of dollar trading volume (VOL_{it}), [3] log of price ($PRICE_{it}$), and [4] turnover ($TURNOVER_{it}$). Following Nagar et al. (2019), we include firm-year fixed effects and use two-way clustering of the standard errors at the firm and day level.

Equation (6b) is similar to equation (1), except that *ARC* stands for *MRC* or *TRC*. To be consistent with equation (6a), we run equation (6b) at the daily level. Equation (6c) extends equation (6a) where we control for *ARC* and *CONTROLS* includes those from both equations (6a) and (6b). For both equations (6b) and (6c), we include firm fixed effects and cluster standard errors at the firm level.[29]

In this system, equation (6b) represents a direct effect of EPU on either MRC or TRC, while equation (6c) quantifies both the direct effect of EPU on information asymmetry and the indirect effect of EPU on information asymmetry through a component of ARC. The product of equation (6b)'s β_1 and equation (6c)'s β_2 represents the extent to which the change in an ARC component due to EPU contributes to the change in information asymmetry due to EPU.

EPU from equations (6a) (Table 7, columns [1]) is significantly positive, consistent with the finding in Nagar et al. (2019) that high EPU increases information asymmetry. For MRC, *EPU* is significantly negative even at the daily level (column [2]). When controlling for *MRC* in the *SPREAD* equation (column [3]), both *EPU* and *MRC* are significantly positive.[30] The product between *EPU* in column [2] and *MRC* in column [3] is negative (-0.009 x 0.119 = -0.001) and is significant at the 1 percent level (z-value = -4.092, p-value = 0.000).[31] Thus, while EPU maintains a direct effect on information asymmetry, the reduction in MRC due to EPU helps reduce this by 2.82 percent (-0.001 / 0.038).

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[29] We cannot include year fixed effects because they are collinear with *EPU* and other macro controls. We also cannot include firm-year fixed effects because all firm-level variables, including those at the daily level, are highly correlated with these fixed effects.
[30] The significantly positive coefficient estimate on *MRC* is consistent with prior research that more reporting complexity leads to more information asymmetry.
[31] Again, we use the delta method in computing the standard error of this product, following Nagar et al. (2019).

For TRC, *EPU* is significantly positive for both *TRC* and *SPREAD* (columns [4] and [5]). In the equation for *SPREAD*, *TRC* is significantly negative. The product between *EPU* in column [4] and *TRC* in column [5] is negative (0.013 x (-0.045) = -0.0006) and is significant at the 5 percent level (z-value = -2.166, p-value = 0.030). Thus, while EPU maintains a direct effect on information asymmetry, the increase in TRC due to EPU helps reduce this by 1.59 percent (-0.0006 / 0.037).[32]

To further examine the consequences of TRC on information asymmetry, we test whether firms with more TRC have lower information asymmetry during times of high EPU. Specifically, we include *TRC* and its interaction with *EPU* on the right-hand side of equation (6a) and include firm fixed effects and cluster standard errors at the firm level. We find that *EPU* is significantly positive (β_1 = 0.220, p-value = 0.001) and its interaction with *TRC* is significantly negative (β_3 = -0.023, p-value = 0.005). This corroborates the evidence that increased TRC helps reduce elevated information asymmetry due to high EPU.

In our study, the XBRL text-block tags' average length reflects textual (qualitative) reporting complexity. Longer texts are more complex because they require more words and/or elaborated sentence structures. They are also mechanically less readable (Bonsall et al., 2017).[33] The key question is whether longer texts are more transparent, i.e., informative. Prior research recognizes two incentives in textual disclosure – to inform or to obfuscate (Bushee et al., 2018; Jiang et al., 2022). We view length and transparency as independent dimensions of textual properties. While length depends on the complexity of the transactions being discussed, transparency depends on managerial disclosure incentives. A longer text can be more or less transparent. Observing only the text length is insufficient to infer the underlying disclosure

[32] Nagar et al. (2019) find that high EPU increases information asymmetry and that management forecasts help mitigate this to a certain extent. The result for *TRC* is comparable to the indirect effect of *EPU* on *SPREAD* through management forecasts (0.94 percent) documented in Nagar et al. (2019, p. 54).

[33] We do not focus on readability because there has been no study measuring readability using text-block XBRL tags. However, in an untabulated analysis, we find that high EPU leads to lower readability, measured by the Bonsall et al. (2017) Bog index based on the whole 10-K, which is consistent with Jiang et al. (2022).

incentive.[34] This is why we test how longer texts affect information asymmetry in the EPU setting. We find that, on average, longer texts lower information asymmetry and conclude that in the EPU context, longer (more complex and less readable) texts can enhance transparency. This finding extends prior perception in the accounting textual literature that longer texts are less transparent.[35]

Overall, the analyses in this section suggest that the changes in both components of ARC help improve the information environment of the firms during times of high EPU. However, because EPU is dominant, the reduction in MRC (increase in TRC) only reduces 2.82 percent (1.59 percent) of the increase in information asymmetry due to high EPU.

7.5. Cross-Sectional Analyses

We perform three cross-sectional tests to further understand the EPU-ARC relationship. To do so, we include in equation (1) *Z* and its interaction with *EPU*, where *Z* stands for the cross-sectional variable specific to each test.

$$ARC_{it} = \beta_0 + \beta_1\, EPU_t + \beta_2\, Z_{it} + \beta_3\, EPU_t \times Z_{it} + CONTROLS_{it} + FE + \varepsilon_{it} \qquad (7)$$

7.5.1. Cross-Sectional Test – Governmental Dependence

The effect of EPU on ARC is probably stronger if firms depend more on the government for their business. To test this, we replace Z in equation (7) with *GOVCUS* and *BETA*. *GOVCUS* equals one if the firm reports the U.S. government as its major customer, and zero otherwise. Meanwhile, *BETA* captures the firm's industry return sensitivity to *EPU* (Bonaime et al., 2018; Brogaard & Detzel, 2015; Duong et al., 2020). To calculate *BETA*, we regress the industry monthly excess returns on *EPU* and other controls over 60 months before the

[34] As an anecdote, an intermediate-level textbook is likely to be longer, i.e., more complex, and less readable than an introductory-level textbook, but its purpose is to enhance students' understanding of accounting. Therefore, longer (more complex and less readable) texts can be informative.

[35] When unconditioned on EPU, longer texts can be less transparent. However, conditioned on high EPU, our empirical results suggest that longer texts tend to be more transparent – the average firm uses longer texts to inform. While there can be firms using longer texts to obfuscate even during high EPU periods, they account for the minority of our sample, or else we would not have observed the average effect documented in this analysis.

beginning of the firm's fiscal year for each industry. *BETA* equals one if *EPU* from this regression is greater than or equal to the median of all industries in a year, and zero otherwise. We expect firms that depend more on the government to reduce their business activities even more in response to EPU, implying a stronger reduction in MRC and a stronger increase in TRC. Thus, we expect β_1 and β_3 in equation (7) to be negative for *MRC* and positive for *TRC*.

For *GOVCUS*, both *EPU* and the interaction term are significantly negative for *MRC* (Table 8, column [1]) and significantly positive for *TRC* (column [2]), consistent with our expectations. We observe the same results for *BETA* (columns [3] and [4]), except that β_3 is insignificant for *TRC* (column [4]). Overall, while the average firm reduces (increases) its MRC (TRC) during high EPU, those depending more on the government do so to a greater extent.

7.5.2. Cross-Sectional Test – Political Risk

We next examine firm-level exposure to political risk. The interaction between market-level EPU and firm-level political risk in the ARC setting can go either way. On the one hand, if firm-level political risk amplifies firm exposure to market-level EPU, the effect of EPU on ARC is amplified for firms with more political risk exposure. On the other hand, uncertainty and risk are conceptually different. While uncertainty describes the inability to forecast future events, risk describes a known probability distribution over a set of events (Bloom, 2014; Knight, 1921). Therefore, while firms halt their business activities when facing uncertainty, they may take actions to mitigate risk.[36] Firms facing high political risk may have higher MRC to report their risk-management activities. These firms may also need more TRC to explain these activities. Alternatively, because these risk-management activities may entail proprietary information, firms may reduce their textual disclosure. Overall, the impact of firm-level political risk on the relationship between EPU and both forms of ARC is an empirical question.

[36] For example, firms facing high political risk actively donate to political campaigns, forge links to politicians, and invest in lobbying activities (Hassan et al., 2019). Firms can also diversify their businesses and/or expand overseas.

We test this by replacing *Z* in equation (7) with a measure of firm-level political risk (*PRISK*) by Hassan et al. (2019). For *MRC*, while *EPU* is negative, its interaction with *PRISK* is positive (Table 8, columns [5]). Thus, firm-level political risk weakens the relationship between *EPU* and *MRC*, suggesting that firm-specific risk-management activities increase for firms with high political risk exposure. The sum of *EPU* and its interaction with *PRISK* remains significantly negative (untabulated), suggesting that while firms more exposed to political risk tend to increase their MRC, they still reduce their net MRC during times of high EPU. For *TRC*, while *EPU* is positive, its interaction with *PRISK* is negative (Table 8, column [6]). Thus, high political risk also weakens the relationship between EPU and TRC, suggesting that while firms increase their political risk-management activities, they avoid discussing these activities to avoid proprietary costs.[37]

7.5.3. Cross-Sectional Test – Proprietary Costs

To ascertain that textual disclosure is indeed voluntary, we examine whether firms facing higher proprietary costs increase their textual length to a lesser extent. We thus replace *Z* in equation (7) with two measures of proprietary costs. The first is $FLUIDITY_{it}$, a measure of product market threats by Hoberg et al. (2014), equal to one if the firm has a fluidity score *greater* than or equal to the sample median, and zero otherwise. The second is $CONCENT_{it}$, a text-based measure of industry concentration by Hoberg & Phillips (2016), equal to one if the firm has the industry concentration score *lower* than the sample median, and zero otherwise. A value of one (zero) for each of these measures indicates higher (lower) proprietary costs.[38] We focus on TRC rather than MRC because only textual disclosure is prone to proprietary costs. While *EPU* remains positive, the interaction between *EPU* and *Z* is negative for both

[37] On a side note, both *EPU* and *PRISK* are negative for *MRC*. This is consistent with the findings in Baker et al. (2016) and Hassan et al. (2019) that both EPU and political risk reduce firms' business activities (e.g., hiring and investment). Similarly, both *EPU* and *PRISK* are positive for *TRC*, suggesting that both constructs increase textual disclosure. Therefore, while political uncertainty and risk are positively correlated, they capture distinct concepts.
[38] We use industry competition to measure proprietary costs because high industry competition exposes firms to more proprietary risk (Ali et al., 2014; Burks et al., 2018; Ellis et al., 2012; X. Li, 2010).

FLUIDITY and *CONCENT* (Table 8, columns [7] and [8]). Therefore, while EPU increases TRC for the average firms, those with higher proprietary costs increase their textual disclosure to a lesser extent.

8. DICUSSION AND CONCLUSION

We examine the effect of economic policy uncertainty (EPU) on accounting reporting complexity (ARC), which entails monetary reporting complexity (MRC) and textual reporting complexity (TRC). While MRC reflects business activities, TRC reflects their textual explanations. Both MRC and TRC increase with the complexity of real business activities, making it challenging to disentangle these components of ARC. The reduction in business complexity thanks to EPU provides a unique setting to examine these components separately. EPU refers to the uncertainty related to the passing of economic policies. During periods of high EPU, firms reduce their hard-to-reverse activities, leading to lower MRC. However, TRC may increase or decrease depending on firms' incentive to inform or obfuscate.

Using the number of unique monetary XBRL tags to measure MRC and the average length of text-block XBRL tags to measure TRC, we find that during periods of high EPU, MRC decreases but TRC increases. These results survive extensive sensitivity checks and hold for all ten categories of policies driving the fluctuation in EPU. We then show that [1] high EPU reduces five categories of monetary tags related to business activities and this, in turn, reduces the overall MRC, [2] EPU reduces MRC, which, in turn, increases TRC; and [3] both the decrease in MRC and the increase in TRC help reduce information asymmetry caused by high EPU. Moreover, the baseline results are stronger for firms relying more on the government and weaker for firms facing more political risk or proprietary risk.

Nagar et al. (2019) and El Ghoul et al. (2020) are particular relevant to our study. Nagar et al. (2019) find that high EPU increases information asymmetry and firm mitigate this to a certain extent by increased voluntary disclosures. While we somewhat overlap with Nagar et al. (2019) in this aspect, they focus on management forecasts and 8-K filings whereas we focus on both the reported monetary values and the length of textual disclosure in 10-K filings.

El Ghoul et al. (2020) find that accounting quality, measured using the Nikolaev (2018) model, increases with EPU because investors pay more attention to firm information to protect themselves during high EPU periods. Consequently, managers are less inclined to manage earnings, resulting in the accounting system measuring firm performance more accurately. Investor attention also plays an important role in our setting. High EPU reduces business transactions due to operating necessities. Being aware that investors may scrutinize their performance, firms discuss more in their 10-Ks to justify this reduction. Thus, increased textual complexity is another consequence of heightened investor attention during high EPU periods.

The findings in El Ghoul et al. (2020) and in our study complement each other. In El Ghoul et al. (p. 239), high EPU depresses economic activities, leading to a reduction in the performance component of accruals and an even stronger reduction in the error component, collectively improving accounting quality under the Nikolaev (2018)'s framework. Meanwhile, in our study, reduced economic activities during high EPU periods lowers monetary complexity but increases textual complexity. Therefore, our study complements El Ghoul et al. by examining another angle for the effect of EPU on accounting reporting via reduced real economic performance.

One caveat in our study is that because EPU is at the market level following Baker et al. (2016), it is impossible to observe the cross-sectional variation of firm-level exposure to EPU. While we perform subsample analyses, EPU remains a macroeconomic construct that only fluctuates over time. Future studies can revisit the relationship between EPU and ARC using more granular approaches to capture EPU (e.g., the cycle of gubernatorial elections) to investigate firms' cross-sectional exposure to EPU.

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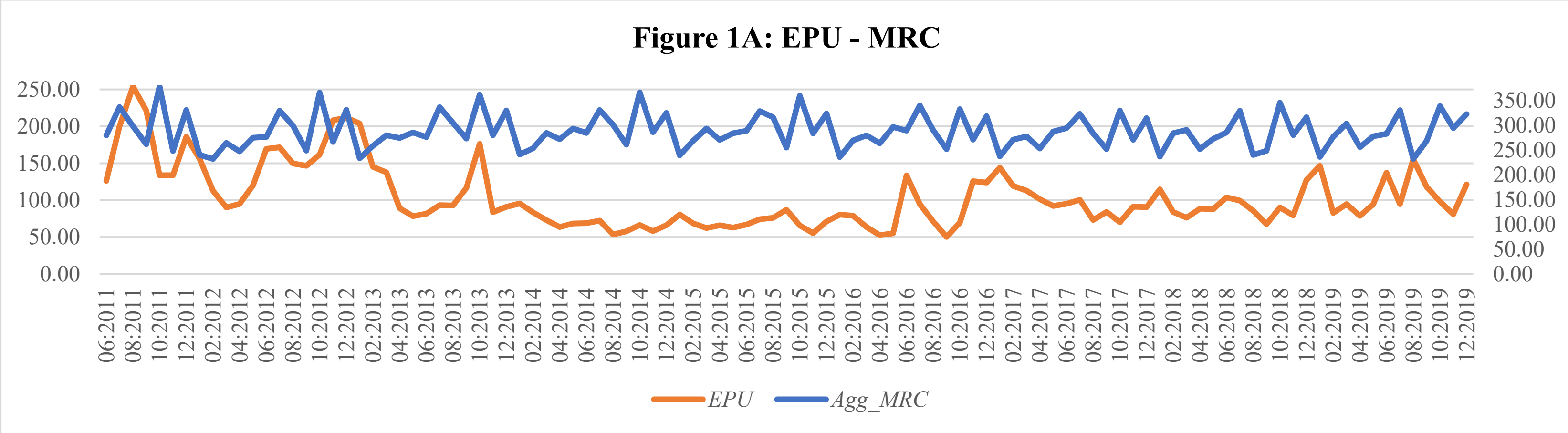
Figure 1

Figure 1 illustrates the time-series of market-level economic policy uncertainty (*EPU*) against market-level monetary reporting complexity (*Agg_MRC*) and textual reporting complexity (*Agg_TRC*) at the monthly level. The monthly *EPU* data come from Baker et al. (2016). We compute *Agg_MRC* and *Agg_TRC* by taking the weighted average of firm-level *MRC* and *TRC* based on the fiscal year-ends using concurrent market capitalization as weights.



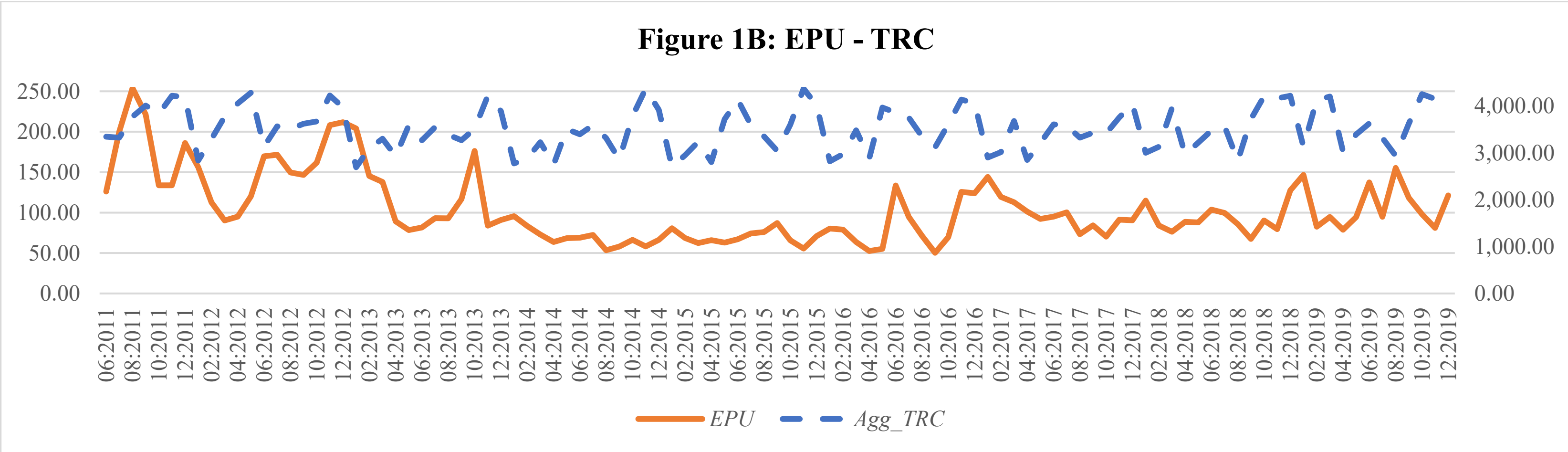


Table 1: Summary Statistics

Panel A: Descriptive Statistics

Panel A shows descriptive statistics of selected variables, including the number of observations (N), mean (MEAN), median (MEDIAN), standard deviation (STD), minimum (MIN), and maximum (MAX) values for a sample of firm-year observations from 2011 to 2019. Variable definitions and data sources are presented in the Appendix. All continuous variables are winsorized at the 1% and 99% percentiles to eliminate the impact of outliers.

	N	**MEAN**	**MEDIAN**	**STD**	**MIN**	**MAX**
MRC_{it}	17,115	5.377	5.421	0.388	4.277	6.103
MRC_TAX_{it}	17,115	5.235	5.283	0.376	4.174	5.903
MRC_EXT_{it}	17,115	3.193	3.296	0.752	0.693	4.654
TRC_{it}	17,115	8.105	8.064	0.366	7.363	9.317
TRC_EXT_{it}	17,115	6.848	6.783	0.698	5.328	8.815
TRC_TAX_{it}	17,115	7.704	7.685	0.299	7.054	8.682
EPU_{t}	17,115	4.811	4.787	0.203	4.467	5.149
$SIZE_{it}$	17,115	6.572	6.641	2.117	1.982	11.579
LEV_{it}	17,115	0.242	0.204	0.231	0.000	1.097
ROA_{it}	17,115	-0.056	0.031	0.284	-1.475	0.344
MTB_{it}	17,115	2.522	1.749	2.337	0.466	14.544
$ACQUISITION_{it}$	17,115	0.390	0.000	0.488	0.000	1.000
$RESTRUCTURE_{it}$	17,115	0.375	0.000	0.484	0.000	1.000
$FOREIGN_{it}$	17,115	0.360	0.000	0.480	0.000	1.000
$ACCRUAL_{it}$	17,115	-0.075	-0.055	0.128	-0.733	0.265
AGE_{it}	17,115	2.779	2.944	0.914	0.000	4.234
$DISTRESS_{it}$	17,115	4.538	5.000	2.803	0.000	9.000
$LOSS_{it}$	17,115	0.436	0.000	0.496	0.000	1.000
$LOSS\_FRQ_{it}$	17,115	0.359	0.200	0.392	0.000	1.000
STD_CF_{it}	17,115	0.079	0.042	0.113	0.005	0.727
STD_SALE_{it}	17,115	0.149	0.102	0.149	0.000	0.842
$BUS\_SEGMENT_{it}$	17,115	0.992	0.693	0.396	0.693	2.773
$GEO\_SEGMENT_{it}$	17,115	1.184	1.099	0.522	0.693	3.989
$BIG4_{it}$	17,115	0.717	1.000	0.450	0.000	1.000
$GDPGR_{t}$	17,115	0.563	0.580	0.111	0.366	0.714
$UNEMRATE_{t}$	17,115	-0.002	-0.002	0.001	-0.003	-0.001
$CSRET_{t}$	17,115	0.012	0.012	0.008	-0.009	0.026
$MUINDEX_{t}$	17,115	0.593	0.583	0.029	0.560	0.645

(Continued on next page)

Panel B: Pearson Correlations

Panel B reports the Pearson pairwise correlation coefficients for all variables used in the main regressions. For brevity, * indicates that the coefficients are statistically significant *at least* at the 5% level of significance.

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]	[23]	[24]	[25]	[26]	[27]	[28]
[1]	MRC_{it}	1.00																											
[2]	MRC_TAX_{it}	0.97*	1.00																										
[3]	MRC_EXT_{it}	0.75*	0.61*	1.00																									
[4]	TRC_{it}	0.01	-0.03*	0.16*	1.00																								
[5]	TRC_TAX_{it}	0.08*	0.04*	0.18*	0.77*	1.00																							
[6]	TRC_EXT_{it}	-0.02*	-0.05*	0.12*	0.83*	0.34*	1.00																						
[7]	EPU_{t}	-0.13*	-0.15*	-0.04*	0.18*	0.18*	0.12*	1.00																					
[8]	$SIZE_{it}$	0.69*	0.69*	0.48*	0.17*	0.27*	0.06*	0.01	1.00																				
[9]	LEV_{it}	0.28*	0.25*	0.27*	0.23*	0.26*	0.14*	-0.03*	0.28*	1.00																			
[10]	ROA_{it}	0.35*	0.39*	0.12*	-0.12*	-0.05*	-0.12*	0.04*	0.48*	-0.01	1.00																		
[11]	MTB_{it}	-0.15*	-0.15*	-0.09*	-0.01	-0.04*	0.01	-0.05*	-0.10*	-0.06*	-0.24*	1.00																	
[12]	$ACQUISITION_{it}$	0.35*	0.37*	0.20*	0.05*	0.11*	-0.01	0.02*	0.35*	0.06*	0.22*	-0.01	1.00																
[13]	$RESTRUCTURE_{it}$	0.37*	0.38*	0.21*	0.09*	0.13*	0.04*	-0.01	0.29*	0.12*	0.12*	-0.17*	0.18*	1.00															
[14]	$FOREIGN_{it}$	0.24*	0.26*	0.12*	-0.00	0.04*	-0.03*	-0.02*	0.13*	-0.05*	0.10*	-0.02*	0.11*	0.19*	1.00														
[15]	$ACCRUAL_{it}$	0.12*	0.13*	0.03*	-0.04*	-0.03*	-0.03*	0.03*	0.19*	-0.09*	0.48*	-0.06*	0.11*	0.02*	0.05*	1.00													
[16]	AGE_{it}	0.34*	0.36*	0.15*	-0.07*	-0.05*	-0.05*	0.00	0.33*	-0.01	0.35*	-0.17*	0.13*	0.19*	0.10*	0.17*	1.00												
[17]	$DISTRESS_{it}$	-0.02*	0.02*	-0.11*	-0.21*	-0.20*	-0.14*	0.00	0.15*	-0.39*	0.38*	0.29*	0.07*	-0.12*	0.02*	0.21*	0.13*	1.00											
[18]	$LOSS_{it}$	-0.29*	-0.31*	-0.11*	0.13*	0.10*	0.09*	-0.04*	-0.45*	0.04*	-0.56*	0.04*	-0.25*	-0.03*	-0.06*	-0.33*	-0.30*	-0.42*	1.00										
[19]	$LOSS\_FRQ_{it}$	-0.37*	-0.41*	-0.14*	0.15*	0.10*	0.12*	0.00	-0.54*	0.02*	-0.65*	0.14*	-0.29*	-0.09*	-0.09*	-0.30*	-0.39*	-0.44*	0.83*	1.00									
[20]	STD_CF_{it}	-0.41*	-0.44*	-0.17*	0.09*	0.00	0.11*	0.01	-0.50*	-0.07*	-0.65*	0.28*	-0.24*	-0.16*	-0.11*	-0.19*	-0.28*	-0.22*	0.37*	0.49*	1.00								
[21]	STD_SALE_{it}	-0.13*	-0.13*	-0.11*	-0.01	-0.03*	-0.00	0.03*	-0.21*	-0.00	-0.03*	0.03*	-0.06*	-0.06*	-0.06*	-0.04*	-0.06*	-0.05*	0.11*	0.10*	0.21*	1.00							
[22]	$BUS\_SEGMENT_{it}$	0.34*	0.35*	0.21*	0.08*	0.12*	0.02*	0.02*	0.32*	0.07*	0.23*	-0.17*	0.23*	0.17*	0.09*	0.11*	0.25*	0.00	-0.20*	-0.26*	-0.24*	-0.02*	1.00						
[23]	$GEO\_SEGMENT_{it}$	0.37*	0.39*	0.16*	-0.03*	0.03*	-0.06*	0.00	0.26*	-0.07*	0.22*	-0.08*	0.20*	0.30*	0.43*	0.10*	0.24*	0.06*	-0.15*	-0.21*	-0.22*	-0.10*	0.21*	1.00					
[24]	$BIG4_{it}$	0.38*	0.39*	0.28*	0.13*	0.17*	0.05*	0.03*	0.57*	0.15*	0.22*	0.02*	0.20*	0.21*	0.08*	0.09*	0.10*	0.11*	-0.23*	-0.25*	-0.23*	-0.14*	0.14*	0.15*	1.00				
[25]	$GDPGR_{t}$	0.12*	0.13*	0.06*	-0.13*	-0.12*	-0.10*	-0.82*	-0.00	0.04*	-0.05*	0.09*	-0.02*	0.01	0.01	-0.00	-0.01	-0.01	0.05*	0.02*	0.01	-0.03*	-0.03*	-0.01	-0.03*	1.00			
[26]	$UNEMRATE_{t}$	0.03*	0.04*	0.02*	0.03*	0.08*	-0.02*	0.16*	-0.00	0.10*	-0.09*	0.02*	-0.03*	0.02*	-0.01	-0.05*	-0.04*	-0.00	0.08*	0.09*	0.05*	-0.02*	-0.05*	-0.05*	-0.05*	-0.12*	1.00		
[27]	$CSRET_{t}$	0.20*	0.20*	0.15*	-0.28*	-0.31*	-0.15*	-0.43*	-0.03*	-0.00	-0.03*	0.05*	-0.03*	0.01	0.00	-0.02*	0.00	-0.01	0.03*	0.01	-0.00	-0.01	-0.01	-0.01	-0.03*	0.48*	-0.00	1.00	
[28]	$MUINDEX_{t}$	-0.07*	-0.07*	-0.06*	0.11*	0.13*	0.06*	0.27*	0.01	0.05*	-0.02*	-0.03*	0.01	0.00	-0.00	-0.04*	-0.01	0.00	0.02*	0.02*	0.01	-0.01	-0.01	-0.01	-0.00	-0.42*	0.32*	-0.51*	1.00

Table 2: Economic Policy Uncertainty and Accounting Reporting Complexity

This table reports the regression results of the following equation for the 2011 – 2019 sample period.

$$ARC_{it} = \beta_0 + \beta_1\, EPU_t + CONTROLS_{it} + FE + \varepsilon_{it} \qquad (1)$$

MRC_{it} (TRC_{it}) stand for total monetary (textual) reporting complexity. Suffices *_TAX* and *_EXT* stand for GAAP-based taxonomy and extended tags, respectively. EPU_t is the natural logarithm of the economic policy uncertainty index by Baker et al. (2016). *CONTROLS* stands for various firm-level and macro-level variables. The Appendix presents variable definitions and data sources. *FE* stands for firm and industry fixed effects. We cluster standard errors at the firm level. Figures in parentheses are *t*-statistics. ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels of significance, respectively.

ACC_{it} =	MRC_{it}		MRC_TAX_{it}		MRC_EXT_{it}		TRC_{it}		TRC_TAX_{it}		TRC_EXT_{it}	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
EPU_t	**-0.255*****	**-0.195*****	**-0.278*****	**-0.226*****	**-0.161*****	**-0.013**	**0.265*****	**0.261*****	**0.214*****	**0.221*****	**0.351*****	**0.347*****
	(-26.01)	**(-18.74)**	**(-31.20)**	**(-24.25)**	**(-6.97)**	**(-0.46)**	**(22.52)**	**(16.93)**	**(21.63)**	**(19.88)**	**(15.33)**	**(9.93)**
$SIZE_{it}$		0.089***		0.086***		0.107***		0.046***		0.050***		0.034*
		(15.09)		(15.62)		(6.49)		(5.55)		(7.30)		(1.91)
LEV_{it}		0.080***		0.081***		0.097**		0.051**		0.060***		0.013
		(4.99)		(5.39)		(2.29)		(2.03)		(3.18)		(0.25)
ROA_{it}		-0.052***		-0.038***		-0.133***		-0.015		-0.007		0.008
		(-3.90)		(-3.16)		(-3.69)		(-0.74)		(-0.52)		(0.18)
MTB_{it}		0.000		-0.001		0.007**		-0.003*		-0.002		-0.005
		(0.19)		(-0.63)		(2.32)		(-1.78)		(-1.34)		(-1.44)
$ACQUISITION_{it}$		0.037***		0.037***		0.056***		0.009*		0.005		0.014
		(9.43)		(10.10)		(5.60)		(1.79)		(1.34)		(1.21)
$RESTRUCTURE_{it}$		0.018***		0.018***		0.014		0.012**		0.007		0.018
		(3.92)		(4.26)		(1.19)		(2.15)		(1.54)		(1.42)
$FOREIGN_{it}$		0.019**		0.013*		0.045*		0.015		0.018*		0.010
		(2.03)		(1.67)		(1.79)		(1.19)		(1.94)		(0.41)
$ACCRUAL_{it}$		0.001		-0.007		0.047		0.008		-0.012		0.020
		(0.05)		(-0.50)		(1.10)		(0.35)		(-0.71)		(0.40)
AGE_{it}		0.203***		0.193***		0.372***		-0.169***		-0.152***		-0.179***
		(17.85)		(18.87)		(11.72)		(-10.75)		(-11.99)		(-5.56)

$DISTRESS_{it}$		-0.003**		-0.002		-0.008**		-0.007***		-0.006***		-0.007*
		(-2.23)		(-1.60)		(-2.14)		(-3.70)		(-4.06)		(-1.72)
$LOSS_{it}$		0.007		0.009		0.023		0.013		0.017**		0.003
		(1.14)		(1.54)		(1.51)		(1.62)		(2.51)		(0.16)
$LOSS\_FRQ_{it}$		0.019		0.007		0.077*		0.077***		0.038**		0.146***
		(1.20)		(0.50)		(1.90)		(3.73)		(2.39)		(3.22)
STD_CF_{it}		-0.006		-0.013		-0.023		0.077		0.096**		0.037
		(-0.16)		(-0.40)		(-0.22)		(1.38)		(2.04)		(0.33)
STD_SALE_{it}		0.040*		0.018		0.109*		0.053*		0.060**		0.028
		(1.77)		(0.90)		(1.77)		(1.71)		(2.57)		(0.44)
$BUS\_SEGMENT_{it}$		-0.008		-0.014		0.008		0.065***		0.052***		0.106***
		(-0.74)		(-1.26)		(0.26)		(4.15)		(4.10)		(3.23)
$GEO\_SEGMENT_{it}$		0.020		0.022*		0.004		0.011		0.026*		-0.015
		(1.49)		(1.93)		(0.12)		(0.62)		(1.87)		(-0.38)
$BIG4_{it}$		0.001		0.000		-0.004		-0.002		0.015		-0.037
		(0.11)		(0.01)		(-0.12)		(-0.11)		(1.14)		(-1.05)
$GDPGR_{t}$		-0.377***		-0.341***		-0.655***		0.511***		0.560***		0.406***
		(-17.14)		(-17.11)		(-10.48)		(16.00)		(22.56)		(5.92)
$UNEMRATE_{t}$		-10.882***		-2.216		-56.063***		38.026***		55.310***		-1.901
		(-4.81)		(-1.07)		(-7.88)		(10.42)		(20.14)		(-0.23)
$CSRET_{t}$		10.252***		9.405***		17.671***		-11.841***		-11.931***		-10.309***
		(30.79)		(31.47)		(23.51)		(-32.20)		(-34.98)		(-17.29)
$MUINDEX_{t}$		0.215***		0.246***		-0.166*		-0.442***		-0.392***		-0.420***
		(7.78)		(9.93)		(-1.94)		(-9.24)		(-12.17)		(-3.63)
Constant	6.602***	5.041***	6.571***	5.094***	3.967***	1.565***	6.831***	7.084***	6.674***	6.758***	5.160***	5.503***
	(140.18)	(76.23)	(153.53)	(84.80)	(35.72)	(8.15)	(120.75)	(71.78)	(140.23)	(91.87)	(46.85)	(23.57)
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.766	0.827	0.790	0.850	0.659	0.702	0.610	0.670	0.579	0.674	0.600	0.615
N	17,115	17,111	17,115	17,111	17,115	17,111	17,115	17,111	17,115	17,111	17,115	17,111

Table 3: Robustness Checks

This table reports robustness checks for the baseline relationship from 2011 to 2019. *MRC, MRC_TAX, and MRC_EXT* are the total monetary reporting complexity and its universal and firm-specific components, respectively, based on Hoitash and Hoitash (2018). *TRC, TRC_TAX, and TRC_EXT* are the average length of text-block tags as well as its universal and firm-specific components, respectively. *EPU* is the natural logarithm of the Baker et al. (2016) economic policy uncertainty index.

Panel A reports the two-stage regression results. In the first stage, we run the following model.

$$EPU_t = \beta_0 + \beta_1\, EPU\_CAN_t + MAC\_CONTROLS_t + FE + \varepsilon_t \qquad (2)$$

EPU is the U.S. *EPU* index, *EPU_CAN* is the Canada *EPU* index, *MAC_CONTROLS* stands for uncertainty index ($MUINDEX_t$), GDP growth rate ($GDPGR_t$), unemployment rate ($UNEMRATE_t$), and returns on the S&P/Case-Shiller US National Home Price Index ($CSRET_t$). The residual value from this equation (EPU_R_t) captures the component of *EPU* that more closely reflects the economic uncertainty of the policymaking process of the U.S. government. In the second stage, we rerun equation (1) using the EPU_R_t as the independent variable. We report the second-stage results in Panel A.

Panel B reports the instrumental variable regression results. In the first stage, we run the following model.

$$EPU_t = \beta_0 + \beta_1\, PCONFLICT_t + CONTROLS_{it} + FE + \varepsilon_t \qquad (3)$$

PCONFLICT, an instrumental variable of policy uncertainty, is the Azzimonti (2018) Partisan-conflict index, a measure of policy disagreements on newspaper articles among lawmakers. In the second-stage regression, we rerun equation (1) using the instrumented *EPU*.

Panel C reports the results using presidential elections as exogenous shocks to *EPU*. We replace *EPU* in equation (1) with $ELECTION_{it}$, which equals one if the fiscal year t of firm i ends within 12 months of a presidential election, and zero otherwise.

Panel D reports the regression results of the change specifications of equation (1), where all variables are changes from year t-1 to year t.

The Appendix presents definitions and data sources for all variables. All regressions include firm- and macro-level controls as well as fixed effects for firm and industry. We omit intercepts, controls, and fixed effects for brevity and cluster standard errors at the firm level in all regressions. Figures in parentheses are *t*-statistics. ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels of significance, respectively.

(Continued on next page)

(Table 3 continued)	*MRC*	*MRC_TAX*	*MRC_EXT*	*TRC*	*TRC_TAX*	*TRC_EXT*
	[1]	[2]	[3]	[4]	[5]	[6]
Panel A: Residual EPU						
EPU_R_t	**-0.314***** **(-20.91)**	**-0.354***** **(-25.88)**	**-0.131***** **(-3.33)**	**0.378***** **(18.36)**	**0.321***** **(20.48)**	**0.489***** **(10.97)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.828	0.850	0.699	0.670	0.675	0.614
N	16,862	16,862	16,862	16,862	16,862	16,862
Panel B: Instrumental Regression						
EPU_t (instrumented)	**-1.160***** **(-22.43)**	**-1.096***** **(-23.13)**	**-1.759***** **(-11.50)**	**1.046***** **(12.40)**	**1.400***** **(23.17)**	**0.035** **(0.17)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes
N	16762	16762	16762	16762	16762	16762
F-statistic for weak identification	2546.48	2546.48	2546.48	2546.48	2546.48	2546.48
Anderson-Rubin Wald Chi^2	586.89	603.65	142.47	158.62	637.00	0.03
Panel C: Presidential Elections						
$ELECTION_{it}$	**-0.037***** **(-7.62)**	**-0.037***** **(-8.35)**	**-0.047***** **(-4.21)**	**0.038***** **(6.29)**	**0.027***** **(5.23)**	**0.062***** **(5.52)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.823	0.844	0.699	0.662	0.666	0.611
N	16,862	16,862	16,862	16,862	16,862	16,862
Panel D: Change Specification						
ΔEPU_t	**-0.285***** **(-21.90)**	**-0.307***** **(-26.21)**	**-0.180***** **(-5.17)**	**0.317***** **(17.65)**	**0.344***** **(24.68)**	**0.297***** **(7.90)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.426	0.441	0.273	0.318	0.444	0.048
N	14,788	14,788	14,699	14,767	14,767	14,361

Table 4: Specific Policies and Accounting Reporting Complexity

This table reports the regression results of the following equation for the 2011-2019 sample period:

$$ARC_{it} = \beta_0 + \beta_1 EPU\_P_t + CONTROLS_{it} + FEs + \varepsilon_{it} \quad (1a)$$

ARC stands for *MRC* (Panel A), which measure the total monetary reporting complexity based on Hoitash and Hoitash (2018), and *TRC* (Panel B), which measure the average length of text block tags within a disclosure. *EPU_P* is the natural logarithm of the Baker et al. (2016) economic policy uncertainty index related to one of the 10 specific policies. Other controls and fixed effects are as in equation (1). The Appendix presents definitions and data sources of all variables. We omit intercepts, controls, and fixed effects for brevity. In all regressions, we cluster standard errors at the firm level. Figures in parentheses are *t*-statistics. ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels of significance, respectively.

***EPU_P* =**	**Monetary**	**Fiscal**	**Tax**	**Government Spending**	**Health Care**	**National Security**	**Entitlement programs**	**Regulation**	**Financial Regulation**	**Sovereign Debt**
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**	**[9]**	**[10]**
Panel A: Monetary reporting complexity (MRC)										
EPU_P$_t$	**-0.053*****	**-0.091*****	**-0.076*****	**-0.085*****	**-0.074*****	**-0.088*****	**-0.033*****	**-0.278*****	**-0.121*****	**-0.100*****
	(-12.84)	**(-21.17)**	**(-18.94)**	**(-24.46)**	**(-20.58)**	**(-22.17)**	**(-8.15)**	**(-22.64)**	**(-20.62)**	**(-18.77)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.823	0.827	0.825	0.832	0.826	0.828	0.823	0.827	0.826	0.826
N	16,862	16,862	16,862	16,862	16,862	16,862	16,862	16,862	16,862	16,862
Panel B: Textual reporting complexity (TRC)										
EPU_P$_t$	**0.057*****	**0.113*****	**0.103*****	**0.090*****	**0.088*****	**0.108*****	**0.070*****	**0.311*****	**0.115*****	**0.096*****
	(9.20)	**(18.51)**	**(16.67)**	**(21.41)**	**(17.09)**	**(19.64)**	**(9.57)**	**(18.80)**	**(14.90)**	**(14.02)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.663	0.669	0.667	0.674	0.667	0.671	0.664	0.668	0.665	0.666
N	16,862	16,862	16,862	16,862	16,862	16,862	16,862	16,862	16,862	16,862

Table 5: Economic Channels of Monetary Reporting Complexity

This table reports the regression results of the following recursive equations for the 2011-2019 sample period:

$$MRC_{it} = \beta_0 + \beta_1\, EPU_t + CONTROLS_{it} + FE + \varepsilon_{it} \quad (4a)$$

$$MRC\_C_{it} = \beta_0 + \beta_1\, EPU_t + CONTROLS_{it} + FE + \varepsilon_{it} \quad (4b)$$

$$MRC_{it} = \beta_0 + \beta_1\, EPU_t + \beta_2\, MRC\_C_{it} + CONTROLS_{it} + FE + \varepsilon_{it} \quad (4c)$$

Equation (4a) is the same as equation (1). In equation (4b), *MRC_C* stands for specific economic components of monetary reporting complexity (*MRC*), including mergers and acquisitions (*MRC_MA*), capital expenditures (*MRC_CAP*), restructuring (*MRC_RES*), borrowing (*MRC_BOR*), and tax planning activities (*MRC_TP*). Equation (4c) is equation (4a) with *MRC_C* added to the right-hand side. The Appendix presents definitions and data sources of all variables. We omit intercepts, controls, fixed effects, and subscripts for brevity. We cluster standard errors at the firm level. Figures in parentheses are t-statistics. ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels of significance, respectively.

MRC_C_{it} =		MRC_MA_{it}		MRC_CAP_{it}		MRC_RES_{it}		MRC_BOR_{it}		MRC_TP_{it}	
Y =	MRC_{it}	MRC_MA_{it}	MRC_{it}	MRC_CAP_{it}	MRC_{it}	MRC_RES_{it}	MRC_{it}	MRC_BOR_{it}	MRC_{it}	MRC_TP_{it}	MRC_{it}
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
EPU_t	**-0.195*****	**-0.220*****	**-0.174*****	**-0.065*****	**-0.190*****	**-0.174*****	**-0.183*****	**-0.611*****	**-0.107*****	**-0.194*****	**-0.116*****
	(-18.74)	**(-5.14)**	**(-17.60)**	**(-4.14)**	**(-18.40)**	**(-5.44)**	**(-18.01)**	**(-16.31)**	**(-11.15)**	**(-10.67)**	**(-13.35)**
MRC_C_{it}			**0.096*****		**0.076*****		**0.071*****		**0.144*****		**0.410*****
			(29.47)		**(8.80)**		**(15.57)**		**(31.49)**		**(34.48)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.827	0.722	0.845	0.697	0.829	0.772	0.833	0.763	0.859	0.829	0.904
N	17,111	17,111	17,111	17,111	17,111	17,111	17,111	17,115	17,115	17,111	17,111
Product			-0.021***		-0.005***		-0.012***		-0.088***		-0.079***
Product SE			0.004		0.001		0.002		0.006		0.008
Z-value			-5.068		-3.746		-5.136		-14.480		-10.197
P-value			0.000		0.000		0.000		0.000		0.000
% of direct (%)			12.07		2.63		6.56		82.24		68.10

Table 6: Mediation Analysis – Economic Policy Uncertainty, Monetary Reporting Complexity and Textual Reporting Complexity

This table reports the regression results of the following recursive equations for the 2011-2019 sample period:

$$TRC_{it} = \beta_0 + \beta_1 EPU_t + CONTROLS_{it} + FE + \varepsilon_{it} \quad (5a)$$

$$MRC_{it} = \beta_0 + \beta_1 EPU_t + CONTROLS_{it} + FE + \varepsilon_{it} \quad (5b)$$

$$TRC_{it} = \beta_0 + \beta_1 EPU_t + \beta_2 MRC_{it} + CONTROLS_{it} + FE + \varepsilon_{it} \quad (5c)$$

In these equations, EPU_t is the natural logarithm of the economic policy uncertainty index by Baker et al. (2016). *MRC* and *TRC* stand for total monetary reporting complexity and textual reporting complexity, respectively. We measure *MRC* (*TRC*) as the log of the sum (average length) of unique monetary (text-block) XBRL tags in 10-K reports. *CONTROLS* is a set of firm-level and macro-level control variables. We include fixed effects for firm and industry and cluster standard errors at the firm level. The Appendix presents definitions and data sources of all variables. In the table, we omit intercepts, controls, and fixed effects for brevity. Figures in parentheses are t-statistics. ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels of significance, respectively.

Y =	TRC_{it}	MRC_{it}	TRC_{it}
	[1]	**[2]**	**[3]**
EPU_t	**0.261***** **(16.93)**	**-0.195***** **(-18.74)**	**0.145***** **(9.56)**
MRC_{it}			**-0.598***** **(-40.96)**
Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
Adjusted R^2	0.670	0.827	0.740
N	17,111	17,111	17,111
Product			0.117***
Product SE			0.007
z-value			17.04
p-value			0.000
% of direct (%)			80.42

Table 7: Consequence of Reporting Complexity – Information Asymmetry

This table reports the regression results of the following recursive equations for the 2011-2019 sample period:

$$IA_{it} = \beta_0 + \beta_1 EPU_t + CONTROLS_{it} + FE + \varepsilon_{it} \quad (6a)$$

$$ARC_{it} = \beta_0 + \beta_1 EPU_t + CONTROLS_{it} + FE + \varepsilon_{it} \quad (6b)$$

$$IA_{it} = \beta_0 + \beta_1 EPU_t + \beta_2 ARC_{it} + CONTROLS_{it} + FE + \varepsilon_{it} \quad (6c)$$

In equation (6a), *IA* stands for daily bid-ask spread (*SPREAD*), while *CONTROLS* stands for squared return (RET^2), log of dollar trading volume (*VOL*), log of price (*PRICE*), and turnover (*TURNOVER*). We control fixed effects for firm and year and cluster standard errors at the firm and day level. Equation (6b) is similar to equation (1) when the dependent variable is *TRC*, except that we run this equation at the daily level. Equation (6c) is similar to the equation (6a), except that we now control for *TRC* and *CONTROLS* includes both controls from equation (6a) and controls from equation (6b). For both equations (6b) and (6c), we control for firm fixed effects and cluster standard errors at the firm level. The Appendix presents definitions and data sources of all variables. We omit intercepts, controls, and fixed effects for brevity and cluster standard errors at the firm level. Figures in parentheses are t-statistics. ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels of significance, respectively.

***Y* =**	***SPREAD$_{it}$***	***MRC$_{it}$***	***SPREAD$_{it}$***	***TRC$_{it}$***	***SPREAD$_{it}$***
***ARC* =**		***MRC***		***TRC***	
	[1]	**[2]**	**[3]**	**[4]**	**[5]**
EPU$_t$	**0.032*****	**-0.009*****	**0.038*****	**0.013*****	**0.037*****
	(6.93)	**(-13.65)**	**(13.07)**	**(12.25)**	**(12.88)**
ARC$_{it}$			**0.119*****		**-0.045****
			(4.29)		**(-2.20)**
RET_{it}^2	0.400		0.469*		0.469*
	(1.62)		(1.83)		(1.83)
VOL$_{it}$	-0.122***		-0.206***		-0.205***
	(-23.60)		(-27.72)		(-27.69)
PRICE$_{it}$	-0.303***		-0.065***		-0.066***
	(-20.04)		(-5.37)		(-5.47)
TURNOVER$_{it}$	-0.001		-0.000		-0.000
	(-1.10)		(-0.07)		(-0.08)
ARC Controls	No	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.588	0.855	0.5245	0.7255	0.5244
N	4,249,538	4,248,561	4,248,529	4,248,561	4,248,529
Product			-0.001***		-0.00059**
Product SE			0.002		0.00026
z-value			-4.092		-2.166
p-value			0.000		0.030
% of direct (%)			2.82		1.59

Table 8: Cross-Sectional Test

This table reports the regression results of the following equation for the 2011-2019 sample period:

$$ARC_{it} = \beta_0 + \beta_1 EPU_t + \beta_2 Z_{it} + \beta_3 EPU_t \times Z_{it} + CONTROLS_{it} + FE + \varepsilon_{it} \tag{7}$$

In columns [1] – [4], *Z* stands for *GOV_CUS* or *BETA*. *GOV_CUS* equals one if the company reports the U.S. government as a major customer, and zero otherwise. *BETA* equals one if the *EPU*-stock return sensitivity is greater than or equal to the annual industry median, and zero otherwise. In columns [5] and [6], *Z* stands for $PRISK_{it}$, an indicator equal to one if the firm-level political risk score by Hassan et al. (2019) is greater than or equal the median value in a given year, and zero otherwise. In columns [7] – [8], Z_{it} stands for $FLUIDITY_{it}$ or $CONCENT_{it}$, two measures of product market competition. $FLUIDITY_{it}$ equals one if the company has a fluidity score, a text-based measure of product market threats by Hoberg et al. (2014), *greater* than or equal to the sample median, and zero otherwise. $CONCENT_{it}$ equals one if the company has an industry concentration score, a text-based measure of industry concentration by Hoberg and Phillips (2016), *lower* than the sample median, and zero otherwise. All other variables are as in equation (1). The Appendix presents definitions and data sources of all variables. All regressions include fixed effects for firm and industry-fixed effects. We omit intercepts, controls, and fixed effects for brevity. In all regressions, we cluster standard errors at the firm level. Figures in parentheses are *t*-statistics. ***, **, and * indicate that the coefficients are statistically significant at the 1%, 5%, and 10% levels of significance, respectively.

***Z* =**	***GOV_CUS$_{it}$***		***BETA$_{it}$***		***PRISK$_{it}$***		***FLUIDITY$_{it}$***	***CONCENT$_{it}$***
***ARC* =**	***MRC***	***TRC***	***MRC***	***TRC***	***MRC$_{it}$***	***TRC$_{it}$***	***TRC$_{it}$***	***TRC$_{it}$***
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**
EPU$_t$	**-0.172***** **(-13.80)**	**0.237***** **(13.11)**	**-0.167***** **(-11.68)**	**0.258***** **(13.15)**	**-0.219***** **(-15.11)**	**0.299***** **(15.91)**	**0.285***** **(15.09)**	**0.289***** **(15.30)**
Z_{it}	0.341** (2.04)	-0.293 (-1.55)	0.201** (2.21)	0.001 (0.01)	-0.226** (-2.51)	0.351*** (3.33)	0.241** (2.08)	0.278** (2.54)
EPU$_t$* × *Z$_{it}$	**-0.074**** **(-2.11)**	**0.069*** **(1.75)**	**-0.040**** **(-2.08)**	**-0.001** **(-0.04)**	**0.047**** **(2.44)**	**-0.074***** **(-3.31)**	**-0.049**** **(-1.99)**	**-0.058**** **(-2.51)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.811	0.665	0.826	0.668	0.827	0.671	0.670	0.670
N	13,184	13,184	16,862	16,862	17,115	17,115	17,115	17,115

APPENDIX: Variable Definitions

Variable	*Definitions*	*Sources*
Accounting reporting complexity		
MRC$_{it}$	The measure of accounting reporting complexity based on Hoitash and Hoitash (2018), which is the count of unique XBRL tags per financial statement disclosures that contains non-repeating monetary facts within a disclosure. *MRC* is the natural logarithm of the count. *MRC* includes *MRC_TAX* and *MRC_EXT*.	Authors' calculation using data from https://www.sec.gov/dera/data/financial-statement-and-notes-data-set.html
MRC_TAX$_{it}$	The count of non-repeating monetary, FASB-approved (U.S. GAAP) taxonomy tags. *MRC_TAX* is the natural logarithm of the count.	Authors' calculation using data from https://www.sec.gov/dera/data/financial-statement-and-notes-data-set.html
MRC_EXT$_{it}$	The count of non-repeating monetary, firm-specific tags (customized extended tags). *MRC_EXT* is the natural logarithm of the count.	Authors' calculation using data from https://www.sec.gov/dera/data/financial-statement-and-notes-data-set.html
MRC_MA$_{it}$	The count of non-repeating monetary XBRL tags related to mergers and acquisitions (M&A). We calculate *MRC_MA* in the same ways as *MRC*. We use the following keywords to search for M&A related tags: "merger", "acquisition", "acquired", "businesscombination."	Authors' calculation using data from https://www.sec.gov/dera/data/financial-statement-and-notes-data-set.html
MRC_CAP$_{it}$	The count of non-repeating monetary XBRL tags related to capital expenditures. We calculate *MRC_CAP* in the same ways as *MRC*. We use the following keyword to search for capital expenditure tags: "capitalexpen."	Authors' calculation using data from https://www.sec.gov/dera/data/financial-statement-and-notes-data-set.html
MRC_RES$_{it}$	The count of non-repeating monetary XBRL tags related to restructuring activities. We calculate *MRC_RES* in the same ways as *MRC*. We use the following keyword to search for capital expenditure tags: "restructuring," "restructure."	Authors' calculation using data from https://www.sec.gov/dera/data/financial-statement-and-notes-data-set.html
MRC_BOR$_{it}$	The count of non-repeating monetary XBRL tags related to borrowing activities. We calculate *MRC_BOR* in the same ways as *MRC*. We use the following keyword to search for capital expenditure	Authors' calculation using data from https://www.sec.gov/dera/data/financial-

	tags: "borrow," "loan," "bond," "debenture," "debtinstrument," "capitallease," "leveragedlease."	statement-and-notes-data-set.html
MRC_TP_{it}	The count of non-repeating monetary XBRL tags related to tax planning. We calculate *MRC_TP* in the same ways as *MRC*. We use the following keyword to search for capital expenditure tags: "incometax."	Authors' calculation using data from https://www.sec.gov/dera/data/financial-statement-and-notes-data-set.html
TRC_{it}	The text reporting complexity, which is the natural logarithm of the average length of all text-block tags within a disclosure.	Authors' calculation. Data are from https://www.sec.gov/dera/data/financial-statement-and-notes-data-set.html
TRC_TAX_{it}	The natural logarithm of the average length of US-GAAP text-block tags.	Authors' calculation. Data are from https://www.sec.gov/dera/data/financial-statement-and-notes-data-set.html
TRC_EXT_{it}	The natural logarithm of the average length of extended text-block tags.	Authors' calculation. Data are from https://www.sec.gov/dera/data/financial-statement-and-notes-data-set.html
Economic policy uncertainty		
EPU_t	Economic policy uncertainty (overall index) measure by Baker et al. (2016). *EPU* is the natural logarithm of the overall annual index.	Baker et al. (2016). Data are updated to 2019 and available at www.policyuncertainty.com
EPU_CAN_t	Canada's economic policy uncertainty by Baker et al. (2016). *EPU_GOVCPI* is the average of the natural logarithm of the annual index.	Baker et al. (2016). Data are updated to 2019 and available at www.policyuncertainty.com
EPU_R_t	Residual of regressing the U.S. policy uncertainty index on Canada's index and the U.S.'s macro-economic conditions.	Authors' calculation
$ELECTION_{it}$	Presidential election, which equals one if the fiscal year t of firm i ends within 12 months of a presidential election and zero otherwise (Dai & Ngo, 2021; Kaviani et al., 2020). We consider three US	Public election records

	presidential elections in 2012, 2016, and 2020 for our sample period from 2011 to 2019. We set *ELECTION* equal to one if the fiscal year ends within 05/11/2011 to 06/11/2012, or 07/11/2015 to 08/11/2016, or 02/11/2019 to 03/11/2020.	
$PCONFLICT_t$	Azzimonti (2018) Partisan-conflict index, which is a measure of policy disagreements on newspaper articles among lawmakers. *PCONFLICT* is equal to the natural logarithm of the annual average of the Partisan-conflict index. We follow Bonaime et al. (2018) and Ng et al. (2020) and use the partisan-conflict index as the instrumental variable of policy uncertainty.	Federal Reserve Bank of Philadelphia's website: https://www.philadelphiafed.org/reseARCh-and-data/real-time-center/partisan-conflict-index
EPU_P_t	Variable standing for 10 categorical EPU indices: (1) monetary policy, (2) fiscal policy, (3) tax, (4) government spending, (5) health care, (6) national security, (7) entitlement programs, (8) regulation, (9) financial regulation, and (10) sovereign debt. We use the natural logarithm of indices.	Baker et al. (2016). Data are updated to 2019 and available at www.policyuncertainty.com
Control variables		
$SIZE_{it}$	Firm size, which is the natural logarithm of total assets	Compustat/CRSP
LEV_{it}	Financial leverage, which is the sum of short term and long-term debt scaled by total assets.	Compustat/CRSP
ROA_{it}	Earnings before extraordinary items scaled by lagged total assets	Compustat/CRSP
MTB_{it}	Market to book ratio, which is equal to market value of equity (the number of shares outstanding times share prices) plus total assets minus book value of equity, all scaled by total assets.	Compustat/CRSP
$ACQUISITION_{it}$	Acquisition activity, which is a dummy variable which takes the value of one if the company has a non-zero value for shares issued for acquisition or cash paid for acquisitions, and zero otherwise.	Compustat/CRSP
$RESTRUCTURE_{it}$	Restructure activity, a dummy variable which takes the value of one if the company has a non-zero value for Compustat's items *RCP* (Restructuring Costs Pretax), *RCA* (Restructuring Costs After-tax), *RCEPS* (Restructuring Costs Basic EPS Effect), or *RCD* (Restructuring Costs Diluted EPS Effect), and zero otherwise (Ashbaugh-Skaife et al., 2007).	Compustat/CRSP
$FOREIGN_{it}$	Foreign operation, which takes the value of one if the company has a non-zero value for foreign	Compustat/CRSP

	currency translation (Compustat's item *FCA*), and zero otherwise (Hoitash & Hoitash, 2018).	
$ACCRUAL_{it}$	Total accruals, which is equal to net income minus cash flows from operations.	Compustat/CRSP
AGE_{it}	The natural logarithm of firm age	Compustat/CRSP
$DISTRESS_{it}$	Altman (1968)'s Z-score. We calculate the decile rank of the Z-score for each industry in each year.	Compustat/CRSP
$LOSS_{it}$	Loss, which takes the value of one if the company reports a negative net income (loss) in the current year or prior year, and zero otherwise.	Compustat/CRSP
$LOSS\_FRQ_{it}$	The probability of loss years in the last five years	Compustat/CRSP
STD_CF_{it}	The standard deviation of cash flows from operations scaled by total assets over the past five years. We require at least three years to calculate the standard deviation.	Compustat/CRSP
STD_SALE_{it}	The standard deviation of sales over the past five years. We require at least three years to calculate the standard deviation.	Compustat/CRSP
$BUS\_SEGMENT_{it}$	The natural logarithm of one plus the number of business segments reported in Compustat Historical Segments file.	Compustat/CRSP
$GEO\_SEGMENT_{it}$	The natural logarithm of one plus the number of geographic segments reported in Compustat Historical Segments file.	Compustat/CRSP
$BIG4_{it}$	An indicator that equals one if the financial statement is audited by a Big Four auditor, and zero otherwise.	Compustat/CRSP
$MUINDEX_t$	Macro uncertainty index by Jurado et al. (2015). This index is the unforecastable component from 279 macroeconomic variables. *MUINDEX* is calculated by taking the average of monthly macro uncertainty index each year.	The data are updated to 2019 and is available at https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes
$GDPGR_t$	GDP growth rate, which is equal to 100 times the annual average of the change in real gross domestic products (GDP), where the change in GDP is equal to GDP in quarter t minus GDP t-1, all scaled by GDP in quarter t-1.	Federal Reserve Bank of St. Louis. Available at https://fred.stlouisfed.org/series/GDPC1
$UNEMRATE_t$	The unemployment rate, which is the annual average of the change in the level of the monthly unemployment rate.	U.S. Bureau of Labor Statistics

$CSRET_t$	Returns on the S&P/Case-Shiller US National Home Price Index, which is equal to annual average of the ratio of the index level in quarter t minus the index level in quarter t-1 scaled by the index level in quarter t-1.	Federal Reserve Bank of St. Louis. Available at https://fred.stlouisfed.org/series/CSUSHPINSA
$GOVCUS_{it}$	The US Government as a major customer, which equals 1 if the company reports the U.S. government as a major customer a given year (*CTYPE* is "*GOVSTATE*," "*GOVLOC*," "*GOVDOM*," or "*GOVFRN*" in the Compustat's historical customer segment file), and 0 otherwise.	Compustat/CRSP
$BETA_{it}$	EPU-stock return sensitivity (Bonaime et al., 2018; Brogaard & Detzel, 2015; Duong et al., 2020). To calculate *BETA*, we firstly regress a firm's value weighted monthly excess stock returns on *EPU_NEWS*, market excess return, *SMB*, and *HML* using a rolling 60-month period prior the beginning of the firm's fiscal year and we run regression for each Fama-French 48 industry. *BETA* equals 1 if *EPU_NEWS* from the regression is greater than or equal to the median of all industries in a given year, and 0 otherwise.	Authors' calculation Data on Fama-French industry and other Fama-French factors come from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.
$FLUIDITY_{it}$	The text-based measure of product market threats by Hoberg et al. (2014). We define *FLUIDITY* as an indicator equal to 1 if the company has a fluidity score *greater* than or equal to the sample median, and 0 otherwise.	https://hobergphillips.tuck.dartmouth.edu/
$CONCENT_{it}$	The text-based measure of industry concentration by Hoberg and Phillips (2016). We define *CONCENT* as an indicator equal to 1 if the company has the industry concentration score (tnic3hhi) *lower* than the sample median, and 0 otherwise.	https://hobergphillips.tuck.dartmouth.edu/
$PRISK_{it}$	Indicator equal to 1 if the firm-level political risk score by Hassan et al. (2019) is greater than or equal the median value in a given year, and 0 otherwise.	https://www.firmlevelrisk.com/
$SPREAD_{it}$	Daily bid-ask spread, measured as (Ask – Bid) / [(Ask + Bid) / 2] Where: Ask = daily ask price Bid = daily bid price	Compustat/CRSP
RET_{it}^2	Squared value of daily stock return.	Compustat/CRSP
VOL_{it}	Log of one plus the product of daily trading volume and the absolute value of daily price.	Compustat/CRSP

$PRICE_{it}$	Log of absolute value of daily price.	Compustat/CRSP
$TURNOVER_{it}$	Daily turnover, measured as daily trading volume scaled by daily share outstanding.	Compustat/CRSP