Fiscal Risk Perception: Evidence from Analyst Forecasts*

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Abstract

In a stylized model with loss aversion, fiscal uncertainty and imperfect information, we demonstrate that analysts under-forecast firm earnings associated with government contracts. Empirically, we construct a *transaction*-level dataset about federal government procurement contracts spanning 2009-2019. The fiscal uncertainty associated with procurement primarily arises from budgetary risks, as the federal government can modify or terminate contracts. We find that firm-quarter actual procurement earnings (as a fraction of revenue) significantly and positively predict analyst earnings surprises. This predictability becomes stronger during periods with heightened budgetary uncertainty (e.g., the elevated macroeconomic uncertainty preceding debt ceiling events) and for firms with weaker bargaining power. In terms of return dynamics, a one standard deviation increase in firm-quarter procurement exposure is associated with an 8.4% per annum increase in abnormal stock returns on earnings announcement days. Overall, while government spending can spur growth, analysts interpret fiscal uncertainty as "bad" uncertainty.

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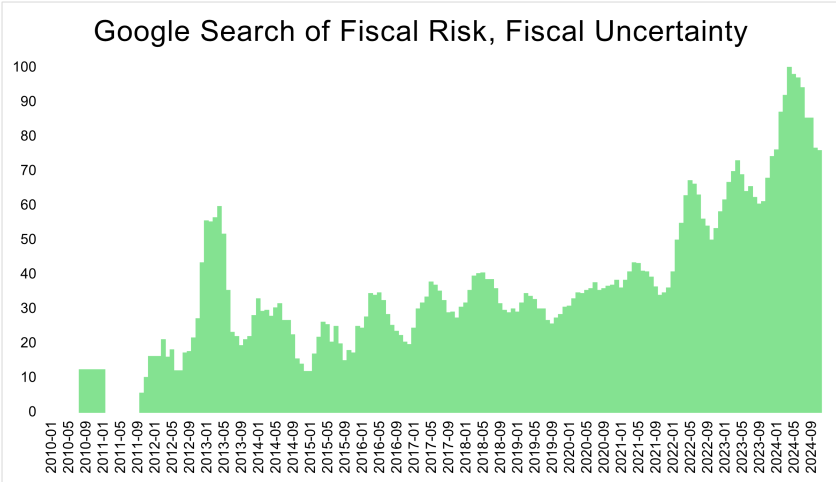
"Current fiscal policy dysfunction," warning that the inability of Congress and the White House to work together on budget and spending bills "creates a level of fiscal uncertainty that is damaging to the U.S. economy." – International Monetary Fund (IMF) Managing Director Christine Lagarde, June 4, 2015; The News & Observer.



1 Introduction

Fiscal uncertainty looms large — policymakers have raised concerns about it, and the general public has taken notice (as discussed above). However, our understanding of how market participants perceive this uncertainty remains limited, despite its potential significance to the economy and financial markets. Attempts to address this lacuna in our knowledge face major empirical challenges, including a lack of large-scale surveys or futures markets to help reveal perceptions and the nature of broad interpretations of fiscal policy.

In this paper, we focus on one major form of fiscal spending, procurement contracts, and construct a *transaction*-level dataset from 2009 to 2019 building on information from USAspending.gov. The type of fiscal uncertainty associated with procurement transactions would be primarily budgetary uncertainty, i.e., the risk that the federal government might change or even terminate contracts. We find that firm-quarter actual procurement earnings significantly and positively predict analyst earnings surprises. The predictability is stronger during periods with heightened budgetary uncertainty (i.e., higher macro uncertainty during the months prior to debt limits events) and for firms with lower bargaining power (i.e., higher micro uncertainty). In the return space, a one SD increase in procurement exposure corresponds to 8.4% per annum abnormal stock returns (over market returns). Through the lens of a rational model featuring investor loss aversion, fiscal uncertainty and imprecise information, we demonstrate this predictability in a closed form solution. Analysts under-forecast firm earnings associated with fiscal uncertainty; in other words, analysts view government contracts as rather risky.

We obtain all archival data from `USAspending.gov`, which is an online portal managed by the federal government to provide detailed information about government spending. For each procurement contract, federal agencies are mandated to report every transaction and its obligated amount, representing the funds committed by the federal government to the recipient. Our two scraping exercises (10/1/2023-1/18/2024 and 8/8/2024–11/5/2024) find that most of the agencies release transactions in a quite *timely* manner, within 30-40 days after the transaction date, except for Department of Defense, which has a 90-day delay mandate for security reasons. Transaction-level data becomes available in 2008 and becomes reliable following the global financial crisis. As a result, our main sample period covers June 2009 to December 2019. Given our empirical design, we focus on a group of firms for which procurement contracts should matter, specifically those that have a positive obligated transaction amount for more than half of our sample period. After we incorporate financial and IBES databases, our final sample includes 474 firms and 19,027 firm-fiscal quarters. As expected, manufacturing, information and utility industries are well-represented, while industries related to retail trades, hotels and arts and entertainment are not.

To stay close to our model's prediction and constructs, our first firm-quarter dependent variable is a simple earnings surprise dummy, "Beat," which equals one if the firm's actual earnings per share (EPS) are greater than the IBES consensus forecast median immediately prior to the announcement. We also use two standardized unexpected earnings (SUE) measures scaled by analyst disagreement or price (e.g., Froot, Kang, Ozik, and Sadka (2017)). The predictor capturing procurement or fiscal exposure is measured as the total transaction obligated amount for each firm-fiscal quarter, scaled by average revenue over the past 4 quarters. Various robustness variables are also considered. This exposure can be quite large; for instance, the construction industry procurement exposure is on average around 7% during the sample period.

We find that actual procurement exposure this quarter significantly and positively predict earnings surprises in one or two months, mostly at the 1% significance level. In terms of economic magnitude, a one standard deviation (SD) increase in fiscal dependence predicts an around 1.97% higher chance of the actual EPS beating the analyst forecast and a 0.2 SD increase in standardized earnings surprises. It is also important to note that the predictability mostly comes from (within industry) across firm variation. This is the first indication from our empirical exercise of a risk-based explanation.

Three additional tests are noteworthy. First, our results are robust after dropping all DoD-related transactions. As mentioned before, they have a 90-day delay mandate to report to the public; while analysts could learn from the firm directly or conduct their own assessment, the predictability of DoD-related transactions may reflect a no-information story. Second, our results are robust at the pure intensive margin, i.e., firm-quarters with strictly positive transactions. Third, we re-estimate the predictability using an eight-quarter rolling window. The predictability is quite significant and strong leading into late 2015, and reaches peaks again in late 2017 and 2019, which is an economically meaningful pattern as it coincides with several major fiscal uncertainty episodes in recent history: the "Fiscal Cliff" of 2013-2014, and the sequence of debt limit suspensions needed from Congress in late 2017 and late 2019. This is our second indication of a risk-based explanation, which guides our mechanism analysis next.

We construct empirical proxies for fiscal uncertainty state variables from two dimensions. First, we use debt limit events to identify a time-series "macro" fiscal uncertainty proxy that should capture specifically government budgetary uncertainty (i.e., higher cash flow uncertainty during the months prior to the debt limit events). In particular, we create a debt limit dummy variable and use an EPU variable that is attributed to uncertainty mentions around the debt ceiling context from newspapers (Baker, Bloom, and Davis (2016)). In a validation exercise, we show that the latter indeed increases significantly in the months prior to debt limit events. Second, we closely follow Brogaard, Denes, and Duchin (2021) and construct proxies for firm bargaining power with the government to identify a cross-firm "micro" fiscal uncertainty proxy (i.e., there is greater cash flow uncertainty for firms with lower bargaining power). In particular, our renegotiation index is an average of three indicators (as documented in Brogaard, Denes, and Duchin (2021)) of bargaining power: chances of increased contract amounts, chances of increased contract lengths, and chances of weaker monitoring. Consistent with our model prediction, we find robust results that predictability increases significantly with fiscal uncertainty, both in the cross section and over time.

In the last part of the paper, we discuss stock market implications and examine empirical possibilities for alternative mechanisms that are conceptualized in our model. We project a log three-day cumulative abnormal return (in excess of value-weighted market returns) from a [-1 day, 1 day] window around the earnings announcement day on our procurement exposure variable, and find weakly significant and positive coefficients. A one SD increase in procurement exposure predicts a 0.7% increase in monthly abnormal returns, which is equivalent to 8.4% per annum abnormal returns. Importantly, with stock returns, we are able to examine whether predictability appears during non-announcement days. We find that procurement exposures explain stock returns significantly only during the earnings announcement period. This is an economically important finding because it shows that fiscal risk is priced into stock returns through earnings surprises.

Our rational expectations model also predicts that predictability diminishes with information timeliness and precision. This channel is empirically difficult to test for this mechanism as we do not have real time data on exactly when each transaction was posted. However, our scraping exercises would suggest that major delays in information disclosure are not likely to be the main channel. In addition, we conduct an event study using the 1000 largest firm-quarter transactions with the assumption that such transactions, given their sheer magnitude and size, should be well-studied and well-informed. We do not find that predictability is greatly decreased when earnings are announced during the next quarter. Finally, the lack of intrinsic attention paid to procurement, though not explicitly modeled in our conceptual framework for simplicity's sake, might be a third channel. We conduct a simple textual analysis in firm-quarter earnings call transcripts and create a firm-quarter variable capturing analyst mentions of procurement-related keywords. We do not find that variation in attention significantly explains the main predictability result.

Our research contributes to three strands of research. First, there is scant research on how market participants form their expectations of fiscal policy – in particular, how they perceive fiscal risk – in the finance and economics literature. Among them, Bianchi, Gómez-Cram, and Kung (2024) and Xu and You (forthcoming) are two recent empirical papers that use various identification strategies (i.e., the timing of tweets by members of Congress and exogenous events such as macroeconomic announcements, respectively). Both document that investors are actively forming expectations about future fiscal policies, with sizable implications for stock prices. Our paper joins this ongoing effort and is among the first to study how one important group of market participants – analysts – perceive fiscal risk. Our use of actual procurement data and wide firm-quarter coverage brings a comprehensive perspective. We find that analysts believe that fiscal uncertainty transmits to the private sector through procurement contracts, which is a new empirical fact to the literature.

Second, our paper contributes to a large group of papers exploring the economics of procurement contracts. Among the many influential works in the public finance and industrial organization literature, Klemperer (2004) discusses how auction design influences bidder behavior and procurement efficiency; Bajari, McMillan, and Tadelis (2009) compare competitive bidding with negotiation in procurement; Søreide (2002) reviews strategies to mitigate corruption in procurement; and Gereffi, Humphrey, and Sturgeon (2005) examine the working of procurement contracts in global value chains. We contribute to this literature from the perspective of financial economists and demonstrate how procurement contracts are vehicles for fiscal uncertainty to enter the financial markets – forecasts and, importantly, asset prices. In general, our main finding also sheds light on the argument that the government is *itself* a source of risk to the financial market (instead of what a traditional model would say, a safety net).

Third, we contribute to the extensive literature on earnings surprises. Among these works, Froot, Kang, Ozik, and Sadka (2017) is especially relevant to our research. They track actual sales (real-time consumer activity data) during the quarter and find that their constructed within-quarter sales is highly predictive of earnings surprises. The channel is private information or delayed information from managers to analysts and the public. Their paper and our paper are similar in the main predictive specification, but our paper differs in the economic nature of the other major source of earnings (government contracts) and the risk-based mechanism. We also formalize our main findings and mechanism in a rational model with a closed-form solution.

In the remainder of the paper, Section 2 provides a conceptual framework and model prediction in a simplified world with investor loss aversion, fiscal uncertainty and imprecise information. Section 3 discusses data. Sections 4 and 5 present the main predictability and mechanism evidence, respectively. Section 6 presents return implications and examines alternative mechanisms. Concluding remarks are included in Section 7.

2 Conceptual Framework

We consider a stylized model of analyst expectations formation, featuring investor loss aversion, fiscal uncertainty and delayed or imprecise information arrival. Time stamp t always denotes when events arrive. Actual earnings (analyst earnings forecasts) of the last period $t-1$ are announced at time t, so firm actual earnings in period $t-1$ is denoted as $X_{t(t-1)}$ ($X^F_{t(t-1)}$), or X_t (X^F_t) for simplicity in the rest of the model. Firm indicator i is dropped for simplicity without loss of generality. Buy-side investors follow sell-side analysts' recommendations and they are loss-averse. Thus, analysts will be penalized more if their forecasts are higher than the realized value. As a result, analysts choose forecast X^F_t in period $t-1$ by solving the following minimization problem:

$$\min_{X_t^F} \mathbb{E}_{t-1} \left[(X_t - X_t^F)^2 + 48\lambda \mathbf{1}_{X_t^F > X_t} \frac{(X_t^F - X_t)^2}{(X_t^F - min(X_t))^2} \right], \tag{1}$$

where λ (> 1) captures the loss aversion of investors/clients. $X_t - X^F_t$ denotes realized earnings surprise. $\frac{48}{(X_t^F - min(X_t))^2}$ are scaling parameters in order to obtain a closed-form solution under uniform distributed shock assumptions.

2.1 The data generating process

Actual earnings of period $t-1$ announced at time t, $X_{t(t-1)}$ or X_t is a flow variable that consists of two components: earnings made by retail sales, R_t, and earnings from the government from existing procurement contracts, G_t;

$$X_t = R_t + \kappa G_t, \tag{2}$$

where κ (which would have a superscript i) measures the fiscal dependence of the firm. In the longer term, $\frac{\kappa\bar{G}}{\bar{R}+\kappa\bar{G}}$ corresponds to fiscal dependence, which is the measure we use in our empirical section.

We assume that analysts can collect sufficient information about retail sales and form rational expectations about $R_{t(t-1)}$ or R_t with uncertainty following a uniform distribution,

$$R_t = \bar{R} + \eta_t, \text{ where } \eta_t \sim U(-1, 1). \tag{3}$$

For government spending during period $t-1$ and known by time t, we assume that $G_{t(t-1)}$ or G_t has three components: G_{t-1}, government spending during period $t-2$ and known by time $t-1$; D_{t-1}, *true* spending deviation from the previous period which, under perfectly timely disclosure of information of these transactions, is known during period $t-1$; and ϵ_t, an error term which is core to our model:

$$G_t = G_{t-1} + D_{t-1} + \epsilon_t, \text{ where } \epsilon_t \sim U\left(-\frac{\phi}{K}, \frac{\phi}{K}\right). \tag{4}$$

Parameter $\phi > 0$ reflects the relative risk associated with fiscal spending. In our context, this could mean that the government could change or terminate contracts. Intuitively, higher ϕ indicates higher fiscal uncertainty. Parameter $K > 0$ controls for how precisely and timely the *true* spending deviation D_{t-1} becomes known to analysts. As K goes to inf, analysts know precise information. Lastly, we assume $E(D_{t-1}) = 0$ and denote $E(G_t) = \bar{G}$. Shocks η_t and ϵ_t i.i.d. from each other.

2.2 Model solution and testable predictions

After substituting the X_t process in Equation (1) and applying the rule of integrals, our minimization problem can be simplified in closed form as:

$$\min_{X_t^F} \Bigg[(\bar{R} + \kappa G_{t-1} + \kappa D_{t-1} - X_t^F)^2 + \frac{1}{3}\left(1 + \frac{\kappa^2 \phi^2}{K^2}\right) + \lambda \cdot \frac{\left(X_t^F - \bar{R} - \kappa G_{t-1} - \kappa D_{t-1} + \frac{\kappa\phi}{K} + 1\right)^2}{\frac{\kappa\phi}{K}} \Bigg].$$

The first-order condition is obtained by differentiating this with respect to X_t^F:

$$X_t^F = \frac{(\kappa G_{t-1} + \kappa D_{t-1} + \bar{R})(2 + \lambda/(\kappa\phi/K)) - \frac{\lambda(\kappa\phi/K+1)}{\kappa\phi/K}}{2 + \lambda/(\kappa\phi/K)}. \tag{5}$$

The expected bias can be derived as a closed-form function, $\text{Surprise}_t(\kappa, \lambda, \phi, K)$:

$$\text{Surprise}_t(\kappa, \lambda, \phi, K) = \bar{R} + \kappa G_{t-1} + \kappa D_{t-1} - X_t^F, \tag{6}$$

$$= \frac{\lambda(1 + \kappa\phi/K)}{\lambda + \kappa\phi/K} > 0. \tag{7}$$

Prediction 1: *Under reasonable parameter assumptions (i.e., $\kappa, \phi, K > 0$ and $\lambda > 1$), it is always optimal for analysts to underestimate earnings.*

Next, we produce three testable predictions that guide our empirical analysis in the rest of the paper. First, we study the relationship between fiscal dependence κ and earnings surprises. The derivative of $\text{Surprise}_t(\kappa, \lambda, \phi, K)$ with respect to κ, $\frac{\partial \text{Surprise}}{\partial \kappa}$, has a closed-form solution that is strictly positive:

$$\frac{\partial \text{Surprise}(\kappa, \lambda, \phi, K)}{\partial \kappa} = \frac{\lambda(\lambda - 1)\phi/K}{(\lambda + \kappa\phi/K)^2} > 0. \tag{8}$$

Prediction 2: *Under reasonable parameter assumptions, earnings surprises monotonically increase with firm fiscal exposure κ.*

Intuitively, when there is imprecise or delayed information ($K! = \infty$), analysts choose to more greatly under-forecast the earnings of a firm with greater exposure to fiscal budgetary risk, leading to a more positive earnings surprise. This is consistent with several influential papers in the accounting literature that discuss the relationship between analyst accuracy and under-forecasting and macro uncertainty (e.g., Moffat (1988), Gong, Li, and Wang (2011), You and Zhang (2009), Bonsall IV, Green, and Muller III (2020)). Our model differs by introducing fiscal uncertainty. In addition, the relationship in Equation (8) should also in a general case increase with fiscal budgetary uncertainty ϕ. This offers an important testable prediction for our empirical analysis. Specifically, the quotient rule solves as follows:

$$\frac{\partial \text{Surprise}(\kappa, \lambda, \phi, K)}{\partial \kappa \partial \phi} = \frac{\frac{\lambda(\lambda-1)}{K}(\lambda + \kappa\phi/K)\left[\lambda - \frac{\phi\kappa}{K}\right]}{(\lambda + \kappa\phi/K)^4} > 0, \text{ if } \lambda > \frac{\phi\kappa}{K}. \tag{9}$$

The denominator, $\frac{\lambda(\lambda-1)}{K}$, and $(\lambda + \kappa\phi/K)$ are always positive. When λ (loss aversion) is sufficiently large relative to $\phi\kappa/K$ (which can be interpreted as scaled fiscal uncertainty), the predictability of fiscal exposure to earnings surprises should increase with fiscal uncertainty ϕ. This is likely the case as empirically κ typically is < 0.1 and we observe timely but not perfect transaction data posting (i.e., a large K). We provide empirical evidence later.

One side product of this optimization is the implication with parameter K, timeliness and precision of information: $\frac{\partial \text{Surprise}(\kappa,\lambda,\phi,K)}{\partial \kappa \partial K} = \frac{-\frac{\lambda(\lambda-1)\phi}{K^2}(\lambda+\kappa\phi/K)(\lambda-\frac{\kappa\phi}{K})}{(\lambda+\kappa\phi/K)^4} < 0$, if $\lambda > \frac{\phi\kappa}{K}$. Under similar reasoning, the predictability of fiscal exposure on earnings surprises should decrease with information precision and timeliness K.

Predictions 3 & 4: *Under reasonable parameter assumptions, the predictability of fiscal exposure to earnings surprises should* ***increase*** *with fiscal uncertainty and* ***decrease*** *with information precision and timeliness.*

3 Data and Summary Statistics

3.1 A transaction-level procurement contract database

In this section, we explain how we use a transaction-level procurement contract database in our research. We first download all *archival* data from `USAspending.gov`, which is an online portal managed by the federal government and its agencies to provide detailed information about government spending.[1] Government spending to firms before 2020 is primarily in the form of government procurement contracts.[2] For each procurement contract, federal agencies are mandated to report every transaction and its obligated amount, representing the funds committed by the federal government to the recipient, in chronological order as recorded on `USAspending.gov`. For instance, Raytheon Technologies Corporation built and delivered 5 drones to the federal government on November 8, 2024 (i.e. "action date") as part of a procurement contract; we observe a data point with the "transaction obligated amount" that corresponds to this action, and this is an accrued earning for Raytheon Technologies Corporation in this fiscal quarter.

For our replication exercise (i.e., we observe both the total contract amount and the transactions), we require transaction obligated amount data, which became sparsely

[1] Link for downloading: `https://www.usaspending.gov/download_center/award_data_archive`. This archival dataset is updated by `USAspending` on a monthly basis.

[2] Xu and You (forthcoming) use firm-level economic stimuli obligations to proxy for market fiscal policy expectations, which are constructed from raw data from `USAspending.gov` as well. In addition, their Figure 7 also shows that stimulus was the main form of government spending during 2020 and 2021, accounting for around 68% of the annual total government spending; from after the Global Financial Crisis (GFC) to the end of 2019, economic stimuli in fact account for a close to zero fraction of annual government spending.

available in 2008 but is quite reliably available after the GFC. As a result, our main sample period covers June 2009 to December 2019. We calculate the total transaction obligated amount for each firm-fiscal quarter. We explain our firm sample after we introduce our financial variables. To the best of our knowledge, we are among the first to use transaction-level data provided on this website in the finance and economics literature.

USAspending.gov also provides contract-level – or what the website calls "award-level" – information, such as award agency, start date, potential end date, contract type, etc. We obtain and merge this information into our analysis as well. Brogaard, Denes, and Duchin (2021) are among the first to systematically examine patterns in these contracts. Internet Appendix IA.1 provides more details about these variables.

3.2 Scraping exercises

We also conduct two scraping exercises designed to help us understand the length of the delay between the actual action date and the actual posting date (to this public domain). Our strategy is to capture real-time transaction posts on the website that have not entered the archival data. On the technical front, we find that USAspending.gov provides multiple API endpoints for accessing more timely data. We mainly utilize two of them to download real-time updated award information[3] and real-time updated historical transaction data related to specific parent awards.[4]

Transactions obtained through the API interface that are not present in the most recent updated archival data represent incremental transactions since the last update of the archival data (of course, these transactions will be included in future updates of the archive data). For each incremental transaction, we calculate an "entry delay days" variable that equals the number of days between the date the transaction is

[3]API endpoint for real-time updated award data: https://api.usaspending.gov/api/v2/search/spending_by_award/

[4]API endpoint for real-time updated transaction data: https://api.usaspending.gov/api/v2/transactions/

retrieved from the API endpoint and its actual action date. This exercise demands massive computational power and data storage, so we conduct it for a total of around 100 days, which is just a bit longer than 3 months.

During our two scraping exercises (10/1/2023-1/18/2024 and 8/8/2024–11/5/2024), we scrape the website daily and capture those incremental transactions. Figure A1 in the Appendix shows consistent results across the two exercises. Most agencies – except for the Department of Defense, due to their 90-day delay mandate for national security reasons – publish their transactions quite quickly, usually around 30-40 calendar days after the transaction. Even if the last transaction is on the last day of the fiscal quarter, in an average case it should be expected to be publicly available ahead of the earnings announcement days.

3.3 Financial datasets

Given the full procurement transaction database that we construct above, we first only consider firms that have positive transaction obligated amounts more than half of the time during our sample period (2009/06-2019/12). This allows us to focus on a group of firms to which procurement contracts should matter. We also exclude NAICS=54 firms, which exhibit categorically and significantly higher (and highly persistent) dependence on government procurement contracts due to the high-tech and often non-profit nature of their business.[5]

Finally, we use the standard treatments when merging firm-time IBES and stock variables. Specifically, we focus on firm-quarters with common shares traded on NYSE, AMEX or NASDAQ, with at least one analyst forecast according to IBES, and with quarterly revenue greater than zero. All other financial data (such as market capitalization, book-to-market, daily returns and so on) are sourced from CRSP. Our final

[5]For example, Leidos, which provides IT and cybersecurity solutions to federal agencies; Booz Allen Hamilton, a firm known for its work with the U.S. government, especially in defense and cybersecurity consulting; AECOM, which works on major public works projects; and RAND Corporation, a nonprofit that undertakes research for policy and decision-making, often funded by government grants and contracts.

sample includes 474 firms and 19,027 firm-fiscal quarters.

3.4 Main variables and summary statistics

At the firm-quarter level $\{i, t\}$, our main dependent variable first considers a simple earnings surprise dummy, "Beat$_{i,t}$," which equals one if the firm's actual earnings per share (EPS) are greater than the IBES consensus forecast median immediately prior to the announcement. This variable is not sensitive to standardization construction and scaling choices by design and is popularly used by industry and investors. We also construct two standardized unexpected earnings (SUE) measures. The first measure SUE$_{1,i,t}$ is constructed as earnings surprises (actual EPS minus the median forecast), divided by analyst disagreement.[6] The second measure, SUE$_{2,i,t}$, is the same as the SUE in Froot, Kang, Ozik, and Sadka (2017) and is constructed as earnings surprises (actual EPS minus mean forecast) divided by the quarter-end stock price. We consider all three measures in all analyses of the paper.

Table A1, Panels A and B, presents summary statistics for these main variables at both the panel and cross-firm levels. There is a 66% chance we observe a Beat, indicating that analysts under-forecast more on average, consistent with the literature. Specifically, the actual EPS is on average 1.2 SD higher than the forecast median.

Another important variable is "Procurement$_{i,t}$," which is constructed as the total transaction obligated amount scaled by average quarterly revenues in the past 4 quarters (including the current quarter). The size adjustment addresses the fact that firm size should positively predict earnings surprises (see, e.g., Loughran and McDonald (2011) among many others). The measure therefore can be interpreted as how much of a firm-quarterly's revenue is sensitive to procurement earnings. For firm-quarters during our sample period, this fiscal exposure is around 2% with a large dispersion.

[6]Specifically, analyst disagreement is the standard deviation (SD) of analyst forecasts from this and the last quarter. We choose to use two quarters because the number of forecasts within one quarter could be too small for standard deviation calculation. Nevertheless, results are not sensitive to this choice and we revisit this point in Section 4.2.

Figure 1 describes our final firm sample by NAICS-2 digit industry classification: number of firms, procurement exposures, and total market capitalization. Out of 474 firms, the manufacturing industry (NAICS=33) – mostly heavier and more complex manufacturing such as metals, machinery, electronics, and transportation equipment – contributes 171 firms. Information and utility industries are also well-represented, while industries related to retail trade, hotels or the arts and entertainment are not in our final firm sample. Construction has the highest average fraction of procurement earnings in revenues, around 7% using all quarters during our sample period and more than 10% using upper 25th of the sample (see Figure IB.1 in the Internet Appendix). In what cannot be easily displayed in a figure, there is massive within-industry variation. Notably, there is close to zero correlation between industry procurement exposure and stock market capitalization (size).

[Insert Figure 1 here]

4 Predictability Results

Under the hypothesis that analysts perceive federal contracts as *risky* due to budgetary uncertainty, our model predicts that analysts should under-forecast more for firm-quarters with more fiscal risk exposure. A firm's share of procurement-based earnings, $\text{Procurement}_{i,t}$, is our empirical proxy for fiscal risk exposure. In this section, we examine the main prediction above. In addition, although contracts must be agreed upon before fulfilling them, an uncertain fiscal environment could make the government change contract lengths, obligated amounts, or monitoring strength or, in an extreme left-tail event, terminate contracts. Section 5 provides direct mechanism tests.

In this section, we examine and establish the predictive power of procurement earnings for earnings surprises at the firm-quarter level. Section 4.1 presents the main predictive results. Sections 4.2 and 4.3 present robustness and additional evidence, respectively.

4.1 Main results

The main specification at the firm-quarter level is as follows:

$$\text{Beat}_{i,t} = \gamma_t \times \alpha_{d(i)} + \beta \text{ Procurement}_{i,t} + \boldsymbol{\delta X_{i,t}} + \varepsilon_{i,t}, \tag{10}$$

where i denotes a firm and t denotes a quarter. $\text{Beat}_{i,t}$ and $\text{Procurement}_{i,t}$, measuring earnings surprises and procurement risk exposures, are both discussed in detail in Section 3.4. $\boldsymbol{X_{i,t}}$ denotes a series of control variables (in logarithms) that are widely used in the literature (see, e.g., Loughran and McDonald (2011), Akbas (2016), Akbas, Jiang, and Koch (2020)); they are market capitalization, book-to-market, past returns during the [-61 days,-12 days] and [-6,-2] windows prior to the earnings announcement day, idiosyncratic volatilities calculated over the [-11,-2] and [-61,-12] windows, and the last earnings surprise. $\gamma_t \times \alpha_{di}$ indicates industry-quarter fixed effects, where we use NAICS two digit codes to indicate industry classifications. β is the coefficient of interest.

Table 1 reports the regression results. Columns (1)-(5) are at the firm-quarter level and Column (6) collapses the data to the industry-quarter level. At the firm-quarter level, the coefficient of procurement exposure is significantly and statistically positive at mostly the 1% level after controlling for industry, quarter, or industry-quarter fixed effects. The coefficient at the industry-quarter level, as shown in Column (6), has the right sign but is statistically weaker. Panel B with control variables further demonstrates highly robust results in terms of economic and statistical significance. In addition, a specification with firm fixed effects would generate a positive but borderline significant coefficient (t=1.66).

Taken together, firms' actual procurement transactions strongly predict earnings surprises, especially in explaining the variation *across firms*. In terms of economic magnitude, a one standard deviation (SD) increase in the fiscal dependence predicts an around 1.97% higher chance of the actual EPS beating the analyst forecast. Empirically, the main variation that procurement exposure explains is in the cross section. It is interesting that analysts constantly miss procurement-related earnings forecasts, and we see no signs of learning (i.e., there is no significant and negative coefficient when we use last quarter procurement exposure). This is our first indication for a risk-based explanation. We discuss possible mechanisms as our model implies (i.e., fiscal uncertainty, attention, delay information) in Sections 5 and 6.

[Insert Table 1 here]

4.2 Robustness

We next provide a series of robustness tests for the same panel specification. To conserve space, Table 2 reports relevant coefficients estimates (of β). Columns (4)-(6), compared to Columns (1)-(3), are results with control variables.

In Panel A, we consider alternative measures of fiscal exposure measures: the logarithm of total transactions obligated and the obligated amount scaled by average quarterly revenues from the past two quarters or scaled by the stock market cap at the end of the quarter. The first measure does not control for size effects, while the literature has shown that size significantly and positively predicts earnings surprises (see, e.g., Loughran and McDonald (2011) among many others). All alternative measures exhibit significant and positive coefficients. In Panel B, we examine the predictive result in the intensive margin, where we include only firms with at least one non-zero transaction obligated amount in every single quarter during our sample period (2009/06-2019/12). Results are robust in terms of both economic and statistical significance. Panel C drops all transactions sponsored by the Department of Defense, which corresponds to 2.23 million out of 10.78 million contracts and 416.06 billion out of 1.84 trillion dollar amounts during the sample period. Therefore, we conduct a jackknife exercise. Results again are not driven by one particularly active federal agency.

Finally, while the $\text{Beat}_{i,t}$ measure is not sensitive to size and scaling choices, we also examine two continuous SUE measures. As introduced in Section 3.4, $\text{SUE}_{1,i,t}$ is actual EPS minus the median forecast all divided by the standard deviation of analyst forecasts from this and last quarters. In Panel D, this β estimate is reported as 2.6074*** (SE=0.9151).[7] In terms of economic magnitude, a one standard deviation increase in procurement earnings leads to a 0.2 SD increase in earnings surprises. This is economically sizable as the average magnitude of SUE_1 in our sample is 1.26 SD, and procurement earnings account for 16% of it. The second measure, $\text{SUE}_{2,i,t}$, is as in Froot, Kang, Ozik, and Sadka (2017), using the quarter-end stock price as the denominator. Results are similarly significant.

While the construction choices of SUE is an ongoing debate, we believe that it is important to examine two conceptually different standardization methods. In the rest of the paper, we consider all three standardized earnings surprises that we introduced so far (i.e., Beat, SUE_1, SUE_2) and always include control variables in the analysis.

[Insert Table 2 here]

4.3 Additional evidence

We provide two additional pieces of evidence, one confirming robust results at the cross-firm level and one exploring some time variation in the main coefficient. First, we collapse the firm-quarter level into the firm level and estimate the predictive coefficient. Table 3 shows significant and positive coefficient estimates at the 1%-5% significance level across all specifications, except for Column (5), which does not include industry fixed effects and uses SUE_2. The economic magnitude is also similar compared to the panel analysis, which is expected given that the predictability of procurement earnings

[7] The predictive coefficient would be 2.2821** (SE=1.0813) if we used the same quarter after dropping firm-quarters with only one forecast recorded, which is comparable to what we report in Panel D.

for earnings surprises appears the strongest at the cross-firm margin (see discussions in Section 4.1), even after controlling for industry-quarter fixed effects.

[Insert Table 3 here]

Figure 2 uses a rolling window of eight quarters to examine potential time variation in the predictive coefficient β (in the specification with control variables). The predictability is quite significant and strong leading into late 2015, and reaches peaks again in late 2017 and 2019. The pattern demonstrates interesting and potentially economically meaningful time variation, coinciding with several major fiscal uncertainty episodes in recent history: the "Fiscal Cliff" during 2013-2014 and the sequence of debt limit suspensions needed in Congress in late 2017 and late 2019.

[Insert Figure 2 here]

5 Fiscal Uncertainty

If the robust predictability is due to fiscal risk, then predictability should increase with uncertainty, both in the cross section and over time. In this section, we provide evidence supporting the risk-based explanation as also implied by the model. We provide two pieces of evidence at varying levels of granularity. In Section **??**, we build on Brogaard, Denes, and Duchin (2021) to construct a firm-level (micro) fiscal uncertainty proxy that reflects the renegotiation and bargaining power of firms with the Federal Government. Firms with a higher renegotiation index – created from actual histories of contract-level data – indicate greater bargaining power and, consequently, lower procurement-based cash flow uncertainty. In Section **??**, we construct a time-series (macro) fiscal uncertainty proxy that specifically captures budgetary uncertainty. For identification, periods characterized by heightened debt limit debates are used as indicators of increased budgetary uncertainty.

5.1 Micro uncertainty

Bajari and Tadelis (2001), in their influential work, argue that firms still face uncertainty about ex post adaptations after a procurement contract is signed. These uncertainties include factors from the firm's side (e.g., design failures, unexpected site and environmental conditions) and the Federal Government's side (e.g., regulatory changes, budgetary risk). In a paper more directly relevant to our work, Brogaard, Denes, and Duchin (2021) study patterns in procurement contracts[8] and find that successful contract renegotiation signals the strong bargaining power and political connectedness a firm has with the Federal Government. Combined with our model's implications, firms with a strong renegotiation history and overall bargaining power should exhibit lower predictability than others, as analysts perceive these firms with less cash flow uncertainty (i.e., if the government decides to change or terminate contracts). We test this implication next.

We construct a firm-level "renegotiation index" based on Brogaard, Denes, and Duchin (2021). The authors identify and develop three variables that capture firm bargaining power and contract improvements through renegotiation. Using their exact method and data source, we compute the cumulative amount changes in the potential award amounts for each contract and create an "award increase" indicator that equals one if the cumulative amount changes are greater than zero. We also compute the cumulative day changes in contract end dates and create an "award extension" indicator that equals one if the cumulative day changes are greater than zero. Lastly, we create a "weak monitoring" indicator that equals one if there are no incentive or performance features associated with the contract.

Given that our research focuses on explaining cross-firm variation, we make two adjustments to their measures. First, the three contract-level indicators are aggregated to the firm level, now interpreted as the likelihood of renegotiation success. Second,

[8]The authors also use `USAspending.gov` as their data source.

recognizing that renegotiation practices may vary depending on the nature of firms and contracts[9] and considering the finding in Brogaard, Denes, and Duchin (2021) (Table 4) that "award increase" and "award extension" are stronger indicators of political power, we impose a (0.4, 0.4, 0.2) weighting scheme on the three indicators to create the firm-level renegotiation index. Results remain robust when using equal weights.

Panel C of Table A1 shows that, for the average firm in our sample, 24% of contracts have been successfully renegotiated, and all firms have engaged in some degree of negotiation (i.e., the minimum is not zero). There is significant cross-firm variation in renegotiation success with the Federal Government, with rates ranging from 1% to 47%. Figure 3 illustrates a well-behaved distribution of our renegotiation index values by industry. There is not much variation across industries in terms of the median renegotiation success rates.

[Insert Figure 3 here]

Table 4 shows the interaction evidence. We find that firms with higher bargaining power with the Federal Government exhibit significantly lower predictability. Specifically, consider two firms, Firm A and Firm B, with the same procurement obligated amounts: analysts under-forecast the earnings of Firm A, which has lower bargaining power, more than those of Firm B. This suggests that analysts associate lower cash flow uncertainty with Firm B. In terms of economic magnitude, a one standard deviation increase in the renegotiation index above the average leads to a decrease of -1 in the procurement coefficient β in predictability, which is economically sizable. This finding remains robust after controlling for industry fixed effects.

[Insert Table 4 here]

[9] For example, military weapons contracts may face strict deadlines and monitoring due to time sensitivities, making renegotiation more likely to occur through changes in the total award amount.

5.2 Macro uncertainty

At the macro level, we aim to construct and identify three empirical proxies that are informative about time-varying government budgetary uncertainty, which is an important state variable in our illustrative model (Section 2). *First*, we construct a dummy variable that equals one for debt limit event months and the month prior (source: `whitehouse.gov`) and zero otherwise. We test and validate its interpretation as uncertainty. Using variables constructed by Baker, Bloom, and Davis (2016), the general measure of fiscal policy uncertainty (henceforth FPU) serves as a first-pass test and is already statistically and significantly higher when our debt limit event indicator equals one (t=2.45). Figure 4 displays this general FPU measure with a green dashed line and highlights our debt limit events using gray shaded areas. The narratives behind major FPU spikes reflect both *budgetary* uncertainty associated with debt limits (e.g., mid-2011's Budgetary Control Act, early 2013's No Budget, No Pay Act, 2013's Fiscal Cliff, late 2013's Obamacare funding debate and government shutdown, 2017's hurricane rescue) and *non-budgetary* uncertainty unrelated to debt limit debates but driven by economic and political events (e.g., 2010's midterm election, early 2015's European debt crisis, late 2016's U.S. election, 2019's trade war).

These facts motivate the construction of our *second* measure, which is the logarithm of 1 plus the amount of EPU attributed to debt ceiling mentions in the news articles.[10] This measure is conceptually closer to budgetary uncertainty and complements our first measure (i.e., a dummy) by incorporating an intensive margin. According to Figure 4 and Table 5, EPU attributed to debt ceilings appears to be quite sizable, particularly during the earlier part of the sample, and is 59.8% higher and statistically significant when our debt limit event indicator equals one (t=2.80). In contrast, market risk aversion (source: Bekaert, Engstrom, and Xu (2022)), VIX (source: CBOE), or the

[10] From `https://www.policyuncertainty.com/categorical_epu.html`, EPU has a category of "fiscal policy" and this is what-we-call "FPU" above. EPU also provides a series called "Ratio: EPU w/DebtCeiling to wo/DebtCeiling." Given EPU and this ratio, we obtain EPU attributed to debt ceiling mentions in the news articles.

22-day realized variance of stock market returns does not change significantly during our debt limit events. These results remain robust with or without year fixed effects. Finally, our *third* measure contributes to the intensive margin by directly using the actual outcome of the debt ceiling events, specifically the percent changes in debt ceilings.

[Insert Figure 4 here]

[Insert Table 5 here]

Next, we discuss the interaction results involving the debt limit dummy and uncertainty variables. This specification is conducted at the firm-quarter level. From Tables 6 and 7, we find that, across various earnings surprise measures (Beat, SUE_1, SUE_2) and the three interaction variables, the predictability result becomes significantly stronger during periods of heightened budgetary uncertainty. The economic magnitude is more straightforward to interpret using the debt limit dummy (Table 6). By comparing the coefficient magnitudes of the main and interaction effects, we observe that the interaction effect accounts for approximately half of the total predictability effect. This explanatory power is slightly higher when continuous SUE measures (rather than the simpler Beat measure) are used as dependent variables.

[Insert Table 6 here]

[Insert Table 7 here]

6 Extensions: Stock Market Implications and Alternative Mechanisms

In this section, we first discuss the stock market implications and then explore the empirical possibilities of alternative mechanisms, such as delayed information (as conceptualized in our model in Section 2) and analyst attention.

6.1 Return Dynamics

We find that announcement-day stock returns respond significantly to procurement exposures in a panel specification. Results are presented in Table 8. Specifically, we project the log of the three-day cumulative abnormal return (i.e., the logarithm of 1 plus the cumulative raw return in excess of the value-weighted market return) over the [-1, 1] window around the earnings announcement day on the procurement exposure variable that we construct and use throughout the paper. Columns (1)-(3) and Columns (4)-(6) show results without and with control variables (as introduced in Table 1), respectively.[11] The results consistently show positive coefficients with similar magnitudes across specifications. A one standard deviation increase in procurement exposure predicts a 0.7% increase in monthly abnormal returns, which translates to an 8.4% per annum stock abnormal returns.

[Insert Table 8 here]

Then, we find that procurement exposures significantly explain stock returns only during the earnings announcement period. This is an economically important finding, as it demonstrates that fiscal risk is priced into stock returns through earnings surprises. To investigate this, we employ a new specification that expands the analysis to the individual firm i-day d level, as follows:

$$aRet_{i,d} = \alpha + \beta_1 \text{Procurement}_{i,t(d)-1} + \beta_2 \text{I}_{i,ann.} + \beta_3 \text{I}_{i,ann.}\text{Procurement}_{i,t(d)-1} + \varepsilon_{i,d}, \tag{11}$$

where $aRet_{i,d}$ denotes a full stock-trading day panel of individual daily abnormal log stock returns, calculated as individual daily log stock return minus the CRSP daily log value-weighted market return (including distributions) for each stock i on trading day d. $\text{Procurement}_{i,t(d)}$ uses the last fiscal quarter's procurement exposure, and therefore

[11] To conserve space, we do not report specific coefficient estimates of control variables, which are available upon request.

$t(d) - 1$ is to indicate the change in frequency. $\mathrm{I}_{i,ann.}$ is an announcement period indicator, using a [-1d, 1d] window where the announcement day corresponds to Day 0. The coefficient of interest is β_3, and we use double-clustered standard errors as in the rest of the paper.

From Table 9, we find that during earnings announcement days, a one standard deviation increase in procurement exposure corresponds to higher abnormal stock returns by 9.1% on an annualized basis. This stock return result remains robustly strong even after adding both *firm* and time fixed effects, whereas our previous result on earnings surprises is robustly strong with industry (or industry $\times$ time) fixed effects but becomes milder when firm fixed effects are used. While the focus of this research is not the relationship between earnings surprises and stock returns, one possible explanation for the pronounced stock return responses is that they also affect the price of risk and the risk premium (i.e., non-expected cash flow state variables) that are not fully captured in earnings expectations.

Figure 5 displays the data and results using high- and low-fiscal exposure firm-day bins, defined using the mean cutoff (see Table A1). Solid bars represent announcement-day average abnormal stock returns, while shaded bars correspond to non-announcement-day averages; both are scaled by the number of days within each bins so that the unit is daily return. As expected, the solid bars are consistently taller than the shaded bars, highlighting the announcement effect. Consistent with the regression results, the high- and low-fiscal-exposure bars for non-announcement days are not statistically different from one another. However, the bars for announcement days display a statistically significant difference, reinforcing the findings.

[Insert Table 9 here]

[Insert Figure 5 here]

6.2 Lack of timely information

Our rational expectation model also predicts that predictability diminishes with information timeliness and precision. Testing this channel empirically is challenging, as we did not work in real time to document when each transaction was posted on `USAspending.gov`, and the website does not report this information. However, our two scraping exercises (10/1/2023-1/18/2024 and 8/8/2024–11/5/2024) discussed in Section 3.2 suggest that most agencies – except for the DoD 90-day mandate due to national security reasons – post transactions to this public domain in a timely manner. It is therefore plausible to believe that major delays in information disclosure are not likely to be the primary mechanism.

In addition, we conduct an event study using the 1,000 largest firm-quarter transactions, assuming that such transactions, due to their sheer magnitude and size, are likely to be well-studied and well-informed. Figure 6 illustrates the results. We do not find evidence that predictability significantly decreased when earnings were announced during the subsequent quarter.

[Insert Figure 6 here]

6.3 Lack of analyst attention to government contracts

Finally, in practice, analysts might pay limited attention to procurement and fiscal risk, which could explain the predictability result. However, this channel appears to have low plausibility given recent literature. Hassan, Hollander, Van Lent, and Tahoun (2019) use state-of-the-art computational linguistics tools and document (among many other findings in their influential paper) that financial analysts are well-attuned to the political risks faced by firms. Nevertheless, we conduct a comprehensive analysis, including some replications of Hassan, Hollander, Van Lent, and Tahoun (2019)'s work. Our findings do not suggest that variation in analyst attention significantly explains the main predictability result.

We first conduct textual analysis in firm-quarter earnings call transcripts (source: Capital IQ), and create a firm-quarter variable that captures analyst mentions of procurement-related keywords. For each transcript, we first identify the total number of words in *paragraphs* spoken by analysts that mention "government contracts" or "procurement contracts" (or their variations) and then divide it by the total number of words in the transcript (excluding operator words) when constructing variable "Analyst_mention1" or by the total number of words spoken by analysts when constructing variable "Analyst_mention2." These two measures are both considered as they capture slightly different concepts. The first measure captures attention to procurement relative to overall length of contents being discussed in the call, while the second measure captures attention to procurement relative to all that analysts talk about.

Figure 7 demonstrates a significant and positive relationship between executive mentions of government contracts and analyst mentions. This observation suggests that active conversations about government contracts occur between executives and analysts, and analyst attention to government contracts reasonably varies with the knowledge shared by firm executives. Then, Table 10 presents the firm-level evidence. Firms with more analyst mentions of government contracts do not exhibit lower predictability.

[Insert Figure 7 here]

[Insert Table 10 here]

7 Conclusion

In this paper, we construct a detailed transaction-level dataset of Federal Government procurement contracts spanning 2009 to 2019. We find that firm-quarter actual procurement earnings (as a fraction of revenue) significantly and positively predict analyst earnings surprises. This predictability intensifies during periods of heightened budgetary uncertainty (e.g., months prior to debt limit events, reflecting higher macro uncertainty) and for firms with lower bargaining power (indicating higher micro uncertainty). The predictability also carries implications for stock returns. Specifically, we find that a one standard deviation increase in procurement exposure corresponds to an 8.4% per annum increase in abnormal stock returns on earnings announcement days.

While government spending can spur growth, deadlines of debt limits each year generate huge uncertainty not only to the political sphere but also the business sphere, which then has real effects. Our paper documents analyst perception of whether and to what extent budgetary uncertainty transmits to the private sector through procurement contracts. Our findings indicate that analysts interpret fiscal uncertainty as “bad” uncertainty.

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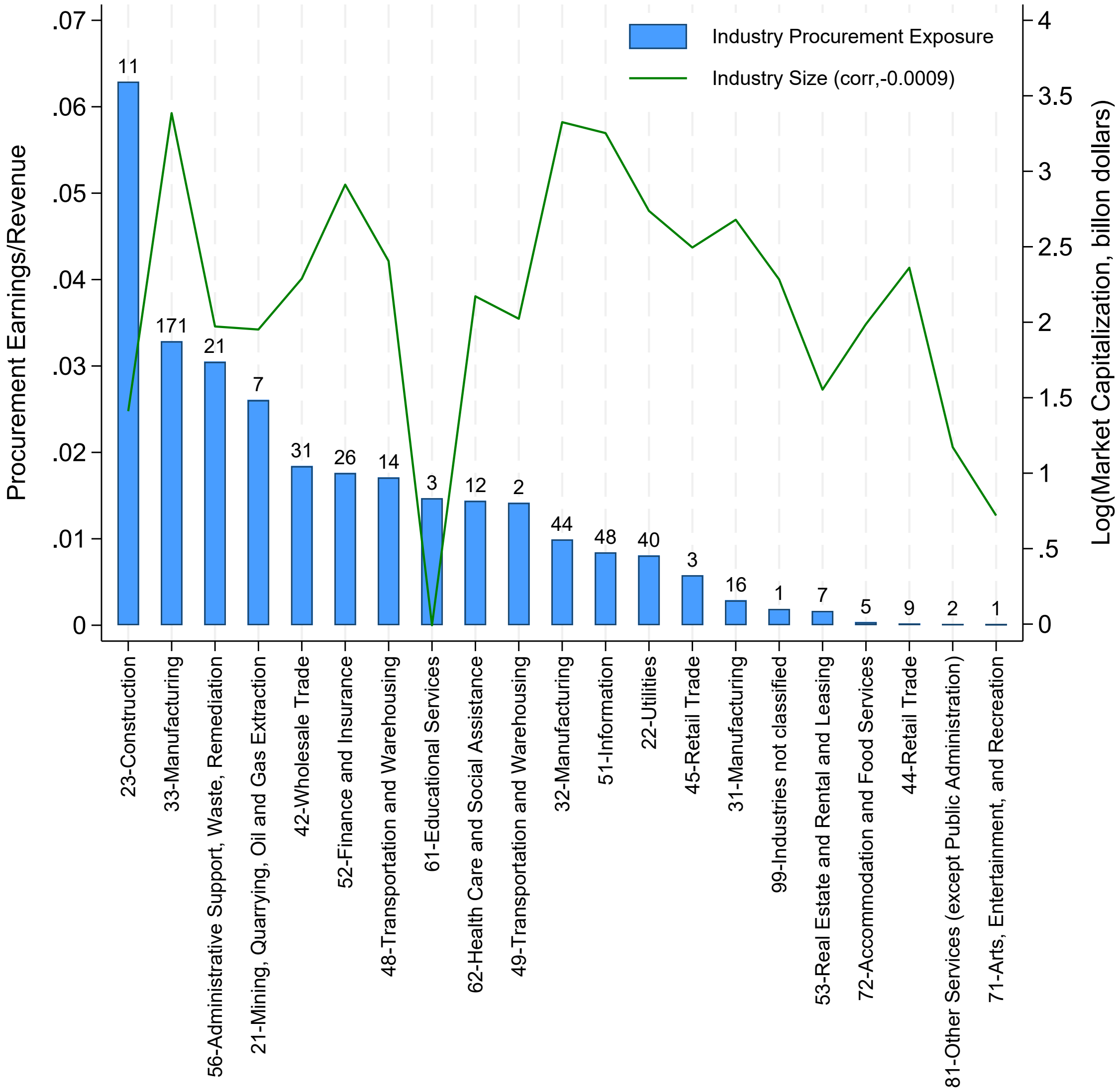


Figure 1: **Firm Sample Description.** This figure describe our firm sample: (1) the number on top of each bar represents the number of firms in each NAICS-2 digit industry classification, and they add up to N=474; (2) the bar denotes average firm-quarter Procurement$_{i,t}$ for each industry, which is calculated as total transaction obligated amount scaled by average quarterly revenues in the past 4 quarters; (3) the solid line denotes the logarithm of total market capitalization (in billion dollars) of each industry represented in our firm sample. The x-axis denotes the industry classification; the left y-axis corresponds to (2), and the right y-axis corresponds to (3). Figure IB.1 in the Internet Appendix also shows where the largest 25% firm-quarter transactions sit.

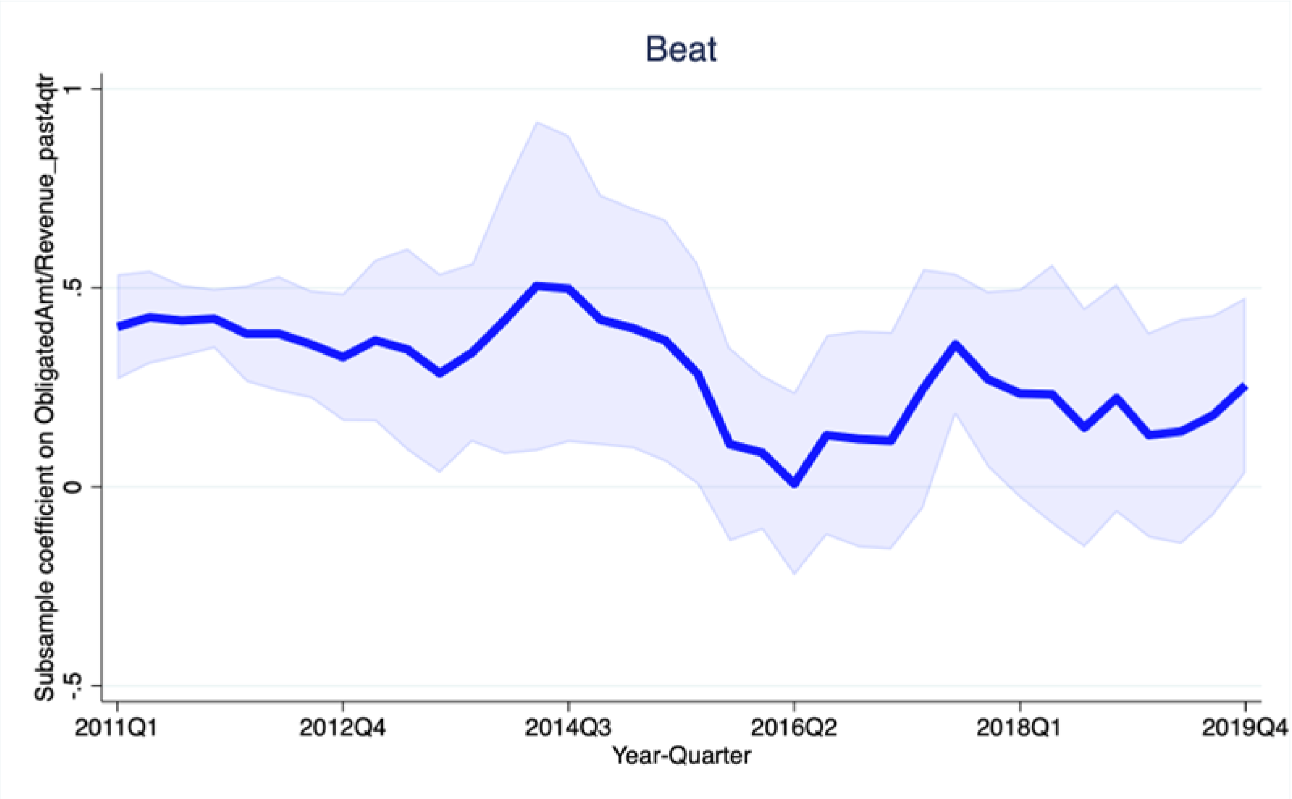


Figure 2: **Rolling Coefficient of the Main Predictive Result.**
This figure depicts the time series of rolling coefficients of "ObligatedAmt/Revenue_past4qtr" in regressions with control variables as shown in Table 1. Each regression uses a rolling window of 8 quarters. Robust standard errors are clustered at firm and calendar year-quarter level. Shaded areas indicate 90% confidence intervals.

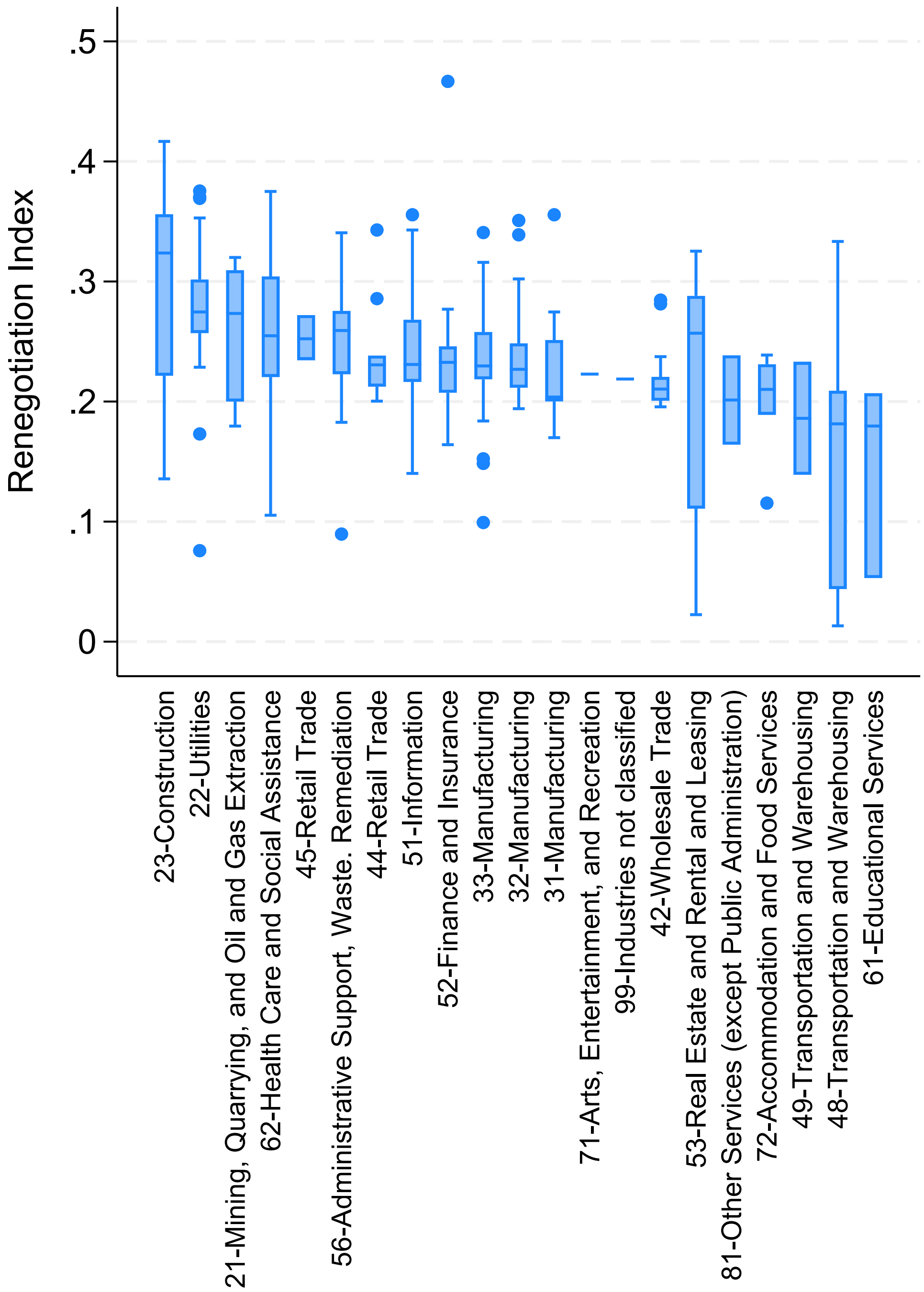


Figure 3: **Renegotiation Index, illustrated by industry.** This plot shows the box plot of firm renegotiation index within each NAICS-2 digit industry.

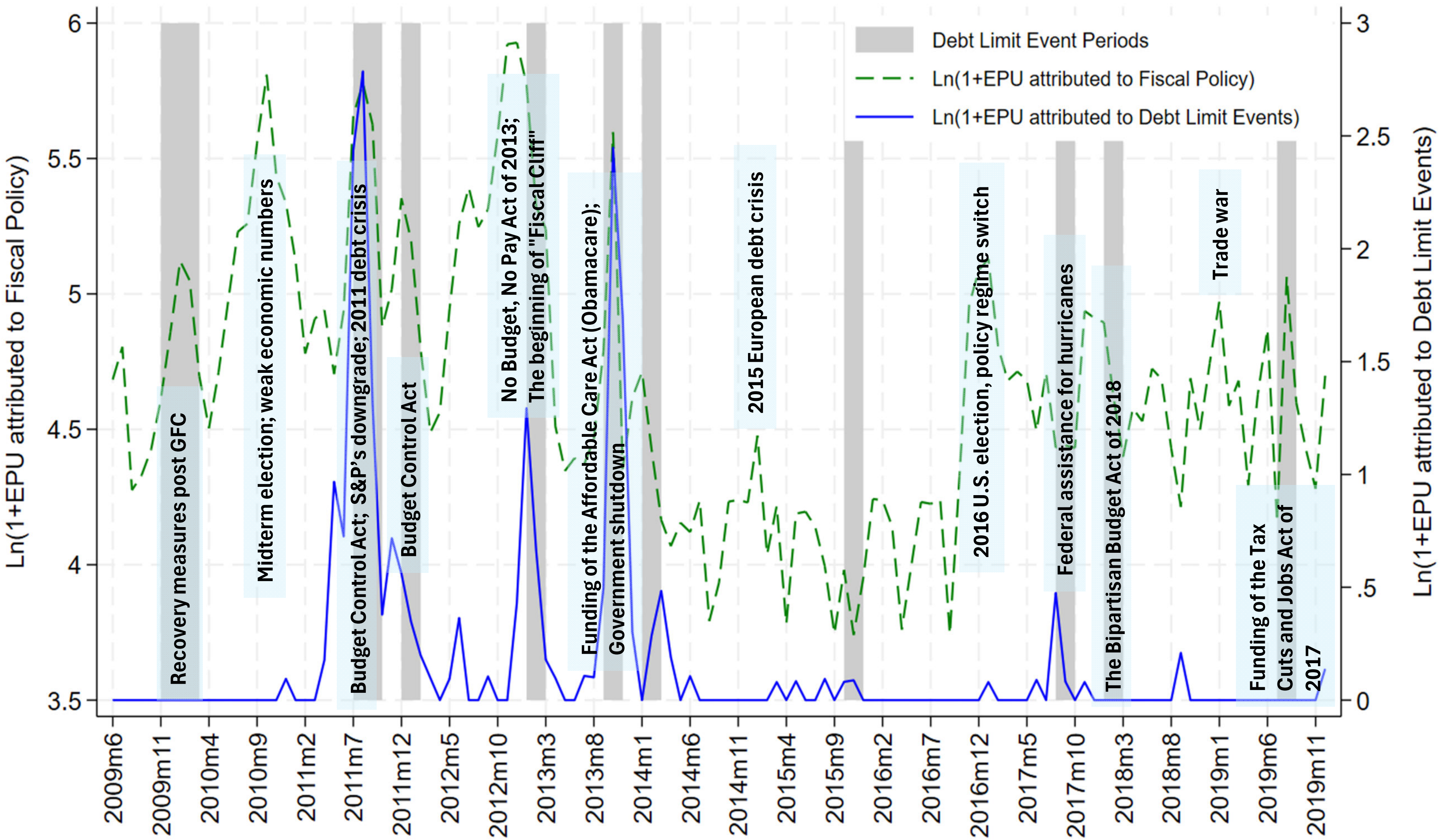


Figure 4: **Fiscal uncertainty interpretation of debt ceiling events.**
This figure illustrates Table 5 in a more direct way; the shaded area indicates the month and the month prior of U.S. debt ceiling events, where the events were obtained from https://www.whitehouse.gov/omb/budget/historical-tables/.

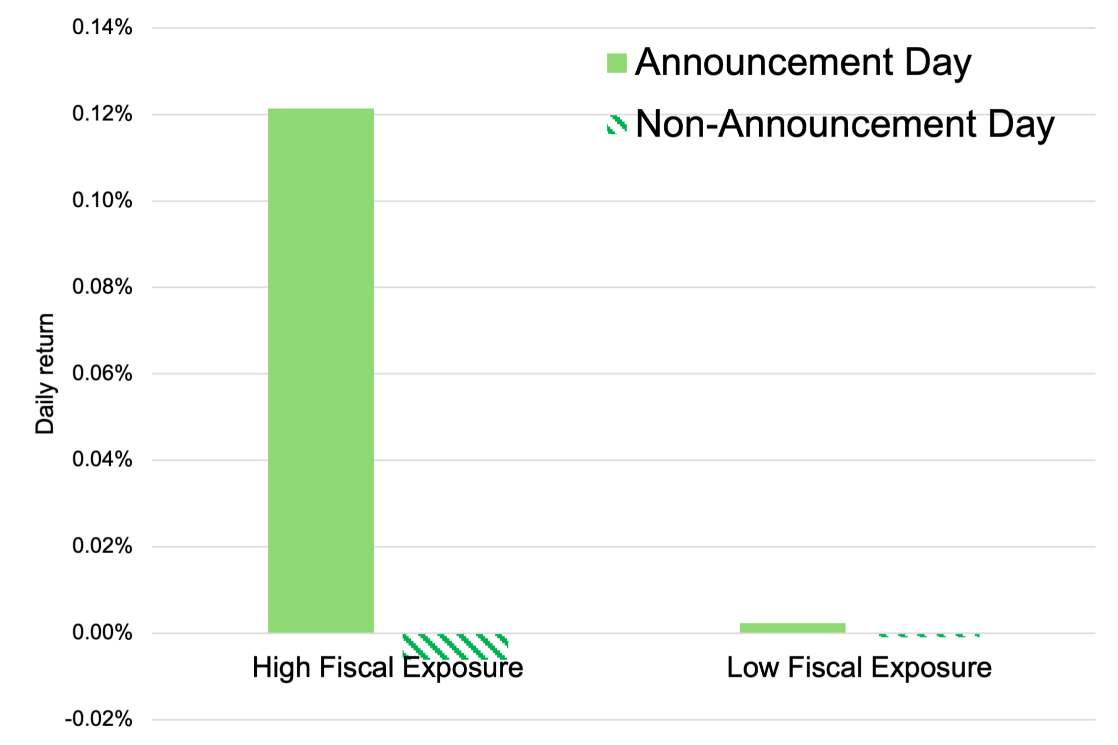
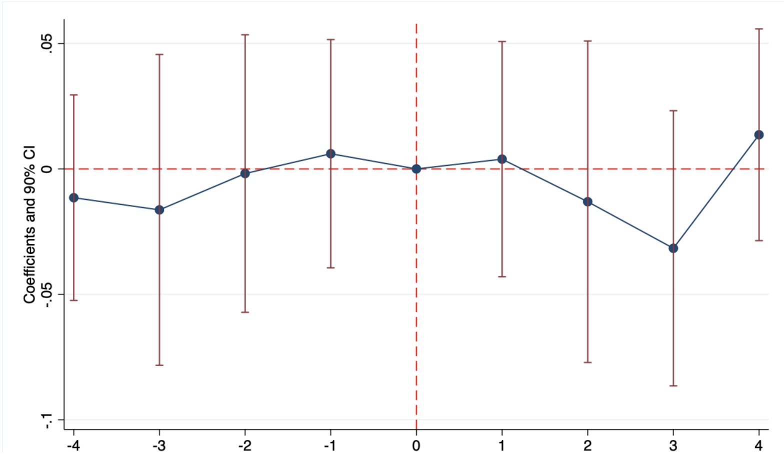
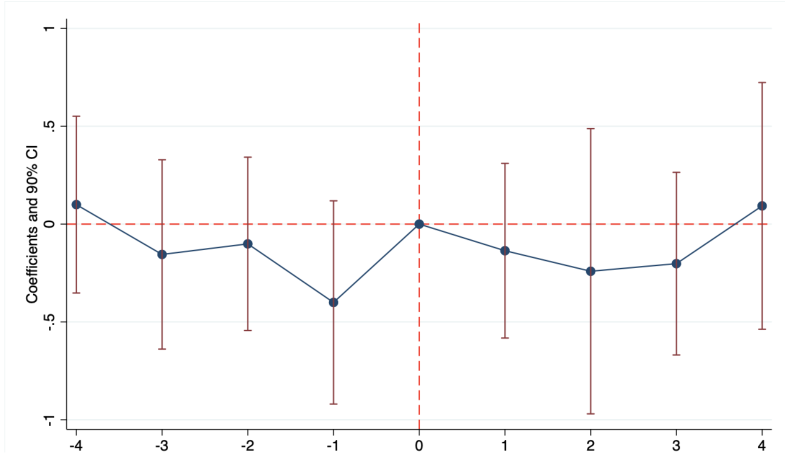


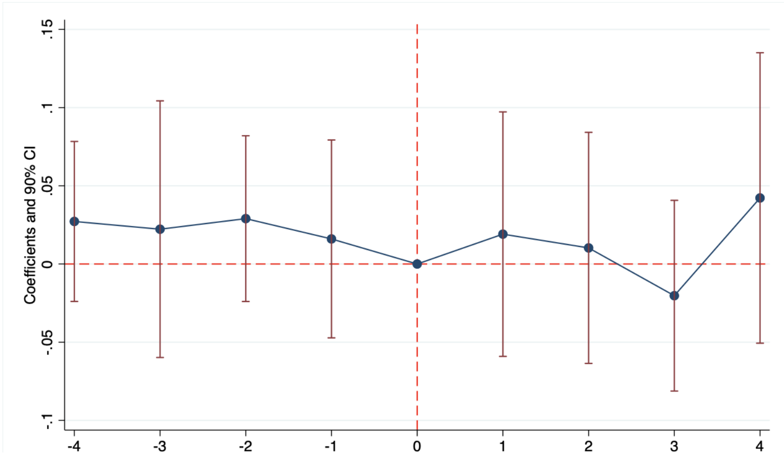
Figure 5: **Announcement vs. Non-announcement day.**
This figure demonstrates average abnormal daily returns in four bins: (high fiscal exposure, low fiscal exposure) x (during announcement periods [-1,1], outside announcement periods). Fiscal exposure is the Procurement variable used as our predictor throughout the paper; and we use its mean as cutoff to separate firm-quarters in high versus low fiscal exposure. This figure demonstrates Table 9 (which uses continuous Procurement measures) in a simple way.



A. Dependent variable: Beat.



B. Dependent variable: SUE_1.

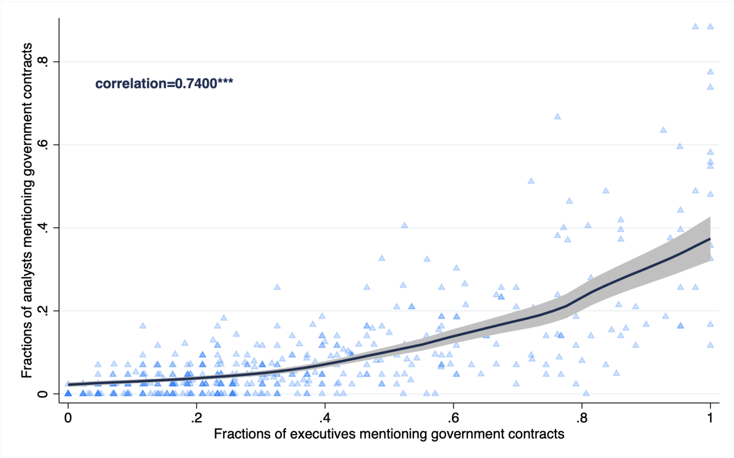


C. Dependent variable: SUE_2.

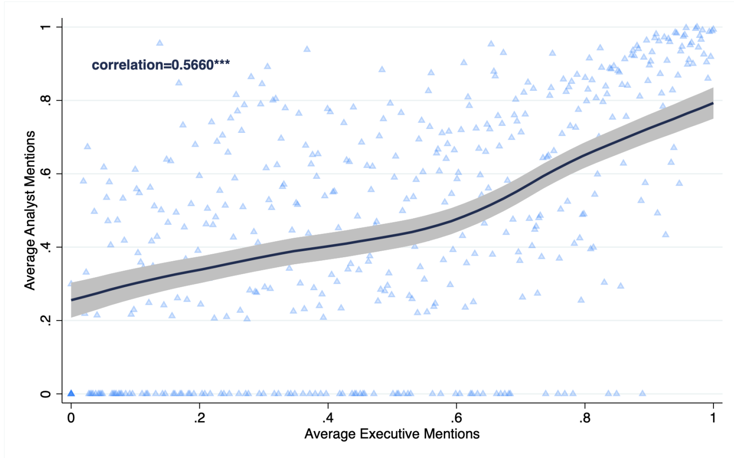
Figure 6: **Event Study using largest 1000 firm-quarter obligated transactions.**
These plots display the regression results of the following specification and show estimates of β_t (and its 90% CI) in the following specification:

$$EarningsSurprise_{i,t} = \alpha_i + \gamma_m + \sum_{t=-4}^{4}(\beta \times (t+5)) + \sum_{t=-4}^{4}(\beta_t \times ObligatedAmt/Revenue\_past4qtr_i \times (t+5)) + \epsilon_{i,t} \ (t \neq 0),$$

where i denotes an event, t denotes the event time (quarter), m denotes the corresponding quarter-end year-month. α_i indicates the event fixed effects, γ_m indicates the year-month fixed effects. $\epsilon_{i,t}$ is the residual term. The three plots use different empirical measures of earnings surprises, as in the rest of the paper.



A. Analyst and executive mentions, scaled by total number of words in the transcript.



B. Analyst and executive mentions, scaled by total number of words in the transcript by analysts and executives, respectively.

Figure 7: **Earnings Call Transcripts: How often do analysts and executives mention government contract-related words?**
This figure demonstrates that analysts' and executives' mentions of government contracts in earnings calls are strongly and positively correlated. Specifically, for each earnings call transcript (firm-time level), we first construct two measures of analyst (executive) mentions of government: (A) number of words in paragraphs spoken by analysts (executives) that mention "government contracts" or "procurement contracts" divided by total number of words in the transcript excluding operator words, (B) and that divided by total number of words in the transcript excluding operator words that are spoken by analysts (executives). For demonstration purpose (as most variation comes from cross-firm), this figure depicts the percentile ranks of firm-level averages. The shaded band (and the solid line within) indicates a local prediction and 95% confidence interval. The correlations using raw analyst and executive averages are 0.67 and 0.74 for plot (A) and (B), respectively.

Table 1: **Main result: Procurement Transactions and Earnings Beat.**
This table shows the main earnings surprise regression results using the panel. The unit of observation is at the firm-quarter level. The specification is also discussed in Equation (xx) or here:

$$\text{Beat}_{i,t} = \gamma_t \times \alpha_{d(i)} + \beta \text{ Procurement}_{i,t} + \boldsymbol{\delta X_{i,t}} + \varepsilon_{i,t},$$

where i denotes a firm and t denotes a quarter. $\text{Beat}_{i,t}$ compares firm i's actual earnings during quarter t and the IBES consensus forecast immediately prior to the earnings announcement (which happens typically some time in quarter $t+1$). $\text{Beat}_{i,t}$ equals 1 if actual beats forecast median, and 0 otherwise. $\text{Procurement}_{i,t}$ is the (obligated) transaction amount from procurement contracts a firm i receives from the government during quarter t, scaled by the firm's past 4 quarter revenue. $\boldsymbol{X_{i,t}}$ denote a series of control variables that are commonly used in the literature. γ_t ($\alpha_{d(i)}$) indicates quarter (industry) fixed effects. Standard errors for columns (1)-(5) are double-clustered at the firm and quarter levels and are reported in parentheses. Column (6) is double-clustered at the NAICS and quarter levels. ***, p-value <1%; **, <5%; *, <10%.

Year-Calendar Quarter FE:		Yes		Yes		Yes
NAICS2 FE:			Yes	Yes		Yes
NAICS2 x Quarter FE:					Yes	
Unit of observation:	Firm-Quarter	Firm-Quarter	Firm-Quarter	Firm-Quarter	Firm-Quarter	NAICS2-Quarter
Panel A: Baseline.						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			*Beat (1 if surprise >0; 0, otherwise)*			
ObligatedAmt/Revenue_past4qtr	0.2722**	0.2676**	0.2716***	0.2656***	0.2624***	0.4781
	(0.1016)	(0.1005)	(0.0946)	(0.0934)	(0.0959)	(0.7051)
Constant	0.6568***	0.6569***	0.6568***	0.6569***	0.6577***	0.6151***
	(0.0100)	(0.0067)	(0.0097)	(0.0062)	(0.0063)	(0.0070)
Observations	16737	16737	16737	16737	16663	824
R-squared	0.0014	0.011	0.014	0.023	0.070	0.18
Panel B: With control variables.						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			*Beat (1 if surprise >0; 0, otherwise)*			
ObligatedAmt/Revenue_past4qtr	0.3074***	0.2983***	0.2860***	0.2752***	0.2693***	0.4221
	(0.0669)	(0.0648)	(0.0665)	(0.0638)	(0.0657)	(0.7636)
Log(1+MarketCap)	0.0232***	0.0236***	0.0269***	0.0272***	0.0272***	0.0056
	(0.0036)	(0.0036)	(0.0037)	(0.0038)	(0.0038)	(0.0317)
Log(1+Book-to-Market)	-0.0793***	-0.0752***	-0.0200	-0.0131	-0.0159	0.0191
	(0.0249)	(0.0265)	(0.0248)	(0.0267)	(0.0281)	(0.1794)
Log(1+Ret_m61tom12)	0.1773***	0.2113***	0.1682***	0.2059***	0.1878***	0.2464*
	(0.0405)	(0.0365)	(0.0410)	(0.0371)	(0.0365)	(0.1409)
Log(1+Ret_m6tom2)	0.6327***	0.6079***	0.6027***	0.5771***	0.5858***	0.7893*
	(0.1040)	(0.1053)	(0.1023)	(0.1047)	(0.1170)	(0.4281)
Log(1+InstitutionOwnPct)	0.2249***	0.2584***	0.1671**	0.1978***	0.1924***	0.5059*
	(0.0586)	(0.0573)	(0.0619)	(0.0603)	(0.0628)	(0.2527)
Log(1+IVOL_m11tom2)	0.2834	0.1834	-0.1873	-0.3836	-0.3237	-3.4837
	(0.6055)	(0.6003)	(0.5693)	(0.5337)	(0.5666)	(2.8030)
Log(1+TOV_m61tom12)	0.5006	-0.3025	0.4217	-0.3888	-0.4311	1.2067
	(1.1470)	(1.1509)	(1.2284)	(1.2030)	(1.2324)	(6.6003)
L.Beat	0.1581***	0.1533***	0.1504***	0.1454***	0.1498***	-0.0278
	(0.0105)	(0.0106)	(0.0107)	(0.0107)	(0.0114)	(0.0568)
Constant	-0.0827	-0.1021	-0.1407	-0.1555	-0.1524	0.2497
	(0.0932)	(0.0941)	(0.0941)	(0.0960)	(0.0964)	(0.8846)
Observations	16696	16696	16696	16696	16622	824
R-squared	0.048	0.056	0.055	0.063	0.11	0.19

Table 2: **Robustness to Table 1: Alternative Measures and Intensive Margin.** This table complements Table 1 by using alternative left-hand-side and right-hand-side variables (from the existing literature) in Panels A and B, respectively, and considering the intensive margin in Panel C. **Notes:** This table only reports the coefficients and SE of main variable of interest, and each column should *not* be read as one regression. For Panels A and B, we discuss exact constructions of alternative measures in Appendix Table IB.1. For Panel C, we include only firms with at least one active transaction (amount!=0) in each quarter (we have 43 quarters in our sample period). Detailed regression results for Panel C is relegated to Appendix Table IB.3. Table IB.4. Standard errors are double-clustered at the firm and quarter levels and are reported in parentheses. ***, p-value <1%; **, <5%; *, <10%.

Year-Calendar Quarter FE:		Yes			Yes	
NAICS2 FE:	Yes	Yes		Yes	Yes	
NAICS2 x Quarter FE:			Yes			Yes
With Controls:				Yes	Yes	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Alternative fiscal dependence measures						
Dependent variable:			*Beat*			
Log(1+ObligatedAmt)	0.0071***	0.0071***	0.0070***	0.0038***	0.0035***	0.0033***
	(0.0012)	(0.0012)	(0.0012)	(0.0011)	(0.0010)	(0.0010)
ObligatedAmt/Revenue_past2qtr	0.2397**	0.2242**	0.2208**	0.2583***	0.2387***	0.2340***
	(0.0977)	(0.0986)	(0.1003)	(0.0690)	(0.0692)	(0.0698)
ObligatedAmt/MarketCap	835.0857***	795.0571**	802.7230**	957.7549***	896.3433***	898.5603***
	(307.7815)	(311.3754)	(314.6267)	(225.4826)	(224.6480)	(224.8623)
Panel B: Intensive margin						
Dependent variable:			*Beat*			
ObligatedAmt/Revenue_past4qtr	0.2570***	0.2434***	0.2479***	0.2162***	0.1886***	0.1896**
	(0.0886)	(0.0873)	(0.0896)	(0.0724)	(0.0694)	(0.0714)
Panel C: Drop Department of Defense-sponsored transactions						
Dependent variable:			*Beat*			
Non-DoD ObligatedAmt/Revenue_past4qtr	1.5338***	1.5205***	1.4992***	1.3415***	1.3041***	1.2687***
	(0.4764)	(0.4845)	(0.5001)	(0.3376)	(0.3423)	(0.3485)
Panel D: Alternative scaled earnings surprise measures						
Dependent variable:			*SUE (surprise, scaled by analyst forecast standard deviation); SUE_1*			
ObligatedAmt/Revenue_past4qtr	3.1667**	3.1109**	3.1061**	2.7052***	2.6122***	2.6074***
	(1.2952)	(1.3056)	(1.3055)	(0.9197)	(0.9207)	(0.9151)
Dependent variable:			*SUE (Froot, Kang, Ozik, and Sadka (2017)); SUE_2*			
ObligatedAmt/Revenue_past4qtr	0.2369*	0.2228*	0.2265**	0.2173*	0.2051*	0.2093**
	(0.1189)	(0.1164)	(0.1091)	(0.1113)	(0.1094)	(0.1009)

Table 3: **Main Result at the Firm Level.**

$$\overline{\text{Beat}}_i = \alpha_{d(i)} + \beta\ \overline{\text{Procurement}}_i + \boldsymbol{\delta}\overline{\boldsymbol{X}}_{\boldsymbol{i}} + \varepsilon_i, \tag{13}$$

where i denotes a firm and the bar above a variable z, $\bar{z}$, denotes average. This table complements Table 1 at the firm level. Panel A collapses variables into the firm level using full sample, 2009-2019, whereas Panel B uses (mostly) equally-spaced subsamples, 2009-2012, 2013-2016, and 2017-2019. Detailed regression results for regressions with controls, (3)-(10), are relegated to Appendix Table IB.5. Standard errors are clustered at the firm level and are reported in parentheses. ***, p-value <1%; **, <5%; *, <10%.

NAICS2 FE		Yes		Yes		Yes
With controls:	Yes	Yes	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Beat	Beat	SUE_1	SUE_1	SUE_2	SUE_2
ObligatedAmt/Revenue_past4qtr	0.3522***	0.3181**	3.9806**	3.9405**	0.2451	0.3103**
	(0.1312)	(0.1249)	(1.6264)	(1.5587)	(0.1911)	(0.1571)
Observations	474	472	474	472	474	472
R-squared	0.25	0.30	0.18	0.25	0.033	0.14

Table 4: **Mechanism Test: Renegotiation and bargaining power with government, micro.**
This table examines whether firms' bargaining power can help explain variation in predictability across firms. For each contract, we first construct three measures of renegotiation level following Brogaard, Denes, and Duchin (2021): (A) an "award increase" indicator that equals one if the cumulative change in potential award amount is greater than zero, (B) an "award extension" indicator that equals one if the cumulative days change in the contract end date is greater than zero, (C) and a "weak monitoring" indicator that equals one if the contract lacks incentive or performance features. We average these three indicator variables within each firm, and further construct the firm-level renegotiation index by summing the three variables with weights of (0.4, 0.4, 0.2). Standard errors are clustered at the firm level and are reported in parentheses. ***, p-value <1%; **, <5%; *, <10%.

NAICS2 FE		Yes		Yes		Yes
With controls:	Yes	Yes	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Beat	Beat	SUE_1	SUE_1	SUE_2	SUE_2
ObligatedAmt/Revenue_past4qtr	1.8460***	1.8182***	2.8207	2.6000*	3.2343**	2.8713***
	(0.6992)	(0.6304)	(1.7933)	(1.3328)	(1.4733)	(1.0401)
Renegotiation Index	-0.1135	-0.1372	0.0403	-0.0123	-0.0757	-0.0807
	(0.1398)	(0.1697)	(0.1279)	(0.1515)	(0.1729)	(0.1765)
ObligatedAmt/Revenue_past4qtr × RenegotiationIndex	-5.7224**	-5.7493**	-7.4934	-6.6797*	-11.5017*	-9.8632**
	(2.8137)	(2.5154)	(5.4513)	(3.9524)	(5.9320)	(4.0963)
Observations	473	471	473	471	473	471
R-squared	0.26	0.31	0.049	0.15	0.070	0.16

Table 5: **Economic interpretations of debt limit events.**
This table provides economic interpretations of debt limit events using time-series regressions and various monthly asset pricing variables. The right-hand-side variable equals one for debt ceiling event month and the previous month, and equals zero otherwise. Figure 4 shows that the debt ceiling events are frequent, typically once a year since 2009. The dependent variables in Columns (1)-(4) are various Baker, Bloom, and Davis (2016)'s Economic Policy uncertainty variables that should capture perceived funamental uncertainty related to fiscal policy, tax, spending, and debt ceiling; for Column (4), we consider a series of EPU divided by EPU without debt ceiling uncertainty. All these EPU series are directly constructed and downloadable from `https://www.policyuncertainty.com/categorical_epu.html`. Columns (5)-(7) capture stock market risk and uncertainty according to the literature, such as Bekaert, Engstrom, and Xu (2022)'s risk aversion index (source: `www.nancyxu.net`), VIX (source: FRED/CBOE), and 22-day realized volatility, the square root of the sum of the daily return-squared within the same month as commonly constructed in the literature (source: authors' calculation; daily S&P500 returns obtained from the DataStream; unit is the same as VIX, i.e., annual volatility percent for comparison purpose). Robust standard errors are reported in parentheses. Columns (5)-(8) also include year fixed effects.

Panel A. Without any fixed effects.

	(1)	(2)	(3)	(4)
Dependent variable:	EPU attributed to Debt Limit Events	Risk Aversion	VIX	RV
is_debtlimit	0.5980***	0.1230	2.1909	2.8876
	(0.2132)	(0.136)	(1.588)	(1.985)
Constant	0.0935***	2.8884***	17.1709***	13.1406***
	(0.0245)	(0.033)	(0.515)	(0.595)
Observations	127	127	127	127
R-squared	0.18	0.014	0.022	0.027

Panel B. With year fixed effects.

	(1)	(2)	(3)	(4)
Dependent variable:	EPU attributed to Debt Limit Events	Risk Aversion	VIX	RV
is_debtlimit	0.4753***	0.0642	1.3420	2.1365
	(0.1529)	(0.103)	(1.071)	(1.603)
Constant	0.1157***	2.8990***	17.3246***	13.2767***
	(0.0298)	(0.022)	(0.377)	(0.548)
Observations	127	127	127	127
R-squared	0.48	0.50	0.55	0.32

Table 6: **Mechanism Test: macro uncertainty, triggered by debt ceiling events.**
This table shows the interaction results using the three dependent variables. "is_debtlimit" is a dummy variable that equals one if a firm-quarter ends in debt limit event month and the month pior (source: whitehouse.gov) and zero otherwise. Standard errors are double-clustered at the firm and quarter levels and are reported in parentheses. ***, p-value <1%; **, <5%; *, <10%.

Year-Calendar Quarter FE:		Yes			Yes			Yes	
NAICS2 FE:	Yes	Yes		Yes	Yes		Yes	Yes	
NAICS2 × Quarter FE:			Yes			Yes			Yes
With Controls:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	Beat	Beat	Beat	SUE_1	SUE_1	SUE_1	SUE_2	SUE_2	SUE_2
ObligatedAmt/Revenue_past4qtr	0.2670***	0.2578***	0.2591***	2.3769**	2.2778**	2.3031**	0.1784	0.1669	0.1773
	(0.0736)	(0.0713)	(0.0734)	(0.9421)	(0.9447)	(0.9392)	(0.1264)	(0.1235)	(0.1131)
is_debtlimit	-0.0079	-0.0063	-0.0072	-0.0921	0.1092	0.0100	-0.0171*	-0.0056	-0.0079
	(0.0102)	(0.0255)	(0.0267)	(0.1045)	(0.2598)	(0.3079)	(0.0101)	(0.0180)	(0.0209)
ObligatedAmt/Revenue_past4qtr × is_debtlimit	0.1195**	0.1062*	0.0621	2.0000**	2.0060**	1.8357**	0.2531**	0.2395**	0.2015**
	(0.0572)	(0.0549)	(0.0773)	(0.7911)	(0.7984)	(0.7773)	(0.1058)	(0.1002)	(0.0906)
Observations	16696	16696	16622	16298	16298	16218	16390	16390	16316
R-squared	0.055	0.063	0.11	0.076	0.083	0.12	0.023	0.030	0.077

Table 7: **Mechanism Robustness: macro uncertainty, triggered by debt ceiling events (intensive margin).** This table complements Table 6 and shows the intensive margin results. For each firm-quarter, Panel A adds an interaction term with Log(1+EPU attributed to debt limit), the logarithm of one plus the monthly average EPU amount attributed to debt ceiling mentions in the news article, whereas Panel B adds an interaction term with the percentage change in the debt ceiling levels if a firm-quarter ends in debt limit event month and the month prior and zero otherwise. Standard errors are double-clustered at the firm and quarter levels and are reported in parentheses. ***, p-value <1%; **, <5%; *, <10%.

Year-Calendar Quarter FE:		Yes			Yes			Yes	
NAICS2 FE:	Yes	Yes		Yes	Yes		Yes	Yes	
NAICS2 × Quarter FE:			Yes			Yes			Yes
With Controls:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	Beat	Beat	Beat	SUE_1	SUE_1	SUE_1	SUE_2	SUE_2	SUE_2
Panel A. Measure with intensive margin: Log(1+EPU attributed to debt limit).									
ObligatedAmt/Revenue_past4qtr	0.2521***	0.2483***	0.2386***	2.3280**	2.2806**	2.2731**	0.1952	0.1875	0.1925*
	(0.0712)	(0.0693)	(0.0717)	(0.9813)	(0.9844)	(0.9765)	(0.1169)	(0.1140)	(0.1050)
Log(1+EPU attributed to debt limit)	-0.0130	-0.0232	-0.0387	-0.1409	0.2437	0.1052	-0.0053	-0.1095	-0.1274
	(0.0111)	(0.0416)	(0.0409)	(0.0869)	(0.3595)	(0.4357)	(0.0095)	(0.1055)	(0.1062)
ObligatedAmt/Revenue_past4qtr × Log(1+EPU attributed to debt limit)	0.1143**	0.0882**	0.1012***	1.2554***	1.0539***	1.0731***	0.0754	0.0621	0.0600
	(0.0492)	(0.0391)	(0.0369)	(0.3582)	(0.3717)	(0.3676)	(0.0699)	(0.0732)	(0.0786)
Observations	16696	16696	16622	16298	16298	16218	16390	16390	16316
R-squared	0.055	0.063	0.11	0.076	0.083	0.12	0.023	0.030	0.078
Panel B. Measure with intensive margin: Percent changes in the actual debt ceiling levels.									
ObligatedAmt/Revenue_past4qtr	0.2679***	0.2576***	0.2562***	2.4817**	2.3957**	2.4243**	0.1897	0.1773	0.1850*
	(0.0705)	(0.0681)	(0.0705)	(0.9251)	(0.9286)	(0.9268)	(0.1187)	(0.1166)	(0.1074)
% Changes in debt ceiling levels	0.0002	0.0014	0.0009	0.0132	0.0349*	0.0291	-0.0013	0.0021	0.0012
	(0.0019)	(0.0019)	(0.0020)	(0.0230)	(0.0200)	(0.0252)	(0.0021)	(0.0018)	(0.0021)
ObligatedAmt/Revenue_past4qtr × % Changes in debt ceiling levels	0.0224***	0.0223***	0.0167**	0.2660***	0.2703***	0.2321***	0.0360**	0.0360**	0.0315**
	(0.0071)	(0.0073)	(0.0075)	(0.0648)	(0.0757)	(0.0732)	(0.0168)	(0.0164)	(0.0152)
Observations	16696	16696	16622	16298	16298	16218	16390	16390	16316
R-squared	0.055	0.063	0.11	0.076	0.083	0.12	0.023	0.030	0.077

Table 8: **Cumulative Abnormal Returns (excess of CRSP value-weighted market returns) on announcement days.**

This table examines fiscal exposure's predictability on cumulative abnormal returns of our panel framework.

$$Log(1 + CAR_{m1to1})_{i,t} = \gamma_t \times \alpha_{d(i)} + \beta \text{ Procurement}_{i,t} + \boldsymbol{\delta X_{i,t}} + \varepsilon_{i,t},$$

where i denotes a firm and t denotes a quarter. $Log(1 + CAR_{m1to1})_{i,t}$ is the cumulative abnormal return (over CRSP value-weighted market return) from day -1 to day 1 around earnings announcement for firm i quarter t. Procurement$_{i,t}$ is the (obligated) transaction amount from procurement contracts a firm i receives from the government during quarter t, scaled by the firm's past 4 quarter revenue. $\boldsymbol{X_{i,t}}$ denote the same series of control variables that used in Table 1. γ_t ($\alpha_{d(i)}$) indicates quarter (industry) fixed effects. Standard errors for columns (1)-(5) are double-clustered at the firm and quarter levels and are reported in parentheses. ***, p-value <1%; **, <5%; *, <10%.

NAICS2 FE	Yes	Yes		Yes	Yes	
Year-Calendar Quarter FE		Yes			Yes	
NAICS2 x Quarter FE			Yes			Yes
With Controls				Yes	Yes	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
			Log(1+CAR_m1to1)			
ObligatedAmt/Revenue_past4qtr	0.0152**	0.0129*	0.0114	0.0142**	0.0130*	0.0117
	(0.0069)	(0.0069)	(0.0073)	(0.0066)	(0.0066)	(0.0071)
Observations	16734	16734	16660	16693	16693	16619
R-squared	0.0020	0.0074	0.054	0.0043	0.0094	0.055

Table 9: **Announcement vs. Non-Announcement Day Stock Excess Returns.**
This table examines the impact of fiscal exposure on stock excess returns around earnings announcement day.

$$aRet_{i,d} = \alpha + \beta_1 \text{Procurement}_{i,t(d)-1} + \beta_2 \text{I}_{i,ann.} + \beta_3 \text{I}_{i,ann.} \text{Procurement}_{i,t(d)-1} + \varepsilon_{i,d},$$

where i denotes a firm and d denotes a trading day. $aRet_{i,d}$ is calculated as individual daily log stock return minus the CRSP daily log value-weighted market return (including distributions) for stock i on trading day d. $\text{Procurement}_{i,t(d)}$ uses the last available fiscal quarter's procurement exposure with a forward filling up to 95 days. $\text{I}_{i,ann.}$ is an announcement period indicator that equals one from day -1 to day 1 around earnings announcement for firm i. Standard errors are double-clustered at the firm and quarter levels and are reported in parentheses. ***, p-value <1%; **, <5%; *, <10%.

Firm FE					Yes	Yes
NAICS2 FE		Yes	Yes			
Year-Calendar Quarter FE	Yes		Yes			Yes
NAICS2 x Quarter FE				Yes		
	(1)	(2)	(3)	(4)	(5)	(6)
			Log Excess Return			
ObligatedAmt/Revenue_past4qtr	-0.0004	-0.0001	-0.0002	-0.0002	0.0001	-0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0009)	(0.0007)
Dummy(In Announcement Day -1 to 1 Window)	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
ObligatedAmt/Revenue_past4qtr × Dummy(In Announcement Day -1 to 1 Window)	0.0054***	0.0054***	0.0054***	0.0055***	0.0054***	0.0054***
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Constant	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	1030270	1030270	1030270	1030270	1030270	1030270
R-squared	0.00043	0.000071	0.00047	0.0020	0.00048	0.00088

Table 10: **Mechanism Test: Lack of Analyst Attention to Government Contracts.**
This table shows whether the cross-firm variation in predictability (from previous tables) can be explained by analyst attention to firms' government contract exposures. Specifically, we construct 2 firm-quarter measures using detailed earnings call transcripts. For each earnings call transcript (firm-time level), we first construct two measures of analyst mentions of government: (A) number of words in paragraphs spoken by analysts that mention "government contracts" or "procurement contracts" divided by total number of words in the transcript excluding operator words, (B) and that divided by total number of words in the transcript excluding operator words that are spoken by analysts. Then, for each firm, "Analyst_measure1" is the average of (A) and "Analyst_measure2" is the average of (B). Results at the firm-quarter level with controls are relegated to Appendix Table IB.6. Standard errors are clustered at the firm level and are reported in parentheses. ***, p-value <1%; **, <5%; *, <10%.

NAICS2 FE:		Yes		Yes
With Controls:	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)
Dependent variable:		Beat		
ObligatedAmt/Revenue_past4qtr	0.3356**	0.3420**	0.3473**	0.3687**
	(0.1673)	(0.1651)	(0.1762)	(0.1729)
Analyst_mention1	1.3365	1.5575		
	(3.2404)	(3.0449)		
ObligatedAmt/Revenue_past4qtr × Analyst_mention1	-2.6421	-10.7303		
	(31.6769)	(31.0956)		
Analyst_mention2			0.3599	0.4666
			(0.5492)	(0.5331)
ObligatedAmt/Revenue_past4qtr × Analyst_mention2			-1.3802	-3.3823
			(5.5642)	(5.5365)
Observations	472	471	472	471
R-squared	0.25	0.30	0.25	0.30

Paper Appendices

A Detailed proof of model in Section 2

(a). Notations.

We first clarify time stamps in the model. Time stamp t always denotes when events arrive. In our context, actual earnings of the last period $t-1$ are announced at time t, so firm actual earnings in period $t-1$ is denoted as $X_{t(t-1)}$, or X_t for simplicity in the rest of the model. Analyst earnings forecast has information set $t-1$ but median forecasts are elicited at time t, so analyst forecast of a firm's cash flow in period $t-1$ is denoted as $X^F_{t(t-1)}$, or X^F_t for simplicity in the rest of the model. Without loss of generality, we ignore firm indicator i for brevity.

(b). Analyst problem.

Analysts solve the following minimization problem:

$$\min_{X^F_t} \mathbb{E}_{t-1}\left[(X_t - X^F_t)^2 + 48\lambda \mathbf{1}_{X^F_t > X_t} \frac{(X^F_t - X_t)^2}{(X^F_t - min(X_t))^2}\right], \tag{A1}$$

where λ (> 1) captures the loss aversion of investors/clients. $X_t - X^F_t$ denotes realized earnings surprise. $\frac{48}{(X^F_t - min(X_t))^2}$ are scaling parameters in order to obtain a closed-form solution under uniform distributed shock assumptions.

(c). Data generating process (for closed-form solution).

Actual earnings of period $t-1$ announced at time t, $X_{t(t-1)}$ or X_t, which is a flow variable, consists of two components: earnings made by retail sales R_t, and earnings paid by government from existing procurement contracts G_t,

$$X_t = R_t + \kappa G_t, \tag{A2}$$

where κ (which would have a superscript i) measures the fiscal dependence of the firm. In the longer term, $\frac{\kappa \bar{G}}{\bar{R} + \kappa \bar{G}}$ corresponds to the fiscal dependence, which is the measure we use in our empirical section.

For simplicity, we assume that analysts can collect sufficient information about retail sales and can form rational expectation about $R_{t(t-1)}$ or R_t with uncertainty following a uniform distribution,

$$R_t = \bar{R} + \eta_t, \text{ where } \eta_t \sim U(-1, 1). \tag{A3}$$

The conditional mean and variance values are then $\mathbb{E}_{t-1}[R_t] = \bar{R}, \mathbb{E}_{t-1}[\eta_t^2] = \frac{1}{3}$.

For government spending during period $t-1$ and known by time t, without loss of generality, we assume that $G_{t(t-1)}$ or G_t has (1) a known smoothing component G_{t-1} (which is government spending during period $t-2$ and known by time $t-1$), (2) a *true* spending deviation from previous period D_{t-1} (which under perfectly timely disclosure and precision of information of these transactions is known during period $t-1$), and (3) an error term ϵ_t:

$$G_t = G_{t-1} + D_{t-1} + \epsilon_t, \tag{A4}$$

$$\epsilon_t \sim U\left(-\frac{\phi}{K}, \frac{\phi}{K}\right). \tag{A5}$$

The error term ϵ_t is core to our model. Parameter ϕ measures the relative risk associated with fiscal spending; in our context, this means that government could change or terminate contracts. Intuitively, higher ϕ indicates higher fiscal uncertainty. Parameter K controls for how precise the *true* spending deviation D_{t-1} is known to analysts. Intuitively, as K goes to inf, analysts know precise information. Lastly, we assume $E(D_{t-1}) = 0$ and denote $E(G_t) = \bar{G}$. The conditional mean and variance values are then $\mathbb{E}_{t-1}[G_t] = G_{t-1} + D_{t-1}, \mathbb{E}_{t-1}[(\epsilon_t)^2] = \frac{\phi^2}{3K^2}$. Both shocks η_t and ϵ_t i.i.d. from each other.

(d). Solving minimizing problem.

Process X_t can be rewritten as

$$X_t = \bar{R} + \kappa G_{t-1} + \kappa D_{t-1} + \eta_t + \kappa \epsilon_t. \tag{A6}$$

After substituting the X_t process to Equation (A1), our minimization problem can be expanded as:

$$\min_{X_t^F} \underbrace{\mathbb{E}_{t-1}\left[(\bar{R} + \kappa G_{t-1} + \kappa D_{t-1} + \eta_t + \kappa\epsilon_t - X_t^F)^2\right]}_{\text{Part 1}}$$
$$+ \underbrace{\mathbb{E}_{t-1}\left[48\lambda \mathbf{1}_{X_t^F > \bar{R} + \kappa G_{t-1} + \kappa D_{t-1} + \eta_t + \kappa\epsilon_t} \frac{(X_t^F - \bar{R} - \kappa G_{t-1} - \kappa D_{t-1} - \eta_t - \kappa\epsilon_t)^2}{(X_t^F - \bar{R} - \kappa G_{t-1} - \kappa D_{t-1} - 1 - \kappa\phi/K)^2}\right]}_{\text{Part 2}}.$$

- Part 1: The first quadratic loss term can be easily derived as $(\bar{R} + \kappa G_{t-1} + \kappa D_{t-1} - X_t^F)^2 + \frac{1}{3}(1 + \kappa^2\phi^2/K^2)$.
- Part 2: The second penalty term has the following closed-form solution: $\lambda \cdot \frac{(X_t^F - \bar{R} - \kappa G_{t-1} - \kappa D_{t-1} + \kappa\phi/K + 1)^2}{\kappa\phi/K}$. We provide the proof next:

- The relevant range is $X_t^F > \bar{R} + \kappa G_{t-1} + \kappa D_{t-1} + \eta_t + \kappa\epsilon_t$. One should integrate only over the range where this condition holds. η_t and ϵ_t are independent, with $f_\eta(\eta_t) = \frac{1}{2} \forall \eta_t \in [-1, 1]$ and $f_\epsilon(\epsilon_t) = \frac{K}{2\phi} \forall \epsilon_t \in \left[-\frac{\phi}{K}, \frac{\phi}{K}\right]$. The joint PDF is $f_{\eta,\epsilon}(\eta_t, \epsilon_t) = f_\eta(\eta_t) \cdot f_\epsilon(\epsilon_t) = \frac{K}{4\phi}, \quad (\eta_t, \epsilon_t) \in [-1, 1] \times \left[-\frac{\phi}{K}, \frac{\phi}{K}\right]$.
- Define $C = \bar{R} + \kappa G_{t-1} + \kappa D_{t-1}$. The double integral question becomes:

$$\text{Part 2} = \tag{A7}$$

$$\frac{48\lambda K}{4\phi(X_t^F - C + 1 + \kappa\phi/K)^2} \cdot \int_{-\frac{\phi}{K}}^{\frac{X_t^F - C + 1}{\kappa}} \underbrace{\int_{-1}^{X_t^F - C - \kappa\epsilon_t} \left(X_t^F - C - \eta_t - \kappa\epsilon_t\right)^2 d\eta_t}_{\text{Part 2.1}} \, d\epsilon_t,$$

And Part 2.1 can be solved as follows:

$$\begin{aligned}
\text{Part 2.1} &= \int_{-1}^{X_t^F - C - \kappa\epsilon_t} \left(X_t^F - C - \eta_t - \kappa\epsilon_t\right)^2 d\eta_t \\
&= \int_{-1}^{X_t^F - C - \kappa\epsilon_t} \left(X_t^F - C - \kappa\epsilon_t\right)^2 d\eta_t + \int_{-1}^{X_t^F - C - \kappa\epsilon_t} -2\left(X_t^F - C - \kappa\epsilon_t\right)\eta_t \, d\eta_t \\
&+ \int_{-1}^{X_t^F - C - \kappa\epsilon_t} \eta_t^2 \, d\eta_t \\
&= \left(X_t^F - C - \kappa\epsilon_t\right)^2 \left(\left(X_t^F - C - \kappa\epsilon_t + 1\right)\right) \\
&- \left(X_t^F - C - \kappa\epsilon_t\right)\left[\left(X_t^F - C - \kappa\epsilon_t\right)^2 - 1\right] \\
&+ \frac{1}{3}\left[\left(X_t^F - C - \kappa\epsilon_t\right)^3 - (-1)^3\right] \\
&= \frac{1}{3}\left(X_t^F - C - \kappa\epsilon_t + 1\right)^3
\end{aligned} \tag{A8}$$

We then substitute Equation (A8) back to Equation (A7), and define $A = X_t^F - C + 1$. The second integral can be solved:

$$\text{Part 2} = \frac{48\lambda K}{4\phi(A + \kappa\phi/K)^2} \cdot \frac{1}{3} \cdot \underbrace{\int_{-\frac{\phi}{K}}^{A/\kappa} \left(A - \kappa\epsilon_t\right)^3 d\epsilon_t}_{\text{Part 2.2}}. \tag{A9}$$

And Part 2.2 can be solved as follows:

$$
\begin{aligned}
\text{Part 2.2} &= \int_{-\frac{\phi}{K}}^{A/\kappa} (A-\kappa\epsilon_t)^3 \, d\epsilon_t \\
&= \int_{-\frac{\phi}{K}}^{A/\kappa} A^3 - 3A^2\kappa\epsilon_t + 3A\kappa^2\epsilon_t^2 - \kappa^3\epsilon_t^3 \, d\epsilon_t \\
&= A^3\left(\frac{A}{\kappa}+\frac{\phi}{K}\right) - \frac{3}{2}A^2\kappa\left(\frac{A^2}{\kappa^2}-\frac{\phi^2}{K^2}\right) + A\kappa^2\left(\frac{A^3}{\kappa^3}+\frac{\phi^3}{K^3}\right) - \frac{\kappa^3}{4}\left(\frac{A^4}{\kappa^4}-\frac{\phi^4}{K^4}\right) \\
&= \frac{1}{4\kappa}A^4 + \frac{\phi}{K}A^3 + \frac{3}{2}\kappa(\frac{\phi}{K})^2A^2 + \kappa^2(\frac{\phi}{K})^3A + \frac{\kappa^3}{4}(\frac{\phi}{K})^4 \\
&= \frac{1}{4\kappa}\left(A+\frac{\kappa\phi}{K}\right)^4. \qquad \text{(A10)}
\end{aligned}
$$

– Finally, we then substitute Equation (A10) back to Equation (A9) and obtain:

$$
\text{Part 2} = \lambda \cdot \frac{(X_t^F - \bar{R} - \kappa G_{t-1} - \kappa D_{t-1} + \kappa\phi/K + 1)^2}{\kappa\phi/K}. \qquad \text{(A11)}
$$

As a result, the objective function can be further simplified into:

$$
\begin{aligned}
\min_{X_t^F} \Bigg[&(\bar{R} + \kappa G_{t-1} + \kappa D_{t-1} - X_t^F)^2 + \frac{1}{3}\left(1+\frac{\kappa^2\phi^2}{K^2}\right) \\
&+ \lambda \cdot \frac{\left(X_t^F - \bar{R} - \kappa G_{t-1} - \kappa D_{t-1} + \frac{\kappa\phi}{K} + 1\right)^2}{\frac{\kappa\phi}{K}} \Bigg].
\end{aligned}
$$

The first-order condition is obtained by differentiating this with respect to X_t^F:

$$
-2(\bar{R} + \kappa G_{t-1} + \kappa D_{t-1} - X_t^F) + \frac{2\lambda}{\kappa\phi/K}(X_t^F - \bar{R} - \kappa G_{t-1} - \kappa D_{t-1} + \kappa\phi/K + 1) = 0. \qquad \text{(A12)}
$$

$$
2(\bar{R} + \kappa G_{t-1} + \kappa D_{t-1} - X_t^F) = \frac{2\lambda}{\kappa\phi/K}(X_t^F - \bar{R} - \kappa G_{t-1} - \kappa D_{t-1} + \kappa\phi/K + 1). \qquad \text{(A13)}
$$

$$
X_t^F = \frac{(\kappa G_{t-1} + \kappa D_{t-1} + \bar{R})(2 + \lambda/(\kappa\phi/K)) - \frac{\lambda(\kappa\phi/K+1)}{\kappa\phi/K}}{2 + \lambda/(\kappa\phi/K)}. \qquad \text{(A14)}
$$

(e). The forecast bias variable.

The expected bias can be derived as a closed-form function, $\text{Surprise}_t(\kappa, \lambda, \phi, K)$:

$$\text{Surprise}_t(\kappa, \lambda, \phi, K) = \bar{R} + \kappa G_{t-1} + \kappa D_{t-1} - X_t^F, \tag{A15}$$

$$= \frac{\lambda(1 + \kappa\phi/K)}{\lambda + \kappa\phi/K} > 0. \tag{A16}$$

Prediction 1: *It is always optimal to underestimate the earnings, as $\kappa, \phi, K > 0$ and $\lambda > 1$.*

(f). Testable predictions.

First, we study the relationship between fiscal dependence κ and Bias. The derivative of Bias with respect to κ, $\frac{\partial \text{Surprise}}{\partial \kappa}$, becomes:

$$\frac{\partial \text{Surprise}}{\partial \kappa} = \frac{\lambda(\lambda - 1)\phi/K}{(\lambda + \kappa\phi/K)^2} > 0. \tag{A17}$$

Prediction 2: *The earnings surprises or biases monotonically increase with fiscal exposure κ, as long as $\lambda > 1$.*

Next, we study how $\frac{\partial \text{Surprise}}{\partial \kappa}$ change with uncertainty ϕ and information precision K, one at a time, more explicitly. We use $g(\phi)$ to denote $\frac{\lambda(\lambda-1)\phi/K}{(\lambda+\kappa\phi/K)^2}$ and differentiate $g(\phi)$ with respect to ϕ using the quotient rule. The numerator is:

$$f(\phi) = \lambda(\lambda - 1)\phi/K,$$

and the denominator is:

$$h(\phi) = (\lambda + \kappa\phi/K)^2.$$

The quotient rule gives:

$$\begin{aligned}
\frac{dg}{d\phi} &= \frac{f'(\phi)h(\phi) - f(\phi)h'(\phi)}{h(\phi)^2}, \\
&= \frac{\frac{\lambda(\lambda-1)}{K}(\lambda + \kappa\phi/K)^2 - \frac{\lambda(\lambda-1)\phi}{K} \cdot 2(\lambda + \kappa\phi/K) \cdot \frac{\kappa}{K}}{(\lambda + \kappa\phi/K)^4} \\
&= \frac{\frac{\lambda(\lambda-1)}{K}(\lambda + \kappa\phi/K)\left[\lambda + \kappa\phi/K - \frac{2\phi\kappa}{K}\right]}{(\lambda + \kappa\phi/K)^4}, \\
&= \frac{\frac{\lambda(\lambda-1)}{K}(\lambda + \kappa\phi/K)\left[\lambda - \frac{\phi\kappa}{K}\right]}{(\lambda + \kappa\phi/K)^4}.
\end{aligned}$$

The denominator of $\frac{dg}{d\phi}$, $\frac{\lambda(\lambda-1)}{K}$, and $(\lambda + \kappa\phi/K)$ are always positive. The key term in the numerator is $\lambda - \frac{\phi\kappa}{K}$. Thus, $\frac{dg}{d\phi}$ is positive if:

$$\lambda > \frac{\phi\kappa}{K}.$$

When λ (loss aversion) is sufficiently large relative to $\phi\kappa/K$ (which can be interpreted as scaled fiscal uncertainty), the predictability of fiscal exposure to earnings surprises or biases (the derivative of the Bias with respect to κ) increases with ϕ. This is likely the case as empirically κ typically is < 0.1 and we observe timely transaction data being posted (i.e., large K).

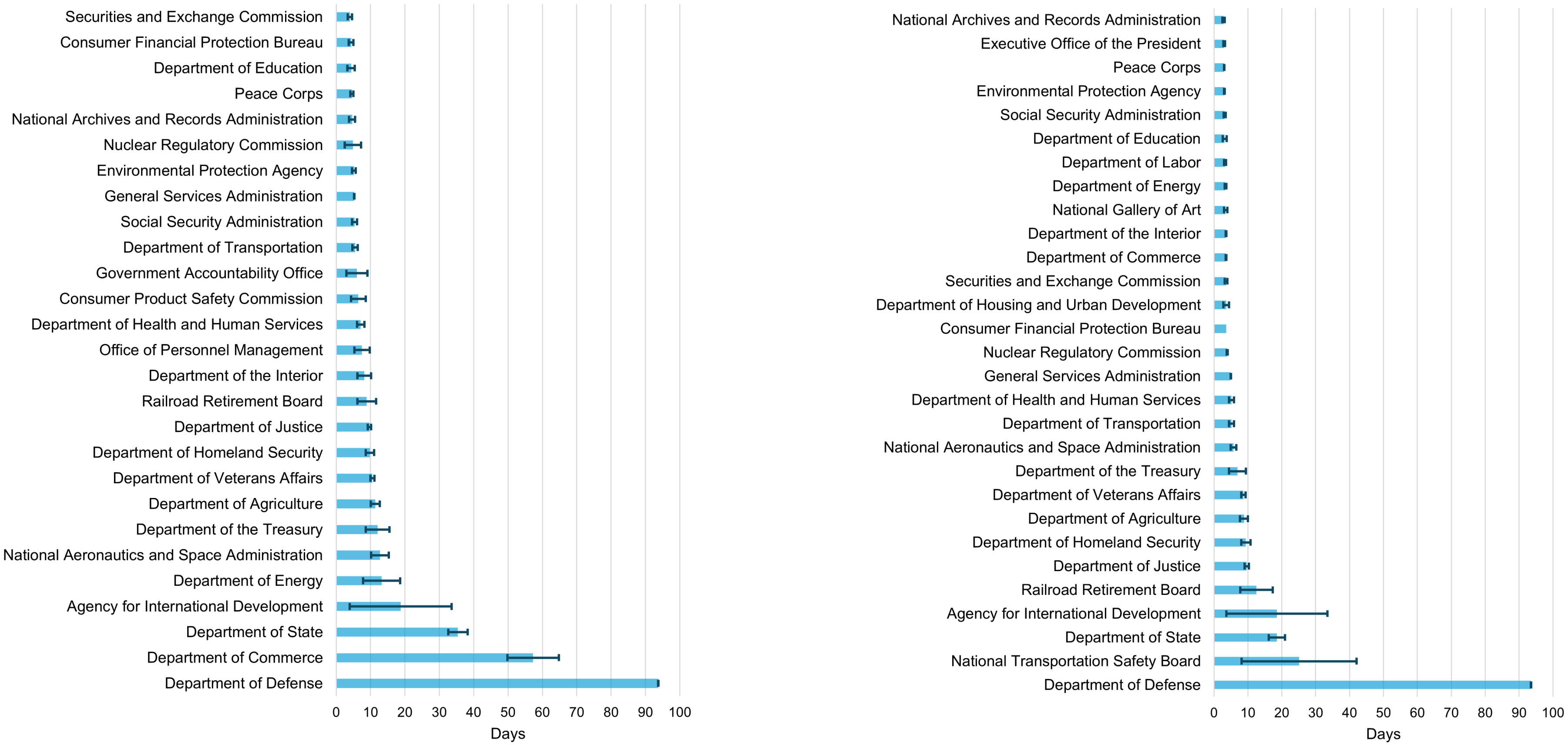
Prediction 3: *Under reasonable parameter assumptions, the predictability of fiscal exposure to earnings surprises or biases should* ***increase*** *with fiscal uncertainty.*

We then use $g(K)$ to denote $\frac{\lambda(\lambda-1)\phi/K}{(\lambda+\kappa\phi/K)^2}$ and differentiate $g(K)$ with respect to K using the quotient rule. Using the quotient rule, let $f(K) = \lambda(\lambda-1)\phi/K$, $h(K) = (\lambda+\kappa\phi/K)^2$. The derivative is:

$$\begin{aligned}
\frac{dg}{dK} &= \frac{f'(K)h(K) - f(K)h'(K)}{h(K)^2}, \\
&= \frac{\left(-\frac{\lambda(\lambda-1)\phi}{K^2}\right)(\lambda+\kappa\phi/K)^2 - \left(\frac{\lambda(\lambda-1)\phi}{K}\right)\left(2(\lambda+\kappa\phi/K)\cdot\frac{-\kappa\phi}{K^2}\right)}{(\lambda+\kappa\phi/K)^4}, \\
&= \frac{-\frac{\lambda(\lambda-1)\phi}{K^2}(\lambda+\kappa\phi/K)(\lambda-\frac{\kappa\phi}{K})}{(\lambda+\kappa\phi/K)^4}.
\end{aligned}$$

The denominator and $(\lambda+\kappa\phi/K)$ is always positive. $(\lambda-\frac{\kappa\phi}{K})$ is positive if $\lambda > \frac{\kappa\phi}{K}$, which is typically satisfied under reasonable parameter values, as also assumed to derive Prediction 3 (see above). Finally, $-\frac{\lambda(\lambda-1)\phi}{K^2}$ is negative if $\lambda > 1$, which is also the general assumption. As a result, $\frac{dg}{dK}$ is negative.

Prediction 4: *Under reasonable parameter assumptions, the predictability of fiscal exposure to earnings surprises or biases should* ***decrease*** *with information precision.*



A. Scraping exercise #1: 10/1/2023–1/18/2024

B. Scraping exercise #2: 8/8/2024–11/5/2024

Figure A1: **Two scraping exercises: Average delay (in days) of transaction data being published on USAspending.gov, sorted by agency.** We discuss the technical details in Section 3.2. In short, on each day, we scrape the entire domain of USAspending.gov; as a result, we capture incremental transactions added and calculate the delay differences in real time. To produce this figure, we sort the transactions by award agencies. The bar chart shows average and its 95% confidence interval.

Table A1: Summary statistics in main results.

	Count	Mean	SD	Min	p5	p25	p50	p75	p95	Max
Panel A. Variables used in the main panel specification (2009/06-2019/12)										
Beat	19027	0.663	0.473	0.000	0.000	0.000	1.000	1.000	1.000	1.000
SUE_1	18602	1.255	3.756	-60.000	-3.250	-0.200	1.000	2.667	6.667	76.000
SUE_2	18710	0.067	0.543	-14.152	-0.390	-0.011	0.044	0.161	0.608	13.757
ObligatedAmt/Revenue_past4qtr	16737	0.021	0.064	0.000	0.000	0.000	0.001	0.008	0.133	0.504
Non-DoD ObligatedAmt/Revenue_past4qtr	16702	0.004	0.013	0.000	0.000	0.000	0.000	0.002	0.027	0.102
Log(1+MarketCap)	19027	22.237	1.766	16.782	19.420	20.979	22.156	23.437	25.356	27.702
Log(1+Book-to-Market)	19027	0.402	0.231	0.001	0.097	0.236	0.365	0.537	0.809	3.450
Log(1+Ret_m61tom12)	19021	0.025	0.124	-1.216	-0.181	-0.038	0.031	0.093	0.206	1.093
Log(1+Ret_m6tom2)	19024	0.003	0.040	-0.685	-0.060	-0.016	0.005	0.024	0.062	0.264
Log(1+InstitutionOwnPct)	19027	0.586	0.099	0.000	0.412	0.534	0.604	0.654	0.707	1.786
Log(1+IVOL_m11tom2)	19023	0.016	0.009	0.002	0.006	0.010	0.014	0.019	0.032	0.197
Log(1+TOV_m61tom12)	19021	0.008	0.005	0.000	0.003	0.005	0.007	0.009	0.016	0.150
Panel B. Variables used in the main cross-sectional specification										
Beat	474	0.660	0.154	0.235	0.395	0.558	0.674	0.767	0.907	1.000
SUE_1	474	1.240	1.328	-4.397	-0.695	0.484	1.114	1.829	3.566	9.169
SUE_2	474	0.068	0.147	-0.700	-0.133	0.020	0.059	0.116	0.288	0.786
ObligatedAmt/Revenue_past4qtr	474	0.021	0.054	0.000	0.000	0.000	0.002	0.013	0.133	0.321
Non-DoD ObligatedAmt/Revenue_past4qtr	474	0.004	0.011	0.000	0.000	0.000	0.001	0.003	0.025	0.065
Log(1+MarketCap)	474	22.182	1.725	17.992	19.350	20.875	22.155	23.399	25.222	26.901
Log(1+Book-to-Market)	474	0.403	0.196	0.026	0.120	0.259	0.378	0.523	0.761	1.438
Log(1+Ret_m61tom12)	474	0.024	0.019	-0.099	-0.004	0.014	0.026	0.036	0.051	0.084
Log(1+Ret_m6tom2)	474	0.003	0.008	-0.038	-0.010	-0.001	0.004	0.007	0.015	0.028
Log(1+InstitutionOwnPct)	474	0.584	0.090	0.185	0.428	0.531	0.602	0.650	0.695	0.752
Log(1+IVOL_m11tom2)	474	0.016	0.005	0.007	0.009	0.012	0.015	0.019	0.025	0.035
Log(1+TOV_m61tom12)	474	0.008	0.003	0.002	0.004	0.005	0.007	0.009	0.014	0.029
Panel C. Interaction variables										
Renegotiation Index	473	0.238	0.052	0.013	0.172	0.211	0.231	0.264	0.324	0.467
is_debtlimit	19027	0.124	0.330	0.000	0.000	0.000	0.000	0.000	1.000	1.000
debtlimit_chgratio	19027	0.006	0.022	0.000	0.000	0.000	0.000	0.000	0.034	0.292
Log(1 + Monthly Average EPU Attributed to Debt Ceiling within each firm-quarter)	19027	0.224	0.540	0.000	0.000	0.000	0.030	0.212	1.147	2.756
Log(1 + Monthly Average Risk Aversion within each firm-quarter)	19027	1.362	0.089	1.254	1.266	1.300	1.340	1.386	1.533	1.669
Log(1 + Monthly Average VIX within each firm-quarter)	19027	2.888	0.259	2.406	2.471	2.753	2.822	3.017	3.419	3.579
Log(1 + Monthly Average RV within each firm-quarter)	19027	2.626	0.354	1.943	2.098	2.418	2.588	2.827	3.300	3.614