Externalities of Accounting Disclosures: Evidence from the Federal Reserve

Edward Li*, Gary Lind**, K. Ramesh**, and Min Shen*

*Baruch College
**Rice University

October 2018

Abstract

Using unique data that track the Federal Reserve's direct access of SEC filings, we provide evidence that accounting disclosures are associated with the Fed's economic forecasts and, by extension, its monetary policy. We find that the Fed's access of SEC filings reflects economic trends as well as the Fed's demand for "granular" firm information to better assess the state of the economy and its prospects. In addition to aggregated quantitative information in accounting disclosures, we show that qualitative information in Fed-accessed filings is predictive of the Fed's economic growth forecasts, beyond information in commercial forecasts. Overall, the study identifies an important macroeconomic externality of accounting disclosures.

JEL Classification: E58, G20, M41, M45
Keywords: Disclosure; Externalities; Federal Reserve; Economic Forecasts; Qualitative Information; SEC Filings

We thank Ray Ball, Anne Beatty, Zahn Bozanic, Mike Drake, Umit Gurun, Jeff Hoopes, Bret Johnson, Yaniv Konchitchki, Venky Nagar, Shiva Rajgopal, Christina Romer, David Romer, Darren Roulestone, Gil Sadka, Siew Hong Teoh, Jake Thomas, Jake Thornock, Mark Wallis (discussant), Leon Zolotoy, the workshop participants at Indiana University, Michigan State University, The Ohio State University, the University of Texas at Dallas, the University of Florida, the University of Utah, and Washington University in St. Louis, as well as attendees at the 2016 Washington University Dopuch Conference PhD Student Poster Session, the 2017 BYU Accounting Research Symposium, the 2018 UTS Australian Summer Accounting Conference, Gabriel Ehrlich and Aditi Thapar of Universtiy of Michigan's Research Seminar in Quantitative Economics, and Steve Sharpe of the Federal Reserve for helpful comments and suggestions. We are also grateful to Dejan Suskavcevic and Amber Lo for their research assistance.

1 Introduction

In this study, we investigate whether the Federal Reserve (the Fed) uses information from mandated accounting disclosures to inform its economic forecasts and, by extension, its monetary policy decisions. Using unique data that track the Fed's *direct* access of corporate SEC filings between Federal Open Market Committee (FOMC) meetings, we show that qualitative information in Fed-accessed filings incrementally explains the Fed's economic forecasts beyond information in commercial forecasts supplied by the Survey of Professional Forecasters (SPF). Consistent with the Fed's posited expertise in predicting macroeconomic outcomes (Romer and Romer 2000; Rossi and Sekhposyan 2016; Peek, Rosengren, and Tootell 2003), we find that such qualitative information is not reflected in the SPF's GDP forecasts, and in fact, we provide evidence that it helps predict SPF forecast errors.

Our findings provide the first empirical evidence that the Fed accesses micro-level accounting disclosures to better understand the state of the macroeconomy. The results on the Fed forecasts incorporating qualitative information from accounting reports are, to our knowledge, novel in the literature, and support the Fed's purported "attention to ... non-quantitative information" (Sims 2002, p.15). Our results indicate that, in addition to incorporating qualitative information, the Fed also uses quantitative data in its forecasts of future economic growth. Given the Fed's crucial role in the macroeconomy and financial markets, our study serves as a preliminary step towards understanding accounting disclosures' externalities, especially on "macroeconomic outcomes" and their "contribution to the stability of financial markets" (Leuz and Wysocki 2016, p. 600-602).

Our investigation is motivated by three observations. First, there is a growing body of evidence that aggregated accounting information contains relevant macroeconomic signals. Studies have shown that aggregate accounting numbers are correlated with macroeconomic indicators such as GDP (Konchitchki and Patatoukas 2014a), inflation (Konchitchki 2011), as well as revisions of macroeconomic indicators (Nallareddy and Ogneva 2017) and monetary policy (Gallo, Hann, and

Li 2016; Crawley 2015). While these results are consistent with a strong association between accounting information and macroeconomic phenomena, there is a lack of evidence directly linking such information to specific macroeconomic uses. Our identification strategy of tracking the Fed's direct access of SEC filings allows us to fill this void.

Second, recent research in economics suggests a granular origin for macroeconomic fluctuations. Gabaix (2011) shows that a large portion of variation in aggregate quantities arises from idiosyncratic shocks to individual firms (Acemoglu et al. 2012; di Giovanni, Levchenko, and Méjean 2014; di Giovanni and Levchenko 2012). Such firms are considered the "incompressible grains" of the economy that characterize a granular origin of aggregate fluctuations. As a result, firm-level financial reports can potentially be useful in explaining and predicting macroeconomic fluctuations. Our ability to track the Fed's access of specific firms' accounting disclosures enables us to test whether this behavior is consistent with the economic theory on the granularity of firm-level shocks.

Lastly, many features of SEC filings make them a desirable information source for the Fed. The filings are mandated, and therefore, all registrants must satisfy a minimum disclosure requirement regardless of managerial incentives. These disclosures are timely and available in both good and bad times, an important consideration for the Fed, whose demand for information likely increases during economic contraction when there are more urgent calls for policy actions. Also, SEC filings are often audited or reviewed and subject to anti-fraud provisions of securities law, which provide assurance of high information quality. Furthermore, these filings also include extensive qualitative information that could be useful in evaluating the state of the economy, as they potentially provide a subjective managerial assessment of economic prospects that cannot be readily quantified (Sims 2002).

Notwithstanding these reasons, we note that the Fed's reliance on firm-level accounting disclosures as a source of information for policymaking is not self-evident. Recent work has shown that, while accounting information is predictive of future GDP growth, even professional macroeconomic forecasters do not fully incorporate such information in their forecasts (Konchitchki and Patatoukas 2014a). Konchitchki and Patatoukas (2014a) also argue that statements and minutes from FOMC meetings rarely, if ever, refer to accounting earnings when discussing overall economic activity (p. 79). Therefore, the ability of the Fed to better incorporate such information is of empirical import. In addition, because aggregated quantitative data are available on a timely basis from services like Compustat (D'Souza, Ramesh, and Shen 2010), it is unlikely that the Fed devotes significant human capital to access and compile such data. However, relying on the Fed's revealed preference for select firm disclosures, we can test whether its ability to extract relevant *qualitative* information from targeted SEC filings is a source of its knowledge capital. Such information is difficult to extract systematically but can add important contextual value (Drake, Roulstone, and Thornock 2016). With vast resources at its disposal (e.g., $398 million in staff salaries for 2016), the Fed is arguably well equipped to decipher such contextual information.[1]

Using the EDGAR Internet traffic data, we base our analysis on 169,003 observations from Fed-accessed SEC filings between March 2003 and February 2015. In the first set of analyses, we test whether the Fed's access varies predictably with the objective of acquiring granular information that helps assess the status of the economy and its financial stability. In the second set of analyses, we examine whether the information in Fed-accessed SEC filings is related to the Fed's macroeconomic forecasts, and if so, whether such information reflects the Fed's knowledge capital when compared to commercial forecasters.

Addressing the first question, we examine factors that determine the intensity of the Fed's access at three different levels. At the macro level, we find that the overall access intensity increases when the economy performs poorly or the financial system becomes less stable. These results hold for both financial and non-financial sectors, with more than 50 percent of the Fed's access focusing on the non-financial sector. At the industry and firm levels, we find that the Fed accesses more filings from the banking industry and from firms with "granular" importance—bellwethers, firms

1. See https://www.federalreserve.gov/publications/2016-ar-federal-system-budgets.htm

designated as Systemically Important Financial Institutions (SIFIs), industry leaders, participants in the commercial paper market, inventory-intensive firms, and firms with a high risk of a stock price crash.

Collectively, such evidence is consistent with our predictions that the Fed acquires more information in times of poor economic performance, and focuses more on industries and firms that are critical to economic growth and financial stability. Importantly, our results highlight the Fed's interest in a broad set of firms beyond the financial sector, which supports the notion that the Fed finds value in collecting micro-level accounting information from a wide range of firms as it seeks to understand the economy.

Turning to the second question, we first test whether information in Fed-accessed filings is related to its economic forecasts. We measure qualitative information by aggregating the Loughran and McDonald (2011) (LM) tone measure of SEC periodic reports that the Fed accesses between FOMC meetings. We regress each FOMC meeting's nominal GDP (NGDP) growth forecasts on this aggregated qualitative information and on aggregated corporate earnings, and find significant economic and statistical relations between the Fed's forecasts and both types of accounting information. Specifically, the results indicate that the Fed's forecasts increase as aggregate earnings increase and decrease as the aggregate tone of Fed-accessed filings becomes more negative. As an important counterfactual analysis, we replace Fed access with all non-Fed, human access of SEC filings between FOMC meetings and find no relationship between the Fed's forecasts and this counterfactual measure. These results support the notion that the Fed's forecasts reflect information from a select set of SEC filings, rather than simply correlate with general trends in tone.

To mitigate concerns that the tone measure is correlated with omitted variables, we include SPF forecasts as controls. These widely-used and respected forecasts are inputs for the Fed's own forecasts (Konchitchki and Patatoukas 2014a), and serve as a proxy for aggregating all other observable economic information (Romer and Romer 2000). In these tests, qualitative information from Fed-accessed filings continues to predict the Fed's forecasts beyond information in SPF's forecasts and aggregated accounting earnings. These results hold across multiple forecast horizons.[2]

To further test the link between Fed-accessed accounting information and its macroeconomic forecasts, we examine the properties of Fed and SPF forecast errors. We find that neither aggregate earnings nor the qualitative information in Fed-accessed filings are related to the Fed's own forecast errors. However, when we repeat these tests using the SPF's forecast errors, we find evidence that the SPF's forecast errors are predictable using the qualitative data from Fed-accessed filings, indicating that the SPF does not fully incorporate such information in its forecasts.

In our final tests, we further show that aggregate earnings data and the qualitative information in Fed-accessed filings predict the Fed's forecasts for components of aggregate supply and demand such as personal consumption expenditures, industrial production, business fixed investment, and housing starts. However, aggregate earnings and negative tone have little to no association with the Fed's inflation forecasts (i.e. the personal consumption price index and the GDP price index), consistent with inflation being inherently more difficult to predict (Sims 2002). Our results are robust to a number of alternative specifications and measures, and paint a consistent picture that both quantitative and qualitative accounting information inform the Fed's macroeconomic forecasts. We also offer evidence that the Fed is able to identify relevant information from a large repository of corporate disclosures. Taken together, the evidence suggests that accounting disclosures have important macroeconomic externalities.

Our results and inferences are subject to several caveats (see Section 4.4). First, we cannot rule out the possibility that the Fed uses the SEC filings of select firms only for the purpose of confirming information it may have obtained from sources that are not publicly observable. Even if that were the case, our findings would still be consistent with the Fed's reliance on granular firm-level information. Second, systemically-important firms could strategically manage their dis-

2. Consistent with professional forecasters not fully capturing the macro information in quantitative accounting disclosures (Konchitchki and Patatoukas 2014a, 2014b), we find that the Fed's forecasts are associated with aggregate earnings after controlling for SPF forecasts and qualitative information in Fed-accessed SEC filings.

closures to influence the Central Bank's monetary policy, thereby eliciting a predictable economic growth forecast from the Fed. While our research design cannot eliminate such a possibility, our evidence still suggests that the Fed is influenced by corporate disclosures. Finally, the Fed, through its own monetary policy, could predetermine the future state of the economy such that its forecasts become self-fulfilling prophecies. However, the Fed's forward-looking monetary policy and the extensive economics literature on Fed forecasts suggest otherwise (Romer and Romer 2000).

The paper continues as follows: Section 2 briefly reviews relevant literature and develops our hypotheses. Section 3 describes our sample and data methods. Section 4 describes our empirical tests and results. Section 5 concludes.

2 Motivation and Hypotheses

2.1 Motivation and Research Design

There is a burgeoning literature on the macroeconomic effects of corporate disclosure. A number of studies test whether well-known firm-level relations regarding such disclosures hold at the aggregate level. For example, Kothari, Lewellen, and Warner (2006) find a negative relation between aggregate earnings and aggregate returns, consistent with a positive covariance between aggregate earnings and discount rate news (Sadka and Sadka 2009). Using a principal component analysis, Ball, Sadka, and Sadka (2009) also show that shocks in aggregate earnings contain a non-diversifiable component that is highly correlated with priced systematic risk. Further, Patatoukas (2014) finds that aggregate earnings are associated with both cash flow news and the expected discount rate news components (Campbell 1991) and suggests that the low/negative earnings response coefficient at the aggregate level stems from the positive relation between cash flow news and discount rate news.

Other studies in this literature examine the relation of aggregate earnings guidance with earnings news and market returns (Anilowski, Feng, and Skinner 2007), aggregate accruals and cash flows with market returns (Hirshleifer, Hou, and Teoh 2009; Bonsall, Bozanic, and Fischer 2013), earnings dispersion with aggregate stock returns (Jorgensen, Li, and Sadka 2012), inflation in the macroeconomy with firm-level cash flows and returns (Konchitchki 2011, 2013), and earnings changes with aggregate corporate bond returns (Gkougkousi 2014). Other research shows that aggregate accounting profitability measures can predict future GDP growth and the likelihood of a recession (Konchitchki and Patatoukas 2014a, 2014b). Collectively, this stream of research has shown important connections between aggregated firm-level information and various facets of the macro economy (for a summary, see Ball and Sadka (2015)).

More recent work explores how aggregate accounting information can affect macroeconomic policy. Gallo, Hann, and Li (2016) find that aggregate earnings contain information about macroeconomic trends and implied future Fed policy, and that the market, inferring the effects on monetary policy, reacts negatively to these policy surprises. Crawley (2015) shows that accounting conservatism aggregates from the firm level into GDP components and thereby influences macroeconomic policy, though these findings are disputed by Laurion and Patatoukas (2016), who argue that accounting conservatism is neutralized in the National Income and Product Accounts. Finally, Nallareddy and Ogneva (2017) connect aggregate accounting information to macroeconomic policy by showing that information in earnings growth dispersion helps predict future restatements to nominal and real GDP growth figures.

We connect this developing literature with recent work in economic theory on the granular origins of macroeconomic fluctuations. Gabaix (2011) shows that the conventional assumption about diversification of idiosyncratic risk breaks down if the distribution of firm size features a fat tail. His tests are consistent with the predictions of his model, suggesting that the idiosyncratic fluctuations of the economy's 100 largest firms explain a third of variations in output growth. di Giovanni, Levchenko, and Méjean (2014) provide further empirical evidence that supports this assertion. Other recent papers have shown that shocks to important sectors can have a "cascade effect" that propagates to the macro level (Acemoglu et al. 2012), and that idiosyncratic shocks to large firms can interact with the size of the economy to create macroeconomic volatility (di Giovanni and Levchenko 2012).

Our study brings together these two literatures to shed light on an externality of accounting disclosures with macroeconomic implications. We do so by examining the Fed's access of SEC filings. These filings are a desirable source of information for the central bank due to their timely and periodic availability and their high quality as shaped by capital market demand and disclosure regulations. These disclosure characteristics are critical for the Fed, especially during economic contraction when there are more urgent economic and political needs for policy interventions (Koenig 2005).

However, the Fed's reliance on accounting information is not self-evident. Results from Konchitchki and Patatoukas (2014a, 2014b) indicate that, despite the fact that quantitative accounting information incrementally predicts future GDP growth, even reputable macroeconomic forecasters (the SPF) seem to underweight such information. In fact, the Fed's use of such information is arguable as Konchitchki and Patatoukas indicate that the Fed's statements and minutes from FOMC meetings do not extensively refer to accounting earnings. On the other hand, as we note below, the Fed has consistently discussed corporate profits and financing in its annual reports when describing the state of the economy and assessing its prospects. Overall, whether or not the Fed relies on accounting disclosures to inform its forecasts of macroeconomic outcomes is an unanswered empirical question that we seek to study.

In testing whether the Fed is informed by accounting disclosures, the challenge is to choose a robust research design for identification. Given that many variables shape the Fed's production function for macroeconomic policy, academic research cannot completely open the black box of the Fed's information capital that shapes such policy. Using the EDGAR Internet traffic data, we take a first step in causation by identifying the specific corporate disclosures the Fed accessed and testing whether the information in such disclosures are predictably associated with time-series variations in the Fed's forecasts.[3]

Because the general public is not contemporaneously aware of the Fed's access patterns, we also test whether the information in the Fed-accessed disclosures is correlated with the SPF's forecasts to provide evidence on a key source of correlated omitted variables, i.e., information relied on by another important macroeconomic agent.[4] While commercial forecasters' reliance on information in Fed-accessed filings would not nullify the Fed's use of such information, it would make the identification more challenging. Furthermore, we conduct additional tests on whether our results can be explained by the SEC filing access activities of the general public, excluding the Fed, as these activities are suggestive of the general, non-Fed demand for macroeconomic information. Collectively, while establishing causation is a challenge, we take a series of steps in our research design and conduct tests to mitigate at least some of the key endogeneity concerns.

In our main analyses we focus on both quantitative and qualitative data from accounting disclosures. Quantitative accounting data are available from data aggregation services like Compustat (D'Souza, Ramesh, and Shen 2010). Therefore, the marginal cost of obtaining them is low. However, research in economics suggests that the Fed's forecasts are in many cases more accurate than commercial forecasters such as the SPF (Romer and Romer 2000; Sims 2002; Rossi and Sekhposyan 2016). This opens up the possibility that this improved accuracy stems from the Fed's consideration of accounting disclosures that other forecasters likely neglect.[5]

More importantly, we focus on qualitative information in SEC filings because such information is difficult to extract systematically but would add contextual value (Drake, Roulstone, and

3. Prior research has relied on EDGAR Internet traffic to identify peer firms based on investor search pattern (Lee, Ma, and Wang 2015), to understand the determinants and consequences of information acquisition by investors (Drake, Roulstone, and Thornock 2015, 2016) to assess investor demand for SEC filings to price newly issued securities (Bauguess, Cooney, and Hanley 2013), and to examine the IRS's attention on public versus private disclosures (Bozanic et al. 2017).

4. Given that the Fed's forecasts are available to the public only after a five-year lag, other economic agents cannot easily infer what information sources the Fed relied on in generating its forecasts, even with a meaningful time lag.

5. An entire literature is devoted to testing the superiority of Fed forecasts over other macro forecasts. Directly addressing this question is beyond the scope of our paper.

Thornock 2016).[6] Moreover, the Fed's reliance on other qualitative information is well documented. Former Fed governor George Mitchell stated in testimony to Congress that it "brings to the committee qualitative judgments that aggregative statistics will always lack" (Federal Reserve Bulletin, March 1964, p.309). Sims (2002) provides a discussion of the Fed's use of non-aggregated information in the context of macroeconomic forecasting. From his interviews with central bankers, Sims notes that Fed forecasters "pay attention to a large amount of data from disparate sources, some of it non-quantitative," and that they understand "how aggregated bits of data feed into the preparation of the aggregate number. . . [which] gives the experts a starting point for their forecasts that is more accurate than data generated at fixed monthly or quarterly intervals" (p.21). These statements are consistent with the fact that the Fed compiles qualitative information for its internal analysis regarding the trajectory of the economy.

We do not suggest that the Fed's access of specific SEC filings is solely done to facilitate its forecasting activities. Rather, we see it as part of the Fed's ongoing investment in the information asset that resides in its human capital and information systems.[7] Building on this intuition, we examine the specific question of whether qualitative disclosures in the filings selected by the Fed are valuable in discharging its key functions. Specifically, we study macro-, industry-, and firm-level factors that are associated with the Fed's search behavior on EDGAR, and how such behavior facilitates the Fed's economic forecasts.

6. Such value is inherently reflected in the SEC's numerous reporting rules and regulations. Notable examples include the Management Discussion and Analysis and Risk Factors sections in form 10-K and the Compensation Discussion and Analysis section in form DEF 14A.

7. Consistent with our arguments, Dr. Evan F. Koenig, currently Senior Vice President and Policy Advisor at Federal Reserve Bank of Dallas, states that the "Federal Reserve System places high value on anecdotal and qualitative information, and its institutional structure facilitates the flow of this type of information to policymakers from a wide range of sectors and regions of the country" (Koenig 2005).

2.2 Determinants of the Fed's Demand for SEC Filings

2.2.1 The Economic State

We ground our hypotheses in the Fed's demand for information that arises from its economic roles and objectives (detailed in Appendix A). These include conducting monetary policy, ensuring the stability of the financial system, and protecting consumers. We focus on monetary policy and financial stability because the Fed has alternative, more direct means of information acquisition for its regulatory practice, including on-site bank regulators with access to transaction-level data and regularly-filed call reports. We therefore do not expect regulation-oriented research to be reflected in the Fed's SEC filings access data, and later provide descriptive evidence that supports this assertion.

A key component of conducting effective monetary policy is identifying not only the timing of economic fluctuations, but the underlying causes. Quantitative data provide information on the timing of economic events, but these underlying causes may have to be inferred qualitatively. As discussed above, the Fed's reliance on qualitative information is well documented, and is reflected in the production and use of the internal document known as the Beige Book.[8]

Koenig (2005, p.250) states that "often policymakers are [more concerned]...about emerging trends in the data" and "[b]usiness executives appear to have a knack for recognizing these trends, and filtering out transitory fluctuations," which explains why corporate disclosures could be a source of such insights. Moreover, the value of qualitative information likely increases during slowdowns as economic and political actions become more urgent. The optimal policy choice can differ widely depending on whether a downturn is caused by financial/credit crises or by aggregate supply and demand fluctuations. Consistent with this intuition, Koenig (2005, p.252) states that "[qualitative] information channels have proven invaluable in times of crisis." Qualitative information aggregated from SEC filings likely reflects corporate America's assessment of the business

8. See Appendix A for details on the Fed's internal documents.

climate, which helps sharpen the Fed's forecasts and policy formulation especially during economic slowdowns, leading to our first hypothesis:

Hypothesis 1a (H1a) *The frequency with which the Fed accesses SEC filings is positively (negatively) associated with negative (positive) economic indicators.*

2.2.2 Industry/Firm Indicators of Financial Stability and Economic Growth

Our next hypothesis focuses on industry and firm characteristics related to systemic risk, financial stability, and economic growth. While these are identified as separate functions, in the Fed's view, "the promotion of financial stability strongly complements the primary goals of monetary policy."[9] As a result, we do not attempt to separate firm and industry characteristics that are important to preserving financial stability versus promoting economic growth.

From the Fed's standpoint, a robust financial sector acts as an important link between financial stability and economic prosperity, and thereby plays a key role in nurturing a well-functioning economy. To mitigate spillover effects and gauge systemic risk, the Fed also closely monitors systemically important financial institutions (SIFIs), so we expect the Fed to be interested in their filings.

Recent work in economics indicates that idiosyncrasy in granular firms can have oversized effects on aggregate economic performance (Gabaix 2011; Acemoglu et al. 2012; di Giovanni and Levchenko 2012; di Giovanni, Levchenko, and Méjean 2014). These results highlight the importance of examining large, industry-leading firms and understanding how their performance can impact the broader economy.

Business entities with high credit quality frequently use the commercial paper market to raise short-term debt, and more so during downturns or when facing increased uncertainty (Calomiris, Himmelberg, and Wachtel 1995; Kahl, Shivdasani, and Wang 2008). The Federal Reserve closely monitors the commercial paper market because defaults in this market can have a systemic and

9. *About the Fed*, federalreserve.gov

contagious impact (Covitz, Liang, and Suarez 2013).[10] For instance, the Fed created the Commercial Paper Funding Facility in response to the failure of Lehman Brothers and the subsequent collapse of the market for commercial paper in 2008 (Anderson and Gascon 2009). Therefore, we expect the Fed to seek qualitative information on firms that participate in the commercial paper market in order to be apprised of systemic threats to the economy.

Lastly, the Fed pays particular attention to corporate investments in inventory and equipment as key factors in assessing business sector performance.[11] Overall, we expect the Fed to access information from granular firms, which we take to be firms in the financial sector, firms whose performance influences the overall economy, and firms with important contributions to systemic risk:

Hypothesis 1b (H1b) *The frequency with which the Fed accesses SEC filings is positively associated with industries and firms that are important to financial stability and economic growth.*

2.3 Fed-Accessed SEC Filings and Fed Macro Forecasts

Our last and most important hypothesis addresses the implications of the Fed's SEC filings access: whether information in Fed-accessed filings is associated with the Fed's economic forecasts. The Fed produces economic forecasts for each of the roughly eight FOMC meetings held every year. The consensus in the economics literature is that these forecasts are of high quality and many argue that this is due to the vast resources the Fed devotes to gathering information (Romer and Romer 2000; Sims 2002; Eksi, Orman, and Tas 2016; Rossi and Sekhposyan 2016). We posit that the Fed's SEC filing access constitutes an important input to its forecasts. To the extent that the Fed collects firm-level qualitative information to provide context and support for its assessment of

10. The Fed reports rates, outstanding levels, volume, etc. on financial, non-financial, and asset-backed commercial paper on a daily basis.

11. During our sample period, the Fed's annual reports from 2003 to 2012 contain sub-sections titled "Fixed Investment" and "Inventory Investment," which account for two of the three topics that the Fed covers regarding the state of the US business sector (the third being corporate profits and financing). Beginning in 2013, the Fed continued to discuss fixed and inventory investments by the business sector, but these discussions were not organized under their own subsections. They are now interspersed throughout the report.

economic performance and risk, we expect such information to be reflected in the Fed's economic forecasts.

Furthermore, research in economics shows that the qualitative information published by the Fed improves forecast accuracy. Balke and Petersen (2002) use in- and out-of-sample tests to show that the qualitative data in the Beige Book have significant predictive content for current and future GDP growth. Armesto et al. (2009) provide similar results based on textual analysis that measures optimism and pessimism in the Beige Book reports. We extend this reasoning on the value of qualitative information and predict that the Fed's economic forecasts reflect information from SEC filings:

Hypothesis 2 (H2) *The Fed's economic forecasts are associated with qualitative information in Fed-accessed SEC filings.*

H2 is consistent with the notion that the Fed's high-quality macroeconomic forecasts reflect contextual information. A corollary prediction is, given that the Fed's filing access efforts signify its unique expertise, other economic agents' forecasts should reflect less the qualitative information in Fed-accessed filings. We consider macroeconomic forecasts by the SPF, a highly-regarded survey that began in 1968 and has been administered by the Federal Reserve Bank of Philadelphia from 1990 onwards. Our first corollary suggests the following:

Corollary 2a (H2a) *When compared to the Fed's forecasts, the SPF's economic forecasts have a weaker association with the qualitative information in the Fed-accessed SEC filings.*

Testing this corollary also provides a verification that the qualitative information in Fed-accessed filings is not simply correlated with trends in the broader economy that other sophisticated economic agents can identify. If such were the case, we would expect SPF forecasts and Fed forecasts to have a similar relationship with qualitative information in Fed-accessed filings. Finding that the relationship differs provides a meaningful identification for the assertion that the Fed's filings access informs its macro forecasts.

An additional corollary relates to the forecast errors of commercial forecasters. If Fed-accessed qualitative information is relevant to future GDP growth but is not fully reflected in SPF forecasts, then we expect such information to be predictive of the SPF's forecast errors.

Corollary 2b (H2b) *The SPF's forecast errors are associated with qualitative information in Fed-accessed SEC filings.*

Our corollaries are not intended to rule out information that SPF forecasters may rely on that the Fed ignores. Our main purpose in using the SPF forecasts as a benchmark is to identify qualitative, contextual information in Fed-accessed filings that is orthogonal to information used by other economic agents. Prior research finds that SPF forecasters underweight information in accounting earnings (Konchitchki and Patatoukas 2014a). Our predictions have a similar flavor, but are in the domain of Fed-accessed *qualitative* information.

An alternative to focusing on macroeconomic forecasts is to examine outcome variables that directly measure monetary policy actions. However, the lack of variation in measures of monetary policy (Gallo, Hann, and Li 2016)[12] and the ambiguous relationship between its implementation and effects (Friedman 1961) combine to make the measurement of monetary policy prohibitively challenging from a research design perspective. For this reason we choose to model the effects of qualitative information on the Fed's forecasts of economic growth. These forecasts are timely, frequent, and are a direct input into the decision-making process for the Fed's macroeconomic policy. Because of this, we infer that accounting data, through their impact on the Fed's economic forecasts, influence the Fed's monetary policy decisions.

12. The Fed implemented near-zero interest rate targets during the 2007 recession, and has only recently raised them. Gallo, Hann, and Li (2016) use federal fund futures as a main variable in their analysis, and are forced to cut their sample short because of this shift in Fed policy.

3 Sample and Data

3.1 The Fed's Access of SEC Filings

The SEC filing access data used in this study are derived from the SEC's EDGAR log files. Each observation represents a form view or "click" of an SEC filing by the Fed. The data include date and timestamps, firm (CIK) and filing (accession number) identification, and a truncated IP address, which we use to identify the Fed's activities.

Our sample extends from the middle of March 2003 to the end of February 2015. As noted in Bauguess, Cooney, and Hanley (2013), the SEC retained very few observations between October 2005 and April 2006 due to a technical issue. We set the SEC filing access data to missing during these months.

We use the number of Fed form views or "clicks" as our proxy for the Fed's access intensity. EDGAR is structured such that all exhibits and attachments to a filing have the same filing ID and firm ID as the main body of the filing. As a result, if a Fed employee were to click on the body of a 10-K filing and on each of nine exhibits attached to it, our data would show ten observations with repeated CIK and accession numbers but with different timestamps.

We choose to include these "duplicate" observations, as they provide a natural weight to the information content of the financial reports. The periodic annual reports (10-Ks) are widely considered as the most comprehensive source for corporate financial information both by length and content, followed by 10-Qs, whereas 8-Ks likely act as a more timely source for market-moving information (Lerman and Livnat 2010). These are the most common filings that include attachments. 10-Ks usually have the most attachments, followed by 10-Qs and then 8-Ks. As such, extra clicks corresponding to these filings likely reflect the Fed's revealed demand for information in these forms. The total number of clicks and the unique clicks at the daily level are highly correlated (.98), and as a robustness check, we run all our tests excluding the "duplicate" observations and find similar results.

Another consideration is the presence of observations on the EDGAR log files from automated web crawlers, or "robots" (Ryans 2017). While the relevance of such data for our study is debatable, we verify that the Fed IP addresses do not meet the classification criteria for automated web crawlers.[13] Additionally, we verify that the timing of Fed access coincides with the attentional patterns attributed to human activity, similar to figure 1 in Li, Ramesh, and Shen (2011) for newswire services. Untabulated tests show that more than 85 percent of our sample observations fall between 8 a.m. and 8 p.m., Eastern time zone.[14]

We limit our analysis to firms present in the Compustat database over our sample period. This excludes relatively few observations. Based on Compustat's SIC codes, we sort firms into Fama-French 48 industries (Fama and French 1997). We also compile data on macroeconomic performance directly from the Fed's website: industrial production, consumer credit, inflation, and unemployment. In addition, we create indicators for months/quarters according to the NBER's classification of business cycle contraction periods. The only contraction period in our sample is the Great Recession, which began in December 2007 and ended in June 2009.[15] We also include the CBOE Volatility Index (VIX), as a proxy for financial volatility, 12-month ahead macroeconomic uncertainty constructed in Jurado, Ludvigson, and Ng (2015) as a measure of uncertainty, and CRSP value-weighted monthly returns as a measure of stock market performance. Appendix B contains descriptions, definitions, and sources for all our measures.

13. According to the strictest screening procedure from Ryans (2017), (1) Humans do not download more than 25 items in a single minute; (2) humans do not download more than 3 different companies' items in a single minute; and (3) humans do not download more than 500 items in a single day. The procedure assumes a single user per IP address, and while our data likely represent the simultaneous behavior of several Fed economists, the trends in our data are broadly well below these thresholds. For instance, the median (75th percentile) download count per minute in our data is 3 (5). The median (75th percentile) for the number of companies searched per-minute is 1 (1); and the median (75th percentile) for the number of items per day is 21 (60). We have also verified that our data fall below the thresholds detailed in the Drake, Roulstone, and Thornock (2015) screening procedure.

14. An exception is views of form N-MFP, the monthly fund holding schedule required of mutual funds. As these firms are not publicly traded and do not file financial statements, we do not include them in our analyses. Additionally, these observations show strong evidence of automated activity. This pattern has also been noted by Bozanic et al. (2017, footnote 9).

15. http://www.nber.org/cycles/cyclesmain.html. See Gorton (2010) for a discussion about the timing of the financial crisis.

3.2 Sample Description

Our final sample consists of 169,003 Fed-accessed records. The composition of form types in our data are presented in Table 1. Periodic reports account for more than 64 percent of all observations. The focus on periodic reports is consistent with the Fed's interest in assessing the financial performance and prospects of corporate America. The Fed also appears to track material events (Form 8-K: 13.09 percent) and possibly executive incentives and compensation practices (DEF 14A: 6.03 percent). In addition to these forms, only submission of insider trading (Form 4: 1.03 percent) and the annual reports of foreign private issuers (Form 20-F: 1.24 percent) elicit access intensity of over one percent of all Fed accessed observations. Overall, a small number of SEC forms represents more than 90 percent of all observations, suggesting that the Fed is targeting specific disclosures of select firms to better assess the state of the economy.

Table 2 presents the frequency of our sample observations by Fama-French 48 industries, sorted in descending order of access intensity. We also include the proportion of firms in Compustat for comparison. The result shows that the Fed has a clear focus on the banking industry, which makes up 37.5 percent of our sample, compared to only 9.7 percent of the observations in Compustat. While the two samples have very different distributions, the top three industries are the same in each sample (Banking, Trading, and Business Services). More than 50 percent of our sample is outside the financial services sector (Banking, Trading, and Insurance), which suggests that the Fed is interested in the filings of a broad cross-section of firms in the economy.[16]

16. In untabulated comparisons we find a striking difference between the Fed's banking industry filing access (37.5 percent) and the FDIC's (69 percent). The FDIC insures and regulates banks, but performs no monetary policy, and so offers a valuable point of reference in our attempts to isolate the Fed's access related to monetary policy and economic forecasting. A Kolmogorov-Smirnov test for equality of distributions rejects the null hypothesis that the Fed and FDIC filing access are similarly distributed by industry ($p < 0.01$).

4 Empirical Research Design and Results

We present model specification and test results of H1a and H1b in Section 4.1, H2 in Section 4.2, and robustness tests in Section 4.3. Caveats are discussed in Section 4.4.

4.1 Determinants of the Fed's SEC Filing Access

4.1.1 Tests of H1a: Macro Determinants of the Fed's SEC Filing Access

To test H1a, we regress a measure of monthly Fed access intensity on measures used by the Fed to describe and forecast the state of the economy and the financial system, and on other indicators of macroeconomic uncertainty. The first category of variables includes industrial production, inflation, and total consumer credit outstanding. The second category includes market returns, 12-month-ahead macroeconomic uncertainty, an indicator for sudden shocks to uncertainty, and an indicator for the recession/financial crisis period. H1a predicts that the Fed's SEC access intensity increases (decreases) with negative (positive) indicators of the economic state. We use these indicators to structure our directional predictions.

The Fed highlights industrial production (*Ind Prod*) as one of only two principal economic indicators on its website, and this variable is frequently discussed in its annual reports. Industrial production is commonly viewed as a leading economic indicator as it provides information on aggregate demand. We therefore predict a negative relationship between industrial production and the Fed's SEC filing access.[17]

The other principal economic indicator used by the Fed is total consumer credit outstanding (*Credit*). This variable is used as a proxy for future spending or consumer demand, which is typically considered a positive economic indicator. On the other hand, an increase in the measure

17. An additional objective of the Fed is to maintain full employment. However, measures of unemployment are highly negatively correlated with industrial production. To mitigate collinearity issues, we run our main tests using only industrial production, but all our results are robust to using the unemployment rate as a substitute.

may indicate delayed repayment of existing loans, thereby signifying a negative outlook.[18] As a result, we do not make a specific prediction regarding the association between consumer credit and Fed access intensity.

We include inflation (*Inflation*) as a determinant of Fed access because maintaining a desirable rate of inflation is one of the Fed's main policy objectives.[19] The relationship between inflation and Fed access intensity depends on whether inflation is above or below the Fed's target of two percent. During the Great Recession and financial crisis, the Fed undertook unprecedented monetary policy action, including extreme open market operations and several rounds of quantitative easing. Given the depth of the crisis, the tendency for deflation during recessions, and the Fed's aggressive policy actions, the threat of inflation was likely not the Fed's primary concern for much of our sample period. To the extent that this effect dominates our sample period, we might find a negative relationship between inflation and Fed access intensity as increases in inflation may be an indication of an impending economic turnaround. We therefore make no directional predictions for this variable.

In the second set of variables, we include value-weighted monthly returns (*Market Ret*) as an indicator of stock market performance, since high market returns are typically correlated with a positive economic outlook. We expect a negative relation between value-weighted returns and the Fed's SEC access intensity.

A maturing literature in economics has shown that economic uncertainty can negatively impact the macroeconomy. While the theoretical effects of the level of uncertainty are ambiguous (Abel 1983; Bernanke 1983), more recent work has shown that sudden increases in uncertainty can have

18. "Rising levels of consumer credit generally result from an increase in consumer demand... the Federal Reserve measures only the total balance of outstanding loans; it does not distinguish between new lending and existing loans. An increase in consumer credit could mean fewer old loans are being paid off while few, if any new loans are being extended." https://www.economy.com/dismal/indicators/definition/usa_credit.

19. See the Federal Reserve's 2015 Annual Report, and a recent statement by Robert Kaplan, president and CEO of the Dallas Federal Reserve Bank: "The Federal Reserve has two primary goals. Full employment, and keeping inflation below two percent." https://www.houstonpublicmedia.org/articles/news/2016/07/14/160380/dallas-fed-chief-in-houston/.

strong negative effects on macroeconomic performance (Bloom 2009; Bachmann, Elstner, and Sims 2013; Jones and Enders 2016). Therefore, we control for both the level of uncertainty using a measure of 12-month-ahead macro uncertainty (*Uncert*) developed by Jurado, Ludvigson, and Ng (2015) for which we make no directional prediction,[20] and an indicator for uncertainty-increasing shocks (*Uncert Shock*), defined as a 1.5 standard-deviation increase in the Jurado et al. measure. The latter measure is similar in spirit to that used in Bloom (2009). We predict a positive relation between *Uncert Shock* and the Fed's access intensity.

Finally, we include an indicator for months identified by the NBER as being part of an economic contraction (*Recession*). Because the value of economic information and the importance of monetary policy likely increase during periods of economic contraction, we expect these months to be more research intensive for the Fed.

Summary statistics in Table 3 Panel A are based on monthly-level data, the frequency at which most macro variables are measured. *All Access* is the number of SEC filings the Fed accessed during a given month, while *Current Access* is the number of the Fed's views of SEC filings that were available for less than a year (Drake, Roulstone, and Thornock 2016). We argue that the Fed's revealed preference best captures their expertise in acquiring qualitative information and therefore use *All Access* as the dependent variable, but we also examine *Current Access* to see if there is a differential effect for more recent information. *All Unique* and *Current Unique* exclude the duplicate observations discussed in Section 3.1.

Table 3 Panel B provides correlations among the macro variables and *All Access/Current Access*. The univariate correlations of the independent variables with *All Access* are as predicted, except for the *Recession* and *Uncert Shock* variables. While we did not have a directional prediction for *Credit*, it appears that the Fed's access intensity increases in consumer credit in our sample

20. This measure captures the common variation in uncertainty across a large number of macroeconomic and financial series. It is derived by aggregating the unpredictable components obtained from conditioning each series on an information set that is constructed to span as large a segment of the available information in the economy as possible.

period. In terms of correlations among explanatory variables, the high positive correlation between *Uncert* and *Recession* is as expected.

To test H1a, we estimate the following model:[21]

$$
\begin{aligned}
\mathit{All\ Access}_t \text{ or } \mathit{Current\ Access}_t = \alpha &+ \beta_1 \mathit{Ind\ Prod}_{t-1} + \beta_2 \mathit{Credit}_{t-1} + \beta_3 \mathit{Inflation}_{t-1} \\
&+ \beta_4 \mathit{Market\ Ret}_{t-1} + \beta_5 \mathit{Uncert}_t + \beta_6 \mathit{Uncert\ Shock}_t \\
&+ \beta_7 \mathit{Recession}_t + \varepsilon_t,
\end{aligned}
\tag{1}
$$

where $\mathit{All\ Access}_t$ or $\mathit{Current\ Access}_t$ are our access intensity measures. Continuous independent variables are standardized to ease interpretation of the coefficients. Definitions and descriptions of all the variables we use are included in Appendix B. We used lagged values of all control variables, excepting *Uncert*, *Uncert Shock*, and *Recession*, to ensure that we are controlling for information that would have been available to the Fed at the time of access. Because these three variables represent the Fed's qualitative assessments of different parameters of the economy, we use contemporaneous values.

The results from regressions of Equation 1 are presented in Table 4.[22] We show results for *All Access* versus *Current Access* as dependent variables with the access intensity aggregated over the entire sample (All), over only the financial sector (Fin),[23] and over the non-financial sectors (Non-Fin). Doing so allows us to test for the different effects of macro and financial stability variables on the two sub-populations. Coefficients on *Ind Prod* are in the predicted direction, and are both economically and statistically significant for all specifications. The coefficient indicates that a standard deviation increase in industrial production corresponds to a 51 percent decrease in the Fed's overall access intensity, with similar results for the financial and non-financial sectors.

21. We test for nonlinear effects in the macro controls by including squared terms, but do not find significant effects.

22. For all our regression models, we run tests for AR(1) serial correlation in regression residuals, which is a common problem with macro series (Cochrane 1997). Where appropriate, we use Prais-Winsten estimation to account for this autocorrelation (Prais and Winsten 1954). Dickey-Fuller, augmented Dickey-Fuller, and Phillips-Perron tests all reject the null hypothesis of the presence of a unit root in our macro series, thus, differencing is unnecessary here.

23. In this paper, we refer to the banking, trading, and insurance industries as the financial sector.

The positive sign on the coefficient for *Credit* may reflect the Fed's concern over excessive debt during the financial crisis. Indeed, the large and significant coefficient for the financial sector (0.51), contrasted with the small and insignificant one for the non-financial sector (-0.06) indicates that changes in consumer credit are interpreted by the Fed as a cause for scrutiny of only the financial sector, consistent with the Fed monitoring the stability of the financial system through its EDGAR research.

The *Inflation* coefficients are negative and statistically significant at the .05 to .10 level in most specifications. The -0.13 coefficient indicates that over our sample period, the Fed views increases in inflation as good economic news reflecting an economic turnaround. *Market Ret* coefficients are similarly significant, and seem to be an additional indicator for financial stability, as the Fed appears to access fewer filings when market returns increase. A standard deviation increase in market returns yields more than a 10-percent decrease in the Fed's access intensity.

Table 3 Panel B shows that *Uncert* and *Recession* have a correlation in excess of 80 percent, but collinearity does not appear to be an issue given both coefficients are statistically significant in Table 4 Panel A. However, unlike the univariate correlation, the sign of *Recession* is positive, consistent with our predictions. For the whole sample, *All Access* (*Current Access*) increases by more than 100 percent (94 percent) during the recession, but the economic significance is much larger for the non-financial sector with a coefficient of 2.34 (1.25), compared to 1.05 (0.90) in the financial sector. Similarly, an uncertainty-increasing shock results in a large and statistically significant increase in the Fed's access intensity, consistent with the Fed's increased attention on this negative indicator, especially for the financial sector. Once we control for uncertainty shocks, we find minimal variation in the level of uncertainty (untabulated). The negative coefficients on the level of uncertainty indicate that the Fed reduces its access intensity as uncertainty increases within this narrow bound. The coefficients for these macro variables add additional weight to our assertion that the Fed uses the filings from a broad range of firms as a source of information when macroeconomic conditions deteriorate. Taken together, the results in Table 4 are consistent with

H1a, and provide evidence that the Fed's demand for firm-level information tracks macroeconomic performance and financial stability.

4.1.2 Tests of H1b: Industry Determinants of the Fed's SEC Filing Access

To test H1b, we examine the Fed's EDGAR research at the industry-month level (this section) and at the firm-quarter level (Section 4.1.3). H1b predicts that the Fed's access intensity is positively related to industries that are important to financial stability and economic growth. Specifically, we estimate the following model:

$$\begin{aligned} \mathit{All\ Access}_{j,t} \text{ or } \mathit{Current\ Access}_{j,t} = {} & \alpha + \beta_1 \mathit{Banking}_j + \beta_2 \mathit{Trading}_j + \beta_3 \mathit{Insurance}_j \\ & + \beta_4 \mathit{Finance}_j \times \mathit{Ind\ Ret}_{j,t} + \beta_5 \mathit{Finance}_j \times \mathit{VIX}_t \\ & + \beta_6 \mathit{Ind\ Ret}_{j,t} + \beta_7 \mathit{VIX}_t + \mathit{Macro\ Controls} \\ & + \mathit{Finance}_j \times \mathit{Macro\ Controls} + \varepsilon_t, \end{aligned} \tag{2}$$

where $\mathit{Banking}_j$, $\mathit{Trading}_j$, and $\mathit{Insurance}_j$ are indicators for industry j being in the banking, trading, or insurance industry, respectively, and $\mathit{Finance}_j$ is an indicator for industry j being in the financial sector ($\mathit{Banking}_j$, $\mathit{Trading}_j$, or $\mathit{Insurance}_j = 1$); $\mathit{Industry\ Ret}_{j,t}$ is the Fama-French 48 industry returns for industry j in month t; VIX_t is the average of daily closing VIX over month t. We include *VIX* as a proxy for volatility in the financial markets that could impact the Fed's access intensity. We predict a positive relationship between *VIX* and Fed access intensity. We consider the financial sector as having the potential to engender systemic effects and include indicator variables and interaction terms for industries in this sector.

In Table 5, we present results using 2-way clustered OLS, 1-way clustered Tobit, and 2-way clustered Tobit regressions. Tobit regressions are used given the high density of industry-months with no Fed access.[24] We include macro variables from Equation 1 and standardize all continuous independent variables as before. We include contemporaneous values for *Industry Ret* and *VIX* as these variables are available at more frequent intervals and are therefore more continually observable.

Coefficients on the macro controls and VIX and their interactions with indicators of the financial sector are consistent with the results presented in Table 4, and are omitted for brevity. Positive and significant coefficients on *Banking*, *Trading*, and *Insurance* indicate that the Fed pays special attention to these industries. The estimates of economic significance from the OLS regressions are large, ranging from more than a 180 percent increase in access intensity in the insurance industry to over 400 percent higher intensity in the banking industry. While the coefficient on *Industry Ret* is largely insignificant, the *Finance*×*Industry Ret* interaction is positive and significant in all specifications. This indicates that the Fed is more likely to acquire information from financial industries when they experience high returns, with a one standard deviation increase in contemporaneous industry returns resulting in 9 percent increase in access intensity. The Fed's behavior might reflect its concern that higher returns indicate excessive risk-taking by the financial firms and the potential for an asset bubble driving those returns.

The coefficients on *VIX* are generally significant only for regressions using *All Access* as the dependent variable. However the *Finance*×*VIX* interactions are positive and strongly significant in the current specifications. As in the case with industry returns, this indicates that the Fed is more likely to access the filings of financial industries during times of current stock market volatility. Overall, the industry-level regression results are consistent with H1b, that the Fed demands relatively more firm-level information of financial industries, and more so when they experience higher stock returns or when the overall financial market volatility is high.

24. Due to the number of clusters relative to zeros in the dependent variables, we are unable to compute standard errors for separate interaction terms in some of the regressions. Instead we use the *Finance* indicator in the interactions, which provides an estimate of the "average" effect of the interactions among the three coefficients for the banking, trading, and insurance industries.

4.1.3 Tests of H1b: Firm Determinants of the Fed's SEC Filing Access

As a further test of H1b and to explore firm-specific characteristics, we model the determinants of the Fed's SEC filing access at the firm-quarter level. In particular, we are interested in testing for incremental effects for granular firms that are integral to the macro economy and/or the financial system. Specifically, we estimate the following model for firm i during quarter t:

$$\begin{aligned} All\ Access_{i,t} \text{ or } Current\ Access_{i,t} = \alpha &+ \beta_1 Bell_{i,t} + \beta_2 SIFI_i + \beta_3 Ind\ Leader_{i,t} + \beta_4 CP_{i,t} \\ &+ \beta_5 Crash\ Risk_{i,t} + \beta_6 Inv\ Intensity_{i,t} + \beta_7 Cap\ Intensity_{i,t} \\ &+ \beta_8 Finance_i \times Bell_{i,t} + \beta_9 Finance_i \times Firm\ Ret_{i,t} \\ &+ \beta_{10} Ind\ Leader_{i,t} \times Banking_i + \beta_{11} Ind\ Leader_{i,t} \times Trading_i \\ &+ \beta_{12} Ind\ Leader_{i,t} \times Insurance_i + \beta_{13} Firm\ Ret_{i,t} \\ &+ \beta_{14} Banking_i + \beta_{15} Trading_i + \beta_{16} Insurance_i \\ &+ Other\ Controls + Finance_j \times Other\ Controls + \varepsilon_t, \end{aligned} \tag{3}$$

where $Bell_i$ is an indicator for bellwether firms; $SIFI_i$ is an indicator for firms with that designation; $Ind\ Leader_{i,t}$ is an indicator for firms in the highest industry quartile of total assets; $CP_{i,t}$ is an indicator for firms with commercial paper ratings outstanding; $Crash\ Risk_{i,t}$, $Inv\ Intensity_{i,t}$, and $Cap\ Intensity_{i,t}$ are indicators for firms being in the top quartiles of firm crash risk, inventory intensity and capital intensity (as defined in Appendix B). $Firm\ Ret_{i,t}$ is firm i's quarter t return; and the remaining variables are as defined earlier. We use quarterly data in this analysis because firm-level accounting measures are available at the quarterly level.

Given the importance of bellwethers to the economy (Anilowski, Feng, and Skinner 2007), we argue that the Fed will closely monitor these firms' disclosures to gauge the current and future states of the economy. In a similar vein, we also consider SIFIs, as defined by the Financial Stability Board, as targets of the Fed's research. We use the *Ind Leader* indicator to represent the Fed's broader focus on all sectors of the economy. We include *CP* because one of the early symptoms of the recent financial crisis was the collapse and freezing of credit markets, starting with the market for commercial paper in 2008. Therefore, information about firms that issue commercial paper may inform the Fed about trends in the financial system and threats to its stability.[25]

We include three indicators for firm characteristics that are relevant in assessing overall economic trends and stability: stock price crash risk, inventory intensity, and capital intensity. Crash risk is included as a proxy for firm-level downside risk, while inventory and capital intensities are included to capture the Fed's focus on corporate investments in inventory and equipment as key factors in assessing business sector performance. Our intensity variables are defined as inventory or PP&E over total assets.

To capture the interactive effects between financial sector and firm characteristics, we include several interaction terms: *Finance*×*Bell* tests for incremental effects among financial firms that are also bellwethers; *Finance*×*Firm Ret* tests for an incremental effect for financial firm returns. Lastly, we include interactions between the *Ind Leader* variable and the three financial industries to test for an incremental effect for leading financial firms.

Tobit regression results are presented in Table 6, where columns (1), (2), and (3) correspond to standard error estimates clustered at the quarter, industry, and firm levels, respectively.[26] Results on the macro controls and interactions are similar to those from previous tests, and are omitted for brevity.

In each of our specifications, the coefficients on the bellwether, SIFI, and industry leader indicators are positive and significant, supporting our predictions that such firms are of special interest to the Fed because of their importance to the economy and the financial system. The coefficients on commercial paper are also positive and strongly significant, suggesting that a firm's

25. The Fed has been reviewing SEC filings of the commercial paper issuers even before the financial crisis, although the incidence of such review increased five-fold after 2008.

26. We do not present results clustered by firm and quarter, although they are quantitatively similar, because we are unable to calculate standard errors for several variables due to the low number of firm clusters relative to the number of zeros in the dependent variable.

participation in that debt market attracts extra attention from the Fed. This supports our conjecture that the Fed scrutinizes these firms because of their importance to financial stability.

The positive and generally significant coefficients on high crash risk suggest that firms with high crash risk are of special concern to the Fed. The positive and significant coefficients on high inventory intensity suggest that the Fed is interested in these firms, likely because their performance reflects underlying trends in the macroeconomy as opposed to short-term volatility in the stock market. Unreported results show that retail and manufacturing firms feature prominently in this group, which is often used as an indicator of consumer demand, and is therefore relevant for forecasting future economic growth.

The negative coefficients on the *Finance*$\times$*Firm Ret* interaction suggest that when a firm in the financial sector experiences higher returns, the Fed accesses its SEC filings less. This is in contrast to results at the industry level, which indicate that when the financial sector as a whole experiences higher returns, the Fed increases its scrutiny. This reflects the Fed's relative indifference to individual financial firms earning high returns, but its increased concern when the entire industry or sector earns high returns, as the latter may be an indication of an asset bubble or other threat to financial stability, while the former is not.

The coefficients on the *Ind Leader*$\times$*Banking*, *Ind Leader*$\times$*Trading*, and *Ind Leader*$\times$*Insurance* interactions indicate that there is an incremental effect for leading firms in these industries. Interestingly, the main effect persists only for the banking industry, which indicates that the Fed monitors individual firms in the banking industry but only the leading firms in the trading and insurance industries. Taken together, our results provide compelling evidence that the intensity of the Fed's SEC filing access is based on firm and industry characteristics that are vital to the macro economy and the financial system, thereby providing credence to the posited role of corporate disclosures in informing Fed's policy formulation.

4.2 Tests of H2: Fed-Accessed SEC Filings and its Macro Forecasts

Finally, we test whether information from Fed-accessed SEC filings is associated with its economic forecasts. The structure of our tests is to regress the Fed's forecasts of economic growth on proxies for qualitative information in the filings the Fed accesses between FOMC meetings. The Fed forecast data are derived from archived copies of the Green Book (now known as part I of the Teal Book). These data are released to the public with a five year lag. As a result, our analyses of the Fed forecasts are limited to the 2003-2010 period. As a comparison and a control, we use commercial forecasts supplied by the SPF in our tests, which are available without a time lag. In our tests of the SPF forecasts, we are able to extend the sample from the second quarter of 2003 to the first quarter of 2015.

Following Drake, Roulstone, and Thornock (2016), we define "qualitative" information as data that are difficult to extract systematically, but could add important contextual value. As discussed earlier, the Fed and other sophisticated market participants can access a multitude of quantitative corporate financial information that is available through structured databases assembled on a timely fashion by well-known data aggregators. As a result, when accessing the EDGAR database, we expect the Fed to look for more unstructured or contextual information of select firms that it may view as valuable for its economic forecasts.

We use the tone of Fed-accessed 10-K/10-Q filings as our proxy for qualitative information. We focus on periodic reports as they are likely to contain corporate America's assessment of financial performance and trends in the spirit of Regulation S-K (17 CFR 229.1 and 229.3). As discussed earlier, the Fed's access pattern (Table 1) shows the primacy of periodic reports as a source of firm-level information. Moreover, this descriptive evidence is consistent with the Fed's staff members' perception that business executives have the ability to identify emerging trends and their persistence (Koenig 2005), and such managerial assessments are likely reflected in our tone measure.

Specifically, our tone measure, negative tone (*Neg Tone*), is the number of negative words from the LM dictionary in a 10-K or a 10-Q filing divided by the total LM dictionary words in the filing.[27] We focus on negative tone due to cautions given in LM that "negative words have a much more pervasive effect" in financial statements, and that the inclusion of a positive dictionary in their paper was "in the interest of symmetry [rather] than in an expectation of discerning an impact on tone identification."[28] This is reflected in the sheer magnitude of the difference in the number of words between the negative and positive dictionaries (2,337 versus 353 words, respectively, per LM).

We stress that our hypotheses do not reflect the notion that the Fed calculates tone measures from accessed filings, rather the Fed's internal information environment is shaped by the SEC filings it accessed. Specifically, we posit that those responsible for gathering information as inputs to the Fed's economic forecasts, such as staff economists, are influenced by the qualitative information from the Fed-accessed filings.

We aggregate our sentiment proxy by taking the daily average of negative tone in Fed-accessed filings, then averaging them over each period between FOMC meetings or the period between SPF forecasts.[29] Doing so limits the higher weighting for repeated access in a given day that would result from taking the simple average of negative tone for all Fed-accessed filings between FOMC meetings (or between SPF forecasts), as it is not uncommon for filings with exhibits, such as 10-Ks, to be accessed multiple times in a row (Ryans 2017).[30]

27. Two observations are in order. First, we do not use the tone of 8-Ks because the Fed's access of these filings is much less frequent than its access of 10-Ks and 10-Qs (5,047 8-K observations compared to 111,396 10-K and 10-Q observations). Second, we examine the impact of the SEC's 2005 changes of the required risk factor disclosures on the measures of tone, but find no shift in the aggregate proportions of negative words around the change.

28. Nevertheless, we run our regressions using net tone (neg – pos), and our inferences are unchanged. We also run our regressions adding positive tone as a separate regressor, obtaining a positive but insignificant coefficient (untabulated).

29. The Fed holds FOMC meetings roughly eight times a year, while the SPF releases forecasts every quarter. Therefore, we aggregate the tone of Fed-accessed filings over the roughly six weeks between FOMC meetings, while we do the same for the three months between SPF forecasts. This also implies that when we use SPF forecasts as controls in our Fed forecast regressions, we do not have a one-to-one mapping between Fed and SPF forecasts in terms of timing, and must therefore use the most recent SPF forecast.

30. While these duplicate views may be consistent with Fed's review of the exhibits to the filing, the tone measure that we use reflects the textual content only from the main portion of the filing (Loughran and McDonald 2011). As

When aggregating over the periods between SPF forecasts, we use the survey deadlines outlined by the Federal Reserve Bank of Philadelphia to ensure that we only include qualitative information that was available to the SPF forecasters at the time of the survey.[31] When aggregating between FOMC meetings, however, we use the dates of the meetings themselves. The choice of using the entire window between FOMC meetings has been shown to improve estimation over short windows in similar contexts (Froyen and Waud 2002).

We regress the Fed or SPF forecasts on aggregate tone and on aggregate earnings for all firms that reported quarterly earnings over the examination period t, as follows:

$$Forecast_t^{t+h} = \alpha + \beta_1 Agg\ Earn_t + \beta_2 Neg\ Tone_t + \varepsilon_t, \tag{4}$$

where $Forecast_t^{t+h}$ is the Fed or SPF forecast, made in quarter t, for nominal GDP growth h quarters ahead, and $Neg\ Tone_t$ is the aggregate negative tone of SEC filings accessed by the Fed between FOMC meetings, or in the case of SPF forecasts, between SPF forecast deadlines. $Agg\ Earn_t$ is the sum of accounting earnings over the sum of lagged market capitalization for all firms that released earnings during the measurement window as defined above. To ease the interpretation of the coefficients, we standardize all variables to have a mean of zero and a standard deviation of one.

Summary statistics and correlations for unstandardized variables used in our forecast analyses are presented in Table 7. The distributions of Fed and SPF forecasts and forecast errors are generally similar. The high correlation between the Fed and SPF forecasts (.79) is expected, given that both forecasts likely rely on common information and that the Fed uses past SPF forecasts as inputs to its own forecasting (Konchitchki and Patatoukas 2014a). The high correlation between Fed and SPF forecast errors (.91) is also consistent with this reasoning.

a robustness check, we repeat our tests of H2 by dropping repeat observations resulting from 10-K and 10-Q exhibits, and obtain nearly identical results.

31. The survey deadline is in the second week of the second month of every quarter. We time our aggregation process to capture only the qualitative information for forms filed between these dates.

Results from estimating Equation 4 are presented in Table 8 for one- to four-quarter-ahead GDP growth forecasts. Panels A and B provide results for regressions with Fed and SPF forecasts as the dependent variables, respectively. Panel C provides results from regressions of Fed forecasts on negative tone, aggregate earnings, and the most recently available SPF forecast as a control. We use Prais-Winsten correction for any autocorrelation present in the residuals.[32]

The positive and significant coefficient of aggregate earnings in Panel A indicates that a standard deviation increase in aggregate earnings is associated with a 0.35 standard deviation increase in the Fed's forecast for one-quarter ahead growth in nominal GDP. This result indicates that the Fed's forecasts are responsive to the information contained in aggregate earnings. The negative and significant coefficients on *Neg Tone* indicate that a standard deviation increase in the negative tone of Fed-accessed filings is related to a 0.45 standard deviation decrease in the forecast for one-quarter ahead growth in nominal GDP. These effects are statistically and economically significant, and offer strong evidence that qualitative information from Fed-accessed SEC filings informs the Fed's economic forecasts. The results hold for forecasts of varying horizons.

To test H2a and verify that our results are attributable to Fed access and not some correlated omitted variable or latent economic factor, we repeat the above analysis using the SPF's forecasts of nominal GDP growth as the dependent variable. If the Fed has unique skills in searching for targeted qualitative information from EDGAR, we should find that the Fed-accessed filings' tone has a weaker association with SPF forecasts. The implication is that commercial forecasters either do not have the expertise to identify the qualitative information that the Fed identifies or they do not weight it similarly.[33] Results are presented in Panel B.

The coefficients on aggregate earnings in the SPF regressions are similar in magnitude to those in the Fed regressions, and are statistically significant. However, the coefficients on negative

32. While Dickey-Fuller, augmented Dickey-Fuller, and Phillips-Perron tests all reject the null hypothesis of the presence of a unit root in our forecast data, we replicate the forecast regressions using a first-difference specification. Our inferences are unchanged.

33. Currently we are unable to identify SEC filings accessed by commercial forecasters, although we are continuing to explore this possibility.

tone for filings accessed by the Fed between SPF forecasts are statistically insignificant in three of four regressions, and much smaller in magnitude, though the sign is consistent with that of the Fed forecast regressions. These results indicate that the information in Fed-accessed filings is not reflected in the SPF forecasts, and provide further confirmation that such information is not simply correlated with observable macroeconomic indicators.

As a further test to ensure that we are capturing the incremental effect of the qualitative information in Fed-accessed filings, in Panel C we re-estimate the Fed forecast regression, but include the most recent SPF forecast as an explanatory variable. While the coefficient on negative tone decreases in magnitude and is no longer statistically significant for the one-quarter ahead regression, the coefficients are statistically significant at the .05 level for the remaining forecast horizons, and offer evidence that Fed-accessed filings inform its forecasts of nominal GDP growth over and above the information in SPF forecasts. These results assuage potential concerns about correlated omitted variables because SPF forecasts are a reasonable proxy for a broad set of economic information relevant for assessing and predicting macroeconomic outcomes.

To test H2b, in Table 9 Panel A we regress the Fed's forecast errors on aggregate earnings and aggregate negative tone, and a *Crisis* indicator for FOMC meetings that fall in the third quarter of 2008, when the financial crisis began in earnest. We do so to control for the sudden spike in forecast errors that occurred due to the unexpected crash of the commercial paper market and the ensuing recession, and to ensure that these observations do not drive our results. We define forecast errors as the realized NGDP growth from quarter $t+h$ minus the Fed's h-quarter-ahead growth forecast made in quarter t.[34] In Panel B we regress the SPF's forecast errors (defined similarly) on these variables to test whether the SPF's errors are predictable using the qualitative information in Fed-accessed filings.

34. Following Konchitchki and Patatoukas (2014a) and Romer and Romer (2000), we use the final realization of GDP growth rather than the advance estimate, as the former is computed with complete data while the latter is based on incomplete data.

Results from Panel A of Table 9 show no relationship between *Neg Tone* and the Fed's NGDP forecast errors for any forecast horizon. This is also the case for aggregate earnings. The low R^2 from these regressions also indicates that these variables explain very little of the variation in the Fed's own forecast errors. This is consistent with the Fed incorporating all relevant information from both the aggregate earnings reported and from the qualitative information in the SEC filings it accesses between FOMC meetings. The *Crisis* indicator, however, loads negatively and significantly for the $t+1$ and the $t+2$ forecast horizons, suggesting that the financial crisis took the Fed by surprise, and realized NGDP growth was much smaller than the Fed forecast.

Panel B reports results for regressions using SPF forecast errors as the dependent variable. The coefficients on *Neg Tone* are negative in six specifications, and statistically significant at the .10 level in three specifications, all of which correspond to SPF forecast errors at horizons $t+1$ and $t+2$. These results indicate that the SPF omits or under-weights the qualitative information in Fed-accessed filings in its forecasts for these horizons. Insignificant coefficients on *Agg Earn (Quarter)* indicate that the SPF's forecast errors are unrelated to aggregate earnings reported between SPF forecasts. While these results contrast with those reported by Konchitchki and Patatoukas (2014a), we note that our use of the Fed's EDGAR data constrain us to less than half of their sample period. Similar to the regressions in Panel A, the negative and significant coefficients on the *Crisis* indicator suggest that, like the Fed, the SPF was taken by surprise by the onset of the financial crisis and great recession in the latter half of 2008.

Finally, Table 10 presents results from regressing different forecast components from the Fed's Green Book data on aggregate earnings and negative tone. We group these forecasts into two general categories: those related to inflation and those related to aggregate supply and demand. Panel A provides a tabulation of the coefficients on *Agg Earn* from these regressions, with the columns corresponding to the dependent variable of each regression, and the rows corresponding to different forecast horizons. Panel B summarizes coefficients on *Neg Tone*. The results indicate that aggregate earnings and negative tone are not strongly associated with proxies for inflation, which speaks to the difficulty of forecasting inflation especially during times of stable prices (Sims 2002), as in our sample period. However, aggregate earnings and negative tone play a significant role in forecasting different elements of aggregate supply and demand.

4.3 Robustness Tests

In addition to the various sensitivity checks discussed above, we also run a battery of robustness tests, the results of which, while omitted for the sake of brevity, are available upon request.

To rule out the Fed's regulatory demand for information in its SEC filings access, we perform an event study around enforcement actions announced by the Fed, using the Fed's access intensity of the targeted banks' SEC filings as the variable of interest. Should the Fed's filing access reflect information demand related to banking industry regulation, we would expect to see a pattern of increased access intensity surrounding these enforcement actions. We find no discernible pattern of increases in the year before or after the announcement of an enforcement action. Indeed, the filings of more than two-thirds of the sanctioned, publicly-traded banks are not accessed by the Fed during the two-year period centered on the public announcement. As a robustness check, we drop these observations and the tenor of our results remains unchanged. Overall, our evidence is consistent with the Fed accessing SEC filings largely for purposes unrelated to banking regulation.

We repeat the macro and forecast regressions using all non-Fed, human access observations from the EDGAR log files as the dependent variable. The macro regression results indicate that aggregate, non-Fed access intensity increases in consumer credit, decreases in industrial production, but is insensitive to all other macroeconomic variables in our analysis. In the forecast regressions, we find no relationship between the Fed's forecasts and the tone of filings accessed by non-Fed users between FOMC meetings.

We repeat our macro regressions using only the 10-K and 10-Q filings accessed by the Fed, as well as only 8-Ks and only DEF 14As. The results from these tests indicate that the Fed access of periodic filings is driven by macroeconomic variables including industrial production, credit, inflation, and uncertainty, while that of the 8-K and DEF 14As is driven only by consumer credit and market returns, and only for firms in the financial industries. This is consistent with financial firms drawing attention to their governance and market-moving filings during times of financial market fluctuations, and with the Fed mining the 10-K and 10-Q forms of non-financial firms for information during bad economic times.

We repeat the industry regressions using lagged values for industry returns and VIX, and find that using the older information reduces the explanatory power of the model. This is consistent with the Fed responding to current information when it is available.

We repeat the forecast regressions, splitting the tone variable into tone from financial firms' filings and non-financial firms' filings. The results indicate that when separated, neither variable loads significantly for shorter-horizon forecasts. However, both financial and non-financial firms' tone have separate predictive ability for longer-horizon forecasts. Overall, the predictive power is much stronger when the tone of both sectors is considered together.

We repeat the forecast regressions using access intensity as an explanatory variable. We find that intensity is negatively related to the Fed's forecasts, consistent with the forecasts becoming more negative as macro conditions deteriorate, which is when Fed access intensity increases, as shown in the tests for H1a. When we include our tone measure and our intensity measures together as explanatory variables, our inferences are unchanged. In our forecast error regressions, we find no significant relationship between Fed access intensity and the Fed's forecast errors.

4.4 Caveats

In our hypothesis motivation we posit that the Fed's forecasts are used as important considerations in its monetary policy making. However, we are unable to determine to what extent the Fed changes its forecasts based on its policy actions. The problem is analogous to asking the driver of a car to forecast his future driving speed. However, this comparison is not entirely apt, as the Federal Reserve does not have the ability to precisely control the economy. As discussed above, monetary policy is implemented with a pronounced lag, and even then its effects are not necessarily obvious (Friedman 1961). Additionally, former Fed Chairwoman Janet Yellen recently stated, "The FOMC also evaluates forecasts from a range of economic models, assessments of key risks to the outlook, and detailed analyses of how different monetary policy strategies would affect projected outcomes and risks... Armed with this wealth of information, the Committee as a whole *then* decides on the most appropriate policy action to adopt at each of its meetings" (emphasis ours),[35] indicating that the Fed's forecasts of economic growth are inputs for its policy making, not vice versa.

An additional concern is the presence of correlated omitted variables. It is possible that our tone measures are correlated with omitted variables that drive the Fed's forecasts (e.g., the Fed's privileged and unobservable communication with firm CEOs). While we cannot rule out the presence of all correlated omitted variables, our inclusion of the SPF forecasts is an attempt to control for commonly observable information in the economy. Using this control allows us to examine the information inputs into Fed forecasts that differ from those of other informed forecasters. Furthermore, even if the true effect comes from other firm-specific information gathered by the Fed through other channels, the apparent high correlation between such information and the qualitative information in Fed-accessed filings validates the potential confirmatory role that the SEC filings play. While it is doubtful that the targeted SEC filings of select firms play only a confirmatory role, we cannot rule out that possibility. More importantly, even if that were the case, our findings would still be consistent with the Fed's reliance on granular firm information. Overall, our study establishes the vital role played by micro firm-level information in shaping the Fed's macroeconomic forecasts.

Lastly, we cannot rule out the possibility that systemically-important firms strategically manage their accounting disclosures in order to influence Fed policy, thereby eliciting a predictable economic growth forecast from the Fed. While this is theoretically possible, we consider it extremely unlikely given the multitude of other more direct stakeholders who demand and monitor

35. Speech at Stanford, January 19, 2017.

firm disclosures. Our research design cannot identify effects from such strategic disclosure behavior, but even if firms were to manipulate their disclosures to influence Fed policy, our evidence would still be consistent with the Fed relying on information in corporate disclosures.

5 Conclusions

In this paper we provide evidence that the Fed accesses corporate SEC filings to understand and forecast future macroeconomic states. We show that the Fed's SEC filing access activity is responsive to trends in the macroeconomy, increasing when the economy deteriorates or financial stability decreases. We also show that granular industries and firms that are important to the macroeconomy and/or to the nation's financial system attract extra attention from the Fed. Most importantly, we provide the first evidence that qualitative information in mandated, firm-level accounting disclosures is associated with the Fed's macroeconomic forecasts.

Our findings suggest that both qualitative and quantitative information from corporate financial disclosures are useful to the central bank, one of the most important players in the modern economy. This adds to prior research suggesting that accounting information is associated with macroeconomic phenomena. Our results pinpoint the SEC's EDGAR database as an important source of information for the Federal Reserve, and contribute some of the first evidence that mandated corporate disclosures have externalities at the macroeconomic level.

References

Abel, Andrew B. 1983. Optimal investment under uncertainty. *The American Economic Review* 73 (1): 228–233.

Acemoglu, Daron, Vasco M Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2012. The network origins of aggregate fluctuations. *Econometrica* 80 (5): 1977–2016.

Anderson, Richard G, and Charles S Gascon. 2009. The commercial paper market, the Fed, and the 2007-2009 financial crisis. *Federal Reserve Bank of St. Louis Review* 91 (6): 589–612.

Anilowski, Carol, Mei Feng, and Douglas J Skinner. 2007. Does earnings guidance affect market returns? The nature and information content of aggregate earnings guidance. *Journal of Accounting and Economics* 44 (1): 36–63.

Armesto, Michelle T, Ruben Hernandez-Murillo, Michael T Oqyang, and Jeremy Piger. 2009. Measuring the information content of the Beige Book: a mixed data sampling approach. *Journal of Money, Credit and Banking* 41 (1): 35–55.

Bachmann, Rüdiger, Steffen Elstner, and Eric R Sims. 2013. Uncertainty and economic activity: evidence from business survey data. *American Economic Journal: Macroeconomics* 5 (2): 217–249.

Balke, Nathan S., and D'Ann Petersen. 2002. How well does the Beige Book reflect economic activity? Evaluating qualitative information quantitatively. *Journal of Money, Credit and Banking* 34 (1): 114–136.

Ball, Ray, and Gil Sadka. 2015. Aggregate earnings and why they matter. *Journal of Accounting Literature* 34:39–57.

Ball, Ray, Gil Sadka, and Ronnie Sadka. 2009. Aggregate earnings and asset prices. *Journal of Accounting Research* 47 (5): 1097–1133.

Bauguess, Scott W, John Cooney, and Kathleen Weiss Hanley. 2013. *Investor demand for information in newly issued securities.* Working Paper.

Bernanke, Ben S. 1983. Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics* 98 (1): 85–106.

Bloom, Nicholas. 2009. The impact of uncertainty shocks. *Econometrica* 77 (3): 623–685.

Bonsall, Samuel B, Zahn Bozanic, and Paul E Fischer. 2013. What do management earnings forecasts convey about the macroeconomy? *Journal of Accounting Research* 51 (2): 225–266.

Bozanic, Zahn, Jeffrey L Hoopes, Jacob R Thornock, and Braden M Williams. 2017. IRS attention. *Journal of Accounting Research* 55 (1): 79–114.

Calomiris, Charles W, Charles P Himmelberg, and Paul Wachtel. 1995. Commercial paper, corporate finance, and the business cycle: a microeconomic perspective. In *Carnegie-rochester conference series on public policy,* 42:203–250. Elsevier.

Campbell, John Y. 1991. A variance decomposition for stock returns. *Economic Journal* 101 (405): 157–79.

Cochrane, John H. 1997. *Time series for macroeconomics and finance.* Unpublished Book Manuscript.

Covitz, Daniel, Nellie Liang, and Gustavo A Suarez. 2013. The evolution of a financial crisis: collapse of the asset-backed commercial paper market. *The Journal of Finance* 68 (3): 815–848.

Crawley, Michael J. 2015. Macroeconomic consequences of accounting: the effect of accounting conservatism on macroeconomic indicators and the money supply. *The Accounting Review* 90 (3): 987–1011.

D'Souza, Julia M, K Ramesh, and Min Shen. 2010. The interdependence between institutional ownership and information dissemination by data aggregators. *The Accounting Review* 85 (1): 159–193.

Drake, Michael S, Darren T Roulstone, and Jacob R Thornock. 2015. The determinants and consequences of information acquisition via EDGAR. *Contemporary Accounting Research* 32 (3): 1128–1161.

———. 2016. The usefulness of historical accounting reports. *Journal of Accounting and Economics* 61 (2): 448–464.

Eksi, Ozan, Cuneyt Orman, and Bedri Kamil Onur Tas. 2016. Has the forecasting performance of the Federal Reserve's Greenbooks changed over time? *Working Paper.*

Fama, Eugene F, and Kenneth R French. 1997. Industry costs of equity. *Journal of Financial Economics* 43 (2): 153–193.

Friedman, Milton. 1961. The lag in effect of monetary policy. *Journal of Political Economy* 69 (5): 447–466.

Froyen, Richard T, and Roger N Waud. 2002. The determinants of Federal Reserve policy actions: a re-examination. *Journal of Macroeconomics* 24 (3): 413–428.

Gabaix, Xavier. 2011. The granular origins of aggregate fluctuations. *Econometrica* 79 (3): 733–772.

Gallo, Lindsey A, Rebecca N Hann, and Congcong Li. 2016. Aggregate earnings surprises, monetary policy, and stock returns. *Journal of Accounting and Economics* 62 (1): 103–120.

Giovanni, Julian di, and Andrei A Levchenko. 2012. Country size, international trade, and aggregate fluctuations in granular economies. *Journal of Political Economy* 120 (6): 1083–1132.

Giovanni, Julian di, Andrei A Levchenko, and Isabelle Méjean. 2014. Firms, destinations, and aggregate fluctuations. *Econometrica* 82 (4): 1303–1340.

Gkougkousi, Xanthi. 2014. Aggregate earnings and corporate bond markets. *Journal of Accounting Research* 52 (1): 75–106.

Gorton, Gary B. 2010. *Questions and answers about the financial crisis.* Working Paper, NBER Working Paper Series 15787. National Bureau of Economic Research.

Hirshleifer, David, Kewei Hou, and Siew Hong Teoh. 2009. Accruals, cash flows, and aggregate stock returns. *Journal of Financial Economics* 91 (3): 389–406.

Jones, Paul M, and Walter Enders. 2016. The asymmetric effects of uncertainty on macroeconomic activity. *Macroeconomic Dynamics* 20 (5): 1219–1246.

Jorgensen, Bjorn, Jing Li, and Gil Sadka. 2012. Earnings dispersion and aggregate stock returns. *Journal of Accounting and Economics* 53 (1): 1–20.

Jurado, Kyle, Sydney C Ludvigson, and Serena Ng. 2015. Measuring uncertainty. *The American Economic Review* 105 (3): 1177–1216.

Kahl, Matthias, Anil Shivdasani, and Yihui Wang. 2008. *Do firms use commercial paper to enhance financial flexibility.* Working Paper.

Koenig, Evan F. 2005. The use and abuse of real-time and anecdotal information in monetary policy making. *Statistics, Knowledge and Policy:* 241–253.

Konchitchki, Yaniv. 2011. Inflation and nominal financial reporting: implications for performance and stock prices. *The Accounting Review* 86 (3): 1045–1085.

———. 2013. Accounting and the macroeconomy: the case of aggregate price-level effects on individual stocks. *Financial Analysts Journal* 69 (6): 40–54.

Konchitchki, Yaniv, and Panos N Patatoukas. 2014a. Accounting earnings and gross domestic product. *Journal of Accounting and Economics* 57 (1): 76–88.

———. 2014b. Taking the pulse of the real economy using financial statement analysis: implications for macro forecasting and stock valuation. *The Accounting Review* 89 (2): 669–694.

Kothari, SP, Jonathan Lewellen, and Jerold B Warner. 2006. Stock returns, aggregate earnings surprises, and behavioral finance. *Journal of Financial Economics* 79 (3): 537–568.

Laurion, Henry, and Panos N Patatoukas. 2016. From micro to macro: does conditional conservatism aggregate up in the national income and product accounts? *Journal of Financial Reporting* 1 (2): 21–45.

Lee, Charles MC, Paul Ma, and Charles CY Wang. 2015. Search-based peer firms: aggregating investor perceptions through Internet co-searches. *Journal of Financial Economics* 116 (2): 410–431.

Lerman, Alina, and Joshua Livnat. 2010. The new form 8-K disclosures. *Review of Accounting Studies* 15 (4): 752–778.

Leuz, Christian, and Peter D Wysocki. 2016. The economics of disclosure and financial reporting regulation: evidence and suggestions for future research. *Journal of Accounting Research* 54 (2): 525–622.

Li, Edward Xuejun, K Ramesh, and Min Shen. 2011. The role of newswires in screening and disseminating value-relevant information in periodic SEC reports. *The Accounting Review* 86 (2): 669–701.

Loughran, Tim, and Bill McDonald. 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-ks. *The Journal of Finance* 66 (1): 35–65.

Nallareddy, Suresh, and Maria Ogneva. 2017. Predicting restatements in macroeconomic indicators using accounting information. *The Accounting Review* 92 (2): 151–182.

Patatoukas, Panos N. 2014. Detecting news in aggregate accounting earnings: implications for stock market valuation. *Review of Accounting Studies* 19 (1): 134–160.

Peek, Joe, Eric S Rosengren, and Geoffrey MB Tootell. 2003. Does the Federal Reserve possess an exploitable informational advantage? *Journal of Monetary Economics* 50 (4): 817–839.

Prais, Sigbert J, and Christopher B Winsten. 1954. *Trend estimators and serial correlation.* Discussion paper. Cowles Commission, Chicago.

Romer, Christina D, and David H Romer. 2000. Federal Reserve information and the behavior of interest rates. *The American Economic Review:* 429–457.

Rossi, Barbara, and Tatevik Sekhposyan. 2016. Forecast rationality tests in the presence of instabilities, with applications to Federal Reserve and survey forecasts. *Journal of Applied Econometrics* 31 (3): 507–532.

Ryans, James P. 2017. *Using the EDGAR log file data set.* Working Paper.

Sadka, Gil, and Ronnie Sadka. 2009. Predictability and the earnings–returns relation. *Journal of Financial Economics* 94 (1): 87–106.

Sims, Christopher A. 2002. The role of models and probabilities in the monetary policy process. *Brookings Papers on Economic Activity* 2002 (2): 1–40.

6 Tables

Table 1: **Frequency of Fed Access by SEC Form**

Form Type	Fed Freq.	% of Sample	Cumulative %
10-K	59,035	34.93	34.93
10-Q	42,613	25.22	60.15
8-K	22,118	13.09	73.24
DEF 14A	10,189	6.03	79.27
10-K405	5,334	3.16	82.42
10-K/A	2,135	1.26	83.69
20-F	2,102	1.24	84.93
4	1,745	1.03	85.96
6-K	1,324	0.78	86.75
S-1	1,256	0.74	87.49
S-1/A	1,182	0.70	88.19
424B2	1,081	0.64	88.83
425	930	0.55	89.38
SC 13D/A	927	0.55	89.93
SC 13G/A	861	0.51	90.44
SC 13G	801	0.47	90.91
Other	15,370	9.97	100
Total	169,003	100	100

Each observation represents a "click" on a filing from the SEC's EDGAR database for firms that match to Compustat between March 2003 and February 2015.

Table 2: **Industry Distributions of Fed Access Vs. Compustat**

Fama-French 48 Industry	Fed Freq.	Compustat Freq.	Fed %	Compustat %
Banking	62,690	10,344	37.50	9.67
Trading	11,317	14,387	6.71	13.45
Business Services	9,786	11,263	5.91	10.53
Insurance	8,135	2,556	4.83	2.39
Electronic Equipment	5,834	5,039	3.52	4.71
Retail	5,769	3,447	3.50	3.22
Petroleum and Natural Gas	5,051	4,276	3.05	4.00
Communication	4,972	3,161	3.01	2.96
Pharmaceutical Products	3,863	7,417	2.36	6.94
Machinery	3,688	2,377	2.20	2.22
Computers	3,391	2,651	2.05	2.48
Wholesale	3,254	2,656	1.97	2.48
Transportation	3,198	2,597	1.90	2.43
Utilities	2,903	3,812	1.73	3.56
Chemicals	2,817	1,828	1.68	1.71
Almost Nothing	2,776	2,407	1.47	2.25
Food Products	2,366	1,267	1.15	1.18
Medical Equipment	1,935	1,026	1.06	2.76
Healthcare	1,738	1,393	1.04	1.30
Steel Works Etc	1,621	1,026	0.96	0.96
Consumer Goods	1,615	1,105	0.93	1.03
Apparel	1,547	882	0.90	0.82
Automobiles and Trucks	1,499	1,288	0.89	1.20
Measuring and Control Equipment	1,495	1,481	0.87	1.38
Restaraunts, Hotels, Motels	1,447	1,434	0.86	1.34
Entertainment	1,405	1,264	0.85	1.18
Construction Materials	1,400	1,211	0.82	1.13
Business Supplies	1,374	754	0.79	0.71
Electrical Equipment	1,329	1,311	0.63	1.23
Personal Services	1,057	914	0.61	0.85
Other	7,731	2,253	4.26	2.10
	169,003	106,943	100.00	100.00

Fed Freq. is the total number of times the Fed accessed SEC forms in the indicated industry over the sample period of March 2003 through February 2015. *Compustat Freq.* is the number of firm-year observations in Compustat for the given industry. We match Compustat SIC codes to the Fama-French 48 industries.

Table 3: **Descriptive Statistics for Macro Sample**

Panel A: Summary Statistics

	N	Mean	SD	Minimum	25%	Median	75%	Maximum
All Access	138	1,224.66	1,771.31	43.00	365.00	663.50	1,592.00	17,332.00
Current Access	138	562.22	483.64	27.00	232.00	428.50	732.00	2,774.00
All Unique	138	457.14	642.51	18.00	145.00	263.00	573.00	6,299.00
Current Unique	138	181.83	145.33	11.00	96.00	136.00	233.00	1,029.00
Ind Prod	138	3,518.32	151.62	3,157.42	3,412.28	3,511.83	3,614.93	3,794.75
Credit	138	2,614.81	347.59	2,001.21	2,415.73	2,609.88	2,824.49	3,368.96
Inflation (%)	138	0.18	0.34	-1.77	0.05	0.19	0.33	1.38
Market Ret (%)	138	0.91	4.33	-18.46	-1.41	1.59	3.71	11.40
Uncert	138	0.94	0.06	0.85	0.90	0.92	0.95	1.15
Uncert Shock	138	0.07	0.25	0.00	0.00	0.00	0.00	1.00
Recession	138	0.14	0.35	0.00	0.00	0.00	0.00	1.00

Panel B: Pearson Correlations

	All	*Current*	*Ind Prod*	*Credit*	*Infl*	*M Ret*	*Uncert*	*Shock*
All Access	1.000							
Current Access	0.886	1.000						
Ind Prod	−0.300	−0.309	1.000					
Credit	0.341	0.307	0.148	1.000				
Inflation	−0.150	−0.182	0.127	−0.166	1.000			
Market Ret	0.022	0.001	−0.129	−0.056	0.087	1.000		
Uncert	−0.272	−0.142	−0.208	−0.165	−0.186	−0.277	1.000	
U Shock	−0.025	0.078	0.191	0.132	−0.036	−0.317	0.384	1.000
Recession	−0.120	−0.027	−0.070	0.031	−0.088	−0.263	0.832	0.320

Data are at the monthly level from March 2003 to February 2015. We exclude observations from October 2005 to April 2006 because the SEC retained very few form views during this period (Bauguess, Cooney, and Hanley 2013). We present *All Access*, *Current Access*, *All Unique*, and *Current Unique* as the sum of form views by the Fed in this table, and use their logarithm form in the following analyses. See Appendix B for variable definitions.

Table 4: **Macro Determinants of the Fed's Access of SEC Filings**

	H1	*All Access$_t$* (All)	*All Access$_t$* (Fin)	*All Access$_t$* (Non-Fin)	*Current Access$_t$* (All)	*Current Access$_t$* (Fin)	*Current Access$_t$* (Non-Fin)
Ind Prod$_{t-1}$	$-$	-0.51^{***}	-0.50^{***}	-0.53^{***}	-0.42^{***}	-0.42^{***}	-0.38^{***}
		(-4.58)	(-5.42)	(-2.93)	(-4.68)	(-4.41)	(-2.84)
Credit$_{t-1}$		0.26^{**}	0.51^{***}	-0.06	0.18	0.41^{***}	-0.23
		(2.05)	(4.73)	(-0.31)	(1.64)	(3.71)	(-1.63)
Inflation$_{t-1}$		-0.13^{**}	-0.11^{*}	-0.15	-0.14^{***}	-0.11^{**}	-0.13
		(-2.24)	(-1.88)	(-1.13)	(-2.74)	(-2.00)	(-1.24)
Market Ret$_{t-1}$	$-$	-0.12^{**}	-0.11^{**}	-0.20^{*}	-0.12^{**}	-0.11^{**}	-0.23^{**}
		(-2.07)	(-2.28)	(-1.80)	(-2.56)	(-2.21)	(-2.52)
Uncert$_t$		-0.76^{***}	-0.55^{***}	-1.33^{***}	-0.55^{***}	-0.44^{***}	-0.88^{***}
		(-5.39)	(-4.31)	(-4.96)	(-4.61)	(-3.56)	(-4.10)
Uncert Shock$_t$	$+$	1.06^{***}	1.21^{***}	0.13	1.17^{***}	1.28^{***}	-0.06
		(3.65)	(4.04)	(0.17)	(4.34)	(4.55)	(-0.10)
Recession$_t$	$+$	1.22^{***}	1.05^{***}	2.34^{***}	0.94^{***}	0.90^{**}	1.25^{**}
		(2.88)	(2.80)	(3.30)	(2.78)	(2.54)	(2.17)
Intercept		6.35^{***}	5.73^{***}	5.08^{***}	5.82^{***}	5.43^{***}	4.25^{***}
		(51.45)	(53.80)	(26.11)	(56.76)	(51.08)	(29.57)
Adj. R^2		0.27	0.37	0.17	0.29	0.31	0.18
N Months		138	138	138	138	138	138
Standard Errors		Robust	Robust	Robust	Robust	Robust	Robust

Regressions are estimated using the Prais-Winsten correction for first-order autocorrelation in the linear model. Data are at the monthly level. The dependent variable is either *All Access$_t$* or *Current Access$_t$*, for the financial sector, the non-financial sector, or the two combined, denoted by the column headings. Continuous independent variables are standardized to have a mean of zero and a standard deviation of one. Estimated coefficients and t-statistics (in parentheses) are presented for each specification. *, **, *** represent statistical significance at two-tailed 0.1, 0.05, and 0.01 levels, respectively. See Appendix B for variable definitions.

Table 5: **Industry Determinants of the Fed's Access of SEC Filings**

	H2	*All Access$_{j,t}$* OLS	*All Access$_{j,t}$* Tobit	*All Access$_{j,t}$* Tobit	*Current Access$_{j,t}$* OLS	*Current Access$_{j,t}$* Tobit	*Current Access$_{j,t}$* Tobit
Banking$_j$	+	4.52***	5.82***	5.82***	4.71***	6.44***	6.44***
		(39.13)	(22.99)	(43.61)	(55.24)	(25.32)	(54.68)
Trading$_j$	+	2.28***	3.49***	3.49***	2.29***	3.90***	3.90***
		(21.81)	(13.96)	(29.17)	(31.18)	(15.56)	(41.57)
Insurance$_j$	+	1.80***	2.97***	2.97***	1.84***	3.35***	3.35***
		(17.33)	(11.92)	(33.01)	(22.51)	(13.48)	(46.38)
Finance$_j$ × *Ind Ret$_{j,t}$*		0.09***	0.15***	0.15***	0.08***	0.14***	0.14***
		(5.24)	(4.16)	(3.45)	(3.65)	(3.73)	(3.37)
Finance$_j$ × *VIX$_t$*		0.23	0.10	0.10	0.41***	0.39**	0.39***
		(1.46)	(0.66)	(0.65)	(3.13)	(2.35)	(2.82)
Industry Ret$_{j,t}$		−0.03	−0.10***	−0.10	−0.03	−0.10***	−0.10
		(−0.69)	(−2.65)	(−1.02)	(−1.13)	(−2.64)	(−1.24)
VIX$_t$		0.26**	0.45***	0.45**	0.04	0.16***	0.16
		(2.31)	(9.49)	(2.18)	(0.69)	(2.84)	(1.02)
Intercept		1.01***	−0.29	−0.29	0.53***	−1.22***	−1.22***
		(8.36)	(−1.14)	(−1.20)	(6.56)	(−4.74)	(−5.61)
Macro Controls		Yes	Yes	Yes	Yes	Yes	Yes
Finance × Macro Controls		Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Pseudo)		0.30	(0.08)		0.42	(0.10)	
N Industry-Months		6,624	6,624	6,624	6,624	6,624	6,624
Standard Errors		2-Way	1-Way	2-Way	2-Way	1-Way	2-Way

Regression estimation methods are denoted in the column headers. Data are at the monthly level. Estimated coefficients and t-statistics (in parentheses) are presented for each specification. *, **, *** represent statistical significance at two-tailed 0.1, 0.05, and 0.01 levels, respectively. Standard error clustering by industry alone is indicated by "1-Way", while clustering by industry and month is indicated by "2-Way". Continuous independent variables are standardized to have a mean of zero and a standard deviation of one. *Macro Controls* contains the macro controls from Table 4. *Finance × Macro Controls* are interaction terms that control for finance-industry specific macro effects. The coefficients on these controls are consistent with those from earlier tests, and are omitted for brevity.

Table 6: **Firm Determinants of the Fed's Access of SEC Filings**

	H2	*All Access*$_{i,t}$			*Current Access*$_{i,t}$		
		(1)	(2)	(3)	(1)	(2)	(3)
Bell$_{i,t}$	+	2.43***	2.43***	2.43***	2.64***	2.64***	2.64***
		(9.60)	(4.46)	(5.26)	(11.49)	(5.23)	(5.87)
SIFI$_i$	+	1.53***	1.53**	1.53***	1.61***	1.61***	1.61***
		(8.24)	(2.43)	(3.38)	(9.86)	(2.83)	(3.70)
Ind Leader$_{i,t}$	+	1.33***	1.33***	1.33***	1.30***	1.30***	1.30***
		(12.80)	(11.70)	(21.90)	(11.39)	(10.89)	(18.41)
CP$_{i,t}$	+	1.58***	1.58***	1.58***	1.50***	1.50***	1.50***
		(14.67)	(12.03)	(17.91)	(12.94)	(11.25)	(15.54)
Crash Risk$_{i,t}$	+	0.08	0.08*	0.08**	0.09	0.09**	0.09**
		(1.13)	(1.76)	(2.15)	(1.44)	(2.11)	(2.35)
Inv Intensity$_{i,t}$	+	0.21***	0.21**	0.21***	0.02	0.02	0.02
		(2.74)	(2.21)	(3.78)	(0.25)	(0.25)	(0.34)
Cap Intensity$_{i,t}$	+	0.14*	0.14	0.14**	0.04	0.04	0.04
		(1.80)	(1.31)	(2.31)	(0.32)	(0.35)	(0.58)
Finance$_i \times$ *Bell*$_{i,t}$		−0.93***	−0.93	−0.93	−1.18***	−1.18*	−1.18
		(−2.59)	(−1.24)	(−1.06)	(−3.74)	(−1.72)	(−1.43)
Finance$_i \times$ *Firm Ret*$_{i,t}$		−0.50	−0.50*	−0.50*	−0.90*	−0.90***	−0.90***
		(−0.79)	(−1.84)	(−1.75)	(−1.87)	(−4.36)	(−2.76)
Ind Leader$_{i,t} \times$ *Banking*$_i$		0.45	0.45***	0.45***	0.48*	0.48***	0.48***
		(1.58)	(3.76)	(2.87)	(1.71)	(3.63)	(3.02)
Ind Leader$_{i,t} \times$ *Trading*$_i$		0.80***	0.80***	0.80***	1.12***	1.12***	1.12***
		(4.21)	(8.09)	(3.13)	(4.09)	(9.08)	(4.12)
Ind Leader$_{i,t} \times$ *Insurance*$_i$		0.90***	0.90***	0.90***	1.35***	1.35***	1.35***
		(3.35)	(5.90)	(3.00)	(4.06)	(7.80)	(4.06)
Firm Ret$_{i,t}$		−0.25	−0.25	−0.25**	−0.07	−0.07	−0.07
		(−0.53)	(−1.40)	(−2.09)	(−0.20)	(−0.47)	(−0.52)
Banking$_i$		2.48***	2.48***	2.48***	2.60***	2.60***	2.60***
		(5.87)	(15.46)	(31.00)	(7.09)	(18.53)	(28.85)
Trading$_i$		0.21	0.21	0.21	0.22	0.22	0.22
		(0.85)	(1.15)	(1.61)	(0.77)	(1.52)	(1.45)
Insurance$_i$		0.42	0.42**	0.42**	0.09	0.09	0.09
		(1.42)	(2.37)	(2.43)	(0.32)	(0.63)	(0.42)
Intercept		−7.46***	−7.46***	−7.46***	−7.75***	−7.75***	−7.75***
		(−18.89)	(−25.95)	(−94.53)	(−18.01)	(−49.78)	(−80.94)
Controls: *Macro* and *VIX*		Yes	Yes	Yes	Yes	Yes	Yes
Finance × Controls		Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2		0.11	0.11	0.11	0.14	0.14	0.14
N Firm-Quarters		241,385	241,385	241,385	241,385	241,385	241,385
SE Clusters		Quarter	Industry	Firm	Quarter	Industry	Firm

Equations are estimated using Tobit. Columns correspond to different clustering levels. Data are at the firm/fiscal quarter level. Estimated coefficients and t-statistics (in parentheses) are presented for each specification. *, **, *** represent statistical significance at two-tailed 0.1, 0.05, and 0.01 levels, respectively. The coefficients on the *Macro* and *VIX* controls are consistent with those from earlier tests, and are omitted for brevity. Clustering by quarters is done by assigning fiscal quarters to calendar quarters. See Appendix B for variable definitions.

Table 7: **Descriptive Statistics for Forecast Sample**

	N	Mean	SD	Minimum	25%	Median	75%	Maximum
Panel A: Summary Statistics								
Fed_t^{t+1}	57	4.1	1.9	-3.0	3.4	4.5	5.2	6.6
SPF_t^{t+1}	45	4.4	1.3	-0.8	4.1	4.5	5.2	6.3
$Fed\ Error_t^{t+1}$	57	0.2	2.4	-9.6	-0.5	0.2	1.0	5.7
$SPF\ Error_t^{t+1}$	45	-0.3	2.3	-8.9	-0.9	-0.0	1.0	4.8
$Agg\ Earn_t$	57	1.2	0.7	-2.3	1.1	1.4	1.5	2.1
$Neg\ Tone_t$	57	1.8	0.2	1.4	1.6	1.7	2.0	2.4
Filings Searched (All)	57	536.8	662.1	55.0	198.0	327.0	556.0	3,648.0
Age of Most Recent SPF_t^{t+h}	57	50.4	23.3	18.0	28.0	39.0	72.0	83.0

Panel B: Pearson Correlations

	Fed_t^{t+1}	SPF_t^{t+1}	$Fed\ Error_t^{t+1}$	$SPF\ Error_t^{t+1}$	$Agg\ Earn_t$	$Neg\ Tone_t$
Fed_t^{t+1}	1.000					
SPF_t^{t+1}	0.794	1.000				
$Fed\ Error_t^{t+1}$	0.067	0.138	1.000			
$SPF\ Error_t^{t+1}$	0.292	0.158	0.913	1.000		
$Agg\ Earn_t$	0.600	0.686	0.013	0.007	1.000	
$Neg\ Tone_t$	−0.617	−0.777	−0.321	−0.321	−0.314	1.000

Data intervals for Fed forecasts correspond to roughly eight FOMC meetings each, beginning with the first meeting in April 2003 after the start of the EDGAR log file and ending with the last meeting in December 2010 for which there is publicly available Teal Book data. Intervals for the SPF forecasts are quarterly, spanning the entire available period of our EDGAR log files, Q2:2003 to Q1:2015. Both samples are further restricted due to the non-retention of EDGAR log files from October 2005 to April 2006. We drop five FOMC meetings from the Fed analyses and three quarters from the SPF analyses that fall in or adjacent to the non-retention period and therefore lack data to calculate our tone proxy. See Appendix B for variable definitions. Correlations between Fed and SPF variables are calculated using the most recent SPF forecasts for each Fed forecast.

Table 8: **NGDP Growth Forecasts and Tone of Fed-Accessed SEC Filings**

Panel A: Fed Forecasts

	H3	Fed_t^{t+1}	Fed_t^{t+2}	Fed_t^{t+3}	Fed_t^{t+4}
Agg Earn (FOMC)$_t$		0.35^{**}	0.22	0.36^{**}	0.39^{***}
		(2.66)	(1.18)	(2.49)	(2.92)
Neg Tone (FOMC)$_t$	–	-0.45^{**}	-0.41^{***}	-0.48^{***}	-0.36^{***}
		(−2.64)	(−3.13)	(−3.94)	(−3.43)
Intercept		0.01	0.03	0.01	0.04
		(0.08)	(0.11)	(0.08)	(0.17)
R^2		0.34	0.24	0.36	0.32
N FOMC Meetings		57	57	57	57
Standard Errors		Robust	Robust	Robust	Robust

Panel B: SPF Forecasts

	SPF_t^{t+1}	SPF_t^{t+2}	SPF_t^{t+3}	SPF_t^{t+4}
Agg Earn (Quarter)$_t$	0.38^{***}	0.21^{***}	0.29^{***}	0.25^{**}
	(3.11)	(3.25)	(6.92)	(2.16)
Neg Tone (Quarter)$_t$	−0.09	−0.26	−0.18	-0.25^{*}
	(−0.43)	(−1.30)	(−1.61)	(−1.69)
Intercept	0.03	0.11	0.15	0.08
	(0.13)	(0.40)	(0.51)	(0.34)
R^2	0.27	0.23	0.26	0.23
N Quarters	45	45	45	45
Standard Errors	Robust	Robust	Robust	Robust

Panel C: Fed Forecasts with SPF as Control					
	H3	Fed_t^{t+1}	Fed_t^{t+2}	Fed_t^{t+3}	Fed_t^{t+4}
Agg Earn (FOMC)$_t$		0.21	0.16	0.31**	0.36***
		(1.51)	(0.93)	(2.23)	(2.79)
Neg Tone (FOMC)$_t$	−	−0.19	−0.28**	−0.34**	−0.29**
		(−1.19)	(−2.02)	(−2.50)	(−2.66)
SPF_t^{t+1}		0.47**			
		(2.03)			
SPF_t^{t+2}			0.38**		
			(2.22)		
SPF_t^{t+3}				0.27**	
				(2.06)	
SPF_t^{t+4}					0.23
					(1.51)
Intercept		0.04	0.04	0.03	0.04
		(0.37)	(0.24)	(0.19)	(0.21)
R^2		0.46	0.35	0.41	0.36
N FOMC Meetings		57	57	57	57
Standard Errors		Robust	Robust	Robust	Robust

Regressions are estimated using the Prais-Winsten correction for serial correlation in the linear model. The dependent variables are listed in the column headings, where Fed_t^{t+h} and SPF_t^{t+h} are the Fed and SPF h-quarter ahead forecasts for NGDP growth made in quarter t, respectively. Regressions using Fed forecasts as the dependent variable are over the available sample period of April 2003 through December 2010. Those using SPF forecasts are from Q2:2003 through Q1:2015. In panel C, to control for SPF forecast information available to the Fed, we match Fed forecasts with the most recently available SPF forecast of the same horizon. To ease interpretation and comparison, all variables are standardized to have a mean of zero and a standard deviation of one. Estimated coefficients and t-statistics (in parentheses) are presented for each specification. *, **, *** represent statistical significance at two-tailed 0.1, 0.05, and 0.01 levels, respectively.

Table 9: **Tone of Fed-Accessed Filings as a Predictor of Fed and SPF Forecast Errors**

Panel A: Fed Forecast Errors

	$Fed\ Error_t^{t+1}$		$Fed\ Error_t^{t+2}$		$Fed\ Error_t^{t+3}$		$Fed\ Error_t^{t+4}$	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Agg Earn (FOMC)$_t$	−0.02	0.02	−0.10	−0.07	−0.20	−0.18	−0.11	−0.10
	(−0.13)	(0.20)	(−0.88)	(−0.67)	(−1.11)	(−0.98)	(−1.06)	(−1.05)
Neg Tone (FOMC)$_t$	−0.10	−0.13	0.25	0.23	−0.06	−0.05	0.21	0.21
	(−0.50)	(−1.13)	(1.64)	(1.60)	(−0.46)	(−0.47)	(1.43)	(1.44)
Crisis$_t$		−3.57***		−0.87*		−1.01		−0.33
		(−8.98)		(−1.72)		(−1.52)		(−0.29)
Intercept	−0.01	0.10	0.09	0.09	0.08	0.10	0.05	0.05
	(−0.04)	(0.76)	(0.27)	(0.33)	(0.24)	(0.34)	(0.14)	(0.16)
R^2	0.01	0.49	0.06	0.09	0.05	0.11	0.04	0.05
N FOMC Meetings	57	57	57	57	57	57	57	57
Standard Errors	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust

Panel B: SPF Forecast Errors

	$SPF\ Error_t^{t+1}$		$SPF\ Error_t^{t+2}$		$SPF\ Error_t^{t+3}$		$SPF\ Error_t^{t+4}$	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Agg Earn (Quarter)$_t$	−0.10	−0.13	−0.09	−0.10	−0.10	−0.11	0.02	0.01
	(−1.33)	(−1.68)	(−0.56)	(−0.68)	(−0.69)	(−0.77)	(0.17)	(0.14)
Neg Tone (Quarter)$_t$	−0.21	−0.26*	−0.21*	−0.24*	−0.12	−0.14	0.01	0.00
	(−1.40)	(−1.86)	(−1.68)	(−2.00)	(−0.95)	(−1.12)	(0.06)	(0.02)
Crisis$_t$		−4.08***		−2.76***		−1.71***		−0.46**
		(−33.47)		(−15.82)		(−8.81)		(−2.29)
Intercept	0.03	0.12	0.04	0.11	0.03	0.07	−0.03	−0.01
	(0.19)	(0.97)	(0.27)	(0.70)	(0.17)	(0.41)	(−0.16)	(−0.09)
R^2	0.04	0.39	0.04	0.19	0.02	0.08	0.00	0.00
N FOMC Meetings	45	45	45	45	45	45	45	45
Standard Errors	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust

Regressions in Panel A are estimated using the Prais-Winsten correction for serial correlation in the Fed forecast data. As serial correlation is absent from the SPF forecast data, the regressions are estimated using OLS. The sample period for the Fed regressions is March 2003 through December 2010. The sample period for the SPF regressions is Q2:2003 to Q1:2015. All variables are standardized to have a mean of zero and a standard deviation of one. Estimated coefficients and t-statistics (in parentheses) are presented for each specification. *, **, *** represent statistical significance at two-tailed 0.1, 0.05, and 0.01 levels, respectively.

Table 10: **Other Economic Forecasts and Tone of Fed-Accessed SEC Filings**

Panel A: *Agg Earn* Coefficients

	Inflation		Supply/Demand			
Forecast Horizon	*PCEPI*	*GDPPI*	*PCE*	*IP*	*BFI*	*HSTART*
t + 1	0.03	0.22**	0.13**	0.56***	0.19***	0.09***
t + 2	0.08	−0.04	0.13*	0.32***	0.30***	0.11***
t + 3	0.05	0.05	0.03	0.34**	0.32***	0.13***
t + 4	0.07	0.08*	0.24***	0.10	0.30***	0.11***

Panel B: *Net Neg Tone* Coefficients

	Inflation		Supply/Demand			
Forecast Horizon	*PCEPI*	*GDPPI*	*PCE*	*IP*	*BFI*	*HSTART*
t + 1	−0.30*	−0.12	−0.25***	−0.30**	−0.18**	−0.06**
t + 2	0.01	0.03	−0.10	−0.43***	−0.32***	−0.09***
t + 3	−0.03	−0.19**	−0.34**	−0.38***	−0.13	−0.09***
t + 4	−0.10*	−0.12**	−0.22**	−0.21**	−0.29***	−0.10***

Regressions are estimated using the Prais-Winsten correction for serial correlation in the linear model. Columns correspond to different forecast components, which we have classified as proxying for either inflation or aggregate supply/demand. Rows correspond to different forecast horizons for those variables. Each dependent variable is the Fed's *h*-quarter ahead growth forecast for the following variables: *PCEPI* is Personal Consumption Expenditure Price Index, *GDPPI* is Gross Domestic Product Price Index, *PCE* is personal consumption expenditures, *IP* is Industrial Production, *BFI* is Business Fixed Investment, and *HSTART* is Housing Starts. The sample period is April 2003 through December 2010. All variables are standardized to have a mean of zero and a standard deviation of one. For brevity, only estimated coefficients are presented for each specification. *, **, *** represent statistical significance at two-tailed 0.1, 0.05, and 0.01 levels, respectively.

Appendices

A Background of the Federal Reserve

The Federal Reserve Act of 1913 created the Federal Reserve System to promote a secure and effective monetary and financial system. The act designated the Fed as the U.S. central bank with power to conduct monetary policy. It also required all nationally chartered banks to become members of the system. A 1933 amendment to the act formed the Federal Open Markets Committee (FOMC). Later, in 1977, another amendment required the Board and FOMC to "promote effectively the goals of maximum employment, stable prices, and moderate long-term interest rates."[36] Since then, the Federal Reserve has assumed the additional roles of regulating the banking sector and stabilizing the nation's financial system.

The Fed has three main tools for meeting its objectives. The first and most important is open market operations, which consists of buying and selling government bonds and other securities. Such transactions adjust liquidity in the currency and affect the economy's money supply.[37] The second tool is setting the federal funds target rate, discussed in detail below.[38] The third tool is setting reserve requirements—the amount of funds that depository institutions must keep on reserve at the Fed in order to meet deposit liabilities.

The federal funds rate is a principal indicator for the effect of monetary policy. It is the interest rate that banks charge one another on loans to meet the Fed's reserve requirements. As a bank's deposit liabilities fluctuate, the required reserve balance also changes. Banks with a surplus reserve balance can briefly loan the excess to banks in need of greater reserve balances. The two parties negotiate the rate for a particular lending agreement and the weighted average of the rates across all such loans is known as the federal funds effective rate. At each of its roughly eight meetings in a year, the FOMC can adjust its target for this rate. The Fed then engages in open market operations or quantitative easing to influence the effective rate banks charge one another. While the federal funds effective rate has fluctuated substantially over time, sometimes reaching as high as 18 percent, both the target and effective rates have been effectively zero since late 2008 as a result of the expansionary monetary policies the Fed enacted to counter the Great Recession.[39]

To conduct meaningful monetary policy, the Fed relies on indicators of past, current, and future macroeconomic activity. To this end, the Fed employs a large team of economists and researchers who prepare a series of internal briefing documents that are circulated in preparation for FOMC meetings. These documents are known today as the Beige Book and the Teal Book. Historical predecessors of these documents include the Red Book, a report commissioned in 1970

36. Fed Website, "About the Fed", accessed March 11, 2017.

37. Since the middle of the great recession and the near-zero interest rates that resulted from the Fed's expansionary monetary policy, open market operations have become ineffective. The Fed's favored tool is now quantitative easing (Gallo, Hann, and Li 2016).

38. Related to this is the Fed's choosing the discount rate for funds borrowed at the Fed's discount window, where banks and other depository institutions can borrow funds in the short term to preserve liquidity. This window is rarely used outside periods of deep financial distress.

39. See the Fed's press release announcing the change.

by Fed Chairman Arthur Burns that focused primarily on qualitative information gathered through the different branches of the Fed; the Green Book, which contained economic analysis and forecasts; and the Blue Book, which contained contextual information on monetary policy actions and alternatives.

In 1983, the Red Book was made public at the request of the House of Representatives, and the color was changed from red to beige. It is made available to the public two weeks prior to each FOMC meeting. In 2010, the Fed combined the Green Book and the Blue Book into the current Teal Book, parts I and II, respectively.[40] These serve as key briefing documents for Fed policymakers in their FOMC meetings. Part I provides summaries and forecasts of economic performance and is typically broken into categories including household, business, government, and external sectors, and subcategories including consumer spending, residential investment, household finance, business fixed investment, inventory investment, business finance, federal and state spending, and net exports. Part II details monetary policy recommendations and alternatives for consideration at the FOMC meetings. The Teal Book is made available to the public with a five-year lag.

Another important role played by the Fed is that of bank regulator. The Fed has supervisory power over nationally chartered banks, state banks that are members of the Federal Reserve System, and bank holding companies, totaling nearly 6,000 institutions in 2015. Regulatory responsibilities include "ensur[ing] the safety and soundness of financial institutions, stability in the financial markets, and fair and equitable treatment of consumers in their financial transactions." Fed regulation can apply selectively to member banks or to the banking industry as a whole (see the Federal Reserve's 2015 Annual Report).

The process of supervision includes both on- and off-site examinations of the regulated entities, with inspections typically occurring every 12 months. Additionally, the Fed has the stated objective of "strengthen[ing] the accounting, audit, and control standards related to financial institutions" (see the Federal Reserve's 2005 publication, *The Federal Reserve System: Purposes and Functions*). The Fed enforces regulation through supervisory actions that range from less formal reports addressed to firm management informing them of shortcomings or requesting the adoption of a board resolution, to more formal enforcement measures including cease-and-desist orders against an institution or individual, fines, the removal of a director or officer, or the permanent barring of a director or officer from the industry.

40. See "Federal Reserve Rolls Out the Teal Book," June 22, 2010, WSJ.com for details on recomposition of the Teal Book, and "The Federal Reserve's Beige Book: A better mirror than a crystal ball" for more information about the history of the Red Book and Beige Book. Accessed January 10, 2017.

B Variable Definitions and Sources

B.1 Macro Determinants of Fed Access

DEPENDENT VARIABLES

- *All Access$_t$* - All Fed access during time t.

  This variable is defined as $\log\left(\sum_{s \in t} Access_s + 1\right)$, where *Access* is either $Access_s$, searches performed by the Fed on day s during time t; $Access_{j,s}$, searches for firms in industry j performed by the Fed on day s during time t; or $Access_{is}$, searches for firm i performed by the Fed on day s during time t.

  (Source: SEC's EDGAR Log File Data Set)

- *Current Access$_t$* - Current Fed access during time t.

  This variable is defined identically to *All Access$_t$*, but restricted to Fed searches for forms that are less than one year old (i.e., days between the search date and the filing date ≤ 365).

  (Source: The SEC's EDGAR Log File Data Set)

INDEPENDENT VARIABLES

- *Ind Prod$_t$* - Industrial production in time t.

  The gross value (in billions of dollars) of final products and nonindustrial supplies, seasonally adjusted, at the monthly level.

  (Source: Board of Governors of the Federal Reserve System (G17/GVIP/GVIP.T50030.S))

- *Credit$_t$* - Consumer Credit in time t.

  The total consumer credit (in millions of dollars) owned and securitized, seasonally adjusted at the monthly level.

  (Source: Board of Governors of the Federal Reserve System(G19/CCOUT/DTCTL.M))

- *Inflation$_t$* - Rate of inflation in time t.

  The consumer price index for all urban consumer. This includes all items (index 1982-1984=100, Monthly, Seasonally Adjusted).

  (Source: St. Louis Fed's FRED Database)

- *Market Ret$_t$* - Market Returns in time t.

  Value weighted returns including distributions (vwretd) from CRSP.

  (Source: Center for Research in Security Prices, University of Chicago)

- *Uncert$_t$* - Macro uncertainty in time t.

  12-month ahead macroeconomic uncertainty from Jurado, Ludvigson, and Ng (2015).

  (Source: Ludvigson's website)

- *Uncert Shock*$_t$ - Uncertainty-increasing shock in time t.

  A 1.5 standard deviation increase in *Uncert*$_t$ relative to *Uncert*$_{t-1}$.

- *Recession*$_t$ - Recession indicator for time t.

  Indicators for months in periods of economic contraction as identified by the NBER. In our sample these include December 2007 through June 2009.

  (Source: NBER.org/cycles)

B.2 Industry Determinants of Fed Access

INDEPENDENT VARIABLES

- *Banking*$_j$ - Banking industry indicator.

  This is an indicator for firms in the Fama-French 48 industry that corresponds to banking (44). This variable is not time varying.

- *Trading*$_j$ - Trading industry indicator.

  This is an indicator for firms in the Fama-French 48 industry that corresponds to trading (47). This variable is not time varying.

- *Insurance*$_j$ - Insurance industry indicator.

  This is an indicator for firms in the Fama-French 48 industry that corresponds to insurance (45). This variable is not time varying.

- *Industry Ret*$_{j,t}$ - Returns for industry j over time t.

  Fama-French 48 Industry returns.

  (Source: All Fama-French data - Ken French's Website, Downloaded 6/22/2016.)

- *VIX*$_t$ - Chicago Board Options Exchange Volatility Index in time t.

  The average of the daily values of the VIX historical price data. We use the closing daily values.

  (Source: Chicago Board Options Exchange website)

- *Finance*$_j$ - Financial sector indicator.

  This is an indicator for firms in the Fama-French 48 industries that corresponds to banking (44), trading (47), or insurance (45). This variable is not time varying.

B.3 Firm Determinants of Fed Access

INDEPENDENT VARIABLES

- $Bell_{i,t}$ - Bellwether indicator.

  This is an indicator for whether firm i is one of the 20 largest firms, by market cap, in the quarter t.

- $SIFI_i$ - Systemically Important Financial Institutions indicator.

  Indicator for whether a firm appears on the lists of Systemically Important Financial Institutions produced by the Financial Stability Board. We use the union of lists from 2015, 2014, and 2011. This variable is not time-varying.

  (Source: Financial Stability Board website)

- $Ind\ Leader_{i,t}$ - Industry leader indicator.

  This is an indicator for whether firm i is in the top Fama-French 48 industry quartile for total assets in quarter t. We use market cap as an alternative measure and find similar results.

- $CP_{i,t}$ - Commercial paper indicator.

  This is an indicator for whether firm i has a non-missing rating for the S&P Domestic Short Term Issuer Credit Rating variable (SPSTICRM) in the Compustat Ratings database at quarter t.

- $Crash\ Risk_{i,t}$ - High crash risk indicator.

  This is an indicator for whether firm i's crash risk is in the top quartile for quarter t, where crash risk is the log of the ratio of the standard deviation of *Firm Returns* below the quarter's mean return to the standard deviation of returns above the quarter's mean.

- $Inv\ Intensity_{i,t}$ - High inventory intensity indicator.

  This is an indicator for whether firm i's inventory intensity is in the top quartile for quarter t, where inventory intensity is defined as inventory over total assets (Compustat variables: invtq / atq).

- $Cap\ Intensity_{i,t}$ - High capital intensity indicator.

  This is an indicator for whether firm i's capital intensity is in the top quartile for quarter t, where capital intensity is defined as property, plant, and equipment over total assets (Compustat variables: ppentq / atq).

- $Firm\ Ret_{i,t}$ - Returns for firm i over quarter t.

  This variable is quarterly firm returns.

  (Source: CRSP Monthly File)

B.4 Inputs to Federal Reserve Forecasts

DEPENDENT VARIABLES

- *Fed*$_t^{t+h}$ - The Federal Reserve's h-quarter-ahead forecast made in quarter t.

  This is the h-quarter ahead growth forecast for a given variable reported in the Green Book/Teal Book, made in quarter t. We use the following abbreviations for these variables: NGDP for nominal gross domestic product, PCEPI for personal consumption expenditures price index, GDPPI for gross domestic product price index, PCE for personal consumption expenditures, IP for industrial production, and HSTART for housing starts. Note that this variable is measured at the Green Book date level, but that the forecasts are in terms of quarters ahead.

  (Source: Federal Reserve Bank of Philadelphia's website)

- *SPF*$_t^{t+h}$ - The Survey of Professional Forecasters' h-quarter-ahead forecast made in quarter t.

  This is the mean value of all SPF forecasters' h-quarter ahead growth forecasts, made in quarter t, for a given variable. We also use this as an independent variable in some specifications. This variable is measured at the quarterly interval.

  (Source: Federal Reserve Bank of Philadelphia's website)

- *Fed Error*$_t^{t+h}$ - The Federal Reserve's h-quarter-ahead forecast error for forecasts made in quarter t.

  This is the h-quarter ahead forecast error for NGDP forecasts made by the Fed in quarter t. This variable is defined as the h-quarter ahead NGDP growth realization, from which we subtract the h-quarter ahead NGDP growth forecast from the Philadelphia Fed's Green Book Dataset. The NGDP realization data is from the Philadelphia Fed's Real Time Data Set for Macroeconomists. We use the final, rather than the advance realization because the final realization is calculated with actual data, while the advanced realization is estimated.

  (Source: Federal Reserve Bank of Philadelphia's website)

- *SPF Error*$_t^{t+h}$ - The Survey of Professional Forecasters h-quarter-ahead forecast error for the forecast made in quarter t.

  This is the h-quarter ahead forecast error for the forecast made by the SPF in quarter t. This variable is defined as the h-quarter ahead NGDP growth realization minus the corresponding mean NGDP growth forecast made by the SPF. We use the final, rather than the advance realization because the final realization is calculated with actual data, while the advanced realization is estimated. These data are available as part of the Survey of Professional Forecasters dataset from the Federal Reserve Bank of Philadelphia's Real-Time Data Research Center.

  (Source: Federal Reserve Bank of Philadelphia's website)

INDEPENDENT VARIABLES

- *Agg Earn (FOMC)$_t$* - Aggregate earnings reported between the FOMC meetings at t and $t-1$.

  This variable is defined as the sum of *Earnings* over the sum of market capitalization for all firms that report earnings before the FOMC Meeting in t, but after the FOMC meeting in $t-1$. *Earnings* is defined as earnings before extraordinary items (ib in Compustat).

- *Neg Tone (FOMC)$_t$* - Negative tone of filings accessed by the Fed between two FOMC meetings.

  This variable is defined as the average negative tone of the 10-K and 10-Q filings accessed by the Fed between two FOMC meetings, where negative tone is *FinTerms_negative* from the Readability and Sentiment data file in the WRDS SEC Analytics Suite.

  (Source: WRDS SEC Analytics Suite)

- *Agg Earn (Quarter)$_t$* - Aggregate earnings reported between the SPF forecast deadlines in quarter t and $t-1$.

  This variable is defined as the sum of *Earnings* over the sum of market capitalization for all firms that report earnings before the SPF forecast deadline in quarter t, but after the SPF forecast deadline in quarter $t-1$.

- *Neg Tone (Quarter)$_t$* - Negative tone of filings accessed by the Fed between two SPF forecast deadlines.

  This variable is defined as the average negative tone of the 10-K and 10-Q filings accessed by the Fed between two SPF forecast deadlines.

  (Source: WRDS SEC Analytics Suite)

- *Crisis$_t$* - Crisis indicator for quarter t containing the August/September 2008 start of the financial crisis of 2007-2008.

  This variable is set to one for quarters or FOMC intervals that contain August or September 2008.