Credit Market Disruptions and Corporate Disclosure*

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Abstract

This paper investigates the effects of credit market disruptions on corporate voluntary disclosure. Using a shift-share design to construct county-level credit supply shocks, I find that managers of more exposed firms issue more earnings guidance and less capital expenditure guidance. The positive effect on disclosure is more concentrated in investment-grade firms, multi-segment firms, and firms with more dispersed ownership. The negative impact is more pronounced among firms with higher operating uncertainty. Collectively, these findings suggest that firms change their disclosure policies in response to disrupted credit markets due to managers' desire to alleviate the adverse selection and agency problems and their concern about increased uncertainty.

Keywords: Financial Constraints; Great Recession; Disclosure; Management Guidance
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1. Introduction

The global financial crisis (GFC) was characterized by disruptions in credit markets. The inception of disruption is dated to August 2007, when BNP Paribas suspended the operations of its sponsored funds due to an inability to value their subprime mortgages. The subsequent failure of Lehman Brothers in September 2008 triggered a far more acute phase of the GFC. Total bank lending to businesses decreased by more than 20% from 2008 to 2010 (Cortés et al., 2019, Gopal and Schnabl, 2020). The fall was even larger for new small business lending, which dropped by almost 40% during the same period (see Figure 1). In this paper, I ask whether these credit market disruptions change corporate disclosure policies and if yes, whether the change is persistent.

I posit that the breakdown of credit markets affects corporate disclosure policies via its effects on firms' funding positions, external monitoring activities, and uncertainty. First, disrupted credit from existing lenders directly affects firms' funding positions, thereby inducing them to seek alternative financing sources from other lenders (e.g., financial companies, fintech lenders, bond markets). However, firms are adversely selected because of the classic information asymmetry between borrowers and outside capital providers (Akerlof, 1970). On top of that, they bear high costs of switching lenders due to the information gap between current lenders and potential new lenders (Rajan, 1992, Sharpe, 1990). In particular, this information gap deepens as incumbent lenders advance their capacity of acquiring and processing borrowers' private and difficult to verify ("soft") information over the course of relationships (Darmouni, 2020, Petersen and Rajan, 2002, Schenone, 2010, Srinivasan, 2014, Stein, 2002).[1] The borrowers' switching cost might be even higher during the turmoil in credit markets because of a relationship-ended stigma (Darmouni, 2020). Borrowers looking for a new lender are inferred to be of lower quality because incumbent lenders being endowed with advantage information do not renew their relationship. To mitigate these problems, disrupted borrowers are more likely to increase their disclosures (Baiman and Verrecchia, 1996, Beyer et al., 2010,

[1] Examples of soft information are opinions, rumors, cultures, social norms, etc. (Fisman et al., 2017, Liberti and Petersen, 2019).

Diamond and Verrecchia, 1991, Myers and Majluf, 1984). Nevertheless, firms will not necessarily change their voluntary disclosures if they can internalize the negative credit supply shock by resorting to internal funds (e.g., cash holdings, capital expenditure, etc.) (Campello et al., 2010, Granja and Moreira, 2020, Kuppuswamy and Villalonga, 2016) or passing it through downstream customers (Costello, 2020).

Second, the credit market disruptions can indirectly affect corporate disclosure by the weakened banks' role as delegated monitors by public capital providers. The classical theory of financial intermediation suggests that banks have superior monitoring capability due to their information advantages (Diamond, 1984, 1991, Holmstrom and Tirole, 1997). Therefore, it is optimal for dispersed outside financiers to delegate the monitoring activities to banks. As banks exit this role, external capital providers may demand for more public information to fulfill their monitoring efforts, and thus firms' incentives to disclose information increase.

Finally, malfunctioning credit markets trigger a spike in uncertainty about macroeconomic conditions and firms' ability to substitute disrupted bank lending. On the one hand, investors concerning about the potential negative effects on the firm's valuation may demand for additional forward-looking information, and managers respond to such increased pressure by disclosing their private information (Bischof, 2014, Chava and Purnanandam, 2011, Lambert et al., 2012, Lo, 2014, Verrecchia, 2001). On the other hand, the heightened uncertainty may lower the quality of managers' information (e.g., greater imprecision), thereby increasing firms' incentives to withhold forward-looking information, particularly if imprecise disclosure imposes additional costs on managers (e.g., higher expected litigation costs, loss of reputation) (Kim et al., 2016, Verrecchia, 1990). At the same time, investors may be more uncertain about managers' information endowment during this negative episode, whereby the pressure exerted by the market on managers to reveal information is deterred. Consequently, managers may reduce voluntary disclosure (Dye, 1985, Jung and Kwon, 1988, Verrecchia, 1990). Given the above arguments, the effects of the credit market disruptions on corporate disclosure policies and whether they are persistent are ultimately empirical questions.

To address these questions, I follow Greenstone et al. (2020) to construct a geographic measure of a firm's exposure to credit market disruptions during the GFC. The measure is based on a shift-share design and exploits pre-crisis variation in a county's exposure to different banks and banks' heterogeneous aggregate small business lending cut during the 2007–2010 period. This approach allows me to study a large number of firms without restricting to firms with publicly available data on financing structure.

I use the issuance of management guidance as my main measure of disclosure. Specifically, I investigate management guidance on all metrics and two specific and prevalent metrics: earnings and capital expenditure ("capex"). While results show no changes in the frequency of management guidance on all metrics, there are differential effects on earnings and capex guidance. In particular, I find that firms more exposed to credit market disruptions issue more earnings guidance and less capex guidance. These effects are large and persist for at least three years after the GFC. The frequency of earnings (capex) guidance of more exposed firms increases (decreases) by 46.2 (63.4) percent over the crisis period and by 43.7 (56.1) percent during the subsequent recovery period, relative to less exposed firms.

Further analyses suggest that firms' incentive to substitute negative credit supply shocks and respond to investors' demand for additional information to restore external monitoring efforts are the main drivers of the positive effect on earnings guidance. Meanwhile, increased uncertainty is the channel that affects the frequency of issuing capex guidance. First, I find that the increase in earnings guidance is more pronounced among investment-grade firms, conglomerates, and firms with more dispersed ownership. Firms with higher uncertainty about substituting the effect of disrupted credit (e.g., firms without access to the bond market and speculative-grade firms) and firms with higher operating uncertainty are more likely to decrease the capex guidance when experiencing dysfunctional credit markets.

Second, my results show that negative credit supply shocks expand the disclosures of good news rather than bad news. This result lends support to the argument that firms try to mitigate the information asymmetry facing prospective lenders (Bischof, 2014).

Furthermore, I find that higher levels of uncertainty do not compromise the horizon and precision of earnings guidance issued by more exposed firms. Overall, the breakdown of credit markets induces firms to change their disclosure policies towards more earnings guidance and less capex guidance. They also adjust earnings guidance characteristics by providing more good news and range forecasts.

This paper contributes to the literature examining the banks' impact on borrowers. Prior studies provide evidence for the effect on borrowers' investment decisions (Amiti and Weinstein, 2018, Chava and Purnanandam, 2011, Ivashina and Scharfstein, 2010), exports (Amiti and Weinstein, 2011), employment (Chodorow-Reich, 2014, Greenstone et al., 2020), output prices (Kim, 2021), accounting methods (Beatty and Weber, 2003), voluntary disclosures (Chen and Vashishtha, 2017, Lo, 2014), mandatory disclosures (Khan and Lo, 2019), and tax planning (Gallemore et al., 2019). This paper is closest to Lo (2014), who provides evidence of borrowers' voluntary disclosure change in response to their banks' financial health. My paper extends Lo in three ways. First, I explicitly examine the credit crunch channel through which banks' health affects borrowers' disclosure policy. As discussed by Bischof (2014), Lo's use of banks' voluntary disclosures of exposures to emerging markets (i.e., Asia, Russia, and Latin America) to measure banks' health may capture an alternative channel (i.e., the bank disclosure channel). I instead use negative credit supply shocks - which are not subject to this concern - as proposed by Greenstone et al. (2020). Second, the geographic measure of exposure to credit market disruptions allows examining a large set of firms rather than firms with access to the syndicated loan market. Generally, the latter are large firms and can tap into alternative financing sources (e.g., the public debt market). Finally, guidance practices have changed significantly since 2000, and managers increasingly provide guidance on metrics other than earnings (e.g., sales, capital expenditure) (Lu and Skinner, 2020). My study reveals that credit market disruptions have differential effects on different forms of guidance and highlights the persistent role of earnings guidance as a tool to alleviate information asymmetry when firms experience extreme financial conditions.

I also add to the prior empirical literature on firms' voluntary disclosure change in response to shocks (e.g., those to firms' cost of equity (Leuz and Schrand, 2009), analyst coverage (Balakrishnan et al., 2014), banks' health (Lo, 2014), and banks' structure (Chen and Vashishtha, 2017)). I extend this literature by examining firms' voluntary disclosure in response to the collapse of credit markets and finding that managers heterogeneously adjust their guidance on earnings and capital expenditure.

The rest of the paper is organized as follows. In Section 2, I discuss the hypothesis development. In Section 3, I describe data and sample construction. Section 4 presents the background and empirical methodology. The results are reported in Section 5. In Section 6, I provide the results of additional analyses. Concluding remarks are in Section 7.

2. Hypothesis Development

During the global financial crisis (GFC), credit markets in the United States experienced unprecedented disruptions. I hypothesize that they affect corporate disclosure policies under three channels: the funding channel, the monitoring channel, and the uncertainty channel.

Under the funding channel, disrupted credit markets have direct and significant effects on firms' funding positions. To substitute bank lending contraction, firms may seek alternative external financing sources (e.g., non-bank lenders, bond markets) (Adrian et al., 2012, Becker and Ivashina, 2014, Chodorow-Reich, 2014, Schwert, 2018). Potential lenders, however, encounter asymmetric information problems. First, there exists the classic asymmetric information between borrowers and lenders (i.e., outside lenders imperfectly observe borrowers' creditworthiness and investment opportunities) (Akerlof, 1970, Diamond, 1984). New lenders also face information asymmetry with incumbent lenders (Rajan, 1992, Sharpe, 1990). Incumbent lenders gain their information advantage through continuous interactions with borrowers during the lending process. Therefore, it is costly for borrowers to switch lenders. During the turmoil of credit markets, the switching costs may increase because outside lenders might infer that a switched borrower is of lower quality (Darmouni, 2020, Dell'Ariccia and Marquez, 2004). Public disclosure provides an efficient and effective solution to alleviate asymmetric information problems facing potential lenders (Baiman and Verrecchia, 1996, Diamond and Verrecchia, 1991). Thus, firms have incentives to increase their disclosures (Beyer et al., 2010, Myers and Majluf, 1984, Schenone, 2010).

However, firms might absorb the adverse effect of the disrupted credit by using internal fundings (e.g., cash holdings, capital expenditures) (Campello et al., 2010, Granja and Moreira, 2020, Kuppuswamy and Villalonga, 2016) or transmitting it through their supply chains (Costello, 2020). Therefore, corporate disclosure may not change in response to credit market disruptions.

Under the monitoring channel, corporate disclosure may change in response to the deterioration of credit markets because banks exit their roles as delegated monitors. In particular, banks' superior information advantage over outside capital providers facilitates their monitoring capability (Diamond, 1984, 1991, Holmstrom and Tirole, 1997, Rajan, 1992). Thus, dispersed capital providers delegating this function to banks may deter their monitoring effort. As the banking crisis worsens, investors' demand for additional information may increase to restore the external monitoring. Hence, managers may respond by disclosing more information.

Under the uncertainty channel, credit market disruptions may heighten investors' uncertainty about firms' ability to seek an alternative funding source and their adverse effects on firms' activities (e.g., declined investments in capital expenditures (Campello et al., 2010, Chava and Purnanandam, 2011, Kahle and Stulz, 2013), decreased innovation (Granja and Moreira, 2020), higher unemployment (Chodorow-Reich, 2014, Greenstone et al., 2020), and increased technical default (Chodorow-Reich and Falato, 2020)). That, in turn, might increase investors' demand for forward-looking information, and subsequently, corporate disclosures (Bischof, 2014, Lambert et al., 2012, Lo, 2014, Verrecchia, 2001).

However, uncertainty about funding substitutability and market conditions may render an increase in forecast inaccuracy. Managers may not be willing to commit to imprecise future targets because they are concerned about their reputation loss (Beyer and Dye, 2012, Stocken, 2000) or potential litigation risk (Skinner, 1994, 1997). Thus, managers are more likely to withhold information (Kim et al., 2016, Verrecchia, 1990). In addition, uncertainty about firms' possession of private information may increase during these extreme episodes. In this case, outside investors might not be able to disentangle whether non-disclosure is due to the absence of the information or its unfavorable content. Hence, the adverse selection is deterred, and managers may withhold information from outsiders (Dye, 1985, Jung and Kwon, 1988).

Therefore, I state my hypothesis in the null:

H1: A credit market disruption is not associated with corporate disclosure.

3. Data and Sample Construction

I construct my sample from several databases. First, I use the Community and Reinvestment Act (CRA) database from the Federal Financial Institutions Examination Council (FFIEC) to measure county-level exposure to credit market disruptions. The CRA data set provides information on the total number and volume of loans to small businesses (i.e., less than $1 million loans) at the bank and borrowers' county level. The information is reported by all commercial and savings banks with total assets exceeding an annually inflation-adjusted threshold (e.g., the threshold is $1 billion in total assets in 2005).

Second, I match the geography-based measure of credit market disruptions with firm data set using firms' headquarters location from the Compustat annual data. My firm sample includes publicly listed firms in the Compustat-CRSP merged database over the 2004-2012 timeframe. Finally, I merge them with firm financial information from Compustat, firm stock price and return data from CRSP, institutional ownership from Thomson Reuters, and analysts forecasts from the IBES. I exclude firms incorporated outside the United States and firms with headquarters locations are in a foreign country. I also drop firms in the financial services (2-digit SIC 60-69) and public administration

(2-digit SIC 90-99). Table 1 presents the sample selection procedures.

I construct the following dependent variables. The number of management guidance, $FreqMF$, is the total number of management guidance that the firm issued during a given year.[2] $FreqMF$ ($Earnings$) is the number of management earnings guidance, and $FreqMF$ ($CapEx$) is the number of capital expenditure guidance. I obtain all management guidance from the IBES Guidance (which originated with First Call database) and restrict my sample period to 2005–2013. My final sample consists of 26,436 firm-year observations.[3]

4. Background and Empirical Methodology

4.1. Background

The credit market deterioration during the GFC stemmed from the subprime mortgage market. The first disruption was initiated in August 2007, when BNP Paribas announced the freeze on redemption from three investment funds. While credit markets were significantly impaired, the financial conditions temporarily stabilized over summer 2008. However, in September 2008, the second and more acute disruption was triggered by the failure of Lehman Brothers. The TED spread,[4] a key barometer of the perceived credit risk of the overall economy, surged by 200 basis points (2 percentage points) in August 2007 and subsequently jumped to its peak of over 450 basis points in October 2008 (see Figure A1).

Prior literature discusses in detail the inception of the GFC outside the corporate sector (Chodorow-Reich, 2014, Darmouni, 2020) and provides evidence of a sharp decrease in bank lending during the GFC (Chodorow-Reich, 2014, Greenstone et al., 2020, Ivashina

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[2] The results are qualitative the same if I treat all guidance provided on the same date as a piece of guidance.

[3] When I include firm- and industry-year fixed effects, there are bins with only one observation. I follow Correia (2015) and exclude those observations resulting in the different number of observations in the regressions.

[4] The TED spread is the difference between the interest rate on interbank lending (i.e., the LIBOR interest rate on three-month eurodollar deposits) and the interest rate on three-month U.S. Treasury bills.

and Scharfstein, 2010). In particular, total commercial and industrial loans decreased by more than 20% from 2008 to 2010 (Gopal and Schnabl, 2020). The drop in new lending to small businesses was even more severe, by nearly 45% from 2007 to 2010 (see Figure 1). I exploit cross-sectional variation in bank credit supply decrease during this particular episode to construct a geographical measure of credit market disruptions as described in the following subsection.

4.2. Measuring Exposure to Credit Market Disruptions

I construct a measure of local credit market disruptions following Greenstone et al. (2020), who propose a refined two-step Bartik approach. Particularly, I first estimate the following regression:

$$\Delta SBL_{b,c}^{07-10} = \gamma_b + \delta_c + \epsilon_{b,c} \tag{1}$$

where the outcome variable is the log change in small business lending originated by bank b in county c between 2007 and 2010, γ_b are bank fixed effects, and δ_c are county fixed effects.[5] The county fixed effects purge the county's unobservable demand shocks or other common county level effects from each bank's nationwide changes in lending. The estimated bank fixed effects from equation 1, $\hat{\gamma}_b$, then capture bank specific supply shocks. Next, the measure of counties' exposure to credit-supply shocks is constructed as follows:

$$Exposure_c^{SBL} = -\sum_b (\hat{\gamma}_b \times s_{b,c}^{07}) \tag{2}$$

where $s_{b,c}^{07}$ is bank b's share of small business loans in county c during 2007. For the following analyses, I standardize the county-level predicted supply shock, $Exposure_c^{SBL}$, by subtracting its mean and dividing by the standard deviation.

This approach exploits the pre-crisis variation in a county's exposure to a bank (i.e., the bank's market share) and cross-sectional variation in small business lending drop

[5] For mergers occurring before the financial crisis, I treat firms that borrowed from the acquired bank as borrowers of the acquirer.

during the GFC. For example, consider a credit market with two banks: JP Morgan Chase and HSBC. Suppose that JP Morgan Chase and HSBC cut their small business lending by 80 percent and 30 percent nationwide over the 2007-2010 period, respectively. Then, firms in counties with higher pre-crisis JP Morgan Chase market share (e.g., 70 percent versus 20 percent) experience a larger credit supply shock.

The first step, however, does not purge out the banks' specialization in certain industries. Thus, to ensure that industry-specific shocks do not affect the results, I include industry-year fixed effects in all following regressions.

The relevance of this measure depends on the extent to which credit markets are local. The local market that I essentially analyze is the county.[6] If the credit markets were not segmented across regions, a decrease in lending at the bank level should not extend to the regional level. Thus, all tests at the firm level are a joint test of whether there is an effect of disrupted credit markets on firms' voluntary disclosure and whether credit markets are sufficiently local.

Figure 2 presents the distribution of the county-level measure of credit market disruptions. Panel A shows its frequency distribution and Panel B plots the spatial distribution. The figure in panel B suggests there is considerable variation in credit market distress across regions with greater exposure in the Southern and Midwestern United States and lower exposure in the East.[7] In robustness tests, I show that my main results are not sensitive to excluding each state in the estimations.

4.3. Empirical Methodology

This section examines whether credit market disruptions induce changes in corporate disclosure. I estimate the following specification for outcomes related to the disclosure of forward-looking information:

[6] This is consistent with prior studies (see Granja et al. (2020), Luck and Zimmermann (2020)).
[7] This spatial distribution is consistent with Greenstone et al. (2020) and Granja and Moreira (2020).

$$Y_{i,t} = \alpha_i + \theta_{jt} + \beta_1 Exposure_c^{SBL} \times I(Crisis) + \beta_2 Exposure_c^{SBL} \times I(PostCrisis) + \rho X_{i,t-1} + \epsilon_{i,t} \tag{3}$$

where i indexes a firm during year t. The dependent variable $Y_{i,t}$ represents a firm's outcome during the year (i.e., the frequency of management guidance, earnings guidance, and capex guidance). $Exposure_c^{SBL}$ is the counties' exposure to credit market disruptions as estimated in section 4.2. $I(Crisis)$ is a dummy variable that takes the value of one for the crisis years of 2008, 2009, and 2010. $I(PostCrisis)$ is a dummy variable that takes the value of one for the years after the crisis (i.e., 2011, 2012, and 2013). My main coefficients of interest, β_1 and β_2, capture the effect of disrupted credit markets on corporate disclosure during and after this stress episode, respectively, relative to the years prior to the disruption. Hence, this approach is similar to a difference-in-differences style estimator. Firm-level control variables, $X_{i,t-1}$, include *Institutional ownership*, *No analysts*, *Size*, *ROA*, *BTM*, *Loss*, *Sales volatility*, *Stock volatility*, *BHAR*, *Leverage*, *Cash*, *Sales*, *CapEx*, *Skewness*, and *Receivables*.

In my baseline specification, I include firm- and industry-year fixed effects. The firm fixed effects, α_i, account for cross-sectional differences in time-invariant firm characteristics. The industry-year fixed effects, θ_{jt}, at the Fama-French 30 industries level absorb unobservable heterogeneity that varies in an industry across time (e.g., investment opportunities, industry-specific demand). The identifying variation then is driven by comparing the disclosure behavior of different firms within the same industry but being headquartered in counties with different exposure to credit market disruptions. I cluster standard errors at the state level throughout all specifications to account for spatial correlation across firms (counties) within a state.[8] All continuous variables are winsorized at the 1% and 99% levels. Appendix A1 provides definitions for all variables.

[8]The results also come through if I cluster the error terms at the county level.

5. Empirical Results

5.1. Summary Statistics

The sample includes firms in 29 industries based on the Fama-French 30 industry classification. Consistent with prior studies (e.g., Rogers and Van Buskirk (2009)), my sample is concentrated in Business Services (SIC 73), Chemical and Allied Products (SIC 28), Electronics (SIC 36), Instruments (SIC 38), and Machinery and Computer Equipment (SIC 35). Table 2 reports the summary statistics for the variables used in my main analyses. Firms in my sample, on average, issued 6 management guidance per year. The most prevalent metric is earnings (EPS). The average firm had book-to-market ratio (BTM) of 0.55, leverage ratio ($Leverage$) of 0.50, return-on-assets (ROA) of -0.04, cash holdings ($Cash$) of 0.21, sales volatility (*Sales volatility*) of 0.07, and stock volatility (*Stock volatility*) of 0.03. On average, 50% of firm shares were owned by institutional investors, and eight analysts followed a firm.

Figure 3 plots the evolution of the frequency of management guidance over the sample period of 2005 to 2013 for two groups: firms located in the counties below the twentieth percentile ("low exposed") and above the eightieth percentile ("high exposed") of the county exposure to credit market disruptions as described in section 4.2. Panel A shows some differential behavior in disclosing guidance on all metrics between firms in two groups during the 2009-2011 period. Panel B reveals that high exposed firms disclose more earnings guidance relative to low exposed firms since 2008. Panel C shows that capex guidance increased for both groups, but the increase was more pronounced for low exposed firms.

5.2. Main Results

Table 3 presents the results for the impact of credit market disruptions on corporate disclosure using the three voluntary disclosure measures described in section 3. Columns (1)-(3) show results using the frequency of issuing guidance on all metrics, $FreqMF$, as the main dependent variable. In column (1), I include only firm- and year-fixed effects. The coefficients on $Exposure_c^{SBL} \times I(Crisis)$ and $Exposure_c^{SBL} \times I(PostCrisis)$ are negative but statistically insignificant. In column (2), I control for other firm-level determinants of voluntary disclosure, the coefficients remain to be negative and not statistically significant. Finally, I augment the model with industry-year fixed effects to account for unobservable time-varying industry characteristics, the coefficients of interest turn positive but are not significant at conventional statistical levels.

Then, I decompose the frequency of issuing guidance on all metrics into the frequency of earnings guidance, $FreqMF$ $(Earnings)$, (columns (4)-(6)) and the frequency of capex guidance, $FreqMF$ $(CapEx)$ (columns (7)-(9)). Similar to the previous analysis, columns (4) and (7) include firm- and year-fixed effects; columns (5) and (8) add a set of firm-level control variables; and columns (6) and (9) augment the specification with industry-year fixed effects.

In columns (4), (5), and (6), the coefficient on $Exposure_c^{SBL} \times I(Crisis)$ is positive and significant at conventional statistical levels. Similarly, the coefficient on $Exposure_c^{SBL} \times I(PostCrisis)$ is positive and statistically significant in columns (5) and (6), when I control for firm-specific characteristics and the common trend at the industry level. These results suggest that an increase in exposure to local credit market breakdown is associated with a persistently increase in the frequency of earnings guidance. Specifically, the specification in column (6) implies that a standard deviation increase in exposure to credit market shocks expanded firms' earning guidance by an average of 46.2 percent during the crisis and 43.7 percent after the crisis.

Across all specifications in columns (7), (8), and (9), the coefficients on $Exposure_c^{SBL} \times I(Crisis)$ and $Exposure_c^{SBL} \times I(PostCrisis)$ are negative and statistically significant at the 1% level. These results are consistent with an increase in exposure to credit market disruptions decreasing firms' issuance of capex guidance. The estimated coefficients in column (9) suggest that a standard deviation increase in exposure to disrupted credit markets lowered capex guidance by approximately 63.4 percent during the crisis and 56.1 percent once the crisis tapered.

Regarding control variables, large firms and firms with greater analyst coverage and lower return skewness generally issue more guidance. Firms experiencing a loss or reserving more cash are likely to issue less earnings guidance. Meanwhile, firms with higher BTM, *Leverage*, *CapEx*, and lower *Receivables* provide more capex guidance.

Overall, I interpret the results as supporting my conjecture that the collapse of credit markets had large and persistent effects on corporate voluntary disclosure, particularly the types of disclosed information.

5.3. Dynamic Results

In addition to the main analysis, I perform an event study analysis based on the measure of exposure to disrupted credit markets by estimating the following regression specification:

$$Y_{i,t} = \alpha_i + \theta_{jt} + \sum_{k \neq 2007} \beta_k (Exposure_c^{SBL} \times \mathbb{1}_{t=k}) + \rho X_{i,t-1} + \epsilon_{i,t} \tag{4}$$

where $Exposure_c^{SBL}$ is the counties' exposure to credit market disruptions estimated in section 4.2. $\mathbb{1}_{t=k}$ is an indicator that equals one in year t, and zero otherwise. Based on this regression analysis, I estimate the effect of the negative credit supply shock for all years in the data.

The estimated coefficients are presented in Figure 4. The figure reveals the dynamic impact of the credit supply shock on management guidance. In Panel A, I plot the effect on general management guidance. The figure shows no evidence that firms more exposed to the disrupted credit markets change the frequency of guidance on all metrics. In Panels B and C of Figure 4, I plot the effect on earnings guidance and capex guidance, respectively. The estimated coefficients are not statistically different from zero before the GFC. However, during and after the crisis era, the coefficients are persistently positive for earnings guidance and negative for capex guidance. These plots suggest no evidence of pre-trends and corporates' immediate and persistent adjustment to their disclosure policies in response to the extreme credit market conditions.

6. Additional Analyses

6.1. Heterogeneity in the Main Effect

In this subsection, I explore the potential mechanisms that malfunctioning credit markets can affect corporate disclosure. If managers response to disrupted credit by increasing earnings guidance because of their desire to offset the negative funding shocks, I expect the results to be more prevalent when firms have relatively easier access to alternative external financing sources and disclosure is a cost-efficient way to mitigate the asymmetric information (e.g., access to the bond market, conglomerates) (Section 6.1.1. and 6.1.2). If investors' demand for information to restore the external monitoring drives the results, the effect should be stronger for firms with greater dispersed ownership (Section 6.1.3.). Finally, I examine whether the decrease in capex guidance is driven by firms' operating uncertainty (Section 6.1.4.).

6.1.1. Access to the Bond Market

Firms with relatively easier access to alternative sources of public financing have a greater ability to substitute the negative effect of banking crises. Public disclosure is an effective way for these firms to resolve information asymmetry with dispersed public financiers (Baiman and Verrecchia, 1996, Diamond, 1991). Thus, I expect the increase (decrease) in earnings (capex) guidance are more (less) pronounced for firms with easier access to the bond market. To test this prediction, I partition firms into three groups: (i) no access to the bond market, (ii) speculative-grade bond issuers, and (iii) investment-grade bond issuers. Specifically, firms without access to the bond market are those that did not have bonds reported in the Mergent Fixed Income Securities Database (FISD) bond database prior to the GFC. Firms are classified as investment-grade (speculative-grade) if their credit ratings were either above (below) Moody's Baa3 or Standard and Poor's BBB-. I estimate the separate effect for each group by interacting the interaction terms $Exposure_c^{SBL} \times I(Crisis)$ and $Exposure_c^{SBL} \times I(PostCrisis)$ in equation 3 with a set of group dummies.

The corresponding results are presented in Table 4, panel A. Column (1) reveals that the negative credit supply shock has an economically large impact on and significant explanatory power for the frequency of earnings guidance at investment-grade firms, but a much smaller impact on and insignificant explanatory power for the disclosure level at speculative-grade firms. The effect is also smaller and statistically significant only during the crisis for firms without access to the bond market. Column (2) indicates that the decrease in capex guidance is more prevalent and economically larger when firms do not have easy access to alternative public capital providers.

6.1.2. Conglomerates versus Single-segment Firms

I expect the positive (negative) effect of credit market disruptions on earnings (capex) guidance to be stronger (weaker) for conglomerates because they may have better access to credit markets due to the imperfect correlation among diversified segment cash flows (Kuppuswamy and Villalonga, 2016, Lewellen, 1971). However, conglomerates also have better access to internal capital markets than single-segment firms, and thus they can internalize credit supply shocks (Kuppuswamy and Villalonga, 2016, Matvos and Seru, 2014). Therefore, the change in earnings guidance in response to the disrupted credit markets may be weaker for conglomerates.

Table 4, panel B shows estimated coefficients of regressions allowing the effect to differ among conglomerates and single-segment firms. Firms are classified as conglomerates if they report more than one business segment in different four-digit Standard Industrial Classification (SIC) codes. Results in column (1) indicate that the increase in earnings guidance is concentrated in conglomerates, consistent with conglomerates' advantage of access to the credit market due to debt coinsurance. Results in column (2), however, show that conglomerates and single-segment firms experience no differential change in capex guidance.

6.1.3. Institutional Ownership Dispersion

Dispersed capital providers are more likely to delegate the monitoring activities to banks. As a result, if public disclosure is used to substitute for a decrease in delegated monitoring, the increase in disclosure should be more pronounced among firms with greater dispersed ownership. I define institutional ownership dispersion as the additive inverse of the sum of the squared percentage holding of each institution. Then, firms are classified as more (less) ownership dispersion if the proxy for institutional ownership dispersion falls above (below or equal to) the pre-crisis sample median.

Table 4, panel C reports the results. Consistent with the monitoring channel, I find the coefficients on $Exposure_c^{SBL} \times I(Crisis)$ and $Exposure_c^{SBL} \times I(PostCrisis)$ are positive and statistically significant at the 1% level for firms with more dispersed institutional ownership. In contrast, they are economically smaller and statistically insignificant in the lower dispersed institutional ownership subsample. The coefficients on $Exposure_c^{SBL} \times I(Crisis)$ and $Exposure_c^{SBL} \times I(PostCrisis)$ are negative and statistically significant in column (2) in both groups with these coefficients being statistically indifferent to each other.

6.1.4. Operating Uncertainty

The increased uncertainty about market conditions and firms' ability to mitigate the adverse effects of the banking crisis renders more difficulties in estimating future performances. Therefore, managers, unwilling to commit to imprecise targets, are more likely to withdraw their forward-looking estimates (Kim et al., 2016, Verrecchia, 1990). If this channel is at work, the decrease in capex guidance should be stronger for firms with higher levels of operating uncertainty. Following Bourveau et al. (2018)), I define a firm with high (low) uncertain operating activities if its standard deviation of return on assets (ROA) or standard deviation of sales growth is above (below or equal to) the pre-crisis sample median.[9]

[9] The results are qualitatively similar if I use the standard deviation of ROA as a proxy for operating uncertainty.

Table 4, panel D reports the corresponding results. Column (1) shows that firms respond to malfunctioning credit markets by increasing their earnings guidance regardless of operating uncertainty. The effect is statistically distinguishable between the two groups. Column (2), however, reveals that the coefficients on $Exposure_c^{SBL} \times I(Crisis)$ and $Exposure_c^{SBL} \times I(PostCrisis)$ are greater in economic magnitude and statistically significant at the 1% level for firms with higher operating uncertainty.

6.2. Characteristics of the Management Guidance

Besides the frequency of guidance, managers also decide the guidance characteristics (Chen and Vashishtha, 2017, Kim et al., 2016, Lo, 2014, Rogers and Van Buskirk, 2009). To understand the nature of adjustments to corporate disclosure policies, I present the analyses on various management earnings guidance characteristics in Table 5.

I first classify earnings guidance into good news and bad news. Following Bourveau et al. (2018), I define an earnings guidance as a good news (bad news) if the forecast news is greater than 10% (smaller than -10%). Forecast news is the difference between management earnings guidance and analyst consensus estimate at the time of issuing management guidance, divided by the absolute value of analyst consensus estimate. The management earnings guidance equals to the point estimate provided or the midpoint of the range estimate. Forecast news is not calculated for open-ended estimates. If the purpose of issuing guidance is to mitigate the information gap between the incumbent lender and potential lenders or to attract new lenders, firms may issue more good news guidance (Bischof, 2014). Columns (1) and (2) of Table 5 report the corresponding results. The coefficients on $Exposure_c^{SBL} \times I(Crisis)$ and $Exposure_c^{SBL} \times I(PostCrisis)$ are statistically significant and positive for good news but not bad news guidance. These results indicate that managers improve the earnings disclosure by increasing good news rather than bad news disclosures during and after the GFC.

Second, I classify earnings guidance into annual and quarterly guidance. On the one hand, managers may want to lower the information asymmetry among lenders, and thus provide more timely information (or longer horizon guidance) to the market (Rogers, 2008). On the other hand, increased uncertainty during the credit market turmoil may induce managers to issue shorter horizon earnings guidance (Kim et al., 2016). Shorter horizon earnings guidance allows managers to provide additional forward-looking information without increasing penalties related to litigation risk or reputation damage. In columns (3) and (4) of Table 5, I document that managers increase the overall level of disclosure by increasing both quarterly and annual earnings guidance during a time of crisis.

Finally, I examine whether the negative credit supply shock changes the precision of management earnings guidance. While highly precise guidance is more informative to investors (Rogers, 2008), the quality of managers' information is more likely to decrease with the increased macroeconomic uncertainty (Kim et al., 2016). Consequently, it is more difficult and riskier for managers to issue highly precise earnings guidance. Columns (5), (6), and (7) of Table 5 present the corresponding results. The dependent variables in columns (5), (6), and (7) are the frequency of point estimates, range estimates, and open-ended estimates, respectively. The coefficient on $Exposure_c^{SBL} \times I(Crisis)$ is positive and statistically significant at the 1% level for range estimates. This result indicates that firms that were highly exposed to a negative credit supply shock do not shift toward less precise forecasts. The coefficient on $Exposure_c^{SBL} \times I(PostCrisis)$ is positive and statistically significant at the 5% level for both range estimates and open-ended estimates, suggesting that range earnings guidance remains to be predominant among the most affected firms after the GFC. These results are also consistent with prior studies' finding that good news disclosures are likely to be point or range forecasts (Skinner, 1994).

6.3. Sales Guidance

Lu and Skinner (2020) show that top-line sales guidance has become more prevalent since 2001 and is nearly as common as earnings guidance by 2018. They also provide evidence that sales guidance news is incrementally informative in explaining earnings announcement period returns. Thus, I examine if management changes the frequency of sales guidance in response to collapsed credit markets. Table A2 presents the results of this analysis. The coefficient on $Exposure_c^{SBL} \times I(Crisis)$ is positive and significant at the 10% level when I include industry-year fixed effects, whereas the coefficient on $Exposure_c^{SBL} \times I(PostCrisis)$ is positive but not statistically significant at conventional levels. These results provide further evidence for managers' differential changes in disclosure behavior.

6.4. Robustness Tests

In this subsection, I perform a set of sensitivity tests to ensure the robustness of my main results. First, I re-estimate my main model by excluding each state at a time. Figure A2 and Table A3 in the Appendix present the results. The coefficients on $Exposure_c^{SBL} \times I(Crisis)$ and $Exposure_c^{SBL} \times I(PostCrisis)$ remain statistically significant at conventional levels and cluster around the full sample estimates. These results mitigate the concern that my results might be driven by a single state.

Second, I use entropy matching following Hainmueller and Xu (2013) to ensure comparability of firms in counties differing on their exposure to the breakdown of credit markets. I partition counties into low (below or equal to the sample median) and high (above the sample median) exposure to the credit market disruptions and reweigh them using entropy balance weights. The entropy weights are obtained such that the covariate moments (i.e., mean, median, and skewness) of the two groups are matched. I consider pre-crisis baseline controls as matching covariates (e.g., size, investment, and performance). Results are reported in Table A4 and show little sensitivity of my estimates to this check.

Third, I test whether my results are robust to the inclusion of county-level conditions. Particularly, I re-estimate equation 3 including the interactions of the indicators $I(Crisis)$ and $I(PostCrisis)$ with a set of county-level controls: $Pop.\ gr$, $Pct.\ black$, $Pct.\ poverty$, $Ln(RGDP\ pc)$, $Ln(income\ pc)$, ΔHPI, $Unemploy.\ rt$, and $Estabs.\ gr$. Results in Table A5 show that the demographic and economic conditions in the firm's county headquarters do not alter my findings.

Fourth, I construct another measure of credit market disruptions following the leave-one-out method proposed by Borusyak et al. (2021). Particularly, the measure is defined as the following expression:

$$Exposure_c^{SBL} = -\sum_b \left(\frac{\sum_{c' \neq c} s_{b,c'}^{07} \Delta SBL_{b,c'}^{07-10}}{\sum_{c' \neq c} s_{b,c'}^{07}} \times s_{b,c}^{07}\right) \tag{5}$$

This method partially mitigates the concern related to credit demand shocks at the county level. For example, let consider the example of JP Morgan Chase and HSBC, which lend to New York County (NY) and other counties. If I use JP Morgan Chase's loan to New York County to measure New York County's exposure to the credit supply shock, this measure mechanically includes the change in credit demand in New York County. To ease this concern, in measuring New York County's exposure to the credit supply shock, I use JP Morgan Chase's lending to all counties excluding New York County. Implementing the same to HSBC, New York County's exposure to credit supply shock is the weighted average across JP Morgan Chase and HSBC, using market shares of those banks in the county as weights. Results using this alternative measure are presented in Table A6 and are consistent with the main findings.

Finally, I conduct a placebo test for the geographical measure of credit market disruptions. Particularly, instead of using the change in lending from 2007 to 2010, I use the change in lending over the period 2005 to 2008 and 2011 to 2014. Table A7 presents the results and there is no evidence that firms change the frequency of earnings and capex guidance in response to change in small business lending outside the GFC.

7. Conclusion

This paper examines how corporate voluntary disclosure changes in response to credit market disruptions during the GFC. Using a modified Bartik approach to predict county-level exposure to a negative credit supply shock, I find that firms that are more exposed to local credit market collapse adjust their disclosure policies. Specifically, they issue more earnings guidance and less capital expenditure guidance. Further analyses reveal that the increase in earnings guidance is driven by managers' incentives to seek for alternative funding sources and response to investors' demand for more information to restore external monitoring. Meanwhile, the decrease in capital expenditure guidance is due to heightened uncertainty rendering lower quality of managers' information.

My findings highlight differential disclosure behavior in response to the negative credit supply shock. Particularly, earnings guidance remains to be the main tool for managers to resolve the asymmetric information problems with external investors, especially during crisis episodes, even if they increasingly provide guidance on a multitude of other metrics (e.g., sales, capital expenditure).

The results also suggest that managers' different incentives in disclosing each financial metric and it is magnified during the GFC. While the GFC increases the incentives to disclose. During the period of disrupted credit markets, the benefits of issuing earnings guidance may outweigh its costs. In the case of capital expenditure guidance, the benefits do not justify the costs due to increased uncertainty. Furthermore, the heightened uncertainty during the GFC may magnify the imprecision in estimating future capital expenditure, a single number, rather than future earnings, a summary number.

My paper, however, is subjected to several caveats. Due to data constraints, the measure of firms' exposure to credit market disruptions using data on small business lending may be more relevant for small firms (Davis and Haltiwanger, 2019, Granja and Moreira, 2020). Nevertheless, to the extent that small business lending is generally hardest hit during the banking crisis, I believe that the results reflect the upper bound of changes in corporate disclosure policies. Furthermore, my paper does not show the effectiveness of increased earnings disclosure in facilitating firms borrowing, decreasing the cost of debt, or increasing returns. I leave this investigation to future research.

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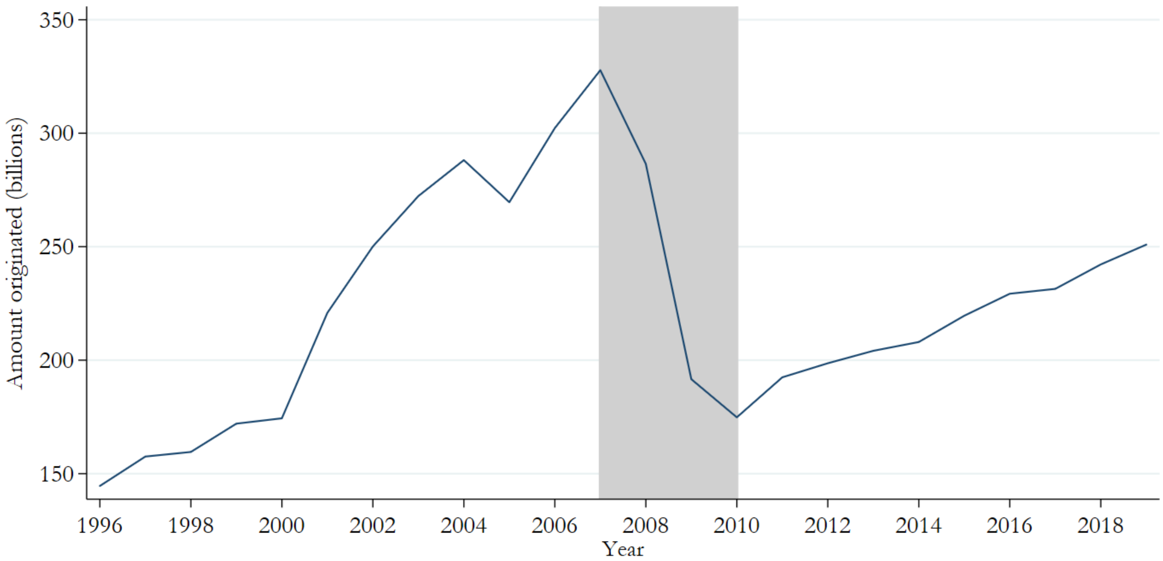
Figures & Tables

Figure 1

Evolution of Small Business Lending

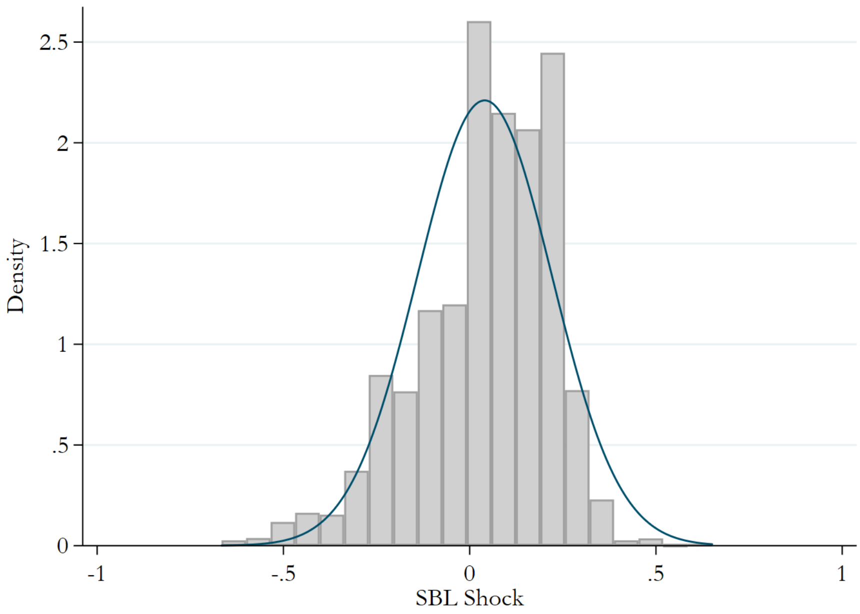


Note: This figure represents the time-series of the aggregate new small business lending over the 1996 to 2019 period. The gray area shows the timing of the global financial crisis, which is used to measure credit market disruptions. Data is obtained from the Community Reinvestment Act (CRA) small business lending dataset.

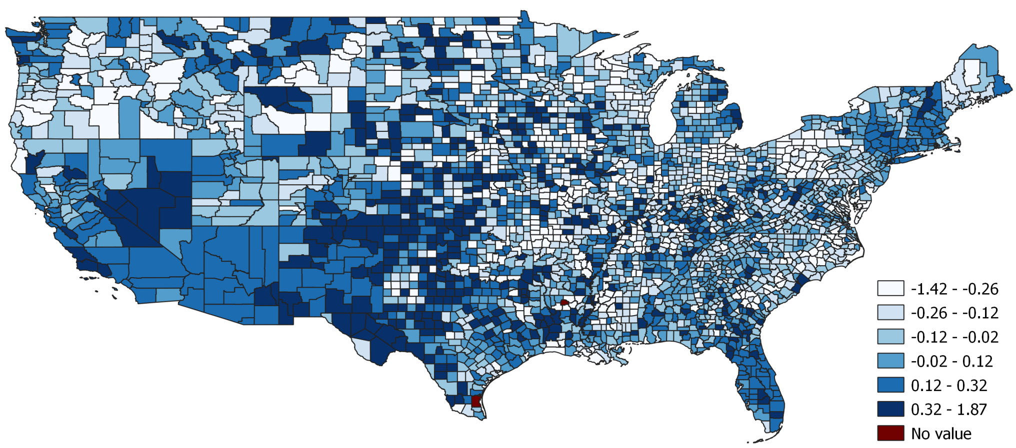
Figure 2

SBL Shock Exposure

Panel A: Histogram



Panel B: Spatial Distribution

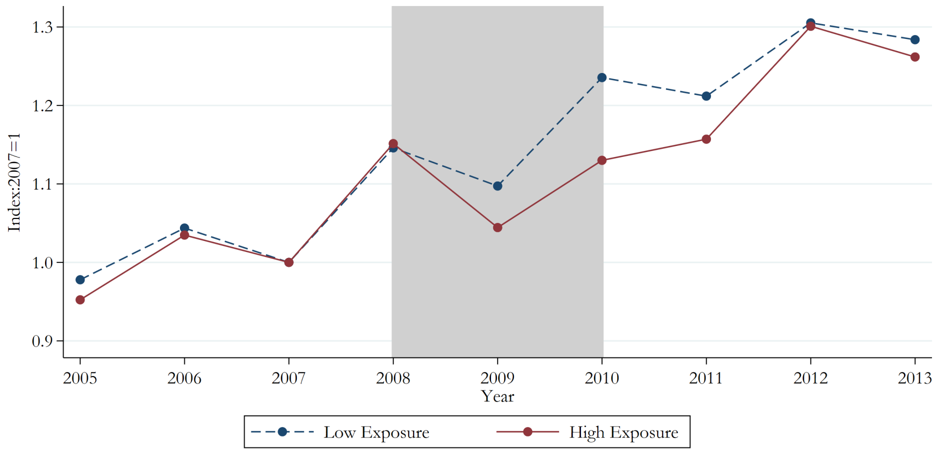


Note: This figure reports the distribution of the geographic measure of credit market disruptions. Panel A displays the frequency distribution. Panel B displays the geographic distribution. Darker shading indicates counties with higher exposure to credit market disruptions.

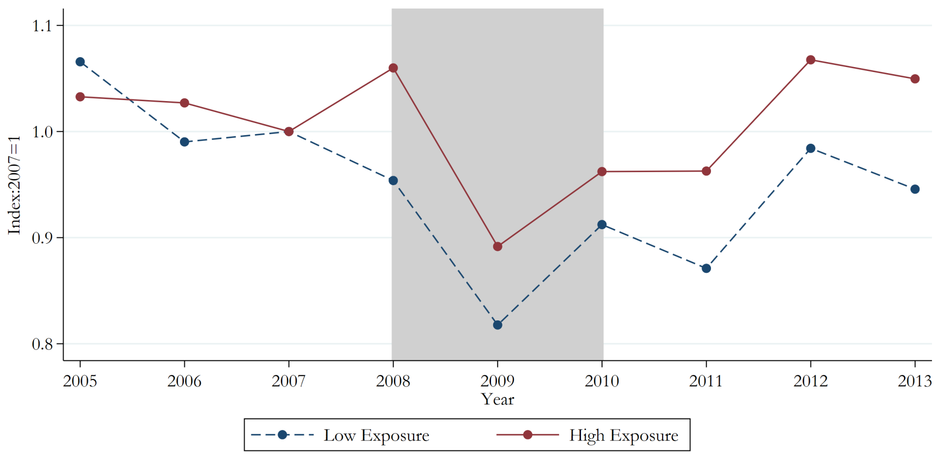
Figure 3

Time Series of Average Number of Management Guidance

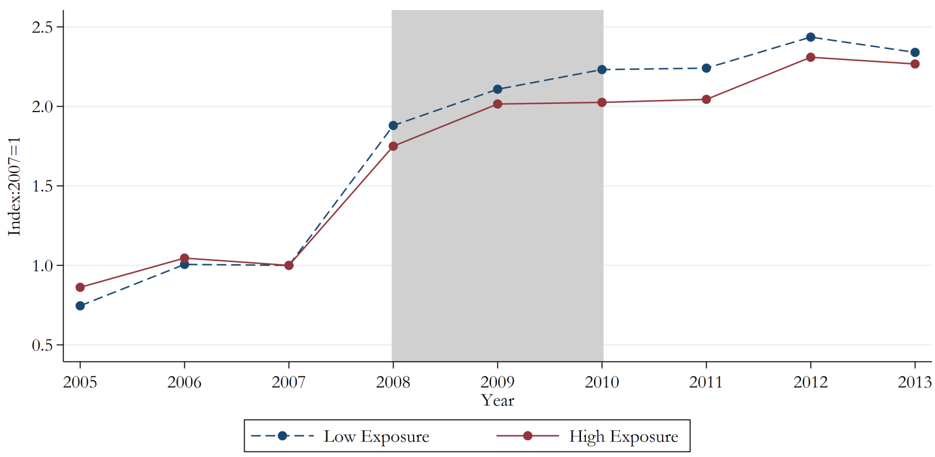
Panel A: All Guidance



Panel B: Earnings Guidance



Panel C: Capital Expenditure Guidance

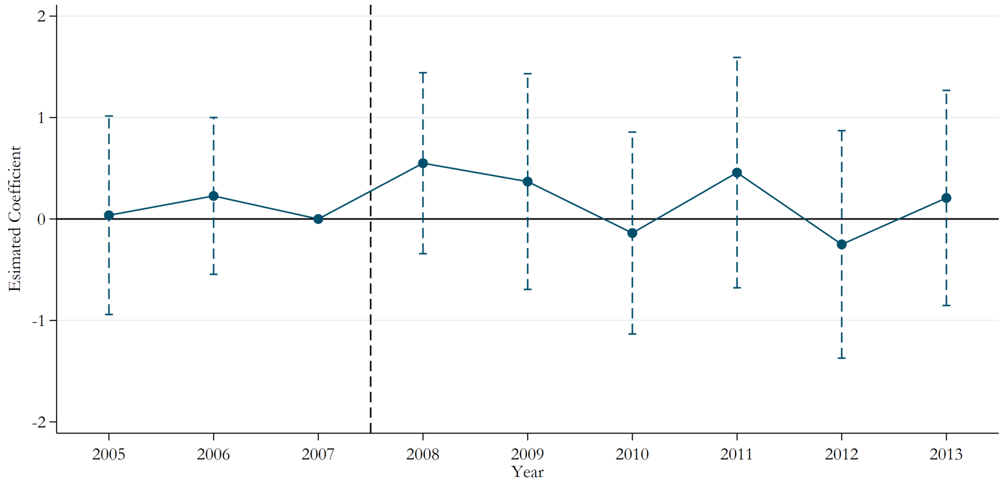


Note: This figure plots the evolution of the average number of management guidance during a calendar year over time. The blue line represents the evolution of the average number of management guidance for the quintile of firms located in counties that were least exposed to the geographic measure of credit market disruptions. The red line represents the evolution of the average number of management guidance for the quintile of firms located in counties most exposed to the geographic measure of credit market disruptions. The gray area shows the timing of the global financial crisis, which is used to measure the credit market disruptions. Panel A represents the average frequency of all management guidance. Panel B represents the average frequency of earnings guidance. Panel C represents the evolution of the average frequency of capital expenditure guidance. All time series plotted are normalized such that 2007 = 1. Data for all figures is obtained from the CRA and IBES Guidance datasets.

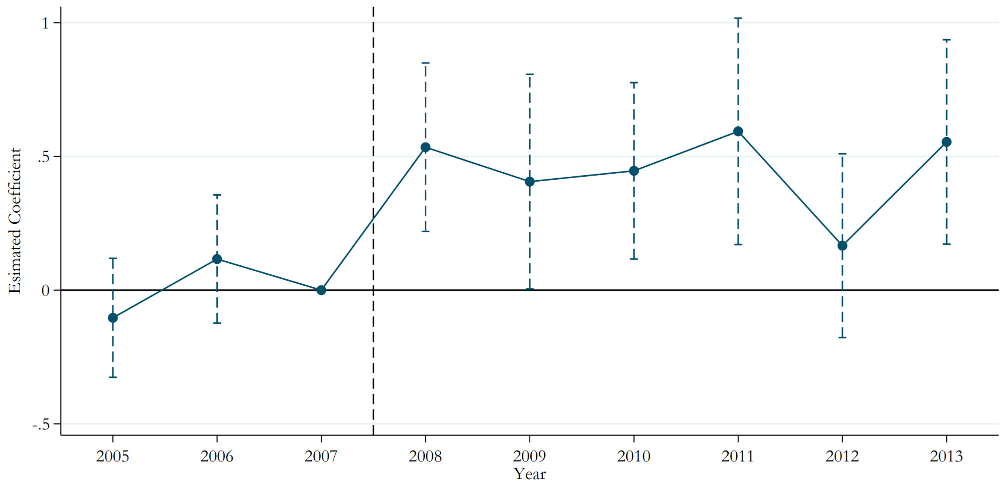
Figure 4

Management Guidance Dynamic and Credit Market Disruptions

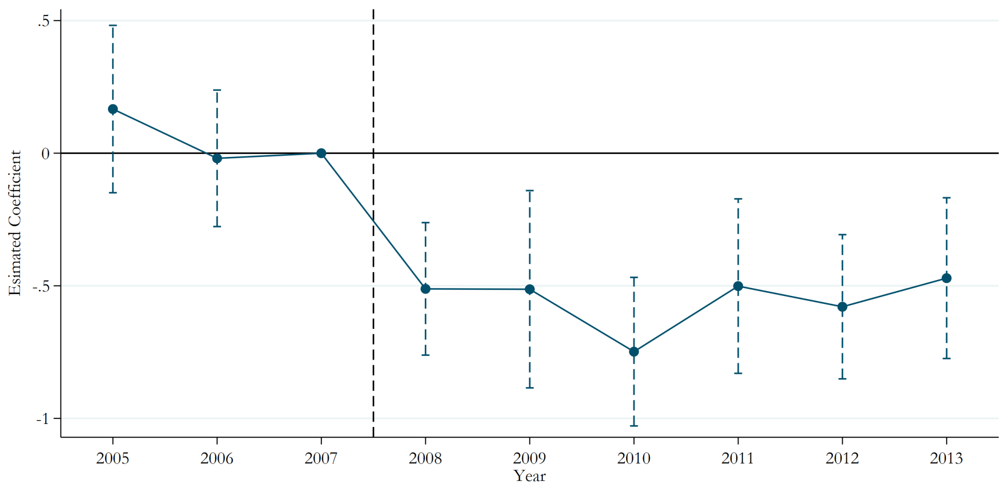
Panel A: All Guidance



Panel B: Earnings Guidance



Panel C: Capital Expenditure Guidance



Note: This figure presents management guidance dynamic. The coefficient estimates of β_t for each year are from equation 4. Vertical bands represent a 95% confidence interval of each point estimate. Standard errors are clustered by state. Black dashed lines indicate the beginning of the global financial crisis. Panel A represents the average frequency of all management guidance. Panel B represents the average frequency of earnings guidance. Panel C represents the evolution of the average frequency of capital expenditure guidance.

Table 1

Sample Construction		
		Sample size
Firms available in CRSP/Compustat for fiscal periods ending in calendar years 2004-2012		17,438
Less:		
Firms not incorporated in US	(4,794)	
Firms not headquartered in US	(478)	
Firms not listed on NYSE, AMEX, or NASDAQ	(3,352)	
Missing data on control variables	(3,016)	
Financial and government firms	(1,289)	
Firms used in the analyses		4,509

Note: This table presents the procedures used to construct the sample for the main tests. The sample consists of firms in the intersection of CRSP, Compustat, Thompson Reuters, and IBES Guidance, with fiscal periods ending in calendar years 2004 through 2012.

Table 2

Descriptive Statistics					
	N	Mean	Std	Min	Max
$FreqMF$	26,436	6.22	7.09	0.00	58.00
$FreqMF\ (Earnings)$	26,436	1.70	2.54	0.00	18.00
$FreqMF\ (CapEx)$	26,436	1.15	1.86	0.00	22.00
$Exposure_c^{SBL}$	26,436	0.04	0.18	-0.67	0.65
$Institutional\ ownership$	26,436	0.50	0.36	0.00	1.14
$No\ analysts$	26,436	8.08	8.23	0.00	36.00
$Size$	26,436	6.09	2.04	1.68	11.01
ROA	26,436	-0.04	0.26	-1.46	0.28
BTM	26,436	0.55	0.53	-1.02	2.87
$Loss$	26,436	0.33	0.47	0.00	1.00
$Sales\ volatility$	26,436	0.07	0.18	0.00	1.30
$Stock\ volatility$	26,436	0.03	0.02	0.01	0.11
$BHAR$	26,436	0.03	0.51	-0.85	2.38
$Leverage$	26,436	0.50	0.27	0.06	1.46
$Cash$	26,436	0.21	0.23	0.00	0.93
$Capex$	26,436	0.05	0.06	0.00	0.33
$Skewness$	26,436	0.43	1.33	-3.48	6.55
$Receivables$	26,436	0.14	0.11	0.00	0.56

Note: This table presents the summary statistics for the dependent and independent variables used in my empirical analyses. My sample period covers the years 2004–2012. All variables are defined in Table A1.

Table 3

Credit Market Disruption and Corporate Disclosure									
	FreqMF			*FreqMF (Earnings)*			*FreqMF (CapEx)*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Exposure_c^{SBL} \times I(Crisis)$	-0.356	-0.072	0.191	0.420**	0.494***	0.462***	-1.077***	-0.968***	-0.634***
	(-0.811)	(-0.170)	(0.482)	(2.653)	(3.186)	(3.249)	(-5.781)	(-5.396)	(-5.755)
$Exposure_c^{SBL} \times I(PostCrisis)$	-0.645	-0.385	0.071	0.332	0.395**	0.437***	-1.130***	-1.014***	-0.561***
	(-0.951)	(-0.634)	(0.137)	(1.672)	(2.112)	(2.871)	(-4.332)	(-4.208)	(-4.018)
Institutional ownership		0.560*	0.595**		0.018	0.007		0.010	0.095
		(1.928)	(2.159)		(0.174)	(0.075)		(0.126)	(1.278)
No analysts		0.059***	0.052***		0.014**	0.014**		0.022***	0.018***
		(3.099)	(2.795)		(2.437)	(2.395)		(3.772)	(3.987)
Size		0.910***	0.870***		0.247***	0.244***		0.203***	0.153***
		(7.803)	(7.351)		(8.901)	(8.068)		(4.853)	(6.357)
ROA		0.276	0.284		0.001	0.011		0.029	0.027
		(1.336)	(1.430)		(0.016)	(0.191)		(0.643)	(0.613)
BTM		0.200*	0.194		-0.020	-0.015		0.119***	0.099***
		(1.706)	(1.602)		(-0.469)	(-0.393)		(4.644)	(2.951)
Loss		-0.635***	-0.626***		-0.303***	-0.278***		0.023	-0.010
		(-6.568)	(-6.247)		(-8.863)	(-8.296)		(0.797)	(-0.398)
Sales volatility		1.276	0.983		0.489	0.488		0.616**	0.295
		(1.637)	(1.390)		(1.351)	(1.479)		(2.155)	(1.086)
Stock volatility		-5.009	-7.034**		-2.491**	-2.294*		3.458***	1.060
		(-1.414)	(-2.033)		(-2.201)	(-2.005)		(3.127)	(1.665)
BHAR		0.039	0.057		-0.021	-0.018		-0.015	0.021
		(0.905)	(1.102)		(-1.340)	(-0.987)		(-0.629)	(1.144)
Leverage		0.435	0.408		-0.081	-0.098		0.225***	0.243***
		(1.281)	(1.116)		(-0.861)	(-0.975)		(3.164)	(3.543)

Cash		-1.067***	-1.123***		-0.444***	-0.455***		-0.022	-0.092
		(-2.959)	(-3.001)		(-3.547)	(-3.499)		(-0.181)	(-0.760)
CapEx		1.934**	1.865**		0.396	0.207		0.986***	1.135***
		(2.432)	(2.313)		(1.305)	(0.752)		(2.952)	(3.809)
Skewness		-0.098***	-0.091***		-0.032***	-0.032***		-0.022***	-0.020***
		(-5.250)	(-5.386)		(-3.153)	(-3.348)		(-3.783)	(-3.522)
Receivables		-0.508	-0.363		-0.200	-0.245		-0.544***	-0.474***
		(-0.413)	(-0.311)		(-0.554)	(-0.721)		(-3.017)	(-2.831)
Constant	6.295***	0.195	0.561	1.708***	0.393*	0.432*	1.194***	-0.531	-0.138
	(557.595)	(0.220)	(0.616)	(486.547)	(1.999)	(2.002)	(248.995)	(-1.608)	(-0.751)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry-year FE	No	No	Yes	No	No	Yes	No	No	Yes
Adj R^2	71.72	72.72	72.96	72.85	73.62	73.93	63.25	63.80	65.30
Observations	25,951	25,951	25,951	25,951	25,951	25,951	25,951	25,951	25,951

Note: This table reports the impact of credit market disruptions on the frequency of management guidance. The dependent variable is $FreqMF$ in columns (1)–(3), $FreqMF$ $(Earnings)$ in columns (4)–(6), and $FreqMF$ $(CapEx)$ in columns (7)–(9). Detailed variable definitions are in Table A1. $I(Crisis)$ is an indicator variable that takes the value of one for the crisis years: 2008, 2009, and 2010. $I(PostCrisis)$ is an indicator variable that takes the value of one for the post crisis years: 2011, 2012, and 2013. The specifications in columns (1)-(2), (4)-(5), and (7)-(8) include firm- and year fixed effects. The specifications in columns (3), (6), and (9) include firm- and industry-year fixed effects. Robust t-statistics are reported in parentheses and calculated using standard errors clustered at the state of incorporation level. ***, **, and * denote significance at the 10%, 5%, and 1% level in two-tailed tests.

Table 4

Cross-Sectional Tests

Panel A: Bond Market Access

	(1)	(2)
	$FreqMF$ $(Earnings)$	$FreqMF$ $(CapEx)$
$Exposure_c^{SBL} \times I(Crisis) \times No\ access$	0.336**	-0.652***
	(2.283)	(-4.763)
$Exposure_c^{SBL} \times I(Crisis) \times Speculative\ grade$	0.320	-0.748***
	(1.273)	(-2.964)
$Exposure_c^{SBL} \times I(Crisis) \times Investment\ grade$	1.507***	-0.138
	(2.678)	(-0.316)
$Exposure_c^{SBL} \times I(PostCrisis) \times No\ access$	0.297	-0.735***
	(1.581)	(-4.116)
$Exposure_c^{SBL} \times I(PostCrisis) \times Speculative\ grade$	0.340	-0.418
	(1.045)	(-1.368)
$Exposure_c^{SBL} \times I(PostCrisis) \times Investment\ grade$	1.347**	0.040
	(2.265)	(0.064)
Controls	Yes	Yes
Firm & Industry-year FE	Yes	Yes
Adj R^2	73.95	65.54
Observations	25,951	25,951

Panel B: Conglomerates versus Single-segment Firms

	(1)	(2)
	$FreqMF$ $(Earnings)$	$FreqMF$ $(CapEx)$
$Exposure_c^{SBL} \times I(Crisis) \times Conglomerates$	0.880***	-0.826***
	(3.261)	(-3.879)
$Exposure_c^{SBL} \times I(Crisis) \times Single\ segment$	0.300*	-0.490***
	(1.795)	(-4.212)
$Exposure_c^{SBL} \times I(PostCrisis) \times Conglomerates$	1.189***	-0.794***
	(4.182)	(-2.992)
$Exposure_c^{SBL} \times I(PostCrisis) \times Single\ segment$	0.075	-0.366**
	(0.329)	(-2.279)
Controls	Yes	Yes
Firm & Industry-year FE	Yes	Yes
Adj R^2	74.35	65.01
Observations	22,950	22,950

Panel C: Institutional Ownership Dispersion		
	(1)	(2)
	FreqMF (Earnings)	*FreqMF (CapEx)*
$Exposure_c^{SBL}$ × $I(Crisis)$ × *Low Dipersion*	0.206	-0.603***
	(1.484)	(-4.313)
$Exposure_c^{SBL}$ × $I(Crisis)$ × *High Dipersion*	0.737***	-0.537**
	(3.789)	(-2.622)
$Exposure_c^{SBL}$ × $I(PostCrisis)$ × *Low Dipersion*	0.053	-0.538***
	(0.222)	(-3.249)
$Exposure_c^{SBL}$ × $I(PostCrisis)$ × *High Dipersion*	0.774***	-0.468*
	(3.384)	(-1.847)
Controls	Yes	Yes
Firm & Industry-year FE	Yes	Yes
Adj R^2	74.34	65.10
Observations	22,950	22,950

Panel D: Firm Operating Uncertainty		
	(1)	(2)
	FreqMF (Earnings)	*FreqMF (CapEx)*
$Exposure_c^{SBL}$ × $I(Crisis)$ × *Low Uncertainty*	0.609**	-0.198
	(2.124)	(-0.841)
$Exposure_c^{SBL}$ × $I(Crisis)$ × *High Uncertainty*	0.481**	-0.791***
	(2.372)	(-5.410)
$Exposure_c^{SBL}$ × $I(PostCrisis)$ × *Low Uncertainty*	0.370	-0.036
	(1.159)	(-0.101)
$Exposure_c^{SBL}$ × $I(PostCrisis)$	0.579**	-0.777***
× *High Uncertainty*	(2.614)	(-4.069)
Controls	Yes	Yes
Firm & Industry-year FE	Yes	Yes
Adj R^2	74.35	65.06
Observations	22,950	22,950

Note: This table reports the cross-sectional impact of credit market disruptions on the frequency of management guidance. The dependent variable is *FreqMF (Earnings)* in column (1) and *FreqMF (CapEx)* in column (2). Panel A presents the results of the impact of credit market disruptions on corporate disclosure for the subsamples of observations with different access to the bond market. Panel B presents the results of the impact of credit market disruptions on corporate disclosure for the subsample of conglomerates versus single-segment firms. Panel C presents the results of the impact of credit market disruptions on corporate disclosure for the subsample of observations with low versus high institutional ownership dispersion. Panel D presents the results of the impact of credit market disruptions on corporate disclosure for the subsample of observations with low versus high operating uncertainty. Detailed variable definitions are in Table A1. All specifications include firm- and industry-year fixed effects. Robust t-statistics are reported in parentheses and calculated using standard errors clustered at the state of incorporation level. ***, **, and * denote significance at the 10%, 5%, and 1% level in two-tailed tests.

Table 5

Properties of Earnings Guidance							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Good News	Bad News	Quarterly Guidance	Annual Guidance	Point Guidance	Range Guidance	Open-ended Guidance
$Exposure_c^{SBL} \times I(Crisis)$	0.129***	0.052	0.136**	0.323**	-0.041	0.445***	0.058
	(2.710)	(0.996)	(2.082)	(2.405)	(-0.491)	(3.591)	(1.427)
$Exposure_c^{SBL} \times I(PostCrisis)$	0.071**	0.118*	0.249***	0.185	-0.051	0.414**	0.073**
	(2.350)	(1.992)	(4.087)	(1.325)	(-0.558)	(2.454)	(2.114)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Adj\ R^2$	22.68	35.46	67.20	72.85	38.49	70.53	19.98
Observations	25,951	25,951	25,951	25,951	25,951	25,951	25,951

Note: This table reports the impact of credit market disruptions on various earnings guidance properties. Columns (1) and (2) report the frequency of good and bad news management earnings guidance, respectively. Columns (3) and (4) report the frequency of optimistic and pessimistic management earnings guidance, respectively. Columns (5)-(7) report the frequency of point, range, and open-ended guidance, respectively. Detailed variable definitions are in Table A1. All specifications include firm- and industry-year fixed effects. Robust t-statistics are reported in parentheses and calculated using standard errors clustered at the state of incorporation level. ***, **, and * denote significance at the 10%, 5%, and 1% level in two-tailed tests.

Online Appendix

Credit Market Disruptions and Corporate Disclosure

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(This version: December 2021)

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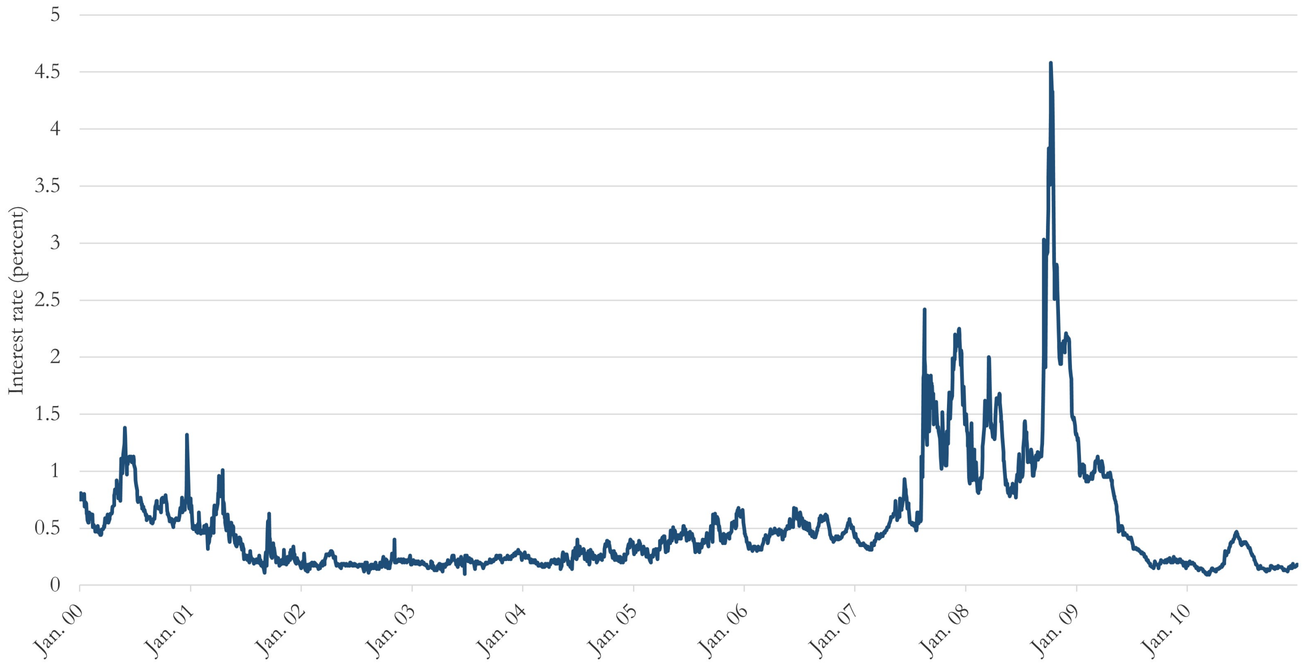
A1. Figures

Figure A1

TED Spread



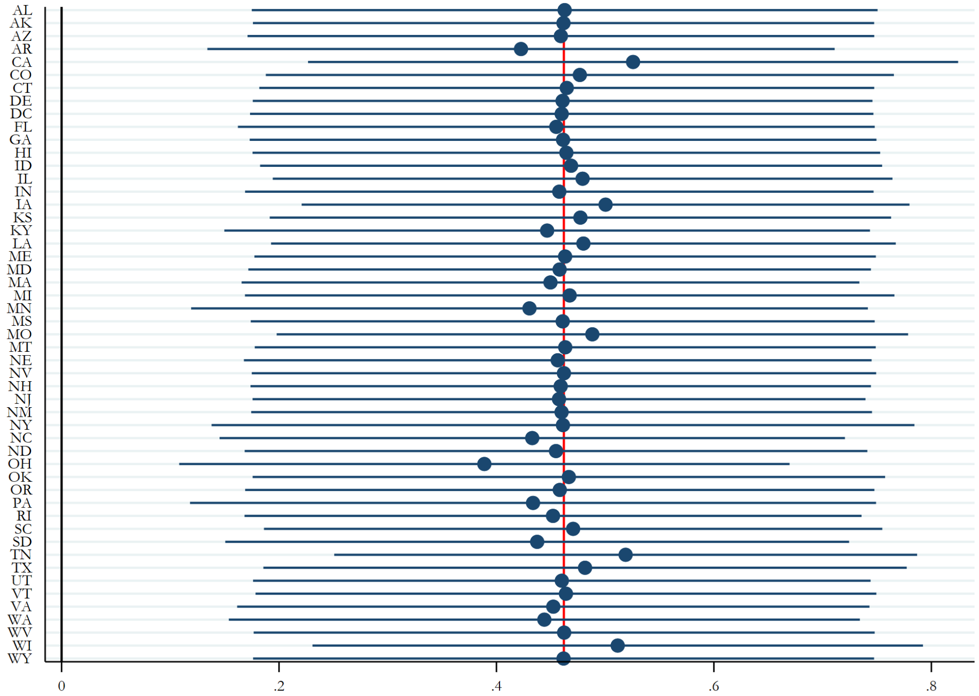
Note: This figure reports the evolution of the TED spread from January 2000 to December 2010. The TED spread is the difference between the LIBOR interest rate on three-month eurodollar deposits and the interest rate on three-month U.S. Treasury bills. Source: FRED, Federal Reserve Bank of St. Louis.

Figure A2

Robustness to Excluding One Lender at a Time

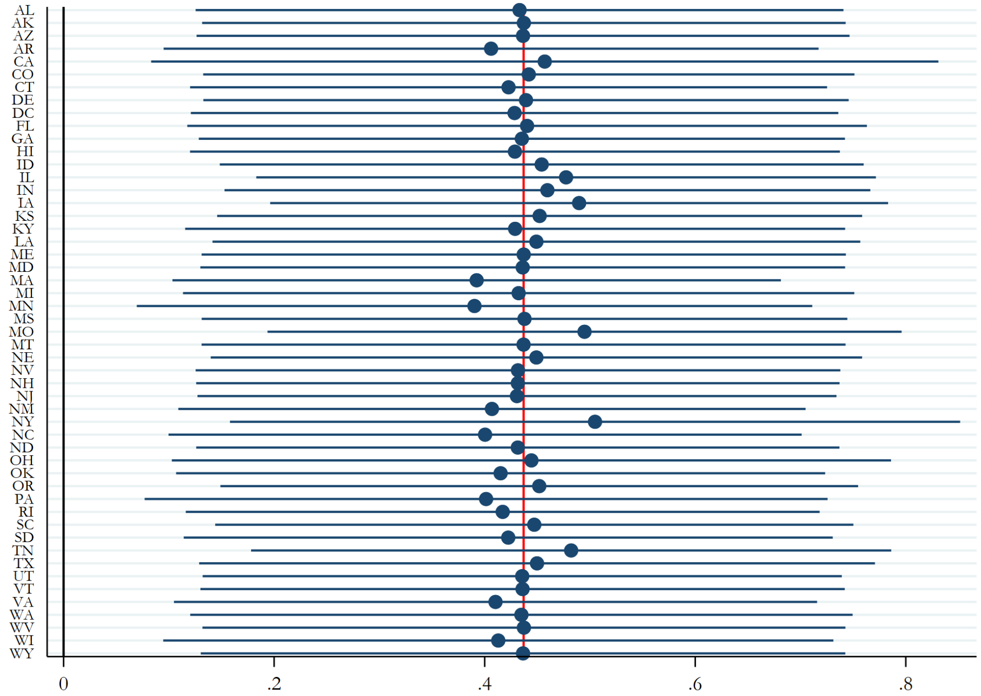
Panel A: Earnings Guidance

$Exposure_c^{SBL} \times I(Crisis)$



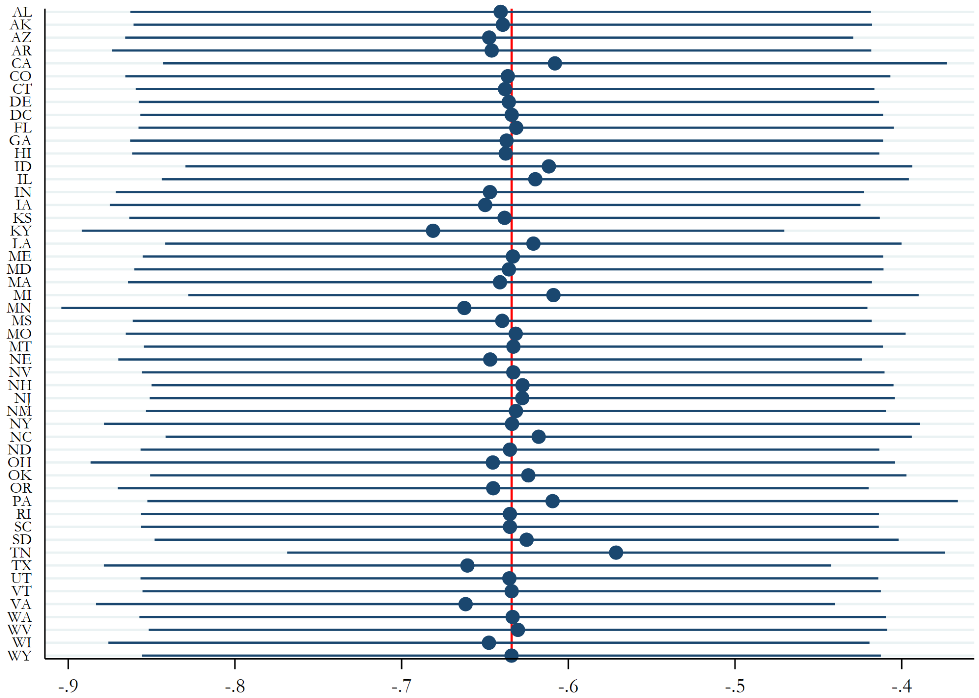
Panel B: Earnings Guidance

$Exposure_c^{SBL} \times I(PostCrisis)$



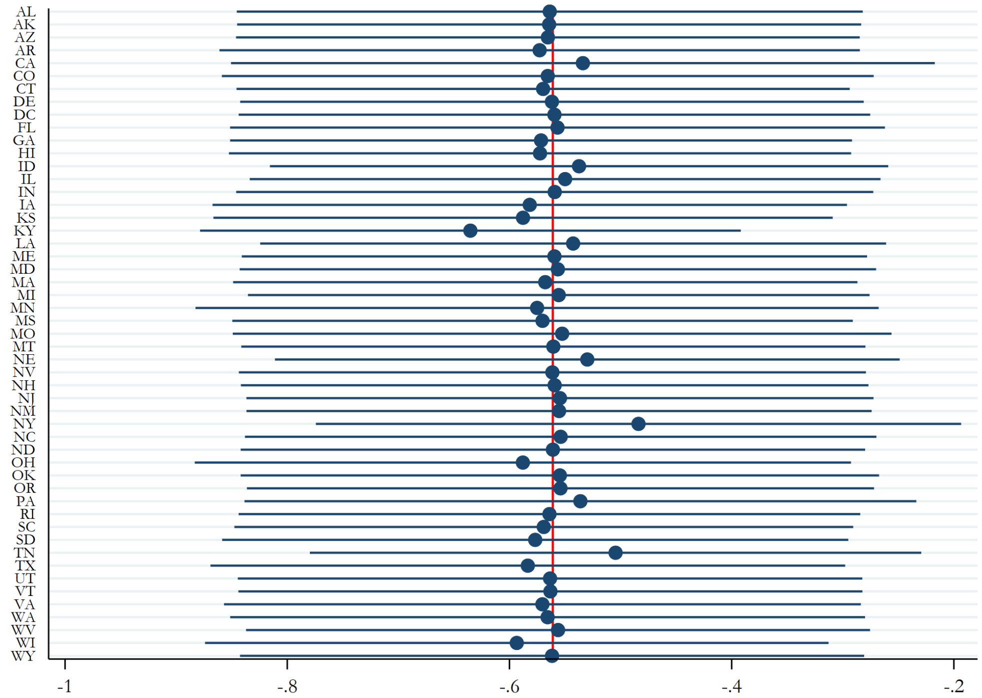
Panel C: Capital Expenditure Guidance

$Exposure_c^{SBL} \times I(Crisis)$



Panel D: Capital Expenditure Guidance

$Exposure_c^{SBL} \times I(PostCrisis)$



Note: The figure reports the point estimates (blue circle) of the interaction terms, $Exposure_c^{SBL} \times I(Crisis)$ (Panel A and C) and $Exposure_c^{SBL} \times I(PostCrisis)$ (Panel B and D), and the 95% confidence intervals (blue line) from repeating the specification shown in column (6) and column (9) of table 3 while dropping one state at a time from the sample. The dependent variable is $FreqMF$ $(Earnings)$ in panels A and B, $FreqMF$ $(CapEx)$ in panels C and D. All specifications include firm- and industry-year fixed effects. The red line shows the value of the coefficients in the full sample.

A2. Tables

Table A1

Variable Definitions		
Variable	Definition	Source
Dependent variables		
$FreqMF$	Number of management guidance on all metrics issued in year t.	IBES Guidance
$FreqMF\ (Earnings)$	Number of management earnings guidance issued in year t.	IBES Guidance
$FreqMF\ (CapEx)$	Number of management capital expenditure guidance issued in year t.	IBES Guidance
Independent variables		
$Exposure_c^{SBL}$	Continuous variable captures county' exposure to credit market disruption. See Section 4.2 for details.	Chicago FED, FFIEC CRA
$I(Crisis)$	Indicator variable set equal to 1 if year from 2008 to 2010, and 0 otherwise.	
$I(PostCrisis)$	Indicator variable set equal to 1 if year from 2011 to 2013, and 0 otherwise.	
Control variables		
$Institutional\,ownership$	Percentage of institutional ownership in a firm over year $t-1$. If a firm is not covered by the database, the institutional ownership variable is coded as zero.	Thomson Reuters 13F
$No\,analysts$	Number of analysts following the firm in year $t-1$. If a firm is not covered by the database, the number of analysts variable is coded as zero.	IBES
$Size$	Natural logarithm of the market value of equity at the beginning of year t.	Compustat
ROA	Return on a firm's assets of year $t-1$, measured as income before extraordinary items divided by total assets.	Compustat
BTM	Book value of equity divided by the market value of equity at the beginning of year t.	Compustat, CRSP
$Loss$	An indicator variable equal to one if income before extraordinary items of year $t-1$ is negative, and zero otherwise.	Compustat

Table A1 - *Continued*

Variable	Definition	Source
Sales volatility	Standard deviation of annual sales over the past 10 years with at least 5 nonmissing observations.	Compustat
Stock volatility	Standard deviation of daily stock returns over year $t-1$.	CRSP
BHAR	Buy-and-hold size-adjusted return over year $t-1$.	CRSP
Cash	Cash holdings scaled by total assets at the beginning of year t.	Compustat
CapEx	Capital expenditures scaled by total assets at the beginning of year t.	Compustat
Skewness	Skewness of daily stock returns over year $t-1$.	CRSP
Receivables	Total accounts receivable scaled by total assets at the beginning of year t.	Compustat
Other variables		
No access	An indicator variable equal to one if the firm did not have issued bonds reported in the Mergent FISD prior to the crisis.	Mergent FISD
Investment grade	An indicator variable equal to one if the firm issued bonds which are reported in the Mergent FISD and rated either above Moody's Baa3 or Standard and Poor's BBB- prior to the crisis.	Mergent FISD
Speculative grade	An indicator variable equal to one if the firm issued bonds which are reported in the Mergent FISD and rated either below Moody's Baa3 or Standard and Poor's BBB- prior to the crisis.	Mergent FISD
Conglomerates	An indicator variable equal to one if the firm reports more than one business segments in different four-digit Standard Industrial Classification (SIC) code, and zero otherwise.	Compustat Segments
Single segment	An indicator variable equal to one if the firm reports one business segments in different four-digit Standard Industrial Classification (SIC) code, and zero otherwise.	Compustat Segments
High (Low) Dispersion	An indicator variable equal to one if the firm's institutional ownership dispersion falls above (below or equal to) the pre-crisis sample median, and zero otherwise. Institutional ownership dispersion is the additive inverse of the sum of the squares of firms' percentage of each institutional ownership.	Thomson Reuters 13F

Table A1 - *Continued*

Variable	Definition	Source
High (*Low*) *Uncertainty*	An indicator variable equal to one if the firm's standard deviation of ROA or sales growth is above (below or equal to) the pre-crisis sample median, and zero otherwise.	Compustat
Good/Bad News	A good news (bad news) guidance is the earnings guidance with forecast news greater than 10% (smaller than -10%). Forecast news is the difference between management forecast and consensus analyst forecast (the outstanding median analyst forecast) at the time of management forecast, scaled by the absolute value of consensus analyst forecast. The manager's estimate is equal to the point estimate provided or the midpoint of the range estimate. It is not calculated for open-ended forecasts.	IBES Guidance
Quarterly/Annual Guidance	Number of management quarterly/annual earnings forecasts issued in year t.	IBES Guidance
Point/Range/Open-ended Guidance	Number of management point/range/open-ended earnings guidance issued in year t.	IBES Guidance

Table A2

Credit Market Disruption and Sales Guidance			
	(1)	(2)	(3)
		$FreqMF$ $(Sales)$	
$Exposure_c^{SBL} \times I(Crisis)$	0.001	0.071	0.154*
	(0.015)	(0.750)	(1.711)
$Exposure_c^{SBL} \times I(PostCrisis)$	-0.024	0.031	0.152
	(-0.116)	(0.156)	(0.921)
$Institutional\ ownership$		0.130	0.117
		(1.552)	(1.428)
$No\ analysts$		0.008**	0.006
		(2.013)	(1.616)
$Size$		0.274***	0.272***
		(6.489)	(6.489)
ROA		0.208***	0.207***
		(4.360)	(4.849)
BTM		0.024	0.025
		(0.981)	(1.039)
$Loss$		-0.138***	-0.134***
		(-5.065)	(-5.158)
$Sales\ volatility$		0.124	0.062
		(0.343)	(0.189)
$Stock\ volatility$		-1.035	-1.735
		(-0.768)	(-1.177)
$BHAR$		-0.013	-0.015
		(-0.694)	(-0.743)
$Leverage$		0.186	0.212
		(1.495)	(1.548)
$Cash$		-0.263**	-0.283***
		(-2.385)	(-2.754)
$CapEx$		0.048	-0.024
		(0.191)	(-0.098)
$Skewness$		-0.028***	-0.027***
		(-3.774)	(-3.465)
$Receivables$		0.142	0.215
		(0.291)	(0.472)
Constant	1.725***	-0.063	-0.019
	(575.115)	(-0.201)	(-0.064)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
Industry-year FE	No	No	Yes
$Adj\ R^2$	68.66	69.29	69.65
Observations	25,951	25,951	25,951

Note: This table reports the impact of credit market disruptions on the frequency of management sales guidance, $FreqMF$ $(Sales)$. Detailed variable definitions are in Table A1. $I(Crisis)$ is an indicator variable that takes the value of one for the crisis years: 2008, 2009, and 2010. $I(PostCrisis)$ is an indicator variable that takes the value of one for the post crisis years: 2011, 2012, and 2013. The specifications in columns (1)-(2) include firm- and year fixed effects. The specification in column (3) includes firm- and industry-year fixed effects. Robust t-statistics are reported in parentheses and calculated using standard errors clustered at the state of incorporation level. ***, **, and * denote significance at the 10%, 5%, and 1% level in two-tailed tests.

Table A3

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Robustness Tests Excluding Each State at a Time							
	$FreqMF$ $(Earnings)$				$FreqMF$ $(CapEx)$			
State	$Exposure_c^{SBL}$ $\times$ $I(Crisis)$	t-stat	$Exposure_c^{SBL}$ $\times$ $I(PostCrisis)$	t-stat	$Exposure_c^{SBL}$ $\times$ $I(Crisis)$	t-stat	$Exposure_c^{SBL}$ $\times$ $I(PostCrisis)$	t-stat
AL	0.463	(3.231)	0.433	(2.829)	-0.641	(-5.794)	-0.564	(-4.021)
AK	0.462	(3.248)	0.437	(2.875)	-0.639	(-5.800)	-0.564	(-4.038)
AZ	0.459	(3.202)	0.436	(2.828)	-0.647	(-5.958)	-0.565	(-4.048)
AR	0.423	(2.944)	0.406	(2.623)	-0.646	(-5.702)	-0.573	(-3.994)
CA	0.526	(3.533)	0.457	(2.457)	-0.608	(-5.197)	-0.534	(-3.387)
CO	0.477	(3.317)	0.442	(2.871)	-0.636	(-5.572)	-0.566	(-3.874)
CT	0.465	(3.302)	0.423	(2.808)	-0.638	(-5.786)	-0.570	(-4.149)
DE	0.461	(3.250)	0.439	(2.880)	-0.636	(-5.753)	-0.562	(-4.023)
DC	0.460	(3.225)	0.428	(2.800)	-0.634	(-5.719)	-0.560	(-3.956)
FL	0.455	(3.123)	0.440	(2.741)	-0.631	(-5.598)	-0.557	(-3.796)
GA	0.461	(3.216)	0.435	(2.851)	-0.637	(-5.669)	-0.572	(-4.104)
HI	0.464	(3.233)	0.429	(2.792)	-0.638	(-5.717)	-0.572	(-4.108)
ID	0.469	(3.292)	0.454	(2.985)	-0.612	(-5.638)	-0.537	(-3.881)
IL	0.479	(3.379)	0.477	(3.259)	-0.620	(-5.558)	-0.550	(-3.893)
IN	0.458	(3.183)	0.460	(3.011)	-0.647	(-5.792)	-0.559	(-3.920)
IA	0.500	(3.597)	0.490	(3.353)	-0.650	(-5.800)	-0.582	(-4.095)
KS	0.477	(3.356)	0.452	(2.967)	-0.638	(-5.697)	-0.588	(-4.238)
KY	0.447	(3.023)	0.429	(2.750)	-0.681	(-6.496)	-0.635	(-5.245)
LA	0.480	(3.357)	0.449	(2.934)	-0.621	(-5.650)	-0.543	(-3.871)
ME	0.463	(3.257)	0.437	(2.871)	-0.633	(-5.730)	-0.560	(-3.996)
MD	0.458	(3.215)	0.436	(2.862)	-0.636	(-5.684)	-0.556	(-3.904)
MA	0.450	(3.181)	0.392	(2.729)	-0.641	(-5.773)	-0.568	(-4.061)
MI	0.467	(3.145)	0.432	(2.725)	-0.609	(-5.585)	-0.556	(-3.991)

MN	0.430	(2.779)	0.390	(2.445)	-0.662	(-5.505)	-0.575	(-3.759)
MS	0.461	(3.228)	0.438	(2.869)	-0.640	(-5.799)	-0.570	(-4.104)
MO	0.488	(3.379)	0.495	(3.302)	-0.632	(-5.426)	-0.553	(-3.746)
MT	0.463	(3.260)	0.437	(2.871)	-0.633	(-5.738)	-0.560	(-4.010)
NE	0.456	(3.177)	0.449	(2.917)	-0.647	(-5.826)	-0.530	(-3.788)
NV	0.462	(3.234)	0.432	(2.833)	-0.633	(-5.712)	-0.561	(-3.998)
NH	0.459	(3.233)	0.432	(2.838)	-0.627	(-5.666)	-0.559	(-3.980)
NJ	0.458	(3.262)	0.431	(2.852)	-0.628	(-5.643)	-0.555	(-3.949)
NM	0.460	(3.237)	0.407	(2.745)	-0.631	(-5.718)	-0.555	(-3.967)
NY	0.461	(2.867)	0.505	(2.925)	-0.634	(-5.202)	-0.484	(-3.348)
NC	0.433	(3.025)	0.400	(2.676)	-0.618	(-5.547)	-0.554	(-3.917)
ND	0.455	(3.192)	0.431	(2.838)	-0.635	(-5.759)	-0.561	(-4.011)
OH	0.389	(2.784)	0.444	(2.614)	-0.645	(-5.374)	-0.588	(-4.001)
OK	0.467	(3.224)	0.415	(2.707)	-0.624	(-5.528)	-0.555	(-3.879)
OR	0.458	(3.182)	0.452	(2.998)	-0.645	(-5.756)	-0.554	(-3.946)
PA	0.434	(2.762)	0.401	(2.487)	-0.609	(-5.037)	-0.536	(-3.564)
RI	0.452	(3.201)	0.417	(2.785)	-0.635	(-5.765)	-0.564	(-4.051)
SC	0.471	(3.325)	0.447	(2.965)	-0.635	(-5.767)	-0.569	(-4.107)
SD	0.437	(3.064)	0.422	(2.754)	-0.625	(-5.628)	-0.577	(-4.114)
TN	0.519	(3.889)	0.482	(3.187)	-0.571	(-5.819)	-0.504	(-3.684)
TX	0.481	(3.271)	0.450	(2.816)	-0.661	(-6.086)	-0.583	(-4.105)
UT	0.460	(3.256)	0.436	(2.884)	-0.635	(-5.770)	-0.563	(-4.029)
VT	0.464	(3.265)	0.436	(2.863)	-0.634	(-5.753)	-0.563	(-4.030)
VA	0.452	(3.125)	0.410	(2.699)	-0.662	(-5.997)	-0.570	(-3.999)
WA	0.444	(3.075)	0.435	(2.778)	-0.633	(-5.686)	-0.566	(-3.979)
WV	0.462	(3.253)	0.437	(2.878)	-0.630	(-5.719)	-0.556	(-3.981)
WI	0.512	(3.662)	0.413	(2.607)	-0.648	(-5.701)	-0.593	(-4.250)
WY	0.462	(3.249)	0.436	(2.865)	-0.634	(-5.751)	-0.562	(-4.018)

Note: This table reports robustness tests excluding one state at a time. The dependent variable is $FreqMF$ ($Earnings$) in columns (1)-(4) and $FreqMF$ ($CapEx$) in columns (5)-(8). Detailed variable definitions are in Table A1. $I(Crisis)$ is an indicator variable that takes the value of one for the crisis years: 2008, 2009, and 2010. $I(PostCrisis)$ is an indicator variable that takes the value of one for the post crisis years: 2011, 2012, and 2013. All specifications include firm- and industry-year fixed effects. Robust t-statistics are reported in parentheses and calculated using standard errors clustered at the state of incorporation level.

Table A4

Robustness Test Using Entropy Balance			
	(1)	(2)	(3)
	FreqMF	*FreqMF (Earnings)*	*FreqMF (CapEx)*
$Exposure_c^{SBL} \times I(Crisis)$	0.210	0.418**	-0.498***
	(0.521)	(2.655)	(-4.356)
$Exposure_c^{SBL} \times I(PostCrisis)$	0.310	0.517***	-0.409**
	(0.606)	(3.182)	(-2.642)
Institutional ownership	0.535	-0.015	0.110
	(1.565)	(-0.109)	(1.366)
No analysts	0.052**	0.018**	0.010**
	(2.486)	(2.626)	(2.657)
Size	0.847***	0.236***	0.144***
	(6.811)	(7.695)	(5.749)
ROA	0.209	-0.022	0.020
	(0.898)	(-0.268)	(0.450)
BTM	0.136	-0.041	0.090***
	(1.269)	(-1.076)	(3.286)
Loss	-0.705***	-0.290***	-0.017
	(-5.303)	(-7.195)	(-0.636)
Sales volatility	1.251	0.469	0.590*
	(1.514)	(1.490)	(1.913)
Stock volatility	-5.423	-1.499	1.076
	(-1.365)	(-1.160)	(1.419)
BHAR	0.012	-0.030	0.008
	(0.179)	(-1.383)	(0.413)
Leverage	0.334	-0.150	0.219***
	(1.027)	(-1.515)	(3.642)
Cash	-1.322***	-0.497***	-0.071
	(-2.844)	(-3.715)	(-0.649)
CapEx	1.516*	0.256	0.692**
	(1.782)	(0.952)	(2.516)
Skewness	-0.075***	-0.028***	-0.014*
	(-3.368)	(-2.792)	(-1.903)
Receivables	-0.647	-0.277	-0.546***
	(-0.540)	(-0.798)	(-3.186)
Constant	1.044	0.538**	-0.121
	(1.090)	(2.260)	(-0.677)
Firm & Industry-year FE	Yes	Yes	Yes
Adj R^2	73.20	73.66	64.73
Observations	23,592	23,592	23,592

Note: This table reports robustness tests using entropy balance. The dependent variable is $FreqMF$ in column (1), $FreqMF$ ($Earnings$) in column (2), and $FreqMF$ ($CapEx$) in column (3). Detailed variable definitions are in Table A1. $I(Crisis)$ is an indicator variable that takes the value of one for the crisis years: 2008, 2009, and 2010. $I(PostCrisis)$ is an indicator variable that takes the value of one for the post crisis years: 2011, 2012, and 2013. All specifications include firm- and industry-year fixed effects. Robust t-statistics are reported in parentheses and calculated using standard errors clustered at the state of incorporation level. ***, **, and * denote significance at the 10%, 5%, and 1% level in two-tailed tests.

Table A5

Robustness Test Controlling for County-level Variables			
	(1)	(2)	(3)
	$FreqMF$	$FreqMF$ $(Earnings)$	$FreqMF$ $(CapEx)$
$Exposure_c^{SBL} \times I(Crisis)$	0.450	0.570***	-0.700***
	(0.848)	(3.018)	(-4.379)
$Exposure_c^{SBL} \times I(PostCrisis)$	0.527	0.556***	-0.577***
	(0.865)	(3.096)	(-3.020)
$Institutional\ ownership$	0.582**	0.005	0.095
	(2.087)	(0.050)	(1.293)
$No\ analysts$	0.052***	0.014**	0.018***
	(2.798)	(2.396)	(3.953)
$Size$	0.870***	0.244***	0.154***
	(7.378)	(8.003)	(6.372)
ROA	0.278	0.008	0.030
	(1.381)	(0.145)	(0.694)
BTM	0.194	-0.016	0.099***
	(1.623)	(-0.412)	(2.954)
$Loss$	-0.626***	-0.277***	-0.009
	(-6.295)	(-8.376)	(-0.368)
$Sales\ volatility$	0.980	0.485	0.295
	(1.391)	(1.444)	(1.092)
$Stock\ volatility$	-7.064**	-2.308*	1.068*
	(-2.041)	(-1.990)	(1.724)
$BHAR$	0.057	-0.018	0.020
	(1.092)	(-0.980)	(1.095)
$Leverage$	0.405	-0.101	0.248***
	(1.108)	(-0.967)	(3.595)
$Cash$	-1.133***	-0.459***	-0.087
	(-2.992)	(-3.494)	(-0.720)
$CapEx$	1.838**	0.205	1.143***
	(2.266)	(0.727)	(3.866)
$Skewness$	-0.091***	-0.032***	-0.020***
	(-5.351)	(-3.308)	(-3.501)
$Receivables$	-0.423	-0.265	-0.477***
	(-0.348)	(-0.747)	(-2.822)
$Pop.\ gr \times I(Crisis)$	5.006	1.170	0.444
	(0.561)	(0.344)	(0.183)
$Pop.\ gr \times I(PostCrisis)$	9.767	1.929	0.710
	(0.847)	(0.423)	(0.272)
$Pct.\ black \times I(Crisis)$	0.185	0.170	-0.348
	(0.266)	(0.848)	(-1.370)

Pct. black $\times$ $I(PostCrisis)$	-0.089	-0.156	-0.276
	(-0.090)	(-0.425)	(-0.868)
Pct. poverty $\times$ $I(Crisis)$	-0.018	-0.003	0.011
	(-0.428)	(-0.217)	(1.170)
Pct. poverty $\times$ $I(PostCrisis)$	-0.051	-0.018	0.020**
	(-1.219)	(-1.173)	(2.009)
Ln(RGDP pc) $\times$ $I(Crisis)$	0.012	0.035	-0.020
	(0.028)	(0.192)	(-0.163)
Ln(RGDP pc) $\times$ $I(PostCrisis)$	0.174	0.172	-0.157
	(0.315)	(0.783)	(-1.020)
Ln(income pc) $\times$ $I(Crisis)$	-0.117	-0.123	0.156
	(-0.167)	(-0.454)	(0.820)
Ln(income pc) $\times$ $I(PostCrisis)$	-0.611	-0.327	0.208
	(-0.767)	(-1.057)	(0.948)
ΔHPI $\times$ $I(Crisis)$	0.037	0.012	0.005
	(1.588)	(1.495)	(0.601)
ΔHPI $\times$ $I(PostCrisis)$	0.030	0.007	-0.001
	(1.171)	(0.606)	(-0.167)
Unemploy. rt $\times$ $I(Crisis)$	-0.079	-0.049	0.045
	(-0.618)	(-1.157)	(1.022)
Unemploy. rt $\times$ $I(PostCrisis)$	0.022	0.024	0.027
	(0.121)	(0.378)	(0.582)
Estabs. gr $\times$ $I(Crisis)$	-17.388**	-4.901	0.233
	(-2.202)	(-1.614)	(0.120)
Estabs. gr $\times$ $I(PostCrisis)$	-18.681*	-3.334	0.586
	(-1.822)	(-0.778)	(0.250)
Constant	10.000*	3.490*	-1.970
	(1.779)	(1.912)	(-1.285)
Firm & Industry-year FE	Yes	Yes	Yes
Adj R^2	72.96	73.94	65.31
Observations	25,951	25,951	25,951

Note: This table reports robustness tests controlling for county-level variables. The dependent variable is *FreqMF* in column (1), *FreqMF* (*Earnings*) in column (2), and *FreqMF* (*CapEx*) in column (3). *Pop. gr* is the county's population growth. *Pct. black* is the county's black population percentage. *Pct. poverty* is the county's percentage of population living in poverty. *Ln(RGDP pc)* is the natural logarithm of the county's real gross domestic product per capita. *Ln(income pc)* is the natural logarithm of the county's income per capita. ΔHPI is the change in county's house price indices. *Unemploy. rt* is the county's unemployment rate. *Estabs. gr* is the county's establishment growth. Detailed variable definitions are in Table A1. $I(Crisis)$ is an indicator variable that takes the value of one for the crisis years: 2008, 2009, and 2010. $I(PostCrisis)$ is an indicator variable that takes the value of one for the post crisis years: 2011, 2012, and 2013. All specifications include firm- and industry-year fixed effects. Robust t-statistics are reported in parentheses and calculated using standard errors clustered at the state of incorporation level. ***, **, and * denote significance at the 10%, 5%, and 1% level in two-tailed tests.

Table A6

Robustness Test - Leave-one-out Measure			
	(1)	(2)	(3)
	FreqMF	*FreqMF (Earnings)*	*FreqMF (CapEx)*
$Exposure_c^{SBL} \times I(Crisis)$	-0.194	0.581***	-0.832***
	(-0.340)	(2.776)	(-4.211)
$Exposure_c^{SBL} \times I(PostCrisis)$	-0.588	0.470*	-0.798***
	(-0.800)	(1.842)	(-3.448)
Institutional ownership	0.603**	0.010	0.097
	(2.194)	(0.103)	(1.285)
No analysts	0.046**	0.012**	0.016***
	(2.365)	(2.149)	(3.569)
Size	0.880***	0.246***	0.158***
	(7.763)	(8.335)	(6.615)
ROA	0.281	0.010	0.026
	(1.425)	(0.172)	(0.589)
BTM	0.198	-0.013	0.099***
	(1.655)	(-0.348)	(2.993)
Loss	-0.628***	-0.279***	-0.009
	(-6.257)	(-8.280)	(-0.377)
Sales volatility	0.935	0.478	0.277
	(1.298)	(1.454)	(0.992)
Stock volatility	-6.961**	-2.286**	1.117*
	(-2.047)	(-2.015)	(1.739)
BHAR	0.051	-0.020	0.018
	(0.992)	(-1.064)	(0.989)
Leverage	0.416	-0.092	0.238***
	(1.141)	(-0.924)	(3.515)
Cash	-1.129***	-0.458***	-0.091
	(-3.025)	(-3.476)	(-0.746)
CapEx	1.897**	0.212	1.140***
	(2.354)	(0.770)	(3.792)
Skewness	-0.092***	-0.032***	-0.020***
	(-5.393)	(-3.358)	(-3.540)
Receivables	-0.353	-0.238	-0.483***
	(-0.303)	(-0.699)	(-2.908)
Constant	0.741	0.151	0.274
	(0.733)	(0.643)	(1.251)
Firm & Industry-year FE	Yes	Yes	Yes
Adj R^2	72.95	73.92	65.28
Observations	25,951	25,951	25,951

Note: This table reports the impact of credit market disruptions on the frequency of management guidance. The dependent variable is $FreqMF$ $(Earnings)$ in columns (1)–(2), and $FreqMF$ $(CapEx)$ in columns (3)–(4). $Exposure_c^{SBL}$ is the geographical measure of the county exposure to credit market disruptions using the leave-one-out method in equation 5. Detailed variable definitions are in Table A1. $I(Crisis)$ is an indicator variable that takes the value of one for the crisis years: 2008, 2009, and 2010. $I(PostCrisis)$ is an indicator variable that takes the value of one for the post crisis years: 2011, 2012, and 2013. All specifications include firm- and industry-year fixed effects. Robust t-statistics are reported in parentheses and calculated using standard errors clustered at the state of incorporation level. ***, **, and * denote significance at the 10%, 5%, and 1% level in two-tailed tests.

Table A7

Credit Market Disruptions and Corporate Disclosure - Placebo				
	(1)	(2)	(3)	(4)
	FreqMF (Earnings)		*FreqMF (CapEx)*	
$Exposure^{SBL}_{c,05-08} \times I(Crisis)$	0.297		-0.124	
	(1.423)		(-0.459)	
$Exposure^{SBL}_{c,05-08} \times I(PostCrisis)$	0.167		-0.281	
	(0.599)		(-1.076)	
$Exposure^{SBL}_{c,11-14} \times I(Crisis)$		0.031		0.157
		(0.160)		(0.841)
$Exposure^{SBL}_{c,11-14} \times I(PostCrisis)$		-0.352		-0.003
		(-1.457)		(-0.013)
Controls	Yes	Yes	Yes	Yes
Firm & Industry-year FE	Yes	Yes	Yes	Yes
Adj R^2	73.91	73.91	65.23	65.22
Observations	25,951	25,951	25,951	25,951

Note: This table reports the impact of the placebo credit market disruptions on the frequency of management guidance. The dependent variable is $FreqMF$ $(Earnings)$ in columns (1)–(2), and $FreqMF$ $(CapEx)$ in columns (3)–(4). $Exposure^{SBL}_{c,05-08}$ is the geographical measure of the county exposure to credit supply shocks during the 2005–2008 period. $Exposure^{SBL}_{c,11-14}$ is the geographical measure of the county exposure to credit supply shocks during the 2009–2012 period. Detailed variable definitions are in Table A1. $I(Crisis)$ is an indicator variable that takes the value of one for the crisis years: 2008, 2009, and 2010. $I(PostCrisis)$ is an indicator variable that takes the value of one for the post crisis years: 2011, 2012, and 2013. All specifications include firm- and industry-year fixed effects. Robust t-statistics are reported in parentheses and calculated using standard errors clustered at the state of incorporation level. ***, **, and * denote significance at the 10%, 5%, and 1% level in two-tailed tests.