Weathering Cash Flow Shocks*

James R. Brown† Matthew T. Gustafson‡ Ivan T. Ivanov§

9/7/2017

Abstract

We show that unexpectedly severe winter weather, which is arguably exogenous to firm and bank fundamentals, represents a significant cash flow shock for the average bank-borrowing firm. Firms respond to such shocks by increasing credit line use, but do not significantly adjust cash reserves, non-cash working capital, or real activities. The increased credit line use occurs within one calendar quarter of the cash flow shock and is accompanied by an increase in credit line size, for all but the most distressed borrowers. These results highlight the role of banks in mitigating transitory cash flow shocks to firms.

*The views stated herein are those of the authors and are not necessarily the views of the Federal Reserve Board or the Federal Reserve System. We thank Heitor Almeida, Mitchell Berlin, Mark Carey, Kristle Romero Cortes, Christopher James, Kathleen Johnson, Ralf Meisenzahl, Atanas Mihov, Joe Nichols, Ben Ranish, Robert Sarama, Antoinette Schoar, Phillip Strahan, Nathan Swem, Bastian von Beschwitz, James Wang and seminar participants at the 13th Annual Conference on Corporate Finance at Washington University in St. Louis, the 2017 SFS Cavalcade, the Federal Reserve Board, the Federal Reserve Bank of Philadelphia, the FDIC, Iowa State University, Penn State University, and the SEC for helpful comments.

†Iowa State University, College of Business, 3331 Gerdin Business Building, Ames, IA 50011; 515-294-4668; jrbrown@iastate.edu.

‡Smeal College of Business, Penn State University, State College, PA 16801, USA; +1-814-867-4042; mtg15@psu.edu.

§Federal Reserve Board, 20th Street and Constitution Avenue NW, Washington, DC, 20551; 202-452-2987; ivan.t.ivanov@frb.gov.

1 Introduction

Despite the extensive literature emphasizing the unique advantages of banks as liquidity providers (e.g., Kashyap, Rajan, and Stein (2002); Gatev and Strahan (2006)), there is little empirical evidence on how bank-dependent firms manage idiosyncratic cash flow shocks. One challenge is the lack of data on the financing activities of private firms, which leads most prior research to study liquidity management in larger publicly-traded firms (e.g., Sufi (2009)). Another challenge is that it is difficult to isolate cash flow variation that is exogenous to firm-level investment opportunities and unrelated to the health of financial intermediaries.

In this paper we introduce a new dataset and a unique empirical setting to overcome these challenges and provide new evidence on the extent to which firms rely on bank financing to mitigate the effects of idiosyncratic cash flow shocks. The dataset we employ, which is only recently available and collected by the Federal Reserve, contains detailed information on bank loan contracts, including credit line limits, credit line drawn amount, and a range of borrower (firm) characteristics. Because the data collection covers the full set of firms in a bank's loan portfolio with outstanding loan commitments of at least $1 million, we observe a much broader cross-section of borrowers than most other research on corporate liquidity management. In particular, our sample is largely comprised of private firms, which tend to be particularly dependent on bank financing (e.g., Robb and Robinson (2014)). For example, in our sample the average credit line is 24% of total assets, which is approximately 50% larger than the average for the publicly traded firms studied in Sufi (2009). Thus, this sample offers a unique opportunity to study the effects of cash flow volatility in a broad sample of private firms, and to directly evaluate how the borrowers that are most reliant on credit lines use them to manage liquidity.

To break the endogenous link between cash flow and factors such as investment opportunities or the financial health of intermediaries, we introduce abnormally severe local winter weather as a shock to corporate cash flows. We obtain data on winter weather at the county level from the National Oceanic and Atmospheric Administration (NOAA). We find that abnormally-severe weather in the first calendar quarter significantly affects total annual firm-level cash flows. For example, a two standard deviation increase in abnormal winter snow cover in a given county reduces the annual cash flow of firms headquartered in that county by 0.36% of total assets. Partitioning by industry reveals that this negative relation between snow cover and cash flow exists in all 8 sectors that each comprise over 3% of our sample, with the effect being statistically significant at the 10% level or better for the transportation, manufacturing, wholesale and construction industries. This result provides large scale support for anecdotal and sector-specific evidence that severe weather adversely affects firm performance (e.g., Tran (2016)).

We use the abnormal winter snow cover in the county of a firm's headquarters as an instrumental variable (IV) for cash flow to investigate how firms manage cash flow shocks. The exclusion restriction is that severe weather affects corporate liquidity management only through its effect on cash flow. The temporary nature of severe winter weather makes this assumption plausible. A typical winter storm is unlikely to affect investment opportunities or access to capital, except through its effect on cash flows. The most severe winter weather events may affect investment opportunities for reasons other than reduced cash flows. Such events do not drive our results as our findings are similar after trimming our measures of abnormal snow cover.

Two-stage least squares (2SLS) regressions reveal an economically large and statistically significant negative relation between cash flow and credit line drawdowns. The coefficient estimates suggest that annual credit line drawdowns increase by between 41 and 61 cents for every $1 reduction in annual cash flow. In addition, the IV estimates indicate a significant negative relation between cash flow and changes in credit line limits. On average, we estimate that the end of year credit limit increases by between 74 cents and $1 and 13 cents for every $1 reduction in firm cash flow. Together, these results show that firms with existing lending relationships rely extensively on credit lines to manage liquidity, and that banks accommodate these firms by adjusting credit line limits.

These findings suggest that the average bank-reliant firm uses credit lines as their primary means of managing liquidity shocks. In contrast, survey evidence in Lins, Servaes, and Tufano (2010) suggests that larger firms use cash to hedge against potential cash flow shortfalls, reserving credit line use primarily to pursue investment opportunities. To investigate whether firms in our sample also use cash to buffer weather induced cash flow shocks, we employ the same IV approach with the change in cash holdings as the second stage dependent variable. We find a positive but statistically insignificant relation between exogenous cash flow shocks and changes in cash, suggesting that cash balances decrease by approximately 20 cents for every \$1 decrease in annual cash flow. We also find a similarly sized but insignificant relation between cash flows and changes in non-cash working capital. Importantly, we find no evidence that cash flow shocks significantly affect the accumulation of either fixed or total assets. Thus, the firms we study fully shield real investment from cash flow shocks, primarily via credit line adjustments.

In our final set of tests, we estimate the direct relation between abnormal winter snow cover and corporate outcomes. Consistent with our two-stage estimates, abnormal snow cover is positively and significantly related to changes in credit line draws and credit line size, but not to other corporate outcomes. A two standard deviation increase in first quarter abnormal snow results in the average firm drawing 0.15% of assets more on their credit line and increasing their credit line size by 0.27% of assets over the course of the year.

An important benefit to this reduced form analysis is that we can examine the relation between severe winter weather and credit line activity on a quarterly basis. Doing so, we find that firms respond to abnormal snow in the first calendar quarter by drawing on and expanding the size of credit lines in the second quarter (i.e., between April 1 and June 30). Interestingly, abnormal snow cover is negatively related to credit line size during the first quarter.[1] Thus, there is some initial hesitance of banks to offer financing, but (on average) this hesitance is short-lived, at least for the cash flows shocks we examine, which are exoge-

[1] There is no significant relation between abnormal first quarter snow cover and credit line activity in the third or fourth calendar quarters.

nous to firm fundamentals.[2] This one-quarter delay in line expansion is consistent with Sufi (2009) and Acharya et al. (2014), who argue that bank financing may not be available to firms experiencing low cash flows or negative profitability shocks. We find further support for this idea when partitioning the sample on the lender's assessment of credit risk. As credit risk increases, credit line size and drawdowns become less related to adverse weather. Thus, bank financing becomes a less viable liquidity source as borrower financial health deteriorates.

Our study contributes most directly to the literature that considers the extent to which firms rely on credit lines as a source of short-term liquidity. Our finding that credit lines are actively used to manage cash flow shocks is consistent with the large theoretical literature arguing that credit lines are a valuable and efficient liquidity management tool (e.g., Shockley and Thakor (1997); Holmstrom and Tirole (1998)). Kashyap, Rajan, and Stein (2002) and Gatev and Strahan (2006) argue that banks are ideal providers of this liquidity because deposits and credit line drawdowns are imperfectly correlated. Our findings also support the idea in Diamond (1991) that bank financing may become less accessible for firms as their financial health deteriorates.

Despite the prominence of credit line use,[3] there is little evidence that firms rely on credit lines to manage idiosyncratic cash flow shocks. Rather, many empirical studies question the extent to which credit lines are a viable source of liquidity when firms face cash flow shortfalls (Sufi (2009); Lins, Servaes, and Tufano (2010)).[4] Our evidence shows that the average bank-dependent firm is able to rely extensively on credit lines to manage unexpected cash

[2]Data limitations prevent us from examining how firms manage their liquidity through sources such as cash buffers and non-cash working capital within the first quarter when credit limits fall.

[3]Sufi (2009) documents that credit lines account for over 80% of bank financing provided to U.S. public firms, with the median credit line size being approximately 16% of a firm's total assets. 65% of the private firms sampled by Demiroglu, James, and Kizilaslan (2012) had a credit line in the year before they were acquired or went public. Lins, Servaes, and Tufano (2010) conduct an international survey and conclude that lines of credit are the dominant source of liquidity for companies around the world. See Demiroglu and James (2011) for a survey of literature on credit line usage.

[4]Other determinants of credit line usage include systemic risk (Acharya, Almeida, and Campello (2013)), time since loan origination and borrower defaults (Jimenez, Lopez, and Saurina (2009)), governance quality (Yun (2009)), and variation in bank lending standards (Demiroglu, James, and Kizilaslan (2012)).

flow shocks that are exogenous to firm fundamentals. This evidence contributes to the large literature on the value of lending relationships (e.g., James and Wier (1990); Petersen and Rajan (1994)) by providing a specific channel through which bank relationships provide increased access to capital.

These findings complement recent evidence on firm use of credit lines during the financial crisis. Campello et al. (2011) survey a large number of CFOs from around the world and find that credit lines helped ease the impact of the financial crisis for firms with available credit. In a related vein, Berospide and Meisenzahl (2016) show that public firms drew on credit lines in late-2007 and used these drawdowns to sustain investment during the crisis, while Ivashina and Scharfstein (2010) document a run on syndicated credit lines leading into the crisis that was followed by some syndicated lenders cutting back available credit. Ivanov and Pettit (2017) study how a number of large lenders managed their entire credit line portfolio during the crisis and find that once bilateral credit lines are taken into account, outstanding credit line draws at these large institutions appear less consequential from a systemic risk standpoint. Our setting is notably different in that we focus on exogenous shocks to corporate cash flow that are uncorrelated with lender financial health. For these types of shocks credit lines appear to be the primary way bank-dependent firms manage liquidity.

We also contribute to the broader liquidity management literature (e.g., Almeida, Campello, and Weisbach (2004); Denis and Sibilkov (2010); Campello et al. (2011)). As Almeida et al. (2014) discuss, this literature emphasizes the increasing importance of cash holdings as a liquidity management tool, particularly for financially constrained firms that face large aggregate liquidity risks. We contribute to this literature by showing that the typical bank-dependent firm manages liquidity very differently than large public firms, which are the focus of this literature.

Our focus on exogenous cash flow shocks also distinguishes our study from most prior evidence on corporate liquidity management. Scholars have long recognized the inherent challenges in identifying the effects of cash flow volatility, due in large part to difficulties in adequately controlling for changes in the profitability of future investment (e.g., Poterba (1988); Erickson and Whited (2000); Alti (2004); Almeida, Campello, and Weisbach (2004); Moyen (2004); Almeida and Campello (2007); Riddick and Whited (2009); Chang et al. (2014)). The correlation between cash flows and other economic factors makes it difficult to interpret any observed associations between cash flow and other corporate outcomes. Indeed, in sharp contrast with our 2SLS estimates, OLS regressions show a positive and statistically significant association between cash flow and bank credit line commitments. That is, although banks almost fully accommodate firms experiencing cash flow shocks that are orthogonal to firm fundamentals, in general credit line commitments actually tend to fall when firm cash flows decline. These findings directly illustrate the importance of isolating the component of cash flow volatility that is free of information about future growth opportunities in order to draw causal inferences about cash flow shocks and corporate liquidity decisions.

Finally, our study contributes to a small but growing literature on the effects of weather and other natural events on firm decision-making and economic activity (e.g., Giroud et al. (2012); Chen et al. (2017)). In particular, Tran (2016) links negative weather shocks with significant reductions in retail sales, and Bloesch and Gourio (2015) find that the winter of 2013-2014 negatively affected the broader U.S. economy. We provide broad evidence on the implications of unanticipated weather shocks for firm-level cash flows. Moreover, we identify an important role of banks in helping small firms deal with these unanticipated weather events. In so doing, our work complements recent evidence showing that local banks play an important role in mitigating the negative effects of natural disasters (Cortes and Strahan (2016); Cortes (2014)).

2 Data construction and sample descriptive statistics

2.1 Federal Reserve's Y-14Q collection

Our main data source is Schedule H.1 of the Federal Reserve's Y-14Q data collection. This data collection began in June of 2012 to support the Dodd-Frank Stress Tests and the Comprehensive Capital Analysis and Review. The reporting panel includes bank holding companies exceeding US $50 billion in total assets. The 35 institutions in the Y-14 collection provide loan-level data on their corporate loan portfolio whenever a loan exceeds $1 million in commitment exposure.[5] We restrict the sample to domestic borrowers, excluding government entities, individual borrowers, foreign entities, and nonprofit organizations.

We build a firm-year-level panel from the loan characteristics and financial statement information in the bank lending portfolios. The majority of firms update their financials only once a year, however some firms report quarterly. To avoid duplicate observations we keep the financial statement information with financial reporting date closest to the end of each calendar year, which typically are the financials as of Q4. We next match the financial statement information for each firm-quarter to the loan data based on the identity of the borrower and the quarter of the loan and financial reports. We aggregate all loan-level variables to the firm-quarter level by summing up the committed/utilized exposure of a given borrower across all lenders in a given quarter.[6]

We exclude likely data errors by requiring that for each firm and financial statement date: 1) EBITDA does not exceed net sales, 2) fixed assets do exceed total assets, 3) cash and

[5] As Bidder, Krainer, and Shapiro (2016) document, the commercial loans in the Y-14 data represent approximately 70% of all commercial loans extended in the United States.

[6] This aggregation does not affect any of the variables constructed from the financial statement information as these pertain to all operating, financing, and investment activities of a given borrower, however it may bias the total bank borrowing of large firms downward to the extent that their loans are syndicated to non-Y14 and smaller banks. This bias is mitigated by the fact that syndicated credit lines are almost always held by banks and Y-14 reporting banks participate in approximately 98% of all banks credit line exposure in the Shared National Credit data between 2011 and 2015. Therefore, changes in the committed and utilized shares of Y-14 banks are likely to mirror changes in overall credit lines. In the FR-Y14Q Schedule H1 between 2012 and 2016 syndicated credit line commitments typically taken by mid-size and large corporate borrowers represented between 54% and 57% of total commercial and industrial credit commitments at the 30-35 largest US banks.

marketable securities do not exceed total assets, and 4) total liabilities do not exceed total assets. In addition, we trim all variables at the 0.5% and 99.5% percentiles to mitigate the effect of outliers. See Appendix A for more detailed description of the data cleaning.

We require data on total assets, fixed assets, cash and marketable securities, non-cash working capital, total liabilities, total sales, total debt, and EBITDA, which we use as our measure of cash flow. For our main tests, we also require at least two consecutive years of bank financing information so that we can compute changes in credit line limits and utilization. After imposing these restrictions, the final sample consists of 97,619 firm-year observations with available information on bank financing and firm characteristics during the period 2012 to 2015.

2.2 Descriptive statistics

Table 1 presents descriptive statistics. Small private firms dominate our sample. The 75th percentile of the book value of total assets is approximately \$91 million, and the average size of firms falling below this threshold is only \$22 million. The firms we study are thus substantially smaller than the majority of firms in studies using COMPUSTAT and survey data. For example, Campello et al. (2011) consider firms "small" if their sales are less than \$1 billion, whereas the 75th percentile of sales in our sample is \$5.5 million (unreported, the sales measure in Table 1 is scaled by total assets).

On average, the firms in our sample are more levered than the typical COMPUSTAT firm, with average leverage (i.e., total liabilities-to-assets) and total deb-to-assets ratios of approximately 60% and 32%, respectively. This is likely due, in part, to the fact that our sample only includes firms that have obtained a bank loan, though the extensive reliance on bank debt is broadly consistent with the evidence on small firm borrowing in Robb and Robinson (2014).

The average credit line size is approximately 24% of total assets, which is considerably larger than the average ratio of credit line commitments to total assets among large publicly-traded firms reported in recent studies (e.g., Sufi (2009)). There is also substantial variation in line size. The 75th percentile of credit line size is approximately 35% of total assets, while the 25th percentile is only 9%. By comparison, cash holdings are somewhat small as a fraction of total assets – the mean is approximately 10% while the median is about 5% – which also highlights an important difference between the bank-dependent firms we sample and the typical public firm (e.g., Bates, Kahle, and Stulz (2009)).

3 Severe weather and cash flow

There is no shortage of anecdotal evidence suggesting that abnormally bad weather has a significant negative impact on firm cash flows, even at the annual level. Recently, this idea has manifested itself during the abnormally cold winters in the Northeast United States during 2014 and 2015. Colvin and Loten (2014) document this phenomenon, citing evidence that bad winter weather in 2014 adversely affected small business sales. A CNBC report in February of 2014 on the manufacturing sector contains a long list of companies detailing the impact of severe winter weather. For example, Fabricated Metal Products cited poor weather impacting their outbound and inbound shipments, and Plastics & Rubber Products said that they experienced many late deliveries due to truck lines being shut down.[7] There is also no shortage of anecdotes in other industries. For example, Todd Smith, VP Sales, at Leonard's Express, a mid-sized trucking company summarizes the effect that winter storms can have in his industry, stating "ultimately, the true cost of a winter weather storm can be staggering. Multiple days of lost productivity, added miles, additional equipment, fuel, snow removal, lost driver wages, and accident/incident costs are all very real results. A midsized trucking company can easily see a financial hit in the tens of thousands of dollars per day."[8]

There is also some academic literature supporting this idea. For example, Tran (2016)

[7]See the February 5, 2014 article entitled "Here's how bad winter weather is hurting the economy" by Kristen Scholer, which can be found online at http://www.cnbc.com/2014/02/05/heres-how-bad-winter-weather-is-hurting-the-economy.html

[8]see http://blog.chrwtrucks.com/carrier/winter-weather-a-trucking-company's-perspective-2/

finds that the worst 5% of weather shocks decrease in-store sales by 20%, with no evidence of substitution toward other forms of purchases. Bloesch and Gourio (2015) find that the unusually cold and snowy winter of 2013-2014 had a temporary but significant effect on the U.S. economy. However, we are not aware of any broad empirical evidence on the extent to which abnormally severe winter weather affects firm cash flows.

To the extent that severe winter weather has an impact on cash flow, it provides a unique opportunity to investigate how firms manage exogenous cash flow shocks. The reason for this is that unexpectedly bad winter weather is unlikely to impact long-run firm outcomes. This is especially true if the severe weather is measured over a relatively short interval and extreme severe weather incidents, which may destroy a jurisdiction's infrastructure and affect the firm's long-run growth prospects, are excluded from the measure. Below, we describe how we develop a measure of unanticipated severe winter weather that has a negative impact on firms' immediate cash flows, but arguably does not affect their long-run investment opportunities.

3.1 Measuring severe winter weather

There are a variety of ways to measure severe winter weather, and the extent to which various aspects of weather affect corporate cash flow is an empirical question. We use normalized measures of severe winter weather, such that they capture the component of winter weather that firms are not already prepared for. Our two primary measures of abnormal weather are the average daily snow cover during the first quarter of each year and the 95th percentile of daily snow cover during the first quarter (i.e., the snow cover on the fourth snowiest day of the quarter). The reason we choose snow cover as our main measure is because it combines the intuitive negative effects that snowfall and cold weather may have on firm cash flow.

We construct these measures using data on daily snow cover (in inches) from the NOAA's website. NOAA reports this measure (SNWD) for each weather station in the United States. For each day and county, we first compute the median value of snow cover across weather stations. We use the median to mitigate the effect of weather in high elevation geographic areas that we do not expect to have as much of an effect on corporate outcomes. We then calculate the average and 95th percentile of daily snow cover in each county-quarter between 2000 and 2015. Finally, we compute the time series average of snow cover in the first calendar quarter for each county-year using the previous 10 years worth of data.[9] We then define *Abnormal Snow* as the difference between the average daily snow cover in a given county-quarter minus the county's average daily snow cover in the same quarter during the previous ten years. *Abnormal Snow* 95 is defined similarly as the 95th percentile of daily snow cover in a county-quarter, which can be interpreted as the snow cover on the fourth most snow covered day during the quarter, minus the average 95th percentile of daily snow cover in the county during the ten previous years.

Panels A and B of Figure 1 present the distribution of these two measures of severe winter weather over our sample period. For the sake of presentation, all of these metrics are divided by 1,000. The figures show a large dispersion in abnormal weather during our sample period, and show that there are a significant number of observations with extreme weather outcomes. However, it is also notable that abnormal snow cover is close to zero in approximately 50% of firm-years. One reason for this concentration around zero is that some counties do not get a lot of snow during our sample period or in the previous ten years.

Both Panels A and B reveal that the distribution of abnormal snow cover exhibits positive skew. In addition, both measures of snow cover contain extreme events. In unreported tests we show that our results are not sensitive to trimming both measures at 2.5% and 97.5% percentiles (in Panel A that is -0.08 and 0.20, while in Panel B that is -0.17 and 0.34, respectively). Thus, it is not just the most severe winter weather events that drive our results.

[9]Results are robust to defining benchmark weather conditions using a fixed ten year period from 2001 through 2010.

3.2 Abnormal weather and cash flow

To investigate if severe winter weather affects corporate cash flow, we regress annual cash flow on the abnormal weather measure of interest, firm-specific control variables, and a set of industry, county, and year-quarter fixed effects. Therefore, we identify the effect of severe weather on cash flows using only within-county severe weather variation over time, while the year-quarter fixed effects control for macro-economic conditions affecting all firms. Equation 1 details this specification:

$$\begin{aligned} Cash\ Flow_{it} = &\alpha_0 + \alpha_1 Abnormal\ Snow_{jt} + \alpha_2 Fixed\ Assets_{it-1} + \\ &\alpha_3 Log(Assets)_{it-1} + \alpha_4 Leverage_{t-1} + \alpha_5 Sales_{t-1} + \\ &\alpha_6 Cash_{t-1} + \alpha_7 Debt_{t-1} + \alpha_8 WorkCap_{t-1} + \boldsymbol{\gamma X} + \varepsilon_{it}, \end{aligned} \tag{1}$$

where $Cash\ Flow_{it}$ denotes the cash flow realization of firm i in year t, and $Abnormal\ Snow_{jt}$ denotes the abnormal snow cover in Q1 for county j corresponding to the location of the headquarters of firm i at time t. We include the following control variables, which we more formally define in Appendix B: $Fixed\ Assets_{it-1}$, which is the total fixed assets for firm i at time $t-1$ scaled by firm total assets at time $t-1$; the natural log of the book value of total assets of firm i at time $t-1$ ($Log(Assets)_{it-1}$); $Leverage_{it-1}$ – total liabilities divided by total assets of firm i both as of time $t-1$; $Sales_{t-1}$ represents the net sales in time $t-1$ divided by total assets of firm i at time $t-1$; $Cash_{t-1}$ represents the balance of cash and marketable securities at time $t-1$ divided by total assets of firm i at time $t-1$; $Debt_{t-1}$ is defined as the total borrowing of firm i at time $t-1$ divided by total assets as of time $t-1$; $WorkCap_{t-1}$ is defined as the non-cash working capital of firm i at time $t-1$ divided by total assets as of time $t-1$. $\boldsymbol{X}$ is a vector of industry, county, and year-quarter fixed effects. Notably, all of these controls are measured as of the beginning of the period over which cash flow is measured.

Table 2 reports estimates of Equation 1 for our sample of firms. Columns 1 through 4 present associations between cash flow and our primary measures of severe winter weather, *Abnormal Snow* and *Abnormal Snow* 95. Comparing Column 1 with Column 2 and Column 3 with Column 4 indicates that the inclusion of control variables has little effect on the relation between severe winter weather and corporate cash flows. This evidence is consistent with our measure of weather capturing a cash flow shock that is exogenous to firm fundamentals.

Across all four columns there is a negative and statistically significant relation between abnormal snow cover and corporate cash flows. Focusing on Columns 2 and 4, which include the full set of control variables, *Abnormal Snow* and *Abnormal Snow* 95 have t-statistics of approximately -3.9 and -4.7, respectively. Given that the standard deviation of *Abnormal Snow* is 0.0765, the coefficient of -0.0236 in Column 2 suggests that a two standard deviation increase in average snow cover results in an annual cash flow decrease of approximately 0.36% of total assets. The magnitude of this cash flow shock is approximately 0.18 standard deviations of annual cash flow (or 2.27% of average cash flow), consistent with abnormally severe weather having an important impact on corporate cash flow.

Undoubtedly, there is significant heterogeneity in the effect of severe weather on cash flow. Small firms are more likely to be affected by our measure of abnormal weather than large firms because their operations are likely to be concentrated around the corporate headquarters, where abnormal weather is defined. For example, we find no consistent evidence that abnormally severe winter weather in the headquarter county of Compustat firms significantly affects annual cash flows. Thus, our sample, which is tilted towards small and middle-market private firms, within which over 75% of firms have total assets less than $100 million, is well suited for this analysis.

Although a negative relation between cash flows and severe winter weather can be rationalized across a wide range of industries, the magnitude of these severe weather effects will likely vary. To examine this, Table 3 presents separate estimates of Equation 1 for 15 different sectors. Of the fifteen sectors, four industries each comprise between 9% and 24%

of our sample, four comprise between 4% and 7% of our sample, and the remaining seven each comprise less than 2.31% of our sample. Of the eight sectors comprising more than 4% of our sample, all exhibit a negative relation between both of our measures of abnormal snow cover and cash flow. For each measure, the negative effect is statistically significant at the 10% level or better in three of these eight sectors. The effect is statistically significant in the transportation and manufacturing sectors using either measure and is significant using one of the two measures in the wholesale and construction industries. The magnitude of the effect is largest in the transportation industry, which is intuitive because transportation is directly affected by snow cover. It is somewhat surprising that the negative relation between abnormal snow and retail cash flows is not more statistically significant, given evidence in Tran (2016) showing that retail sales are adversely affected by rain.

Since we are primarily interested in the effect of abnormally severe weather as an exogenous shock to cash flow in the context of a 2SLS procedure, we leave additional discussion of the heterogeneous effect of weather on corporate cash flow to future research. What is important for the validity of our 2SLS procedure is that the F-statistics in the first stage are large enough to mitigate weak instrument concerns. The F-statistics in Columns 2 and 4 are approximately 15 and 22, respectively. This makes it unlikely that we encounter a weak instruments problem. For example, Table 2 in Stock and Yogo (2005) shows that potential bias of the IV estimate attributable to weak instruments could be at most 10% of the size of the IV coefficient whenever the first-stage F-statistic is 16 or higher. The two-stage procedure we employ in the following section will identify the effect of exogenous cash flow shocks on liquidity outcomes for a given firm-year only to the extent that severe winter weather meaningfully affects cash flow. Thus, our identification is likely to come primarily from small firms and industries with high sensitivities of cash flow to winter weather.

4 Managing Exogenous Cash Flow Shocks

The results in Section 3 show that abnormal weather leads to reduced cash flows. In this section, we investigate how this affects corporate outcomes. For empirical estimation, we use a 2SLS procedure, where the second stage regresses corporate outcomes on the fitted value of cash flows from the model reported in Column 2 or 4 of Table 2. Formally, we estimate the following system of equations using 2SLS:

$$\begin{aligned} Cash\ Flow_{it} = &\alpha_0 + \alpha_1 Abnormal\ Snow_{jt} + \alpha_2 Fixed\ Assets_{it-1} + \\ &\alpha_3 Log(Assets)_{it-1} + \alpha_4 Leverage_{t-1} + \alpha_5 Sales_{t-1} + \\ &\alpha_6 Cash_{t-1} + \alpha_7 Debt_{t-1} + \alpha_8 WorkCap_{t-1} + \boldsymbol{\gamma X} + \varepsilon_{it}, \end{aligned} \tag{2a}$$

$$\begin{aligned} Y_{it} = &\beta_0 + \beta_1 \widehat{Cash\ Flow}_{it} + \beta_2 Fixed\ Assets_{it-1} + \beta_3 Log(Assets)_{it-1} + \\ &\beta_4 Leverage_{t-1} + \beta_5 Sales_{t-1} + \beta_6 Cash_{t-1} + \\ &\beta_7 Debt_{t-1} + \beta_8 WorkCap_{t-1} + \boldsymbol{\delta X} + \epsilon_{it} \end{aligned} \tag{2b}$$

where $Cash\ Flow_{it}$, $Abn\ Weather\ Q1_{jt}$, $Fixed\ Assets_{it-1}$, $Log(Assets)_{it-1}$, $Leverage_{t-1}$, $Sales_{t-1}$, $Cash_{t-1}$, $Debt_{t-1}$; $WorkCap_{t-1}$ and $\boldsymbol{X}$ are defined as in Section 2. Y_{it} represents the second-stage outcome of interest, such as credit line drawdowns, change in credit line limit, change in cash, or real investment.

4.1 Liquidity Management

Despite extensive literature investigating corporate cash reserves and credit lines, there is little direct evidence on how firms use credit lines to deal with unanticipated liquidity shocks. The evidence on credit line use that does exist is mixed and comes primarily from surveys or studies of large firms. Lins, Servaes, and Tufano (2010) provide survey evidence that firms typically rely on cash buffers to manage liquidity shocks, while short-term debt in the form of credit lines is used primarily to pursue investment opportunities. However, managers surveyed in Campello et al. (2011) and Campello et al. (2012) indicated that credit lines were an important source of liquidity during the financial crisis. A goal of this paper is to provide broad-based, direct evidence on how firms manage random fluctuations in cash flow. Notably, our analysis occurs outside of the crisis period and centers on small U.S. firms with access to bank lenders.

In Table 4 we investigate the extent to which firms use credit lines to manage exogenous cash flow shocks. Column 1 of Table 4 presents an OLS regression in which the dependent variable is the year over year change in drawn credit line amount scaled by the beginning of period total assets. The explanatory variable of interest is cash flow. The OLS analysis in column 1 reveals a negative and significant relation between cash flow and credit line drawdowns, but the point estimate is small (-0.005). It is difficult to pinpoint the driving forces behind this estimate given the correlation between cash flows and omitted variables, such as investment opportunities (e.g., Riddick and Whited (2009)) and the availability of credit (e.g.,Sufi (2009)).

In Columns 2 and 3 of Table 4 we present the IV results, which isolate the effect of exogenous cash flow fluctuations on changes in credit line draws. Column 2 uses *Abnormal Snow*, which is the average daily abnormal snow cover in the first calendar quarter, to instrument for annual cash flow, while Column 3 uses *Abnormal Snow* 95 – the snow cover during the 95th percentile of daily snow cover during the first quarter. The coefficients in Columns 2 and 3 of Table 4 are negative, statistically significant, and range from -0.41 to -0.61, suggesting that firms with access to bank debt cover the majority of a weather related cash flow shock with credit line draws.

These findings highlight the value of our two-stage procedure. By focusing on exogenous shocks to cash flow, we identify the effect of cash flow changes on credit line drawdowns in a manner that is not confounded by the high correlations between cash flows and other factors, such as unobserved investment opportunities (e.g., Riddick and Whited (2009)). Our results suggest that these correlations between cash flow and other factors are sufficiently strong to camouflage the extent to which credit lines are used to buffer unanticipated shocks to cash flow.

In unreported results, we conduct two additional tests that offer circumstantial support for our identifying assumption that abnormally severe winter weather affects firm outcomes only through its effect on corporate cash flows. First, we replicate our analyses using trimmed weather IVs, which drop the most extreme 2.5% of abnormal snow outcomes. We obtain very similar coefficient estimates of -0.3657 and -0.8162, which mitigates any concern that the most severe weather events, which may impact investment opportunities, drive our findings. Second, we replicate our findings excluding firm-level controls (i.e., using Columns 1 and 3 of Table 2 as the first-stage regression). As would be expected if abnormally severe winter weather represents a shock to corporate cash flows that is unrelated to firm characteristics, we find qualitatively similar second-stage estimates for the effect of cash flows on credit line use.

Next, we investigate how firms use alternative sources of liquidity such as cash balances and non-cash working capital to manage cash flow shocks. The OLS estimate in Column 1 of Table 5 reveals a small but significantly positive association between cash flow and changes in cash. These results are consistent with a large literature on the cash flow sensitivity of cash, such as Almeida, Campello, and Weisbach (2004) and Khurana, Martin, and Pereira (2006), and suggest that firms draw on cash balances when cash flow declines. As with the OLS estimates in Table 4, however, it is difficult to draw causal inferences from this positive relation regarding the use of cash as a buffer for cash flow shocks.

In Columns 2 and 3, we estimate the two stage regressions with changes in cash as the dependent variable. The coefficient on cash flow increases to 0.17 in Column 2 and 0.16 in Column 3, but the standard error also increases substantially and the point estimate is no longer statistically significant. Columns 4 through 6 yield similar estimates using non-cash working capital as the dependent variable (point estimates of 0.16 and 0.24, respectively).[10]

Overall, the point estimates in Tables 4 and 5 suggest that for every dollar an exogenous cash flow shock costs a firm, approximately 41 to 61 cents are reflected in increased credit line drawn amount, and approximately 20 cents each are reflected in reduced cash and non-cash working capital balances. Thus, credit lines are the primary way that firms with bank lending relationships manage exogenous cash flow shocks.

4.2 Credit Line Size Adjustments

Next, we investigate whether cash flow shocks cause firms to adjust their credit line size. Credit lines of public firms are frequently renegotiated – Roberts and Sufi (2009) and Roberts (2015) find that the average bank loan in their sample is renegotiated once every 6-9 months, and that most renegotiations are not due to impending covenant violations. Within our sample, credit line sizes are adjusted in almost half of firm-years. This raises the possibility that banks work with firms to adjust available credit in response to exogenous cash flow shocks.

Interestingly, the OLS evidence in Column 1 of Table 6 indicates the opposite relation. When cash flow is high, credit line size expands. This is consistent with profitable firms having greater demand for, or access to, bank credit. This is also consistent with Sufi (2009), who finds that the availability of credit lines can be dependent on maintaining high levels of cash flow as lenders may reduce credit line availability following cash flow shortfalls by using financial covenants to force loan renegotiation (also see Smith (1993) and Smith and Warner (1979)).

Although this may be the predominant relation in the data, we expect the opposite response if banks work with firms to manage exogenous liquidity shocks. Columns 2 and 3 examine this question using IV regressions with the change in credit line size (as a percentage

[10] Once again, using the trimmed weather IVs provides similar evidence on firm use of cash and non-cash working capital to respond to exogenous cash flow shocks (coefficients of 0.067 and 0.029 for cash, and 0.07 and 0.189 for non-cash working capital).

of beginning of period total assets) as the second stage dependent variable. In Columns 4 through 6 we replicate the OLS and IV specifications using an indicator equal to one if the firm experiences a credit line increase over the previous year as the dependent variable.

Columns 2 and 3 indicate that there is a negative relation between exogenous cash flow shocks and credit line size. These results are consistent with banks accommodating random cash flow fluctuations with credit line adjustments. The coefficient of -0.74 in Column 2 and -1.13 in Column 3 indicate that in our sample of firms – all of which have established bank lending relationships – a one dollar reduction in cash flow due to the weather shock is associated with approximately a one dollar increase in credit line size. The coefficients of -3.31 and -3.92 in Columns 5 and 6 indicate that increasing cash flows by 1% of total assets increases (decreases) the probability of a credit line increase (decrease) by between 3 and 4%. Again, these effects are similar when using the trimmed weather variables as IVs.

We posit that the reason firms seek this additional credit is to maintain sufficient liquidity as they draw down their existing credit line. Consistent with this, we cannot reject the null hypothesis that the increased credit line drawdown (in Table 4) is the same size as the credit line size increase. It is also possible that a portion of the credit line size increase we observe is due to firms adjusting their beliefs regarding the probability of future cash flow shocks. Such behavior would be consistent with evidence in Dessaint and Matray (2017) who find that managers temporarily overestimate hurricane risk when there have been recent hurricanes in nearby areas. In either case, our findings provide new evidence on how firms work with banks to adjust their available credit in response to cash flow shocks.

Overall, the results in Tables 4 and 6 indicate that bank-borrowing firms rely on their credit lines as an important source of liquidity. Not only do firms use existing credit when faced with exogenous cash flow shocks, but they are also able to work with their lender to expand available credit.

4.3 Investment and Cash Flow

An important question is whether the credit line adjustments documented in the previous section are sufficient to prevent cash flow shocks from affecting other corporate outcomes. To address this question, we use our 2SLS framework to investigate how exogenous cash flow shocks relate to changes in fixed assets, total assets, and (in unreported tests with a smaller sample) net capital expenditures.

We present evidence on the relation between cash flow and the change in fixed assets in the first three columns of Table 7. In the first column, the OLS estimates show a positive and significant association between cash flow and investment in fixed assets. In the second and third columns, we report IV estimates, using two measures of abnormal snow cover to instrument for cash flow. In both cases, the coefficient on cash flow is negative, small, and statistically insignificant. This result is interesting because it suggests that small firms with access to credit lines are able to buffer investment from exogenous cash flow shocks. This finding also underscores how misleading OLS estimates of the investment-cash flow sensitivity can be, particularly when, as in this case, controls for investment opportunities are imperfect (e.g., Erickson and Whited (2000); Alti (2004); Moyen (2004); Almeida and Campello (2007)).

In Columns 4 through 6 of Table 7, we investigate whether exogenous cash flow shocks affect asset growth. Although there is a positive OLS relation between cash flows and asset growth, this effect becomes statistically insignificant using our two-stage procedure. Comparing the magnitude of the 2SLS estimate to the cash and working capital estimates in Table 5, reveals that any change in assets that does exist appears to be attributable to changes in cash and working capital. Analyses using net CAPEX are qualitatively similar to those we report in Columns 1 through 3 (using the change in fixed assets as the second stage dependent variable). However, these results should be interpreted with caution since net CAPEX is not always reported in our sample. Overall, the evidence in this section suggests that the average bank-borrowing firm manages exogenous cash flow shocks primarily via credit line adjustments. The effect of these cash flow shocks does not spill over into other corporate activities.

5 Reduced Form Analyses

In our final set of analyses, we more directly investigate the effect of abnormally severe winter weather on corporate outcomes. We continue to maintain our identifying assumption used in the 2SLS approach, which is that severe winter weather only affects corporate outcomes through its effect on corporate cash flow. If this instrument is indeed an important determinant of random variation in cash flow, then abnormally severe winter weather should directly predict corporate outcomes when plugged into the second stage regressions.

5.1 Direct Effect of Winter Weather

A benefit to this analysis is that it allows us to directly examine the economic magnitude of the effect of severe winter weather on corporate activity. The results in the previous section suggest that severe winter weather will be positively related to credit line use and size, but not other corporate outcomes. The evidence in Table 8 supports this prediction. Panels A and B show that both measures of abnormal snow are positively and significantly related to changes in credit line drawn amount and credit line size, but not other corporate outcomes. The magnitude of the effect of severe weather on credit line use is economically meaningful. Given that the standard deviation of *Abnormal Snow* is 0.0765, the coefficient of 0.0098 in Column 1 of Table 8 Panel A suggests that a two standard deviation increase in abnormal snow results in the average firm drawing 0.15% of assets more on their credit line over the course of the year. The coefficient in Column 2 suggests that severe winter weather has almost double that effect on the change in credit line size. Consistent with our earlier findings, weather has no statistically or economically significant effect on cash balances, fixed assets, or total assets.

5.2 Quarterly Credit Line Adjustments

This reduced form analysis also allows us to examine the relation between severe first quarter weather and credit line activity on a quarterly basis. We cannot conduct such an analysis using cash flows or any of our other dependent variables because we only observe financial data at an annual frequency. In Panel A of Figure 2 we decompose the annual effect of *Abnormal Snow* 95 on the change in credit line drawn amount, estimated in Column 1 of Table 8 Panel B, into its quarterly components. Specifically, each point on the solid line in the figure represents the estimated effect of abnormal first quarter snow cover on credit line draw downs during the calendar quarter indicated on the x-axis. The dashed lines represent the 95% confidence interval for these estimates. Panel A of Figure 2 indicates that the effect of abnormal first quarter snow on credit line use is concentrated in the second calendar quarter, meaning that firms respond to bad weather between January 1 and March 31 by drawing on their credit line at some point between April 1 and June 30th. Panel B of Figure 2 shows that, similar to the credit line drawdowns, the credit line size increases that occur in response to severe winter weather happen during the second calendar quarter. Interestingly, during the first quarter we find that line size decreases in response to severe winter weather.

Taken together, the evidence in Figure 2 is consistent with banks providing liquidity to firms experiencing exogenous cash flow shocks, but not immediately. It is possible that firms manage exogenous cash flow shocks by tapping cash or working capital reserves in the very short-run. One reason for this might be that firms only meet with their banks sporadically, however this is unlikely to be the entire story because it does not explain the credit line size reduction in the first quarter or the delay with which firms draw on their credit line.

Our findings seem more consistent with banks being cautious about extending additional credit to firms whose cash flows have declined, preferring to take "a wait and see" approach. This explanation is consistent with Sufi (2009) and Acharya et al. (2014) who argue that bank financing may not be available to firms experiencing low cash flows or negative profitability shocks. However, our results suggest that the hesitance of banks to offer financing in these situations is (on average) short-lived when the cash flow shock is exogenous to firm fundamentals, making credit lines an important way that firms manage their liquidity in response to exogenous cash flow shocks.

5.3 Partitioning on Borrower Financial Health

In our final set of tests we delve deeper into the possibility that bank liquidity may not be available for some firms when they need it. For example, Diamond (1991) shows theoretically that low- and medium-credit risk borrowers can rely on bank financing, while high credit risk borrowers may not be able to obtain bank financing when needed. We therefore partition the sample based on the credit quality of the borrower as of the year-end immediately prior to the weather shock, quarter 4 of year $t-1$. Our measure of credit quality is the borrower's internal risk rating assigned by the lender converted to a ten-grade S&P ratings scale.[11]

In Table 9 we partition the sample into two groups – BB and better and B and below. Approximately 94% of the sample is contained within the B, BB, and BBB rating categories. Specifically, the breakdown of the sample in terms of credit quality is as follows – B-rated (14.54%), BB-rated (52.75%), BBB-rated (26.50%), below B (3.31%), above BBB (2.90%). Panel A shows that cash flow is adversely impacted by weather in both subsamples (compare columns 1 and 2 to columns 3 and 4) and that these adverse effects are somewhat stronger in the poor-credit quality subsample. Columns 1 through 4 of Panel B show that more severe abnormal weather is associated with larger annual increases in credit line draw and credit line size for the borrowers with ratings of BB and better, while columns 5 through 8 indicate the lack of an association between adverse weather and credit line use.

The absolute value of the coefficients in the first two columns of both Panels A and B are all approximately 0.01. This suggests that a given increase in adverse weather leads to a decrease in cash flows and an increase credit line draws that are of similar magnitude. Thus,

[11] Each bank is required to provide its internal risk rating together with a concordance mapping to a 10-grade S&P scale ranging from AAA to D. These internal ratings are available for almost all borrowers in our sample – 96,251 borrower-years out of a total of 97,619 borrower-years. To the extent that a borrower has financing from multiple banks we use the most conservative among these ratings.

medium- and high-credit quality firms appear to buffer cash flow shocks entirely with credit line draw downs. In contrast, low-credit quality firms do not draw on their lines of credit in response to more severe winter weather, even though such weather shocks significantly affect cash flows. These results illustrate that only medium- and high-credit quality firms can rely on their credit lines to buffer adverse transitory cash flow shocks. In unreported tests, we find no significant relation between severe winter weather and either cash reserves or working capital within either subsample. Rather, the inability of low credit quality firms to buffer cash flow shocks appears to result in reductions in total assets (with t-statistics ranging between -1.4 and -1.6).

6 Concluding Remarks

This study uses a unique dataset on bank lending portfolios to study how firms manage liquidity in the face of exogenous cash flow shocks. Starting in 2012, the Federal Reserve has collected comprehensive data on bank lending activities as part of the Dodd-Frank Stress Tests and Comprehensive Capital Analysis and Review. The resulting data (the Federal Reserve Y-14 collection) contains a rich set of information on bank lending terms and borrower financial information. Notably, the FR Y-14 collection has broad coverage of lending and financial activity of the small private firms that rely extensively on external credit, but typically do not appear in publicly available databases.

We show that these firms rely extensively on credit lines as a source of finance. To identify the causal connection between cash flow shocks and corporate liquidity management, we construct an instrument for cash flow based on abnormal adverse weather conditions in the county in which the company is located. Using this instrument to predict firm-level cash flows, we find that firms manage negative cash flow shocks by drawing on their credit lines rather than tapping their cash reserves or adjusting their real activities. In addition, negative cash flow shocks are accompanied by significant increases in the size of the firm's overall credit line, indicating that banks accommodate borrowers confronted with unexpected cash flow shortfalls. Taken together, these results show that, for firms with lending relationships, credit lines are the primary means of corporate liquidity management.

References

Acharya, Viral, Heitor Almeida, and Murillo Campello. 2013. "Aggregate risk and the choice between cash and lines of credit." *Journal of Finance* 68:2059–2116.

Acharya, Viral, Heitor Almeida, Filippo Ippolito, and Ander Perez. 2014. "Credit lines as monitored liquidity insurance: Theory and evidence." *Journal of Financial Economics* 112 (3):287–319.

Almeida, Heitor and Murillo Campello. 2007. "Financial constraints, asset tangibility, and corporate investment." *Review of Financial Studies* 20 (5):1429–1460.

Almeida, Heitor, Murillo Campello, Igor Cunha, and Michael Weisbach. 2014. "Corporate Liquidity Management: A Conceptual Framework and Survey." *Annual Review of Financial Economics* 6:135–162.

Almeida, Heitor, Murillo Campello, and Michael Weisbach. 2004. "The Cash Flow Sensitivity of Cash." *Journal of Finance* 59 (4):1777–1804.

Alti, Aydogan. 2004. "How sensitive is investment to cash flow when financing is frictionless?" *Journal of Finance* 58 (2):707–722.

Bates, Thomas W., Kathleen M. Kahle, and Renee M. Stulz. 2009. "Why Do U.S. Firms Hold So Much More Cash than They Used To?" *Journal of Finance* 64 (5):1985–2021.

Berospide, Jose and Ralf Meisenzahl. 2016. "The Real Effects of Credit Line Drawdowns." Working Paper.

Bidder, Rhys M., John R. Krainer, and Adam H. Shapiro. 2016. "Drilling into Bank Balance Sheets: Examining Portfolio Responses to an Oil Shock." Working Paper.

Bloesch, Justin and Francois Gourio. 2015. "The effect of winter weather on U.S. economic activity." *Economic Perspectives, FRB Chicago.*

Campello, Murillo, Erasmo Giambona, John Graham, and Campbell Harvey. 2011. "Liquidity management and corporate investment during a financial crisis." *Review of Financial Studies* 24:19441979.

———. 2012. "Access to Liquidity and Corporate Investment in Europe during the Financial Crisis." *Review of Finance* 16 (2):323–346.

Chang, Xin, Sudipto Dasgupta, George Wong, and Jiaquan Yao. 2014. "Cash-flow sensitivities and the allocation of internal cash flow." *Review of Financial Studies* 27 (12):3628–3657.

Chen, Yangyang, Po-Hsuan Hsu, Edward J. Podolski, and Madhu Veeraraghavan. 2017. "In the Mood for Creativity: Weather-Induced Mood, Inventor Productivity, and Firm Value." Working Paper.

Colvin, R and A Loten. 2014. "Small-Business' Sales Decline Amid Winter Weather." *Wall Street Journal*, February 19th.

Cortes, Kristle Romero. 2014. "Rebuilding after disaster strikes: How local lenders aid in the recovery." FRB of Cleveland Working Paper No. 14-28.

Cortes, Kristle Romero and Philip E. Strahan. 2016. "Tracing out capital flows: How financially integrated banks respond to natural disasters." *Journal of Financial Economics* forthcoming.

Demiroglu, Cem and Christopher James. 2011. "The use of bank lines of credit in corporate liquidity management: A review of empirical evidence." *Journal of Banking and Finance* 35 (4):775–782.

Demiroglu, Cem, Christopher James, and Atay Kizilaslan. 2012. "Bank lending standards and access to lines of credit." *Journal of Money, Credit and Banking* 44 (6):1063–1089.

Denis, David and Valeriy Sibilkov. 2010. "Financial constraints, investment, and the value of cash holdings." *Review of Financial Studies* 23 (1):247–269.

Dessaint, Olivier and Adrien Matray. 2017. "Do managers overreact to salient risks? Evidence from hurricane strikes." Journal of Financial Economics, Forthcoming.

Diamond, Douglas. 1991. "Monitoring and Reputation: The choice between bank loans and directly placed debt." *Journal of Political Economy* 99 (4):689–721.

Erickson, Timothy and Toni Whited. 2000. "Measurement error and the relationship between investment and q." *Journal of political economy* 108 (5):1027–1057.

Gatev, Evan and Phillip Strahan. 2006. "Banks' Advantage in Hedging Liquidity Risk: Theory and Evidence from the Commercial Paper Market." *Journal of Finance* 61 (2):867–892.

Giroud, Xavier, Holger M. Mueller, Alex Stomper, and Arne Westerkamp. 2012. "Snow and Leverage." *Review of Financial Studies* 25 (3):680–710.

Holmstrom, Bengt and Jean Tirole. 1998. "Private and Public Supply of Liquidity." *Journal of Political Economy* 106 (1):1–40.

Ivanov, Ivan and Luke Pettit. 2017. "Credit Line Dynamics during the Great Recession." Working Paper.

Ivashina, Victoria and David Scharfstein. 2010. "Bank lending during the financial crisis of 2008." *Journal of Financial Economics* 97 (3):319–338.

James, Christopher and Peggy Wier. 1990. "Borrowing relationships, intermediation, and the cost of issuing public securities." *Journal of Financial Economics* 28 (1-2):149–171.

Jimenez, Gabriel, Jose Lopez, and Jesus Saurina. 2009. "Empirical Analysis of Corporate Credit Lines." *The Review of Financial Studies* 22 (12):5069–5098.

Kashyap, Anil, Raghuram Rajan, and Jeremy Stein. 2002. "Banks as Liquidity Providers: An Explanation for the Co-Existence of Lending and Deposit-Taking." *Journal of Finance* 57 (1):33–37.

Khurana, Inder K., Xiumin Martin, and Raynolde Pereira. 2006. "Financial Development and the Cash Flow Sensitivity of Cash." *Journal of Financial and Quantitative Analysis* 41 (4):787–807.

Lins, Karl, Henry Servaes, and Peter Tufano. 2010. "What drives corporate liquidity? An international survey of cash holdings and lines of credit." *Journal of Financial Economics* 98 (1):160–176.

Moyen, Nathalie. 2004. "Investmentcash flow sensitivities: Constrained versus unconstrained firms." *Journal of Finance* 59 (5):2061–2092.

Petersen, Mitchell A. and Raghuram G. Rajan. 1994. "The Benefits of Lending Relationships: Evidence from Small Business Data." *Journal of Finance* 49 (1):3–37.

Poterba, James M. 1988. "Comment on 'Financing constraints and corporate investment'." *Brookings Papers on Economic Activity* 1988 (1):200–204.

Riddick, Leigh and Toni Whited. 2009. "The corporate propensity to save." *Journal of Finance* 64 (4):1729–1766.

Robb, Alicia and David T. Robinson. 2014. "The capital structure decisions of new firms." *Review of Financial Studies* 27 (1):153–179.

Roberts, Michael R. 2015. "The role of dynamic renegotiation and asymmetric information in financial contracting." *Journal of Financial Economics* 116 (1):61–81.

Roberts, Michael R. and Amir Sufi. 2009. “Renegotiation of nancial contracts: Evidence from private credit agreements.” *Journal of Financial Economics* 93 (2):159–184.

Shockley, Richard and Anjan Thakor. 1997. “Bank Loan Commitment Contracts: Data, Theory and Tests.” *Journal of Money, Credit and Banking* 29 (4):517–534.

Smith, Jr., Clifford W. 1993. “A Perspective on Accounting-Based Debt Covenant Violations.” *The Accounting Review* 68 (2):289–303.

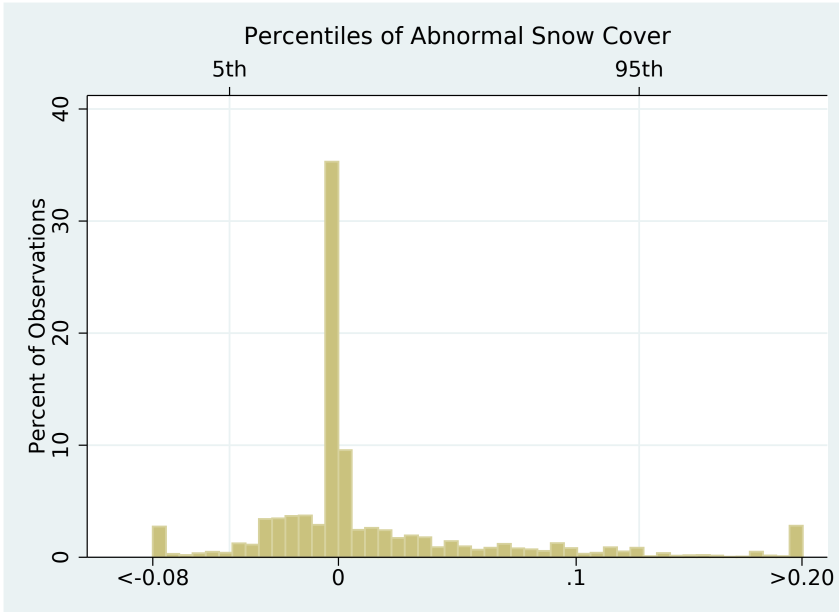
Smith, Jr., Clifford W. and Jerold B. Warner. 1979. “On Financial Contracting.” *Journal of Financial Economics* 7 (1):117–161.

Stock, James and Motohiro Yogo. 2005. “Testing for Weak Instruments in Linear IV Regressions.” *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg.*

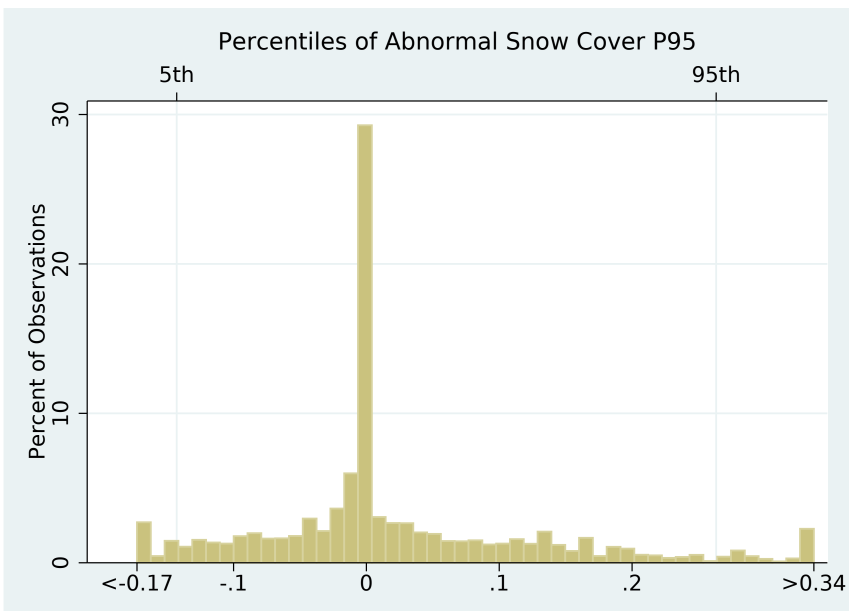
Sufi, Amir. 2009. “Bank lines of credit in corporate finance: An empirical analysis.” *Review of Financial Studies* 22 (3):1057–1088.

Tran, Brigitte Roth. 2016. “Blame it on the Rain Weather Shocks and Retail Sales.” Working Paper.

Yun, Hayong. 2009. “The choice of corporate liquidity and corporate governance.” *Review of Financial Studies* 22 (4):1447–1475.

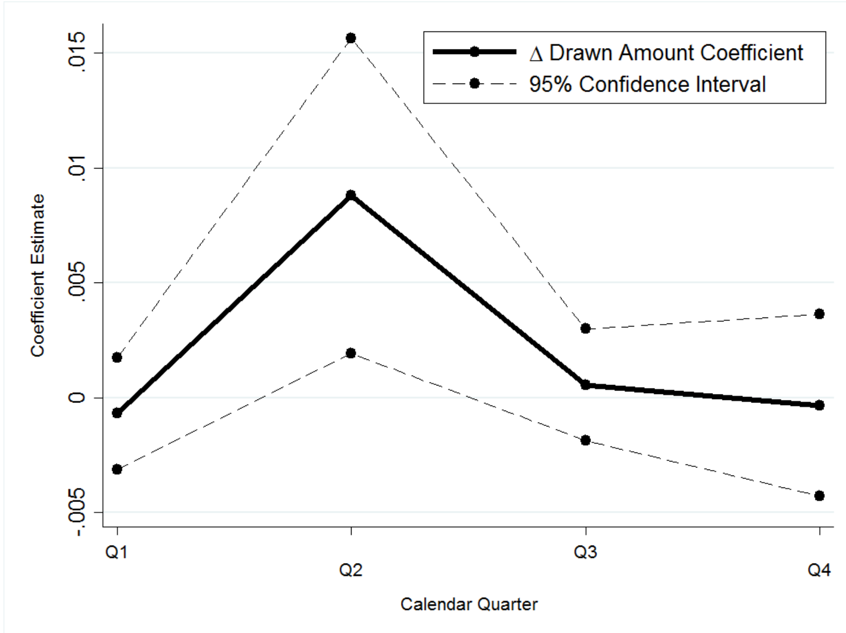


(a) *Abormal Snow Cover*

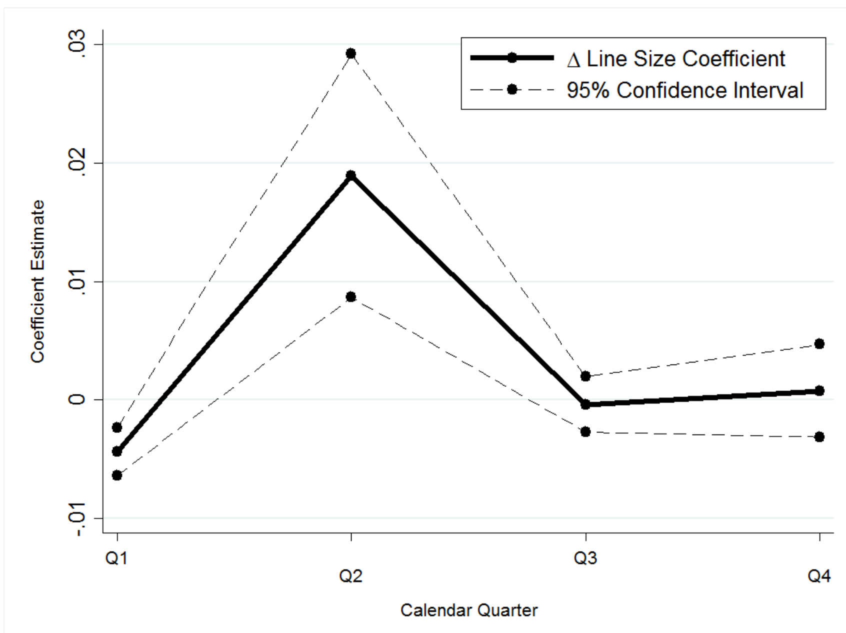


(b) *Abnormal Snow Cover P95*

Figure 1: Distribution of Abnormal Snow Cover. This figure presents the distribution of abnormal snow cover during the first calendar quarter for the 97,619 firm-years in our sample. The distribution in Panel A is constructed based on the average daily snow cover during the first calendar quarter, while Panel B uses the 95th percentile of snow cover during the first calendar quarter. Abnormal snow cover is defined relative to the the time-series average of first calendar quarter snow cover in each county over the previous 10 years.



(a) $\Delta Draw$



(b) $\Delta Line\ Size$

Figure 2: Credit Line Dynamics Following the Weather Shock This figure decomposes the annual effect of abnormal snow on change in credit line drawn amount (Panel A) or credit line size (Panel B), estimated in Columns 1 and 4 of Table 8 Panel B, into its quarterly components. Specifically, each point on the solid line in the figure represents the estimated effect of abnormal first quarter snow cover on quarterly change in credit line drawn amounts or credit line size during the calendar quarter indicated on the x-axis (for example, Q1 represents the change in credit line drawn amount or line size between the end of Q4 of the previous year and the end of Q1 of the current year). The dashed lines represent the 95% confidence interval for these estimates.

Table 1: Descriptive Statistics. This table presents descriptive statistics for our sample of 97,619 observations with available borrower and loan characteristics. Columns 1 and 2 present the mean and standard deviation, while Columns 3 through 5 present the 25th, 50th, and 75th percentiles, respectively. All explanatory variables are defined in Appendix B.

	Mean	*SD*	*P25*	*P50*	*P75*
Total Assets ($ Millions)	726.9890	3668.5250	8.4290	22.0430	90.6961
Cash Flow	0.1584	0.2011	0.0635	0.1177	0.1987
Leverage	0.6004	0.2042	0.4609	0.6209	0.7572
Fixed Assets	0.2933	0.2668	0.0680	0.2109	0.4562
Sales	2.2846	1.8593	1.0880	1.9588	3.0008
Cash	0.0975	0.1234	0.0124	0.0501	0.1348
Debt	0.3168	0.2337	0.1230	0.2908	0.4746
WorkCap	0.1015	0.2022	−0.0288	0.0787	0.2236
Line Size	0.2419	0.1913	0.0892	0.1974	0.3517
Draw	0.0866	0.1539	0.0000	0.0000	0.1163
Δ*Line Size*	0.0267	0.1064	0.0000	0.0000	0.0101
Δ*Draw*	0.0153	0.0803	0.0000	0.0000	0.0101
Δ*Cash*	0.0084	0.0701	−0.0136	0.0006	0.0249
Δ*WorkCap*	0.0075	0.0915	−0.0292	0.0045	0.0450
Δ*Liabilities*	0.0422	0.1600	−0.0437	0.0119	0.0978
Δ*Debt*	0.0214	0.1243	−0.0357	0.0000	0.0576
Δ*Assets*	0.0752	0.1895	−0.0267	0.0433	0.1400
Δ*Fixed Assets*	0.0188	0.0894	−0.0111	0.0008	0.0258

Table 2: Cash Flow and Abnormal Weather. This table contains estimated coefficients from an OLS regression of $Cash\ Flow_{it}$ on *Abnormal Snow* (columns 1 and 2) and *Abnormal Snow P*95 (columns 3 and 4). We include a number of control variables (defined in Appendix B), as well as three-digit NAICS 2012 industry indicators, county, and year-quarter fixed effects. The standard errors are clustered at the three-digit NAICS 2012 industry level.

	$Cash\ Flow_{it}$			
	(1)	(2)	(3)	(4)
Abnormal Snow	−0.0217***	−0.0236***		
	(0.00593)	(0.00603)		
*Abnormal Snow P*95			−0.0139***	−0.0148***
			(0.00355)	(0.00317)
$Log(Assets_{it-1})$		−0.00484***		−0.00484***
		(0.00182)		(0.00182)
$Fixed\ Assets_{it-1}$		0.0930***		0.0930***
		(0.0200)		(0.0200)
$Leverage_{it-1}$		−0.0521		−0.0521
		(0.0324)		(0.0324)
$Sales_{it-1}$		0.0250***		0.0250***
		(0.00853)		(0.00853)
$Cash_{it-1}$		0.240***		0.240***
		(0.0570)		(0.0570)
$Debt_{it-1}$		−0.0111		−0.0111
		(0.0361)		(0.0361)
$WorkCap_{it-1}$		0.0373***		0.0373***
		(0.0132)		(0.0132)
Industry Fixed Effects	YES	YES	YES	YES
County Fixed Effects	YES	YES	YES	YES
Year-Quarter Fixed Effects	YES	YES	YES	YES
Adjusted R-Squared	0.0183	0.152	0.0183	0.152
Observations	97,619	97,619	97,619	97,619

Standard errors in parentheses

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 3: Cash Flow and Abnormal Weather: Industry Partitions This table contains estimated coefficients from an OLS regression of $Cash\ Flow_{it}$ on *Abnormal Snow* in a model with identical controls to that in Specifications (2) and (4) of Table 2. Each row in the table restricts the sample to one of fifteen sectors, which are indicated in Column 1. Columns 2 and 3 present the estimates (and standard errors below in parentheses) for the coefficients on *Abnormal Snow* and *Abnormal Snow* $P95$, respectively. We include a number of control variables (defined in Appendix B), as well as three-digit NAICS 2012 industry indicators, county, and year-quarter fixed effects. The standard errors are clustered at the three-digit NAICS 2012 industry level.

	$IV1\ Coeff$ (SE)	$IV2\ Coeff$ (SE)	*Percent Obs*	*Obs*
MANUFACTURING	−0.0267*	−0.0189**	24.16%	23,583
	(0.0148)	(0.00756)		
WHOLESALE	−0.0206	−0.0128**	17.14%	16,729
	(0.0126)	(0.00628)		
RETAIL	−0.00251	−0.00494	14.16%	13,823
	(0.0126)	(0.00732)		
BUSINESS SERVICES	−0.0591	−0.0300	9.32%	9,098
	(0.0441)	(0.0274)		
CONSTRUCTION	−0.0498*	−0.0134	7.12%	6,947
	(0.0264)	(0.0121)		
REAL ESTATE	−0.0291	−0.0103	7.43%	7,252
	(0.0227)	(0.0113)		
EDUCATION & HEALTH	−0.0166	−0.0149	4.44%	4,335
	(0.0815)	(0.0382)		
TRANSPORTATION	−0.0554**	−0.0257**	4.43%	4,325
	(0.0264)	(0.0130)		
ACCOMODATION & FOOD	−0.0464	−0.0117	2.31%	2,253
	(0.0693)	(0.0412)		
AGRICULTURE	−0.0234	−0.0242	1.94%	1,898
	(0.0371)	(0.0219)		
INFORMATION	0.0694	0.0108	1.92%	1,870
	(0.0835)	(0.0436)		
MINING & EXTRACTION	0.0655	0.0560	1.86%	1,819
	(0.0764)	(0.0367)		
LEISURE	−0.0957	−0.0630	1.46%	1,429
	(0.0780)	(0.0427)		
UTILITIES	−0.0193	−0.0182	1.34%	1,314
	(0.0288)	(0.0163)		
OTHER	0.113*	0.0578	0.97%	944
	(0.0630)	(0.0376)		

Standard errors in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4: Credit Line Use and Cash Flow Column 1 present OLS estimates from regressions of $\Delta Draw_{it}$ on $Cash\ Flow_{it}$ and controls. Columns 2 and 3 present 2SLS estimates of IV regressions of $\Delta Draw_{it}$ on instrumented $Cash\ Flow_{it}$ and controls using *Abnormal Snow* and *Abnormal Snow P*95 as IVs, respectively. IV1 and IV2 correspond to *Abnormal Snow* and *Abnormal Snow P*95, respectively. We include a number of control variables (defined in Appendix B), as well as three-digit NAICS 2012 industry indicators, county, and year-quarter fixed effects. The standard errors are clustered at the three-digit NAICS 2012 industry level.

	$\Delta Draw_{it}$		
	OLS	$IV1$	$IV2$
	(1)	(2)	(3)
$Cash\ Flow_{it}$	−0.0049***	−0.4140**	−0.6050***
	(0.0012)	(0.1821)	(0.2143)
$Log(Assets)_{it-1}$	−0.0019***	−0.0039***	−0.0048***
	(0.0004)	(0.0014)	(0.0018)
$Fixed\ Assets_{it-1}$	−0.0131***	0.0250	0.0427**
	(0.0033)	(0.0165)	(0.0190)
$Leverage_{it-1}$	0.0027	−0.0186	−0.0286
	(0.0027)	(0.0140)	(0.0216)
$Sales_{it-1}$	0.0014***	0.0117**	0.0165***
	(0.0005)	(0.0047)	(0.0061)
$Cash_{it-1}$	−0.0281***	0.0701	0.1160*
	(0.0056)	(0.0460)	(0.0600)
$Debt_{it-1}$	0.0096***	0.0050	0.0028
	(0.0034)	(0.0126)	(0.0189)
$WorkCap_{it-1}$	−0.0009	0.0144	0.0215**
	(0.0023)	(0.0090)	(0.0107)
Industry FE	YES	YES	YES
County FE	YES	YES	YES
Year-Quarter FE	YES	YES	YES
Adjusted R-Squared	0.0641	.	.
Observations	97,619	97,619	97,619

Standard errors in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5: Other Liquidity Management and Cash Flow Columns 1 and 4 present OLS estimates from regressions of $\Delta Cash_{it}$ and $\Delta WorkCap_{it}$ on $Cash\ Flow_{it}$ and controls. Columns 2 and 3 present 2SLS estimates of IV regressions of $\Delta Cash_{it}$ on instrumented $Cash\ Flow_{it}$ and controls, while Columns 5 and 6 present 2SLS estimates of IV regressions of $\Delta WorkCap_{it}$ on instrumented $Cash\ Flow_{it}$ and controls. IV1 and IV2 correspond to *Abnormal Snow* and *Abnormal Snow P*95, respectively. We include a number of control variables (defined in Appendix B), as well as three-digit NAICS 2012 industry indicators, county, and year-quarter fixed effects. The standard errors are clustered at the three-digit NAICS 2012 industry level.

	$\Delta Cash_{it}$			$\Delta WorkCap_{it}$		
	OLS (1)	*IV1* (2)	*IV2* (3)	*OLS* (4)	*IV1* (5)	*IV2* (6)
$Cash\ Flow_{it}$	0.0543***	0.1748	0.1583	0.0488***	0.1591	0.2392
	(0.0073)	(0.1268)	(0.1119)	(0.0095)	(0.2610)	(0.2482)
$Log(Assets)_{it-1}$	−0.0008***	−0.0002	−0.0003	−0.0014***	−0.0009	−0.0005
	(0.0002)	(0.0007)	(0.0007)	(0.0003)	(0.0014)	(0.0014)
$Fixed\ Assets_{it-1}$	−0.0030	−0.0142	−0.0126	−0.0221***	−0.0323	−0.0398*
	(0.0027)	(0.0120)	(0.0104)	(0.0019)	(0.0232)	(0.0218)
$Leverage_{it-1}$	−0.0106**	−0.0043	−0.0052	0.0174***	0.0232	0.0273
	(0.0046)	(0.0089)	(0.0079)	(0.0031)	(0.0160)	(0.0173)
$Sales_{it-1}$	0.0004	−0.0026	−0.0022	−0.0021***	−0.0049	−0.0069
	(0.0004)	(0.0029)	(0.0025)	(0.0004)	(0.0066)	(0.0067)
$Cash_{it-1}$	−0.0829***	−0.1118***	−0.1078***	0.0134**	−0.0131	−0.0323
	(0.0050)	(0.0293)	(0.0247)	(0.0061)	(0.0619)	(0.0615)
$Debt_{it-1}$	−0.0151**	−0.0138	−0.0139	−0.0130***	−0.0118**	−0.0109
	(0.0072)	(0.0109)	(0.0103)	(0.0037)	(0.0060)	(0.0080)
$WorkCap_{it-1}$	0.0065***	0.0020	0.0026	−0.0287***	−0.0328***	−0.0358***
	(0.0024)	(0.0059)	(0.0053)	(0.0051)	(0.0083)	(0.0080)
Industry FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Adjusted R-Squared	0.0354	.	.	0.0196	.	.
Observations	97,619	97,619	97,619	97,619	97,619	97,619

Standard errors in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 6: Credit Line Adjustments and Cash Flow. Columns 1 and 4 present OLS estimates from regressions of $\Delta Line\ Size_{it}$ (in Column 1) and $Line\ Increase_{it}$ (in Column 4) on $Cash\ Flow_{it}$ and controls. Columns 2 and 3 present 2SLS estimates of IV regressions of $\Delta Line\ Size_{it}$, while columns 5 and 6 present estimates of IV regressions of $Line\ Increase_{it}$ on instrumented $Cash\ Flow_{it}$ and controls. IV1 and IV2 correspond to *Abnormal Snow* and *Abnormal Snow P*95, respectively. We include a number of control variables (defined in Appendix B), as well as three-digit NAICS 2012 industry indicators, county, and year-quarter fixed effects. The standard errors are clustered at the three-digit NAICS 2012 industry level.

	$\Delta Line\ Size_{it}$			$Line\ Increase_{it}$		
	OLS (1)	*IV1* (2)	*IV2* (3)	*OLS* (4)	*IV1* (5)	*IV2* (6)
$Cash\ Flow_{it}$	0.0128***	−0.7407**	−1.1320***	0.0537***	−3.3060***	−3.9155***
	(0.0040)	(0.3041)	(0.3823)	(0.0145)	(1.1841)	(1.0810)
$Log(Assets)_{it-1}$	−0.0021***	−0.0058**	−0.0077**	0.0397***	0.0235**	0.0205*
	(0.0004)	(0.0023)	(0.0032)	(0.0026)	(0.0099)	(0.0107)
$Fixed\ Assets_{it-1}$	−0.0217***	0.0484*	0.0848**	−0.1370***	0.1754	0.2320**
	(0.0050)	(0.0292)	(0.0357)	(0.0259)	(0.1077)	(0.0908)
$Leverage_{it-1}$	0.0114***	−0.0278	−0.0482	0.0426*	−0.1322	−0.1639
	(0.0037)	(0.0285)	(0.0430)	(0.0241)	(0.1062)	(0.1343)
$Sales_{it-1}$	0.0028***	0.0217**	0.0314***	0.0059**	0.0900***	0.1052***
	(0.0007)	(0.0085)	(0.0112)	(0.0023)	(0.0297)	(0.0306)
$Cash_{it-1}$	−0.0485***	0.1324	0.2263*	−0.3207***	0.4856	0.6319**
	(0.0055)	(0.0925)	(0.1241)	(0.0350)	(0.3119)	(0.3224)
$Debt_{it-1}$	0.0072	−0.0012	−0.0056	0.0624***	0.0248	0.0180
	(0.0056)	(0.0270)	(0.0403)	(0.0155)	(0.1233)	(0.1417)
$WorkCap_{it-1}$	−0.0032	0.0249	0.0396*	−0.0524***	0.0732	0.0960
	(0.0030)	(0.0160)	(0.0210)	(0.0186)	(0.0809)	(0.0784)
Industry FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Adjusted R-Squared	0.1111	.	.	0.1335	.	.
Observations	97,619	97,619	97,619	97,619	97,619	97,619

Standard errors in parentheses

$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 7: Investment and Cash Flow Columns 1 and 4 present OLS estimates from regressions of $\Delta Fixed\ Assets_{it}$ (in Column 1) and $\Delta Assets_{it}$ (in Column 4) on $Cash\ Flow_{it}$ and controls. Columns 2 and 3 present 2SLS estimates of IV regressions of $\Delta Fixed\ Assets_{it}$, while columns 5 and 6 present estimates of regressions of $\Delta Assets_{it}$ on instrumented $Cash\ Flow_{it}$ and controls. IV1 and IV2 correspond to *Abnormal Snow* and *Abnormal Snow P*95, respectively. We include a number of control variables (defined in Appendix B), as well as three-digit NAICS 2012 industry indicators, county, and year-quarter fixed effects. The standard errors are clustered at the three-digit NAICS 2012 industry level.

	$\Delta Fixed\ Assets_{it}$			$\Delta Assets_{it}$		
	OLS (1)	*IV1* (2)	*IV2* (3)	*OLS* (4)	*IV1* (5)	*IV2* (6)
$Cash\ Flow_{it}$	0.0391***	−0.0541	−0.1472	0.1781***	0.3972	0.1833
	(0.0107)	(0.2526)	(0.2321)	(0.0373)	(0.3634)	(0.3141)
$Log(Assets)_{it-1}$	0.0018*	0.0014	0.0009	0.0009	0.0020	0.0009
	(0.0010)	(0.0009)	(0.0009)	(0.0011)	(0.0022)	(0.0018)
$Fixed\ Assets_{it-1}$	−0.0115	−0.0028	0.0058	−0.0232***	−0.0436	−0.0237
	(0.0118)	(0.0172)	(0.0161)	(0.0069)	(0.0347)	(0.0286)
$Leverage_{it-1}$	−0.0200**	−0.0249	−0.0297	−0.0071	0.0043	−0.0068
	(0.0087)	(0.0207)	(0.0201)	(0.0115)	(0.0278)	(0.0220)
$Sales_{it-1}$	−0.0003	0.0020	0.0043	0.0045***	−0.0010	0.0043
	(0.0006)	(0.0062)	(0.0059)	(0.0016)	(0.0096)	(0.0083)
$Cash_{it-1}$	−0.0250**	−0.0027	0.0197	−0.0685***	−0.1211	−0.0697
	(0.0099)	(0.0550)	(0.0511)	(0.0131)	(0.0978)	(0.0780)
$Debt_{it-1}$	0.0026	0.0015	0.0005	−0.0302**	−0.0278	−0.0302**
	(0.0066)	(0.0050)	(0.0070)	(0.0145)	(0.0202)	(0.0141)
$WorkCap_{it-1}$	−0.0171**	−0.0136*	−0.0101	0.0175**	0.0093	0.0173
	(0.0082)	(0.0070)	(0.0073)	(0.0085)	(0.0169)	(0.0143)
Industry FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Adjusted R-Squared	0.0370	.	.	0.0577	.	.
Observations	97,619	97,619	97,619	97,619	97,619	97,619

Standard errors in parentheses

$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 8: Direct Weather Plugin and Corporate Outcomes This table presents the direct association between *Abnormal Snow* (Panel A) or *Abnormal Snow P*95 (Panel B) and corporate liquidity management, saving, and investment outcomes. The dependent variables are $\Delta Draw_{it}$ (in Column 1), $\Delta Cash_{it}$ (in Column 2), $\Delta WorkCap_{it}$ (in Column 3), $\Delta Line\ Size_{it}$ (in Column 4), $\Delta Fixed\ Assets_{it}$ (in Column 5), and $\Delta Assets_{it}$ (in Column 6). Controls variables are defined in Appendix B. All models include all firm-level variables from Table 7 except $Cash\ Flow_{it}$ in addition to three-digit NAICS 2012 industry indicators, county, and year-quarter fixed effects. The standard errors are clustered at the three-digit NAICS 2012 industry level.

Panel A: *Abnormal Snow Cover*

	$\Delta Draw_{it}$	$\Delta Cash_{it}$	$\Delta WorkCap_{it}$	$\Delta Line\ Size_{it}$	$\Delta Fixed\ Assets_{it}$	$\Delta Assets_{it}$
	(1)	(2)	(3)	(4)	(5)	(6)
Abnormal Snow Cover	0.00977**	−0.00412	−0.00375	0.0175***	0.00128	−0.00937
	(0.00391)	(0.00296)	(0.00625)	(0.00627)	(0.00606)	(0.00834)
Adjusted R-Squared	0.0640	0.0149	0.00986	0.111	0.0305	0.0274
Observations	97,619	97,619	97,619	97,619	97,619	97,619

Panel B: *Abnormal Snow Cover P*95

	$\Delta Draw_{it}$	$\Delta Cash_{it}$	$\Delta WorkCap_{it}$	$\Delta Line\ Size_{it}$	$\Delta Fixed\ Assets_{it}$	$\Delta Assets_{it}$
	(1)	(2)	(3)	(4)	(5)	(6)
*Abnormal Snow Cover P*95	0.00893***	−0.00234	−0.00353	0.0167***	0.00217	−0.00271
	(0.00294)	(0.00158)	(0.00377)	(0.00481)	(0.00337)	(0.00471)
Adjusted R-Squared	0.0642	0.0149	0.00987	0.111	0.0305	0.0274
Observations	97,619	97,619	97,619	97,619	97,619	97,619

Table 9: Credit Line Use, Weather Shocks, and Credit Quality This table presents the direct association between *Abnormal Snow* or *Abnormal Snow P*95 and cash flow (in Panel A) or credit line use (Panel B) for low- and high-credit quality firms, where high-credit firms are defined as those with BB ratings or better. Controls variables are defined in Appendix B. All models include all firm-level variables from Table 7 except $Cash\ Flow_{it}$ in addition to three-digit NAICS 2012 industry indicators, county, and year-quarter fixed effects. The standard errors are clustered at the three-digit NAICS 2012 industry level.

Panel A: Weather Shocks and Cash Flow

	$Cash\ Flow_{it}$			
	BB and better		B and worse	
	(1)	(2)	(3)	(4)
Abnormal Snow	−0.0109		−0.0575***	
	(0.00677)		(0.0183)	
*Abnormal Snow P*95		−0.00925**		−0.0250**
		(0.00351)		(0.00975)
Observations	79,124	79,124	17,127	17,127
Adjusted R-Squared	0.152	0.152	0.122	0.122

Panel B: Weather Shocks and Credit Lines Use

	$\Delta Draw_{it}$	$\Delta Draw_{it}$	$\Delta Line\ Size_{it}$	$\Delta Line\ Size_{it}$	$\Delta Draw_{it}$	$\Delta Draw_{it}$	$\Delta Line\ Size_{it}$	$\Delta Line\ Size_{it}$
	BB and better				B and worse			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abnormal Snow	0.0124**		0.0227***		−0.000134		0.00345	
	(0.00475)		(0.00700)		(0.00830)		(0.0131)	
*Abnormal Snow P*95		0.0112***		0.0205***		0.00208		0.00810
		(0.00343)		(0.00549)		(0.00528)		(0.00647)
Observations	79,124	79,124	79,124	79,124	17,127	17,127	17,127	17,127
Adjusted R-Squared	0.0703	0.0705	0.128	0.129	0.0671	0.0671	0.0773	0.0774

Appendix A - Data Cleaning

We use the IRS tax identification (TIN) number to identify borrowers in the Y-14 data. While the TIN is likely to be the unique firm ID for small and mid-market firms, large firms are likely to have multiple subsidiaries that may have different TINs than the parent company.[12] If we were solely relying on the TIN from the Y-14 data, we would erroneously treat some subsidiaries of large firms as separate companies. To address this issue, we supplement the TIN from the Y-14 collection with additional borrower identifying information from the quarterly reports from the Shared National Credit (SNC) spanning 2009 through present. Specifically, the examiners at the Shared National Credit program create a unique borrower identifier of each borrowers participating in the syndicated loan market and link all TINs associated with it including that of the parent company and any subsidiaries. Even though the quarterly SNC data collection only tracks the syndicated participations of the 18 largest banks in the United States, these banks participate in the vast majority of syndicated bank loans and as a result this correction is likely to capture most subsidiaries that would be otherwise identified as separate firms.

First, to minimize the effect of errors we exclude financial statement information if the financial statement date is missing or comes later than the data report date if: (1) there are no other valid financial statement date observations for the given borrower as of the data report date (2) there are multiple other valid financial statement dates for this borrower as of the report date. We also exclude likely data errors by requiring that for each firm and financial statement date: 1) EBITDA does not exceed net sales, 2) fixed assets do exceed total assets, 3) cash and marketable securities do not exceed total assets, and 4) total liabilities do not exceed total assets.

Next, we correct errors related to the dollar units of reporting. In some cases the financial statement information may be reported in thousands of US dollars instead of raw dollar amounts as instructed. To address this potential reporting irregularity, we multiply

[12] Please see https://www.irs.gov/businesses/small-businesses-self-employed/do-you-need-a-new-ein.

all financial statement information by 1,000 if either the utilized loan exposure in a given reporting quarter exceeds total liabilities by a factor of 100 or more, or if total assets are less than \$100,000. Given that the reporting criteria only includes loans larger than \$1 million, it is highly unlikely that the borrower has total assets below \$100,000.

Last, to address the possibility that some large corporations are borrowing through their subsidiaries, for each borrower and financial statement date we only keep the financial statement information corresponding to the observation with the largest value of total assets. Given that the financials and physical location information we observe always correspond to the entity that is directly responsible for loan repayment, in the case of large firms the financial statement information could be that of a subsidiary instead of the ultimate parent company. For example, to the extent that for a given borrower-quarter one financial institution reports the financials of a corresponding subsidiary while another institution reports financials associated with the parent entity, then we will retain the financials of the parent entity. If, however, certain companies only borrow through their subsidiaries, we may understate the size of some firms in our sample.

Additionally, given that we rely on the time series aspect of the data, we require that currently-reported borrower total assets for the prior year are within 2.5% of the 1-year lagged value of currently-reported borrower total assets. This filter eliminates observations in which the Y-14 reporters switch reporting of financial statement information between subsidiaries and the parent company of the borrower.

Appendix B - Variable Definitions

Below we present variable definitions, the item numbers of data fields refer to Schedule H1 of the Y-14Q data on the Federal Reserve's website:

$https://www.federalreserve.gov/reportforms/forms/FR\_Y-14Q20160930\_i.pdf$

$\boldsymbol{Total\ Assets_{it-1}}$ – is defined as the first annual lag of the book value of total assets as of the current financial statement date, 'Total Assets Current Year' (item #70) data field in Y-14Q Schedule H1. To the extent that 'Total Assets Current Year' is missing, we replace it with the book value of total assets as of exactly one year prior to the current financial statement date, 'Total Assets Prior Year' (item #71).

$\boldsymbol{Cash\ Flow_{it}}$ – we primarily rely on the sum of 'Operating Income' (item #56) and 'Depreciation & Amortization' (item #57) to arrive at a measure of EBITDA. To the extent that the 'Operating Income' field is not populated in our data, we fill in missing values with the 'EBITDA' field that is overall available for a smaller fraction of the data. We then scale the resulting variable by $Total\ Assets_{it-1}$ to arrive at $Cash\ Flow$.

$\boldsymbol{Sales_{it-1}}$ is defined as the net sales from time $t-2$ to $t-1$, 'Net Sales Prior Year' (item #55) divided by total assets of firm i at time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{Leverage_{it-1}}$ is defined as the first annual lag of the value of total liabilities of firm i, 'Total Liabilities' (item #80), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{Fixed\ Assets_{it-1}}$ is defined as the first annual lag of the value of total fixed assets of firm i, 'Fixed Assets' (item #69), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{WorkCap_{it-1}}$ is defined as the first annual lag of the value of current assets of firm i, 'Current Assets Current' (item #66), minus the first annual lag of the value of current liabilities, 'Current Liabilities Current' (item #76)', minus first annual lag of the value of cash and marketable securities of firm i, 'Cash & Marketable Securities' (item #61). Then the resulting value is divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

To the extent that 'Current Assets Current' and 'Current Liabilities Current' are missing, we replace it with 'Current Assets Prior Year' (item #67) and 'Current Liabilities Prior Year' (item #77) which are the values current assets and current liabilities exactly one year prior to the current financial statement date.

$\boldsymbol{Cash_{it-1}}$ is defined as the first annual lag of the value of cash and marketable securities of firm i, 'Cash & Marketable Securities' (item #61), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{Debt_{it-1}}$ is defined as the first annual lag of the value of total debt of firm i, 'Short-Term Debt' (item #74) + 'Long-Term Debt' (item #78), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{Lines_{it-1}}$ is defined as the first annual lag of the total value of credit line commitments of firm i ('Commitment Exposure Global' (item #24) aggregated for each firm-quarter in our sample), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{Draw_{it-1}}$ is defined as the first annual lag of the total value of drawn amount under all credit line commitments of firm i ('Utilized Exposure Global' (item #25) aggregated for each firm-quarter in our sample), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{\Delta Line\ Size_{it}}$ is defined as the annual change of the total value of credit line commitments of firm i ('Commitment Exposure Global' (item #24) aggregated for each firm-quarter in our sample), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{Line\ Increase_{it}}$ is an indicator variable that takes the value of one whenever the total credit line commitments of firm i in year t exceed the total credit line commitments of firm i in year $t-1$.

$\boldsymbol{\Delta Draw_{it}}$ is defined as the annual change of the total value of drawn amount under all credit line commitments of firm i ('Utilized Exposure Global' (item #25) aggregated for each firm-quarter in our sample), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{\Delta Cash_{it}}$ is defined as the annual change of the value of cash and marketable securities of firm i ('Cash & Marketable Securities' (item #61)), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{\Delta Liabilities_{it}}$ is defined as the annual change of the value of total liabilities of firm i ('Total Liabilities' (item #80)), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{\Delta Debt_{it}}$ is defined as the annual change of of the value of total debt of firm i ('Short-Term Debt' (item #74) + 'Long-Term Debt' (item #78)), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{\Delta Assets_{it}}$ is defined as the annual change of the value of total assets of firm i (we use 'Total Assets Current Year' (item #70) to build the current value of total assets), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{\Delta Fixed\ Assets_{it}}$ is defined as the annual change of the value of total fixed assets of firm i ('Fixed Assets' (item #69)), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{\Delta WorkCap_{it}}$ is defined as the annual change of the value of non-cash working capital of firm i ($WorkCap$) between years $t-1$ and t, divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.