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# Examining the Financial Accelerator: Bank Responses to the 2014 Oil Price Shock

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**Abstract**

We exploit the 2014 decline in oil prices to understand how banks change contract terms for distressed firms. Using panel data on new and existing loans, we find that firms most financially affected by the 2014 oil price shock initially increased their use of credit. However, those same firms ultimately saw increased borrowing costs, smaller loan sizes, and fewer originations and renewals than less affected firms as the oil price decline persisted. We then demonstrate that credit spreads rose more than might be predicted based on changes in firm risk alone, suggesting that lending standards tightened for distressed firms. Our results suggest that bank credit can cushion the effect of transitory economic shocks while amplifying more persistent downturns.

**JEL Classification:** E44, G21, G28
**Keywords:** bank credit, loan standards, financial accelerator, oil price shocks

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# 1 Introduction

What role do banks play in determining the magnitude of business cycles? Banks produce and analyze information to attenuate the asymmetric information problems that affect all credit transactions [Diamond, 1984, 1991; Ramakrishnan and Thakor, 1984]. In the process of gathering information and setting contract terms on the loan, banks not only adjust for risk but also improve borrower incentives. Accordingly, it has been argued that banks are better informed than other sources of debt in setting loan contract terms [James, 1987; Lummer and McConnell, 1989; Ashcraft, 2005; Billett, Flannery, and Garfinkel, 2006]. This information advantage is especially useful during times of industry- or economy-wide financial distress when other market sources of credit may tighten considerably. At the same time, however, changes in bank loan terms can also amplify the effects of real or financial shocks via propagation mechanisms such as the financial accelerator [Bernanke, Gertler, and Gilchrist, 1996, 1999]. Under certain conditions, banks may tighten credit availability to businesses and households following adverse shocks. Reduced credit access can further exacerbate the initial shock because firms cannot offset any effects through changes in borrowing levels. Overall, tighter lending standards can amplify the initial impulse, which may further reduce spending and production.

Empirically estimating how banks evaluate changes in borrower creditworthiness following economic shocks poses significant challenges. For example, studies that examine how loan terms change across borrowers based on creditworthiness at origination likely suffer unobserved heterogeneity problems. In other cases, identification problems are exacerbated by the varying degree to which information obtained by the bank in the course of evaluating the borrower is actually recorded on the borrower's file ("hard information"), undermining the ability to statistically estimate bank responses [Stein, 2002]. Additionally, tracking loans of the same borrower-lender pair over time to evaluate banks' assessments of borrower creditworthiness can be problematic, as a large relationship lending literature argues, because loan terms can change in ways unrelated to borrower creditworthiness throughout a lending relationship. For example, loan terms could change because banks have better information about borrower creditworthiness over the course of the lending relationship [Petersen and Rajan, 1994; Boot, 2000] or because monopoly rents are extracted by the lender over time [Petersen and Rajan, 1995].

In this paper, we exploit the 2014 oil price shock to study how banks adjust loan contract terms due to changes in borrower credit quality. Beginning in mid-2014, oil prices collapsed 71 percent from their recent, all-time highs. For individual energy firms that profited from record oil prices after the global financial crisis, the significant drop in oil prices was largely unanticipated [Kilian, 2015; Baumeister and Kilian, 2016a,b].[1] Using loan level data collected from the largest U.S. banks, we determine the effect of the exogenous oil price shock in 2014 on changes in loan contract terms of oil firms. The use of large bank data gives us a unique perspective to observe how banks price an increase in risk following a fundamental shock. While large banks make a significant number of loans to energy producers, energy lending does not constitute a material portion of large bank balance sheets. Thus, lending to the energy sector was unlikely to cause financial distress at large, systemically important banks. However, due to the large volume of loans these banks make, we are able to look at a significant number of loans made to the energy sector during this period.

Our empirical identification strategy is contingent on the fact that the depth of the oil price crash was unanticipated by markets and exogenous to the banking system. Due to the nature of this shock, we are able to observe heterogeneous responses across the energy sector. In doing so, we are able to show how fundamental business shocks affect firms' financial conditions and how firms are able to respond to those changes. We argue that firms generally respond by offsetting revenue shocks by reducing production costs unless existing frictions do not allow them to do so. In those cases, inflexible firms are more likely to declare bankruptcy and are thus more affected by the shock.

In the second part of our analysis, we examine how large U.S. banks responded to the affected firms. The use of large bank data gives us a unique opportunity to

[1] We refer the oil and gas industry as the energy sector throughout the text. While these firms produce and process a wide array of energy commodities (e.g., oil, natural gas, and natural gas liquids), business operations in the U.S. are highly sensitive to oil prices as a majority of energy sector revenues come from oil production[EIA, 2021].

observe how banks price an increase in risk following a fundamental shock. We hypothesize that the most affected firms were more likely to experience adverse impacts to their lending outcomes. We find that firms in the most affected sectors were more likely to drawdown their lines of credit but also had more adverse lending outcomes including higher costs, smaller commitment sizes, and reduced likelihood of new loan originations.

While these results are suggestive of tighter financial conditions, they may simply reflect the increase in observable risk or lower demand for credit among affected firms. To resolve this issue, we estimate an "excess loan premium" based on changes in loan risk ratings using a methodology similar to Gilchrist and Zakrajšek [2012]. The excess loan premium measures deviations in the expected loan spread based on the historical cost of bank debt for a given level of risk. Thus, a positive excess loan premium indicates that bank loan rates are higher, or financial conditions tighter, than would be expected for a given risk level.

As expected, we find that banks reported a sharp deterioration in risk ratings for firms most affected by the oil price drop. However, our excess loan premium estimates suggest that borrowing costs rose more than would be expected based on historical pricing dynamics. This is especially true for term loans which are fully amortizing loans generally originated by banks but later sold to non-bank investors.

Overall, our results demonstrate the dual nature that banks play in propagating shocks to the real economy. Bank-issued, revolving lines of credit help offset the initial impulse by providing much needed cash to firms suffering financial losses. However, following a persistent shock that permanently reduces creditworthiness, banks tighten lending conditions, likely resulting in lower investment and employment activity.

Our results confirm several important insights from the macroeconomic literature that consider the banking sector. First, we demonstrate that affected firms were less profitable and likely had sharply lower collateral values and, in response to increased riskiness, bank credit access declined, as suggested by models of Kiyotaki and Moore [1997] and Bernanke et al. [1999]. Second, we show that banks respond to these shocks by tightening loan standards to affected firms, meaning loan terms changed more than would be expected based only on the effects of the fundamental shock. Together, the two channels we highlight, the initial shock and the further tightening in credit access, suggest the loan supply curve constricts more than would otherwise be expected from a deterioration in firm credit risk.

Our results also highlight how bank loans are critical to understanding credit intermediation. During stress periods, businesses rely heavily on bank lines of credit for financing [Kashyap, Rajan, and Stein, 2002; Acharya and Mora, 2015]. For example, in the financial fallout from the COVID-19 outbreak during March 2020, bank lines of credit were the first resort of financing for most non-financial businesses [Li, Strahan, and Zhang, 2020; Acharya and Steffen, 2020]. However, our results demonstrate that such support is limited. Instead, should borrower creditworthiness deteriorate persistently, the price of credit will rise, further hampering affected firms. Therefore, our results provide further evidence on the need for credit support policies during sharp economic downturns like those experienced during the COVID-19 pandemic [Hong and Lucas, 2023].

In addition to the macro literature on financial frictions, our paper is also related to an emerging literature on bank responses to the 2014 oil price shock. Bidder, Krainer, and Shapiro [2017], using similar data to our own, show that banks more exposed to the energy sector decreased business and portfolio mortgage lending but increased lending to securitizable residential real estate. These results are consistent with our own findings that banks pulled back from affected sectors and took steps to decrease exposure to risky loans. Our results differ from those of Bidder et al. [2017], however, because we are able to trace the effects to specific segments of the energy industry and show that those affected firms are observably riskier than other energy sector firms. Our paper is also related to previous analysis by Sengupta, Marsh, and Rodziewicz [2017] that finds that syndicated loan prices to the most affected segments rose following the oil price crash. Our current paper differs from this analysis because it uses a wider set of loans, better controls for lender-borrower relationships, and investigates a wider variety of pricing and lending channels.

The remainder of the paper is as follows: Section 2 discusses the effect of the oil price crash on the energy industry. Section 3 discusses the necessary identification assumptions and empirical strategy implemented in our study as well as the loan level dataset we utilize. Section 4 discusses the response of banks to affected firms on loan prices and terms. Section 5 estimates the risk-adjusted excess loan premium. Section 6 concludes.

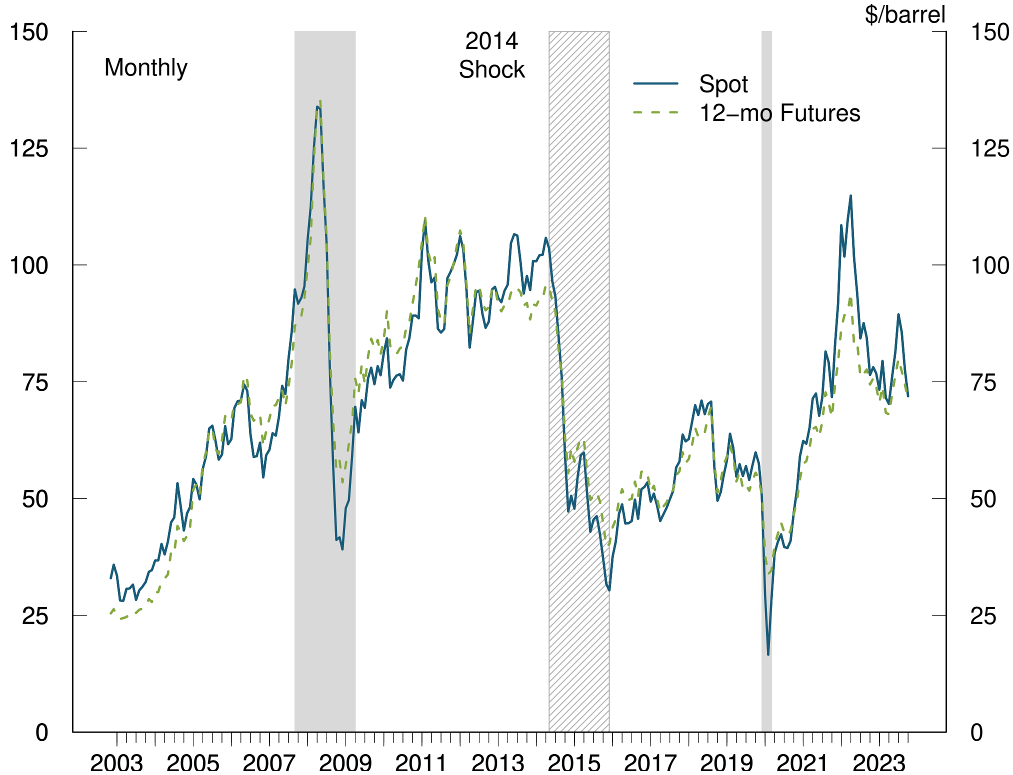
# 2 The 2014 Oil Price Shock and the Energy Sector

We study changes in bank lending conditions to firms in the energy supply chain to understand how real economic shocks are propogated through the banking system. In order to identify how banks adjust loan terms for energy companies following an oil price shock, it is essential to understand the structure of the energy sector and the characteristics of oil price shocks. The energy sector consists of several segments that work together to bring oil from the well to the end consumer. Together these segments comprise the energy supply chain. While oil prices are volatile, large oil price shocks are rare and are typified by pronounced and unanticipated declines in crude oil prices. The reasons for these significant shocks vary and are driven by supply or demand factors, with circumstances unique to each episode [Kilian, 2009, 2015; Davig, Çakir Melek, Nie, Smith, and Tuzemen, 2015; Baumeister and Kilian, 2016a,b]. Oil price shocks unevenly impact specific segments of the oil and gas industry due to differences in business operations, assets, and customer bases. That is, firm responses to oil price shocks will differ depending on each firm's position in the supply chain.

## 2.1 Recent Oil Price Shocks

Recent decades witnessed three major oil price shocks that occurred in 2008, 2014, and 2020. Notably, oil price shocks during 2008 and 2020 coincided with deep economic recessions (see, for example, Hamilton [2009]). The 2014 oil price shock, however, is unique because the crude oil price declines that occurred during that period were coincident with a broader economic expansion, meaning the price shock

Figure 1: West Texas Intermediate Crude Prices




Note: Solid shaded areas denote NBER recessions in 2008 and 2020. Hashed shaded area denotes the peak-to-trough oil price decline from August 2014 to February 2016.
Source: Energy Information Agency (spot price) and NYMEX (futures), Haver Analytics.

can be seen as energy sector specific [Baumeister and Kilian, 2016b; Prest, 2018].[2] We focus our analysis on the shock that occurred in late 2014 because, while partly driven by global demand factors, this shock had a significant impact on the energy industry at a time when broader economic activity was still expanding. Thus, this episode, provides a valuable opportunity to study the effects of oil price changes on the energy sector.

[2]While oil price shocks typically coincide with economic recessions, the 2014 shock not only occurred during a period of economic expansion, but may have even provided a minor boost to the U.S. economy during that time period, further underscoring how this shock was largely concentrated to energy companies [Baumeister and Kilian, 2016c].

Figure 1 shows that oil price declines starting in 2014 were significant, even in relation to the 2008 and 2020 price shocks. Oil prices dropped precipitously starting in late 2014 after reaching nearly half decade highs. By year-end 2014, prices had fallen almost 50 percent from their June levels. The slide continued through 2015 and into early 2016 when oil prices finally reached their trough at just over $30 per barrel, a cumulative decline of nearly 70 percent from their 2014 highs. Overall, the 2014 price shock was severe in magnitude and long in duration, placing great stress on energy firms throughout this episode.

## 2.2 The Energy Supply Chain

While the anatomy and characteristics of individual oil price shocks are interesting, for our purposes the transmission of price declines through the energy sector is the most important consideration. Energy companies are highly sensitive to oil prices and suffer lower revenues, tighter margins, and declining profits during periods of oil price declines. Additionally, the energy sector is a capital intensive business with high fixed capital costs and a greater than average debt burden, meaning oil price shocks may further amplify financial stress given the structure of the industry (see appendix section A).

However, not all companies in the energy industry are equally affected by oil prices. The oil and gas supply chain is comprised of four distinct firm types: *upstream, midstream, downstream, and support services.* Three of the four firm types make up the oil and gas supply chain– upstream, midstream, and downstream– while support services companies provide technical and equipment services to other aspects of the supply chain, most predominately upstream firms. Upstream and support services firms are most sensitive to oil price fluctuations while those further down the supply chain – midstream and downstream – are somewhat insulated from oil price shocks [Sengupta et al., 2017; API, 2024].[3]

[3]The fifth type of oil and gas firm are integrated companies. These companies are typically larger firms involved in upstream activity and at least one other aspect of the supply chain (e.g., midstream or downstream). We exclude these firms from our analysis due to their complexity and diversification across the supply chain.

*Upstream* firms are the beginning of the oil supply chain. Upstream companies own the leasing rights to develop crude oil reserves and are responsible for finding, drilling, and extracting raw oil and gas products. The assets of upstream firms typically consist of developed and undeveloped oil reserves and their revenue is generated by extracting and selling unrefined crude oil. Upstream firm financial well-being is sensitive to crude oil prices. Not only do the sale prices of their products change with spot oil prices, but production levels typically decline in response to lower oil prices as well [Rodziewicz, 2018; EIA, 2021]. Furthermore, the value of upstream assets can also fluctuate meaningfully with the price of oil adding additional financial stressors for these companies during downturns [Kaiser, 2013; Ewing and Thompson, 2016; OCC, 2016].

*Midstream* firms are in the middle of the supply chain and primarily transport and store crude oil, natural gas, and refined products. Midstream firms provide transportation options to upstream firms including pipelines, trucking, rail services, and tanker services. They also transport refined products (e.g., gasoline and diesel) from downstream refiners to retail distributors. Importantly, fee structures for midstream firms are fixed for many transportation options over medium time horizons. For example, some forms of transportation and storage require long-term contracts with fees to access pipelines or storage space. In addition, there are usually per barrel charges for quantities shipped or stored and many contracts include "take or pay" clauses, which require upstream companies to pay for transportation services even if volumes are lower than originally contracted. The fixed fee agreements provide some measure of risk protection against price volatility when production falls.

*Downstream* firms are at the end of the oil and gas supply chain. These companies refine and process crude oil into finished petroleum products like gasoline, diesel, and jet fuel. Downstream firm profitability is determined by the spread between input costs (crude oil prices) and finished petroleum product prices. These firms typically hedge their input costs and output prices [Ji and Fan, 2011]. Furthermore, because their business model is based on the spread between crude oil prices and refined products (e.g., gasoline, diesel), profitability may remain steady during oil price shocks if demand for refined products is strong [EIA, 2014, 2015a]. All together, downstream firms are largely buffered from downturns in the oil market.

*Support services* firms provide materials, equipment, and other services to the rest of the energy supply chain. Most servicer activity is focused on providing drilling support and geo-technical services to upstream firms. As a result, firm profitability is highly linked to activity in the upstream sector. During the 2014 oil price shock, rig counts and drilling activity dropped precipitously resulting in lower revenues and profitability for support services companies [EIA, 2015b; Çakir Melek, 2015; Anderson, Kellogg, and Salant, 2018].

## 2.3 Post-2014 Oil Price Shock Energy Segment Performance

To validate our statements about energy segment performance across the oil supply chain, we investigate the effects of the 2014 oil price decline on individual energy sector firms relative to non-energy firms. We collect quarterly income statement and balance sheet data from S&P Global Market Intelligence's Compustat database of U.S. publicly traded firms. Using these data, we estimate the model shown by equation 1 for firm $i$ in quarter $t$. We define a post-oil-price shock indicator, $Post_t$, as the three years following the start of the the 2014:Q3 oil price shock. We define indicators for each of the four energy segments described above: upstream, mid-stream, downstream, and support services. Finally, we include firm ($\eta_i$) and quarter ($\tau_t$) fixed effects to control for average, idiosyncratic differences in outcomes across firms and common, time-varying shocks to all firms, respectively. Standard errors are clustered by firm and our sample runs from 2012:Q3 to 2017:Q2.[4]

$$y_{i,t} = \beta_0 + \beta_1 Post_t \times subsector_j + \tau_t + \eta_i + \varepsilon_{i,t} \tag{1}$$

We define the outcome variable, $y_{i,t}$, as one of several financial outcomes for the

[4] Our sample of quarterly public firm observations in Compustat runs from 2012:Q3 to 2017:Q2 and compares firm performance in the 3yr period following the start of the 2014 oil price shock (2014:Q3) compared to 3yrs prior. We chose a three year period following the star of the 2014 oil price shock because oil prices started to climb meaningfully in 2017, marking and end to the episode (see Figure 1). The sample for this firm level initial analysis includes 132,373 quarterly observations, 8,634 unique companies, and 913 unique energy companies.

firm. We examine sales growth, expenses growth, and net operating income growth. We also examine the return on assets (ROA) and the net profit margin of firms. Firms that are unaffected by subsector specific outcomes should have no significant effect to the shock on the outcome variable. Other types of firms may have more flexible cost structures and thus may be able to offset lower sales growth by reducing expenses. However, those that cannot offset the oil price shock will see reduced profitability measures.

The coefficient of interest is the interaction of the subsector flag and the post-shock indicator. The components of this interaction are not included separately because they are absorbed by the firm and quarter fixed effects, respectively. The omitted group from the interaction is the non-oil sector so comparisons are relative to firms outside the energy sector. If all firms across the energy sector respond similarly to the shock, then we would expect the coefficients across the different subsectors to be similar in size and significance. Likewise, if the shock is common to all firms– energy and non-energy alike– then we expect the effects of the oil price crash will be measured by the time fixed effects and the subsector specific coefficients will be insignificant.

The firm-level results are shown in Table 1. Our results are consistent with the energy sector descriptions earlier in this section: upstream and support services companies were most impacted by the 2014 oil price shock, while midstream and downstream firms were largely insulated from the shock.

Upstream and support service companies faced a material decline in sales growth compared to non-oil firms (column 1). At the same time, upstream company expense growth was statistically indistinguishable from non-oil companies (column 2), due in part to large and irreversible fixed costs. Support companies, on the other hand, witnessed lower expense growth relative to non-oil firms as demand for drilling activity and associated services fell sharply during this period. Both upstream and support services firms witnessed significantly lower operating income growth (column 3) and tighter operating margins (column 4) compared to non-oil firms during this period. Consequently, these firms also realized lower asset returns following large revenue and cost shocks (column 5). Overall, the results for upstream and support service

Table 1: Oil Shock Effects By Energy Subindustry

| | (1) Sales | (2) Expenses | (3) Oper. Inc | (4) Margin | (5) ROA |
|---|---|---|---|---|---|
| *Upstream × Post* | -14.83*** | 1.62 | -26.16*** | -51.39*** | -11.37*** |
| | (1.68) | (1.70) | (3.43) | (11.43) | (1.12) |
| *Support × Post* | -17.35*** | -18.44*** | -31.32*** | -6.46** | -5.47*** |
| | (1.66) | (1.53) | (3.65) | (2.80) | (1.00) |
| *Midstream × Post* | -6.19** | -9.10*** | 6.70 | 14.79** | 0.63 |
| | (2.76) | (3.09) | (5.41) | (5.79) | (1.00) |
| *Downstream × Post* | -18.02*** | -14.19*** | -4.10 | 28.03* | 2.72 |
| | (3.02) | (3.55) | (6.72) | (14.37) | (2.49) |
| Observations | 79,700 | 91,291 | 87,819 | 84,941 | 94,497 |
| Adjusted $R^2$ | 0.37 | 0.34 | 0.21 | 0.74 | 0.82 |

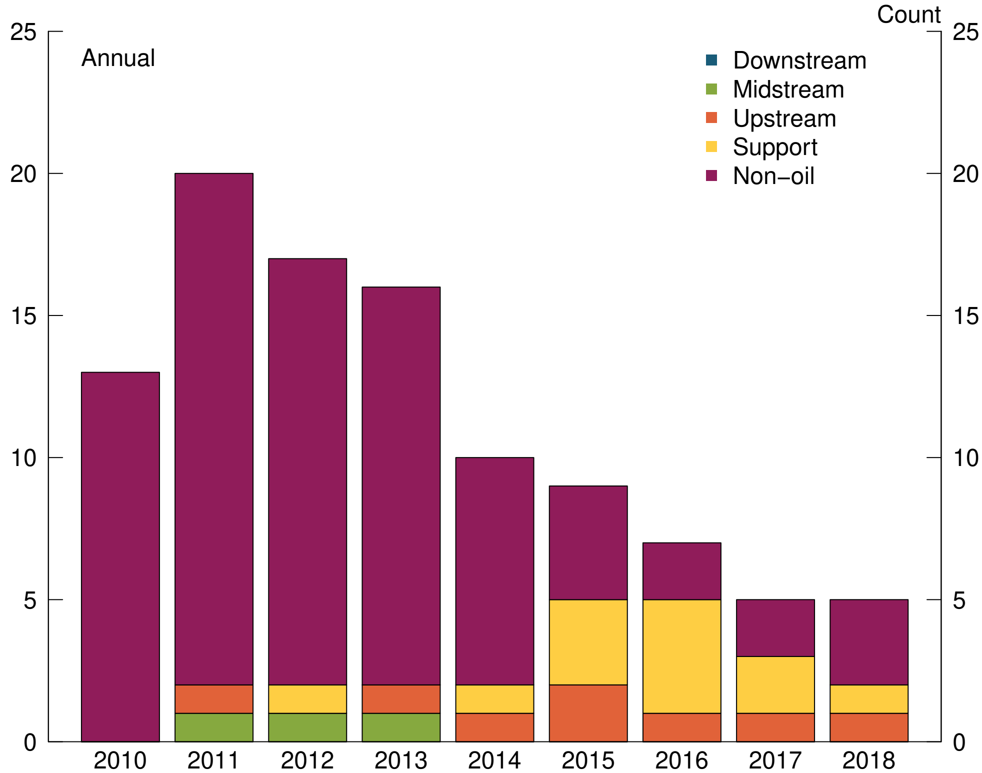
Firm clustered standard errors in parentheses.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

firms are consistent with energy segments that were inordinately impacted by the 2014 oil price shock.[5]

In contrast, midstream and downstream firms were largely insulated from the 2014 oil shock. While sales growth was lower for midstream and downstream firms compared to non-oil firms, those lower sales were largely offset by lower expenses as their input costs declined. As a result, operating income growth was essentially unchanged. Operating margins were higher than non-oil firms, but our results are only weakly significant. Still, these higher margin results are consistent with other evidence on how well downstream firms performed during the 2014 episode [EIA, 2014, 2015a]. Finally, asset returns were statistically indistinguishable from non-oil

[5]Asset returns (ROA) for upstream firms may be confounded by downward adjustments in reserves during the 2014 oil price shock. Oil and gas reserves fluctuate with market prices and upstream firms witnessed above average downward reserve revisions during the 2014 oil shock [EIA, 2016, 2024; Herr, 2021]. Downward reserve revisions are a net negative for upstream companies, as these adjustments constitute a write-off in assets and impose reduced returns in the quarter incurred. However, these revisions also cause asset returns to look better in subsequent periods because on-balance sheet assets are now lower. Despite, these downward reserve revision issues, we still find lower ROA for upstream firm during this time period.

Figure 2: Annual Bankruptcies




Note: Bankruptcies definition from Corbae and D'Erasmo [2017].
Source: S&P Global Market Intelligence Compustat.

firms suggesting these segments of the energy sector were mostly insulated from the 2014 oil price shock. Our findings align closely with the description of the oil and gas supply chain earlier in this section.

Bankruptcy information following the 2014 oil price shock further reinforces the fact that upstream and support services companies faced greater financial stressors than firms in the midstream or downstream energy segments. Figure 2 shows total public company bankruptcies as reported in the annual Compustat data since 2010.[6]

[6] We follow Corbae and D'Erasmo [2017] to define Chapter 7 and Chapter 11 bankruptcies in Compustat. We use bankruptcy data for publicly traded companies to remain consistent with our analysis in Table 1. However a similar intuition could be arrived at using industry data non-public energy firm information – upstream and support bankruptcies rose materially following the 2014

Upstream and support services bankruptcies rose in the aftermath of the 2014 oil price shock, while midstream and downstream bankruptcies were non-existent. Non-oil bankruptcies were in steep decline during this time period. By these measures, there were no reported bankruptcies in the oil sector in 2010 and bankruptcies rose in 2011 for energy firms. By 2015, the year following the oil price shock, the energy sector accounted for nearly all public company bankruptcies reported. Upstream and support service segment bankruptcies accounted for about three quarters of total public firm bankruptcies. Furthermore, upstream and support services firm bankruptcies held steady in 2016 before declining slowly through 2017 and 2018. In contrast, non-oil bankruptcies from 2011 to 2018 fell gradually, reflecting improvements in overall economic conditions following the Global Financial Crisis. These bankruptcy data are yet another way of illustrating the financial stressors upstream and support services segments faced following the 2014 oil price shock while midstream, downstream, and non-oil firms were relatively unaffected during this period.

# 3 Empirical Strategy and Loan Data

The canonical financial accelerator can be defined as the exacerbation of a real economic shock by the banking system [Bernanke et al., 1996, 1999]. Banks, as external financiers, face significant information asymmetries in financing firms in times of distress. Consequently, the higher cost of bank financing (relative to internally generated funds) reflects the agency costs of lending. In turn, the external finance premium that firms pay decreases with their net worth. In particular, firms with fewer internal funds (liquid assets) and lower collateral values (illiquid assets) will pay higher premiums on their bank loans. Moreover, a fall in firm net worth also raises the amount of external finance required. Taken together, a real economic shock, such as an oil price decline, raises the external finance premium and the amount of financing required, both of which serve to reduce the borrower's investment and production. Lower investment and production further reduces the firm's net worth, creating a

oil price shock [Boone, 2022].

negative feedback loop that reduces the firm's credit availability by tightening credit conditions. In this way, financial frictions amplify the effect of the initial real shock on real outcomes.

## 3.1 Identification Assumptions

Identifying banks' margins of adjustment in response to a real economic shock requires two necessary conditions. First, the initial (real) shock must be exogenous to the banking sector. Observed tightening of credit can be driven by either an initial shock to the firm's creditworthiness or by a bank's concerns about its own capital adequacy.[7] Therefore, only observed shocks that affect borrower creditworthiness, but ultimately have little impact on bank balance sheets or solvency, can isolate bank credit supply shifts in response to changes in borrower net worth. Second, identification requires that the economic shock be at least partially unanticipated, otherwise banks would adjust lending standards in anticipation of the economic shock and firms would change their business practices prior to the downturn.[8]

The 2014 oil price shock is arguably an ideal natural experiment that meets these requirements for two reasons. First, the oil price decline was driven mainly by supply and demand decisions of global energy market participants rather than bank-led decisions that affected the energy supply chain. While the economic literature has openly debated the supply and demand side factors at play during the 2014 oil price shock[Arezki and Blanchard, 2015; Davig et al., 2015; Baumeister and Kilian, 2016a], financial market factors, including excessive bank lending, are not consid-

[7] Economic shocks can originate from within the financial system during financial or banking crises. While the economic outcomes (declining economic activity) for firms and industries during banking crises mimic the financial accelerator, these two phenomena have meaningfully different causal mechanisms. Our analysis addresses the underlying mechanics of financial accelerators and leaves aside broader banking or financial crises such as those discussed in Lee, Posenau, and Stebunovs [2020], Aikman, Kiley, Lee, Palumbo, and Warusawitharana [2017],Reinhart and Rogoff [2009], Kindleberger and Bernstein [2000], and Minsky [1970].

[8] We do not necessarily require that the decline in oil prices are fully unanticipated; only that prices declined much further than expected. If the crash had been fully anticipated, then borrowers and lenders could hedge against price risk or proactively change their business models to insulate themselves from the dynamics of the crash.

ered a major driver of the supply shock. Second, the literature on oil price shocks points towards a conclusion that the 2014 episode was at least partially unanticipated. While the causes, and by proxy the forecast-able nature of the shock, have been a hotly debated topic in the macroeconomic literature, the argument settles toward at least a partially unanticipated shock. Importantly, Kilian [2015] and Baumeister and Kilian [2016a,b] show that the price decline could be partly predicted based on publicly available data. However, model-based forecasts would have anticipated only about half of the ultimate collapse in prices. Thus, we argue that the full magnitude of the collapse in oil prices was unexpected.

Our results in table 1 further reinforce that energy firms did not fully anticipate the oil price shock, especially at the most affected energy segments (i.e., upstream and support). Had those firms fully anticipated oil price declines in 2014, they would have hedged or adapted their business models in preparation of lower prices. Those actions would have softened the blow from the price shock, resulting in limited impacts for those firms. Instead, profitability declined considerably at affected energy segment firms following the oil price crash, resulting in sharp increases in industry bankruptcies (see figure 2).

Lastly, bank balance sheet data supports the assumption that large banks were largely unaffected by the 2014 oil price. Table 2 reports statistics on lending at large, systemically important banks which we consider in our later analysis. On average, these banks hold about $500 billion in total assets and have tier 1 capital ratios of about 13 percent, well above minimum required levels. Large banks also hold significant shares of liquid assets and energy lending commitments constitute only about 12 percent of total commitments. Figure B3 in the appendix further reports the range of energy lending exposures as a percent of Tier 1 capital. These estimates tend to fall well below 100 percent of Tier 1 capital which is a typical benchmark used for assessing capital adequacy of loan portfolios.[9] Overall, these summary statistics suggest that large bank exposures to the energy sector were relatively low, meaning even a significant oil price shock that affected only the energy industry would be

[9]See, for example, interagency guidance on commercial real estate lending [Bassett and Marsh, 2017].

unlikely to materially impact bank operations or induce outsized financial stress at systemically important banks.

Table 2: Bank Level Summary Stats

| | (1) |
|---|---|
| *Oil Loan Share* | 11.639 |
| | (7.635) |
| *Assets ($ billions)* | 483.176 |
| | (672.232) |
| *Tier 1 Ratio* | 13.456 |
| | (3.636) |
| *Liquid Asset Share* | 29.032 |
| | (13.971) |
| Observations | 936 |

Table reports characteristics of sample banks between 2012:Q2 and 2017:Q2. Variable means shown, standard deviations in parentheses. Oil loan share is average quarterly total commitments to firms in the energy value chain as a percent of total commitments. Liquid assets are balances due from DIs, U.S. treasuries and Agency MBS held, federal funds sold, and repo agreements.

### 3.2 Empirical Estimation

Our empirical analysis seeks to understand the strength of the financial accelerator using the period following the 2014 oil price shock. Oil price declines have broad macroeconomic effects due to the important and wide-ranging role that oil plays in the economy [Hamilton, 1983]. As a result, net worth may fluctuate widely across industries in response to price changes. The financial accelerator theory suggests that banks will respond to these unanticipated net worth shocks by changing credit availability in the economy.

To estimate credit standards, we calculate risk-adjusted borrower loan spreads following the oil price shock across energy segments and those on loans to firms outside the energy sector. To do so, we estimate firm and industry level "excess loan premia" (ELP) following a similar methodology to Gilchrist and Zakrajšek [2012]'s corporate bond application. Most crucially, our ELP measure controls for time-varying changes in firm risk. The risk-adjusted ELP allows us to disentangle pricing changes resulting from an increase in default probability among affected firms from changes in pricing terms dictated by banks. More specifically, the ELP provides a time-varying estimate of the price banks charge *for a given risk level*. We interpret changes in the ELP as a measure of bank loan standards where a positive (negative) ELP suggests tighter (easier) loan standards because observed spreads are higher (lower) than historical norms for a given risk level.

## 3.3 Loan Level Data and Summary Statistics

We utilize loan level data on large corporate loans from the Federal Reserve's FR-Y14Q to estimate the ELP. The FR-Y14Q is a loan level dataset collected for stress testing purposes by the Federal Reserve Board. We focus on commercial and industrial (C&I) loans which are collected for commitments of $1 million or greater from systemically important banks. The data collection begins in 2011 but we follow standard FR-Y14Q use conventions and eliminate the first several quarters when data errors are most likely prominent. Our sample runs from 2012:Q3 to 2017:Q2 – the three years before the start of the 2014 oil price shock (2014:Q3) to three years after.

We exclude loans based on several criteria from the FR-Y14Q sample. We delete loans that are observed for only one quarter, loans with missing reporting quarters, loan purposes, and facility types, loans without taxpayer identification numbers (TINs), and loans that are reclassified to another loan schedule at any point in their history, which likely reflects a coding error. We also drop loans to banking, insurance, or administrative entities, loans to individuals, loans whose borrowers are missing or marked confidential, and loans to special purpose vehicles and foreign obligors. We drop loans with negative interest rate spreads, loans with missing commitment or outstanding values, and evergreen loans that never report a maturity date. Finally, we drop loans that are observed after maturity and those to firms that have negative sales or assets.

In total, our FR-Y14Q sample has about 1.4 million loan quarters. Summary statistics by industrial sector for the loans in our sample are reported in table 3. Firms are classified into those unrelated to the energy industry (non-oil) and those in various segments of the energy industry. The table shows that upstream and support service firms pay slightly higher interest rates over the full sample than other energy segments and non-energy firms. Commitment sizes and outstanding loan amounts are higher for energy firms compared to non-oil, underscoring the industry's demand for bank financing. Energy sector loan maturities are similar to those of non-energy firms and most loans in our sample are revolving lines of credit which are used for general, working capital purposes. Some energy segments, such as upstream and midstream, rely heavily on bank funded revolving loans compared to other segments and the non-oil sector which is roughly evenly split with term loans. Approximately 30 percent of our loan quarters can be attributed to public firms matched to S&P's Global Market Intelligence Compustat data.[10]

Table 4 reports summary statistics for borrowers in our FR-Y14Q loan sample. Overall the energy sector has assets, returns (ROA), and financial leverage similar to non-oil firms. While energy firms have higher fixed assets compared to non-oil firms, only upstream and support services firms have greater capital expenditures than the average non-oil firm. Midstream and downstream companies deploy capital in long-lived capital projects (e.g., pipelines and refineries) that last for multiple decades. On the other hand oil and gas wells are shorter-lived investments by comparison. Thus, upstream and support firms are constantly reinvesting in drilling and completing new oil wells. Overall, this table underscores that the energy industry is capital intensive, especially upstream and support firms.

[10]Public firms tend to be larger and hence usually have larger loan commitments. Public firm commitments are about 50 percent of total commitments.

Table 3: Loan Level Summary Stats

| | (1)<br>Non-oil | (2)<br>Downstream | (3)<br>Midstream | (4)<br>Support Services | (5)<br>Upstream |
|---|---|---|---|---|---|
| ***Interest Rates*** | | | | | |
| ln(*Spread*) | 5.240 | 5.199 | 5.235 | 5.454 | 5.378 |
| | (0.655) | (0.546) | (0.524) | (0.592) | (0.476) |
| *Spread* | 138.110 | 114.528 | 135.722 | 173.208 | 168.791 |
| | (138.274) | (123.012) | (123.578) | (161.453) | (142.715) |
| ***Loan Terms*** | | | | | |
| *Commitment ($ millions)* | 17.659 | 38.125 | 30.706 | 24.273 | 44.683 |
| | (42.303) | (69.826) | (39.202) | (45.923) | (56.531) |
| *Outstanding ($ millions)* | 6.583 | 7.991 | 10.015 | 7.892 | 15.679 |
| | (18.185) | (19.848) | (17.088) | (13.369) | (20.297) |
| *Maturity (years)* | 2.657 | 3.148 | 2.778 | 2.668 | 2.993 |
| | (2.756) | (2.939) | (2.097) | (1.982) | (1.972) |
| *Public(% loans)* | 0.163 | 0.223 | 0.185 | 0.246 | 0.297 |
| | (0.370) | (0.416) | (0.388) | (0.431) | (0.457) |
| ***Loan Type*** | | | | | |
| *Revolver* | 0.549 | 0.561 | 0.722 | 0.540 | 0.812 |
| | (0.498) | (0.496) | (0.448) | (0.498) | (0.391) |
| *Term* | 0.247 | 0.219 | 0.149 | 0.263 | 0.092 |
| | (0.431) | (0.414) | (0.356) | (0.440) | (0.289) |
| *Other* | 0.204 | 0.220 | 0.129 | 0.197 | 0.096 |
| | (0.403) | (0.414) | (0.336) | (0.398) | (0.294) |
| *Undrawn* | 0.290 | 0.399 | 0.302 | 0.271 | 0.260 |
| | (0.454) | (0.490) | (0.459) | (0.445) | (0.439) |
| ***Loan Purpose*** | | | | | |
| *General Purpose* | 0.694 | 0.700 | 0.798 | 0.725 | 0.773 |
| | (0.461) | (0.458) | (0.401) | (0.446) | (0.419) |
| *Acquisition* | 0.061 | 0.045 | 0.043 | 0.039 | 0.045 |
| | (0.239) | (0.207) | (0.202) | (0.193) | (0.207) |
| *Project Financing* | 0.073 | 0.048 | 0.060 | 0.126 | 0.045 |
| | (0.260) | (0.214) | (0.237) | (0.332) | (0.208) |
| *Financial Backup* | 0.061 | 0.070 | 0.040 | 0.056 | 0.076 |
| | (0.239) | (0.255) | (0.195) | (0.230) | (0.265) |
| *Real Estate/Ag* | 0.023 | 0.040 | 0.008 | 0.004 | 0.016 |
| | (0.151) | (0.196) | (0.092) | (0.065) | (0.126) |
| *Other* | 0.089 | 0.097 | 0.051 | 0.049 | 0.045 |
| | (0.284) | (0.296) | (0.220) | (0.217) | (0.208) |
| Observations | 1,340,030 | 14,549 | 24,982 | 24,329 | 33,713 |

Table reports summary stats for loan-level Y14 data from 2012:Q2 to 2017:Q2. Variable means shown, standard deviations in parentheses. Public firms are borrowers matched to compustat data.

Table 4: Loan Level Borrower Summary Stats

| | (1) Non-oil | (2) Downstream | (3) Midstream | (4) Support Services | (5) Upstream |
|---|---|---|---|---|---|
| ln(*Assets*) | 19.023 | 20.235 | 20.104 | 19.677 | 21.116 |
| | (3.213) | (2.986) | (3.107) | (3.077) | (2.633) |
| *ROA* | 14.046 | 11.648 | 10.872 | 11.200 | 8.622 |
| | (19.168) | (14.876) | (16.700) | (19.683) | (21.219) |
| *Leverage* | 42.836 | 39.772 | 43.263 | 41.050 | 49.925 |
| | (31.835) | (28.297) | (29.097) | (30.254) | (32.035) |
| *Debt EBITDA* | 6.311 | 4.886 | 6.666 | 5.818 | 7.390 |
| | (8.609) | (6.995) | (7.658) | (8.469) | (9.220) |
| *Capex to Total Assets* | 6.358 | 5.881 | 5.919 | 7.830 | 9.393 |
| | (10.889) | (10.884) | (12.018) | (13.019) | (15.053) |
| *Fixed Assets to Total Assets* | 34.588 | 54.625 | 51.743 | 50.893 | 76.416 |
| | (30.550) | (22.364) | (29.566) | (28.655) | (22.194) |
| *Tangible Assets to Total Assets* | 85.815 | 91.040 | 91.259 | 88.122 | 97.096 |
| | (21.847) | (12.694) | (12.581) | (17.803) | (10.461) |
| Observations | 1,340,030 | 14,549 | 24,982 | 24,329 | 33,713 |

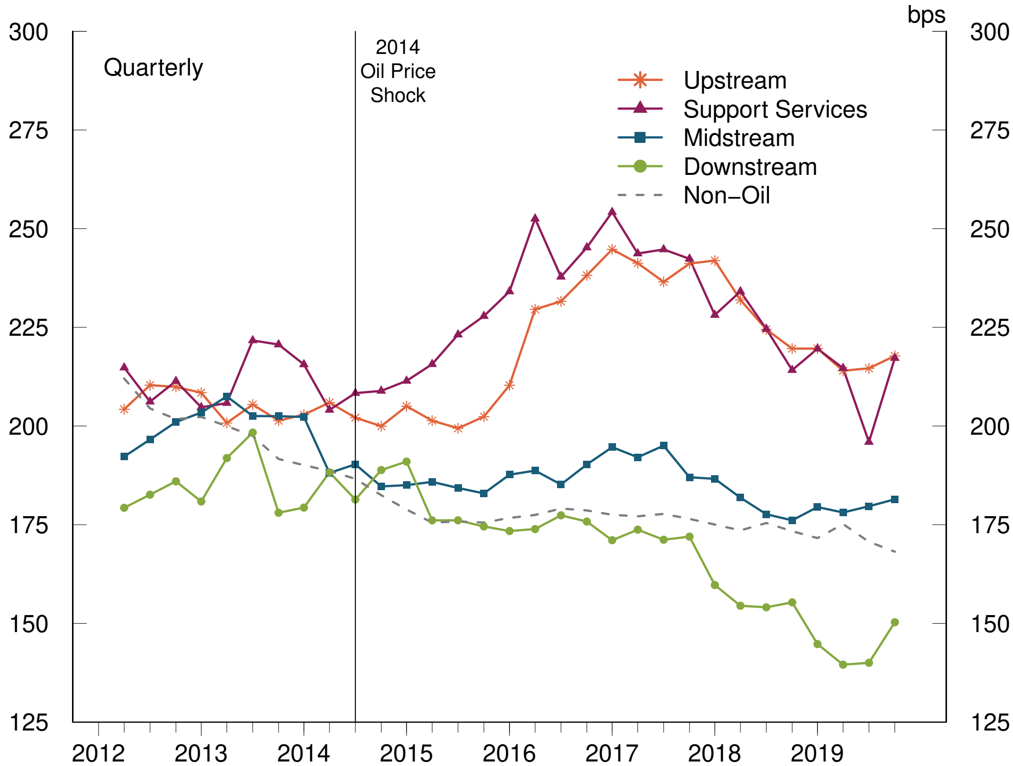
Table reports summary stats for borrower characteristics reported in the loan-level FR-Y14 data from 2012:Q2 to 2017:Q2. Variable means shown, standard deviations in parentheses.

# 4 Bank Responses to the 2014 Oil Price Shock

Due to their informational advantages, we expect that banks will respond differentially to industries most impacted by an economic shock. Intuitively, lower profitability and higher bankruptcy probability should raise the cost of bank loans for affected firms. While higher loans spreads for riskier firms seems obvious, it is less clear how spreads may vary for the same level of risk over time, a condition that may indicate changing lending standards. If banks can accurately discern the most affected industry segments, we expect to see an increase in risk-adjusted spreads for affected firms. On the other hand, if banks are concerned that risks from falling oil prices will spill over to the broader economy and affect a wider variety of firms, then borrowing costs may rise more generally across the energy spectrum and potentially for non-energy firms too.

Figure 3 shows that following the 2014 oil price shock, average spreads increased on loans to upstream and support services firms, the most affected energy segments (see section 2). Average spreads, weighted by commitment size, increased about 50

Figure 3: Weighted Average Loan Spreads to LIBOR




Note: Spreads are weighted by total commitment size. Spreads are only available for drawn loans. Source: FR Y14Q (Federal Reserve Board) and author's calculations.

basis points for the upstream and support service segments beginning in late-2014 as oil prices plummeted. While there was limited movement in spreads in late-2014 to early-2015, spreads on loans to upstream and support services firms rose steadily from mid-2015 to mid-2017 as the price slump lingered on. While some of these lagged increases reflect contractual issues that likely prevent banks from immediately repricing loans, they also reflect the steady deterioration in the financial conditions of upstream and support services companies beginning in mid-2015 that resulted in increased bankruptcies [Boone, 2022]. For lenders, it likely became clear by mid-2015 that the oil price shock was persistent and affected borrower credit quality had deteriorated significantly, causing banks to increase average loan spreads.[11]

Average spreads for firms other than upstream and support services firms remained stable or even declined from 2012 to 2017, reflecting continued improvement in broader economic conditions during this time underscoring the fact that these other firms were largely insulated from the 2014 oil shock. While our analysis ends in 2017:Q2, spreads for upstream and support services companies level off in 2017 and begin declining by late 2017, coinciding with rising oil prices and improving fundamentals for these energy segments (see figure 1).

In addition to rising loan prices, loan commitments also fell for the most affected firms. Figure 4 reports aggregate loan commitments across the non-oil and energy segments from 2012 to 2020. Overall, aggregate loan commitments increased during this period as shown by the rising level of commitments for non-oil firms. However, commitments to upstream and support services firms declined steadily after oil prices declined, coincident with the increase in loan spreads. Conversely, borrowing by midstream and downstream firms was rising and steady, respectively, over this period.[12]

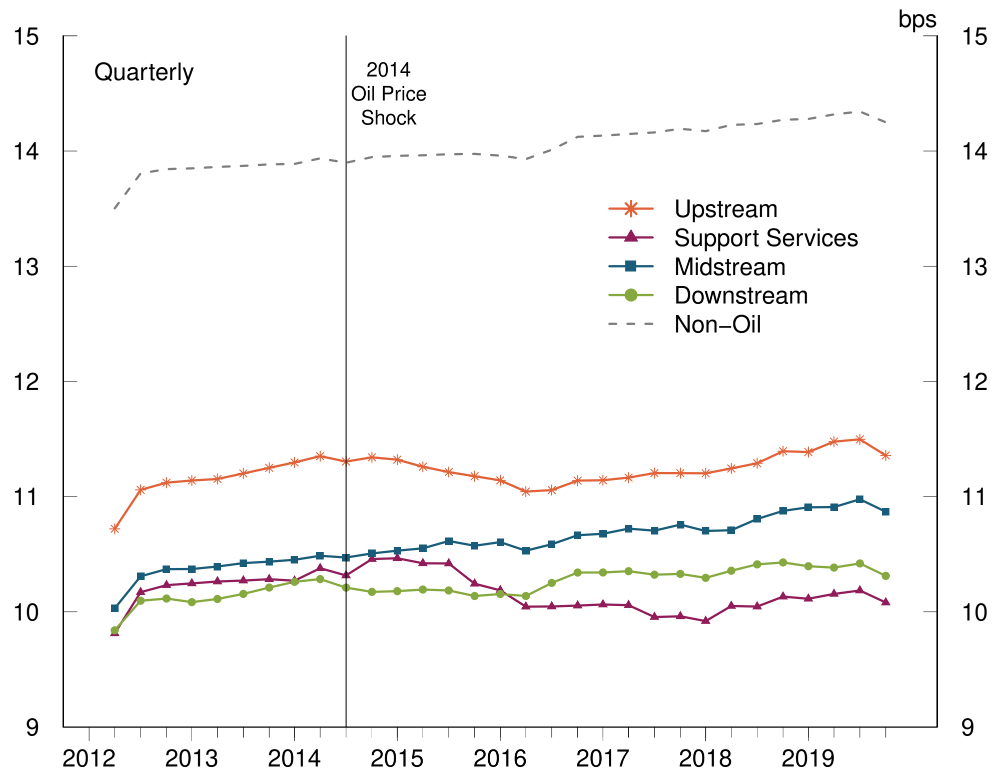
We formally test that credit constraints were rising for affected firms following the oil price shock using a two-way fixed effects model of the form shown in equation 2. This specification regresses an outcome variable ($y_{i,t}$) of loan $i$ at time $t$ on a set of loan ($\gamma_i$) and time ($\tau_t$) fixed effects and a set of interactions of indicators for energy borrower subsectors and an indicator for the post oil-price shock period, $Post_t$.[13] That is, the subsector-by-post-shock indicator denotes firms which we believe to be

[11] Credit ratings agency downgrades during this period further confirm the expected long-term deterioration upstream and support services firm conditions. See for example Offshore Energy [2016].

[12] Appendices C and D report aggregate commitments on outstanding and new loans, respectively, by term and revolving loan types. These totals suggest that aggregate lending declined for both loan types following the oil price shock, but revolving commitments fell most precipitously. This suggests that banks drove the tightening in lending standards during this period because non-bank investors are more likely to be the ultimate holders of term loans.

[13] In alternative specifications reported in appendix E, we include replace the loan fixed effects with loan controls such as remaining maturity, commitment, and loan type because loan fixed effects soak up nearly all the reported variation as discussed later. We report regressions that include bank fixed effects which control for average differences in loan spreads across loan issuers.

Figure 4: Total Loan Commitments




Source: FR Y14Q (Federal Reserve Board) and author's calculations.

"treated" following the decline in oil prices. We estimate this regression using the loan sample from 2012:Q3 to 2017:Q2 and the $Post_t$ indicator denotes the three year period following the 2014:Q3 oil price shock.

$$y_{i,t} = \beta_1 subsector_j \times Post_t + \gamma_i + \tau_t + \varepsilon_{i,t} \tag{2}$$

The results are shown in Table 5. We estimate the specification for all loans in our sample and then separately for revolving and term loans. We consider loan spreads and commitment sizes as outcome variables whose combined movements may indicate tightening of loan terms and standards as discussed above. In addition, we consider a binary outcome variable which is one for newly originated loans. This variable captures the propensity of banks to originate new loans. For revolving loans we also consider usage rates as an outcome variable which captures the drawn share of the loan relative to the total committed balance available to the firm. The coefficients, $\beta_i$, can be interpreted as the difference in the average outcome for an affected sector and the non-oil control group in the post-shock period. Standard errors are clustered by time and lending bank.

Consistent with the descriptive evidence shown in figures 3 and 4, our regression results suggest that credit availability tightened to firms most affected by the oil price decline. Panel A shows that, among all loans in our sample, spreads increased between 6 and 8 percent for upstream and support services firms in the three years following the oil price decline (column 1) compared to non-oil firms. For the full loan sample, we find only limited evidence that commitments declined for energy firms, however, the probability of observing a loan origination fell during this period for the upstream and support services firms. Together, these results suggest that the industry segments most affected by the oil price shock saw higher borrowing costs, smaller loans, and likely tighter origination standards following the collapse in oil prices.

In panel B, we examine revolving loans. Revolving loans are made with a specified commitment size and subject to demand withdraws by the borrower. Importantly, revolving loans are usually held on bank balance sheets because banks have the ability to fund the draws on demand whereas non-bank investors do not usually have sufficient liquidity to do so. In that regard, the revolving loan results provide stronger evidence of how banks tightened credit availability. In these specifications, we see that our main results from the full sample hold with greater statistical significance. We find that spreads on revolving loans increased about 7 to 8 percent for upstream and support services firms while loan commitments declined by around 10 percent. In addition, new loans were about 5 percent less likely to be originated. Finally, column (4) shows that upstream firms turned to additional bank financing by drawing on their existing lines of credit during the stress period with usage rates rising about 4 percent on average compared to non-oil firms.

Panel C examines the same outcomes for term loans. Term loans are gener-

Table 5: Price and Non-Price Terms

| Panel A: All Loans | Spread (1) | Commitment (2) | Orig (3) | Usage (4) |
|---|---|---|---|---|
| *Upstream × Post* | 0.063$^{***}$ | -0.048 | -0.027$^{**}$ | |
| | (0.022) | (0.035) | (0.012) | |
| *Support × Post* | 0.081$^{***}$ | -0.104$^{**}$ | -0.043$^{***}$ | |
| | (0.025) | (0.037) | (0.013) | |
| *Midstream × Post* | 0.024 | 0.005 | -0.021 | |
| | (0.016) | (0.021) | (0.013) | |
| *Downstream × Post* | 0.024 | 0.006 | -0.002 | |
| | (0.018) | (0.011) | (0.010) | |
| Observations | 730,903 | 1,378,438 | 1,378,438 | |
| Adjusted $R^2$ | 0.864 | 0.970 | 0.098 | |

| Panel B: Revolving Loans | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Upstream × Post* | 0.075$^{***}$ | -0.122$^{***}$ | -0.043$^{***}$ | 4.166$^{***}$ |
| | (0.026) | (0.038) | (0.012) | (1.250) |
| *Support × Post* | 0.079$^{***}$ | -0.094$^{**}$ | -0.046$^{***}$ | 1.169 |
| | (0.027) | (0.037) | (0.015) | (1.004) |
| *Midstream × Post* | 0.032 | -0.034 | -0.031$^{**}$ | -2.247 |
| | (0.019) | (0.021) | (0.014) | (1.315) |
| *Downstream × Post* | 0.043 | -0.012 | -0.015$^{*}$ | 2.387 |
| | (0.032) | (0.015) | (0.008) | (1.381) |
| Observations | 402,575 | 772,776 | 772,776 | 772,776 |
| Adjusted $R^2$ | 0.839 | 0.971 | 0.096 | 0.773 |

| Panel C: Term Loans | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Upstream × Post* | 0.014 | 0.021 | -0.054$^{*}$ | |
| | (0.014) | (0.048) | (0.028) | |
| *Support × Post* | 0.062$^{**}$ | -0.074 | -0.045$^{**}$ | |
| | (0.028) | (0.047) | (0.020) | |
| *Midstream × Post* | 0.002 | -0.007 | -0.033 | |
| | (0.033) | (0.038) | (0.029) | |
| *Downstream × Post* | 0.011 | 0.064$^{**}$ | 0.042$^{**}$ | |
| | (0.020) | (0.026) | (0.015) | |
| Observations | 200,199 | 330,892 | 330,892 | |
| Adjusted $R^2$ | 0.915 | 0.970 | 0.101 | |

Bank-time clustered standard errors in parentheses.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

ally fully-funded, amortizing loans that are held by non-bank investors because they generate a steady flow of interest payments. Hence, in the case of term loans, commitment amounts reflect the unpaid portion of the loan which may be callable. We find that term loan spreads increased about 6 percent for support services firms, but there was not a statistically significant effect for other energy segments. Consistent with the fact that term loan commitments are fully funded at origination, and hence not always subject to cuts due to borrower hardship, we find no evidence of lower commitments. Finally, term loan origination probabilities declined about 5 percent for both upstream and support services firms following the oil price decline.

Overall, the results of table 5 suggest that credit availability declined significantly for the energy segments most effected by the oil price declines. Revolving loans, which are typically subject to a number of loan covenants and material adverse change clauses which when triggered permit banks to change loan terms, showed rising spreads, falling commitments, and fewer originations. Term loans, whose characteristics are more rigid, had declining origination volumes. That is, term loan investors likely simply passed on renewing expiring loans or funding new projects due to the downturn in financial conditions at upstream and support services firms. Notably, pricing terms were more likely to change during this time as evidenced by the adjusted-$R^2$ reported in table 5. Because the adjusted-$R^2$ reports the explained share of variation, it will naturally rise when the outcome variables are less likely to change within loan over time. Overall, the reported adjusted-$R^2$s are typically high due to the inclusion on loan fixed effects which suggests few changes within existing loans. That said, there appears to be much greater variation in loan spreads than commitment amounts over the sample period. That is, banks were likely to increase the cost of debt but less likely to cut the commitment size. This may be due to the fact that usage rates increased at the onset of the shock when firms needed cash to offset revenue declines, leaving little room for banks to cut commitment amounts later once material change conditions were reached.

Next, we utilize an event study methodology to understand the time-varying nature of changes in credit conditions. To do so, we estimate equation 3 using our loan level sample. We interact the subsector classification indicator, $subsector_i$, with a quarter fixed effect, $\tau_t$. Loan ($\eta_i$) and quarter ($\tau_t$) fixed effects are included separately. We omit the quarter just prior to the oil price shock, 2014:Q2, as the reference category. We plot the quarterly coefficients on loan spreads in figure 5. Estimated 95 percent confidence intervals based on bank-clustered standard errors are reported in the blue shaded region. The loan spread result is qualitatively similar to the results for spreads and commitments on revolving loans which are reported in appendix F along with results for term loans.

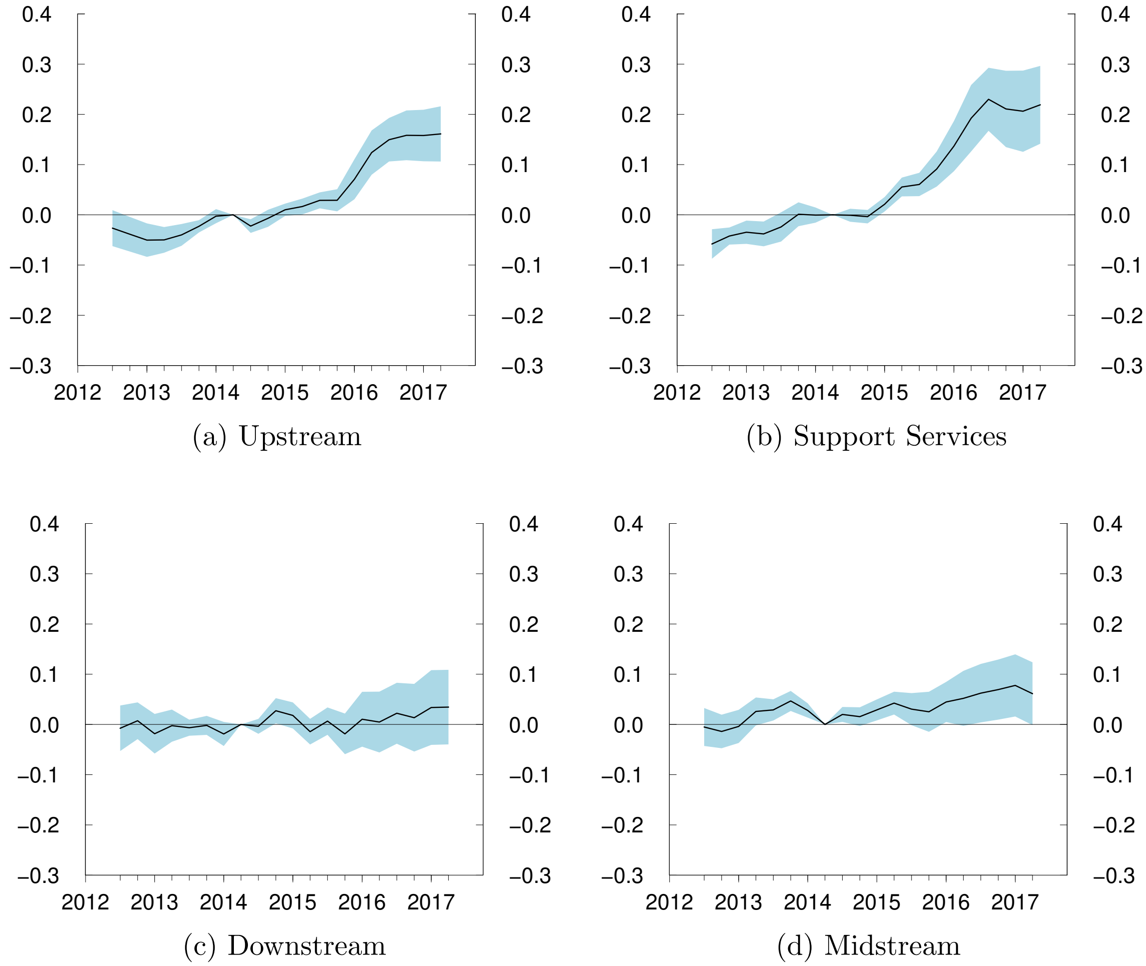
$$\ln(spread)_{i,t} = \sum^{J} \sum^{T} \beta_t subsector_j \times \tau_t + \eta_i + \tau_t + \varepsilon_{i,t} \tag{3}$$

The top two panels of Figure 5 show the interaction coefficients for upstream and support services firms. Loan spreads for each of these energy segments appear to have been rising modestly just prior to the shock. However, it is clear that spreads increased sharply in the quarters following the oil price collapse. For upstream firms, in panel 5a, spreads reached as high as 16 percent above comparable non-oil firms. Spreads on loans to support services firms rose by a similar magnitude, peaking at just above 23 percent relative to spreads just prior to the shock.

Midstream and downstream firms do not show the same increase in spreads as the upstream and support services segment, shown in panels 5c and 5d. Downstream firms have no statistically significant difference in spreads compared to non-oil firms throughout our post-2014 shock sample window. Midstream firms demonstrate weak and inconsistent statistical significance for higher post-2014 spreads. The magnitudes for higher spreads is also much lower than upstream or support at just under 8 percent – results that are consistent with the view that midstream firms were broadly unaffected the 2014 shock.

Overall, these event study results reflect the fact that banks increased loan pricing on firms that faced the most severe stress. However, this pricing effect took place gradually and followed the general contours of a persistent and deepening shock. Additional results in the appendix show that commitment amounts also declined in a similar fashion for upstream and support services firms, suggesting that affected firms faced a significant supply shock following the decline in oil prices. As demonstrated

Figure 5: Loan Spread Event Study Plots




(a) Upstream

(b) Support Services

(c) Downstream

(d) Midstream

Note: Solid line shows parameter estimates. Shaded area shows 95 percent confidence interval based on bank clustered standard errors. Results are relative to non-oil firms in the 2014:Q2 period (ie. the omitted groups).

with the two-way fixed effects results, these results are strongest for the revolving loan sample, over which banks have greater discretion to modify loan terms as stress increases on the firms.

# 5 Lending Terms and Real Outcome Effects

While changes in spreads, commitments, and origination probabilities are suggestive of tightening credit conditions, these observations are equilibrium outcomes driven by both supply and demand effects. For example, new origination volume may fall if demand for credit declines when profitable investment opportunities become more scarce. Similarly, borrowers may demand smaller loan sizes should investment opportunities fall or operating costs decline in the medium to long-run and credit needs diminish, explaining lower total commitments. Spreads, on the other hand, are expected to rise as firm risk increases so it is unclear that rising credit costs among financially stressed firms indicates credit tightening.

To better identify changes in bank-led credit conditions, we turn to a risk-adjusted measure of credit costs which we deem the "excess loan premium" (ELP). We calculate the ELP by closely following the excess bond premium methods of Gilchrist and Zakrajšek [2012]. Specifically, we estimate a regression in the form of equation 4 for each loan $i$ and quarter $t$. In this equation, we regress the log of the loan spread on a time-varying measure of loan risk, $PD_{i,t}$, and a set of loan and firm controls. We estimate this equation for the full FR-Y14Q sample to 2019:Q4 and use the parameters to calculate predicted spreads conditional on loan risk at time $t$. That is, $\alpha_1$ is the average price of risk over the full sample for a given level of $PD_{i,t}$. We then define the ELP as the difference between the observed spread and the predicted spread, $\ln(\widehat{spread})$, as shown in equation 5.

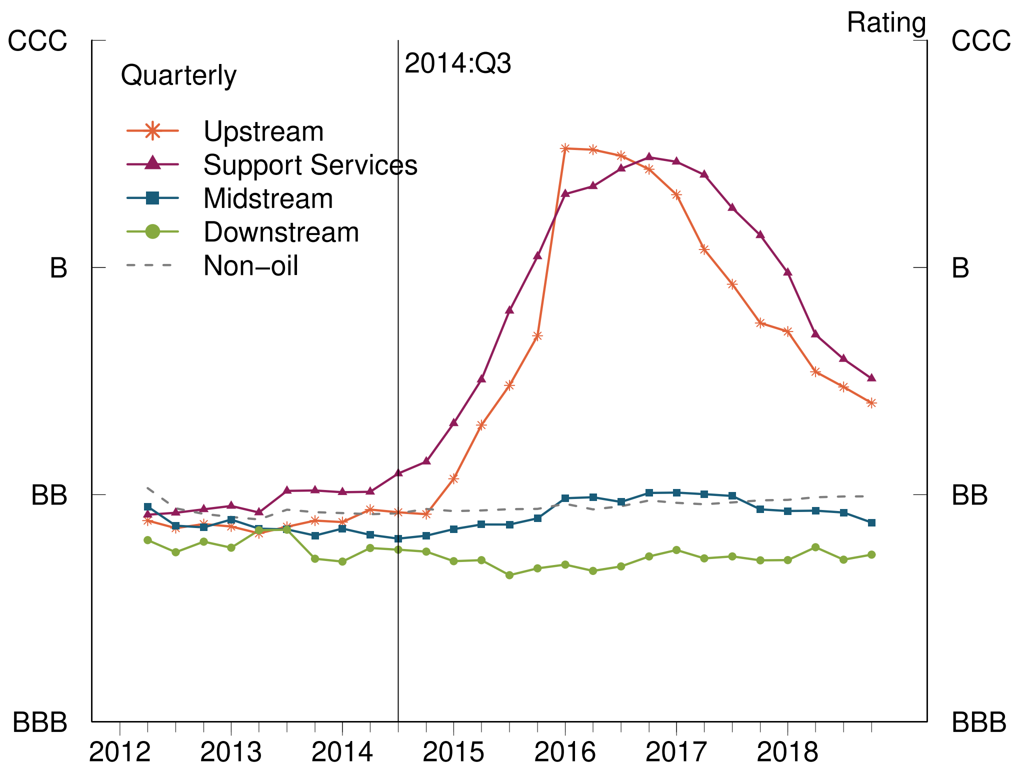
$$\ln(spread) = \alpha_0 + \alpha_1 PD_{i,t} + \alpha_2 X_{i,t} + \varepsilon_{i,t} \quad (4)$$

$$ELP = \ln(spread) - \ln(\widehat{spread}) \quad (5)$$

The predicted spread in equation 4 quantifies the expected loan spread based on historical pricing dynamics in the sample for a given level of risk. The ELP is the additional price that banks charge over and above what they have historically demanded for a given risk level. We interpret a positive ELP as a tightening of credit conditions because the ELP quantifies the additional amount firms are paying for credit after taking into account any increase in risk. Finally, it should be noted that the ELP cannot help us separate loan pricing changes resulting from cash flow changes and changes in collateral values, such as declines in the value of oil reserves. Therefore, sufficient statistics for the $PD_{i,t}$ measure must reflect both expected future cash flows and the current market value of assets.

To measure loan risk, we use the internal risk rating assigned by the bank holding company to each loan at time $t$. These risk ratings are used institutionally to calcu-

Figure 6: Average Loan Ratings by Sector




Note: Average loan rating is calculated by converting a standardized Moody's rating scale to a numeric scale where AAA is 1 and D is 11 and averaging across all loans. Unrated loans are removed from figure 6.

Source: FR Y14Q (Federal Reserve Board) and author's calculations.

late expected losses on the bank's commercial loan portfolio. As such, the underlying methodologies should be subject to review by supervisory teams and banks have a strong incentive to accurately update these measures periodically. Indeed, figure 6 shows that average quarterly loan ratings deteriorated sharply for the most affected energy segments following the decline in oil prices while average loan ratings in other sub-industries were mostly flat.

Table 6 reports the results of estimating equation 4. We bucket loan ratings into the Moody's rating scale by including an indicator variable for each ratings notch. The omitted category are unrated loans. We also control for loan size and the loan maturity. Columns 1 to 5 of table 6 report specifications with various fixed effects for reporting bank, reporting quarter, bank-time, industry, and loan. In general, spreads are associated with risk measures as we would expect across specifications. Lower risk loans tend to have lower spreads as indicated by the negative and significant coefficients on the internal loan ratings notches. Similarly, large loans, which are likely issued to large firms, have lower spreads while longer maturity loans have higher spreads consistent with a positively sloped yield curve.

We use the estimates from table 6 to calculate our ELP measure.[14] In table 7, we regress our ELP measure in the three years following the oil price collapse on a set of loan and firm characteristics. As expected, the ELP is associated with common risk metrics. For example, larger firms, those with greater turnover, or revenue per asset dollar, and firms with higher interest coverage ratios have lower ELPs. Our ELP measure is also lower for larger loans and again higher for longer-maturity loans following the oil price shock. In addition, non-revolving loans, which are those more likely to be sold to non-bank investors, have higher ELPs than bank serviced revolving loans. Finally, ELPs fall with internal loan risk ratings during this period.

Figure 7 reports the quarterly average ELP by industry segment. Consistent with deterioration in financial well-being, ELPs increased primarily for upstream and support services segments after the oil price decline. In contrast, ELPs declined

[14] We follow Gilchrist and Zakrajšek [2012] to convert the ELP to basis points by calculating $\widehat{S_{i,t}} = \exp\left[\widehat{\ln S_{i,t}} + \frac{\hat{\sigma}^2}{2}\right]$ where $\hat{\sigma}^2$ is the model error variance from equation 4.

Table 6: Market-Based Firm Default Risk and Loan Spreads

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| ***Internal Loan Rating*** | | | | | |
| *AAA* | -1.613*** | -0.863*** | -0.851*** | -0.704*** | -0.502* |
| | (0.3175) | (0.1859) | (0.1849) | (0.1658) | (0.2706) |
| *AA* | -0.727*** | -0.662*** | -0.652*** | -0.674*** | -0.230** |
| | (0.1350) | (0.1210) | (0.1201) | (0.1213) | (0.0855) |
| *A* | -0.633*** | -0.501*** | -0.492*** | -0.520*** | -0.224** |
| | (0.1246) | (0.1173) | (0.1167) | (0.1191) | (0.0851) |
| *BBB* | -0.466*** | -0.363*** | -0.353*** | -0.381*** | -0.204** |
| | (0.1238) | (0.1174) | (0.1166) | (0.1189) | (0.0848) |
| *BB* | -0.245** | -0.161 | -0.151 | -0.175 | -0.160* |
| | (0.1239) | (0.1179) | (0.1170) | (0.1194) | (0.0847) |
| *B* | -0.087 | 0.010 | 0.020 | -0.004 | -0.108 |
| | (0.1231) | (0.1171) | (0.1162) | (0.1185) | (0.0842) |
| *CCC* | 0.063 | 0.153 | 0.162 | 0.128 | -0.018 |
| | (0.1232) | (0.1152) | (0.1144) | (0.1180) | (0.0846) |
| *CC* | 0.096 | 0.174 | 0.193 | 0.174 | 0.015 |
| | (0.1251) | (0.1194) | (0.1183) | (0.1205) | (0.0853) |
| *C* | 0.103 | 0.206 | 0.221* | 0.194 | 0.033 |
| | (0.1327) | (0.1274) | (0.1265) | (0.1291) | (0.0870) |
| *D* | 0.302** | 0.292** | 0.304** | 0.274** | 0.029 |
| | (0.1287) | (0.1229) | (0.1216) | (0.1239) | (0.0843) |
| ***Loan Terms*** | | | | | |
| ln(*commitment*) | -0.044*** | -0.032*** | -0.032*** | -0.031*** | 0.005 |
| | (0.0024) | (0.0027) | (0.0028) | (0.0029) | (0.0037) |
| ln(*maturity*) | 0.061*** | 0.024*** | 0.025*** | 0.024*** | -0.006*** |
| | (0.0040) | (0.0028) | (0.0029) | (0.0028) | (0.0010) |
| Observations | 983,772 | 983,772 | 983,772 | 983,772 | 968,613 |
| Adjusted $R^2$ | 0.089 | 0.227 | 0.228 | 0.270 | 0.855 |
| Industry FE | No | Yes | Yes | Yes | No |
| Bank FE | No | Yes | Yes | No | No |
| Time FE | No | No | Yes | No | Yes |
| Bank-Time FE | No | No | No | Yes | No |
| Loan FE | No | No | No | No | Yes |

Two-way firm-time clustered standard errors in parentheses.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 7: ELP Associations with Firm and Loan Characteristics

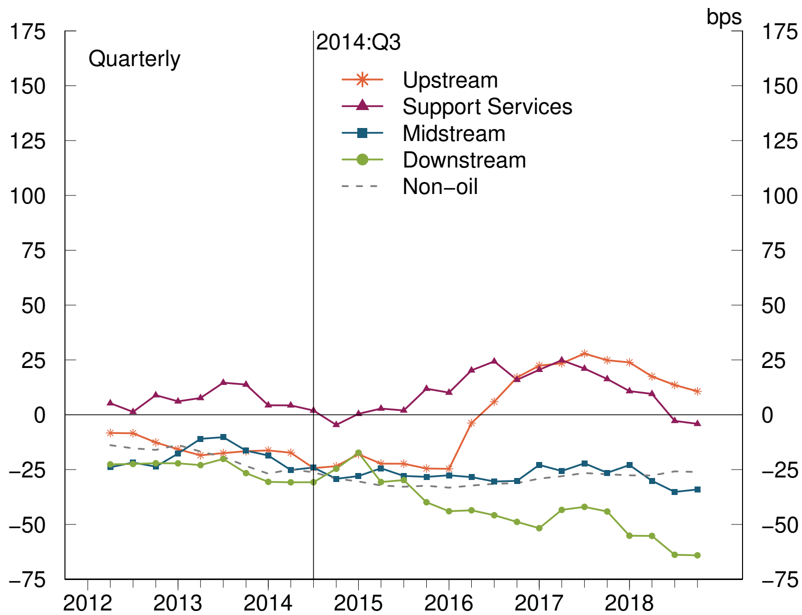
| | | |
|---|---|---|
| ***Borrower Characteristics*** | | |
| ln(*assets*) | -4.565*** | (1.045) |
| *Turnover* | -0.039*** | (0.011) |
| *Interest Coverage* | -0.024* | (0.014) |
| *ROA* | -0.059 | (0.238) |
| ***Loan Characteristics*** | | |
| ln(*commitment*) | -6.426*** | (2.294) |
| ln(*maturity*) | 6.628*** | (1.455) |
| *Term* | 24.851*** | (6.748) |
| *Other Loans* | 19.583*** | (6.041) |
| ***Loan Ratings*** | | |
| *AAA* | -114.107*** | (32.627) |
| *AA* | -131.283*** | (22.204) |
| *A* | -124.544*** | (21.953) |
| *BBB* | -109.411*** | (21.268) |
| *BB* | -79.986*** | (20.651) |
| *B* | -42.647*** | (10.349) |
| *CCC* | -40.365** | (19.640) |
| *CC* | -30.933* | (18.360) |
| *C* | -36.284* | (20.773) |
| *D* | 19.038 | (22.778) |
| *Constant* | 157.308*** | (26.811) |
| Observations | 395,544 | |
| Adjusted $R^2$ | 0.146 | |

Note: Regressions report association between the ELP and firm and loan characteristics reported on the FR-Y14Q in the 3-year following the oil price shock (2014:Q3-2017Q3). Return-on-assets (ROA) and interest coverage ratios are windsorized at the 1 percent level. Regressions also control for loan purpose (not reported). Two-way, firm-time clustered standard errors in parentheses.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

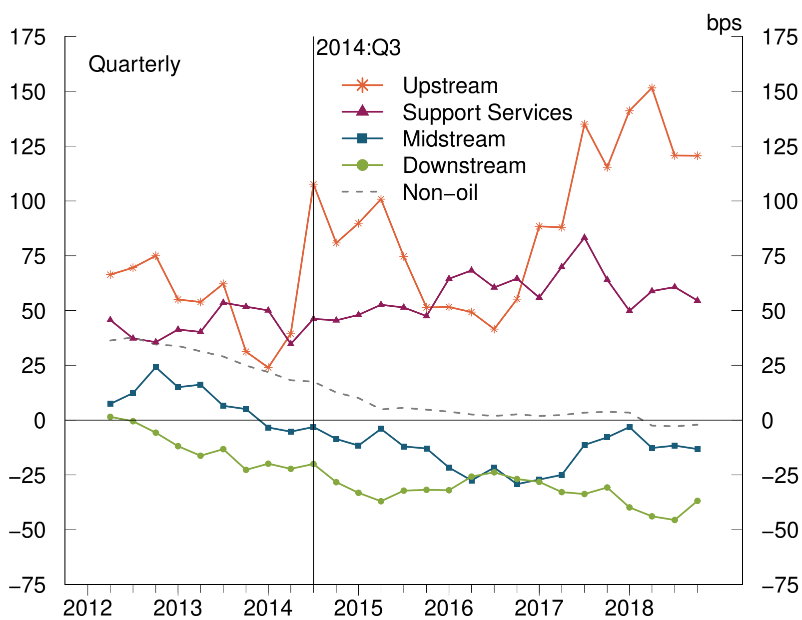
for most other economic sectors consistent with a broad improvement in economic conditions.

However, the ELP level varies drastically across loan types. Estimated ELPs

Figure 7: Average Excess Loan Premia




(a) Revolving Loans




(b) Term Loans

peaked at around 25 basis points for revolving loans compared to nearly 150 basis points for term loans. This likely reflects differences in the ultimate loan holders for these loan types. These differences may also reflect the information advantages of banks who tend to hold and service the revolving loans. That is, banks may be better able to assess the true financial condition of the borrowing firm using relationship histories and contacts which results in lower borrowing spreads compared to term loan borrowers where information asymmetries may be more acute.

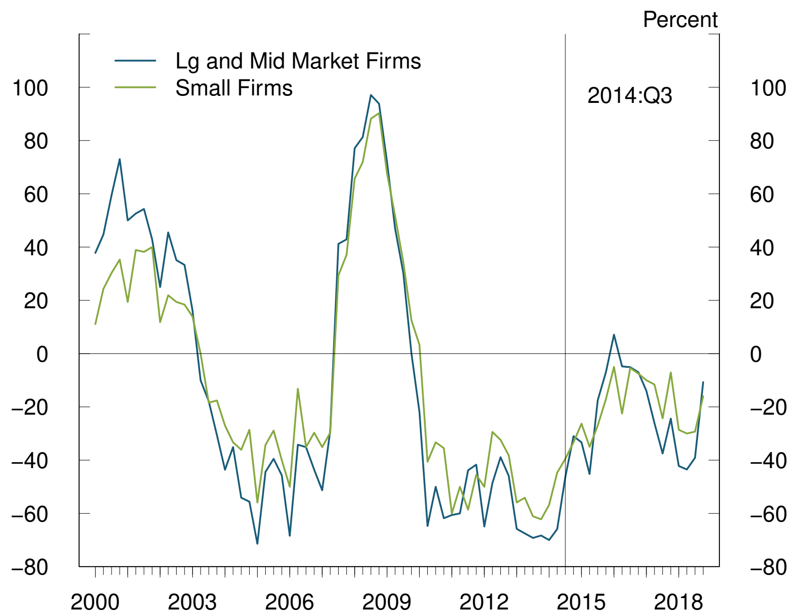
It should also be noted that while ELPs increased after the 2014 oil price shock, they did so only with a significant lag for revolving loans. This delay on committed lines of credit likely provides an important safety valve for distressed borrowers. That is, firms suffering revenue shocks can draw on committed lines for credit to smooth out income volatility. Only after some time can banks act to reduce credit limits, increase borrowing costs, and restrict loan originations.[15]

To better support our interpretation of the ELP as a measure of credit conditions, figure 8a shows reported changes in terms and standards on bank loans during the same period from the Federal Reserve's Senior Loan Officer Opinion Survey. Prior to the oil price collapse, about 60 percent of banks reported they were decreasing spreads across the commercial loan portfolio as shown in the left panel. Following the shock, however, banks, on net, reported no change in spreads for commercial loans. These trends held across the small, middle, and large market portfolios. Similarly, about 20 percent of banks reported increasing risk premia on commercial loans after the oil price collapse. These survey results are consistent with a sharp, but limited and selective, tightening of credit conditions following the decline in oil prices in 2014:Q3.

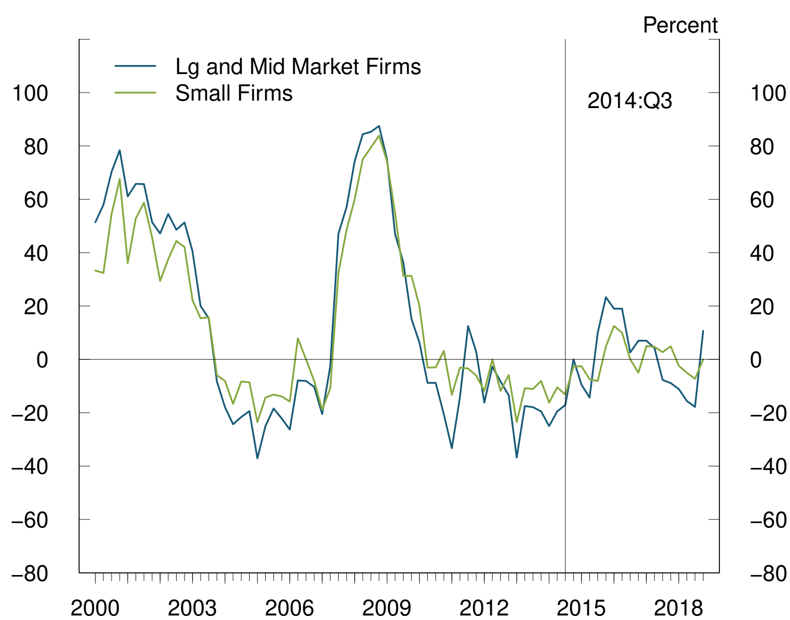
Overall, our results are consistent with several features of the literature. We find that revolving bank loans provide an important source of funds at the onset of a real economic shock to counter revenue losses and working capital needs. This support may give firms time to reduce costs by cutting production or reducing labor inputs

[15] Appendix G reports an alternative ELP measure based on Merton distance to default measures using equity prices of public firms rather than internal loan rating. Those results show a similar increase for affected firms. In addition, we that rising ELPs are associated with lower employment and investment outcomes using available firm-level data.

Figure 8: Changes in Large Bank C&I Loan Terms




(a) Increasing Spreads




(b) Increasing Risk Premia

Source: Senior Loan Officer Opinion Survey, Federal Reserve Board.

in response to an aggregate slowdown. However, during a persistent shock, bank credit availability falls with a lag, likely putting additional stress on firms as they work through the long-run implications of the shock.

## 6 Conclusion

We investigate how banks respond to oil price shocks that affect borrowers. We show that among energy firms, certain segments, namely those involved in the oil extraction business, were more affected. In response, these firms had poorer loan outcomes than firms less affected by the oil price shock. Moreover, banks tightened lending standards on loans to these firms, resulting in higher credit spreads than they otherwise would have faced.

Our results suggest firms face a dual shock from banks during adverse conditions. First, the shock itself can adversely affect profitability and asset values, reducing the ability of the firm to post collateral in order to lend. Second, the bank may respond by increasing pricing on fundamental risk, further constraining the firm's ability to borrow. Thus, affected firms likely face a sharp leftward shift in their loan supply curve, reducing credit availability.

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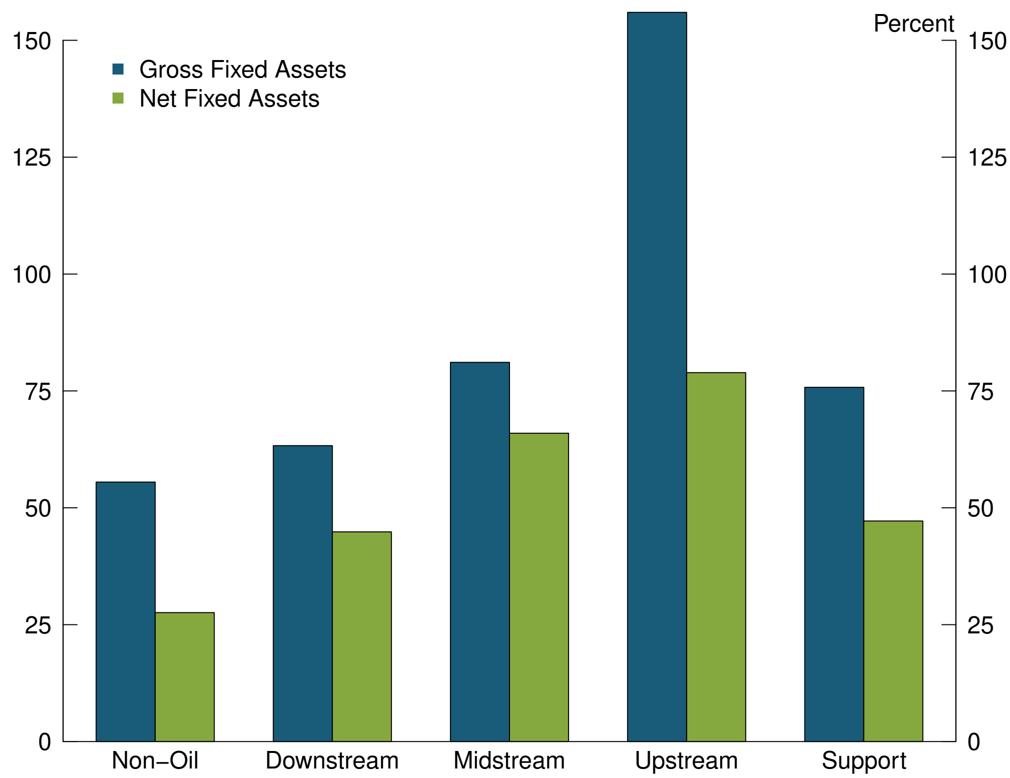
# 7 Appendices

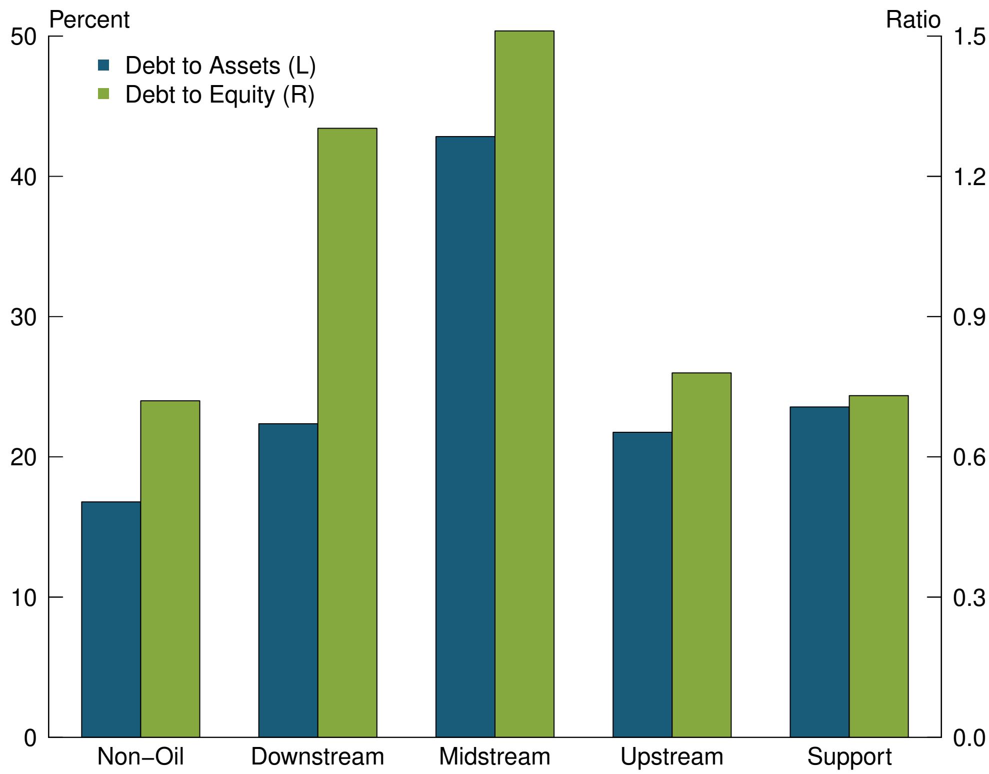
# A Energy Firm Assets and Financial Leverage

Figure A1: Average Fixed Asset Shares, 2012-2017




Source: S&P Global Market Intelligence Compustat.

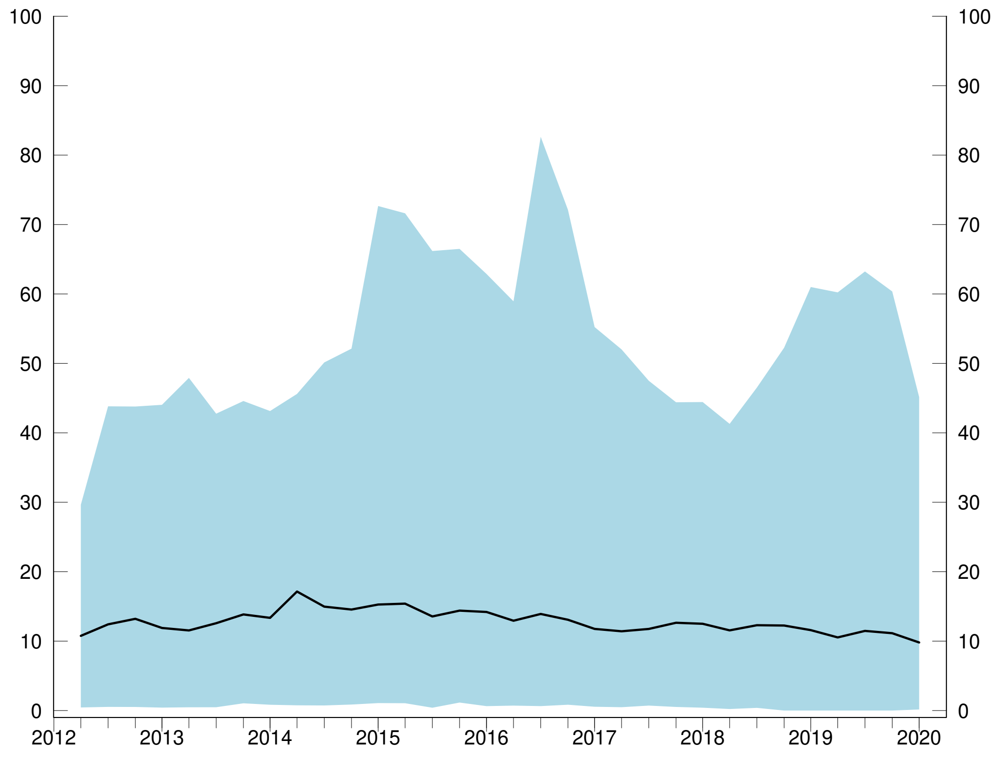
Figure A2: Median Leverage Ratios, 2012-2017




Source: S&P Global Market Intelligence Compustat.

# B Bank-level Oil Loan Exposures

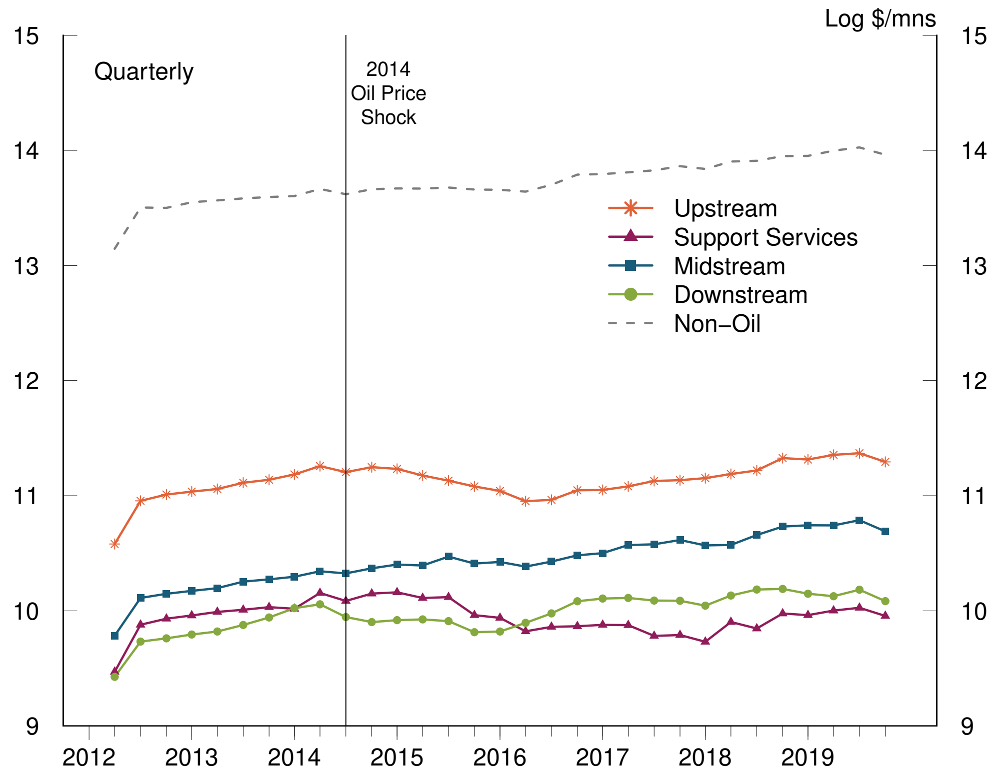
Figure B3: Reported energy loans as a Share of Tier 1 Capital




Note: Shaded area shows interquartile range of exposure as a percent of Tier 1. Black line shows median exposure share.
Source: Y14Q and FR-Y9C.

# C Total Loan Commitments

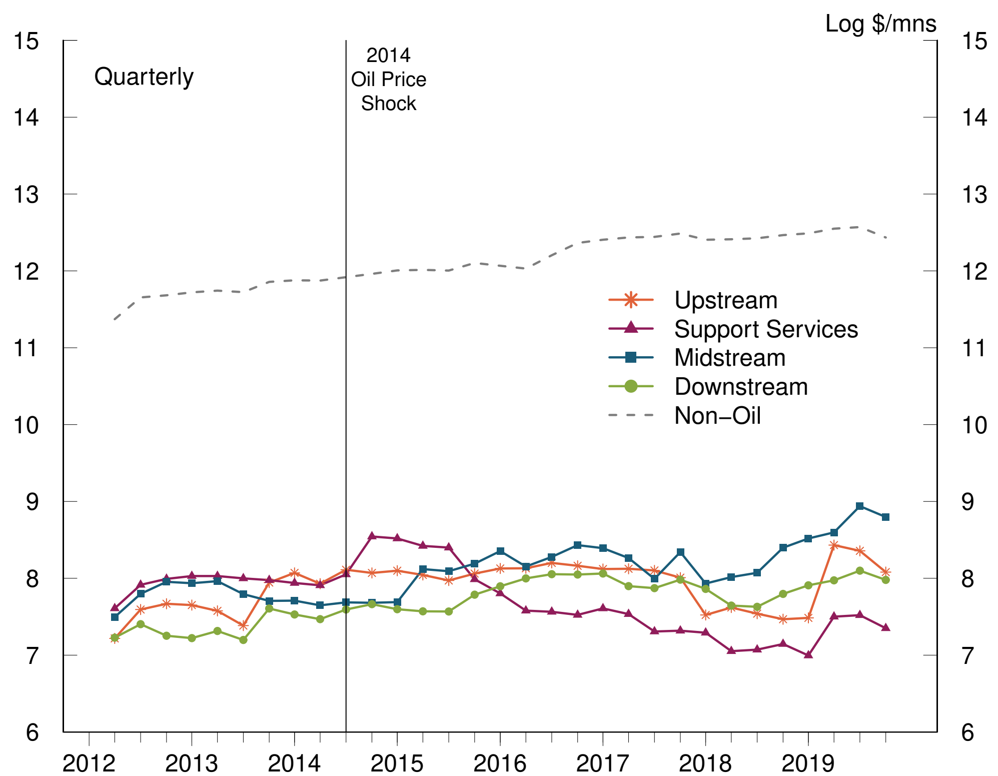
Figure C4: Revolving Loan Commitments




Note: Commitments in log scale.

Source: Federal Reserve Board, FR-Y14Q

Figure C5: Term Loan Commitments



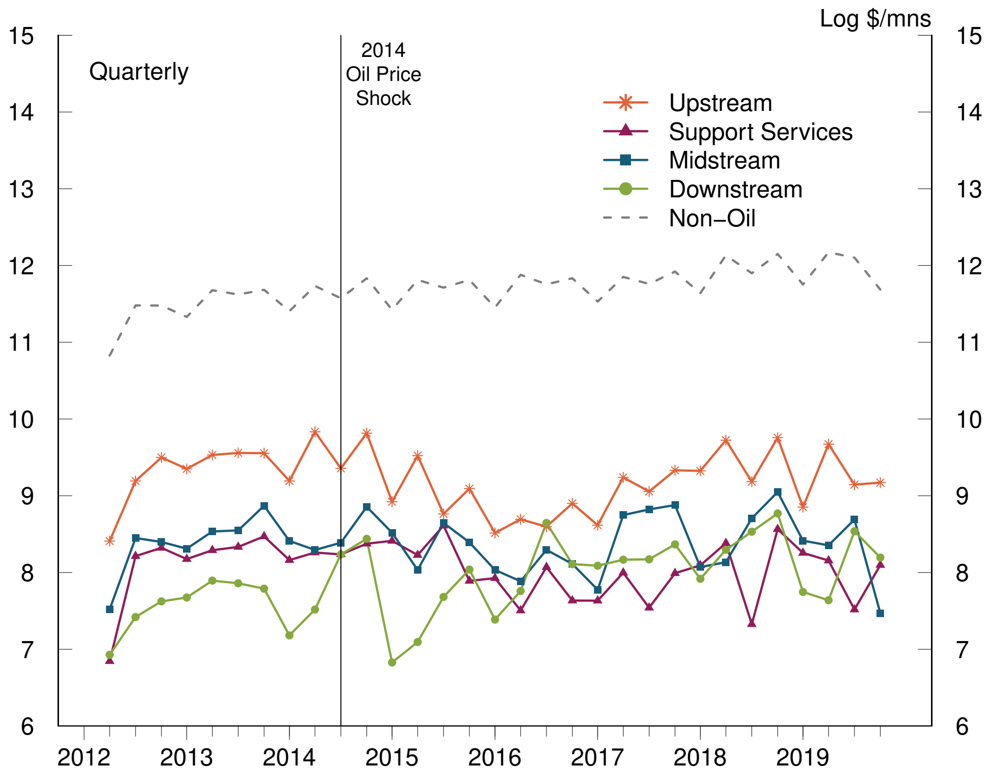

Note: Commitments in log scale.

Source: Federal Reserve Board, FR-Y14Q

# D Newly Originated Loan Commitments

# E Two-way Fixed Effects Regressions

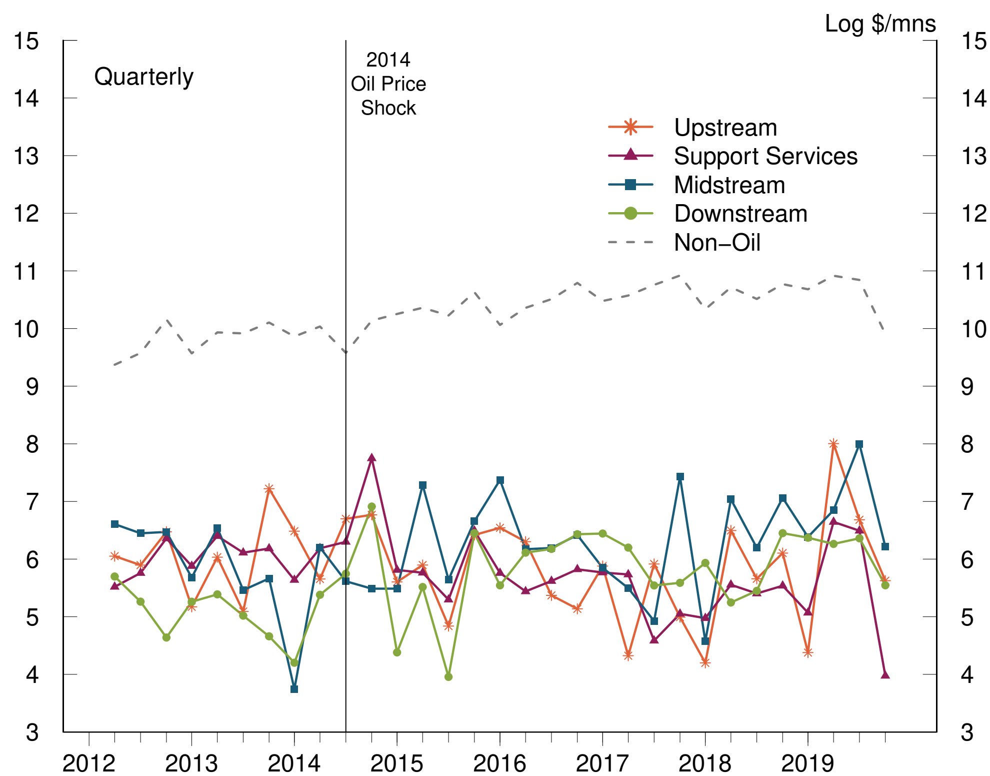
Figure D6: Newly Originated Revolving Loan Commitments




Note: Commitments in log scale.

Source: Federal Reserve Board, FR-Y14Q

Figure D7: Newly Originated Term Loan Commitments




Note: Commitments in log scale.

Source: Federal Reserve Board, FR-Y14Q

Table E1: Price and Non-Price Terms - All Loans

| Panel A: Spreads | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Upstream × Post* | 0.117*** | 0.097*** | 0.091*** | 0.063*** |
| | (0.028) | (0.025) | (0.025) | (0.022) |
| *Support × Post* | 0.108*** | 0.102*** | 0.110*** | 0.081*** |
| | (0.027) | (0.027) | (0.028) | (0.025) |
| *Midstream × Post* | -0.011 | -0.011 | -0.012 | 0.024 |
| | (0.020) | (0.017) | (0.017) | (0.016) |
| *Downstream × Post* | -0.029 | -0.044 | -0.038 | 0.024 |
| | (0.047) | (0.039) | (0.040) | (0.018) |
| Observations | 743,644 | 743,644 | 736,639 | 730,903 |
| Adjusted $R^2$ | 0.006 | 0.146 | 0.179 | 0.864 |
| Loan FE | N | N | N | Y |
| Loan Controls | N | N | Y | N |
| Bank FE | N | Y | Y | N |

| Panel B: Commitments | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Upstream × Post* | 0.013 | -0.022 | -0.016 | -0.048 |
| | (0.035) | (0.014) | (0.011) | (0.035) |
| *Support × Post* | 0.080** | 0.010 | 0.028 | -0.104** |
| | (0.036) | (0.043) | (0.050) | (0.037) |
| *Midstream × Post* | 0.175*** | 0.136** | 0.135** | 0.005 |
| | (0.051) | (0.062) | (0.052) | (0.021) |
| *Downstream × Post* | 0.054 | 0.017 | 0.050 | 0.006 |
| | (0.069) | (0.064) | (0.064) | (0.011) |
| Observations | 1,390,261 | 1,390,261 | 1,377,617 | 1,378,438 |
| Adjusted $R^2$ | 0.030 | 0.107 | 0.281 | 0.970 |
| Loan FE | N | N | N | Y |
| Loan Controls | N | N | Y | N |
| Bank FE | N | Y | Y | N |

| Panel C: Originations | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Upstream × Post* | -0.017** | -0.016** | -0.014* | -0.027** |
| | (0.007) | (0.007) | (0.008) | (0.012) |
| *Support × Post* | -0.027*** | -0.026** | -0.021** | -0.043*** |
| | (0.009) | (0.009) | (0.009) | (0.013) |
| *Midstream × Post* | -0.007 | -0.007 | -0.005 | -0.021 |
| | (0.006) | (0.006) | (0.006) | (0.013) |
| *Downstream × Post* | 0.002 | 0.003 | 0.004 | -0.002 |
| | (0.007) | (0.007) | (0.008) | (0.010) |
| Observations | 1,390,261 | 1,390,261 | 1,377,617 | 1,378,438 |
| Adjusted $R^2$ | 0.001 | 0.004 | 0.021 | 0.098 |
| Loan FE | N | N | N | Y |
| Loan Controls | N | N | Y | N |
| Bank FE | N | Y | Y | N |

Bank-time clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# Table E2: Price and Non-Price Terms - Revolving Loans

| Panel A: Spreads | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Upstream* × *Post* | 0.112*** | 0.080** | 0.072** | 0.075*** |
| | (0.038) | (0.034) | (0.033) | (0.026) |
| *Support* × *Post* | 0.104** | 0.078** | 0.065* | 0.079*** |
| | (0.036) | (0.037) | (0.036) | (0.027) |
| *Midstream* × *Post* | -0.001 | -0.011 | -0.014 | 0.032 |
| | (0.028) | (0.023) | (0.022) | (0.019) |
| *Downstream* × *Post* | -0.027 | -0.069 | -0.066 | 0.043 |
| | (0.057) | (0.049) | (0.048) | (0.032) |
| Observations | 411,125 | 411,125 | 406,283 | 402,575 |
| Adjusted $R^2$ | 0.007 | 0.162 | 0.181 | 0.839 |
| Loan FE | N | N | N | Y |
| Loan Controls | N | N | Y | N |
| Bank FE | N | Y | Y | N |

| Panel B: Commitments | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Upstream* × *Post* | 0.007 | -0.027** | -0.008 | -0.122*** |
| | (0.035) | (0.012) | (0.015) | (0.038) |
| *Support* × *Post* | 0.025 | -0.072 | -0.004 | -0.094** |
| | (0.052) | (0.072) | (0.067) | (0.037) |
| *Midstream* × *Post* | 0.158*** | 0.117** | 0.124*** | -0.034 |
| | (0.027) | (0.043) | (0.039) | (0.021) |
| *Downstream* × *Post* | 0.086 | 0.049 | 0.100 | -0.012 |
| | (0.096) | (0.092) | (0.081) | (0.015) |
| Observations | 778,945 | 778,945 | 770,584 | 772,776 |
| Adjusted $R^2$ | 0.033 | 0.140 | 0.327 | 0.971 |
| Loan FE | N | N | N | Y |
| Loan Controls | N | N | Y | N |
| Bank FE | N | Y | Y | N |

| Panel C: Originations | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Upstream* × *Post* | -0.006 | -0.006 | -0.003 | -0.043*** |
| | (0.007) | (0.007) | (0.007) | (0.012) |
| *Support* × *Post* | -0.025** | -0.024** | -0.022** | -0.046*** |
| | (0.010) | (0.010) | (0.010) | (0.015) |
| *Midstream* × *Post* | -0.006 | -0.006 | -0.004 | -0.031** |
| | (0.008) | (0.008) | (0.008) | (0.014) |
| *Downstream* × *Post* | -0.001 | -0.001 | 0.003 | -0.015* |
| | (0.007) | (0.007) | (0.007) | (0.008) |
| Observations | 778,945 | 778,945 | 770,584 | 772,776 |
| Adjusted $R^2$ | 0.002 | 0.007 | 0.024 | 0.096 |
| Loan FE | N | N | N | Y |
| Loan Controls | N | N | Y | N |
| Bank FE | N | Y | Y | N |

| Panel D: Usage Rate | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Upstream* × *Post* | 4.071** | 3.756** | 4.202** | 4.166*** |
| | (1.813) | (1.751) | (1.577) | (1.250) |
| *Support* × *Post* | 0.850 | 1.298 | 1.152 | 1.169 |
| | (1.218) | (1.118) | (1.098) | (1.004) |
| *Midstream* × *Post* | -0.678 | -0.532 | -0.270 | -2.247 |
| | (2.264) | (2.077) | (2.054) | (1.315) |
| *Downstream* × *Post* | 0.764 | 0.114 | -0.059 | 2.387 |
| | (3.195) | (2.967) | (2.633) | (1.381) |
| Observations | 778,945 | 778,945 | 770,584 | 772,776 |
| Adjusted $R^2$ | 0.006 | 0.037 | 0.057 | 0.773 |
| Loan FE | N | N | N | Y |
| Loan Controls | N | N | Y | N |
| Bank FE | N | Y | Y | N |

Bank-time clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E3: Price and Non-Price Terms - Term Loans

| Panel A: Spreads | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Upstream × Post* | 0.170* | 0.193** | 0.194** | 0.014 |
| | (0.094) | (0.089) | (0.090) | (0.014) |
| *Support × Post* | 0.171*** | 0.180*** | 0.193*** | 0.062** |
| | (0.044) | (0.037) | (0.040) | (0.028) |
| *Midstream × Post* | -0.071*** | -0.058*** | -0.057** | 0.002 |
| | (0.024) | (0.020) | (0.023) | (0.033) |
| *Downstream × Post* | -0.021 | 0.006 | 0.020 | 0.011 |
| | (0.059) | (0.052) | (0.051) | (0.020) |
| Observations | 204,279 | 204,279 | 203,382 | 200,199 |
| Adjusted $R^2$ | 0.012 | 0.173 | 0.189 | 0.915 |
| Loan FE | N | N | N | Y |
| Loan Controls | N | N | Y | N |
| Bank FE | N | Y | Y | N |

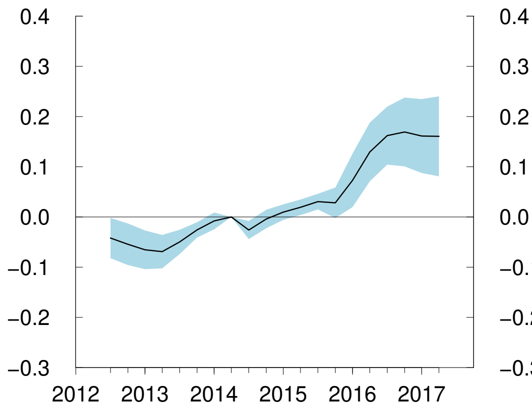
| Panel B: Commitments | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Upstream × Post* | 0.085 | -0.047 | -0.073 | 0.021 |
| | (0.097) | (0.113) | (0.107) | (0.048) |
| *Support × Post* | 0.006 | 0.020 | 0.050 | -0.074 |
| | (0.065) | (0.075) | (0.066) | (0.047) |
| *Midstream × Post* | 0.224* | 0.077 | 0.099 | -0.007 |
| | (0.127) | (0.116) | (0.099) | (0.038) |
| *Downstream × Post* | 0.199 | 0.174 | 0.232* | 0.064** |
| | (0.128) | (0.115) | (0.123) | (0.026) |
| Observations | 336,388 | 336,388 | 335,057 | 330,892 |
| Adjusted $R^2$ | 0.012 | 0.152 | 0.219 | 0.970 |
| Loan FE | N | N | N | Y |
| Loan Controls | N | N | Y | N |
| Bank FE | N | Y | Y | N |

| Panel C: Originations | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Upstream × Post* | -0.070** | -0.067** | -0.062** | -0.054* |
| | (0.029) | (0.029) | (0.028) | (0.028) |
| *Support × Post* | -0.033** | -0.032* | -0.025 | -0.045** |
| | (0.015) | (0.016) | (0.016) | (0.020) |
| *Midstream × Post* | -0.006 | -0.004 | -0.001 | -0.033 |
| | (0.012) | (0.012) | (0.012) | (0.029) |
| *Downstream × Post* | 0.015 | 0.021** | 0.017* | 0.042** |
| | (0.012) | (0.009) | (0.009) | (0.015) |
| Observations | 336,388 | 336,388 | 335,057 | 330,892 |
| Adjusted $R^2$ | 0.002 | 0.005 | 0.015 | 0.101 |
| Loan FE | N | N | N | Y |
| Loan Controls | N | N | Y | N |
| Bank FE | N | Y | Y | N |

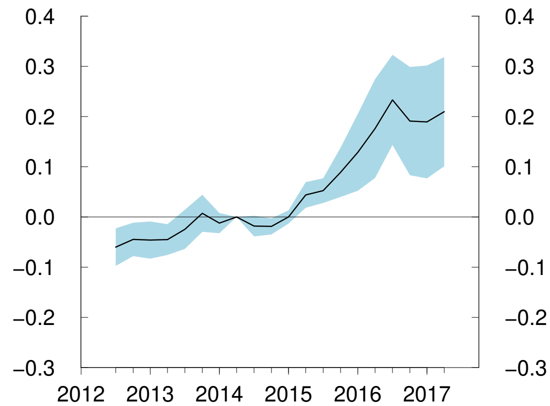
Bank-time clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# F Additional Event Study Plots

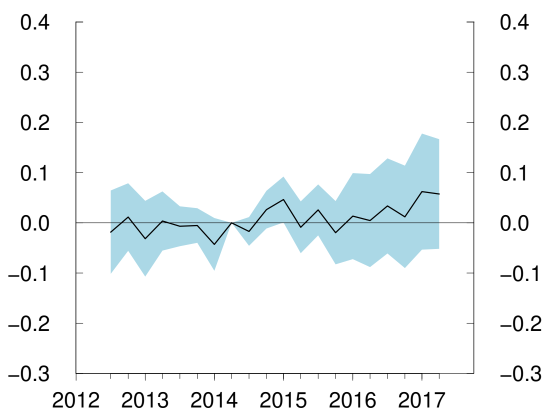
Figure F8: Revolver Spreads Event Study Plots



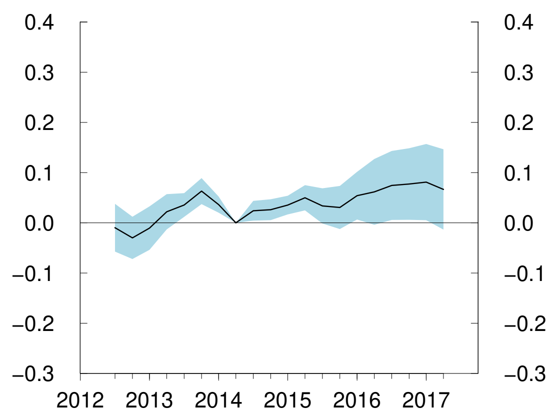

(a) Upstream




(b) Support Services



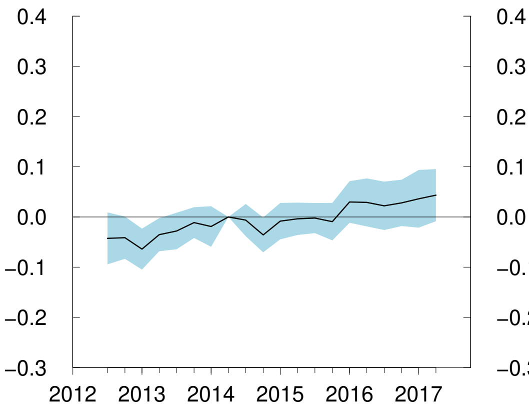

(c) Downstream



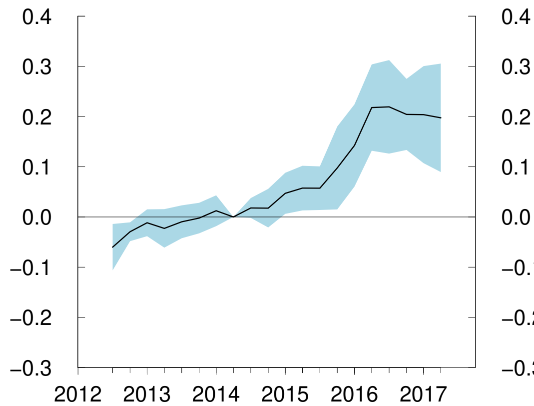

(d) Midstream

Note: Solid line shows parameter estimates. Shaded area shows 95 percent confidence interval based on bank clustered standard errors. Results are relative to non-oil firms in the 2014:Q2 period (ie. the omitted groups).

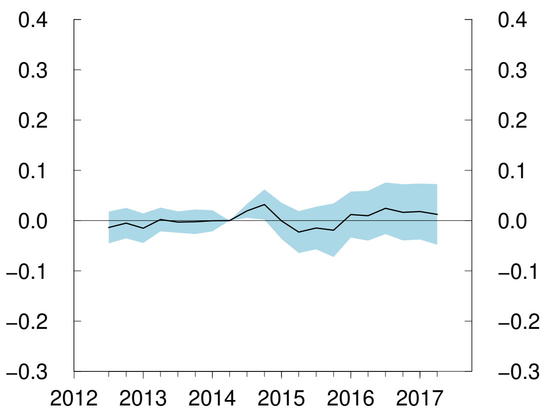
Figure F9: Term Spreads Event Study Plots



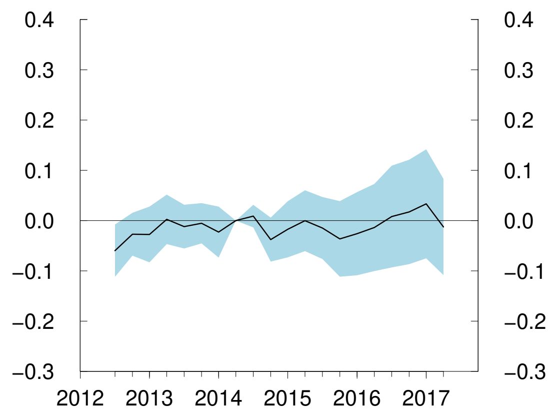

(a) Upstream




(b) Support Services



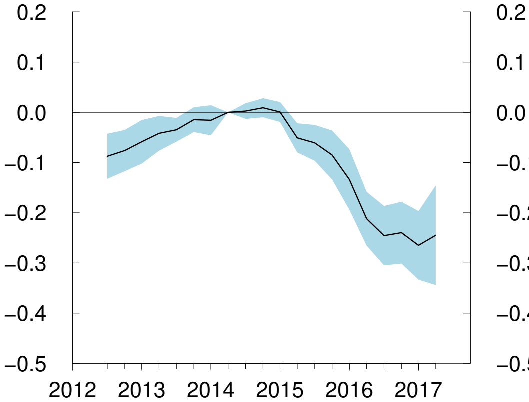

(c) Downstream



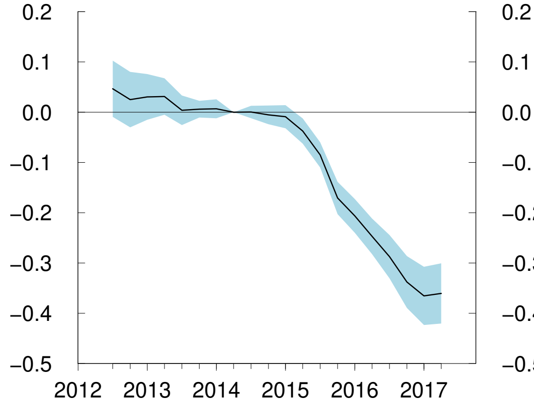

(d) Midstream

Note: Solid line shows parameter estimates. Shaded area shows 95 percent confidence interval based on bank clustered standard errors. Results are relative to non-oil firms in the 2014:Q2 period (ie. the omitted groups).

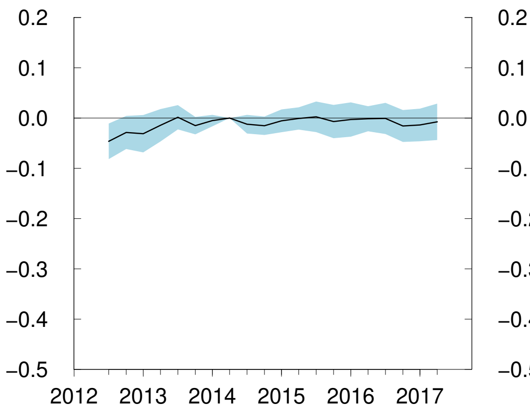
Figure F10: Commitment Event Study Plots



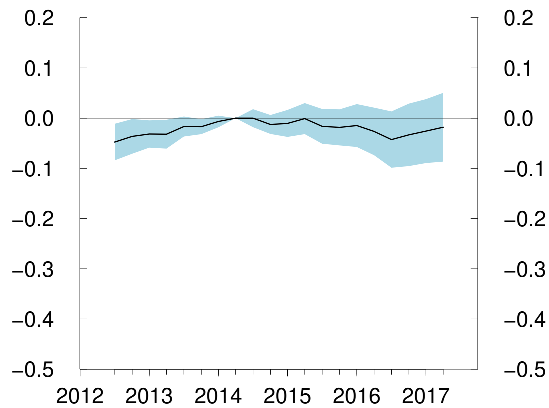

(a) Upstream




(b) Support Services



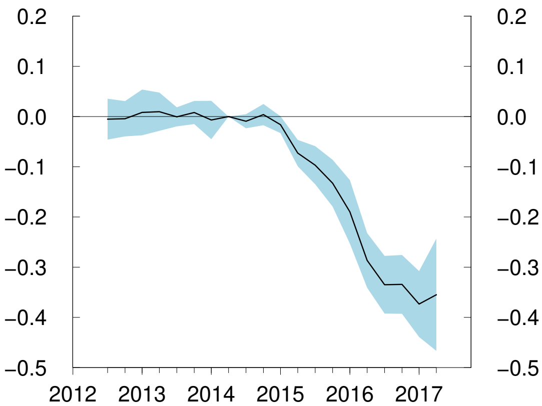

(c) Downstream



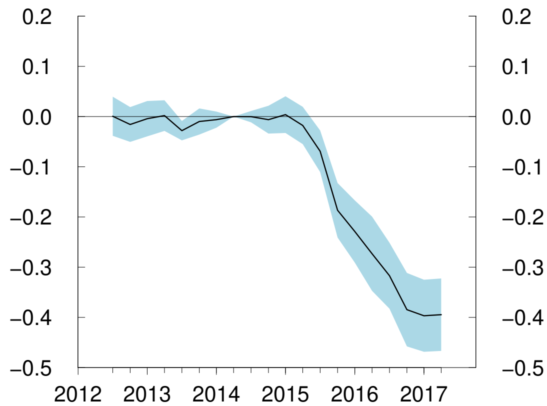

(d) Midstream

Note: Solid line shows parameter estimates. Shaded area shows 95 percent confidence interval based on bank clustered standard errors. Results are relative to non-oil firms in the 2014:Q2 period (ie. the omitted groups).

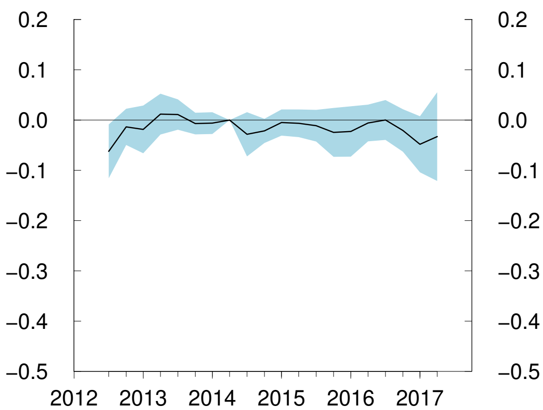
Figure F11: Revolver Commitment Event Study Plots



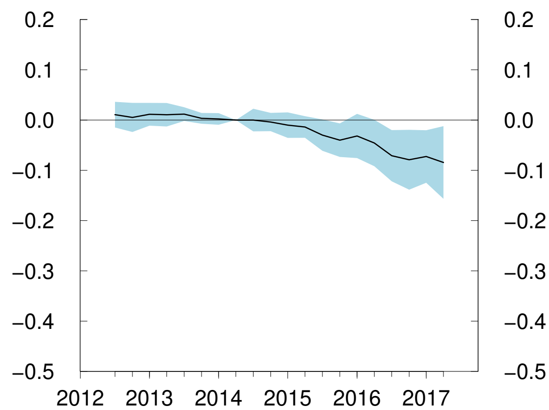

(a) Upstream




(b) Support Services



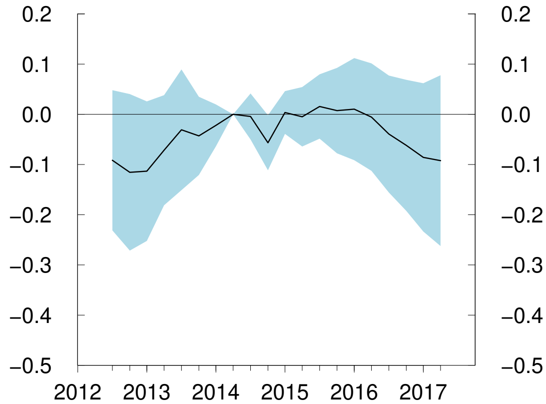

(c) Downstream



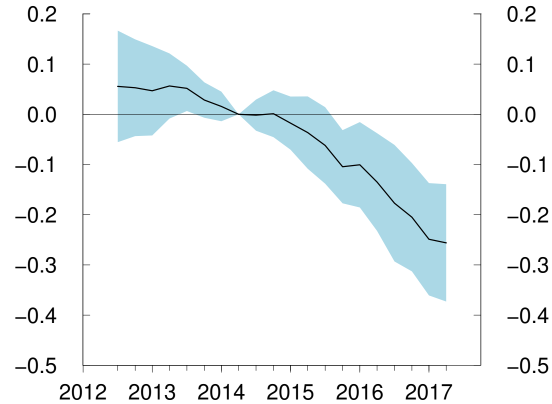

(d) Midstream

Note: Solid line shows parameter estimates. Shaded area shows 95 percent confidence interval based on bank clustered standard errors. Results are relative to non-oil firms in the 2014:Q2 period (ie. the omitted groups).

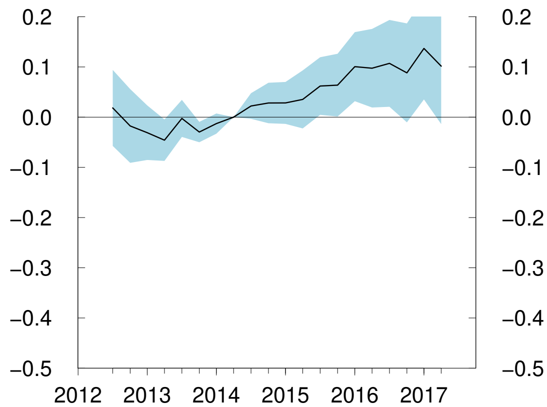
Figure F12: Term Commitment Event Study Plots



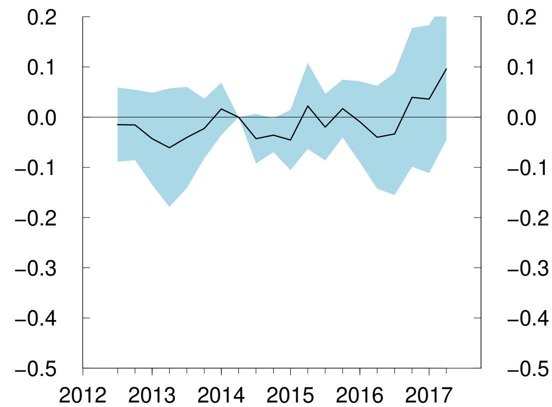

(a) Upstream




(b) Support Services




(c) Downstream



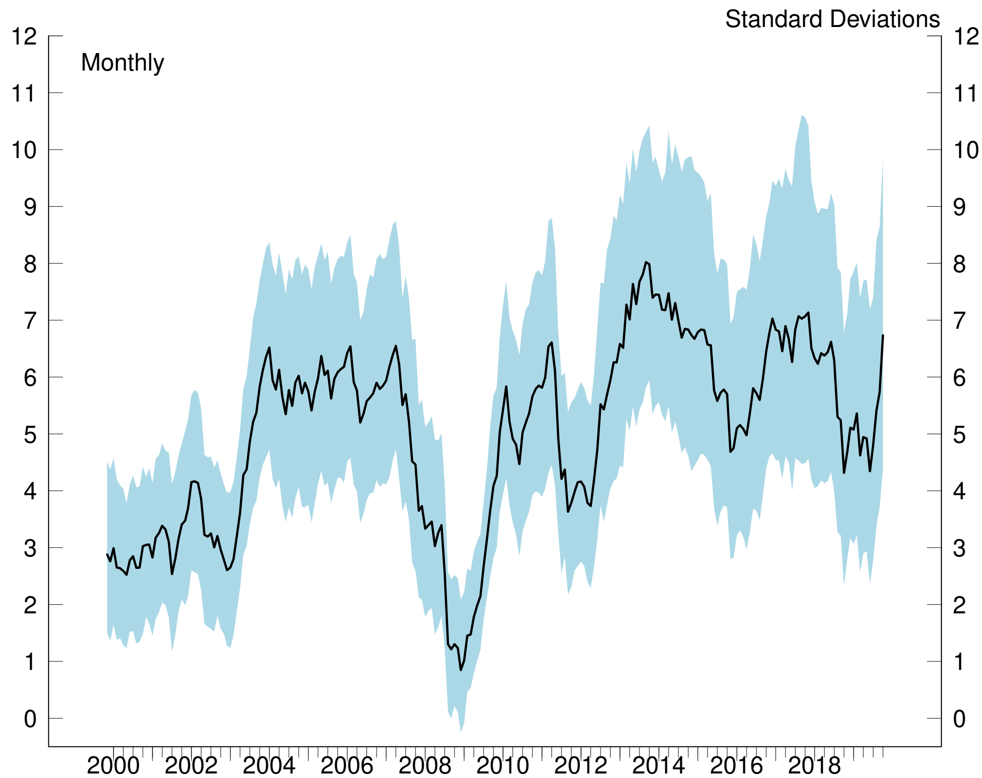

(d) Midstream

Note: Solid line shows parameter estimates. Shaded area shows 95 percent confidence interval based on bank clustered standard errors. Results are relative to non-oil firms in the 2014:Q2 period (ie. the omitted groups).

# G Merton Default Distance Based ELP Estimates

In this section, we link our loan sample to compustat for borrowers. We use equity price data from S&P 1500 to determine the implied default probability from a Merton

Figure G13: S&P 1500 Merton Default Distances




Note: Shaded area shows interquartile range of estimates across firms. Solid line shows median value. Source: S&P Global Market Intelligence Compustat and author's calculations

model. Estimates of the Merton default probability across S&P 1500 firms are shown in Figure G13. We then regress the observed loan spreads on the Merton default distance. Using these coefficients, we predict the spread for each loan implied by the parameter estimates. We then generate an "excess loan premium" for each loan in our sample matched to an S&P 1500 firm.

We begin this analysis by regressing the log of the loan spread on the Merton default distance and time varying loan controls.[16] We include a number of fixed effects in different specifications to test the robustness of our results. Our preferred spec-

[16]We follow Gilchrist and Zakrajšek [2012] and use the negative of the Merton default distance so that an increase in the measure reflects an increase in default probability.

ification includes industry and bank-time fixed effects. The bank-time fixed effects control for time-varying shocks banks that may disrupt credit supply independently of changes in firm default risk. Industry fixed effects control for differences in pricing across sectors. We follow Gilchrist and Zakrajšek [2012] and cluster standard errors by firm-time.

Table G4: Market-Based Firm Default Risk and Loan Spreads

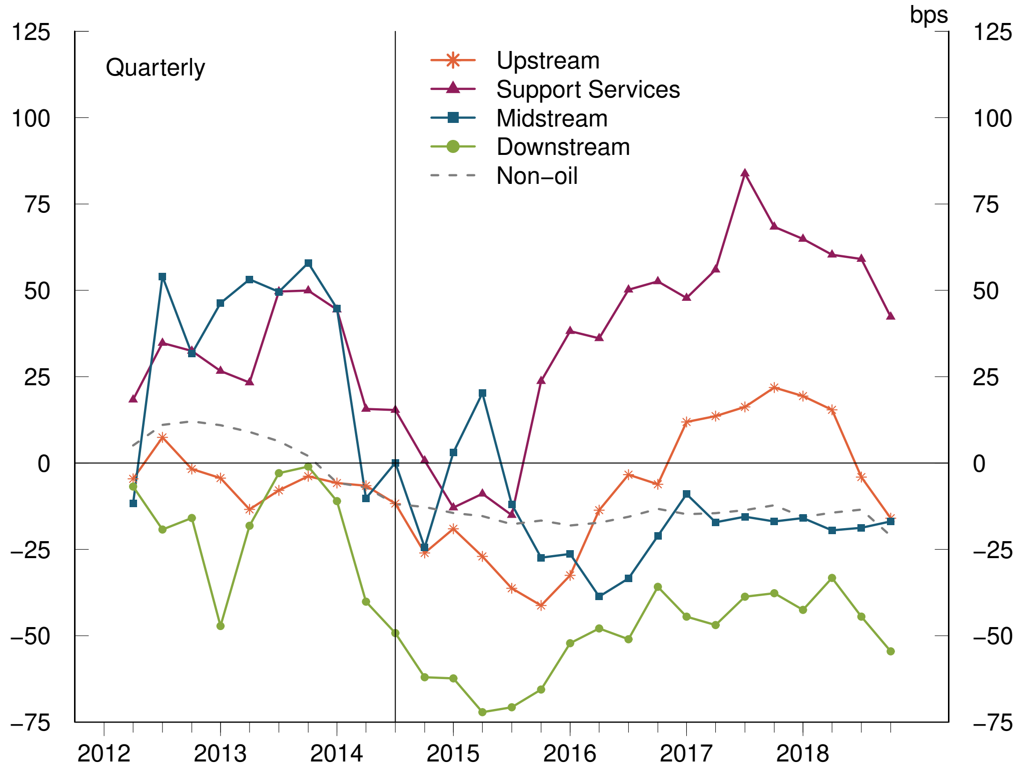
| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| -*DD* | 0.04*** | 0.04*** | 0.05*** | 0.04*** | 0.01*** |
| | (0.0024) | (0.0021) | (0.0025) | (0.0025) | (0.0018) |
| ln(*commitment*) | -0.10*** | -0.10*** | -0.09*** | -0.09*** | -0.01 |
| | (0.0066) | (0.0057) | (0.0058) | (0.0058) | (0.0085) |
| ln(*maturity*) | 0.06*** | 0.03*** | 0.03** | 0.03** | -0.05*** |
| | (0.0179) | (0.0113) | (0.0116) | (0.0115) | (0.0089) |
| Observations | 137,616 | 137,616 | 137,616 | 137,616 | 134,479 |
| Adjusted $R^2$ | 0.104 | 0.413 | 0.423 | 0.559 | 0.756 |
| Industry FE | No | Yes | Yes | Yes | No |
| Bank FE | No | Yes | Yes | No | No |
| Time FE | No | No | Yes | No | Yes |
| Bank-Time FE | No | No | No | Yes | No |
| Loan FE | No | No | No | No | Yes |

Two-way firm-time clustered standard errors in parentheses.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

The results of this regression are shown in Table G4. As expected, firms with higher default risk are charged higher loan spreads. A decline in the standard deviations to default, which is an increase in the negative default distance measure, denoted by $-DD$, results in about a 4 percent higher loan spread. This is similar to the approximately 7 percent increase on corporate bond spreads found in Gilchrist and Zakrajšek [2012]. The quantitative result is similar across specifications.

Using this information, we then estimate the average excess loan premium charged by sector. We first calculate the excess loan premium for each loan using the results from Table G4. We then calculate the simple average over these ELP by industry to

Figure G14: Average Excess Loan Premia




Source: FR Y14Q (Federal Reserve Board), S&P Global Market Intelligence Compustat, and author's calculations.

arrive at a measure of the increased spread charged to energy firms by banks. These averages over the sample period are shown in Figure G14.

Figure G14 shows that following the initial crash, excess loan premia declined for some time. This reflects the fact that equity markets likely repriced stock quickly following the shock, but loan spreads took some time to reprice due to contractual features. However, once this repricing period cleared, excess loan premia increased sharply for Support Service and Upstream firms. For Support Firms, excess loan premia reached as high as 75 basis points on average while spreads for Upstream firms were an additional 25 basis points higher. Reflecting the persistence of the shock, excess spreads charged to downstream firms also increased several years after the initial shock.

Finally, we explore the economic significance of these increased spreads. To do so, we use our Compustat-firm paired data sample and construct measures of investment and employment. For investment, we consider quarterly capital expenditures scaled by fixed assets from the quarterly Compustat data. For employment, use interpolate the change in annual employees reported linearly across all quarters and scale these employee counts by total assets. We then regress these firm measures on average ELP by firm, in the case that the firm has multiple loans, and the firm's default frequency. We also control for firm size. Standard errors are clustered by firm.

Table G5 shows that higher average ELP at the firm level is associated with significantly lower investment, even after controlling for firm default risk. However, we do not find the same impact for employment. The result that investment is more impacted is consistent with theories that financial frictions are more likely to be associated with reduced investment spending, as much of this would be financed via external debt. In terms of economic magnitude, the coefficients suggest that a 75 basis point increase in the ELP, as faced by the Support Services sector, would reduce investment spending as a share of total assets by about 60 basis points. This is economically significant considering that average investment to fixed assets is about 6 percent in our sample, so about a 10 percent decline in average investment spending.

Table G5: Effect of Excess Loan Premia on Real Firm Outcomes

| | (1) Employment | (2) Investment |
|---|---|---|
| *Avg. Excess Loan Premium* | -0.0002** | -0.0045*** |
| | (0.0001) | (0.0016) |
| *-DD* | -0.0027* | -0.1917*** |
| | (0.0015) | (0.0447) |
| $\ln(assets)$ | -0.1642*** | 1.5267** |
| | (0.0254) | (0.5972) |
| *Constant* | 1.8062*** | -0.1745 |
| | (0.1872) | (4.4065) |
| Observations | 20,815 | 15,021 |
| Adjusted $R^2$ | 0.059 | 0.038 |

Firm clustered standard errors in parentheses.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$