Finance and Pollution: Do Credit Conditions Affect Toxic Emissions?

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Abstract

We evaluate the impact of credit conditions on firms' emissions of toxic pollutants. There are differing influences: tighter credit might (a) stifle firm production, reducing toxic emissions, (b) induce firms to economize on noncore business functions, such as pollution abatement, increasing pollution; (c) have no effect on pollution if environment regulations bind. Using four identification strategies, we find that shocks that tighten a firm's credit conditions increase its emissions of toxic pollutants, and those that ease a firm's access to credit reduce its toxic emissions. The estimates suggest that finance exerts a large impact on firms' emissions of toxic pollutants.

JEL: G21, O16, Q52, Q53, Q40

Keywords: Bank Liquidity Shocks, Pollution, Toxic Emissions, Credit Conditions

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1. Introduction

Pollution increases the incidence of cancer, cardiovascular and respiratory diseases, reproductive and neurodevelopmental disorders, and premature death (e.g., Chay and Greenstone 2003; Ebenstein et al. 2015; Currie and Neidell 2005; Knittel, Miller and Sanders 2016; Schlenker and Walker 2016; IIsen, Rossin-Slater, and Walker 2017).[1] Research indicates that about 16% of all deaths in the world in 2015 were attributable to pollution, with two-thirds of those premature deaths caused by air pollution and the remainder caused by water, soil, and occupational pollution (Lancet 2017). In the United States, the *State of the Air 2017* report by the American Lung Association shows that more than 40% of the U.S. public live in counties that have unhealthful levels of air pollution, and the U.S. Environmental Protection Agency (EPA) (2013) reports that more than half of the country's rivers, streams, and waterways are so polluted that they cannot support healthy aquatic life and that tens of millions of people in the U.S. drink tap water with chemicals linked to cancer and other diseases, even though the water satisfies the conditions of the Clean Water Act (Duhigg 2009). Furthermore, firms release much of this pollution. For example, studies by the U.S. EPA (2014, 2015, 2016, 2018) indicate that industry accounts for about 22% of greenhouse gas emissions, 30% of total toxic air pollutants, and the bulk of toxic pollutants released into the land and water. Given pollution's health effects, these statistics motivate research into the factors shaping firm pollution.

In this paper, we evaluate the impact of credit conditions on firms' emissions of toxic pollutants. Although decreasing pollution has long-run benefits, such as reducing expected fines from violating regulatory limits on toxic

[1] In addition to harming public health, pollution reduces housing prices (e.g., Currie, Davis, Greenstone and Walker 2015), lower labor productivity (e.g., Zivin and Neidell 2012), and influences industrial production (e.g., Greenstone 2002).

emissions, augmenting the health and productivity of workers (e.g. Zivin and Neidell 2012), and enhancing the firm's reputation, reducing pollution requires large upfront expenditures (e.g., Walker 2013).[2] Accordingly, firms facing tighter credit conditions might choose to economize on noncore business functions, such as pollution abatement, to cushion the effects of tighter credit on profits, thereby increasing toxic emissions. There may, however, be countervailing influences. Effective regulatory systems might prevent firms from increasing pollution, and tighter credit might stifle investment and production, reducing toxic emissions. In this paper, we evaluate the impact of credit condition on toxic emissions.

We employ four empirical strategies for identifying the impact of credit conditions on pollution. The first two strategies are based on a shock that eased firm credit conditions, and the second two strategies exploit shocks that tightened credit. We first describe the methods and results based on the credit-easing shock and then explain the analyses based on the credit-tightening shock.

Our first two empirical strategies start by exploiting shale-induced liquidity shocks to individual banks. Gilje, Loutskina, and Strahan (2016) show that (1) unexpected technological breakthroughs in fracking made shale gas production economically viable; (2) following these technological breakthroughs, the energy industry began rapidly purchasing shale mineral leases from landowners in promising areas, i.e., in "shale counties;" (3) the landowners then deposited a portion of these mineral-lease payments in local banks, boosting bank liquidity; and (4) banks receiving shale liquidity shocks from their branch networks in shale counties increased their residential mortgage lending in non-shale counties, i.e., counties that did not have shale development activities. Thus,

[2] The EPA (a) estimates that companies spent more than $13.7 billion in 2016 to control pollution (https://www.epa.gov/enforcement/enforcement-annual-results-fiscal-year-2016) and (b) reports that fees/ penalties from for violating environmental laws reached $6 billion in 2016.

we first confirm for our sample that (1) shale discoveries increased local bank deposits in shale counties, and (2) these banks increased their supply of credit to corporate clients in non-shale counties.

Our first identification strategy uses these shale liquidity shocks to individual banks to construct measures of shocks to the credit conditions facing firms in non-shale counties. Specifically, after constructing measures of the degree to which banks in non-shale counties receive liquidity shocks through their branch networks in shale counties, we evaluate how these shocks influence pollution in those non-shale counties. For the dependent variable in these county-level analyses, we use county-year measures of air pollution, which are collected from EPA monitoring stations across the country. Importantly, we focus on changes in credit conditions and environmental outcomes in counties without any shale discoveries or drilling activities. This mitigates concerns that our results are driven by changes in local economic conditions or environment quality resulting from shale development (Muehlenbachs, Spiller, and Timmins 2015; Hill and Ma 2017). Moreover, we control for county and year fixed effects, as well as time-varying county traits. Conceptually, therefore, our first strategy compares the environmental outcomes in two otherwise similar non-shale counties, except that banks in one county receive greater liquidity shocks through their branch networks in shale counties than banks in the other county.

We discover that a positive shock to the supply of bank credit in a county lowers toxic pollution in the county. That is, when a non-shale county's banks are more exposed to positive liquidity shocks through their branches in counties experiencing shale discoveries, we observe sharp reductions in pollution in those treated, non-shale counties. These results hold when (a) controlling for time-varying county traits along with county and year fixed effects, (b) analyzing different toxic pollutants, and (c) employing different measures of the intensity of air pollution. In terms of magnitudes, consider Benzene, the most monitored hazardous air pollutant by the EPA in our sample. We find that in counties where banks received a shale-liquidity shock equal to one standard deviation of the cross-county distribution of such shocks, Benzene concentration levels fell by 24% of the standard deviation of Benzene concentration across counties. It is worth mentioning that we show that the pollution-reducing effects of positive county liquidity shocks cannot be explained by differential pre-trends in pollution.

Our second strategy uses the shale liquidity shocks to individual banks to construct measures of shocks to the credit conditions facing individual firms. To construct firm-specific credit shock indicators, we measure the degree to which banks in the county where a firm has its headquarters receive shale liquidity shocks. Specifically, we limit the analyses to firms with headquarters in non-shale counties and construct measures of the degree to which banks in those non-shale counties receive liquidity shocks through their branch networks in shale counties. We then evaluate the impact of those firm-specific credit shocks on toxic emissions by the firm's plants, where we also limit the analyses to plants in non-shale counties. This second identification strategy relies on the assumption that a firm's credit conditions are influenced by credit conditions in the county in which the firm has its headquarters. Extensive research provides empirical support for this assumption, e.g., Petersen and Rajan (2002), Berger et al. (2005), Agarwal and Hauswald (2010), and Berger, Bouwman, and Kim (2017).

These plant-level analyses have advantages over the county-level strategy. First, the county-level analyses use air pollution data collected from EPA monitors, not measures of toxic emissions by plants. For the plant-level analyses, we use data from the EPA's Toxic Release Inventory (TRI) program on toxic emissions from each plant in each year. Second, the county-level analyses measure credit shocks and pollution in the same non-shale county. In the plant-level analyses, we examine credit shocks to the plant's headquarters and examine toxic releases by its plants. Critically, we omit all plants and headquarters located in shale counties—and in robustness checks we also omit plants and headquarters located in counties neighboring shale counties. Third, we include county-year fixed effects throughout the plant-level analysis, which distinguishes treatment effects—the easing of firm credit conditions—from local economic conditions that might affect plant behavior. We can include county-year effects because not all plants located in a county have their headquarters in the same county. Conceptually, therefore, our plant-level analyses compare the toxic releases by two otherwise similar plants operating in the same non-shale county, except that one plant has its headquarters in a county with banks that receive greater liquidity windfalls than the other plant.

We find that positive shocks to the credit conditions facing firms reduce emissions of toxic pollutants by their plants. Our sample contains 94,304 plant-year observations involving 12,296 plants affiliated with 4,035 private and public firms over the period from 2000 through 2013. The results are robust to controlling for plant, county-year, industry-year, and (headquarters)state-year fixed effects, as well as time-varying plant characteristics. The estimated economic magnitudes are material. For example, consider two otherwise similar plants, except that one receives a positive, sample mean liquidity shock due to its headquarters in a county with banks exposed to shale liquidity windfalls, while the other does not. The coefficient estimates indicate that toxic emissions from the "shocked" plant would fall by 6%.

In an extension, we evaluate whether—and confirm that—the pollution-attenuating effects vary in a theoretically predictable manner across firms. Specifically, we differentiate plants by whether they are affiliated with privately-held or publicly-listed firms. Since public firms tend to have greater access to finance beyond the credit provided by banks operating in the firms' headquarters-county, we expect shocks to local credit conditions to have a smaller impact on public firms. Consistent with this view, we discover that the pollution-reducing effects from bank liquidity shocks in a firm's headquarters-county are much stronger among private firms.

In a second extension, we conduct two-stage least squares (2SLS) regressions. In the first stage, we use shale discoveries as an instrument for changes in banks deposits, and in the second stage we evaluate the impact of shocks to bank deposits in firms' headquarters county on toxic emissions by their plants. As in all of the analyses, we limit the analyses to firms with headquarters in non-shale counties and measure the degree to which banks in those non-shale counties receive liquidity shocks through their branch networks in shale counties. The 2SLS extension allows us to assess the economic magnitude of a positive liquidity shock—now measured as the percentage change in deposits—on pollution. The 2SLS results both confirm that easing firms' credit constraints tends to reduce toxic emissions by their plants and indicate that the effects are large: A 1 percentage point increase in bank deposits in a firm's headquarters-county reduces toxic emissions by its plants by about 8%.

The third identification strategy exploits a shock that tightened credit—the global financial crisis—and develops a firm-level proxy for the credit-tightening impact of the crisis on each firm. Following Almeida et al. (2012), and Cohn and Wardlaw (2016), we use heterogeneity in the degree to which firms have debt maturing in the year prior to the crisis to proxy for the credit-tightening impact of the crisis on firms. Since (a) the financial crisis made it difficult for firms to roll over maturing debts (Acharya and Mora 2015) and (b) firms were unlikely to have anticipated the crisis when taking on those debts prior to the crisis, we use the interaction between firms' pre-determined debt structure and the onset of the crisis as an exogenous source of variation in the severity of the credit crunch shocking individual firms. We then examine the impact of this credit tightening on toxic emissions by the firms' plants.

Our fourth identification also begins with the global financial crisis but we now exploit cross-bank differences in their pre-crisis holdings of private-label mortgage-backed securities (MBS). Compared to agency-backed MBSs, research suggests that private-label MBSs exposed banks to substantial losses and risks during the financial crisis, which was triggered by the collapse of the housing market (Ellul and Yerramilli 2013). Erel, Nadauld, and Stulz (2013) show that banks that held more securitized products before the crisis performed significantly worse during the crisis. Thus, we first develop a bank-specific measure of exposure to private-label MBSs before the crisis and show that this measure is strongly, positively associated with bank losses and the contraction of credit during the crisis. We then develop a measure of the degree to which banks in each firm's headquarters county are exposed to these MBS-induced negative shocks, and use this firm-specific measure of credit tightening to evaluate the impact of credit conditions on toxic emissions by firms' plants.

Consistent with the findings based on shale-discovery shocks, we find that credit tightening triggered by the global financial crisis increased toxic emissions. First, when using heterogeneity in firms' debt structures to proxy for the severity of credit tightening caused by the crisis, we discover that firms that experienced greater credit tightening increased toxic emissions through their affiliated plants. These results are robust to including plant, county-year, industry-year, (headquarters)state-year fixed effects, and an assortment of time-varying firm-level traits. Second, when banks in a firm's headquarters county are more exposed to private-label MBSs, the financial crisis triggered a greater increase in toxic emissions by the firm's plants. Thus, both the third and fourth identification strategies indicate that adverse shocks to firms' credit conditions increase pollution by the firm's plants. These results further emphasize that when credit conditions tighten, firms tend to economize on noncore business activities such as pollution abatement, leading to an increase in pollution emissions.

Our key contribution in this paper is assessing how shocks to a firm's credit conditions influence its omissions of toxic pollutants. Although researchers have shown that credit conditions shape a range of economy-wide features, such as economic growth (e.g., King and Levine 1993, Jayaratne and Strahan 1996, Levine and Zervos 1998, Rajan and Zingales 1998), business cycle fluctuations (e.g., Bernanke and Gertler 1989), and the distribution of income (e.g., Beck, Levine, and Levkov 2010), we are unaware of previous research that evaluates the impact of credit conditions on the environment. Given the enormous costs associated with pollution, our research highlights the broader ramifications of financial frictions on the economy and society.

The paper proceeds as follows. Section 2 describes the data and variables. Section 3 describes the technological breakthroughs in fracking and shale discoveries, and the shocks to credit conditions. Section 4 presents the county-level results and Section 5 provides the plant-level analyses. Section 6 employs two additional identification strategies and assesses how adverse shocks to credit conditions affect toxic emissions by plants. Section 7 concludes.

2. Data and Variables

2.1 Toxic air pollutants concentration from EPA monitoring stations

To evaluate the impact of an increase in the supply of bank credit on the local environment, we start our analysis by using EPA data on the concentration of hazardous airborne pollutants collected at outdoor monitors across the nation. The EPA (2017) defines hazardous airborne pollutants as "those pollutants that are known or suspected to cause cancer or other serious health effects (including reproductive effects or birth defects), or adverse environmental effects." For each monitor, the EPA annual summary files contain pollutant-by-pollutant statistics on the arithmetic mean, 50th, 75th, and 90th percentiles of the readings from each monitor over each year. This provides annual measures of pollutant concentrations across geographic locations. We focus on (1) the five toxic pollutants with the most comprehensive data (Benzene, Toluene, Ethylbenzene, o-Xylene, and m/p Xylene) and (2) the standardized index of the top-10 most covered toxic pollutants (the five just mentioned and Styrene, Dichloromethane, Carbon tetrachloride, Tetrachloroethylene, and Chloroform), which we call *Top-10 Toxins*. We construct this index by (a) standardizing each of the top-10 toxic pollutants into a variable that falls between zero and one and (b) taking the average across those ten standardized values for each monitor in each year.[3]

To calculate the concentration of each hazardous air pollutant at the county-year level, we compute the average of each summary statistic—mean, median, 75th percentile, etc.—across monitors within the county and year. The average number of monitoring sites in a county equals 1.76, and the median value equals one. In the main text, we provide results using the mean values of these toxic pollutant concentrations. The results hold when using the median, 75th, and

[3] We standardize the variable X into a [0, 1] range using (X– MIN(X)) / (MAX(X) – MIN(X)).

90th percentiles, as reported in the Online Appendix. Table 1 Panel A presents cross-county summary statistics on the annual mean values of *Top-10 Toxins*, and each of the five hazardous pollutant concentrations in our sample. Online Appendix Table A1 provides detailed variable definitions.

2.2 Plant-specific toxic emissions from Toxic Release Inventory

We also conduct analyses at the plant-level by obtaining pollutant emissions information on each individual plant from the Toxic Release Inventory (TRI) basic dataset, which is maintained by the U.S. Environmental Protection Agency (EPA). TRI collects information on the release of toxic chemicals from over 40,000 plants in the U.S. Starting in 1987, the TRI program tracks the release of toxic chemicals that cause significant adverse effects on human health or the environment. Industrial plants that (a) are involved in manufacturing, metal mining, electric power generation, chemical manufacturing and hazardous waste treatment, (b) have more than 10 full-time employees, and (c) use or produce more than threshold levels of TRI-listed toxic substances must report their releases of toxins to the TRI. The TRI provides self-reported toxic emissions data at the plant-level, along with information on the plant's physical location, and its parent company's name and firm ID.

For each plant in a year, we measure its emissions of pollutants as the total amount of toxic chemicals released by the plant. Specifically, *Total Toxic Releases* is the logarithm total amount of toxic chemicals released (including air emissions, water discharges, underground injection, etc.) from each plant.[4] To address the concern that our analyses might be driven by changes in local

[4] We also conducted these analyses at the firm-level, rather than the plant-level. For each firm in each year, we measure its emissions of pollutants by summing up pollution emissions by its plants in non-shale counties. As shown in the Online Appendix, all of the results hold.

economic conditions resulting from the shale development activities, we exclude TRI plants located in counties where there has been shale development since 2003 (i.e., shale counties), and plants affiliated with firms headquartered in shale counties. Our final TRI pollutant emission sample includes 94,304 plant-year observations over the 2000 – 2013 sample period, involving toxic release records from 12,296 plants affiliated with 4,035 private and public parent companies that are successfully matched with additional plant-year data that we describe next.

2.3 National Establishment Time-Series (NETS) database

We match the TRI data with detailed data on each plant and its firm using the National Establishment Time-Series (NETS) database, offered by Dun and Bradstreet. NETS follows over 58.8 million establishments as of January each year from 1990 to 2014, covering essentially the universe of businesses in the U.S. These data allow us to examine the pollution outcomes for both publicly listed and private firms and their plants. For each establishment, NETS contains dynamic information on its ultimate parent company and the geographic location of firm's headquarters and all of its plants. We determine the headquarters-county for each plant by linking the plant's parent firm in TRI with firms in NETS using the common Dun & Bradstreet Number provided in both datasets.

2.4 Shale wells data and bank liquidity shocks

To create bank-specific measures of their exposure to shale discoveries, we begin with *IHS Markit Energy*, which is a comprehensive database that provides detailed information on the date, location, and well orientation for more than 100,000 shale wells drilled across the U.S over the period of 2003 – 2013. For each county in each year, we calculate the number of shale wells drilled since

2003, which is when technological innovations made "fracking" commercially viable.[5] $Wells_{jt}$ denotes the number of shale wells drilled in county *j* as of year *t*.

To measure a bank's liquidity gains from shale discoveries, we combine U.S. counties' shale drilling activities with the bank's local branch networks. We retrieve information on each bank's branch structure, location of its branches, and deposit balances in those branches from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits database.

Based on (a) the geographic distribution of a bank's branches and (b) the number of shale wells drilled in each county, we construct two measures of each bank's exposure to shale-induced liquidity shocks in each year. The first measure, *Bank liquidity gain1*, equals the logarithm of one plus the number of shale wells drilled across counties in which a bank has at least one branch, where the number of wells in each county is weighted by the bank's market share in each county, divided by the total number of branches owned by the bank. Formally:

$$Bank\ liquidity\ gain1_{b,t} =$$
$$Ln\left[1 + \sum_j \left(Wells_{jt} * 1\left(Branches_{bjt} > 0\right) * MktShr_{bjt}\right) / \ Branches_{bt}\right], \quad (1a)$$

where *b* represents bank, *j* denotes county, and *t* denotes year. $Wells_{jt}$ denotes the number of shale wells drilled in county *j* from 2003 as of year *t*; $1(Branches_{bjt} > 0)$ denotes an indicator that equals one if bank *b* has branches in county *j* at year *t* and zero otherwise; $MktShr_{bjt}$ equals the proportion of all deposits held within county *j* in year *t* that are held at bank *b*'s branches within county *j*; $Branches_{bt}$ equals the total number of branches owned by bank b in year *t*. By weighting the number of wells in a county by a bank's market share in that county, this measure assumes that a bank's liquidity inflows in a shale-

[5] Following existing research, we treat horizontal wells as the measure of shale-related activities. According to Gilje, Loutskina, and Strahan (2016), almost all horizontal wells in the U.S. are drilled to extract shale or other unconventional resources after 2002.

development county are proportional to its market share in that county. Note that *Bank liquidity gain1* equals zero for (a) banks without branches in shale development counties, and (b) all banks before 2003, which is before the technological breakthrough that fostered fracking. As shown in Table 1 Panel C, *Bank liquidity gain1* has a sample average of 0.08, with a higher value indicating greater liquidity shocks. And, among banks that are exposed to shale liquidity shocks, the sample average of *Bank liquidity gain1* equals 0.6.

Second, *Bank liquidity gain2*, takes the first measure and further weights by whether each branch is in a shale-boom county or not. We define a shale-boom county as one in which the number of wells drilled in a year is in the top quartile for all shale-county-years in our sample. Following Gilje, Loutskina, and Strahan (2016), once categorized as a shale-boom county, it retains that categorization in all subsequent years. Formally:

$$Bank\ liquidity\ gain2_{b,t} = Ln[1 + \sum_j \left(Wells_{jt} * 1\left(Branches_{bjt} > 0\right) * MktShr_{bjt} * 1\left(Boom_{jt}\right)\right) / Branches_{bt}], \quad (1b)$$

where *b* represents bank, *j* denotes county, and *t* denotes year, and the other components, $Wells_{jt}$, $1\left(Branches_{bjt} > 0\right)$, $MktShr_{bjt}$, and $Branches_{bt}$ are defined the same as above. $Boom_{jt}$ is a dummy variable that equals one if the number of shale wells drilled in county *j* during year *t* is above the top quartile of county-years with shale development activities, and zero otherwise. Thus, this second measure captures each bank's exposure to the shale liquidity shock through its branch networks across shale-boom counties only.

3. Shale Discoveries and Bank Liquidity Gains

In this section, we (1) describe shale development during the 2000s, (2) show that banks exposed to shale discoveries through their branches in areas with shale discoveries experience sharp increases in bank liquidity (i.e., deposits), and (3) develop measures of the degree to which counties and firms are exposed to these liquidity shocks. In Sections 4 and 5, we use these measures to evaluate the impact of credit conditions on toxic emissions.

3.1 "Fracking" and shale discoveries

In late 2002, a technological breakthrough, known as "fracking," combined horizontal drilling with hydraulic fracturing to make shale gas production economically viable. Therefore, we use 2003 as the first year when the oil and gas industry started large-scale investment in shale development. Fracking had an enormous impact on the energy market. According to *Annual Energy Outlook* (AEO 2016), shale gas went from accounting for less than 1% of U.S. natural gas production in the late 1990s to nearly 50% of total U.S. natural gas production by the end of 2015.

3.2 Shale development and bank liquidity windfalls

Given the technological improvements in fracking, oil and gas companies increased their purchase of mineral leases from landowners in promising areas. With mineral leases, local property owners typically receive payments, including a large upfront bonus, based on the number of leased acres, plus a royalty percentage on the extracted resources from the lease.

These purchases significantly boosted deposits in local banks. As described in Plosser (2015), leasing contracts typically involve a bonus that varies between \$10 and \$30,000 per acre, and a royalty percentage ranging from 10% to 25%. Accordingly, if a family owns one square mile of land (equivalent to 640 acres) and leases this out at an average value of \$15,005 per acre, they would receive an upfront payment of \$9.6 million plus future royalties. Gilje, Loutskina, and Strahan (2016) show that deposits grow faster among banks exposed to shale boom counties compared to unexposed banks.

We reassess and confirm this finding in our sample using the following regression:

$$Deposit\ growth_{b,t} = \varphi_1 Bank\ liquidity\ gain_{b,t} + \varphi_2{}'\Pi_{b,t-1} + \alpha_b + \alpha_t + \varepsilon_{b,t}, \qquad (2)$$

where b and t denote bank and time, respectively. *Deposit growth*$_{b,t}$ is the growth rate of domestic deposits for bank b during year t. *Bank liquidity gain*$_{b,t}$ represents one of the two measures on a bank's exposure to shale drilling activities described above (i.e., *Bank liquidity gain1* or *Bank liquidity gain2*). The coefficient of interest is φ_1, which captures the extent to which a bank's deposits grow in response to the shale development activities in its branch network. If shale-well drilling indeed brings a large liquidity windfall to local branch offices, we expect φ_1 to be positive and statistically significant. We also control for an array of time-varying bank specific characteristics measured at the beginning of each period ($\Pi_{b,t-1}$), namely *Total asset*, *Capital asset ratio*, *Deposit/Total assets*, *Liquid assets/Total assets*, *Mortgages/Total assets*, *C&I loans/Total assets*, *Loan commitments/Total assets*, and *Letters of credits/Total assets*. We construct firm-specific controls using data from Reports of Condition and Income ("Call Reports"). We include bank and year fixed effects, α_b and α_t, throughout the analyses. Standard errors are clustered at the bank level.

The results reported in Table 2 indicate that shale-well drilling activities within a banking institution's branch networks lead to a significant increase in that bank's deposit growth. As shown in columns 1 and 2, both measures on bank liquidity gains enter the regressions positively and significantly. The economic magnitudes are meaningful. The coefficient estimates from column 1 indicate that deposits in banks that are exposed to the shale development activities with an average value of *Bank liquidity gain1* (= 0.6) would grow 1.8 percentage points (=0.6*0.031) faster than banks without such exposure. This is equivalent to about 22% of the sample mean of deposit growth.

We also show that bank liquidity gains induce a material increase in the supply of credit. As reported in Table 2, we discover a strong, positive association between a bank's exposure to shale liquidity shocks and the growth rate of its commercial and industrial (C&I) loans. The coefficient estimates reported in column 3 suggest that when a bank receives an average shale liquidity shock, i.e., *Bank liquidity gain1* = 0.6, the bank's C&I loans grow 2.4 percentage points (=0.6*0.04) faster than banks that are not exposed to shale development. This is large, as the estimated accelerate in growth is equivalent to 34% of the sample mean of *C&I Loan growth*.

Several factors suggest treating shale-drilling activities as exogenous liquidity windfalls for local bank branches. First, the technological breakthroughs in fracking were unexpected. Second, the economic viability of shale wells is often driven by broader macroeconomic factors, such as demand for natural gas and prices of natural gas (Lake et al., 2013), that are unlikely to be correlated with local economic conditions (Gilje, Loutskina, and Strahan 2016). Third, at least two facts suggest that banks cannot strategically adjust branch networks to gain greater exposure to shale windfalls: (a) the discoveries of shale formations in different geographies are uncertain, as it is difficult even for the oil and gas companies to predict how many wells an area needs to drill before producing shale gas; and (b) mineral leasing by the oil and gas companies usually occurs at a very rapid pace. As reported by *Times-Picayune* in 2008, several years after the technological breakthroughs, the signing bonuses for buying mineral rights in Louisiana's Haynesville Shale area increased from about \$100 per acre to between \$10,000 and \$30,000 per acre within one year.

3.3 County- and firm-level liquidity shocks

Having established that shale oil discoveries influence bank liquidity through their branches in areas exposed to these discoveries, we construct county-specific measures of the degree to which banks in non-shale counties—counties in which shale was not discovered—receive liquidity shocks through their branch networks in shale counties.

For each non-shale county in each year, we compute two county-level liquidity shocks measures based on the two bank-specific shale liquidity shock measures defined above and weight them by the share of the county's deposits held by each bank. From *Bank liquidity gain1*, we construct:

$$County\ liquidity\ gain1_{j,t} = \sum \kappa_{b,j,t} * Bank\ liquidity\ gain1_{b,t}, \quad (3)$$

where *County liquidity gain1*$_{j,t}$ represents the extent to which banks in non-shale county j at time t received shale liquidity shocks via their branch networks in shale counties, *Bank liquidity gain1*$_{b,t}$ denotes the bank-specific shale liquidity shock measure for bank b in year t (Equation 1a), and $\kappa_{b,j,t}$ is the share of county j's total deposits in year t that are held in bank b's branches located in county j. *County liquidity gain2*, is computed similarly based on *Bank liquidity gain2*$_{b,t}$.

We also construct measures of shocks to each firm's credit conditions by gauging the extent to which banks in the firm's headquarters-county receive shale liquidity shocks. Specifically, for each plant we identify the firm's headquarters-county using the NETS database and compute the two corresponding county liquidity gain measures for that headquarters-county. Thus, for each plant, we assign the shale liquidity shock values associated with banks in the county in which its parent firm is headquartered. We refer to these measures as *Firm-county liquidity gain1* and *Firm-county liquidity gain2*.

4. County-Level Liquidity Shocks and Environmental Quality

4.1 County liquidity shocks and county pollution

To evaluate the impact of county-level liquidity shocks on air pollution in these counties, we use the following regression specification.

$$Poll_{j,t} = \beta_1 County\ liquidity\ gain_{j,t} + \beta_2' \Pi_{j,t} + \alpha_j + \alpha_t + \varepsilon_{j,t}. \quad (4)$$

The dependent variable, $Poll_{j,t}$, is based on either *Top-10 Toxins* or one of the pollution concentration measures. For *Top-10 Toxins* and each of the five pollutants (Benzene, Toluene, Ethylbenzene, o-Xylene, and m/p Xylene), we conduct regression analyses on the mean, 50th, 70th, and 90th percentile readings at the monitors within county *j* during year *t*. The explanatory variable of interest, *County liquidity gain*$_{j,t}$ represents one of the two county-level liquidity shock measures defined by Equation (3), where we focus on *County liquidity gain1*$_{j,t}$ and *County liquidity gain2*$_{j,t}$. We include a set of county characteristics, $\Pi_{j,t}$, namely *Ln(Per capita personal income)*, *Ln(Population)*, *Labor market participation*, and *Unemployment* to account for time-varying economic conditions, and county and year fixed effects, α_j and α_t to condition out time-invariant factors across counties and time specific effects.

In this way, we are comparing toxic pollutant concentrations between otherwise similar non-shale counties in which banks receive different liquidity shocks through their branch networks in shale counties. It is worth emphasizing that we reduce the possibility that the results will be affected by changes in the demand side emanating from shale discoveries by examining only counties in which there are no shale discoveries. Banks in these non-shale counties, however, may receive liquidity shocks through their branch networks in shale-counties. We estimate Equation (4) using OLS, with standard errors clustered at the county level, and report the results in Tables 3 and 4.

We find that county-level liquidity shocks materially reduce pollution. Table 3 reports the results for *Top-10 Toxins* and each of the five toxic air pollutants on the two measures of county-specific liquidity shocks. We provide the results on the mean values of each of the pollutants collected by EPA monitoring stations during each year in Table 3. As shown, the two county-level liquidity shock measures, *County liquidity gain1* in columns 1 – 6 and *County liquidity gain2* in columns 7 – 12, enter negatively and significantly across all of the regressions reported in Table 3. Positive liquidity shocks are associated with sharp decreases in average toxic air pollution concentrations. The estimated economic magnitudes are large. For example, the coefficient estimates from column 2 indicate that the annual mean level of Benzene fell by 0.34 (= 3.155*0.108) in non-shale counties in which banks received a one standard deviation (0.108) boost in liquidity from shale oil discoveries via their branches in shale counties. This is equivalent to 24% (= 0.34/1.404) of the standard deviation of *Benzene, mean* in our sample. As reported in Online Appendix Table A2, these results are robust to examining extreme toxic pollutant concentrations. In particular, rather than focusing on the mean or median pollutant readings at monitors, we examine pollution levels at the 75th and 90th percentiles of readings at each monitor during each year—and confirm the Table 3 findings.

Next, we use two strategies to address concerns that the results are driven by pre-existing differences in the level or trends of toxic pollutants across. First, we redo our baseline county-level analysis while adding to the explanatory variables county-level time trends prior to the shale discovery period. Specifically, *County trends* correspond to a full set of interactions between county dummies and a time trend variable, so that *County trends* equals $County\ dummy_c \times Trends$, where $County\ dummy_c$ represents a vector of 300 county dummy variables, and *Trends* equals one in 2000, two in 2001, three for 2002, and zero for years over the post-shale-discovery period. As shown in Table 4 columns 1 and 2, both county liquidity gain measures remain negative and statistically significant when controlling for a full set of county pre-trends, which condition out any differences in pre-trends across counties.

Our second strategy directly tests whether the level of pollution prior to shale developments varies systematically with the degree to which a county is exposed to subsequent bank liquidity shocks. We run the following regressions:

$$Poll_{j,pre2003} = \lambda_1 County\ liquidity\ gain_{j,post2003} + \lambda_2 X_{j,pre2003} + e_j, \tag{5}$$

where $Poll_{j,pre2003}$ equals the *Top-10 Toxins* readings in county *j* averaged over the pre-shale discovery period 2000 – 2002. $County\ liquidity\ gain_{j,post2003}$ is the average exposure of county *j* to bank liquidity gains during the post-2003 period, and $X_{j,pre2003}$ includes the same set of county specific controls as above (*Ln(Per capita personal income), Ln(Population), Labor market participation, and Unemployment*), averaged over the 2000 – 2002 period.

As shown in Table 4, we find no relation between pollution during the 2000-2002 period and bank liquidity shocks in the post-2003 period: *County* *liquidity gain1, post2003* and *County liquidity gain2, post2003* enter insignificantly when examining toxic emissions before shale discovery. Overall, the results in Table 4 suggest that the pollution-reducing effects of positive county liquidity shocks cannot be explained by differential pre-trends in pollution.

4.2 County liquidity shocks and county pollution: heterogeneous effects

To provide additional evidence on whether county-level liquidity shocks affect pollution, we assess whether the drop in pollution associated with a given bank liquidity shock is greater in counties in which firms have paid more EPA fines. Specifically, we conjecture that (1) when firms believe that they face a more intense monitoring by the EPA regarding regulatory limits on toxic emissions, this increases the expected value of making pollution abatement investments and (2) when there are more EPA fines in a county, this tends to increase firms' assessments of EPA monitoring intensity.[6] Thus, we evaluate whether easing access to credit has an especially pronounced effect on pollution abatement in counties in which there have been more substantial EPA fines.

To conduct this evaluation, we use a county-level indicator of penalties for violating the Clean Air Act (CAA) based on EPA's compliance and enforcement data. For each county in each year, we calculate the total dollar amount of CAA penalties over the past five years across plants located in the county. We define *EPA Penalties* as equal to one if the total penalty amount in a county is above the median value of county-years in the EPA's compliance and enforcement dataset, and zero otherwise. To test our conjecture above, we

[6] For example, with more fines, firms' perceptions of the likelihood of being fined might increase because of increases in the actual intensity with which regulators examine and penalize pollution in that county or because of increases in the degree to which firms are aware that regulators are monitoring their emissions, i.e., the salience of the environment regulatory regime to the firms.

interact *EPA Penalties* with the county-specific liquidity shock measure, include that interaction term in Equation (4), and report the regression results in Table 5.

We find that the pollution-reducing effects of liquidity shocks are greater in counties with a more intense regulatory focus, as measured by *EPA Penalties*. Table 5 provides the results on the mean values for *Top-10 Toxins* and each of the five toxic air pollutants. As can be seen from columns 1 – 6, the interaction of county-specific liquidity shocks and penalties for violating CAA, *County liquidity gain1*EPA Penalties*, enters negatively and significantly across the annual mean values for *Top-10 Toxins* and four out of the five toxic parameters. Columns 7 – 12 show that the results remain highly robust when using the other county-level liquidity shock measure, *County liquidity gain2*, which further differentiates shale counties by whether they experience a shale boom or not. The estimated economic magnitudes are large: the coefficients from column 1 in Table 5, for example, suggest that the Top-10-Toxins-reducing effects of credit supply in counties with a higher amount of penalties for violating the CAA are about four times as large as those in counties with a relatively lower amount.

5. Firm-Level Liquidity Shocks and Plant-Level Toxic Emissions

We now assess the relationship between a firm's credit conditions and its plants' emissions of toxic pollutants. There are two key differences with the county-level analyses. First, the county-level analyses use data from EPA monitors. We now examine plant-level toxic emissions, using TRI data. In particular, *Total Toxic Releases* equals the logarithm of the total amount of toxic chemicals released (including air emissions, water discharges, underground injection, etc.) from each plant in a year. Second, the county-level analyses measure credit shocks and pollution in the same county, i.e., *Poll* and *County* *liquidity gain* are measured in the same non-shale county, where *County liquidity gain* measures the degree to which banks in the non-shale county receive liquidity shocks through their branch networks in shale counties. In our plant-level analyses, we examine credit shocks to the plant's headquarters, which is typically located in a different county from the plant.[7] That is, we compute the degree to which banks in the county where the plant's headquarters is located receive liquidity shocks through branch networks in other counties. We omit all plants and headquarters located in shale counties—and in robustness checks we also omit plants and headquarters located in counties neighboring shale counties.

5.1 Shale liquidity shocks and plant emissions: Core analyses

We first evaluate how plants adjust their toxic emissions when banks operating in the plants' headquarters counties—*Headquarters(county)*—receive shale liquidity shocks in their branches in other counties. We estimate the following regressions at the plant-year level.

$$Total\ toxic\ releases_{p,i,t} = \beta_1 Firm\_county\ liquidity\ gain_{i,hdqcnty,t} + \beta_2' \Pi_{p,t} + \alpha_p + \alpha_{cnty,t} + \alpha_{ind,t} + \alpha_{hdqst,t} + \varepsilon_{p,i,t}, \qquad (6)$$

where the dependent variable, $Total\ toxic\ releases_{p,i,t}$, is the log amount of toxic chemical releases (measured in pounds) by plant *p* located in county *cnty*, affiliated with firm *i* in industry *ind*, headquartered in county *hdqcnty* and state *hdqst* in year *t*. $Firm\_county\ liquidity\ gain_{i,hdqcnty,t}$ is one of the two measures of the extent to which the banks operating in county *hdqcnty* receive positive liquidity shocks through their branch networks in other counties, and is defined above in Section 3. Plant-specific traits ($\Pi_{p,t}$) include *Total sales* and

[7] In particular, 77,951 observations are in a different county from the plant's headquarters, and 16,353 observations are in the same county as its headquarters.

Sales growth. We include plant, county-year, industry (2-digit SIC)-year, and headquarters (state)-year fixed effects, α_p, $\alpha_{cnty,t}$, $\alpha_{ind,t}$, and $\alpha_{hdqst,t}$, to condition out any time-invariant differences across plants and time-varying differences across (plants') counties, industries and (headquarters') states. We estimate the model using OLS, with standard errors clustered at the firm level. To the extent that companies effectively devote more resources to limiting toxic emissions when they receive better credit conditions, we expect $\beta_1 < 0$.

We interpret these shale liquidity shocks to banks in the firm's headquarters-county as changes in the credit conditions facing the firm based on the assumption that firms tend to obtain loans from geographically close banks. Extensive research support this assumption, e.g., Petersen and Rajan (2002), Berger et al. (2005), Agarwal and Hauswald (2010), and Berger, Bouwman, and Kim (2017). For example, Petersen and Rajan (2002) find that the median distance between bank and borrower is 4 miles.

It is worth noting that we include county-year fixed effects throughout the analysis. This addresses concerns that our results are driven by economic or regulatory variations across counties, such as local credit demand shocks, local environmental regulations, and other omitted variables that might affect pollution emissions. We can include county-year effects because not all plants located in a county have their headquarters in the same county, which enables us to distinguish the treatment effects from local economic conditions.

We discover that plants pollute less after banks in the county in which its parent firm is headquartered receive positive liquidity shocks. As shown in columns 1 – 4 of Table 6, the key explanatory variable—the degree to which banks in the county in which a firm is headquartered receive positive liquidity shocks (i.e., *Firm-county liquidity gain1*, or *Firm-county liquidity gain2*)—enters negatively and significantly in all specifications. These results suggest that improvements in firms' access to finance lead the firm's plants to emit less toxic pollutants. These results are unlikely to be driven by (a) changes in local economic conditions triggered by shale development because we exclude both plants in shale counties and firms headquartered in shale counties, and (b) changes in local economic conditions due to other omitted factors because we include a full set of county-year fixed effects.

To interpret the economic magnitudes of the estimated coefficients, consider two otherwise similar plants, except that one plant has its parent firm headquartered in a county that receives a positive, sample mean liquidity shock (i.e., *Firm-county liquidity gain1* = 0.05 as shown in Table 1 Panel B), while the other is headquartered in a county that does not receive the shock (i.e., *Firm-county liquidity gain1* = 0). The coefficient estimates from column 1 of Table 6 indicate that toxic emissions from the "shocked" plant would be 6% (= 0.05*1.19) lower than those of the other plant.

We were concerned that activities in counties that neighbor (are geographically adjacent to) shale counties could drive our results and lead to spurious results. Thus, we repeat the analyses, but further exclude plants and firms headquartered in counties adjacent to shale counties. As shown in columns 5 – 8, all of the results hold.

5.2 Liquidity shocks and plant pollution: differentiating by bank dependence

We extend this examination by assessing whether the pollution-reducing effects of liquidity shocks to banks in a plant's headquarters-county vary across firms in a predictable manner. If liquidity shocks to banks in the headquarters-county affect firms by easing credit constraints, then the impact should be stronger among firms that rely more heavily on local banks. To measure the extent to which firms rely on local banks for credit, we differentiate between privately-held or publicly-listed firms. Based on a considerable body of research (e.g., Pagano, Panetta, and Zingales 1998; Saunders and Steffen 2011; Borisov, Ellul, and Sevilir 2017), we assume that publicly-listed firms have, on average, greater access to credit beyond banks operating in their headquarters-county than privately-held firms. We test whether the impact of liquidity shocks on plants' toxic emissions is larger among plants affiliated with privately-held firms than among plants affiliated with publicly-listed firms.

Consistent with this view, we find larger pollution-reducing effects from positive bank liquidity shocks among plants affiliated with privately-held firms. As shown in Table 7, the key explanatory variable, which is either *Firm-county liquidity gain1* or *Firm-county liquidity gain2*, enters negatively and significantly among plants affiliated with privately-held firms but enters insignificantly when examining publicly-listed firms.

5.3 Instrumental variable estimation

In this subsection, we conduct 2SLS regressions where the intermediating variable is the change in deposits. This allows us to (a) examine whether a firm's headquarters-county exposure to shale discoveries influences its plant pollutant emissions through boosting liquidity of banks operating in that county, and (b) further assess the economic magnitude of the impact of liquidity shocks—measured as the percentage change of bank deposits—on pollution.

To do this, we calculate a county-specific measure of deposit growth. Specifically, for each county in each year, *County-bank deposit growth* equals the weighted average of deposit growth across banks in the county, where we weight each bank by its market share in the county. We then instrument this *County-bank deposit growth* with measures of county exposure to shale development, *County liquidity gains 1* and *County liquidity gains 2*. We first note that both county liquidity gains measures are strongly, positively correlated with *County-bank deposit growth*. As shown in Table 8 Panel B, both *County liquidity gains 1* and *County liquidity gains 2* enter the first-stage regressions positively and statistically significantly. In addition, the F-statistics of the weak instrument test range from 50 – 61, further rejecting the null hypothesis that our instrument is irrelevant to the instrumented variable.

The second-stage results reported in Table 8 Panel A suggest that positive shocks to bank liquidity in a county ease credit conditions facing firms headquartered in the county, and this easing of firm credit constraints reduce toxic emissions by the firm's plants. The IV estimates suggest an economically large effect. For example, the estimated coefficients from column 1 of Panel A indicate that if bank deposits in a county grow by 1 percentage points, the plant toxic pollution emissions would drop by about 8%.[8]

6. Toxic Emissions and Adverse Liquidity Shocks

In this section, we employ our third and fourth identification strategies and assess the impact of adverse liquidity shocks on pollution. While the earlier sections focused on positive liquidity shocks triggered by shale discoveries, this section uses two strategies for analyzing the impact of the negative liquidity shocks triggered by the global financial crisis on toxic emissions.

6.1 Adverse liquidity shocks: Differentiating by firms' debt maturity structure

[8] Online Appendix Table A6 reports 2SLS regressions results at the firm-level, which yield similar results to the plant-level results discussed above.

To obtain firm-specific adverse liquidity shocks, we examine the tightening of credit conditions associated with the onset of the global financial crisis, while differentiating firms by their debt maturity structures. Intuitively, to the extent that firms with more debt maturing in 2008 faced greater liquidity constraints when the financial crisis hit—as found by Acharya and Mora (2015), we can use the maturing debt ratio at the onset of the crisis as a proxy for the impact of the financial crisis on firms' credit constraint.[9] Thus, we follow Almeida et al. (2012), and Cohn and Wardlaw (2016) and exploit heterogeneity in the maturity structure of firms' debt at the onset of the financial crisis in late 2007. In particular, we differentiate firms by the amount of debt due in one year, measured at the end of the 2007 fiscal year as a proportion of firm assets (*Maturing debt as of 2007*). Since firms were unlikely to have anticipated the advent of the crisis when scheduling their debt maturity before the crisis, we exploit firms' pre-determined debt structure as an exogenous source of variation in the severity of the credit crunch following the onset of the crisis and examine the impact of this credit tightening on plants' emissions of toxic pollutants.

We employ the following model specification.

$$Total\ toxic\ releases_{p,i,t} = \theta_1 Maturing\ debt\ as\ of\ 2007_i * Crisis_t + \theta_2' \kappa_{i,t} + \alpha_p + \alpha_{cnty,t} + \alpha_{ind,t} + \alpha_{hdqst,t} + \varepsilon_{p,i,t}, \tag{7}$$

where the dependent variable, $Total\ toxic\ releases_{p,i,t}$, is the log amount of toxic chemical releases by plant *p* located in county *cnty*, affiliated with firm *i* in industry *ind*, headquartered in state *hdqst* in year *t*. *Maturing debt as of 2007*$_i$ is the amount of debt due in one year, measured at the end of fiscal year 2007 as a

[9] In a different setting that illustrates the importance of leverage and firm's network of plants, Giroud and Mueller (2016, 2019) show that plants of highly levered firms respond more strongly to declines in local consumer demands, which spill over to geographically distant regions through firms' internal networks.

proportion of firm *i*'s assets. *Crisis* equals one in 2008 and after, and otherwise equals zero. Firm-specific traits ($\kappa_{i,t}$) include *Total sales*, *Sales growth*, and one-year-lagged *Profitability*. Similar to Equation (6) above, we include plant, county-year, industry (2-digit SIC)-year, and headquarters (state)-year fixed effects, α_p, $\alpha_{cnty,t}$, $\alpha_{ind,t}$, and $\alpha_{hdqst,t}$, to condition out any time-invariant differences across plants and time-varying differences across (plants') counties, industries and (headquarters') states. We estimate the model using OLS, with standard errors clustered at the firm level. Our variable of interest, the interaction term—*Maturing debt as of 2007*Crisis*—represents an exogenous change to the liquidity conditions facing each firm, and θ_1 captures the impact of these shock to liquidity conditions on associated plant emissions of toxic pollutants. We conduct the analyses over the 2006-2008 period and the 2006-2009 period, as the crisis might have had enduring effects on the liquidity conditions and hence the toxic emissions of firms and plants.

As shown in Table 9, when firms receive an adverse liquidity shock, their associated plants tend to increase toxic emissions. Whether examining the 2006-2008 or 2006-2009 period, *Maturing debt as of 2007*Crisis* enters positively and significantly. The estimates suggest an economically large effect. The column 1 estimates indicate that a one standard deviation increase in a firm's maturing debt ratio would boost toxic pollution emissions by about 9%. Furthermore, neither the estimated coefficient nor its statistical significance on the interaction term varies much when including or excluding the control for firm sales, sales growth, and lagged profitability. Thus, the positive impact of the adverse liquidity shock on toxic emissions does not simply reflect firm performance. Furthermore, the results hold when including plant, county-year, industry-year and (headquarters) state-year fixed effects. These findings are consistent with the view that a tightening of credit conditions induces firms to devote fewer resources toward pollution abatement, boosting plant emissions of toxic pollutants.

6.2 Bank holdings of private MBS

For our fourth identification strategy, we examine the tightening of credit conditions associated with the global financial crisis, while differentiating banks by their holdings of private-label MBSs. Research suggests that banks holding more private-label MBSs were subject to greater losses and risks during the financial crisis, which was triggered by the collapse of the housing market (e.g., Agarwal et al. 2012; Ellul and Yerramilli 2013; Nadauld, and Stulz 2013). Thus, we use the interaction between MBS exposure and the crisis as a bank-specific measure of a banks' adverse liquidity shock. After first showing that banks with greater exposure to private-label MBSs contracted their supply of credit more than other banks, we (1) construct measures of each county's exposure to this negative bank liquidity shocks based on the banks operating in the county, and (2) use these measures to evaluate the impact of tightening credit conditions in a firm's headquarters-county on toxic emissions by the firm's plants.

We use the following specification to examine whether pre-crisis exposure to private-label MBSs influences bank profits and supply of credit.

$$\Delta Y_{b,2007-2010} = \rho_1 Private\ MBS_{b,2007} + \rho_2{}' X_{b,2007} + e_b, \qquad (8)$$

where the dependent variable, $\Delta Y_{b,2007-2010}$, equals changes in *C&I Loan growth* (or *Return on assets*) for bank b from 2007 to 2010. $Private\ MBS_{b,2007}$ is the total value of private-label mortgage-backed securities held by bank *b*, scaled by book value of total assets, measured as of 2007. $X_{b,2007}$ denotes a set of bank-specific controls as above (*Total asset, Deposit/Total assets, Liquid assets/Total assets, Mortgages/Total assets, C&I loans/Total assets, Loan commitments/Total* *assets, and Letters of credits/Total assets*), measured as of 2007. We report the estimation results in Table 10.

As shown in Table 10 Panel B, banks that held a larger ratio of private-label MBSs to total assets at the onset of the financial crisis experienced a greater contraction of profits and C&I loan growth. *Private* MBS_{2007} enters the regressions of *ΔROA* and *ΔC&I Loan Growth* negatively and significantly, suggesting that larger holdings of private MBSs lead banks to suffer more profits losses and credit supply reductions. The results hold whether using periods over 2007 – 2010 (columns 1 – 4) or 2007 – 2009 (columns 5 – 8). The economic impact is large. The coefficient estimates from column 2 of Panel B indicate that banks with an average ratio of MBSs to total assets (i.e., *Private* MBS_{2007} = 0.023) would reduce C&I loans by 3 percentage points more than banks that do not hold any private MBSs. This is large given that the median value of the C&I loan growth rate as of 2007 was 8 percentage points.

After confirming that holdings of MBS have a material negative impact on bank credit supply, we next construct a measure of county-specific (and thus firms' headquarters-county) exposure to this negative bank liquidity shock based on banks operating in the county, and use this measure to evaluate the impact of tightening credit conditions in a firm's headquarters-county on toxic emissions by the firm's plants. We construct the county-specific measure using a similar strategy to our earlier analyses. For each county, we compute county exposure to MBS-induced liquidity shocks as the weighted average of bank-specific *Private* MBS_{2007} across banks operating in the county as of 2007, where we weight each bank by its market share in the county. Similar to our strategy earlier, for each plant, we assign the values of MBS exposure associated with banks in the county in which its parent firm is headquartered. We refer to this measure as *Firm-*

county exposure to private MBS_{2007}. We estimate the following cross-section model to assess the impact of tightening credit conditions on toxic emissions.

$$\Delta Total\ toxic\ releases_{p,i,2007-2010} = \theta_1 Firm\_county\ private\ MBS_{i,hdqcnty,2007} + \theta_2{}' \Pi_{p,2007} + \alpha_{cnty} + \alpha_{ind} + \alpha_{hdqst} + e_{p,i}, \quad (9)$$

where $\Delta Total\ toxic\ releases_{p,i,2007-2010}$ is the change of the log amount of toxic chemical releases by plant *p* located in county *cnty*, affiliated with firm *i* in industry *ind*, headquartered in county *hdqcnty* and state *hdqst* over the period 2007 – 2010. $Firm\_county\ private\ MBS_{i,hdqcnty,2007}$ measures the extent to which banks operating in county *hdqcnty* were exposed to private-label MBS as of 2007. Plant-specific traits ($\Pi_{p,2007}$) include *Total sales* and *Sales growth*, measured as of 2007. We include county, industry, and headquarters (state) fixed effects to condition out any differences across (plants') counties, industries and (headquarters') states. We estimate the model using OLS, with standard errors clustered at the firm level.

Consistent with previous findings, the results in Table 11 suggest that when firms receive a negative shock to their credit conditions, their plants tend to emit more toxic pollutants. *Firm-county exposure to private MBS_{2007}* enters positively and significantly in all columns. The coefficient estimates from column 1 indicate that if the pre-crisis MBS holdings of banks operating in a firm's headquarters-county increase by one standard deviation, toxic emissions by the firm's plants would increase by about 13%. The results hold whether including or excluding the control for firm sales, sales growth, and whether using bank MBS holdings as of 2007 or 2006. Furthermore, the results hold when including county, industry and (headquarters) state fixed effects. These findings confirm the view that an adverse shock to firms' credit conditions induces them to devote fewer resources toward pollution abatement, leading to an increase in plant toxic emissions.

7. Conclusion

In this study, we evaluate the impact of changes in the credit conditions facing firms on their plants' emissions of toxic pollutants. To make this assessment, we use four empirical strategies to identify shocks to the credit conditions facing firms. The first two strategies begin with the technological breakthroughs that triggered shale development in several counties across the U.S. and corresponding liquidity windfalls at bank branches in those counties. We construct measures of the degree to which banks in non-shale counties receive liquidity shocks through their branch networks in shale counties and implement the first two empirical strategies. We evaluate (1) how these shocks to county credit conditions influence the emissions of toxic pollutants in those counties, and (2) how these shocks to a firm's headquarters county influence its plants' emissions of toxic pollutants.

The next two identification strategies focus on adverse credit shocks triggered by the global financial crisis. First, we differentiate firms by the ratio of maturing debt at the onset of the crisis to total assets and use this as a proxy for the adverse impact of the financial crisis on firms' credit constraints. We then evaluate whether firms with higher debt maturity ratios emitted more toxic pollutants during and after the crisis. Second, we differentiate banks by their holdings of private-label MBSs right before the crisis and use MBS exposure as a proxy for the adverse impact of the financial crisis on banks' supply of credit. This provides a measure of the degree to which the financial crisis tightens credit offered by banks in each county. We then evaluate the impact of tightening credit conditions in a firm's headquarters-county on toxic emissions by the firm's plants.

Across all four empirical strategies, we find that finance exerts a strong influence on pollution. Shocks that ease firms' credit constraints induce a sharp reduction in toxic emissions, and shocks that tighten credit constraints trigger material increases in toxic pollutants. This work highlights that credit conditions shape firms' decisions regarding the release of toxic pollutants.

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Table 1 Summary Statistics

Panel A: County Sample

Variable	N	Mean	SD	P25	P50	P75
County-Specific Liquidity Shock						
County liquidity gain1	2225	0.067	0.108	0.000	0.014	0.093
County liquidity gain2	2225	0.060	0.099	0.000	0.010	0.078
Hazardous Pollutant Concentration						
Top-10 Toxins, mean	2225	0.027	0.018	0.016	0.024	0.033
Benzene, mean	2209	1.846	1.404	1.026	1.505	2.187
Toluene, mean	2149	4.434	4.054	1.926	3.257	5.480
Ethylbenzene, mean	2123	0.680	0.661	0.276	0.504	0.883
o-Xylene, mean	2098	0.782	0.791	0.284	0.570	1.003
m/p Xylene, mean	2037	2.038	2.132	0.726	1.445	2.585
County Characteristics						
Ln(Per capita personal income)	2225	10.484	0.291	10.298	10.463	10.650
Ln(Population)	2225	12.625	1.280	11.867	12.748	13.581
Labor market participation	2225	0.506	0.049	0.481	0.511	0.537
Unemployment	2225	0.064	0.027	0.045	0.057	0.078
EPA Penalties, in thousand dollar	2225	1305.773	3833.652	15.625	139.620	758.174

Panel B: Toxic Emission Plants

	N	Mean	SD	P25	P50	P75
Positive Shock						
Firm-county liquidity gain1	94304	0.050	0.089	0.000	0.009	0.058
Firm-county liquidity gain2	94304	0.045	0.083	0.000	0.006	0.050
Total toxic releases	94304	7.897	3.994	5.583	8.603	10.664
Sales	62380	16.979	1.681	16.042	17.120	18.064
Sales growth	62380	0.003	0.263	-0.035	0.001	0.055
Negative Shock, Maturing Debt as of 2007						
Debt maturing in one year as of 2007	10577	0.042	0.056	0.005	0.023	0.053
Crisis	10577	0.484	0.500	0	0	1
Total toxic releases	10577	7.111	4.492	3.367	7.842	10.456
Sales	10560	8.845	1.509	7.814	8.931	9.948
Sales growth	10560	0.008	0.183	-0.070	0.051	0.114
Profitability	10560	0.060	0.073	0.033	0.062	0.091

Panel C: Banks

	N	Mean	SD	P25	P50	P75
Bank liquidity gain1	105579	0.080	0.367	0	0	0
Bank liquidity gain2	105579	0.049	0.313	0	0	0
Bank liquidity gain1, exposed only	14202	0.593	0.834	0.024	0.153	0.834
Bank liquidity gain2, exposed only	14202	0.362	0.785	0.000	0.000	0.068
Deposit growth	105579	0.085	0.172	0.000	0.051	0.118
C&I Loan growth	102555	0.069	0.332	-0.096	0.048	0.203
Total assets	105579	11.776	1.284	10.908	11.647	12.471
Capital asset ratio	105579	0.111	0.051	0.084	0.098	0.121
Deposit/Total assets	105579	0.824	0.093	0.796	0.847	0.883
Liquid assets/Total assets	105579	0.061	0.058	0.028	0.042	0.070
Mortgages/Total assets	105579	0.422	0.181	0.295	0.428	0.555
C&I loans/Total assets	105579	0.094	0.071	0.044	0.078	0.125
Loan commitments/Total assets	105579	0.101	0.083	0.045	0.083	0.135
Letters of credits/Total assets	105579	0.004	0.007	0.000	0.002	0.005

Table 2 Positive Liquidity Shocks and Bank Deposit & Loan Growth

This table presents the bank-year regressions of bank deposit growth on liquidity shock from the shale-drilling activities from 2000 – 2013. The dependent variable is deposit growth in columns 1 and 2, and C&I loan growth in columns 3 and 4. For each bank in a year, we construct two measures of shale liquidity shocks, *Bank liquidity gain1* and *Bank liquidity gain2*. Both measures capture the extent to which each bank receives liquidity gains resulting from shale development through its branch networks across counties. Appendix Table A1 provides detailed variable definitions. Bank specific controls include *Total asset*, *Capital asset ratio*, *Deposit/Total assets*, *Liquid assets/Total assets*, *Mortgages/Total assets*, *C&I loans/Total assets*, *Loan commitments/Total assets*, and *Letters of credits/Total assets*, all measured at the beginning of each year. We include Bank and Year fixed effects throughout the table. P-values are calculated using heteroscedasticity robust standard errors clustered at the bank level, and reported in parentheses. *,**, and *** indicate significance at 10%, 5%, and 1%.

	Deposit Growth		C&I Loan Growth	
	(1)	(2)	(3)	(4)
Bank liquidity gain1	0.031***		0.040***	
	(0.000)		(0.000)	
Bank liquidity gain2		0.028***		0.034***
		(0.000)		(0.000)
Total assets (lag)	-0.160***	-0.161***	-0.170***	-0.170***
	(0.000)	(0.000)	(0.000)	(0.000)
Capital asset ratio (lag)	0.983***	0.984***	1.407***	1.409***
	(0.000)	(0.000)	(0.000)	(0.000)
Deposit/Total assets (lag)	-0.626***	-0.626***	-0.128***	-0.127***
	(0.000)	(0.000)	(0.001)	(0.001)
Liquid assets/Total assets (lag)	-0.079***	-0.080***	0.012	0.011
	(0.000)	(0.000)	(0.742)	(0.745)
Mortgages/Total assets (lag)	0.084***	0.084***	-0.176***	-0.176***
	(0.000)	(0.000)	(0.000)	(0.000)
C&I loans/Total assets (lag)	0.241***	0.243***	-2.505***	-2.502***
	(0.000)	(0.000)	(0.000)	(0.000)
Loan commitments/Total assets (lag)	0.451***	0.451***	0.675***	0.676***
	(0.000)	(0.000)	(0.000)	(0.000)
Letters of credits/Total assets (lag)	0.336**	0.338**	1.142***	1.145***
	(0.019)	(0.019)	(0.000)	(0.000)
BHC Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	105,579	105,579	102,555	102,555
R-squared	0.547	0.546	0.290	0.290
# of banks	10617	10617	10217	10217

Table 3 Positive Liquidity Shocks and Hazardous Air Pollution, County-Level Analyses Using Data from EPA Pollution Monitoring Stations

This table reports the regression results of the effects of county-level liquidity shocks on the concentration of hazardous airborne pollutants based on EPA monitoring stations. Our county-year sample includes only non-shale counties, i.e., those counties with no local shale development. The dependent variable is the arithmetic mean of each of the air pollutants collected by EPA monitoring stations during each year. We report the results on the average standardized density of top 10 most monitored pollutants, and each of the five most monitored hazardous pollutants, namely, Benzene, Toluene, Ethylbenzene, o-Xylene, and m/p Xylene. The key explanatory variable is one of the county-specific, time-varying measures on the extent to which banks in a county are exposed to shale development via its branch located in shale-boom counties, i.e., *County liquidity gain1* or *County liquidity gain2*. For each county in a year, we calculate its banks' shale liquidity shock by taking the average of bank-specific shale liquidity shock (i.e., *Bank liquidity gain1* or *Bank liquidity gain2*), weighted each bank by its local market share in that particular county. We provide detailed variable definitions in Appendix Table A1. County controls include *Ln(Per capita personal income)*, *Ln(Population)*, *Labor market participation*, and *Unemployment*. We include county and year fixed effects across columns. P-values are calculated using heteroscedasticity robust standard errors clustered at the county level, and reported in parentheses. *,**, and *** indicate significance at 10%, 5%, and 1%.

	Top-10 Toxins	Benzene	Toluene	Ethylbenzene	o-Xylene	m/p Xylene	Top-10 Toxins	Benzene	Toluene	Ethylbenzene	o-Xylene	m/p Xylene
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
County liquidity gain1	-0.020**	-3.155***	-5.425***	-0.595**	-0.690**	-2.476***						
	(0.015)	(0.000)	(0.000)	(0.048)	(0.044)	(0.008)						
County liquidity gain2							-0.021**	-3.313***	-5.660***	-0.583*	-0.635*	-2.434**
							(0.010)	(0.000)	(0.000)	(0.071)	(0.083)	(0.015)
County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,225	2,209	2,149	2,123	2,098	2,037	2,225	2,209	2,149	2,123	2,098	2,037
R-squared	0.661	0.672	0.681	0.669	0.689	0.702	0.661	0.671	0.681	0.669	0.688	0.702
# of counties	300	300	288	287	285	274	300	300	288	287	285	274

Table 4 Positive Liquidity Shocks and County-Level Hazardous Air Pollution, Pre-Trends

This table reports the regression results of the effects of county-level liquidity shocks on the concentration of hazardous airborne pollutants based on EPA monitoring stations, while controlling for differential trends within counties. In columns 1 & 2, *County trends* correspond to a full set of interactions between county dummy and the time trends variable, $County\,dummy_c \times Trends$, where $County\,dummy_c$ represents a vector of 300 county dummy variables, and *Trends* is a time trend indicator that equals one in 2000, two in 2001, three for 2002, and zero for years over the post-shale-discovery period. The dependent variable in columns 1 & 2 is the average standardized values of the top 10 pollutants collected by EPA monitoring stations during each year. The key explanatory variable is one of the county-specific, time-varying measures on the extent to which banks in a county are exposed to shale development via its branch located in shale-boom counties, i.e., *County liquidity gain1* or *County liquidity gain2*. County controls in columns 1 & 2 include *Ln(Per capita personal income)*, *Ln(Population)*, *Labor market participation*, and *Unemployment*. In columns 3 & 4, we regress county-level pollutants over the pre-shale discovery period, 2000-2002, on county exposure to bank liquidity shocks since 2003. The dependent variable is the average standardized values of the top 10 pollutants collected by EPA monitoring stations during the pre-shale period, 2000 – 2002. The key explanatory variable is *County liquidity gain1* (or *County liquidity gain2*) averaged over the post-shale period, 2003 – 2013. County controls in columns 3 & 4 include *Ln(Per capita personal income)*, *Ln(Population)*, *Labor market participation*, and *Unemployment* averaged over the pre-shale period. We provide detailed variable definitions in Appendix Table A1. We include county and year fixed effects across columns. P-values are calculated using heteroscedasticity robust standard errors clustered at the county level, and reported in parentheses. *,**, and *** indicate significance at 10%, 5%, and 1%.

	Top-10 Toxins		Top-10 Toxins, pre2003	
	Controlling for Pre-trends		Pre-shale Pollution and Post-shale Liquidity Shocks	
	(1)	(2)	(3)	(4)
County liquidity gain1	-0.018**			
	(0.029)			
County liquidity gain2		-0.018**		
		(0.028)		
County liquidity gain1, post2003			0.007	
			(0.773)	
County liquidity gain2, post2003				0.007
				(0.776)
County Controls	Yes	Yes	Yes	Yes
County Trends	Yes	Yes	No	No
County FE	Yes	Yes	No	No
Year FE	Yes	Yes	No	No
Observations	2,225	2,225	157	150
R-squared	0.728	0.728	0.289	0.283

Table 5 Heterogeneity Effects of Positive Liquidity Shocks on County-Level Hazardous Air Pollution, by EPA Penalties

This table reports the heterogeneous effects of county-level liquidity shocks on hazardous air pollutants concentration from EPA monitoring stations, while differentiating counties by the intensity of EPA penalties. Consistent with the previous tables, our county-year sample includes only non-shale counties, i.e., counties with no local shale development. *EPA Penalties* is an indicator that equals one if the dollar amount of penalties imposed on a county's establishments for violating Clean Air Act over the past five years are greater than the sample median value, and zero otherwise. The dependent variable is the mean values of each of the air pollutants concentration collected by EPA monitoring stations during each year. We report the results on the average standardized density of top 10 most monitored pollutants, and each of the five most monitored hazardous pollutants, namely, Benzene, Toluene, Ethylbenzene, o-Xylene, and m/p Xylene. The key explanatory variable is one of the county-specific, time-varying measures on the extent to which banks in a county are exposed to shale development via its branch located in shale-boom counties, i.e., *County liquidity gain1* or *County liquidity gain2*. We provide detailed variable definition in Appendix Table A1. County controls include *Ln(Per capita personal income)*, *Ln(Population)*, *Labor market participation*, and *Unemployment*. We include county and year fixed effects across columns. P-values are calculated using heteroscedasticity robust standard errors clustered at the county level, and reported in parentheses. *,**, and *** indicate significance at 10%, 5%, and 1%.

	Top-10 Toxins	Benzene	Toluene	Ethylbenzene	o-Xylene	m/p Xylene	Top-10 Toxins	Benzene	Toluene	Ethylbenzene	o-Xylene	m/p Xylene
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
County liquidity gain1 * EPA Penalties	-0.019***	-1.167**	-2.364	-0.777***	-0.709**	-2.655***						
	(0.006)	(0.032)	(0.171)	(0.005)	(0.042)	(0.003)						
County liquidity gain1	-0.006	-2.321***	-3.782**	-0.023	-0.183	-0.583						
	(0.419)	(0.000)	(0.032)	(0.931)	(0.544)	(0.458)						
County liquidity gain2 * EPA Penalties							-0.020***	-1.202**	-2.584	-0.850***	-0.753*	-2.865***
							(0.007)	(0.047)	(0.180)	(0.007)	(0.052)	(0.004)
County liquidity gain2							-0.006	-2.446***	-3.881**	0.048	-0.097	-0.392
							(0.445)	(0.000)	(0.045)	(0.865)	(0.767)	(0.648)
EPA Penalties	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,225	2,209	2,149	2,123	2,098	2,037	2,225	2,209	2,149	2,123	2,098	2,037
R-squared	0.663	0.673	0.683	0.671	0.690	0.705	0.663	0.672	0.682	0.671	0.690	0.704
# of counties	300	300	288	287	285	274	300	300	288	287	285	274

Table 6 Positive Liquidity Shocks and Plant Toxic Releases, Plant-Level Analyses

This table reports the plant-year regressions of a plant's releases of toxic pollutants on its headquartered county liquidity shocks. Columns 1 – 4 exclude plants and firms in counties with shale development activities (i.e., shale counties), and columns 5 – 8 further exclude plants and firms in counties adjacent to a shale county. The dependent variable is the logarithm of the total volume of toxic chemical releases in all columns. The key explanatory variable is one of the firm-county measures on the extent to which banks in a plant's headquarters county are exposed to shale development via their branch located in shale counties, i.e., *Firm-county liquidity gain1* or *Firm-county liquidity gain2*. Plant controls include *Sales* and *Sales growth*. We provide detailed definitions in Appendix Table A1. We include Plant, County-year, Industry-year, and Headquarters (State)-year fixed effects in all specifications. P-values are calculated using heteroscedasticity robust standard errors clustered at the firm level, and reported in parentheses. *,**, and *** indicate significance at 10%, 5%, and 1%.

	Total Toxic Releases							
	Excl. firms & plants located in shale counties				Excl. firms & plants located in shale & neighboring counties			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm-county liquidity gain1	-1.192**	-1.745**			-1.409**	-2.455***		
	(0.038)	(0.017)			(0.049)	(0.007)		
Firm-county liquidity gain2			-1.193**	-1.699**			-1.534**	-2.568***
			(0.045)	(0.025)			(0.042)	(0.008)
Sales		0.029		0.029		0.016		0.017
		(0.227)		(0.223)		(0.515)		(0.508)
Sales growth		0.005		0.005		-0.007		-0.007
		(0.885)		(0.892)		(0.853)		(0.845)
Plant fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Headquarters(State)-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	94,304	62,380	94,304	62,380	75,972	51,022	75,972	51,022
R-squared	0.909	0.919	0.909	0.919	0.914	0.924	0.914	0.924
# of plants	12296	8636	12296	8636	11349	7956	11349	7956

Table 7 Positive Liquidity Shocks and Plant Toxic Releases, Heterogeneity by Bank Dependence

This table reports the regressions of a plant's releases of toxic pollutants on its headquartered county liquidity shocks, while differentiating plants by the extent to which their parent firms have access to outside sources of financing, and thus their reliance on banks within the headquarters-county. We exclude plants and firms in shale counties. We use the status of private or publicly traded to proxy for a firm's dependence on bank credit within the headquarters-county. Columns with the odd number use a sample of plants owned by private firms, and columns with the even number focus on plants affiliated with publicly listed firms. The dependent variable is the logarithm of the total volume of toxic chemical releases in all columns. The key explanatory variable is one of the firm-county measures on the extent to which banks in a firm's headquarters county are exposed to shale development via their branch located in shale counties, i.e., *Firm-county liquidity gain1* or *Firm-county liquidity gain2*. Plant controls include *Sales* and *Sales growth*. We provide detailed definitions in Appendix Table A1. We include Plant, County-year, Industry-year, and Headquarters (State)-year fixed effects in all specifications. P-values are calculated using heteroscedasticity robust standard errors clustered at the firm level, and reported in parentheses. *,**, and *** indicate significance at 10%, 5%, and 1%.

	Total Toxic Releases							
	Private	Public	Private	Public	Private	Public	Private	Public
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm-county liquidity gain1	-2.869***	0.051	-3.722***	-0.987				
	(0.000)	(0.960)	(0.000)	(0.453)				
Firm-county liquidity gain2					-2.874***	0.014	-3.797***	-0.846
					(0.000)	(0.990)	(0.000)	(0.549)
Plant controls	No	No	Yes	Yes	No	No	Yes	Yes
Plant fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Headquarters(State)-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,781	48,463	23,913	31,609	37,781	48,463	23,913	31,609
R-squared	0.914	0.921	0.920	0.935	0.914	0.921	0.920	0.935
# of plants	5133	6347	3405	4460	5133	6347	3405	4460

Table 8 Positive Liquidity Shocks, Deposit Growth, and Plant Toxic Releases, 2SLS Results

This table reports the 2SLS regressions of a plant's releases of toxic pollutants on its headquartered county-specific liquidity shocks. We exclude plants and firms in shale counties. The dependent variable is the logarithm of the total volume of toxic chemical releases across all columns for each plant in a given year. The explanatory variable, *County-bank deposit growth*, equals the weighted average of bank deposit growth, where each bank is weighted by its local market share in a particular county. Our instruments are one of the county-specific, time-varying measures on the extent to which banks in a county are exposed to shale development via its branch located in shale-boom counties, i.e., *Firm-county liquidity gain1* or *Firm-county liquidity gain2*. Plant controls include *Sales* and *Sales growth*. We provide detailed definitions in Appendix Table A1. We include Plant, County-year, Industry-year, and Headquarters (State)-year fixed effects in all specifications. P-values are calculated using heteroscedasticity robust standard errors clustered at the firm level, and reported in parentheses. *,**, and *** indicate significance at 10%, 5%, and 1%.

Panel A: Second-Stage Results

	Total Toxic Releases			
	(1)	(2)	(3)	(4)
County-bank deposit growth	-8.062**	-10.451**	-7.387*	-9.397**
	(0.046)	(0.029)	(0.051)	(0.037)
Plant controls	No	Yes	No	Yes
Plant fixed effects	Yes	Yes	Yes	Yes
County-year fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes
Headquarters(State)-year fixed effects	Yes	Yes	Yes	Yes
Observations	94,169	62,280	94,169	62,280
R-squared	0.902	0.909	0.903	0.911
Weak_ID_FTest	57.40	49.82	61.62	53.52
# of plants	12291	8633	12291	8633

Panel B: First-Stage Results

	County-bank deposit growth			
	(1)	(2)	(3)	(4)
Firm-county liquidity gain1	0.149***	0.168***		
	(0.020)	(0.024)		
Firm-county liquidity gain2			0.163***	0.183***
			(0.021)	(0.025)
Plant controls	No	Yes	No	Yes
Plant fixed effects	Yes	Yes	Yes	Yes
County-year fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes
Headquarters(State)-year fixed effects	Yes	Yes	Yes	Yes
Observations	94,169	62,280	94,169	62,280
R-squared	0.796	0.803	0.796	0.803

Table 9 Negative Liquidity Shocks and Plant Toxic Releases, Maturing Debt

This table reports the estimates of the effects of a firm's maturing debt at the onset of the 2007-2008 financial crisis on its plants' releases of toxic pollutants. The analysis uses plants affiliated with public firms for which we observe a firm's debt maturity structure as of the end of fiscal year 2007. In this experiment, we restrict the sample period to the 2006 – 2008 in columns 1 and 2, and 2006 – 2009 in columns 3 and 4. *Crisis* is defined as an indicator that equals one in year 2008 (and 2009), and zero in 2006 and 2007. We measure a firm's exposure to maturing debt at the onset of the crisis as follows: *Maturing debt as of 2007* equals the amount of debt maturing within one year as a proportion of the total assets as of fiscal year-end 2007. The dependent variable is the logarithm of the total volume of toxic chemical releases in all columns. Firm controls include *Sales*, *Sales growth*, and one-year-lagged *Profitability*. We provide detailed definitions in Appendix Table A1. We include Plant, County-year, Industry-year, and Headquarters (State)-year fixed effects in all specifications. P-values are calculated using heteroscedasticity robust standard errors clustered at the firm level, and reported in parentheses. *,**, and *** indicate significance at 10%, 5%, and 1%.

	Total Toxic Releases			
	2006 - 2008		2006 - 2009	
	(1)	(2)	(3)	(4)
Maturing debt as of 2007 * Crisis	1.702***	1.708***	1.775***	1.680***
	(0.003)	(0.003)	(0.007)	(0.009)
Sales		0.587**		0.689***
		(0.026)		(0.010)
Sales growth		-0.456*		-0.302
		(0.053)		(0.144)
Profitability, lag		0.397		0.725
		(0.427)		(0.101)
Plant fixed effects	Yes	Yes	Yes	Yes
County-year fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes
Headquarters(State)-year fixed effects	Yes	Yes	Yes	Yes
Observations	7,995	7,994	10,577	10,560
R-squared	0.971	0.971	0.963	0.963
# of plants	2820	2820	2930	2930

Table 10 Holdings of Private MBS and Bank Loan Growth

This table presents the cross-section regressions of changes in bank profits and loan growth on their pre-crisis holding of private-label mortgage-backed securities (MBS). Panel A provides the summary statistics for the bank sample. Panel B reports the regression results. The dependent variable in columns 1 – 4 is changes in return on assets from 2007 to 2010, $\Delta ROA_{2007\text{-}2010}$, and the change in the commercial and industrial loan growth from 2007 to 2010, Δ*C&I Loan Growth*$_{2007\text{-}2010}$. The dependent variable in columns 5 – 8 is changes in return on assets from 2007 to 2009, $\Delta ROA_{2007\text{-}2009}$, and the change in the commercial and industrial loan growth from 2007 to 2009, Δ*C&I Loan Growth*$_{2007\text{-}2009}$. The key explanatory variable, *Private MBS*, equals the total value of private-label mortgage-backed securities held in both trading and investment portfolios, scaled by book value of total assets, measured at the end of 2007. Bank characteristics include *Total asset*, *Deposit/Total assets*, *Liquid assets/Total assets*, *Mortgages/Total assets*, *C&I loans/Total assets*, *Loan commitments/Total assets*, and *Letters of credits/Total assets*, all measured at the year of 2007. P-values are calculated using heteroscedasticity robust standard errors, and reported in parentheses. *,**, and *** indicate significance at 10%, 5%, and 1%.

Panel A: Summary Statistics for the Bank Sample

	N	Mean	SD	P25	P50	P75
$\Delta ROA_{2007\text{-}2010}$	6678	-0.005	0.014	-0.008	-0.002	0.001
ΔC&I Loan Growth$_{2007\text{-}2010}$	6231	-0.127	0.363	-0.327	-0.123	0.075
$\Delta ROA_{2007\text{-}2009}$	7013	-0.008	0.016	-0.010	-0.004	0.000
ΔC&I Loan Growth$_{2007\text{-}2009}$	6523	-0.133	0.363	-0.338	-0.128	0.067
Private MBS$_{2007}$	7724	0.003	0.016	0.000	0.000	0.000
Private MBS$_{2007}$, exposed banks	1001	0.023	0.039	0.003	0.010	0.027
Total assets,$_{2007}$	8082	11.927	1.430	10.988	11.785	12.668
Deposit/Total asset,$_{2007}$	8033	0.959	0.254	0.877	0.997	1.110
Liquid assets/Total assets,$_{2007}$	8073	0.047	0.055	0.022	0.032	0.050
C&I loans/Total assets,$_{2007}$	8021	0.100	0.081	0.046	0.083	0.133
Mortgages/Total assets,$_{2007}$	8021	0.444	0.205	0.308	0.462	0.600
Loan commitments/Total assets,$_{2007}$	8021	0.124	0.114	0.054	0.101	0.161
Letters of credits/Total assets,$_{2007}$	8071	0.007	0.016	0.000	0.002	0.007

Panel B: Regression Results

	2007 – 2010				2007 – 2009			
	ΔROA$_{2007\text{-}2010}$		ΔC&I Loan Growth$_{2007\text{-}2010}$		ΔROA$_{2007\text{-}2009}$		ΔC&I Loan Growth$_{2007\text{-}2009}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Private MBS$_{2007}$	-0.026**	-0.033***	-1.264***	-1.115***	-0.040***	-0.038***	-1.279***	-1.097***
	(0.017)	(0.003)	(0.000)	(0.000)	(0.008)	(0.007)	(0.001)	(0.003)
Bank characteristics, 2007	No	Yes	No	Yes	No	Yes	No	Yes
Observations	6,596	6,596	6,052	6,052	6,927	6,927	6,333	6,333
R-squared	0.001	0.079	0.002	0.056	0.001	0.094	0.002	0.066

Table 11 MBS-Induced Negative Liquidity Shocks and Plant Toxic Releases

This table presents the effects of MBS-induced liquidity shocks to a firms' headquartered county on its plants' releases of toxic chemicals. The unit of analyses is the cross-section at the plant level. The dependent variable is the log change of total amount of toxic emissions by a plant from 2007 to 2010. The key explanatory variable, *Firm-county exposure to private MBS*$_{2007\ (or\ 2006)}$, equals the weighted average of banks' holding of private MBS across banks operating in a firm's headquarters county as of 2007 (or 2006), where we weight each bank by its market share in the county. *Plant controls* include *Sales* and *Sales growth* as of 2007. We include County, Industry-year, and Headquarters (State) fixed effects in all specifications. P-values are calculated using heteroscedasticity robust standard errors clustered at the firm level, and reported in parentheses. *,**, and *** indicate significance at 10%, 5%, and 1%.

	Δ Total Toxic Releases$_{2007\text{-}2010}$			
	(1)	(2)	(3)	(4)
Firm-county exposure to private MBS$_{2007}$	22.035***	30.455***		
	(0.001)	(0.000)		
Firm-county exposure to private MBS$_{2006}$			15.323***	17.508***
			(0.004)	(0.006)
Plant controls	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Headquarters(State) FE	Yes	Yes	Yes	Yes
Observations	7,876	5,086	7,876	5,086
R-squared	0.178	0.241	0.178	0.241