Journal of Environmental Economics and Management 84 (2017) 189–208

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

Do credit constraints favor dirty production? Theory and plant-level evidence

Dana C. Andersen

Department of Economics, University of Alberta, 9-23 HM Tory, Edmonton, Alberta, Canada T6G 2W1

ARTICLE INFO

Article history:
Received 17 March 2016
Available online 7 April 2017

JEL classification:
G32
L6
Q53

Keywords:
Pollution emissions
Credit constraints
Manufacturing plants

ABSTRACT

This paper explores the effect of credit constraints on production-generated pollution emissions. I develop a theoretical model wherein polluting firms borrow externally to finance investment in various assets, subject to a credit constraint. The main insight of the model is that credit constraints distort the composition of assets towards over-investment in tangible assets, which can be pledged as collateral, thereby increasing the intensity of emissions. The predictions of the model are tested using a unique dataset consisting of plant-level measures of pollution emissions and creditworthiness. The empirical results indicate that credit constraints significantly increase pollution emissions (even after accounting for the scale effect), and the results withstand multiple robustness checks. Moreover, the effect of credit constraints is particularly acute in industries with greater reliance on external credit. Finally, I demonstrate that firm-level credit constraints distort the composition of assets and that the composition of assets influences pollution emissions.

Introduction

External credit is indispensable to financing firm investment. Accordingly, credit intermediation entails overcoming a number of obstacles, such as contractual incompleteness and asymmetric information.[1] One approach to overcoming these credit constraints, elucidated by the incomplete contracts literature, is to invest in physical assets that can be pledged as collateral (Williamson, 1988; Hart and Moore, 1994). Specifically, tangible assets, such as buildings and structures, equipment, and natural resources, retain greater residual value to lenders in the case that the firm defaults or repudiates the contract (Braun, 2003; Manova, 2012).[2] Conversely, intangible assets, such as human capital (worker and manager training), product and process innovation (research and development), and marketing, tend to be inalienable and firm specific in nature and therefore have less residual value to lenders.[3] Credit constraints therefore bias investment towards tangible assets at the expense of intangible assets. Because pollution emissions are linked to the composition of assets in production (this paper demonstrates that emissions are positively related to the share of tangible assets), credit constraints have negative repercussions for the environment.

E-mail address: dca@ualberta.ca

[1] The literature is vast, see Hubbard (1998) and Stein (2001) for survey articles. Empirical studies document that credit constraints bear on firm investment and performance. For example, Midrigan and Xu (2012) find that credit frictions reduce total factor productivity by up to 40%, and Hennessy and Toni (2007) find that credit frictions represent 13 and 25% of financing costs for large and small firms.

[2] Retaining greater residual value implies that shifting control from firms to creditors is less costly, or equally, that a greater fraction can be pledged as collateral (collateralized debt).

[3] Intangible assets are considered broadly to include all factors contributing to total output not caused by tangible assets.

http://dx.doi.org/10.1016/j.jeem.2017.04.002
0095-0696/

While significant attention has been given to the role of credit constraints in firm investment and performance, far less attention has been given to the role of credit constraints in environmental performance. The contribution of this paper consists of two related parts. First, this paper develops a theoretical model incorporating external borrowing and endogenous asset composition to analyze the link between credit constraints and pollution emissions. Second, the predictions of the model are tested using a unique dataset that matches plant measures of creditworthiness and pollution emissions. Both the theory and empirics attest that credit constraints increase pollution emissions.

While several studies have explored the relationship between various measures of financial performance and environmental performance, few studies have attempted to theoretically link financial status and environmental outcomes.[4] Earnhart and Kathleen (2012) (henceforth E&S) is the first paper, to my knowledge, to theoretically assess various dimensions of financial status on environmental performance, focusing on the effect of profitability, solvency risks, and liquidity, on the efficacy of environmental regulations in reducing emissions.[5] Andersen (2016) investigates the role of endogenous technology upgrading and industry composition in the link between economy-wide credit constraints and aggregate environmental performance using a general equilibrium model with heterogeneous firms. This paper contributes to the literature by focusing on external borrowing, which is the primary financing source for most firms (Fazzari et al., 1988),[6] and the role of credit constraints in investment in tangible and intangible assets.

On the empirical side, E&S conduct an empirical analysis for wastewater discharges of 508 "major" publicly held chemical manufacturing facilities using indirect measures of liquidity and solvency risks. This paper takes advantage of a recently-released dataset containing data for both privately and publicly-held plants in all manufacturing industries (nearly 30,000 in total) that includes a plant-level measure of credit constraints, which is a direct measure of the parameter in the theoretical model, and a comprehensive measure of pollution emissions.[7] This paper finds significant effects of credit constraints on pollution emissions, and documents direct evidence of the mechanisms linking credit constraints and emissions.

More broadly, this paper adds to the literature investigating the relationship between various measures of environmental performance and financial constraints. Using proxies for credit constraints (e.g., cash flow), Hong et al. (2012) find that less constrained corporations have better corporate social responsibility, while Amore and Bennedsen (2016) find that good corporate governance promotes green innovation, especially among corporations in industries that rely on external borrowing. At the country level, Andersen (2016) finds that credit market reforms, which reduced credit constraints, significantly improve country-level air pollution concentrations. The results of this paper are therefore consistent with the broader literature that documents various environmental benefits of reducing credit constraints. Finally, this paper is also related to studies in corporate finance that investigate the relationship between credit constraints and asset structure, which document that pledgeable (tangible) assets facilitate lending (Almeida and Campello, 2007; Campello and Giambona, 2013), and that credit constraints distort investment decisions (Garmaise, 2008; Pérez-Orive, 2016).[8]

This paper develops a conceptual model focusing on the partial equilibrium analysis of a representative firm that produces a homogeneous final good using intermediate factors of production–tangible and intangible assets. Financing production of tangible and intangible assets requires external lending, which entails satisfying a participation constraint (credit constraint) with a risk-neutral lender. Due to price and production risks, as well as contractual incompleteness and asymmetric information, lenders assign a positive probability to the event that the firm defaults, in which case a fraction of the investment is recovered by the lender. The participation constraint requires that the lender's expected return must exceed an exogenous reservation return. The model demonstrates that greater assigned probability to the default state strengthens the credit constraint and increases the incentive to invest in tangible assets, which retain greater residual value in default states. Thus, credit constraints increase the intensity of pollution emissions whenever the intensity of pollution emissions is positively associated with the share of tangible assets in production.

The empirical analysis explores the impact of credit constraints on pollution emissions for a panel of manufacturing plants, using the Environmental Protection Agency's Risk-Screening Environmental Indicators and the National Establishment of Time Series, among several other datasets. Specifically, I investigate the impact of credit constraints, using measures

[4] For example, Gray and Mary (1996) and Shadbegian and Wayne (2005) find that more profitable firms are not more likely to comply with environmental standards, whereas Maynard and James (2001) find that more profitable firms are more likely to invest in a clean technology. Using industrial firms in the Czech Republic, Earnhart and Lizal (2006) find that profits are positively associated, whereas Earnhart and Lizal (2010) find that value added is negatively associated, with air pollution emissions.

[5] E&S develop a "crime and punishment" (Becker, 1968) model examining optimal pollution abatement for compliance with an emissions standard in the presence of liquidity and solvency constraints, focusing on the conditional effect of expected punishments on compliance, which is not considered in this paper.

[6] Fazzari et al. (1988) report that for manufacturing firms the majority of funding is long-term bank debt, except for large firms with over 250 million in assets, which use around 60% retained earnings.

[7] E&S use the firm's current ratio as a measure of solvency and the year end cash stock as a measure of liquidity. The empirical analysis also departs from E&S by using a more comprehensive measure of emissions (releases to air, water, landfill) and employing multiple emissions measures capturing both pounds and the health risk of emissions. One drawback of using only major publicly-held companies is that publicly held companies have unique capital structures, financing investments mostly through retained earnings and equity, and are therefore less affected by credit and liquidity constraints.

[8] More precisely, Almeida and Campello (2007) find that, among financially constrained firms, an increase in pledgeable assets supports greater borrowing; Campello and Giambona (2013) find that an increase in asset tangibility increases firm leverage; Pérez-Orive (2016) finds that firms respond to credit constraint shocks by investing in short-run projects that confer assets to pledge; and Garmaise (2008) finds that financially constrained firms employ more labor than capital.

of creditworthiness from Dunn and Bradstreet, on several measures of pollution emissions, including total pounds of emissions, the potential risk of emissions to human health, and the actual risk of emissions to human health given the characteristics of the exposed surrounding population. The empirical analysis also estimates the effect of credit constraints on output, thereby distinguishing between "technique" and "scale" effects of credit constraints on pollution emissions. Finally, using the Compustat annual industrial dataset, I explore the intermediate relationships between firm-level credit constraints and the share of tangible assets, and the share of tangible assets and aggregate firm-level emissions.

The results suggest that credit constraints significantly increase pollution emissions (even after accounting for the countervailing scale effect) using both Pooled OLS and Fixed Effects. I find that a standard-deviation increase in creditworthiness reduces pollution emissions by approximately 4.5%. The results are statistically significant and withstand numerous robustness checks. Moreover, investigating heterogeneous effects demonstrates that the effect of credit constraints on pollution emissions is particularly acute in industries with greater reliance on external credit. The firm-level analysis validates the intermediate relationships–credit constraints are positively associated with the share of tangible assets, and the share of tangible assets is positively associated with pollution emissions. Finally, because firms own plants in multiple industries, I disentangle the technique and (firm-level) composition effects of the share of tangible assets on pollution emissions and find that the former is the primary effect.

The remainder of this paper is organized as follows. Section Conceptual model presents the conceptual model, generates the primary estimation equation, and outlines the identification strategy. Section Empirical analysis describes the data and empirical model specifications, presents the regression analysis and robustness checks, and discusses the findings. Finally, Section Conclusion concludes.

Conceptual model

This section develops a simple theoretical model exploring the relationship between credit constraints and pollution emissions. The model focuses on the static partial equilibrium analysis of a representative firm that produces a final good using two intermediate goods (tangible and intangible assets) and relies on external credit to finance investments. I model production and pollution emissions following standard models in the environmental economics literature, where emissions are treated as an additional factor of production (Cropper and Wallace, 1992; Copeland and Taylor, 2003). The lending participation constraint is similar to Manova (2012), with the generalization that the composition of assets is endogenous.

Production

Firms produce a homogeneous final good (q) using two intermediate goods–tangible and intangible assets (x and y, respectively). In turn, both intermediate assets are produced using two primary inputs–labor and capital (l and k, respectively). Production of intermediate assets generates a joint bad (pollution), and firms allocate an endogenous fraction $0 \le A_x, A_y \le 1$ of intermediate assets to pollution abatement.[9] I assume that production of intermediate assets is Cobb-Douglas with constant returns to scale. That is,

$$x = (1 - A_x) l_x^{\eta_x} k_x^{1-\eta_x} \quad \text{and} \quad y = (1 - A_y) l_y^{\eta_y} k_y^{1-\eta_y} \tag{1}$$

Expression (1) can be interpreted as firms producing potential outputs $\bar{x} = l_x^{\eta_x} k_x^{1-\eta_x}$ and $\bar{y} = l_y^{\eta_y} k_y^{1-\eta_y}$, and using A_x and A_y shares of potential output as inputs for abatement.[10] Following Copeland and Taylor (2003), I adopt the following functional form for abatement and pollution emissions:

$$z_x = \bar{e}_x (1 - A_x)^{1/\alpha_x} l_x^{\eta_x} k_x^{1-\eta_x} \quad \text{and} \quad z_y = \bar{e}_y (1 - A_y)^{1/\alpha_y} l_y^{\eta_y} k_y^{1-\eta_y} \tag{2}$$

where $0 \le \alpha_x, \alpha_y \le 1$. Expression (2) implies that allocating resources to abatement reduces pollution, but marginal reductions in pollution are decreasing as the amount of abatement resources increase. The parameters $\bar{e}_x$ and $\bar{e}_y$ can be interpreted as emissions intensities in the absence of abatement. Expressions (1) and (2) imply that production and abatement choices can be represented by the following production-pollution technologies[11]:

$$x = \begin{cases} z_x^{\alpha_x} l_x^{\beta_x} k_x^{1-\alpha_x-\beta_x} & \text{if} \quad z_x/x < \bar{e}_x \\ l_x^{\eta_x} k_x^{1-\eta_x} & \text{if} \quad \text{otherwise} \end{cases} \tag{3}$$

[9] Pollution abatement is broadly defined, including adoption of cleaner production processes and end-of-pipe abatement.

[10] Examples of tangible pollution abatement include emissions control devices such as scrubber systems or catalytic converters, while examples of intangible pollution abatement include research and development in cleaner products and production processes, as well as worker knowledge and skill in pollution abatement or conservation of energy and materials.

[11] To be precise, $x = (1/\bar{e}_x)^{\alpha_x} z_x^{\alpha_x} \left(l_x^{\eta_x} k_x^{1-\eta_x} \right)^{1-\alpha_x}$ whenever $z_x/x < \bar{e}_x$, and $y = (1/\bar{e}_y)^{\alpha_y} z_y^{\alpha_y} (l_y^{\eta_y} k_y^{1-\eta_y})^{1-\alpha_y}$ whenever $z_y/y < \bar{e}_y$. Expressions (3) and(4) are innocuous as the results are not affected by the constant parameters $(1/\bar{e}_x)^{\alpha_x}$ and $(1/\bar{e}_y)^{\alpha_y}$.

and

$$y = \begin{cases} z_y^{\alpha_y} l_y^{\beta_y} k_y^{1-\alpha_y-\beta_y} & \text{if } z_y/y < \bar{e}_y \\ l_y^{\eta_y} k_y^{1-\eta_y} & \text{if} \quad \text{otherwise} \end{cases} \tag{4}$$

The fact that abatement cannot be negative limits the degree of substitutability between pollution emissions and other inputs in production. In particular, emissions intensities cannot exceed $\bar{e}_x$ and $\bar{e}_y$. This rules out the possibility that, when pollution is free (or sufficiently low), firms would attempt to substitute more and more pollution for labor and capital.

Labor inputs are purchased at the exogenous market rate w. Because environmental regulations take many forms, such as emissions fees, tradable permits, and standards (and firms might have an incentive to reduce pollution even in the absence of regulations), there are many approaches to modelling regulations. As conventional in models where pollution is an input in production, regulations are modelled as a per-unit cost of pollution emissions τ.[12] In the baseline analysis, I assume that τ is sufficiently high to induce some pollution abatement, implying that emissions intensities are strictly less than $\bar{e}_x$ and $\bar{e}_y$.[13]

A key question is, after accounting for endogenous abatement, whether the intensity of emissions are greater in production of tangible or intangible assets. Section Asset tangibility and emissions documents empirical evidence that the intensity of pollution emissions is increasing in the share of tangible assets, implying that $\alpha_y < \alpha_x$. For simplicity, I assume that $0 = \alpha_y < \alpha_x$, and in Appendix A, I demonstrate that all of the results hold under the weaker assumption that $0 \leq \alpha_y < \alpha_x$.

Production of the final good exhibits constant elasticity of substitution (CES) with an elasticity of substitution $\sigma > 1$.[14]. Production is written as

$$q \equiv \phi\left[(1-\gamma)x^{\frac{\sigma-1}{\sigma}} + \gamma y^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{5}$$

where x and y are tangible and intangible assets, respectively. Because assets are broadly defined, there are various approaches to aggregate assets in production.[15] Adopting the specific functional form given by (5) retains tractability of the model and focuses attention on issues that are of first order importance.

Financing

Capital is purchased at an exogenous market rate r, but capital purchases must be financed from an external lender. Lenders have an outside reservation return and financing capital purchases entails satisfying the lender's participation constraint. Thus, the cost of capital depends on both the market rate and the cost associated with external borrowing.

Productivity and solvency shocks, as well as contractual incompleteness and asymmetric information, imply that lending entails "default risk." That is, default risk implies that the lender associates an ex-ante subjective probability with the event that the loan will not be repaid, in which case a fraction of the loan is recovered by the lender. The consequence of greater default risk is therefore that risk-neutral lenders will require a higher rate of return (interest rate).

Lenders

Lenders are risk neutral and, without loss of generality, have a reservation rate of return normalized to 0. The lender's participation constraint for an arbitrary loan of amount $h > 0$ is therefore

$$-h + (1-\lambda)Rh + \lambda\xi h \geq 0 \tag{6}$$

where $R \geq 0$ is the (endogenous) rate of return to the lender in the case that the firm does not default (that is, the "non-default rate of return"), $\lambda \in (0, 1)$ is the lender's subjective probability assigned to the default state, and $\xi \in (0, 1)$ is the percentage of the loan that can be pledged as collateral.[16] In other words, ξ is the lender's residual value of the loan. Therefore, the second term is the payoff in the non-default state, while the third term is payoff in the default state. Thus, the participation constraint implies that the loan must not exceed the lender's expected return.

Firms make a one-time offer to lenders, varying the non-default rate of return, implying that the lender's participation

[12] Copeland and Taylor (2003) argue that modelling environmental regulations as an emissions fee is advantageous to retain tractability and avoid issues related to policy inefficiencies. Moreover, because a restriction on emissions per unit of output (pollution intensity standard) is equivalent to an emissions tax combined with an output subsidy, modelling environmental regulations as an intensity standard would not affect the results.

[13] In the supplementary web Appendix A, I demonstrate that the qualitative results are similar even in the absence of regulations (τ is less than sufficiently high or zero)whenever the ratio $\bar{e}_x/\bar{e}_y$ is "sufficiently large" ($\bar{e}_x > \bar{e}_y$ is neither necessary nor sufficient).

[14] The parameters γ and ϕ are share and productivity coefficients, respectively. That $\sigma > 1$ is a conventional assumption in similar CES models focusing on clean and dirty inputs (Acemoglu et al., 2012)

[15] For example, aspects of intangible assets, such as research and development and human capital, are typically modelled as factor-neutral and labor-augmenting technical change, respectively. Moreover, marketing is typically modelled as an increase the demand (or price) of the final good. In Appendix A, I demonstrate that, under some conditions, the qualitative results hold under alternative modelling approaches, such as modelling intangible assets as factor-neutral technical change and labor-augmenting technical change.

[16] To be precise, λ is the subjective probability measure associated with the default state, in a discrete sample space consisting of default and non-default states. Because the firm and lender are risk-neutral, the second moment of the probability measure is immaterial.

constraint will be binding in equilibrium. That is,

$$R \geq \frac{1 - \lambda\xi}{1 - \lambda} \tag{7}$$

Differences in the fraction of capital that can be pledged as collateral between tangible and intangible capital therefore imply differences in the lender's participation constraint. Recall that a greater fraction of tangible capital, relative to intangible capital, can be pledged as collateral ($\xi_x > \xi_y$). For simplicity, I assume that $\xi_x = 1$ and $\xi_y = 0$, which implies that

$$R_x = 1 \quad \text{and} \quad R_y = \frac{1}{1 - \lambda} > 1 \tag{8}$$

where R_x and R_y are the non-default rates of return associated with financing tangible and intangible capital. Expression (8) demonstrates that financing tangible capital does not entail an additional cost of borrowing whenever tangible capital can be entirely pledged as collateral. On the other hand, financing intangible capital entails an additional borrowing cost whenever there is a positive probability of default.

Capital costs

The firm's capital cost consists of the exogenous market cost of capital multiplied by the additional cost of borrowing, weighted by the share of tangible and intangible capital purchased. Thus, the per-unit cost of capital is

$$\psi = r\left[\theta R_x + (1 - \theta)R_y\right] \tag{9}$$

Lemma 1. *Investment in intangible capital entails an additional borrowing cost, which is increasing in default risk. In particular, tangible and intangible capital costs are given by*

$$r_x = r \quad \text{and} \quad r_y = r\mu \geq r \tag{10}$$

where $\mu = 1 + \lambda/(1 - \lambda) > 1$.

Proof. Use (8) in (9) and differentiate (9) with respect to θ and $1 - \theta$. □

The variable $\mu > 1$ represents the additional borrowing cost associated with the credit constraint, which is monotonically increasing in default risk. I refer to an increase in μ as an increase in credit constraints.[17]

Production decisions

Firm cost minimization implies the following per-unit cost functions of tangible and intangible assets[18]

$$c_x = \tau^{\alpha_x} w^{\beta_x} r^{1-\alpha_x-\beta_x} \quad \text{and} \quad c_y = w^{\beta_y}(r\mu)^{1-\beta_y} \tag{11}$$

and the per-unit cost of the final good is

$$c_q = \frac{1}{\phi}\left[(1 - \gamma)^\sigma (c_x)^{1-\sigma} + \gamma^\sigma (c_y)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \tag{12}$$

Shepherd's lemma implies that the ratio of tangible to intangible assets is

$$\frac{x}{y} = \left[\left(\frac{1 - \gamma}{\gamma}\right)\left(\tau^{-\alpha_x} w^{\beta_y-\beta_x} r^{\alpha_x+\beta_x-\beta_y} \mu^{1-\beta_y}\right)\right]^\sigma \tag{13}$$

I define the above ratio between tangible and intangible assets as "asset tangibility."

Result 1. *Asset tangibility is decreasing in the emissions fee, and increasing in the cost of capital and labor whenever tangible assets employ these factors more intensively than intangible assets. Finally, asset tangibility is increasing in credit constraints. In other words, credit constraints distort the optimal asset ratio, leading to over-investment in tangible assets.*

Proof. Follows from (13). □

[17] Asymmetric financing costs reported in Lemma 1 are the consequence of asymmetric residual value of assets. Another source of variation, not explicitly modelled, is heterogeneous input risks associated with tangible and intangible assets. If default risk is positively associated with employing intangible assets then incorporating input risks would reinforce Lemma 1.

[18] Because the lender is the residual claimant in the default state, default risk does not distort production decisions. The results would be reinforced if the firm were also a residual claimant and tangible assets were less costly to liquidate than intangible assets.

Expression (13) demonstrates that asset tangibility is determined by (i) the production technology, (ii) relative factor prices, and (iii) credit constraints. The focus of this paper is the influence of credit constraints, thus it is useful to isolate its influence on asset tangibility. That is,

$$\kappa \equiv \frac{x}{y} = \bar{\kappa}\mu^{\sigma(1-\beta_y)} \tag{14}$$

The value $\bar{\kappa}$ is therefore the prevailing asset ratio absent credit constraints, representing the influence of the production technology and relative factor prices.[19] The residual term represents the distortion generated by credit constraints, which increases endogenous asset tangibility.

Emissions intensity

Define emissions intensity as $e = z/q$. Shepherd's Lemma implies that emissions intensity is

$$e \equiv e(\tau, c_x, c_y) = \left(\frac{\phi c_q}{c_x}\right)^{\sigma-1}\left(\frac{c_q\alpha_x(1-\gamma)^\sigma}{\tau}\right) \tag{15}$$

Emissions intensity is therefore determined by the price of pollution emissions and the per-unit cost of tangible and intangible assets.

The following Lemma elucidates the intermediate relationship between asset tangibility and emissions intensity.

Lemma 2. *Pollution emissions intensity is determined by asset tangibility, as well as exogenous factor prices and the production technology. Specifically, emissions intensity and asset tangibility are positively related. That is,*

$$e \equiv e(\kappa, \tau, w, r) \quad \text{where} \quad \frac{\partial e/e}{\partial\kappa/\kappa} = \frac{\left(\frac{\sigma-1}{\sigma}\right)}{1+\left(\frac{1-\gamma}{\gamma}\right)\kappa^{\frac{\sigma-1}{\sigma}}} > 0 \tag{16}$$

Proof. Using expressions (11)–(15) imply that

$$e = \frac{\alpha_x c_q}{\tau\left(1+\left(\frac{\gamma}{1-\gamma}\right)\kappa^{\frac{1-\sigma}{\sigma}}\right)} \qquad \square \tag{17}$$

The next result explicates the comparative statics between credit constraints and emissions intensity.

Result 2. *Credit constraints increase emissions intensity. Moreover, pollution emissions intensity can be expressed as the following reduced-form equation*

$$e \equiv e(\mu, \tau, w, r) \quad \text{where} \quad \frac{\partial e/e}{\partial\mu/\mu} = (1-\beta_y)\sigma\gamma^\sigma\left(\frac{\phi c_q}{c_y}\right)^{\sigma-1} > 0 \tag{18}$$

Proof. Follows from (11), (12) and (15). $\square$

Lemma 2 and Result 2, which explicate the intermediate and reduced-form relationships, are the primary empirical predictions of the model.

Empirical analysis

Empirical model specification

This section generates the reduced-form model to be estimated. In the supplementary web Appendix A, I demonstrate that pollution emissions can be expressed by the reduced-form relationship

$$\hat{z} = \hat{q} + \Delta_\mu\hat{\mu} + \Delta_\tau\hat{\tau} + \Delta_w\hat{w} + \Delta_r\hat{r} - \hat{\phi} + \Psi \tag{19}$$

[19] That is, $\bar{\kappa} \equiv \left[\left(\frac{1-\gamma}{\gamma}\right)\left(\tau^{-\alpha_x}w^{\beta_y-\beta_x}r^{\alpha_x+\beta_x-\beta_y}\right)\right]^\sigma$.

where circumflex denotes relative change and Ψ is the net effect of various production-technology parameters.[20] The Δ parameters represent the elasticity of pollution emissions with respect to various variables holding output constant, which can be interpreted as the elasticity of emissions intensity. The primary coefficient of interest is the elasticity of emissions with respect to credit constraints Δ_μ, which is positive from Result 2.[21]

The empirical analysis uses plant-level measures of pollution emissions as the dependent variable (z). Because credit constraints (μ) are monotonically increasing in the subjective probability of default (λ), an ideal measure of credit constraints is not the actual risk of default, which is unobservable, but the value that lenders assign to default. Because lenders rely on measures of creditworthiness to determine credit risk, I use plant-level measures of creditworthiness as a measure for credit constraints. Since creditworthiness is inversely related to credit constraints, the expected sign of the coefficient is negative.

I use plant-level sales (deflated by industry) for output (q), and a plant-level measure of labor productivity for productivity (ϕ). The empirical model specification indicates that the former increases emissions, whereas the latter decreases emissions. State by year and industry by year fixed effects control for pollution policy and market factor prices (τ, w, and r).[22] Employing state by year and industry by year effects also controls for all time-varying unobservable factors at the industry and state levels that influence emissions. This includes, for example, technical change and demand shocks that influence specific industries and states over time. Finally, production intensity and share parameters (γ, σ, α_x, β_x, β_y) are accounted for using plant Fixed Effects and industry by year effects. Employing plant Fixed Effects also controls for all time-invariant unobservable factors.

Data description

The empirical analysis explores the impact of credit constraints on plant-level pollution emissions for manufacturing plants (Standard Industrial Classifications 20–39) in the United States over two decades (1990–2009). The unit of observation is a plant (also known as establishment or facility), which is a single physical location that produces or distributes goods and services.[23] Additionally, the relationships between asset tangibility and pollution emissions, and credit constraints and asset tangibility, are investigated using firm-level data.

I rely on four data sources, which provide a unique dataset.[24] First, I use the Environmental Protection Agency's (EPA) Risk-Screening Environmental Indicators (RSEI) as a measure of plant-level pollution emissions. Second, I use Dunn and Bradstreet's (D&B) National Establishment Time Series (NETS) data, which contains plant-level measures of creditworthiness. Third, I rely on the Compustat annual industrial database, which contains detailed firm-level data for publicly-held companies. Finally, I deflate plant sales using the National Bureau of Economic Research NBER-CES Manufacturing Industry Database by Bartelsman and Gray (1996).

Pollution emissions

The RSEI is a computer-based tool that uses chemical release data from the EPA's Toxic Release Inventory (TRI) to assess the aggregate damages caused by a plant's pollution emissions.[25] The TRI is an annual collection of approximately 650 toxic chemicals, including the quantity and disposal media (air, water, landfill, etc.) of each chemical released.[26]

The RSEI accounts for the chemical toxicity, the fate and transport of the chemical, the pathway of human exposure, and the population exposed using epidemiological and demographic information. It generates three primary measures of pollution emissions: Pounds, Hazard, and Risk. The Pounds measure is, simply, the unweighted sum of all chemical releases. The Hazard measure weights each chemical released by its toxicity level, as measured by epidemiological studies. The Risk measure incorporates the toxicity and the disposal media of each chemical, coupled with population characteristics of the

[20] Relative change in pollution emissions, for example, describes $\hat{z} = dz/z$. Recall q is output, μ is credit constraints (increasing transformation of default risk), ϕ is productivity, and, τ, w, and r, are the market prices of emissions, labor, and capital, respectively. The production technology parameters are $\Psi \equiv \Psi(\gamma, \sigma, \alpha_x, \beta_x, \beta_y)$.

[21] An alternative approach to estimating Δ_μ would be to subtract $\hat{q}$ from (19) and use $\hat{e} = \hat{z} - \hat{q}$ as a dependent variable. However, this would require unit elasticity of emissions with respect to output, which is a strong assumption to impose on the empirical model. A third alternative would be to use emissions intensity as a dependent variable and use output as an independent variable, but there would be an endogeneity concern due to output being both an independent variable and in the denominator of the dependent variable.

[22] The emissions "fee" is broadly-defined to include all potential costs of emissions, such as liability threats and pressure from consumers and investors, which are the subject of studies investigating "self-regulation" (Anton et al., 2004).

[23] Firms are dissimilar from plants because firms often own or control several plants, which might be geographically dispersed.

[24] See Table B1 in the supplementary web Appendix B for a list of all variables, sources, and descriptions.

[25] The RSEI-TRI default package includes TRI data starting in the reporting year 1996. I extended the dataset by removing the default TRI data and replacing it with TRI data starting in the reporting year 1990. The TRI data from 1990 to 1996 is available from the EPA upon request.

[26] Plants are required to report all of the approximately 650 toxic chemical releases and release media under the Emergence Planning Community Right-to-Know Act (EPCRA) of 1986. The EPCRA applies to all manufacturing plants that employ at least ten employees and release at least one of the covered toxic chemicals in excess of the designated threshold. Releases are self-reported and, under the EPCRA, the EPA can assess a maximum civil penalty of $25,000 per violation for not reporting or misreporting releases, but plants are not penalized for the amount of releases reported. Plants, therefore, have an incentive to accurately report their emissions. While some misreporting is possible, Marchi and James (2006) only find evidence of misreporting in two, of the twelve investigated, chemicals. Similarly, the EPA investigated reductions in reported emissions and found that at least half, and likely more, of the reductions could be attributed to actual reductions in emissions (U.S. Environmental Protection Agency, 1993).

surrounding area exposed (from the U.S. Census Bureau). Each chemical is therefore weighted by the fate and transport in the environment, the pathway of human exposure, and the population and sensitivity of exposed populations.

While Risk emissions are important from a policy point of view, consistency with the theoretical model entails that chemical releases should be weighted according to their productive capacity (or abatement cost). While I rely on all three measures of pollution, I emphasize the Hazard measure for the following reasons. The Pounds measure assigns equal weights to chemicals that are very heterogeneous and have highly unequal abatement cost, whereas the Risk measure is influenced by extraneous factors, such as population characteristics. On the other hand, chemicals with greater toxicity are likely to have higher abatement cost than chemicals with less toxicity. Otherwise, regulators could reduce the overall abatement cost for a given level of pollution damages by increasing the relative stringency of regulations for chemicals with greater toxicity. Thus, while regulations may be inefficient to some degree, it is plausible that chemicals with greater toxicity might tend to have higher abatement cost, suggesting that the Hazard measure is relatively more consistent with the theoretical model. From a practical point of view, the pollution measures are highly correlated, and the results are similar across the various measures.

Plant characteristics

The RSEI data is matched to longitudinal plant data from the NETS.[27] The NETS is proprietary data compiled by Walls and Associates from D&B's credit monitoring and marketing information archives. The NETS essentially covers all plants and firms in the United States. I match the RSEI emissions data, which contains the EPA's facility identification numbers reported in the TRI, using a correspondence I created in collaboration with Walls and Associates.[28]

This paper employs a measure of creditworthiness from the NETS as a measure of credit constraints. The NETS contains annual plant measures of creditworthiness from D&B, called PayDex Scores, which are generated using payment history from all relevant credit and business relationships, such as suppliers and vendors. PayDex Scores range between 0 and 100 (in integer values) in ascending order of creditworthiness. According to D&B, the Score is a measure of both late payment and default risk, where a score above 80 indicates low risk and below 50 indicates high risk.[29]

The PayDex Score is an ideal measure of credit constraints for several reasons. While most empirical analyses employ indirect measures of credit constraints, Paydex Scores are direct measures of credit constraints and, importantly, are determined by an institution external to the firm.[30] Second, credit scores are the yardstick by which creditors access creditworthiness, which implies that it accords particularly well with the conceptual model. While credit scores are not included in most datasets, several studies have employed various credit ratings as variation in credit constraints. For example, Garmaise (2008) uses an alternative D&B firm credit score as an instrumental variable for credit constraints, while Muûls (2015) uses European Coface credit scores for Belgian firms to explore the impact of access to credit on exporting decisions.[31]

The NETS also contains information on plant sales, employment, industry, location, and numerous other variables. The primary variables employed are Sales, deflated by industry deflators from Bartelsman and Gray (1996), and Labor Productivity, calculated as the ratio of sales to employees.

Firm characteristics

The Standard and Poor's Compustat annual industrial database contains detailed firm-level financial data for publicly-held companies, beginning in 1950 and ending in 2010. The data are matched using the ultimate parent headquarters company name in the NETS dataset and addresses are used to corroborate the match.[32] Employing plant and firm-level variables entails several drawbacks. First, publicly-held companies have unique capital structures and tend to be less influenced by credit constraints. Second, aggregate firm-level data cannot be attributed to particular plants and emissions data are only available for the subset of plants that report emissions to the EPA, potentially resulting in measurement error. Thus, I emphasize the plant-level results, and use the firm-level analysis to shed light on several complementary questions.

Asset Tangibility is defined, following Braun (2003) and Manova (2012), as the share of Net Property, Plant, and Equipment in Total Book-Value Assets. I use standard measures of credit constraints, including the Current Ratio (Current Assets to Current Liabilities) and the Cash to Total Assets Ratio. The ratio of Total Liabilities to Total Assets is employed as a proxy for long-run solvency. Additional controls include the Market to Book Ratio, the Sales to Assets Ratio, and Return on Assets (Earnings Before Interest and Taxes to Total Assets).

[27] Neumark et al. (2011) investigate the quality of the NETS data and find that the accuracy of the employment data is of similar quality as the Current Population Survey (CPS) and the Current Employment Statistics (CES) Payroll data. The primary drawback to the NETS is that it does not include information on capital stocks, precluding the possibility of estimating a production function.

[28] The correspondence matches 414,602 of 453,224 (91%) of plant-year observations in the RSEI dataset (missing values further reduce the sample size as I will discuss in the subsequent section).

[29] For more information on PayDex Scores, see http://paydex.net/.

[30] Indirect measures of credit constraints include, firm size, age, dividend policy, bond rating, debt-to-asset ratios, and interest coverage ratios. See Claessens and Tzioumis (2006) for an overview of the various measures of firms' access to finance.

[31] Muûls (2015) also demonstrates that the Coface credit scores generate the same ordinal measure of credit constraints as conventional measures of credit constraints.

[32] The matched dataset consists of 1,053 firms and 9,517 plants.

Summary statistics

The final sample consists of an unbalanced panel of 29,817 plants and 248,153 plant-year observations, where the median number of years in the sample is 7 years. Table B2 in Appendix B provides more details regarding the selection procedure and demonstrates that the final sample is representative of the larger matched sample in terms of observable plant characteristics.

Because the pollution data are highly skewed, I apply a log transformation to all pollution measures.[33] Table 1 reports summary statistics (mean and standard deviation) by 2-digit SIC industry.[34] Metals and Industrial Machinery are the dirtiest industries, whereas Leather and Food are the cleanest industries. Table 1 demonstrates that there is significant variation in pollution emissions, both between and within industries.

The mean Credit Score is 74.5 and the associated standard deviation is 6.45. Recall, D&B classify plants with Credit Scores above 80 as being low risk of default, thus most plants have Credit Scores indicating at least some risk of default. Table 1 also reports summary statistics for Sales and Productivity, where Productivity is defined as Sales divided by the number of employees.

Baseline regression analysis

Model specification

The motivation for the model specification is discussed in Section Empirical model specification. The baseline model is the following

$$\text{Emissions}_{psit} = \delta_1 \text{Credit Score}_{psit-1} + \delta_2 \text{Sales}_{psit} + \delta_3 \text{Labor Productivity}_{psit} + \nu_{st} + \nu_{it} + u_{psit} \tag{20}$$

where p indexes plants, s indexes states, i indexes industry, and t indexes time. Year by state and year by industry (2-digit SIC) effects are captured by the variables ν_{st} and ν_{it}, respectively.

I express all variables in logarithms, with the exception of Credit Score. Hence, δ_2 and δ_3 are elasticities. Because Credit Score is not an ordinal measure, I use Credit Score as a linear variable. The coefficient δ_1 is therefore the percentage change in Emissions due to a one-point increase in Credit Score. Because the impact of Credit Score is not immediate, I use Credit Score with a one-year lag. All other variables are contemporaneous.

I denote all of the explanatory variables as X_{psit}. As usual, the composite error term consists of a plant-specific and a random component, $u_{psit} = \alpha_{psi} + \varepsilon_{psit}$. Recall, employing Pooled Ordinary Least Squares (Pooled OLS) requires $E\left(\varepsilon_{psit} \middle| X_{psit}\right) = 0$. Employing plant Fixed Effects (henceforth, Fixed Effects), relaxes this assumption, requiring that $E\left(\varepsilon_{psit} \middle| \alpha_{psi}, X_{psit}\right) = 0$. Fixed Effects allows the random error component to be correlated with the plant time-invariant component, but requires that X_{psit} be uncorrelated with $(u_{psit} - \alpha_{psi})$. This paper employs both Pooled OLS and Fixed Effects. Because it is likely that the error term is correlated over time for a given plant, I use cluster-robust standard errors that cluster on plants.

Fig. 1 plots predicted Hazard emissions (vertical scale) over Credit Scores (horizontal scale) using Credit Score as a set of indicator variables (98 dummies ranging between 2 and 99) using Pooled OLS.[35] For Credit Scores less than 75, there appears to be no effect of Credit Score on Hazard emissions; however, starting around 78 and ending around 80, there appears to be a significant reduction in Hazard emissions. Hazard emissions also decline between 81 and 84 and rises thereafter, but the effects are not statistically significant.

That there is a precipitous drop between 78 and 80 is consistent with expectations given that D&B explicitly establish categories for risk (for example, a credit score of 80 and above is classified as "Low risk").[36] Creditors might rely on the categories established by D&B for credit approvals or for setting rates in particular and lending terms in general, though this assertion cannot be verified.

Results

Table 2 reports Pooled OLS and Fixed Effects estimations, using Pounds, Hazard, and Risk emissions, as dependent variables. In all specifications, Credit Score has a negative and statistically significant (1% significance level) impact on Emissions. Specifically, increasing Credit Score by 1 point reduces Hazard emissions by 3.3% using Pooled OLS and 0.7% using Fixed Effects. The impact of Credit Score is greatest for Hazard emissions and least for Pounds emissions using both Pooled OLS and Fixed Effects. One potential explanation for the larger impact for Hazard emissions is that the distribution exhibits more variation as demonstrated by Fig. B1.[37] Because unobservable time-invariant plant characteristics are likely to be

[33] Fig. B1 in Appendix B demonstrates that the transformed data are single-peaked and roughly symmetrical.

[34] Table B3 in Appendix B demonstrates that the three measures are highly correlated. Table B4 in Appendix B also reports normalized summary statistics by 2-digit SIC for Pounds, Hazard, and Risk, emissions.

[35] The figure omits the bottom and top 1% of Credit Scores because the confidence intervals overwhelm the graph. The predicted values are at the sample values and then averaged (average marginal effect). The figure is similar using Fixed Effects, although the drop is less precipitous, as the regression analysis demonstrate. Predicted Pounds and Risk emissions follow a similar pattern and the graphs can be found in Appendix B (Figs. B2 and B3).

[36] Information on categories can be found at http://mycredit.dnb.com/glossaries/paydex/.

[37] Standardizing the Credit Score coefficients for Pounds and Hazard emissions by dividing both coefficients by the corresponding standard deviation implies that the coefficients are similar in terms of standard-deviation impacts on pollution. That is, increasing Credit Score by 1 point reduces Pounds and Hazard emissions by 0.0010 and 0.0012 standard deviations, respectively.

Table 1
Summary statistics by 2-digit SIC industry: mean and (Std. Deviation).

	Emissions		Credit Score		Sales		Productivity	
Food	1.85	(3.79)	77.53	(4.96)	39.79	(70.03)	124.49	(183.49)
Tobacco	5.11	(3.97)	75.19	(6.96)	200.84	(421.89)	164.86	(56.45)
Textiles	2.81	(4.59)	76.12	(5.78)	29.41	(51.42)	95.61	(76.57)
Apparel	3.58	(4.73)	75.53	(5.26)	23.41	(28.52)	77.06	(31.48)
Lumber	3.47	(4.25)	78.12	(5.17)	14.35	(20.00)	92.89	(87.51)
Furniture	2.98	(4.45)	75.78	(6.59)	24.65	(56.76)	68.76	(37.12)
Paper	4.82	(4.90)	75.59	(5.93)	35.15	(65.82)	102.57	(78.82)
Printing	2.53	(3.40)	76.60	(6.32)	24.19	(35.48)	82.59	(49.63)
Chemicals	4.69	(5.14)	74.15	(6.26)	18.43	(48.84)	132.98	(344.48)
Petroleum and Coal	5.91	(5.52)	75.27	(6.24)	19.51	(68.10)	131.41	(291.46)
Rubber and Plastics	3.22	(4.56)	74.47	(6.68)	17.09	(26.58)	94.49	(344.36)
Leather	0.75	(6.12)	76.53	(5.76)	16.80	(18.69)	87.60	(66.85)
Stone, Clay, and Glass	4.75	(6.16)	75.67	(5.98)	18.17	(29.51)	101.21	(68.78)
Primary Metals	8.57	(5.77)	74.76	(6.45)	27.62	(64.06)	124.87	(248.05)
Fabricated Metal	7.30	(5.91)	74.42	(6.80)	13.09	(25.25)	82.34	(110.80)
Industrial Machinery	8.25	(6.58)	73.44	(6.21)	65.43	(628.50)	144.50	(642.42)
Electronics	5.99	(4.66)	73.06	(6.38)	302.69	(2458.49)	444.17	(2030.34)
Transportation Equipment	7.32	(6.28)	72.89	(6.95)	106.93	(225.95)	139.73	(122.03)
Instruments	5.31	(5.73)	73.78	(5.65)	80.17	(192.39)	148.93	(86.73)
Misc. Manufacturing	3.78	(5.27)	75.26	(6.73)	29.79	(55.08)	124.48	(111.65)
Total	5.72	(5.78)	74.54	(6.45)	55.89	(746.95)	142.99	(659.19)

Notes: Emissions are log Hazard emissions. Sales are deflated sales in million 2008 US$. Productivity is deflated sales in thousand 2008 US$ divided by the number of employees.

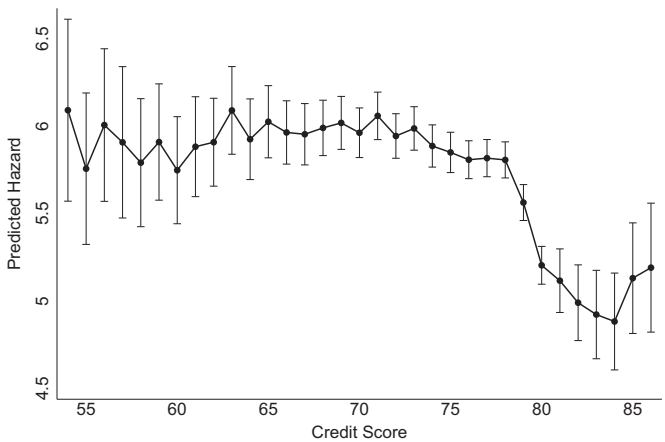

Fig. 1. Predicted hazard emissions and 95% confidence interval.

positively (negatively) correlated with Emissions and negatively (positively) correlated with Credit Score, the magnitude of the impact of Credit Score suggested by Pooled OLS is likely to be biased upwards. Thus, Fixed Effects estimates are likely more precise.

Multiplying the coefficients by the Credit Score standard deviation (6.45) sheds light on the effect of a standard-deviation change in Credit Score on pollution emissions. That is, a standard-deviation increase in Credit Score would reduce Hazard emissions by approximately 4.5%. While this paper emphasizes Hazard emissions, the estimates for Pounds emissions lead to more concrete interpretations. That is, because plants generate 15,766 pounds of emissions on average (not reported), a standard-deviation increase in Credit Score would reduce emissions by around 335 pounds. Extrapolating this effect to all plants in the sample (29,817) implies that a standard-deviation increase in Credit Score across all plants would reduce emissions by around 10 million pounds (assuming there are no general equilibrium effects).

The impact of Sales on Emissions is positive and significant at the 1% significance level. The elasticity of Emissions with respect to Sales ranges between 0.63 and 0.99 using Pooled OLS, and between 0.10 and 0.14 using Fixed Effects. Therefore, it is possible to rule out unit elasticity of emissions with respect to output ($\delta_2 = 1$) for Fixed Effects, but not for Pooled OLS. This result is consistent with the handful of studies demonstrating that larger producers tend to generate less emissions per unit of output than smaller producers (Harrison and Werner, 2003). Both the Pooled OLS and Fixed Effects estimates suggest that

Table 2
Pollution emissions using pooled OLS and fixed effects.

	Pooled OLS			Fixed Effects		
	Pounds	Hazard	Risk	Pounds	Hazard	Risk
Credit Score	−0.0102***	−0.0327***	−0.0216***	−0.0033***	−0.0070***	−0.0038***
	(0.0017)	(0.0035)	(0.0030)	(0.0009)	(0.0014)	(0.0014)
Sales	0.6334***	0.9902***	0.6885***	0.0973***	0.1384***	0.1037 ***
	(0.0131)	(0.0250)	(0.0211)	(0.0110)	(0.0185)	(0.0166)
Labor Productivity	−0.4492***	−0.6127***	−0.4004***	−0.1199***	−0.2018***	−0.0530
	(0.0286)	(0.0541)	(0.0458)	(0.0294)	(0.0418)	(0.0416)
Adj. R-sq	0.146	0.202	0.098	0.034	0.026	0.029
R-sq (within)				0.039	0.031	0.035
R-sq (between)				0.000	0.001	0.003
R-sq (overall)				0.000	0.001	0.004
Plants	29,817	29,636	27,092	29,817	29,636	27,092
Observations	248,153	246,324	219,095	248,153	246,324	219,095
State × Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All estimations use cluster-robust standard errors that are clustered on plants. Credit Score is lagged one year. All variables are in log-scale, except Credit Score, which is an ordinal measure. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

an increase in Labor Productivity significantly reduces Emissions (1% significance level, except in one specification).[38]

Further empirical analyses

One of the primary concerns of identification is the confounding effects of omitted variables. While Fixed Effects accounts for all time-invariant factors, and the control variables account for important time-varying factors, the presence of unobserved time-varying factors that are correlated with changes in Credit Score and Emissions remains a concern. To the extent that these confounding factors are correlated with Credit Score, the model would compensate for the missing factor by misattributing it to Credit Score.

One potential source of omitted variable bias is changes in managerial quality due to changes in personnel (plant managers) or changes in the incentives managers face. For example, Bloom et al. (2010) document that better managed firms are less energy intensive, suggesting that managerial quality and pollution emissions might be inversely related. In this case, if better managed firms also have higher Credit Scores then the model would compensate for missing managerial quality by over-estimating the impact of Credit Score. Other sources of omitted variable bias include trade status (Holladay, 2015) and ownership characteristics (Collins and Richard, 2002; Earnhart and Lizal, 2006).[39] Similarly, not accounting for these factors would bias the Credit Score coefficient to the extent that these factors are correlated with Credit Score.

The remainder of this section focuses on addressing the problem of omitted variable bias by exploring heterogeneous effects, employing additional control variables, and using lagged dependent variables, which are discussed in turn.

Heterogeneous effects

To allay the concern regarding omitted variable bias, this section exploits exogenous variation in external finance dependence following Rajan and Zingales (1998) and Manova (2012). Rajan and Zingales (1998) and Manova (2012) argue that variation in external finance dependence across industries is shaped by technological factors that are inherent to the production process, wherein certain industries require more external borrowing to finance investments. To this end, external finance dependence (Fin-Dep) is defined as the 4-digit SIC industry ratio of Capital Expenditures less Cash Flow From Operations to Capital Expenditures (in other words, industry capital expenditures not financed with cash flow from operations).

To the extent that reliance on external credit is exogenous, differencing the Credit Score coefficients according to reliance on external credit would remove the bias due to common confounders, thereby isolating the causal effect of credit constraints. Because the causal effect of credit constraints might be greater than zero in magnitude even among firms with the least reliance on external credit, the difference in the Credit Score coefficients according to reliance on external credit represents a lower bound. Overcoming omitted variable bias, however, requires that the bias generated by confounders should not vary according to the dimensions of heterogeneity. For example, differencing the Credit Score coefficients would

[38] The result that productivity and emissions are inversely related is consistent with other empirical studies (Cole et al., 2005; Shapiro and Walker, 2015).

[39] In particular, Holladay (2015) finds that exporters generate less pollution, while Earnhart and Lizal (2006) find that environmental performance depends on whether the firm is publicly or privately owned, and Collins and Richard (2002) find that performance depends on whether the firm is domestic or foreign owned.

remove the bias generated by unobserved managerial quality, but the confounding effect of managerial quality should be orthogonal to reliance on external credit. This is highly plausible as better management should improve environmental performance irrespective of the extent that the firm relies on external credit. However, it is possible that better management might improve environmental performance to a greater extent in more pollution-intensive industries simply because there is more room for improvement, which would be problematic if pollution-intensive industries are also more dependent on external borrowing. To rule out this possibility, Fig. B4 in Appendix B demonstrates that there is no relationship between the impact of credit constraints and the pollution-intensity of the industry.

Similar to reliance on external credit, there are several other, perhaps less obvious, dimensions such that the effect of credit constraints should be more acute. I enumerate these dimensions below and provide a brief argument for each of the predictions. In all of the cases, the predicted associations with the impact of Credit Score of Emissions are negative, which implies that the expected sign of the interaction with Credit Score is positive (as indicated in the parentheses).

1. **Corporation** (+): Corporation is a dummy variable indicating that the legal status of the plant is a corporation. Corporations are less likely to be credit constrained and affected by their credit scores for a number of reasons. First, corporations tend to have greater liquidity, at least in absolute terms, due to being larger than non-corporations. Greater liquidity reduces dependency on external financing and affords greater flexibility to allocate funds across plants.[40] Moreover, the assets of the corporation can be used as collateral, which reduces the risk to creditors. Finally, corporations have transferrable ownership, which reduces the cost of defaulting.
2. **Headquarters Size** (+): Headquarters Size is a categorical variable indicating the size of the plant's parent headquarters, in terms of the number of plants reporting that headquarters as a parent. The categories include (i) plant has no parent headquarters, (ii) plant has a "small" parent headquarters (1–3 plants), (iii) plant has a "large" parent headquarters (4 or more plants). For similar reasons as corporate legal status, having a large headquarters confers greater liquidity and collateral to be pledged to creditors.
3. **Sales** (+): Plants that are larger have more assets to pledge as collateral and greater liquidity.
4. **Public Facility** (+): Public facility is a dummy variable indicating that the facility is publicly owned. All else constant, lenders might believe that public facilities are less likely to default. Moreover, public facilities might have access to credit that is not available to private plants.

Table 3 demonstrates that all of the hypotheses are supported. Apart from inclusion of interactive terms, the specification is identical to Table 2, column 2.[41] The interactive terms are either indicator variables (dummy or categorical variable used as a set of dummies) or terciles based on continuous variables (denoted T) The omitted category for the terciles is the first tercile (the bottom one-third of the distribution). The variables employed interactively are also used as controls in all specifications, but only the interacted estimates are reported. The results indicate that the impact of Credit Score is significantly more acute in industries with greater external finance dependence (Fin-Dep), where the Credit Score coefficient ranges from -0.026 to -0.042, and the corresponding lower bound estimates range between -0.008 and -0.016. The impact of Credit Score on Emissions also depends on Corporation, Headquarters Size, Sales, and Public Facility, and all of the interactive terms have the predicted signs and are statistically significant at the 1% significance level.

Added controls

A common approach to demonstrating the exogeneity of explanatory variables, in the absence of experimental or quasi-experimental data, is by assessing whether the point estimates are sensitive to the inclusion of additional control variables. This approach has been employed, informally, for several decades and has been formalized by Altonji et al. (2005). The aim of the approach is to select a full range of observables that have significant explanatory power to account for the full range of observable and unobservable factors. One shortcoming of the NETS is that many of the variables are time-invariant, precluding the use of plant Fixed Effects. Therefore, I use Pooled OLS and Random Effects, which allow for the estimation of time-invariant variables.

Recall that the primary concerns regarding omitted variable bias include omitted managerial quality, trade status, and ownership status. Consequently, the following sets of added controls are employed: (1) ownership characteristics, (2) internationalization, (3) firm dynamics, and (4) various plant features.[42] While these variables are not direct measures of the variables of interest in some instances, the purpose of employing added controls is to select sets of variables that are correlated with the variables of interest. For example, while there is no direct measure of managerial quality, managerial

[40] For example, plants belonging to large corporations are less vulnerable to solvency shocks because the corporation can absorb shocks to individual plants by reallocating funds across plants.

[41] To save space, I do not include the Fixed Effects estimates. The results are similar; however, several of the interactive terms are not significant, while all of the Credit Score estimates are significant at the 1% significance level.

[42] Table B1 in Appendix B provides details of the variables. Ownership characteristics include dummy variables for Subsidiary and Public Facility, and categorical variables indicating Legal Status, Plant's Headquarters (size), and if the Plant is Headquarters. Internationalization includes Trade status and a dummy variable for Foreign Owned. Firm dynamics include plant Age (quadratic polynomial), lagged Sales Growth and Productivity Growth, and dummy variables indicating Move Often and Industry Change. Finally, plant features include dummy variables indicating if the plant is Minority Owned, Women Owned, is Cottage designated, and a categorical variable for Executive gender.

Table 3
Heterogeneous effects using pooled OLS (Dep Var: Hazard Emissions).

Credit Score	−0.0259***	−0.0344***	−0.0401***	−0.0419***	−0.0417***
	(0.0034)	(0.0037)	(0.0035)	(0.0035)	(0.0037)
$\mathbb{T}_2$ Fin-Dep × Credit	−0.0080***				
	(0.0011)				
$\mathbb{T}_3$ Fin-Dep × Credit	−0.0161***				
	(0.0011)				
Corporation × Credit		0.0051***			
		(0.0019)			
Small HQs × Credit			0.0078***		
			(0.0014)		
Large HQs × Credit			0.0173***		
			(0.0011)		
$\mathbb{T}_2$ Sales × Credit				0.0137***	
				(0.0011)	
$\mathbb{T}_3$ Sales × Credit				0.0248***	
				(0.0017)	
Public Facility × Credit					0.0096***
					(0.0010)
Adjusted R-sq	0.2355	0.2326	0.2395	0.2366	0.2354
Plants	28,801	28,801	28,790	28,801	28,801
Observations	237,984	237,984	237,961	237,984	237,984

Notes: T_2 is a dummy equal to one if the continuous variable is in the second tercile, and so on. All variables interacted with Credit are also included as control variables (not reported). All estimations use cluster-robust standard errors that are clustered on plants. All models include state × year and industry × year effects. *p < 0.10, **p < 0.05 and p < 0.01.

quality (and the incentives managers face) is likely correlated with ownership characteristics and firm dynamics (in particular, sales and productivity growth), as well as plant features.

In the presence of omitted variables, employing added controls would eliminate the bias generated by confounding factors to the extent that the added controls are correlated to the confounding factors. Because the added controls are not perfectly correlated to the omitted variables, employing added controls would only partially eliminate omitted variable bias. However, eliminating part of the bias sheds light on the direction and extent of the bias generated by omitted variables. In particular, if the coefficients of interest change markedly after the inclusion of added controls then it is likely that omitted variables are severely biasing the estimates. For example, if managerial quality is correlated to sales and productivity growth then sensitivity of the Credit Score coefficient to the inclusion of the added controls suggests that omitted variable bias is a potential concern. On the other hand, if the coefficients are unchanged then it can be inferred that omitted variable bias must be relatively modest.

The results for the Added Controls regressions using Hazard emissions as a dependent variable are reported in Tables B5 and B6 in Appendix B. In all specifications, Credit Score is negative and significant at the 1% significance level. The point estimate in the baseline Pooled OLS model suggests that a one-point increase in Credit Score reduces Hazard emissions by 3.3%, while the added controls suggest that the reduction ranges between 4.4% and 5.6%. The point estimate in the baseline Fixed Effects model implied that a one-point increase in Credit Score reduces Hazard emissions by 0.70%, while the added controls using Random Effects imply that the reduction ranges between 0.67% and 0.79%. The Random Effects estimates are therefore remarkably similar to the Fixed Effects estimates after controlling for observables, and the point estimates are not influenced by the inclusion of added controls. In sum, the inclusion of added controls does not have an apparent effect on the Credit Score coefficients, suggesting that omitted variable bias is modest.

Lagged dependent variable

A common alternative to the Fixed Effects model is employing Lagged Dependent Variables (LDV). The former is suitable whenever the most important omitted variables are time-invariant, whereas the latter is suitable whenever the most important omitted variables are time-variant. The identifying assumption using Lagged Dependent Variables is that $E\left(\varepsilon_{psit} \middle| Y_{psi\,t-1}, X_{psit}\right) = 0$, where $Y_{psi\,t-1}$ represents lagged Emissions. Employing LDV accounts for all lagged time-varying omitted variables, such as capital stocks and accumulated manager and worker skills.

Table B7 in Appendix B reports variations of the LDV and First Difference models for Hazard emissions.[43] All estimations use a similar set of covariates as the estimations in Table 2 and use cluster-robust standard errors that are clustered on plants. The first column performs Pooled OLS using a lagged dependent variable, without plant fixed effects. The second column employs a First Difference model without a lagged (difference) dependent variable (for comparison), while the third column employs a First Difference model with a lagged (difference) dependent variable.

Guryan (2004) points out that Fixed Effects overstates coefficient estimates if LDV is the correct specification, whereas LDV understates coefficient estimates if Fixed Effects is the correct specification. Thus, FE and LDV therefore bound the causal effect above and below, respectively. Table B7 (column 1) demonstrates that a one-point increase in Credit Score reduces Emissions by 0.34% (significant at 1% significance level), which implies that the effect of Credit Score is bounded between 0.34% and 0.70%. The First Difference model (column 2) implies that a one-point increase in Credit Score reduces emissions by 0.39% (significant at the 1% level), while the First-Difference model with a lagged (difference) dependent variable implies that a one-point increase in Credit Score reduces emissions by 0.19% (significant at the 5% level).

Scale and technique effects

Because credit constraints might impact output, credit constraints might bear on pollution emissions through the scale of output, thereby generating scale effects (in addition to the estimated technique effects). This section is interested in "adding-up" the two effects in order to determine the net effect of Credit Score on Emissions. In particular, because the scale and technique effects influence pollution emissions in opposing directions (whenever credit constraints are negatively related to output), this section is interested in determining which effect dominates.

One approach to adding-up the scale and technique effects is to simply regress Credit Score on Sales. To this end, I use a similar approach as before, using Sales as a dependent variable and lagged Credit Score as an independent variable. Table B8 in Appendix B, column 1, estimates the determinants of Sales, using Fixed Effects and an identical set of controls as Table 2. The results suggest that a one-point increase in Credit Score increases Sales by 0.13% (significant at the 1% significance level).

Using these results, it is possible to determine the scale effect, and in turn the net effect of Credit Score on Emissions. Because a one-percent increase in Sales increases Emissions by 0.14% (Table 2, column 5), a one-point increase in Credit Score increases Emissions by 0. 13*0.14 = 0.018%, via the scale effect. On the other hand, recall that a one-point increase in Credit Score reduces emissions by roughly 0.70% via the technique effect (Table 2, column 5). Therefore, the net effect of a one-point increase in Credit Score is a 0.68% reduction in emissions, implying that the technique effect vastly overwhelms the scale effect.

The conclusion that the technique effect dominates the scale effect holds even if we suppose that the estimated scale effect is significantly underestimated. For example, suppose that the elasticity of emissions with respect to output were equal to one, as implied by a constant returns to scale production technology. Under this assumption, an increase in Credit Score by one point would increase emissions, via the scale effect, by 0.13%, implying that the net effect is a reduction by 0.58%.[44] Thus, it is highly implausible that the net effect of credit constraints is to decrease pollution emissions.

Second, I exclude plant Sales, which implies that the Credit Score coefficient would reflect both technique and scale effects. While I rely on Fixed Effects to control for baseline plant size, excluding Sales might exacerbate the problem of omitted variable bias. Table B8, column 2, reports the Credit Score coefficient excluding Sales from the model. As expected, the impact of Credit Score is smaller if Sales is omitted because the estimate captures the countervailing scale effect. The exclusion of Sales reduces the Credit Score estimate from -0.70% to -0.55% (significant at the 1% significance level). The two approaches thus lead to similar conclusions with respect to the net effect of credit constraints on pollution emissions.

Firm-level analysis

Exploring the intermediate relationship between credit constraints and pollution emissions is hindered by the fact that the composition of assets is not reported at the plant level and pollution emissions are only reported at the plant level. The aim of this section is twofold. First, to explore the relationship between firm-level asset tangibility and aggregate firm-level pollution emissions. Second, to explore the relationship between credit constraints and asset tangibility.

Table 4 presents firm-level summary statistics (mean and standard deviation) by 2 digit SIC industry. Table B9 in Appendix B presents additional summary statistics and reports that the typical firm has roughly 14 plants that, in sum, produce 4 product varieties (8 digit SIC) in 2.4 industries (4 digit SIC). Moreover, plants within the same firm exhibit marked variation in various characteristics: the standard deviations of Emissions and Credit Score are 4.1 and 4.6, respectively.

Asset tangibility and emissions

This section explores the intermediate relationship between Asset Tangibility and Emissions. Towards this end, I estimate the following model

[43] Using a First Difference model provides a robustness check as the identifying assumption is slightly weaker (weak exogeneity). Holtz-Eakin et al. (1988), among others, point out that the First Difference model with a lagged (difference) dependent variable produces biased coefficient estimates due to endogeneity of the lagged dependent variable. However, it is beyond the scope of this paper to remedy this issue.

[44] In fact, the elasticity of emissions with respect to output would need to be greater than 5 in order for the scale effect to dominate the technique effect.

Table 4
Firm-level summary statistics: mean and (Std. Deviation).

	Emissions		Sales		Asset Tangibility		Credit Score	
Food	5.31	(4.48)	18.93	(1.81)	0.35	(0.15)	77.54	(3.86)
Tobacco	6.47	(2.56)	19.04	(1.71)	0.11	(0.05)	75.82	(1.86)
Textiles	5.73	(5.29)	17.79	(1.36)	0.35	(0.12)	76.84	(5.07)
Apparel	2.02	(4.94)	17.30	(0.12)	0.20	(0.05)	70.14	(7.40)
Lumber	6.58	(5.01)	17.59	(1.26)	0.44	(0.18)	78.32	(4.24)
Furniture	7.72	(6.90)	18.50	(1.60)	0.25	(0.09)	74.40	(4.68)
Paper	9.87	(4.56)	18.71	(1.50)	0.52	(0.15)	75.87	(3.40)
Printing	2.63	(3.60)	16.70	(0.80)	0.47	(0.12)	78.16	(4.07)
Chemicals	10.86	(6.23)	18.33	(1.95)	0.31	(0.15)	73.65	(3.96)
Petroleum and Coal	14.22	(3.71)	18.01	(1.61)	0.54	(0.16)	74.92	(2.49)
Rubber and Plastics	6.44	(6.60)	17.53	(1.98)	0.34	(0.12)	75.59	(4.77)
Stone, Clay, and Glass	10.58	(5.47)	17.81	(1.58)	0.42	(0.16)	76.98	(5.20)
Primary Metals	15.09	(4.61)	18.76	(1.62)	0.36	(0.14)	74.28	(3.62)
Fabricated Metal	12.80	(5.86)	17.76	(1.97)	0.29	(0.14)	74.08	(5.10)
Industrial Machinery	12.10	(6.05)	18.38	(1.60)	0.23	(0.11)	73.22	(4.08)
Electronics	8.67	(5.45)	19.15	(2.26)	0.27	(0.13)	73.09	(4.55)
Transportation Equipment	12.17	(6.92)	19.09	(1.75)	0.28	(0.12)	72.36	(4.08)
Instruments	9.22	(6.33)	18.33	(1.76)	0.23	(0.11)	74.27	(3.81)
Misc. Manufacturing	7.16	(6.62)	17.98	(1.75)	0.24	(0.07)	74.72	(5.52)
Total	10.28	(6.34)	18.51	(1.90)	0.30	(0.15)	74.14	(4.46)

Notes: Emissions are the sum of Hazard emissions across all plants. Sales are the sum and Credit Score is the mean across all plants. Asset Tangibility is the firm-level ratio of Tangible Assets to Total Assets. Emissions and Sales are in log scale.

$$\sum_{p=1}^{p_f} \text{Emissions}_{pfit} = \delta_4 \text{Asset Tangibility}_{fit} + \delta_5 \sum_{p=1}^{p_f} \text{Sales}_{pfit} + \delta_6 (1/p_f) \sum_{p=1}^{p_f} \text{Credit Score}_{pfi\,t-1} + \Gamma'_{fit}\Omega + \vartheta_{it} + u_{fit} \tag{21}$$

where f indexes firms, i indexes industries, t indexes year, and p_f is the number of plants in firm f.

The dependent variable is the sum of Hazard emissions across all plants in a given year. Additional firm-level variables include measures of credit constraints, including the Current Ratio and the Cash to Assets Ratio. Additional controls include the Liabilities to Assets Ratio, which is a measure of long-run solvency, and the Market to Book Ratio and the Sales to Assets Ratio, which are measures of potential and actual profitability, respectively.[45] The variable ϑ_{it} accounts for industry by year effects. I use both Pooled OLS and Fixed Effects with cluster-robust standard errors that are clustered on firms.

The primary variable of interest is δ_4, the elasticity of Emissions with respect to Asset Tangibility. Because emissions data are not reported for every plant (many plants do not release any toxic chemicals), the interpretation of δ_4 is the impact on reported emissions. Because p_f represents only a subset of plants, omitted variable bias is a potential concern and the direction of bias depends on the differences between plants in the sample and out of the sample.[46]

Table 5 reports that Asset Tangibility is positively associated with Hazard emissions using both Pooled OLS and Fixed Effects. In particular, using Fixed Effects, a one-percent increase in Asset Tangibility is associated with an increase in Emissions ranging between 0.36% and 0.46%. While the impact of Credit Score is similar in magnitude to the results in the previous sections, the effect is no longer significant. One interpretation is that credit constraints do not influence Emissions beyond their influence through Asset Tangibility. However, as mentioned, Credit Score is measured with an error since not all plants are included and the sample of plants might not be representative. Pooled OLS suggests that credit constraints (Current Ratio and Cash/Assets) increase Emissions, whereas Fixed Effects suggests that credit constraints do not influence Emissions.

To overcome the concern regarding endogeneity of Asset Tangibility, Almeida and Campello (2007) propose using market conditions of tangible assets as an instrumental variable for asset structure. Specifically, Almeida and Campello (2007) argue that ownership of tangible assets is inversely related to the size of the tangible asset resale market, and employ the 4-digit SIC industry-year ratio of sales of tangible assets to the sum of sales of tangible assets and capital expenditures as an instrumental variable. Following Almeida and Campello (2007), this paper uses this variable as an instrumental variable (defined as Industry Resale) for Asset Tangibility.

Table B10 in Appendix B reports Pooled OLS and Fixed Effects Instrumental Variable (IV) estimations using Hazard emissions as a dependent variable.[47] The credibility of the IV approach hinges on the instrument being correlated with Asset

[45] The results are similar including Return on Assets as an additional control for profitability, though missing values reduce the sample size. The Market to Book Ratio includes intangible assets, which are sometimes excluded because they possess no resale value.

[46] A potential source of bias is that the error term consists of the emissions of plants not in the sample. Since reporting emissions to the EPA is a necessary condition for being in the sample, it is likely that plants not in that sample generate less emissions on average. The direction of the bias therefore depends on the correlation between Asset Tangibility and the emissions of plants not in the sample.

[47] The estimations use two-stage least-squares (2SLS) and cluster-robust standard errors that are clustered on firms.

Table 5
Firm-level determinants of aggregate hazard emissions.

	Pooled OLS				Fixed Effects			
Asset Tangibility	1.3863***	1.3849***	1.1983***	1.2526***	0.4583***	0.4550**	0.4330**	0.3545**
	(0.3143)	(0.3139)	(0.3168)	(0.3118)	(0.1792)	(0.1796)	(0.1792)	(0.1756)
Sales	1.0009***	1.0012***	1.0128***	0.9850***	0.4295***	0.4297***	0.4307***	0.4152***
	(0.1211)	(0.1211)	(0.1188)	(0.1220)	(0.0814)	(0.0816)	(0.0819)	(0.0821)
Total Assets	0.8200***	0.8190***	0.8221***	0.8807***	0.2929***	0.2945***	0.2848***	0.4236***
	(0.1348)	(0.1347)	(0.1405)	(0.1562)	(0.1547)	(0.1547)	(0.1551)	(0.1670)
Credit Score		−0.0155	−0.0124	−0.0121		−0.0082	−0.0080	−0.0086
		(0.0301)	(0.0301)	(0.0293)		(0.0126)	(0.0126)	(0.0126)
Current Ratio			0.0661	1.0442***			−0.0503	−0.0347
			(0.3626)	(0.3900)			(0.1713)	(0.1796)
Cash/Assets			−0.4491***	−0.3556***			−0.0241	−0.0401
			(0.1053)	(0.1031)			(0.0437)	(0.0439)
Liabilities/Assets				1.4585***				−0.1342
				(0.4498)				(0.2454)
Market/Book Ratio				−0.2125				0.1813***
				(0.1851)				(0.0806)
Sales/Assets				0.5366				0.4796***
				(0.4395)				(0.2092)
R-sq	0.372	0.372	0.380	0.388	0.063	0.063	0.063	0.067
R-sq (within)					0.106	0.106	0.106	0.110
R-sq (between)					0.195	0.190	0.211	0.221
R-sq (overall)					0.184	0.184	0.200	0.204
Firms	785	785	785	785	785	785	785	785
Observations	7,554	7,554	7,554	7,554	7,554	7,554	7,554	7,554
Industry × Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All estimations use cluster-robust standard errors that are clustered on firms. The dependent variable is the sum of Hazard emissions across all plants. Sales are the sum and Credit Score is the mean across all plants. Asset Tangibility is the firm-level ratio of Tangible Assets to Total Assets. The remainder of the variables are at the firm-level. All of the variables are in log-scale, except Credit Score. The following variables are lagged one year: Current Ratio, Cash/Assets, Liabilities/Assets, Market/Book Ratio, and Sales/Assets. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Tangibility but not correlated to the corresponding error term. Investigation of the first stage indicates that the instrument is not weakly correlated to Asset Tangibility.[48] While testing over-identifying restrictions requires multiple instruments, the instrument is not a significant determinant of Hazard Emissions in the second stage after controlling for Asset Tangibility, suggesting that the instrument is exogenous.[49] The IV estimates are consistent with the baseline results, with slightly smaller coefficient estimates for Asset Tangibility. The IV estimates are also slightly less precisely estimated and are significant at the 5 and 10% significance levels using Pooled OLS and Fixed Effects, respectively.[50]

Decomposing the technique and composition effects

Since firms own plants in multiple industries, the effect of Asset Tangibility on Emissions consists of technique and firm-level composition effects. This section tests the null hypothesis that Asset Tangibility influences the composition of output across sectors. Rejection of the null hypothesis suggests that the effect of Asset Tangibility on Emissions represents plant-level technique effects.

Towards this end, I estimate the following model

$$\sum_{p=1}^{p_f}\left(\frac{\text{Emissions}_{it}}{\text{Sales}_{it}}\right)\text{Sales}_{pfit} = \tilde{\delta}_4\text{Asset Tangibility}_{fit} + \tilde{\delta}_5\sum_{p=1}^{p_f}\text{Sales}_{pfit} + \tilde{\delta}_6(1/p_f)\sum_{p=1}^{p_f}\text{Credit Score}_{pfit-1} + \Gamma'_{fit}\tilde{\Omega} + \tilde{\vartheta}_{it} + \tilde{u}_{fit} \tag{22}$$

where f indexes firms, i indexes industries, t indexes year, and p_f is the number of plants in firm f. The left hand side is the sum of plant sales (output) multiplied by the average industry (4-digit SIC) pollution intensity. Changes in the dependent

[48] The first stage F-test values exceed the Staiger and James (1997) rule-of-thumb value of 10 for one endogenous variable.

[49] Ashraf and Galor (2013) argue that insignificance of the instrument in the second stage (when both the instrument and endogenous covariate are control variables) demonstrates that the instrument is related to the dependent variable only through the endogenous covariate, which suggests that the exclusion restriction holds. The p-values of coefficients of the instruments are 0.70 and 0.79 in the Pooled OLS and Fixed Effects, respectively.

[50] The results are not statistically significant when the standard errors are clustered by industry. However, because there are only 19 industries, simulation studies (Cameron et al., 2015) suggest that clustering the standard errors with such "few" clusters will result in severely overestimated standard errors.

variable therefore reflect changes associated with the composition of production but not the intensity of production within sectors. The dependent variable is log-transformed and the explanatory variables are identical to the set discussed in the previous section.

Table B11 in Appendix B reports that Asset Tangibility does not influence the composition of production after accounting for firm-level controls and using Fixed Effects. Moreover, using Fixed Effects, the standard errors of Asset Tangibility are roughly similar to the corresponding standard errors in the previous section and it can be ruled out that the coefficient estimates are similar to the corresponding estimates in the previous section (at the 10% significance level). Thus, the results suggest that the impact of Asset Tangibility on Emissions is achieved as a consequence of technique effects.

Credit constraints and asset tangibility

This section investigates the theoretical prediction that credit constraints distort investment towards greater asset tangibility. Thus, I estimate the following

$$\text{Asset Tangibility}_{fit} = \delta_7 \text{Current Ratio}_{fit-1} + \delta_8 \text{Cash/Assets}_{fit-1} + \delta_9 \text{Liabilities/Assets}_{fit-1} + \Lambda'_{fit} X + \vartheta_{it} + u_{fit} \tag{23}$$

where f indexes firms, i indexes industries, and t indexes year. X is a vector of additional firm controls, which are included in some estimations, including the Market to Book Ratio, Sales to Assets Ratio, and Return on Assets. The variable ϑ_{it} accounts for industry by year effects. All variables are in logs and all explanatory variables are lagged one year. I use both Pooled OLS and Fixed Effects with cluster-robust standard errors that are clustered on firms.

Because this section focuses on the intermediate relationship between credit constraints and asset tangibility, it is not necessary to restrict the sample to firms reporting emissions, which significantly increases the sample size. Only firms in similar SIC industries as the previous estimations are included in the sample. The primary variables of interest are measures of credit constraints, including the Current Ratio and Cash to Assets Ratio. Table 6 reports the determinants of Asset Tangibility using Pooled OLS and Fixed Effects. Columns 1 and 4 are the baseline specifications and columns 2 and 5 add additional firm controls. In all specifications, the coefficient estimates for Current Ratio and Cash/Assets have the expected signs and are significant at the 1% significance level. Specifically, the elasticity of Asset Tangibility with respect to the Current Ratio is -0.040, and the elasticity with respect to Cash/Assets is -0.038 (column 4). The results therefore corroborate that credit constraints increase asset tangibility.

One potential concern with the results is reverse causality as tangible assets might relax credit constraints, thereby promoting external borrowing (Campello and Giambona, 2013). Because the credit constraint variables are lagged, the exact concern regarding reverse causality is that lagged credit constraints might be endogenous due to correlation with future credit constraints. I undertake a number of measures to allay this concern. First, similar to Section Heterogeneous effects, I exploit exogenous variation in external finance dependence to investigate the differential effect of credit constraints according to reliance on external credit. To this end, columns 3 and 6 of Table 6 interact the credit constraint variables with a dummy variable indicating that the firm belongs to an industry with financial dependency greater than the median (Fin-Dep). The results indicate that credit constraints have more acute effects on Asset Tangibility in industries with greater dependency on external borrowing using both Pooled OLS and Fixed Effects.

Second, I investigate the concern regarding reverse causality by employing future values of credit constraints. Using future credit constraints (using subscript $t + 1$), Table B12 in Appendix B reports the determinants of Asset Tangibility using Pooled OLS and Fixed Effects. Columns 1 and 3 indicate that future credit constraints are significant determinants of Asset Tangibility, suggesting that reverse causality might be a concern. However, columns 2 and 4 include both forward and lagged credit constraints, and indicate that the lagged credit constraint coefficients are robust after controlling for future credit constraints.[51] Because reverse causality is a concern to the extent that lagged credit constraints are correlated to Asset Tangibility through future credit constraints, this result reduces the concern regarding reverse causality.

In sum, while there does appear to be some evidence of reverse causality, there is consistent evidence that credit constraints distort investment towards more tangible assets, particularly among firms in industries that rely on external credit.

Using the Fixed Effects results from Table 6 (the Current Ratio and Cash/Assets coefficients from column 4) and Table 5 (the Asset Tangibility coefficient from column 8), a one-percent increase in the Current Ratio and the Cash to Assets Ratio reduces Emissions, via a reduction in Asset Tangibility, by 1.41% (0. 35*0.0402) and 1.33% (0. 35*0.0379), respectively. This result entails imprecision as the impact of credit constraints on Asset Tangibility estimated in Table 6 might not be representative of the subsample of firms estimated in Table 5.[52]

Discussion of results

The empirical analysis demonstrates that credit constraints increase pollution emissions, even after accounting for the countervailing scale effect. Moreover, the effect appears quantitatively large and statistically significant. While the results are robust with

[51] The lagged credit constraint coefficients are consistent when both forward and contemporaneous credit constraint proxies are included (not reported).

[52] Estimating the models in Table 6, which includes 108,239 firms, for the 785 firms estimated in Table 5 results in insignificant coefficient estimates for Asset Tangibility due to the small sample size.

Table 6
Determinants of firm-level asset tangibility.

	Pooled OLS			Fixed Effects		
Current Ratio	−0.0760***	−0.2953***	−0.0679***	−0.0402***	−0.0409***	−0.0379***
	(0.0166)	(0.0201)	(0.0201)	(0.0112)	(0.0126)	(0.0126)
Cash/Assets	−0.2058***	−0.1125***	−0.1244***	−0.0379***	−0.0386***	−0.0361***
	(0.0051)	(0.0051)	(0.0051)	(0.0031)	(0.0029)	(0.0082)
Liabilities/Assets	0.0140	0.0434**	0.0110	−0.0538***	−0.0059	−0.0063
	(0.0171)	(0.0207)	(0.0168)	(0.0125)	(0.0140)	(0.0111)
Fin-Dep × Current Ratio			−0.0452*			−0.0190*
			(0.0226)			(0.0108)
Fin-Dep × Cash/Assets			−0.0883***			−0.0135**
			(0.0096)			(0.0060)
Fin-Dep × Liabilities/Assets			0.0051			0.0060
			(0.0137)			(0.0095)
Market/Book Ratio		−0.1228***			−0.0281***	
		(0.0075)			(0.0043)	
Sales/Assets		−0.0434*			0.1199***	
		(0.0224)			(0.0182)	
Return on Assets		0.0814***			−0.0034	
		(0.0067)			(0.0037)	
R-sq	0.120	0.149	0.172	0.007	0.026	0.008
R-sq (between)				0.160	0.146	0.165
R-sq (overall)				0.095	0.091	0.097
Firms	9,641	6,626	9,641	9,641	6,626	9641
Observations	108,239	65,774	108,239	108,239	65,774	108,239

Notes: All estimations use cluster-robust standard errors that are clustered on firms. Asset Tangibility is the ratio of Tangible Assets to Total Assets, Current Ratio is Current Assets to Current Liabilities, Assets are Total Assets. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

respect to several modeling and identification assumptions, the data are not experimental and therefore do not support strong conclusions about causality. I therefore consider several possible interpretations of the results. The first interpretation, as this paper advances, is that credit constraints causally influence asset tangibility, thereby increasing pollution emissions.

The second interpretation is that credit constraints are correlated with some unobservable factor that influences pollution emissions. While the primary focus of the robustness checks were aimed at mitigating the problem of omitted variable bias, I cannot rule out this interpretation. However, it is unlikely that the results would pass a battery of robustness checks unless credit constraints accounted for at least part of the estimated effects. Moreover, the results are consistent using firm-level analysis and examining the intermediate relationships. Thus, while the results might reflect some degree of omitted variable bias, there is significant evidence that credit constraints have at least some causal role in generating pollution emissions.

The third interpretation is that credit constraints do causally impact pollution emissions, but for reasons not explicated herein. While I demonstrate that credit constraints influence asset tangibility and that asset tangibility influences pollution emissions, it is difficult to assess the contribution of the asset tangibility channel due to limited plant-level data. The finding that credit constraints do not influence pollution emissions after controlling for asset tangibility suggests that asset tangibility is the primary channel in which credit constraints influence pollution emissions. However, it is possible that asset tangibility represents one of potentially several other channels that influence pollution emissions and it is the task of future research to disentangle these effects. In any case, the conclusions of the paper and the policy implications remain.

Conclusion

This paper explores the relationship between credit constraints and production-generated pollution emissions. Towards this end, I develop a conceptual model demonstrating that credit constraints distort the composition of assets towards over-investment in tangible assets at the expense of intangible assets, thereby increasing the intensity of pollution emissions.

This paper investigates the impact of credit constraints on pollution emissions using plant-level pollution emissions and unique plant-level measures of creditworthiness. The results suggest that credit constraints significantly increase pollution emissions–a standard-deviation increase in creditworthiness reduces pollution emissions by 4.5%. The results are statistically significant using both Pooled OLS and Fixed Effects and withstand numerous robustness checks, including exploring

heterogeneous effects, added controls, and lagged dependent variables. I find that while credit constraints also reduce output, the net effect of credit constraints on pollution emissions is positive. Finally, I investigate the intermediate relationships, finding that firm-level asset tangibility is positively associated with pollution emissions and that firm-level credit constraints are positively associated with asset tangibility.

What are the policy implications of the paper? While governments routinely intervene to reduce credit constraints, the benefits and costs of such programs are intensely debated. This paper demonstrates that, if these programs are effective at reducing credit constraints, then they might confer environmental benefits. While inherent production uncertainty will always entail a premium to external funds, contractual incompleteness and asymmetric information are shaped by legal and institutional factors, which exhibit variation both within and across countries and are amenable to change. This is especially true in the context of developing countries, which typically have weak property rights, imperfect contract enforcement, underdeveloped information systems, among other credit market imperfections. While this paper focuses on the context of the manufacturing sector in a developed country, it is possible that overcoming credit constraints might improve environmental quality in developing countries as well.

There are many avenues for future research. First, future research should attempt to identify sources of exogenous variation in credit constraints to rule out potential bias. Second, studies should attempt to disentangle the effect of real solvency risks on the one hand and asymmetric information and imperfect property rights on the other hand. While the conceptual analysis suggests that all factors increasing the perceived riskiness of lending will increase the intensity of pollution emissions, extrapolation of the results to all causes of credit constraints should not be taken for granted. Third, future studies should explore the impact of credit constraints on the extensive margin–that is, the impact on firm entry and exit. An important channel in which credit constraints might influence aggregate pollution emissions is by preventing firms that employ more intangible assets from entering the market. Thus, overlooking the extensive margin might understate the impact of credit constraints on aggregate pollution emissions. Finally, determining the impact of credit constraints on the extensive margin will shed light on the general equilibrium effects of credit constraints, which is necessary to evaluate the welfare impacts of credit constraints on the environment.

Acknowledgements

I thank Ramón López, Lint Barrage, Robert Chambers, Roberton Williams, Pinar Gunes, Sebastian Houde, Asif Islam, Anand Murugesan, Ariel Ortiz-Bobea, Sean Sylvia, Magda Tsaneva, and participants at the 15th Annual CU Environmental and Resource Economics Workshop, University of Maryland, University of Alberta, and the California Air Resources Board (CARB), for comments. I also thank two anonymous reviewers for their comments and suggestions.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jeem.2017.04.002.

References

Acemoglu, Daron, Aghion, Philippe, Bursztyn, Leonardo, Hemous, David, 2012. The environment and directed technical change. Am. Econ. Rev. 102, 131–166.
Almeida, Heitor, Campello, Murillo, 2007. Financial constraints, asset tangibility, and corporate investment. Rev. Financ. Stud. 20, 1429–1460.
Altonji, Joseph G., Todd, E. Elder, Christopher, R. Taber, 2005. Selection on observed and unobserved variables: assessing the effectiveness of Catholic schools. J. Polit. Econ. 113, 151–184.
Amore, Mario Daniele, Bennedsen, Morten, 2016. Corporate governance and green innovation. J. Environ. Econ. Manag. 75, 54–72.
Andersen, Dana, 2016. Credit constraints, technology upgrading, and the environment. J. Assoc. Environ. Resour. Econ. 3, 283–319.
Anton, Wilma Rose Q., Deltas, George, Khanna, Madhu, 2004. Incentives for environmental self-regulation and implications for environmental performance. J. Environ. Econ. Manag. 48, 632–654.
Ashraf, Quamrul, Galor, Oded, 2013. The 'Out of Africa' hypothesis, human genetic diversity, and comparative economic development. Am. Econ. Rev. 103, 1–46.
Bartelsman, Eric J., Gray, Wayne B., 1996. The NBER manufacturing productivity database. NBER Technical Working Paper Series 1–31.
Becker, Gary S., 1968. Crime and punishment: an economic approach. J. Polit.Econ. 76, 169–217.
Bloom, Nicholas, Genakos, Christos, Martin, Ralf, Sadun, Raffaella, 2010. Modern management: good for the environment or just hot air? Econ. J. 120, 551–572.
Braun, Matias, 2003. Financial Contractability and Assets' Hardness: Industrial Composition and Growth. Unpublished manuscript, Department of Economics, University of California Los Angeles.
Cameron, A., Colin, Miller, Douglas L., 2015. A practitioner's guide to cluster-robust inference. J. Hum. Resour. 50, 317–372.
Campello, Murillo, Giambona, Erasmo, 2013. Real assets and capital structure. J. Financ. Quant. Anal. 48, 1333–1370.
Claessens, Stijn, Konstantinos, Tzioumis, 2006. Measuring Firms' Access to Finance, Unpublished manuscript, World Bank.
Cole, Matthew A., Robert, J.R. Elliott, Shimamoto, Kenichi, 2005. Industrial characteristics, environmental regulations and air pollution: an analysis of the UK manufacturing sector. J. Environ. Econ. Manag. 50, 121–143.
Collins, Alan, Richard, I.D. Harris, 2002. Does plant ownership affect the level of pollution abatement expenditure? Land Econ. 78, 171.
Copeland, Brian R., Taylor, M. Scott, 2003. Trade and the Environment. Princeton University Press, Princeton.
Cropper, Maureen L., Wallace, E. Oates, 1992. Environmental economics: a survey. J. Econ. Lit. 30, 675–740.
Earnhart, Dietrich, Lizal, Lubomir, 2006. Effects of ownership and financial performance on corporate environmental performance. J. Comp. Econ. 34, 111–129.
Earnhart, Dietrich, Lizal, Lubomir, 2010. Effect of corporate economic performance on firm-level environmental performance in a transition economy. Environ. Resour. Econ. 46, 303–329.

Earnhart, Dietrich, Kathleen, Segerson, 2012. The influence of financial status on the effectiveness of environmental enforcement. J. Public Econ. 96, 670–684.
Fazzari, Steven, Hubbard, R. Glenn, Petersen, Bruce C., Blinder, Alan S., Poterba, James M., 1988. Financing constraints and corporate investment. Brook. Pap. Econ. Act. 1, 141–206.
Garmaise, Mark J., 2008. Production in entrepreneurial firms: the effects of financial constraints on labor and capital. Rev. Financ. Stud. 21, 543–577.
Gray, Wayne B., Mary, E. Deily, 1996. Compliance and enforcement: air pollution regulation in the US steel industry. J. Environ. Econ. Manag. 31, 96–111.
Guryan, Jonathan, 2004. Desegregation and black dropout rates. Am. Econ. Rev. 94, 919–943.
Harrison, Kathryn, Werner, Antweiler, 2003. Incentives for pollution abatement: regulation, regulatory threats, and non-governmental pressures. J. Policy Anal. Manag. 22, 361–382.
Hart, Oliver, Moore, John, 1994. A theory of debt based on the inalienability of human capital. Q. J. Econ. 109, 841–879.
Hennessy, Christopher A., Toni, M. Whited, 2007. How costly is external financing? Evidence from a structural estimation. J. Financ. LXII.
Holladay, J. Scott, 2015. Exporters and the Environment. Department of Economics, University of Tennessee, Unpublished Manuscript.
Holtz-Eakin, Douglas, Newey, Whitney, Rosen, Harvey S., 1988. Estimating Vector Autoregressions with Panel Data. 56, 1371–1395.
Hong, Harrison, Jeffrey, Kubik, Jose, Scheinkman, 2012. Financial constraints on corporate goodness. NBER Working Paper 18476, National Bureau of Economic Research, Cambridge, MA, 18476, 1–46.
Hubbard, R. Glenn, 1998. Capital-market imperfections and investment. J. Econ. Lit. 36, 193–225.
Manova, Kalina, 2012. Credit constraints, heterogenous firms, and international trade. Rev. Econ. Stud. 0, 1–34.
Marchi, Scott de, James, T. Hamilton., 2006. Assessing the accuracy of self-reported data: an evaluation of the toxics release inventory. J. Risk Uncertain. 32, 57–76.
Maynard, Leigh J., James, S. Shortle, 2001. Determinants of cleaner technology investments in the U.S. bleached kraft pulp industry. Land Econ. 77, 561–576.
Midrigan, Virgiliu, Xu Daniel Yi, Finance and Misallocation: Evidence from Plant-level Data, Am. Econ. Rev. 104 (2), 2014, 422–458.
Muûls, Mirabelle, 2015. Exporters, importers and credit constraints. J. Int. Econ. 95, 333–343.
Neumark, David, Wall, Brandon, Zhang, Junfu, 2011. Do small businesses create more jobs? New evidence for the United States from the national establishment time series. Rev. Econ. Stat. 93, 16–29.
Pérez-Orive, Ander, 2016. Credit constraints, firms' precautionary investment, and the business cycle. J. Monet. Econ. 78, 112–131.
Rajan, Raghuram G., Zingales, Luigi, 1998. Financial dependence and growth. Am. Econ. Rev. 88, 559–586.
Shadbegian, Ronald J., Wayne, B. Gray, 2005. Pollution abatement expenditures and plant-level productivity: a production function approach. Ecol. Econ. 54, 196–208.
Shapiro, Joseph S., Reed, Walker, 2015. Why is pollution from U.S. manufacturing declining? The Roles of Trade, Regulation, Productivity, and Preferences. Unpublished manuscript, Department of Economics, Yale University.
Staiger, Douglas, James, H. Stock, 1997. Instrumental variables regression with weak instruments. Econometrica 65, 557.
Stein, Jeremy C., 2001. Agency, Information and Corporate Investment. National Bureau of Economic Research. U.S. Environmental Protection Agency, 1993. Assessment of Changes in Reported TRI Releases and Transfers Between 1989 and 1990. Environmental Protection Agency, Washington, DC.
Williamson, Oliver E., 1988. Corporate finance and corporate governance, J. Financ. 43, 567–591.