UNIVERSITY OF ALBERTA
FACULTY OF ARTS
Department of Economics

Working Paper No. 2017-08

Default Risk, Productivity, and the Environment: Theory and Evidence from U.S. Manufacturing

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August 2017

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Abstract

This paper develops a general equilibrium model with heterogeneous firms to analyze the effect of default risk on production-generated pollution emissions. The model analytically divides the effect of default risk into three distinct effects: the market-size, technology-upgrading, and selection effect. Conceptually, an increase in default risk raises equilibrium borrowing costs, thereby precluding investment in a technology upgrade among a subset of firms (technology-upgrading effect). As a consequence, the economy consists of more numerous (market-size effect) but less productive and more pollution-intensive firms (selection effect). Because the effects are confounding in nature, the effect of default risk on aggregate pollution emissions and emissions intensity is an empirical question. To answer this question, this paper estimates the model's key parameters using a unique dataset with establishment-level credit scores and a composite measure of pollution emissions for a panel of manufacturing firms in the United States. Using a two-step procedure where default risk is estimated in the first stage, the results indicate that the estimated elasticity of emissions intensity and productivity with respect to default risk is 0.89 and -0.16, respectively. Next, I use the theoretical model to leverage the coefficient estimates to estimate the effect of economy-wide default risk on aggregate pollution emissions, demonstrating that default risk increases aggregate emissions and emissions intensity, primarily as a consequence of the technology-upgrading effect. Finally, this paper demonstrates that historical changes in economy-wide default risk can generate economically significant changes in pollution emissions.

JEL Classifications: D50, L60, Q50
Keywords: Default risk, pollution emissions, firm heterogeneity, general equilibrium

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1 Introduction

Firms undertake investment decisions in the context of uncertainty with respect to remaining in the market, and banks extend credit in the context of uncertainty with respect to repayment (default risk), which bears on firm borrowing costs and in turn technology choices.[1] Technology choices include investment in technologies that reduce variable input requirements, including fuel and material requirements in production, as well as investment in pollution abatement technologies. Moreover, economy-wide default risk affects exit and entry decisions, which in the context of firm heterogeneity, bears on the number of firms in the market and their average productivity and emissions intensity. Because pollution emissions are dependent on technology decisions and the number and composition of firms in the market, default risk is inextricably linked to environmental performance.

The contribution of this paper is threefold. First, I develop a general equilibrium model to analyze the effect of default risk on the environment. The model divides the impact into three distinct effects: (1) the market-size effect, (2) the technology-upgrading effect, and (3) the selection effect. Second, this paper estimates the model's key parameters, demonstrating that an increase in firm-level default risk increases emissions intensity and decreases productivity among manufacturing firms in the United States. Third, this paper uses the theoretical model to leverage the empirical results in order to estimate the effect of an increase in the economy-wide default risk on aggregate pollution emissions, and to empirically quantify the various disaggregate effects. More generally, this paper contributes to the recent environmental economics literature that incorporates firm heterogeneity and endogenous entry and exit decisions into general equilibrium models (Kreickemeier and Richter, 2013; Konishi and Tarui, 2015; Shapiro and Walker, 2015), and as far as I know, this is the first study to take the model to the data to numerically estimate the model.[2]

To analyze the effect of default risk on aggregate pollution emissions, this paper develops a general equilibrium model with heterogeneous firms based on the Dixit and Stiglitz (1977) model of monopolistic competition. Firm heterogeneity accounts for the wide dispersion of productivities and emissions intensities across firms. More importantly, firm heterogeneity provides a basis to analyze the effect of default risk on entry and exit decisions, as well as technology-upgrading decisions. The model demonstrates that default risk, by raising equilibrium borrowing costs, precludes investment in a technology upgrade for a subset of

[1] Default risk is defined as the probability of the event that (1) a firm exits the market (goes out of business) and (2) the firm's creditors are repaid a lesser amount than otherwise. This paper does not consider default risk arising from other sources, such as asymmetric information (e.g., Stiglitz and Weiss, 1981) and contractual incompleteness (e.g., Hart and Moore, 1994).

[2] One exception is Shapiro and Walker (2015), who employ a similar model to uncover the factors responsible for the decline in pollution from the U.S. manufacturing sector.

firms that would otherwise find the investment profitable. Moreover, in the long-run, default risk leads to an economy consisting of less productive and more pollution-intensive firms.

What are the repercussions of default risk on the environment? Reducing default risk widens the subset of firms investing in the technology upgrade, thereby increasing productivity and output among impacted firms. Consequently, pollution emissions increase through the "scale effect." On the other hand, the technology upgrade decreases emissions intensity through the "technique effect" to the extent that productivity and emissions intensity are inversely related, as evidenced by several empirical studies (Cole et al., 2005, 2008; Shapiro and Walker, 2015), or the technology upgrade uses a cleaner production process or mix of inputs. In sum, reducing default risk increases emissions through the scale effect and decreases emissions through the technique effect, and the net effect depends on the relative magnitude of the two opposing effects.

Default risk is also inextricably linked to pollution emissions at the general-equilibrium level through firm selection. In particular, reducing default risk increases the scale of production among impacted firms, thereby crowding out firms that are less productive in general and more pollution-intensive in particular. Consequently, reducing default risk results in an economy consisting of less numerous firms through the "market-size effect," but firms that are, on average, more productive and less-pollution intensive through the "selection effect." Similar to the partial-equilibrium effect, the general-equilibrium effect consists of confounding effects as reducing default risk reduces emissions through the market size effect, while it increases average output and decreases average emissions intensity through the selection effect.

The empirical analysis investigates the effect of default risk on pollution emissions and productivity for a panel of manufacturing facilities, using a unique dataset from the Environmental Protection Agency's Risk-Screening Environmental Indicators and the National Establishment of Time Series. To this end, I employ a two-step procedure to estimate the elasticity of emissions intensity and productivity with respect to default. In the first stage, measures of creditworthiness from Dunn and Bradstreet are used to predict firm death (going out of business). In the second stage, the predictions are employed as measures of default risk (probability of firm death) using establishment-level measures of emissions intensity and productivity as dependent variables. This paper also employs a two-step bootstrap procedure to account for the presence of imputed regressors to generate consistent standard errors. The results indicate that the estimated elasticity of emissions intensity and productivity with respect to default risk are 0.89 and -0.16, respectively. Finally, this paper exploits variation in the magnitude of default risk shocks across industries in an alternative difference-in-differences approach. The Wald estimator generated from this alternative approach yields coefficient estimates that are similar to the baseline results.

Second, this paper leverages the coefficient estimates, coupled with parameters estimated by previous studies, to estimate the effect of an increase in the economy-wide default risk. In particular, I estimate the elasticity of aggregate output, emissions, and emissions intensity with respect to default risk, and divide the effects into the (1) market-size, (2) technology-upgrading, and (3) selection effects.[3] The numerical model results indicate that average output and average emissions are decreasing in default risk. After accounting for the market-size effect, however, aggregate output is decreasing, whereas aggregate pollution emissions are increasing, in default risk. Consequently, aggregate emissions intensity is increasing in default. Using historical default risk shocks, this paper sheds light on the magnitude of the numerical model results, demonstrating that changes in economy-wide default risk can generate economically significant changes in pollution emissions and emissions intensity in particular. For example, the numerical model results suggest that, all else constant, the increase in average default risk between 1998 and 1999 generated a 14% increase in aggregate pollution emissions, and a 38% increase in aggregate emissions, for the manufacturing sector.

Because economy-wide default risk is shaped by a wide-range of factors, including laws and institutions, fiscal and monetary policy, and regulations, this paper has implications with respect to public policy and environmental policy in particular. For example, empirical evidence documents that environmental regulations increase default risk, as evidenced by an increase in firms exiting the market (Greenstone et al., 2012), which implies that reductions in pollution from regulations might be offset by greater default risk. Consequently, optimal environmental policy might include provisions that mitigate the impact on default risk, while maintaining an overall level of stringency. To give a concrete example, even when monitoring and enforcement of regulations is costly, an environmental agency might prefer a policy instrument with greater certainty and lesser severity of punishment, in order to mitigate the increase in default risk.[4]

This paper is related to the literature exploring the relationship between firm environmental performance and broadly-defined financial performance. Financial performance is typically defined as a measure of profitability, and the literature generally focuses on narrowly defined industries. Gray and Deily (1996) and Shadbegian and Gray (2005) find a negative relationship between profitability and compliance with environmental standards, whereas Maynard and Shortle (2001) find that more profitable and less leveraged firms are

[3]This paper also uses a two-step bootstrap procedure to estimate consistent standard errors for all of the estimated numerical model results.

[4]That is, greater severity of punishments has the advantage of reducing enforcement cost for a given expected penalty; however, firms might be liquidity constrained and forced to default as a consequence of a large penalty.

more likely to invest in a clean technology upgrade. Using a panel of Czech manufacturing firms, Earnhart and Lizal (2006, 2010) report that profits are positively associated with air pollution emissions, whereas value added is negatively associated with air pollution emissions, among Czech firms. Earnhart and Segerson (2012) contribute to the literature by pointing out that the correlation, if one exists, between financial performance and environmental performance might be the consequence of correlation between profits and unobservable factors, such as liquidity and solvency risk. Earnhart and Segerson (2012) propose a "crime and punishment" (Becker, 1968) model of environmental compliance to analyze the role of liquidity and solvency risks in compliance with an environmental standard, demonstrating that the effects are confounding in nature, and that financial status does not in general play an important role in industrial wastewater discharges of chemical manufacturing facilities.

Similar to the present paper, Andersen (2016) proposes a general equilibrium model with heterogeneous firms to analyze the effect of economy-wide credit constraints on aggregate pollution emissions, and empirically demonstrates that reducing country-level credit constraints improves aggregate environmental performance. Using credit scores as a proxy for credit constraints, Andersen (2017) documents empirical evidence that credit constraints increase plant-level pollution emissions as a consequence of bearing on capital-investment decisions. On the other hand, this paper focuses on default risk rather than credit constraints. More importantly, the primary contribution of the present paper is to estimate the key model parameters at the establishment-level, and leverage the theoretical model to estimate the aggregate effects of default risk on pollution emissions. In contrast to the partial equilibrium analysis of Andersen (2017), this approach permits estimating general-equilibrium effects, and uncovers the various channels in which default risk is linked to aggregate pollution emissions.

Finally, this paper also contributes to the recent literature investigating the role of macroeconomic business cycles in environmental policy design (Fischer and Springborn, 2011; Heutel, 2012; Fischer and Heutel, 2013). An important parameter in the literature is the elasticity of pollution emissions (e.g., carbon dioxide emissions) with respect to output, which is positive but inelastic according to estimates by Heutel (2012). Consequently, productivity shocks generate changes in pollution emissions that are smaller in magnitude than changes in output because emissions intensity changes over business cycles (e.g., emissions intensity increases during negative productivity shocks). The insights of this paper provide a potential explanation for the patterns of emissions intensity over the business cycles. That is, because productivity shocks are inextricably linked to changes in default risk, recessions would reduce technology upgrading, and lead to an economy consisting of less productive and more pollution-intensive firms, as a consequence of increasing economy-wide default risk.

The remainder of this paper is organized as follows. Section 2 presents the theoretical model. Section 3 discusses the data, estimation strategy, results, and numerical model simulations. Section 4 concludes.

2 Model

2.1 Overview

This section presents a general equilibrium model with heterogeneous firms based on the Dixit and Stiglitz (1977) model of monopolistic competition.[5] Time is discrete with an infinite horizon, and in each time period, a pool of initially identical potential entrants face a dynamic forward looking entry decision, where paying a market entry cost confers a draw of a random productivity parameter. Firms drawing a productivity parameter conferring present value profits in excess of a fixed production cost will take up production, while firms with lower productivity draws will immediately exit. Firms not exiting will remain in the market in subsequent periods but face an exogenous default risk; that is, probability that a random shock will force them to exit. There exists a discrete technology upgrade that is financed from external borrowing, and therefore includes an endogenous borrowing cost. With a given technology, firms produce a final good using a variable composite input, and generate pollution emissions as a byproduct of production, which depends on the technology employed.

2.2 Consumers

Utility of a representative consumer exhibits constant elasticity of substitution (CES) with elasticity of substitution $\sigma > 1$

$$U = \left[\int_{v \in V} q(v)^{\frac{\sigma-1}{\sigma}} dv \right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

[5]The Dixit and Stiglitz (1977) model has been widely adopted in various economic fields, such as international trade (e.g., Melitz, 2003). Because the theoretical predictions of Melitz (2003) are consistent with empirical regularities in manufacturing sectors, and because many pollution-intensive sectors have become differentiated-good industries (such as chemicals and metals industries) (Konishi and Tarui, 2015), several papers have adapted the Melitz (2003) framework to account for pollution emissions (Kreickemeier and Richter, 2013; Konishi and Tarui, 2015; Shapiro and Walker, 2015; Andersen, 2016, among others).

where $q(v)$ is demand for variety v, and V is the set of available varieties.[6] Expenditure of the representative consumer is denoted Y and the price of variety v is denoted $p(v)$. Utility maximization, subject to the budget constraint $\int_{v \in V} p(v)q(v)dv = Y$, yields the isoelastic demand function for variety v

$$q(v) = YP^{\sigma-1}p(v)^{-\sigma} \tag{2}$$

where P is the CES price index.

2.3 Producers

There is a continuum of firms, each producing a unique variety. Production is linear in a composite input (labeled "labor" for convenience), which includes human capital, physical capital, fuel, materials, and so on. That is, $q = \phi l$, where l is labor and ϕ is the firm's productivity parameter. The input market is perfectly competitive, with an equilibrium wage rate w, implying that marginal production costs are w/ϕ. The technology upgrade increases productivity by a fixed scalar parameter $\delta > 0$, implying that marginal production costs are $w/[\phi(1+\delta)]$. As in Bustos (2011), the technology upgrade can be interpreted, in general, to represent firm actions to reduce the marginal cost of production or to increase the quality of the product.

For notation, firms not adopting the more productive technology are denoted with the superscript b (baseline), while firms adopting the technology are denoted with the superscript u (upgrading). Profit maximization implies that firms set prices equal to a constant markup over marginal cost

$$p^b(v) = \frac{w/\phi}{\rho} \quad \text{and} \quad p^u(v) = \frac{w/[\phi(1+\delta)]}{\rho} \tag{3}$$

where $\rho \equiv (\sigma-1)/\sigma$. Using the derived isoelastic demand function implies that equilibrium output and revenue for firms not investing in the upgrade are given by

$$q^b(\phi) = YP^{\sigma-1}\left(\frac{w}{\phi\rho}\right)^{-\sigma} \quad \text{and} \quad r^b(\phi) = YP^{\sigma-1}\left(\frac{w}{\phi\rho}\right)^{1-\sigma} \tag{4}$$

Moreover, firms adopting the technology upgrade set lower prices, produce more, and

[6]Because the model abstracts from endogenous pollution policy responses, I do not consider disutility associated with environmental damage. However, incorporating environmental damage using a weakly-separable utility function (e.g., $W(Z, U)$ where U is given by equation (1) and Z is aggregate pollution) would not change the analysis as the marginal rate of substitution (and thus the elasticity of substitution) of two varieties would be independent of pollution.

generate more revenue. That is,

$$\frac{q^u(\phi)}{q^b(\phi)} = (1+\delta)^\sigma > 1 \text{ and } \frac{r^u(\phi)}{r^b(\phi)} = (1+\delta)^{\sigma-1} > 1 \tag{5}$$

Pollution is emitted as a joint output of production, and is equal to emissions intensity (emissions per unit of output) times output. Similar to Andersen (2016), I assume that emissions intensities are given by

$$e^b(\phi) = \frac{1}{\phi^\alpha} \text{ and } e^u(\phi) = \frac{\gamma}{(\phi(1+\delta))^\alpha} \tag{6}$$

Emissions intensity therefore changes monotonically with firm productivity, with the technology parameter α determining the extent to which this is the case. The parameter γ reflects the difference in emissions intensity associated with the upgrade that are not due to differences in productivity.[7] The following lemma highlights the necessary and sufficient condition such that the technology upgrade reduces emissions intensity.

Lemma 1. *The technology upgrade reduces emissions intensity ($e^b \geq e^u$) if and only $\gamma^{1/\alpha} \leq 1+\delta$.*

For simplicity and clarity, it is expedient to distinguish between output and emissions associated with the endowed baseline technology and "additional" output and emissions associated with the technology upgrade, which I denote using the superscript a. For example, additional output is given by $q^a = q^u - q^b$. I will refer to variables corresponding to the endowed technology production as "baseline" values, while variables corresponding to the additional values associated with the technology adoption as "additional" values.

It follows that additional output and revenue are given by

$$q^a(\phi) = ((1+\delta)^\sigma - 1)\, q^b(\phi) \text{ and } r^a(\phi) = \lambda^r r^b(\phi) \tag{7}$$

where $\lambda^r \equiv ((1+\delta)^{\sigma-1} - 1) > 0$ is the percentage increase in revenue associated with the technology upgrade relative to baseline revenue. Expression 7 demonstrates that additional output and revenue are proportional to output and revenue generated by the endowed technology. Similarly, pollution emissions are given by

$$z^b(\phi) = \frac{q^b(\phi)}{\phi^\alpha} \text{ and } z^a(\phi) = (\Gamma - 1) z^b(\phi) \tag{8}$$

[7]From a theoretical point of view, expression (6) is a generalization of the Cobb-Douglas pollution-production technology adopted by (Copeland and Taylor, 2003), in which α can be interpreted as the cost share of non-pollution inputs (Shapiro and Walker, 2015). See Andersen (2016) for an extended discussion of the assumption and interpretation.

where $\Gamma = \gamma(1+\delta)^{\sigma-\alpha} > 0$. Expression 8 demonstrates that the technology upgrade reduces pollution emissions, that is $z^a(\phi) < 0$, whenever $\Gamma < 1$.

2.3.1 Fixed and Upgrading Costs

All firms have a fixed production and distribution cost wf, where f is the input requirement in the fixed investment and w is the corresponding wage rate. Firms adopting the technology upgrade have additional input requirement and incur an additional cost associated with financing the investment. Specifically, let $\lambda^c > 0$ represent the percentage increase in fixed costs associated with the additional input requirement (relative to baseline fixed costs), and $b > 1$ represent the gross interest rate paid on the loan. Firms adopting the technology upgrade therefore have an additional input requirement $\lambda^c f$ and incur an additional cost $\lambda^c bwf$.

Define net revenue as revenue less variable input costs, and profits as net revenue less fixed input costs. Baseline profits are therefore net revenue less fixed input costs:

$$\pi^b = \frac{r^b}{\sigma} - wf \tag{9}$$

while additional profits are given by

$$\pi^a = \pi^u - \pi^b = \frac{\lambda^r r^b}{\sigma} - b\lambda^c wf \tag{10}$$

Because net revenue is proportional to revenue, λ^r can be interpreted as the percentage increase in net revenue relative to baseline net revenue.

Baseline profits and additional profits define the zero-baseline profits and zero-additional profits cutoffs as follows:

$$\frac{r^b(\phi^b)}{\sigma} = wf \quad \text{and} \quad \frac{r^b(\phi^u)}{\sigma} = \frac{b\lambda^c wf}{\lambda^r} \tag{11}$$

where ϕ^b is the cutoff productivity for producing in the market, while ϕ^u is the cutoff productivity for investing in the technology upgrade. I assume firms that invest in the technology upgrade also find it profitable to produce without the technology upgrade, which implies that $\phi^b < \phi^u$.

Lemma 2. *Define the ratio of additional net revenue to additional fixed costs as the parameter $\Lambda = \lambda^r/\lambda^c$, where $0 < \Lambda < b$. Then the ratio of the thresholds is given by the following* *expression:*

$$\frac{\phi^b}{\phi^u} = \left(\frac{\Lambda}{b}\right)^{\frac{1}{\sigma-1}} \in (0,1) \tag{12}$$

Proof. Follows from expression (8) and (11). □

Note that because additional revenue and additional fixed costs are in percentage of the corresponding baseline, technology upgrading can be profitable even with a ratio less than unity.

2.3.2 Default Risk and Borrowing Costs

Until now, firm profits have been defined over a non-default outcome. However, in every period, firm profits are random variables defined over two possible outcomes: non-default and default. Recall that in the non-default state, firms investing in the technology upgrade borrow $(\lambda^c wf)$ and repay $b(\lambda^c wf)$, where b is the equilibrium gross interest rate paid on the loan. As conventional, I assume that the default state is an absorbing state with exogenous probability $0 < \eta < 1$, and that the firm receives zero profits in the default state.[8] From this point forward, I will refer to the probability of the default state as simply default risk.

In the supplementary web appendix A, I demonstrate that (under a set of conditions) the equilibrium borrowing cost is an increasing function of default risk whenever the lender receives a lesser sum in the default state than the non-default state. To maintain generality, I use a reduced-form parameter representing the elasticity of borrowing costs with respect to default risk $\epsilon_{b\eta}$.

Lemma 3. *Borrowing costs are an increasing function of the firm's default risk. That is,*

$$\epsilon_{b\eta} = \frac{\partial b/b}{\partial \eta/\eta} > 0 \tag{13}$$

Proof. See appendix A. □

2.3.3 Firm Entry and Exit

There is an unbounded pool of potential entrants deciding on paying a fixed market entry cost wf^e, which allows them to draw a random productivity from the common distribution $G(\phi)$. After realizing their productivity, firms then decide whether to start producing and whether to invest in the technology upgrade.

[8] An absorbing state is one in which it is impossible to leave–that is, firms that exit the market cannot reenter the market in later periods.

I assume that firm productivities are Pareto distributed, with the lower bound normalized to one, $G(\phi) = 1 - \phi^{-k}$ and $g(\phi) = k\phi^{-(k+1)}$.[9] To ensure that average per-firm output is finite, I assume that $k > \sigma$. With the ex-ante productivity distribution being Pareto, the ex-post productivity distributions of active firms and firms investing in the technology upgrade are Pareto. That is,

$$\mu^b(\phi) = \frac{k}{\phi}\left(\frac{\phi^b}{\phi}\right)^k \quad \text{and} \quad \mu^u(\phi) = \frac{k}{\phi}\left(\frac{\phi^u}{\phi}\right)^k \tag{14}$$

Free entry implies that the ex-ante present value of expected profits has to be equal to the cost of entering the productivity draw in equilibrium. Recall that there is an infinite number of time periods, and every period an exogenous negative shock forces the firm to exit the market, which implies that

$$\left(\phi^b\right)^{-k}\frac{\bar{\pi}}{\eta} = wf^e \tag{15}$$

where $\bar{\pi}$ is average profits of active firms, and $\left(\phi^b\right)^{-k}$ is the ex-ante probability that the firm produces. The left hand side is the present value of expected profits from the point of view of a potential entrant that does not yet know its productivity, which is equal to the cost of entry in equilibrium.

Denote the mass of firms of entering the productivity draw as M^e, and the mass of firms taking up production and the mass of firms investing in the technology upgrade as M^b and M^u ($M^b > M^u$), respectively. In steady-state equilibrium, the mass of firms taking up production is equal to the mass of firms stopping production, implying that

$$(\phi^b)^{-k}M^e = \eta M^b \tag{16}$$

where the left hand side is the mass of firms taking up production while the right hand side is the mass of firms exiting.

Lemma 4. *Define the probability of upgrading as the probability that a random firm in the market invests in the technology upgrade, which is denoted as $\theta \equiv M^u/M^b$. Then the probability of upgrading is decreasing in default risk. That is,*

$$\theta \equiv \frac{M^u}{M^b} = \left(\frac{\Lambda}{b}\right)^{\frac{k}{\sigma-1}} \quad \textit{and} \quad \frac{\partial\theta/\theta}{\partial\eta/\eta} = -\left(\frac{k}{\sigma-1}\right)\epsilon_{b\eta} \tag{17}$$

Proof. Follows from expression (13). □

[9] Eaton et al. (2011), among others, document that firm size approximately follows this distribution.

2.3.4 Labor Market Clearing

Full employment in production, as well as market entry, is written as

$$L = M^e f^e + M^b \left(f + \int_{\phi^b}^{\infty} \frac{q^b}{\phi} \mu^b(\phi) d\phi \right) + M^u \left(f\lambda^c b + \int_{\phi^u}^{\infty} \frac{q^a}{\phi(1+\delta)} \mu^u(\phi) d\phi \right) \tag{18}$$

where L is the exogenous labor supply. Appendix A1 demonstrates that using conditions (4), (7), (11), (14), (15), and (16) in the employment condition (18) solves for the equilibrium mass of firms in the market

$$M^b = \frac{L}{\sigma F} \left(\frac{k}{k - (\sigma - 1)} \right) \tag{19}$$

where $k/(k-(\sigma-1)) > 0$ is a fixed parameter and $F \equiv f(1 + \theta\lambda^c b) > 0$ is average fixed costs paid by firms in the market.

2.4 Analysis

Consider the following representation of output and pollution emissions:

$$Q = M^b \bar{q} \quad \text{and} \quad Z = M^b \bar{z} \tag{20}$$

where M^b is the mass of firms in the market, Q is aggregate output, $\bar{q}$ is average output, Z is aggregate pollution emissions, and $\bar{z}$ is average pollution emissions. Consequently, aggregate emissions intensity is the ratio of average pollution emissions to average output $E = Z/Q = \bar{z}/\bar{q}$. The effect of default risk on aggregate output and pollution emissions can therefore be decomposed into market-size effects and average effects. That is,

$$\frac{\partial Q/Q}{\partial \eta/\eta} = \frac{\partial M^b/M^b}{\partial \eta/\eta} + \frac{\partial \bar{q}/\bar{q}}{\partial \eta/\eta} \quad \text{and} \quad \frac{\partial Z/Z}{\partial \eta/\eta} = \frac{\partial M^b/M^b}{\partial \eta/\eta} + \frac{\partial \bar{z}/\bar{z}}{\partial \eta/\eta} \tag{21}$$

where the first-term is the market-size effect, where the second term is the average output and average pollution effects.

Result 1. Market-Size Effect. *The mass of firms is increasing in default risk. That is,*

$$\frac{\partial M^b/M^b}{\partial \eta/\eta} = -\frac{\partial F/F}{\partial \eta/\eta} = \left(\frac{k}{\sigma - 1} - 1 \right) \left(\frac{\lambda^c \theta b}{1 + \lambda^c \theta b} \right) \epsilon_{b\eta} > 0 \tag{22}$$

Proof. Follows from expression (19). □

Corollary 1.1. *The productivity threshold in which firms take up production is decreasing* *in default risk. That is,*

$$\frac{\partial \phi^b/\phi^b}{\partial \eta/\eta} = -\frac{1}{k}\left(1 + \frac{\partial M^b/M^b}{\partial \theta/\theta}\right) < 0 \tag{23}$$

Proof. See appendix A1. □

We can further decompose the average output and average pollution emissions effects into selection and technology-upgrading effects using the following representation of output and pollution emissions. That is,

$$\bar{q} = \int_{\phi^b}^{\infty} q^b \mu^b(\phi) d\phi + \theta \int_{\phi^u}^{\infty} q^a \mu^u(\phi) d\phi = \bar{q}^b + \theta \bar{q}^a \tag{24}$$

$$\bar{z} = \int_{\phi^b}^{\infty} z^b \mu^b(\phi) d\phi + \theta \int_{\phi^u}^{\infty} z^a \mu^u(\phi) d\phi = \bar{z}^b + \theta \bar{z}^a \tag{25}$$

Result 2. Average Output Effect. *The effect of default risk on average output can be decomposed into selection and technology-upgrading effects. That is,*

$$\frac{\partial \bar{q}/\bar{q}}{\partial \eta/\eta} = \frac{\bar{q}^b}{\bar{q}} \frac{\partial \bar{q}^b/\bar{q}^b}{\partial \eta/\eta} + \frac{\theta \bar{q}^a}{\bar{q}} \left(\frac{\partial \theta/\theta}{\partial \eta/\eta} + \frac{\partial \bar{q}^a/\bar{q}^a}{\partial \eta/\eta}\right) \tag{26}$$

where the first term corresponds to the selection effect and the second term corresponds to the technology-upgrading effect. Moreover, average output is decreasing in default risk. That is,

$$\frac{\partial \bar{q}/\bar{q}}{\partial \eta/\eta} = -\frac{1}{k} - \left[\frac{1}{k}\left(\frac{k}{\sigma - 1} - 1\right)\left(\frac{\lambda^c \theta b}{1 + \lambda^c \theta b}\right) + \frac{\theta \bar{q}^a}{\bar{q}}\left(\frac{k - \sigma}{\sigma - 1}\right)\right] \epsilon_{b\eta} < 0 \tag{27}$$

where

$$\frac{\theta \bar{q}^a}{\bar{q}} = \left(1 + \left(\frac{\theta^{\frac{\sigma - k}{k}}}{(1+\delta)^{\sigma} - 1}\right)\right)^{-1} \tag{28}$$

Proof. See appendix A. □

Result 3. Average Emissions Effect. *The effect of default risk on average emissions can be decomposed into selection and technology-upgrading effects. That is,*

$$\frac{\partial \bar{z}/\bar{z}}{\partial \eta/\eta} = \frac{\bar{z}^b}{\bar{z}} \frac{\partial \bar{z}^b/\bar{z}^b}{\partial \eta/\eta} + \frac{\theta \bar{z}^a}{\bar{z}} \left(\frac{\partial \theta/\theta}{\partial \eta/\eta} + \frac{\partial \bar{z}^a/\bar{z}^a}{\partial \eta/\eta}\right) \tag{29}$$

where the first term corresponds to the selection effect and the second term corresponds to the technology-upgrading effect. Moreover, average emissions is given by the following:

$$\frac{\partial \bar{z}/\bar{z}}{\partial \eta/\eta} = -\frac{1-\alpha}{k} - \left[\frac{1-\alpha}{k}\left(\frac{k}{\sigma - 1} - 1\right)\left(\frac{\lambda^c \theta b}{1 + \lambda^c \theta b}\right) + \frac{\theta \bar{z}^a}{\bar{z}}\left(\frac{k - \sigma + \alpha}{\sigma - 1}\right)\right] \epsilon_{b\eta} \tag{30}$$

where

$$\frac{\theta \bar{z}^a}{\bar{z}} = \left(1 + \left(\frac{\theta^{\frac{\sigma-\alpha-k}{k}}}{\Gamma - 1}\right)\right)^{-1} \tag{31}$$

Proof. See appendix A. □

The average-emissions effect is ambiguous because $\bar{z}^a$ is ambiguous. A sufficient, but not necessary, condition such that the average emissions effect is negative is $\bar{z}^a > 0$.

Result 4. Aggregate Emissions Intensity Effect. *The effect of default risk on aggregate emissions intensity can be decomposed into selection and technology-upgrading effects.*

$$\begin{aligned} \frac{\partial E/E}{\partial \eta/\eta} = \frac{\partial \bar{z}/\bar{z}}{\partial \eta/\eta} - \frac{\partial \bar{q}/\bar{q}}{\partial \eta/\eta} &= \left[\frac{\bar{z}^b}{\bar{z}} \frac{\partial \bar{z}^b/\bar{z}^b}{\partial \eta/\eta} - \frac{\bar{q}^b}{\bar{q}} \frac{\partial \bar{q}^b/\bar{q}^b}{\partial \eta/\eta}\right] \\ &+ \left[\frac{\theta \bar{z}^a}{\bar{z}} \left(\frac{\partial \theta/\theta}{\partial \eta/\eta} + \frac{\partial \bar{z}^a/\bar{z}^a}{\partial \eta/\eta}\right) - \frac{\theta \bar{q}^a}{\bar{q}} \left(\frac{\partial \theta/\theta}{\partial \eta/\eta} + \frac{\partial \bar{q}^a/\bar{q}^a}{\partial \eta/\eta}\right)\right] \end{aligned} \tag{32}$$

where the first bracketed term corresponds to the selection effect and the second bracketed terms corresponds to the technology-upgrade effect. Moreover, the average emissions intensity effect is given by the following:

$$\begin{aligned} \frac{\partial E/E}{\partial \eta/\eta} &= \frac{\alpha}{k}\left[1 + \left(\left(\frac{k}{\sigma-1} - 1\right)\left(\frac{\lambda^c \theta b}{1+\lambda^c \theta b}\right) - \frac{\theta \bar{z}^a}{\bar{z}}\left(\frac{k}{\sigma-1}\right)\right)\epsilon_{b\eta}\right] \\ &+ \left(\frac{k-\sigma}{\sigma-1}\right)\left(\frac{\theta \bar{q}^a}{\bar{q}} - \frac{\theta \bar{z}^a}{\bar{z}}\right)\epsilon_{b\eta} > 0 \end{aligned} \tag{33}$$

Proof. Follows from (27) and (30). □

Similarly, the aggregate emissions-intensity effect is ambiguous because $\bar{z}^a$ is ambiguous. Because the average-output effect is negative, the aggregate emissions intensity-effect is greater than the average-emissions effect.

Result 5. Aggregate Output Effect. *The effect of default risk on aggregate output can be decomposed into (i) market-size, (ii) selection, and (iii) technology-upgrading effects. Moreover, the effect of default risk on aggregate output is given by the following:*

$$\frac{\partial Q/Q}{\partial \eta/\eta} = -\frac{1}{k} + \left[\left(\frac{k-1}{k}\right)\left(\frac{k}{\sigma-1} - 1\right)\left(\frac{\lambda^c \theta b}{1+\lambda^c \theta b}\right) - \frac{\theta \bar{z}^a}{\bar{z}}\left(\frac{k-\sigma+\alpha}{\sigma-1}\right)\right]\epsilon_{b\eta} \tag{34}$$

Proof. Follows from (21), (22), and (27). □

Result 6. Aggregate Pollution Emissions Effect. *The effect of default risk on average emissions can be decomposed into (i) market-size, (ii) selection , and (iii) technology-upgrading effects. Moreover, the effect of default risk on aggregate pollution emissions is* *given by the following:*

$$\frac{\partial Z/Z}{\partial \eta/\eta} = -\frac{1-\alpha}{k} + \left[\left(\frac{k+\alpha-1}{k} \right) \left(\frac{k}{\sigma-1} - 1 \right) \left(\frac{\lambda^c \theta b}{1+\lambda^c \theta b} \right) - \frac{\theta \bar{z}^a}{\bar{z}} \left(\frac{k-\sigma+\alpha}{\sigma-1} \right) \right] \epsilon_{b\eta} \quad (35)$$

Proof. Follows from (21), (22), and (30). □

2.5 From Theory to Estimation

The primary objective of this paper is to determine the effect of economy-wide default risk on aggregate pollution emissions, and to decompose the effect along the lines of Results 1 to 6. To this end, this paper estimates the elasticity of productivity and emissions intensity with respect to default risk. Section 3.5 demonstrates that these composite parameters, coupled with parameters from previous studies, are sufficient statistics to numerically estimate the results in the model.

Because only firms operating in the market are observed ($\phi \geq \phi^b$), productivity of producing firms is given by:

$$\phi^* = \begin{cases} \phi & \text{if } \phi < \phi^u \\ \phi(1+\delta) & \text{if } \phi \geq \phi^u \end{cases} \quad (36)$$

Because technology choice is not observable in the dataset, productivity is a random variable with conditional expectation equal to

$$E[\phi^*] = \phi(1-\theta) + \phi(1+\delta)\theta = \phi(1+\delta\theta) \quad (37)$$

where θ is the probability that a firm invests in the technology upgrade as defined in Lemma 4.

Similarly, emissions intensity of producing firms is given by (see equation 6):

$$e^* = \begin{cases} \frac{1}{\phi^\alpha} & \text{if } \phi < \phi^u \\ \frac{\gamma}{((1+\delta)\phi)^\alpha} & \text{if } \phi \geq \phi^u \end{cases} \quad (38)$$

Consequently, emissions intensity is also a random variable with conditional expectations equal to

$$E[e^*] = \left[\frac{1}{\phi^\alpha} \right] (1-\theta) + \left[\frac{\gamma}{((1+\delta)\phi)^\alpha} \right] \theta = \frac{1}{\phi^\alpha}(1+\tilde{\gamma}\theta) \quad (39)$$

where $\tilde{\gamma} = \gamma(1+\delta)^{-\alpha} - 1$.

Expressions (37) and (39) generate the reduced-form specifications used to estimate the elasticity of productivity and emissions intensity with respect to default risk. In particular, variation in productivity (differential change) is explained by the following expression:

$$\frac{dE[\phi^*]}{E[\phi^*]} = -\left[\frac{\delta\theta}{1+\delta\theta}\left(\frac{k}{\sigma-1}\right)\epsilon_{b\eta}\right]\frac{d\eta}{\eta} + \frac{d\phi}{\phi} + \left[\frac{\delta\theta}{1+\delta\theta}\left(\frac{k}{\sigma-1}\right)\right]\frac{d\Lambda}{\Lambda} + \left(\frac{\delta\theta}{1+\delta\theta}\right)\frac{d\delta}{\delta} \tag{40}$$

which implies that the elasticity of productivity with respect to default risk is given by the following:

$$\frac{dE[\phi^*]/E[\phi^*]}{d\eta/\eta} = -\frac{\delta\theta}{1+\delta\theta}\left(\frac{k}{\sigma-1}\right)\epsilon_{b\eta} < 0 \tag{41}$$

Similarly, variation in emissions intensity is explained by the following expression:

$$\frac{dE[e^*]}{E[e^*]} = -\left[\frac{\tilde{\gamma}\theta}{1+\tilde{\gamma}\theta}\left(\frac{k}{\sigma-1}\right)\epsilon_{b\eta}\right]\frac{d\eta}{\eta} - \alpha\frac{d\phi}{\phi} + \left[\frac{\tilde{\gamma}\theta}{1+\tilde{\gamma}\theta}\left(\frac{k}{\sigma-1}\right)\right]\frac{d\Lambda}{\Lambda} + \left(\frac{\tilde{\gamma}\theta}{1+\tilde{\gamma}\theta}\right)\frac{d\tilde{\gamma}}{\tilde{\gamma}} \tag{42}$$

which implies that the elasticity of emissions intensity with respect to default risk is given by the following:

$$\frac{dE[e^*]/E[e^*]}{d\eta/\eta} = -\frac{\tilde{\gamma}\theta}{1+\tilde{\gamma}\theta}\left(\frac{k}{\sigma-1}\right)\epsilon_{b\eta} \tag{43}$$

By Lemma 1, the technology upgrade reduces emissions intensity whenever $\gamma^{1/\alpha} < 1+\delta$, which implies that $\tilde{\gamma} < 0$. Intuitively, default risk reduces the likelihood of investing in the technology upgrade, implying that (43) is positive if and only if the technology upgrade reduces emissions intensity.

3 Empirical Analysis

3.1 Data Sources and Description

This paper uses establishment-level panel data for manufacturing facilities in the United States. To this end, I combine two primary datasets. First, I use the Environmental Protection Agency's (EPA) Risk-Screening Environmental Indicators (RSEI) as a comprehensive measure of establishment-level pollution emissions. Second, I merge the RSEI dataset with establishment-level data from Dunn and Bradstreet's (D&B) National Establishment Time Series (NETS). The NETS dataset contains information on establishment-level annual sales, employment, and other characteristics. Moreover, the NETS also contains establishment-level measures of creditworthiness, compiled by D&Bs DUNS Marketing Information archive.

3.1.1 Pollution Emissions

The RSEI aggregates chemical release data from the EPA's Toxic Release Inventory (TRI) to assess the aggregate damages caused by an establishment's pollution emissions. The TRI contains annual data on approximately 650 toxic chemicals, including the quantity and disposal media (air, water, landfill, etc.) of each chemical released.[10] The RSEI includes three primary measures of aggregate pollution emissions: Pounds, Hazard, and Risk. Pounds of emissions is the unweighted sum of all chemical releases. Hazard emissions weights each chemical released by its toxicity level, as measured by epidemiological studies. Risk emissions incorporates toxicity and the disposal media of each chemical, coupled with population characteristics of the surrounding area exposed (from the U.S. Census Bureau). While Risk emissions is arguably the most important measure in terms of impacts to human health, the measure is problematic from a descriptive point of view because it is influenced by factors that are extraneous to the model (e.g., population characteristics). Therefore, I focus on Hazard emissions as the primary measure of pollution emissions.[11]

The TRI has become the primary source by which researchers, regulators, and environmentalists, assess establishment-level environmental performance; however, a number of shortcomings have been pointed out. It is beyond the scope of this paper to address these issues adequately and I refer to Marchi and Hamilton (2006) for a paper devoted to exploring the accuracy of the TRI. The primary concern is that, because the data are self-reported, emissions might not be reported accurately as consequence of devoting insignificant effort to measurement or due to deliberate misreporting. While some misreporting is possible, Marchi and Hamilton (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 (EPA, 2012).

3.1.2 Establishment Characteristics

The NETS database is proprietary data compiled by Walls and Associates from D&B's credit monitoring and marketing information archives. The database essentially covers all plants and firms in the United States, beginning in 1990 and extending to 2010.[12]

The NETS dataset contains annual establishment-level measures of creditworthiness from

[10]Establishments 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.

[11]Using pounds of releases is problematic because chemicals are very heterogeneous, even within various subgroups. The primary results are similar using Risk emissions, and are available upon request.

[12]The data are matched with the RSEI using the unique D&B numbers (DUNS). Among the 453,224 establishment-year observations in the RSEI dataset, 414,602 (91 percent) were matched.

D&B, called PayDex Scores, which range between 0 and 100 in ascending order of creditworthiness.[13] The NETS dataset also contains information on the age of the establishment (year start) and the year in which the establishment went out of business (if applicable). Equipped with this information, it is possible to verify if in fact PayDex scores are related to default risk, and to construct measures of default risk, which I discuss in the subsequent section.

The NETS dataset contains information on establishment-level sales, employment, industry classification, and various other characteristics. Using these variables, I construct measures of output by deflating by deflating establishment-level sales using industry price deflators from Bartelsman and Gray (1996), and productivity by dividing output by employees.[14] One drawback to the NETS database is that it does not include information on hours worked as well as capital stocks, precluding estimating total factor productivity.[15] 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.

3.2 Sample of Analysis and Summary Statistics

The data consists of an unbalanced panel of manufacturing plants in 2-digit Standard Industrial Classification (SIC) 20 to 39, starting in 1990 and ending in 2009.[16] The RSEI dataset does not distinguish between missing and zero-valued emissions; hence, I exclude all plants with non-positive value of emissions. Finally, because there are very few establishments in the "Tobacco" and "Apparel" sectors (11 and 32, respectively), and no instances of establishments exiting the market in these sectors, I omit all establishments in these sectors because generating a measure of default risk is not possible.[17] The final sample consists of 25,847 establishments and 216,506 establishment-year observations.

[13] According to D&B, PayDex Scores a measure of both payment history and default risk, where a score above 80 indicates low risk and below 50 indicates high risk. The model used by D&B to generate scores is proprietary, and the company does not provide information regarding the interpretation of PayDex Scores in terms of the corresponding default probability. For more information on PayDex Scores, see http://paydex.net/.

[14] Establishment-level prices are unavailable and would be endogenous, thereby complicating the analysis.

[15] Labor productivity might vary across industries due to variation in capital intensity. However, the baseline analysis uses log labor productivity and accounts for establishment fixed effects, which implies that variation in productivity is in terms of percentage changes from an establishment's mean labor productivity. Moreover, the baseline analysis accounts for industry by year fixed effects, and the coefficient estimates do not vary systematically across industries (results available upon request).

[16] Because the sample consists of only establishments reporting pollution releases, the sample is not representative of the manufacturing sector in general.

[17] Few establishments in these sectors report pollution emissions because they tend to be the least polluting among the manufacturing sector. It is therefore not particularly consequential to omit these establishments.

Table 1 reports summary statistics by industry (in ascending order of 2-digit SIC). The first column reports the number of unique establishments by sector, while the second column reports the corresponding average number of years establishments are observed in the sample. For example, the "Chemicals" sector consists of 4,143 unique establishments, and establishments are observed for 9.36 years on average.

Because pollution emissions and labor productivity are not denoted in meaningful units, both measures are normalized to fit a standard normal distribution for comparison. Specifically, Emissions is the ratio of hazard pollution emissions to deflated Sales, while Productivity is the ratio of deflated sales to the number of employees. The Table demonstrates that both variables exhibit significant variation, both within and between sectors. Sales is establishment-level sales (divided by 1 million) in constant 2014 US dollars (USD). Average sales is approximately 55 million USD and the standard deviation is around 155 million USD, demonstrating that the distribution of sales are positively skewed. The mean Credit Score is 74.6 and the corresponding standard deviation is 6.4. Recall, D&B classify plants with Credit Scores above 80 as being low risk of default, suggesting that most establishments have at least some risk of default. Default risk is defined and described in the subsequent section.

3.3 Default Risk

Estimating the elasticity of productivity and emissions intensity with respect to default risk requires a measure of default risk in terms of the probability of default, which is not available at the establishment or firm level. The aim of this section is to generate an appropriate measure of default risk using information on the year in which establishments go out of business (exit the market) and variation in credit scores across establishments. To this end, I estimate the following pooled binary choice model:

$$\text{Prob}(\text{Death}_{ist+1} = 1|\mathbf{x}_{ist}) = \mathbf{\Phi}(\alpha_t + \alpha_s + \alpha_1 \text{Credit Score}_{ist}) \tag{44}$$

where i indexes establishments, s indexes sectors, and t indexes years. The dependent variable, Death_{ist+1}, is a binary variable equal to 1 if the firm exits the market in the subsequent period $t+1$.[18] The independent variables include year and 3-digit SIC-industry fixed effects and Credit Score The cumulative distribution function $\mathbf{\Phi}$ is assumed to be normal or logistic, giving rise to the probit and logit model, respectively.

[18]Firms exiting in period t do not report in that period, precluding estimation of a contemporaneous model. Exiting the market is an "absorbing" state as there are no instance of establishments taking up production in subsequent years.

The 3-digit SIC-industry fixed effects accounts for default-risk heterogeneity across narrowly defined industries (345 industries), while the year fixed effects account for common time-varying factors, such as technology and demand shocks.[19] Credit Score is included to account for variation in default risk within industries and over time.

In many instances, the choice between probit and logit does not make much difference. However, because the difference between the two distributions is primarily in the tails (logistic distribution has heavier tails), the two models might generate different predictions when the dependent variable is highly uneven. Because there are only 655 instances of firm death among 25,847 (2.5%) in the sample of analysis, the two models might give substantively different results and, on theoretical grounds, it is difficult to justify one model or another.[20] Therefore, both models are used.

Figure 1 presents the distribution (univariate kernel density estimation) of credit scores among non-surviving ($\text{Death}_{ist+1} = 1$) and surviving ($\text{Death}_{ist+1} = 0$) establishments. While both distributions are skewed to the left, the distribution of non-surviving establishments exhibits more negative skewness as the left tail is relatively fatter. That is, non-surviving establishments are more likely to have low credit scores relative to surviving firms.

Table 2, columns (1) and (3), report the baseline probit and logit regressions results, respectively. As anticipated, Credit Score is inversely related to Death, and the relationship is statistically significant at all conventional levels of significance.[21] Columns (2) and (4) are discussed in the subsequent section.

The primary purpose of this section is to assign default risk to establishments using the predicted values generated from the regression given in 44. To this end, I define

$$\text{Default Risk}_{ist} = \text{E}[\text{Death}_{ist+1}|\mathbf{x}_{ist}] \tag{45}$$

The interpretation of $\text{Default Risk}_{ist}$ is the predicted probability that the establishment will exit the market (default) in a given year, which is consistent with the theoretical model. The generated variable is, however, measured with error, which has implications that are discussed in the subsequent section.

Figure 2 plots the distribution (univariate kernel density estimation) of (log) default risk generated from the probit and logit regressions. The figure demonstrates that the two models

[19] Alternative specifications also control for 4-digit SIC industry fixed effects and industry by year fixed effects. However, maximum likelihood estimation drops almost all of the additional fixed effects because Death is a relatively rare event, and consequently there is no variation in the dependent variable within these fixed effects categories.

[20]

[21] Because prediction is the primary purpose of the analysis, I do not interpret the coefficients or report marginal effects.

generate nearly identical default risk distributions, suggesting that the choice between probit and logit should not make much difference.

The last two columns in the summary statistics table (Table 1) report the mean and standard deviation of default risk across sectors.[22] The mean default risk among all establishments in the sample is around 0.2%, and the standard deviation is around 0.3%.[23] Default risk varies across sectors, ranging from 0.15% to over 0.80%, as well as within sectors, as the standard deviation within sectors is similar to the overall standard deviation.

Figure 3 plots the mean default risk by year (solid line) and the corresponding 90% confidence interval over the 1990 to 2009 period. The annual exit rate (percentage of establishments exiting the market by year) is also plotted (dash line with point marker). The figure demonstrates that the actual exit rate is highly consistent with the number of establishment deaths predicted by the regression model. The figure also demonstrates that default risk varies systematically, and quite significantly in percentage terms, over time, ranging from less that 0.05% in the mid-1990s and 2000s to over 0.5% in the early 2000s.

3.4 Productivity and Emissions Intensity

The theoretical model generates the empirical specifications used to estimate the elasticity of productivity and emissions intensity with respect to default risk. Recall that variation in productivity is determined by variation in η, ϕ, Λ, and δ, while variation in emissions intensity is determined by variation in η, ϕ, Λ, and $\tilde{\gamma}$. The empirical strategy is to account for variation in the technological parameters, Λ, δ, and $\tilde{\gamma}$, using flexible industry by year fixed effects. Moreover, establishment fixed effects are used to account for variation in the productivity draw ϕ. Expressions (40) and (42) therefore recommend the following reduced-form relationships:

$$\ln \text{Productivity}_{ist} = \beta_1 \ln \text{Default Risk}_{ist} + \beta_i + \beta_{st} + \epsilon_{ist} \tag{46}$$

and

$$\ln \text{Emissions Intensity}_{ist} = \zeta_1 \ln \text{Default Risk}_{ist} + \zeta_i + \zeta_{st} + \varepsilon_{ist} \tag{47}$$

where (as before) i indexes establishments, s indexes sectors, and t indexes years. Establishment fixed effects are captured by the parameters β_i and ζ_i, while industry by year fixed effects are captured by the variables β_{st} and ζ_{st}. The establishment fixed effects account for

[22] For the remaineder of this section, default risk is generated using the probit model. The results are similar using the logit model, and are available upon request.

[23] While the mean default risk is less than the manufacturing sector in general, this observation is not unexpected as the sample is not necessarily representative of the manufacturing sector and polluting establishments tend to be larger and more capital intensive on average.

establishment unobserved effects, while the industry by year effects account for aggregate industry time effects.[24] Because the panel is short, estimation is by Fixed Effects where the establishment-specific effects β_i and ζ_i are eliminated using a within transformation. The parameter β_1 is the elasticity of productivity with respect to default risk and ζ_1 is the elasticity of emissions intensity with respect to default risk.[25]

The proposed two-step procedure using unobserved regressors generated from a first-stage auxiliary econometric model has been analyzed by Murphy and Topel (1985) and Pagan (1984). Consistent estimates of the second-stage parameters (β_1 and ζ_1) requires (i) consistent estimation of the first-stage parameters and (ii) strict exogeneity of the regressors in the second-stage. Because Default Risk is imputed from the first-stage model, strict exogeneity implies that Credit Score is uncorrelated with the random components ϵ_{ist} and ε_{ist}. That is, Credit Score is not directly related to Productivity and Emissions Intensity, it is only related to the dependent variables through Default Risk, which I discuss in more detail below.

While the two-step procedure generates consistent estimates of the parameters in the second-stage regression, it is well known that failing to account for the presence of imputed regressors yields inconsistent estimates of their standard errors. Consequently, the naïve standard errors are in general biased downward, leading to over-rejection of the null hypothesis. To remedy this issue, this study employs a two-step bootstrapping procedure to correct the standard errors, which I discuss in more detail in the subsequent section.

3.4.1 Regression Results

Columns (1) and (4) of Table 3 report the baseline regression results using Productivity (Panel A) and Emissions Intensity (Panel B) as dependent variables. Columns (1) and (4) correspond to Default Risk generated in Table 2 columns (1) and (3), respectively. The standard errors are cluster-robust standard errors that cluster on industry (bootstrap estimates of the standard errors are reported in the subsequent section). The results indicate that the elasticity of labor productivity with respect to default risk is negative (as expected), while the elasticity of emissions intensity with respect to default risk is positive (consistent with upgrading reducing emissions intensity). In particular, the elasticity of labor productivity is –0.16 and –0.17, while the elasticity of emissions intensity is 0.89 and 0.93 in specifications (1) and (4), respectively. Thus, the coefficient estimates are similar across first-stage model specifications (probit and logit), and are significant at conventional significance levels.

Recall one threat to consistency is that (within-establishment) variation in Credit Score

[24] The results are robust to the inclusion of state by year fixed effects, which are available upon request.

[25] That is, $\beta_1 = -(\delta\theta/(1+\delta\theta))(k/(\sigma-1))\epsilon_{b\eta}$ and $\zeta_1 = -(\tilde{\gamma}\theta/(1+\tilde{\gamma}\theta))(k/(\sigma-1))\epsilon_{b\eta}$.

might be linked to variation in Productivity and Emissions Intensity through channels unrelated to default risk. While variation in Credit Score is arguably not directly linked to variation in Productivity and Emissions Intensity, both might be linked to time-varying omitted factors, such as variation in managerial skill. For example, hiring a high-skilled manager might increase productivity and reduce pollution emissions, as well as increase Credit Score, which would lead to inconsistent estimates.

One approach to address this issue is to exploit variation in the differential impact of Credit Score on Default Risk, and control for Credit Score in the second-stage model. To this end, this paper exploits variation in the impact of Credit Score on Default Risk across publicly-owned and privately-owned establishments (the sample of analysis consists of 32% publicly-owned and 68% privately-owned establishments). In particular, publicly-owned establishments can finance operating costs and investments using retained earnings and equity, while privately-owned establishments are relatively more dependent on external lenders, and credit scores are the yardstick by which lenders assess creditworthiness. Consequently, publicly-owned establishments are less likely to go out of business as a consequence of negative credit shock.

Table 2, columns (2) and (4), report the first-stage probit and logit regression results, respectively, using Credit Score interacted with a dummy variable equal to 1 for publicly-owned facilities (Public Facility).[26] The results suggest that there is significant variation in the effect of Credit Score across publicly-owned and privately-owned facilities.[27] In particular, the coefficient estimate for Credit Score for privately-owned facilities (-0.04 and -0.12) is approximately twice the size of the corresponding estimate for publicly-owned facilities (-0.02 and -0.06).[28] Moreover, as expected, publicly-owned facilities are far less likely to go out of business than privately-owned facilities.

Exploiting variation in the differential effect of Credit Score permits controlling for it in the second stage. Consequently, consistency requires, in this case, that the interaction between Credit Score and Public Facility is uncorrelated with the random components in the second stage (ownership status is time invariant in the sample). The threat to consistency is that the differential effects of a credit score shock on variation in default risk might be related to differential effects on variation in Productivity and Emissions Intensity (through channels unrelated to differential effects on default risk). Let's reconsider the example of

[26]Similar to (44), I estimate the following model $\text{Prob}(\text{Death}_{ist+1} = 1|\mathbf{x}_{ist}) = \mathbf{\Phi}(\alpha_t + \alpha_s + \alpha_1 \text{Credit Score}_{ist} + \alpha_2 \text{Credit Score}_{ist} \times \text{Public Facility}_{is} + \alpha_3 \text{Public Facility}_{is})$.

[27]Figures A1 and A2 in the supplementary web appendix B plots the kernel density distributions of default risk for public and private establishments generated using probit (A1) and logit (A2) regressions.

[28]The statistical significance of the interaction term Credit $\text{Score}_{ist} \times \text{Public Facility}_{is}$ demonstrates that the difference between the coefficient estimates is significant at the 1 percent significance level.

managerial skill as an omitted variable to clarify this assumption. Suppose, for example, hiring a high-skilled manager improves a facility's credit score to an equal extent for both publicly-owned and privately-owned facilities, but it reduces default risk to a greater extent for privately-owned facilities. Consistency requires that the effect of hiring a high-skilled manager on productivity and emissions intensity should not vary according to ownership status. For example, if hiring a high-skilled manager increases productivity and reduces pollution emissions to a greater extent in privately-owned facilities, and it increases credit scores to the same extent, then the estimates would not be consistent.

Columns (2) & (3) and (5) & (6) of Table 3 report the regression results using the Default Risk generated in columns (2) and (4) of Table 2, respectively. Moreover, columns (2) and (5) do not control for Credit Score, whereas columns (3) and (6) control for Credit Score, in the second-stage regressions. Employing the Public Facility interaction term in the first-stage regressions without controlling for Credit Score in the second-stage generates slightly smaller estimated effects of default risk on labor productivity (Panel A, columns 2 and 5) and emissions intensity (Panel B, columns and 5), while controlling for Credit Score in the second-stage generates slightly larger estimated effects of default on labor productivity (Panel A, columns 3 and 6) and emissions intensity (Panel B, columns 3 and 6).

3.4.2 Alternative Difference-in-Differences Approach

Panel regressions are often subject to criticism for omitting relevant time-varying factors and other endogeneity issues. This section uses an alternative difference-in-differences (DID) approach using variation in Default Risk at the industry level to analyze the elasticity of productivity and emissions intensity with respect to default risk.

Figure 3 demonstrates that Default Risk (and the corresponding exit rate) is subject to large systematic shocks over time. While Default Risk is correlated within years, Default Risk shocks are not uniform across industries as large shocks tend to be particularly acute among a subset of industries. For example, average Default Risk increased sharply from 1998 (0.001%) to 1999 (0.060%), representing over a 5-fold increase in Default Risk (or a 1.8 increase in log Default Risk), which was the largest Default Risk shock in the period. However, the average change in log Default Risk by industry varied from around 1.46 to 2.21.[29] To exploit variation in the differential impact of the 98/99 Default Risk shock on productivity and emissions intensity, the following model is estimated using ordinary least squares:

[29]For comparison, the average log change in Default Risk over the period is -0.05, while the average absolute-value log change over the period is 0.56. Thus, the difference in the magnitude of the 98/99 shock across industries (0.7) exceeded the magnitude of the average shock over the period (0.75).

$$\Delta \ln \text{Productivity}_{ist} = \tilde{\beta}_1 \Delta \ln \text{Default Risk}_{st}^{-i} + \tilde{\beta} + \tilde{\epsilon}_{ist} \tag{48}$$

and

$$\Delta \ln \text{Emissions Intensity}_{ist} = \tilde{\zeta}_1 \Delta \ln \text{Default Risk}_{st}^{-i} + \tilde{\zeta} + \tilde{\varepsilon}_{ist} \tag{49}$$

where (as before) i indexes establishments, s indexes sectors, and t indexes years. The dependent variables are (establishment-level) differences in productivity and emissions intensity from 1999 to 1998, and the primary independent variable is the difference in average industry default risk, excluding the default risk of establishment i.[30] The intercept terms $\tilde{\beta}$ and $\tilde{\zeta}$ control for changes in productivity and emissions intensity not due to differential variation in the impact of the 98/99 Default Risk shock. The estimations use cluster-robust standard errors that are clustered on industries.

The primary advantage of the alternative DID approach is its simplicity and potential to overcome the endogeneity issues that arise in panel regressions. The parameters $\tilde{\beta}_1$ and $\tilde{\zeta}_1$ represent the reduced-form elasticity of productivity and emissions intensity with respect to industry-level default risk. Consistency requires that variation in the 98/99 Default Risk shock across industries is uncorrelated with the random components $\tilde{\epsilon}_{ist}$ and $\tilde{\varepsilon}_{ist}$. That is, variation in the Default Risk shock across industries should be uncorrelated to factors related to changes in productivity and emissions intensity. For example, if industries experiencing more acute Default Risk shocks are subject to less stringent environmental regulations then the assumption would be violated.

The reduced-form results are consistent with the panel regressions, with parameter estimates (standard errors) equal to $\tilde{\beta}_1 = -0.083$ (0.018) and $\tilde{\zeta}_1 = 0.511$ (0.210).[31] The elasticity of productivity and emissions intensity with respect to default risk can be calculated by dividing the reduced-form parameter estimates by the appropriate-first stage parameters (Wald estimator).[32] Because the elasticity of establishment-level Default Risk with respect industry-level Default Risk (standard error) is 0.808 (0.002), the elasticity of productivity and emissions intensity with respect to default risk is $-0.083/0.808 = -0.103$ (0.022) and $0.511/0.808 = 0.632$ (0.241). The Wald estimators generated from the alternative DID approach are highly consistent with the primary results.

The 98/99 Default Risk shock was selected as a quasi-natural experiment to perform an alternative DID estimation because it generated the largest shock in Default Risk, as well

[30] Precisly, $\Delta \ln \text{Productivity}_{ist}$=$\ln \text{Productivity}_{is1999} - \ln \text{Productivity}_{is1998}$, and $\Delta \ln \text{Default Risk}_{st}^{-i} = \ln \text{Default Risk}_{s1999}^{-i} - \ln \text{Default Risk}_{s1998}^{-i}$, where $\text{Default Risk}_{s1999}^{-i}$ is the average Default Risk of industry i in year 1999 (and similar for 1998), excluding establishment i.

[31] The corresponding p-values are $p = 0.00$ and $p = 0.02$.

[32] In this case, the following first-stage model $\Delta \ln \text{Default Risk}_{st}^{-i} = \tilde{\alpha} \Delta \ln \text{Default Risk}_{ist} + u_{ist}$, is estimated using OLS.

as the most variation across sectors. However, there were secondary Default Risk shocks in 06/07 and 02/03. In particular, average log Default Risk decreased from 2002 to 2003 by 1.34, with industry averages ranging from -1.65 to -0.93, while average log Default Risk increased from 2006 to 2007 by 1.17, with industry averages ranging from 0.77 to 1.61. In addition to corroborating the previous results, exploring the second and third largest Default Risk shocks also explores whether the effects of negative and positive Default Risk shocks generate symmetric effects.

Using the same approach to generate the DID estimate for the 98/99 Default Risk shock in all years spanning the sample of analysis, Figure 4 reports the DID estimates for all years and the corresponding 90% confidence intervals using Productivity and Emissions Intensity as dependent variables in the top and bottom panels, respectively. Figure 4 also includes time series on average industry changes in Default Risk by year (solid line), plotted below the DID estimates in both panels. The series demonstrates that three largest Default Risk shocks occurred in 98/99, 06/07, and 02/03 (in descending order of magnitude), which are indicated using gray vertical bars. In addition, Figure A3 in supplementary web Appendix B reports the distribution (univariate kernel density estimation) of changes in Default Risk by year, indicating that the three largest Default Risk shocks also generated the largest dispersion in Default Risk across industries.

Figure 4 demonstrates that the Productivity DID estimate (top panel) is consistent in 06/07 Default Risk shock, but is not statistically signifiant in the 02/03 Default Risk shock.[33] The Emissions Intensity DID estimate (bottom panel) is consistent in the 06/07 and 02/03 Default Risk shocks, but the latter is not statistically significant as the confidence interval contains zero within it's lower bound.[34] Exploiting the three largest Default Risk shocks therefore results in consistent results in the two positive Default Risk shocks, and insignificant results in the one negative Default Risk shock. More generally, the Productivity DID estimate is negative in most years, while the Emissions Intensity DID estimate is positive in most years, with relatively narrower confidence intervals around years relatively larger Default Risk shocks.

3.5 Numerical Model Simulations

The aim of this section is twofold. First, to correct the naïve standard errors in the two-stage regression analysis. Second, to numerically estimate the model using the estimated

[33] In particular, the Productivity DID estimate (standard error) is -0.283 (0.037) in 06/07 and 0.017 (0.016) in 02/03.

[34] In particular, the Emissions Intensity DID estimate (standard error) is 0.653 (0.316) in 06/07 and 0.360 (0.266) in 02/03.

elasticities, coupled with parameter estimates from previous studies, and to generate the corresponding standard errors.

3.5.1 Parameterization

Because it is beyond the scope of this paper to estimate the wide-range of parameters, this paper relies on parameter estimates from previous studies. In section 3.5.5, I undertake a sensitivity analysis using a wide range of the parameter values.

The first set of parameters are from Shapiro and Walker (2015), who estimate a similar model with heterogeneous firms and monopolistic competition (but no endogenous technology upgrading) using establishment level data from the U.S. manufacturing sector. In particular, Shapiro and Walker (2015) estimate that the elasticity of emissions intensity with respect to productivity $\alpha = 0.99$, the elasticity of substitution across varieties $\sigma = 4.75$, and the Pareto shape parameter $k = 5.70$.[35] Second, Midrigan and Xu (2014) extend the Hopenhayn (1992) model of industry dynamics to include financing frictions and endogenous technology decisions, and estimate that relative efficiency of technology adoption around $\delta = 0.27$ using establishment-level data from the Korean manufacturing sector.[36] Finally, using micro-level data from U.S. nonfinancial firms, Gilchrist and Zakrajšek (2012) estimate that the average bond has an expected return of 204 basis points above the risk-free rate, suggesting that borrowing costs are approximately $b = 1.02$.[37]

The last parameter to pin down is the ratio of additional net revenue to additional fixed costs (both in percentage terms) $\Lambda = \lambda^r/\lambda^c$, which as far as I know cannot be inferred from previous studies. Recall from Lemma 2 that, *a priori*, $0 < \Lambda < b = 1.02$. I assume, as a baseline, that the rate of return to the technology upgrade is normalized such that $\lambda^r = \lambda^c$, which implies that $\Lambda = 1$. The implication of this normalization is that percentage increase in net revenue associated with the technology upgrade (relative to the baseline net revenue) is exactly equal to the percentage increase in fixed costs (relative to the baseline fixed costs). Consequently, in the absence in borrowing costs, all firms in the economy would invest in the technology upgrade. Because there is no empirical evidence supporting this assumption, this paper considers a wide range of values for Λ in the sensitivity analysis.

[35] Using Productivity (i.e., the dependent variable in 48) as an explanatory variable of Emissions Intensity (i.e., estimating equation 49), I find that elasticity of emissions intensity with respect to productivity is very similar to Shapiro and Walker (2015) (available upon request).

[36] The Hopenhayn (1992) model analyzes long-run industry dynamics, accounting for entry, exit, and firm heterogeneity.

[37] Gilchrist and Zakrajšek (2012) sample consists of firms covered by the S&P's Compustat database, which are large, publicly-traded firms and arguably have lower borrowing costs. In the sensitivity analysis, this paper considers borrowing costs as high as $b = 1.20$.

3.5.2 Bootstrap Procedure

As mentioned, the two-step estimation method yields consistent estimates of the coefficients in the second stage, but inconsistent estimates of their standard errors. Similar to Ashraf and Galor (2013), this paper employs a two-step bootstrapping procedure to produce consistent standard errors in the second stage. In addition, this paper applies the procedure to produce standard errors of the numerical model results. The bootstrap estimates of the standard errors are constructed using the following algorithm. First, a random sample of establishments with replacement is drawn, and predicted Default Risk measures are estimated in the first-stage regression (equation 44).[38] The second-stage regressions (equations 46 and 47) are then estimated on this random sample and the second-stage coefficients are stored. This procedure is repeated 1,000 times and the standard deviations of the second-stage coefficients are the bootstrap standard errors of the coefficients in the second stage.

Standard errors of the numerical model results are estimated by extending the two-step estimation method as follows. First, the model results are solved numerically using the parameter values given in Section 3.5.1 in terms of the second-stage coefficients. Second, after estimating the second-stage regressions on the random sample of establishments with replacement, the numerical model results are calculated as a function of the second-stage coefficients, and the model results are stored. This procedure is similarly repeated 1,000 times, and the standard deviations of the model results are the bootstrapped standard errors of the numerical model results.

3.5.3 Numerical Model Results

Table 4 reports the coefficients and bootstrapped standard errors using the two-step bootstrap procedure explained above. The results demonstrate that not accounting for the presence of generated regressors seriously underestimates the productivity and emissions intensity elasticity standard errors as the bootstrapped standard errors are around 4 and 5 times larger than the corresponding naïve standard errors reported in Table 3, respectively.[39] Even with the larger bootstrapped standard errors, the estimated elasticities remain statistically significant at the 5 percent significance level. Moreover, the estimated standard errors associated with the various model effects indicate that the numerical model results are statistically significant at least at the 10 percent significance level, and in most instances at the 1 percent significance level.

[38] Predicted Default Risk is estimated using the probit model specification reported in column (1) of Table 2. The bootstrap standard errors are similar using other specifications, and are available upon request.

[39] As expected, the estimated Productivity Elasticity and Emissions Intensity Elasticity are identical to the corresponding coefficients reported in Table 3, column (1).

Recall that average output and emissions effects consists of Selection and Upgrading Effects. The results indicate that the output Selection and Upgrading Effects are -0.07 and -0.22, implying that the average output effect is -0.29, and that the Selection and Upgrading Effects account for 23% and 77% of the effect, respectively. The emissions Selection and Upgrading Effects are -0.002 and -0.073, implying that the average emissions effect is -0.075, and that the Selection and Upgrading Effects account for 3% and 97% of the average emissions effect, respectively. The emissions-intensity Selection and Upgrading Effects are 0.06 and 0.15, implying that the Aggregate Emissions-Intensity Effect is 0.21, and that the Selection and Upgrading Effects account for 29% and 71% of the effect, respectively.[40] Finally, the estimated Market-Size Effect is 0.15.

Recall that the Aggregate Output and Emissions Effects are the sum of Average Output and Emissions Effects and the Market-Size Effect. Because the Market-Size Effect increases output and emissions, and the Average Output and Emissions Effects decrease output and emissions, the sign of the Aggregate Effects depends on the relative magnitude of the two opposing effects. The Aggregate Output Effect is -0.13, while the Aggregate Emissions Effect is 0.08.[41] That is, the magnitude of Average Output Effect is larger than the Market Size Effect, while the magnitude of the Average Emissions Effect is smaller than the Market Size Effect.

Figure 5 plots the stored second-stage coefficients, and the corresponding numerical model results. In particular, for 1,000 random draws with replacement, the scattered markers represent the Emissions Intensity and Productivity Elasticity coefficients, and the corresponding Aggregate Effect on Output, Emissions, and Emissions Intensity. The solid vertical and horizontal lines represent the coefficient estimates, and the dashed lines represent the corresponding 90% confidence intervals. Finally, the distributions below the scattered markers are univariate kernel density distributions for Emissions Intensity and Productivity Elasticities. The figure demonstrates that the magnitude of the Aggregate Effect on Output is decreasing in Emissions Intensity Elasticity and increasing in Productivity Elasticity, and the magnitude of the Aggregate Effect on Emissions and Emissions Intensity is increasing in Emissions Elasticity and decreasing in Productivity Elasticity. Figure A4 in the supplementary web Appendix B plots the kernel density distributions for the stored second-stage coefficients, and all of the numerical model results (disaggregated according to Market-Size Effect, Selection Effect, Upgrading Effect, and Aggregate Effect).

[40] Recall that the emissions-intensity Selection Effect is the emissions Selection Effect less the output Selection Effect, and the emissions-intensity Upgrading Effect is the emissions Upgrading Effect less the output Upgrading Effect.

[41] Recall that the Aggregate Output (Emissions) Effect is the elasticity of output (emissions) with respect to default risk.

In general, the numerical model results support the following set of conclusions. First, default risk reduces average output, with most of the effect due to reduced technology upgrading, and increases the mass of firms. Because the reduction in average output is approximately twice as large as the increase in the mass of firms, default risk reduces aggregate output. Second, default risk reduces average emissions, with nearly all of the effect due to reduced technology upgrading. Because the reduction in average emissions is approximately half as large as the increase in the mass of firms, default risk increases aggregate emissions. Third, because default risk reduces average output by a larger extent than it reduces average emissions (by a factor of 3.8), default risk increases emissions intensity.

3.5.4 Default Risk Shocks and Aggregate Pollution Emissions

The aim of this section is to leverage the estimated numerical model results to estimate the impact of historical Default Risk shocks on output, pollution emissions, and emissions intensity. I focus on the two largest shocks, the 98/99 shock, which increased log Default Risk by 1.8, and the 02/03 shock, which decreased log Default Risk by 1.3. Because the numerical model results are in terms of percentage changes, the results are independent of the level of output and pollution emissions. Moreover, because the empirical analysis focuses on the manufacturing sector, the numerical models results should be interpreted as percentage changes in output and pollution emissions from the manufacturing sector.

The numerical model results indicate that the 98/99 (positive) Default Rate shock would generate a 24% reduction in output, a 14% increase in pollution emissions, and a 38% increase in emissions intensity. On the other hand, the 02/03 (negative) Default Risk shock would generate a 18% increase in output, a 10% reduction in pollution emissions, and a 28% reduction in emissions intensity. Using the lower bound of the magnitude of numerical model results suggests that the 98/99 (positive) Default Rate shock would generate, more conservatively, a 19% reduction in output, a 4% increase in pollution emissions, and a 31% increase in emissions intensity. On the other hand, the 02/03 (negative) Default Risk shock would generate a 14% increase in output, a 1.4% reduction in pollution emissions, and a 23% reduction in emissions intensity. Therefore, historical changes in economy-wide default risk can generate economically significant changes in pollution emissions, and pollution emissions intensity in particular.

3.5.5 Parameter Value Sensitivity Analysis

Section 3.5.1 tied down the necessary parameters such that the second-stage coefficients can be leveraged to numerically solve the model's key results. In this section, I fix the second-stage coefficients using the regression results presented in Section 3.4.1, and investigate the numerical model results over various ranges of parameter values.[42] Investing the numerical model results under various parameter values has two related aims. First, to perform a robustness check to assess the sensitivity of the numerical model results to changes in parameter values. Second, to investigate the numerical model results under counterfactual parameter values in order to shed light on the results in alternative counterfactual environments. For example, to assess the findings in the context of an economy with high default risk and correspondingly higher borrowing costs.

Because the elasticity of substitution across varieties and the Pareto shape parameter are relatively well-established in the literature, I take these parameter values for granted, and investigate the numerical results over four key parameters. In particular, holding all other parameter values constant ($b = 1.02$, $\Lambda = 1$, $\delta = 0.27$, and $\alpha = 0.99$), I investigate the numerical results over $b \in [1, 1.2]$, $\Lambda \in [0.75, 1.02]$, $\delta \in [0, 0.5]$, and $\alpha \in [0.7, 1.1]$. The Aggregate Effects of default risk on Output, Emissions, and Emissions Intensity, over the range of parameter values are plotted in Figure 6, while the disaggregate effects (Market-Size, Selection, and Upgrading Effects) are plotted in Figures A5, A6, and A7, in supplementary web appendix B. Figure 6 demonstrates that the Aggregate Effect on Output is mostly constant over the various parameter values, ranging between -0.12 and -0.14. Figure A5 demonstrates that the Aggregate Effect on Output is constant due to confounding effects. Below, I discuss the ranges of parameters, and the corresponding range of numerical model results in terms of emissions and emissions intensity effects.

First, the Aggregate Effect of default risk on Output, Emissions, and Emissions Intensity, over the range of borrowing costs (b) are plotted in the northwest quadrant of Figure 6. I assume that (gross) borrowing costs range between 1 (0% interest rate) and 1.2 (20% interest rate). Figure 6 demonstrates that the Aggregate Effect on Emissions and Emissions Intensity are increasing in borrowing costs (ranging between 0.07 and 0.15, and 0.21 and 0.28, respectively). Figure A6 demonstrates that the Aggregate Effect on Emissions is increasing in borrowing costs because the Upgrading and Market-Size Effects are increasing in borrowing costs, while Figure A7 demonstrates that the Aggregate Effect on Emissions Intensity is increasing because the Upgrading Effect is increasing in borrowing costs.

Second, the Aggregate Effects of default risk on Output, Emissions, and Emissions Intensity, over the range of Λ are plotted in the northeast quadrant of Figure 6. Recall that, from a theoretical point of view, Λ is bound between 0 and the gross borrowing cost (b). I

[42] In particular, I assume that the elasticity of productivity and the elasticity of emissions intensity are -0.16 and 0.89. These coefficients correspond to the baseline model as reported in Table 3, column (1), which are representative of the various model specifications.

exclude relatively low values of Λ, and assume that Λ ranges between 0.75 and 1.02. Figure 6 demonstrates that the Aggregate Effect on Emissions and Emissions Intensity is decreasing in Λ (ranging between 0.24 and 0.07, and 0.37 and 0.21, respectively). Figure A6 demonstrates that the Aggregate Effect on Emissions is decreasing in Λ because the Upgrading and Market-Size Effects are decreasing in Λ, while Figure A7 demonstrates that the Aggregate Effect on Emissions Intensity is decreasing because the Selection Effect is decreasing in Λ.

Third, the Aggregate Effects of default risk on Output, Emissions, and Emissions Intensity, over the range of δ are plotted in the southwest quadrant of Figure 6. I assume that δ ranges between 0 (upgrading increases productivity by 0%) and 0.5 (upgrading increases productivity by 50%). Figure 6 demonstrates that the Aggregate Effect on Emissions and Emissions Intensity is decreasing in δ (ranging between 0.25 and 0.03, and 0.38 and 0.17, respectively). Figure A6 demonstrates that the Aggregate Effect on Emissions is decreasing in δ because the Upgrading and Market-Size Effects are decreasing in δ, while Figure A7 demonstrates that the Aggregate Effect on Emissions Intensity is decreasing because the Upgrading Effect is decreasing in δ.

Fourth, the Aggregate Effects of default risk on Output, Emissions, and Emissions Intensity, over the range of α are plotted in the southeast quadrant of Figure 6. Because α can be interpreted as the Cobb-Douglas share of non-pollution inputs in production according to the Copeland and Taylor (2003) pollution-production technology, α is bounded between 0 and 1. I assume, more generally, that α ranges between 0.7 and 1.1. Figure 6 demonstrates that the Aggregate Effect on Emissions and Emissions Intensity is increasing in α (ranging between 0.03 and 0.10, and 0.17 and 0.23, respectively). Figures A6 and Figure A7 demonstrate that the Aggregate Effect on Emissions and Emissions Intensity is increasing in α because the Selection Effect is increasing in α.

What general conclusions can be drawn from the sensitivity analysis? To the extent that $b = 1.02$ is lower bound and $\Lambda = 1$ is an upper bound, the magnitude of the Emissions and Emissions Intensity Effects are lower bounds of potentially larger effects. However, it is not clear whether smaller or larger parameters are more likely for δ and α, implying that magnitude of the numerical model results are potentially smaller or larger. However, we can conclude that the numerical model results do not change qualitatively over a wide range of parameter values. In particular, the magnitude of the Aggregate Output Effect is mostly constant over the parameter values. The magnitude of the Aggregate Emissions Intensity Effect exhibits some variation over the parameter values, but remains relatively large in all instances (> 0.17). Finally, the magnitude of the Aggregate Emissions Effect exhibits some variation over the parameter values, but remains larger than zero in all instances (> 0.03).

4 Conclusion

This paper develops a general equilibrium model to analyze the effect of default risk on aggregate pollution emissions. The model demonstrates that, by raising borrowing costs, default risk reduces investment in technology upgrading, and results in an economy consisting of more numerous firms, but firms that are on average less productive and more pollution intensive. Specifically, this paper demonstrates that default risk generates three conceptually distinct effects, which I refer to as the (1) market-size effect, (2) technology-upgrading effect, and (3) selection effect.

The empirical analysis explores the effect of default risk on pollution emissions and productivity for a panel of manufacturing facilities. Using a two-stage procedure where default risk is estimated in the first stage, the results indicate that the estimated elasticity of emissions intensity and productivity with respect to default risk is 0.89 and -0.16, respectively. This paper also employs an alternative difference-in-differences approach, exploiting variation in the magnitude of default risk shocks across industries, which yields consistent results.

This paper uses the coefficients from the empirical analysis, coupled with parameters estimated by previous studies, to estimate the effect of an increase in the economy-wide default risk on aggregate pollution emissions, and to divide the effects into market-size, technology-upgrading, and selection effects. The numerical model results demonstrate that average pollution emissions are decreasing in default risk, with most of the effect due to the technology-upgrading effect, while aggregate pollution emissions are increasing in default risk due to the confounding market-size effect. Moreover, because aggregate output is decreasing in default risk, emissions intensity is increasing in default risk to an even greater extent than aggregate emissions. Finally, this paper demonstrates that historical changes in economy-wide default risk can generate economically significant changes in pollution emissions. For example, the increase in average default risk between 1998 and 1999 generated a 14% increase in aggregate pollution, and a 38% increase in emissions intensity.

This paper represents a first step in understanding the role of default risk in aggregate pollution emissions; however, there are many avenues for future research. For example, while the results of this paper are relevant to a composite measure of pollution emissions for the manufacturing sector, future research might investigate alternative pollution emissions, such as carbon dioxide emissions, and explore the effects across industries within the manufacturing sector or other industries, such as emissions generated by the electricity-generation sector. Future research might also attempt to identify other sources of exogenous variation in default risk, to rule out potential bias. Finally, this paper might be more intricately linked to the broader literature investigating the role of macroeconomic dynamics in pollution emissions.

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Tables Appendix

Table 1: Summary Statistics: Mean and (Standard Deviation)

	#Est.	#Years	Emissions		Productivity		Sales (mil)		Credit Score		Default Risk	
Food	1624	7.60	–0.75	(0.71)	–0.04	(1.07)	65.49	(112.69)	77.48	(4.91)	0.20	(0.26)
Textiles	230	8.56	–0.47	(0.80)	–0.11	(0.71)	46.21	(82.48)	75.52	(6.45)	0.34	(0.49)
Lumber	887	7.27	–0.01	(0.91)	–0.26	(0.80)	27.25	(36.82)	78.02	(5.50)	0.25	(0.33)
Furniture	616	6.75	–0.52	(0.76)	–0.54	(0.60)	46.53	(108.91)	75.85	(6.56)	0.21	(0.30)
Paper	737	8.12	–0.22	(0.81)	–0.10	(0.84)	60.55	(96.49)	75.52	(5.85)	0.15	(0.20)
Printing	267	6.22	–0.60	(0.60)	–0.34	(0.69)	43.58	(67.54)	76.44	(6.36)	0.37	(0.40)
Chemicals	4,143	9.36	–0.10	(0.86)	0.15	(0.89)	36.03	(94.98)	74.18	(6.18)	0.19	(0.24)
Petroleum and Coal	474	8.70	0.13	(0.91)	–0.19	(1.25)	40.73	(171.43)	75.28	(6.22)	0.25	(0.30)
Rubber and Plastics	1,774	8.84	–0.41	(0.77)	–0.27	(0.66)	27.59	(41.72)	74.53	(6.59)	0.21	(0.25)
Leather	96	7.53	0.44	(1.44)	–0.27	(0.76)	29.75	(33.37)	75.90	(6.59)	0.84	(0.77)
Stone, Clay, & Glass	1,224	7.81	–0.19	(1.00)	–0.07	(0.77)	30.31	(46.63)	75.84	(6.00)	0.16	(0.24)
Primary Metals	2,491	9.63	0.50	(0.96)	0.06	(0.88)	45.74	(107.09)	74.81	(6.38)	0.27	(0.35)
Fabricated Metals	3,859	8.63	0.39	(1.02)	–0.50	(0.95)	22.22	(40.77)	74.47	(6.72)	0.18	(0.25)
Industrial Machinery	2,119	8.14	0.41	(1.15)	–0.05	(0.94)	62.02	(136.70)	73.50	(6.13)	0.24	(0.30)
Electronics	2,465	7.54	–0.12	(0.85)	0.73	(1.45)	87.63	(190.60)	73.11	(6.31)	0.31	(0.39)
Transportation Equip.	1,691	8.13	0.08	(1.07)	0.43	(0.72)	180.39	(392.12)	72.88	(6.93)	0.26	(0.31)
Instruments	750	7.00	–0.23	(1.03)	0.49	(0.84)	126.81	(289.23)	73.84	(5.64)	0.27	(0.38)
Misc. Manufacturing	400	7.23	–0.35	(0.93)	0.13	(0.98)	52.19	(90.68)	75.35	(6.62)	0.39	(0.46)
Total	25,847	8.38	–0.00	(1.00)	0.00	(1.00)	55.06	(156.99)	74.63	(6.40)	0.23	(0.31)

Table 2: Probit/Logit Analysis of Firm Death

	Probit		Logit	
	(1)	(2)	(3)	(4)
Credit Score	–0.0112†	–0.0419†	–0.0352†	–0.1241†
	(0.0027)	(0.0081)	(0.0080)	(0.0236)
Credit Score×Public Facility		0.0236†		0.0686†
		(0.0059)		(0.0173)
Public Facility		–1.6613†		–4.8172†
		(0.4377)		(1.2838)
Log Likelihood	–3,198.03	–3,186.97	–3,196.55	–3,185.95
Observations	216,506	216,506	216,506	216,506
Industry Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes

NOTES.—The dependent variable is equal to 1 if the firm exits the market in the next period (Death_{ist+1}= 1), and 0 if otherwise. Standard errors are in parenthesis. Significance levels: *0.10, **0.05, and †0.01.

Table 3: Productivity and Emissions Intensity Elasticities

	Probit First-Stage			Logit First-Stage		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Labor Productivity						
Default Risk	–0.1582†	–0.1013†	–0.1542†	–0.1733†	–0.1156†	–0.1941†
	(0.0181)	(0.0098)	(0.0162)	(0.0175)	(0.0105)	(0.0190)
Credit Score			–0.0044†			–0.0055†
			(0.0007)			(0.0008)
Adj. R-sq	0.128	0.125	0.128	0.128	0.126	0.129
Observations	216,506	216,506	216,506	216,506	216,506	216,506
Panel B: Emissions Intensity						
Default Risk	0.8866†	0.5463†	0.9563†	0.9304†	0.6066†	1.1808†
	(0.0840)	(0.0570)	(0.0711)	(0.0895)	(0.0665)	(0.0859)
Credit Score			0.0344†			0.0401†
			(0.0040)			(0.0043)
Adj. R-sq	0.024	0.023	0.025	0.024	0.023	0.025
Observations	216,506	216,506	216,506	216,506	216,506	216,506
Industry$\times$Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes

NOTES.—The dependent variables are log Labor Productivity (deflated sales divided by employees) in Panel A, and log (Hazard) pollution emissions intensity (pollution emissions divided by deflated sales) in Panel B. Specifications (1)-(3) use Default Risk predicted using a first-stage probit model (Table 2, columns 1 and 2), while specifications (4)-(6) use Default Risk predicted using a first-stage logit model (Table 2, columns 3 and 4). Specifications (1) and (4) correspond to first-stage regressions reported in columns (1) and (3) of Table 2, while specifications (2) & (3) and (5) & (6) correspond to first-stage regressions reported in columns (2) and (4), respectively. The estimations use cluster-robust standard errors that are clustered on 3-digit SIC industries, and are in parenthesis. Significance levels: *0.10, **0.05, and †0.01.

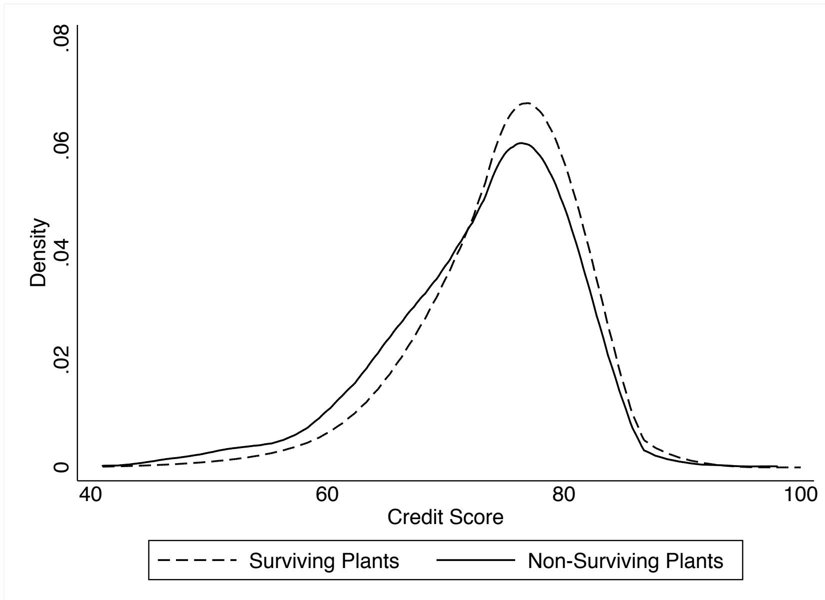
Table 4: Numerical Model Results

	Productivity Elasticity	Emissions Elasticity	Market-Size Effect
	–0.1582**	0.8866**	0.1537**
	(0.0705)	(0.4355)	(0.0685)
	Selection Effect	**Upgrading Effect**	**Aggregate Effect**
Output	–0.0653†	–0.2232†	–0.1348†
	(0.0039)	(0.0465)	(0.0181)
Emissions	–0.0015†	–0.0725**	0.0798*
	(0.0004)	(0.0311)	(0.0415)
Emissions Intensity	0.0638†	0.1507†	0.2145†
	(0.0037)	(0.0216)	(0.0248)

NOTE.—The standard errors are estimated using the two-step bootstrap procedure explained in Section 3.5.2, wherein 1,000 random samples of establishments are drawn with replacement. Significance levels: *0.10, **0.05, and †0.01.

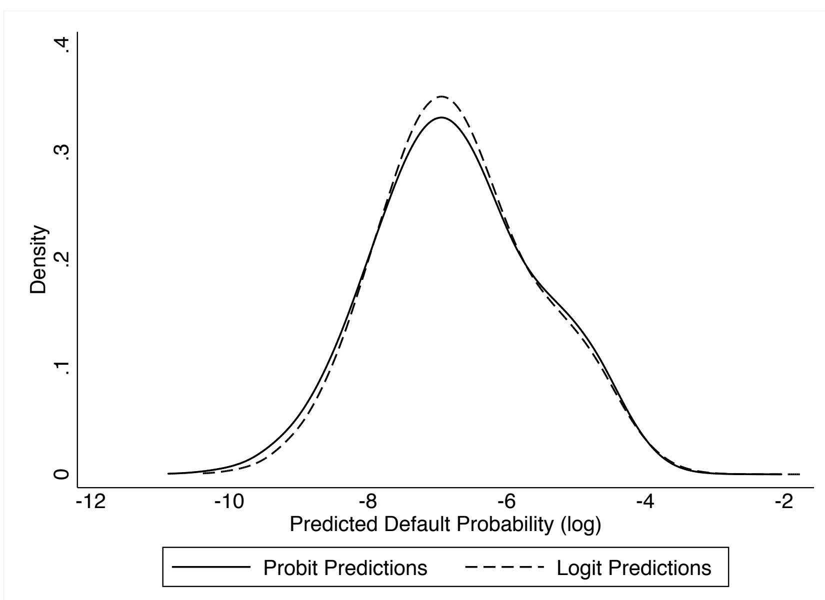
Figures Appendix

Figure 1: Kernel Density of Credit Scores



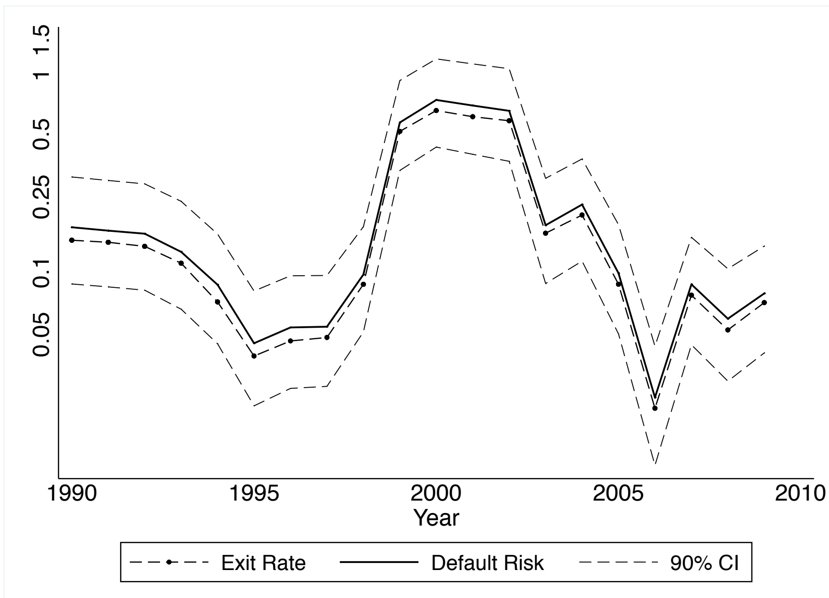
NOTE.—The figure plots the kernel density distributions of Credit Score for surviving (Death_{ist+1}= 0) and non-surviving (Death_{ist+1}= 1) establishments.

Figure 2: Kernel Density of Predicted Default Probabilities for Probit and Logit Estimations



NOTE.—Predicted probabilities are generated from the model estimated in Table 2, columns 1 and 3.

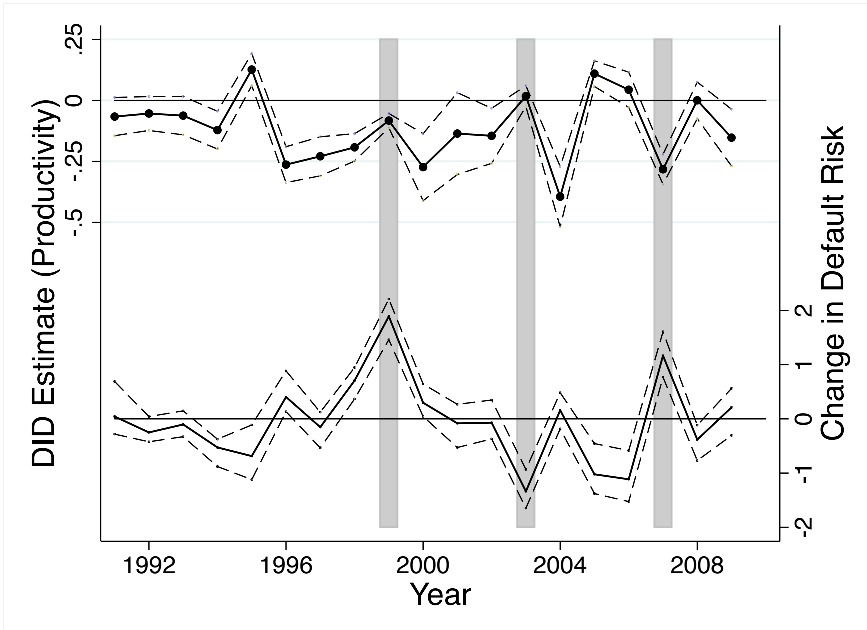
Figure 3: Exit Rate and Default Risk Time Series



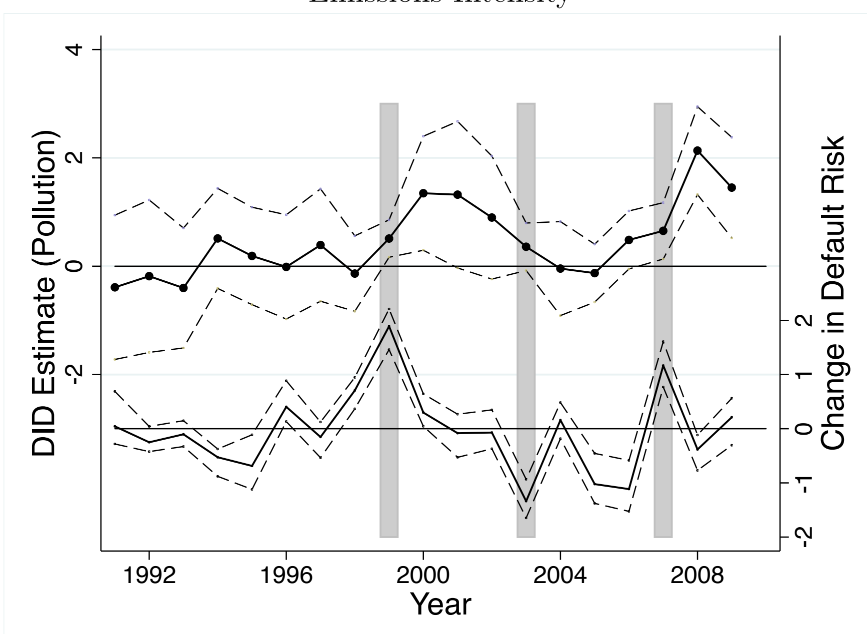
NOTE.—The Exit Rate is the number of establishments exiting the market as a percentage of the total number of establishments in the market for a given year. Default Risk is average predicted Default Risk generated from the regression reported in Table 2 column 1.

Figure 4: DID Estimate by Year

Productivity

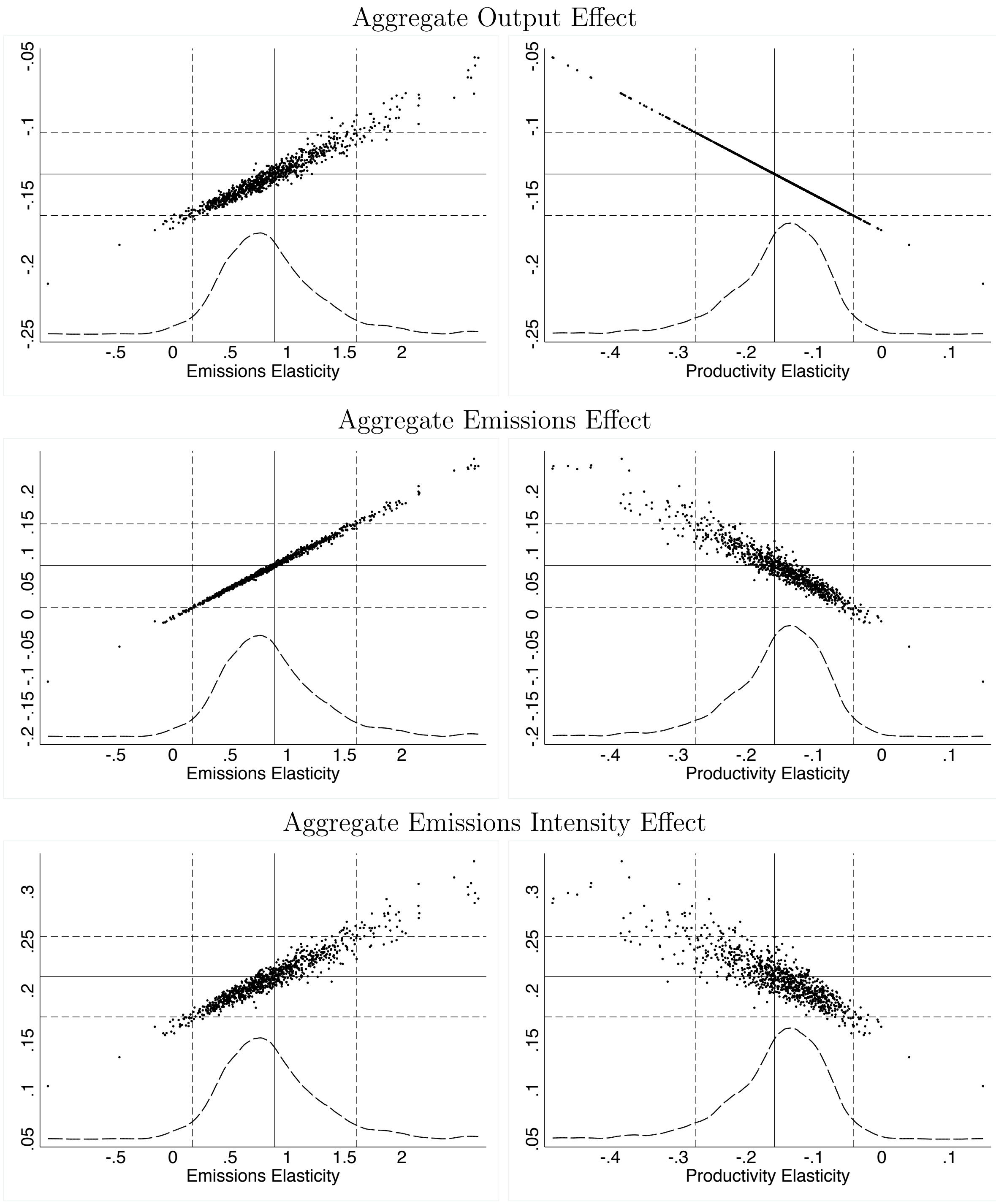


Emissions Intensity



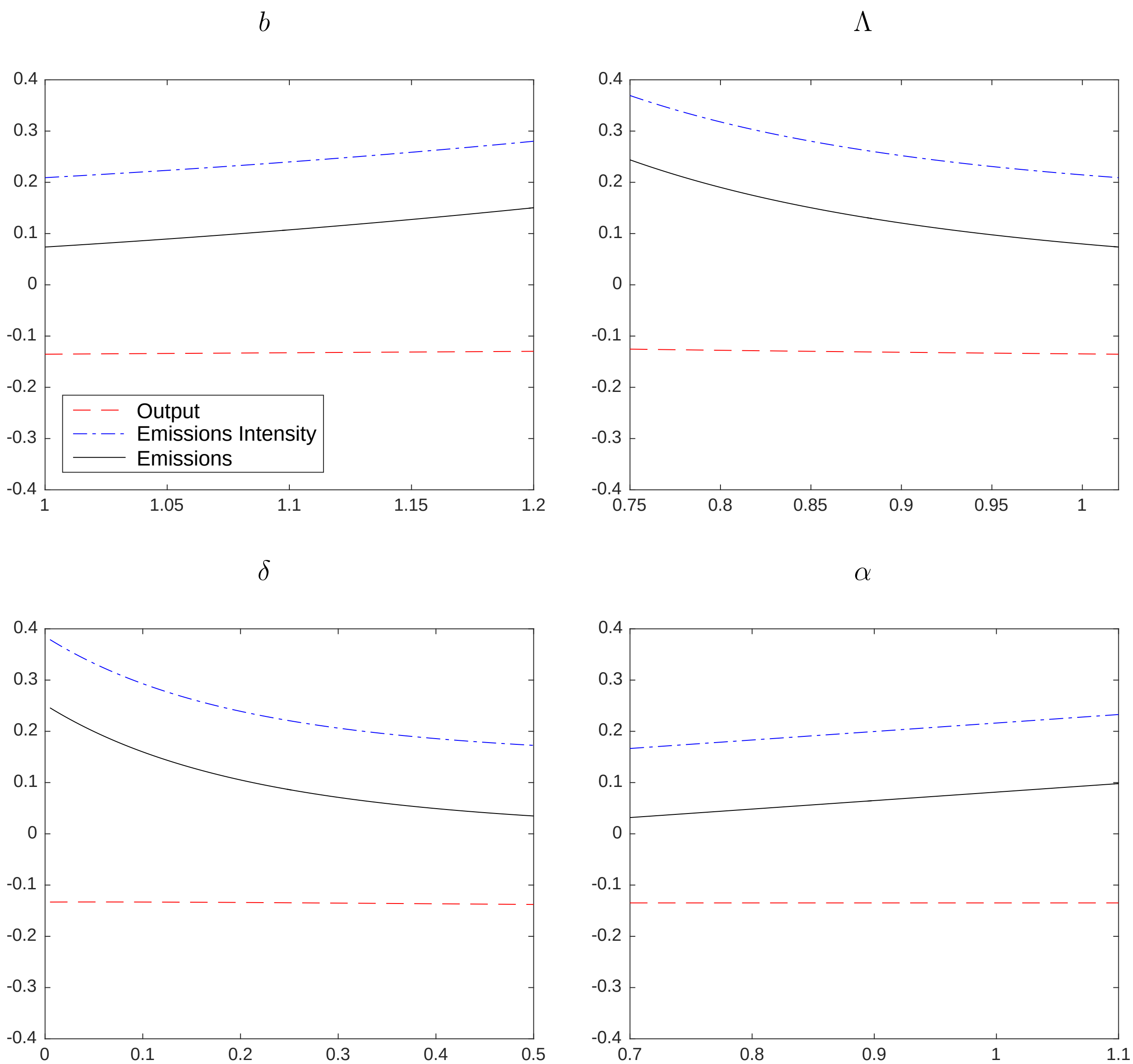
NOTE.—The top (solid) connected line is the DID estimate for (log) Productivity (top panel) and (log) Emissions Intensity (bottom panel) by year and the corresponding 90% confidence interval (dashed lines), where the scale is indicated on the left axis. The bottom (solid) connected line is the log change in average industry Default Risk and the corresponding minimum and maximum average industry Default Risk (dashed lines), where the scale is indicated on the right axis.

Figure 5: Numerical Model Simulations



NOTE.— The scattered markers are coefficient estimates for Emissions Intensity Elasticity (left hand side) and Productivity Elasticity (right hand side) and the corresponding numerical model results for 1,000 random samples of establishments drawn with replacement (For more details, see Section 3.5.2). The solid lines represent the coefficient estimates, and the dashed lines represent the corresponding 90% confidence intervals. The distributions below the scattered markers are univariate kernel density distributions of Emissions Intensity Elasticity (right hand side) and Productivity Elasticity (left hand side), where the scale is suppressed.

Figure 6: Sensitivity Analysis: Aggregate Output, Emissions, and Emissions Intensity



NOTE.—The above figures plot the Overall Output, Emissions, and Emissions Intensity Effects over various parameter values, holding the values of the other parameters constant ($b = 1.02$, $\Lambda = 1$, $\delta = 0.27$, and $\alpha = 0.99$).

Supplementary Web Appendix

This section is an "online-only" appendix.

A Theoretical Model Appendix

Equilibrium Borrowing Costs and Lemma 3

This subsection demonstrates that the equilibrium borrowing cost is an increasing function of default risk under a certain set of conditions. Lenders are risk neutral and have a reservation (risk-free) rate of return equal to $\tilde{r}$. Borrowing costs are determined in equilibrium such that the expected return to lending must equal the lender's reservation return, where the expected return is defined over a non-default state in which the loan is repaid (with interest) and a default state in which a lesser sum is received. The probability of the default state is $0 < \eta < 1$ and it is assumed that the payoff to the lender in the default state is $0 < \xi < 1$ multiplied by the value of the loan (i.e., ξ is the share of the loan that the lender can recover if the firm defaults on the loan). To finance the investment in the technology upgrade, firms are required to borrow $w\lambda^c f$ and repay $wb\lambda^c f$ whenever in the non-default state. The equilibrium lending condition is therefore

$$- w\lambda^c f + \eta\xi w\lambda^c f + (1-\eta)bw\lambda^c f = (1+\tilde{r})w\lambda^c f \tag{A1}$$

where the right hand side is the lender's expected return to lending the firm $w\lambda^c f$ and the right hand side is the lender's reservation return to lending the same amount. Condition (A1) solves for the equilibrium gross interest rate (or borrowing cost). That is,

$$b = \frac{(1+\tilde{r}) + (1-\eta\xi)}{1-\eta} \tag{A2}$$

Equation (A2) demonstrates, as expected, that equilibrium borrowing costs are a function of default risk, among other factors. It follows from A2 that $\epsilon_{b\eta} > 0$.

Derivation of equation (19)

First, expected profits in equation (15) is given by the following:

$$\bar{\pi} = \bar{\pi}^b + \theta\bar{\pi}^u = \left(\frac{\bar{r}^b}{\sigma} - wf\right) + \theta\left(\frac{\bar{r}^a}{\sigma} - wb\lambda^c f\right) \tag{A3}$$

where

$$\bar{r}^b = \int_{\phi^b}^{\infty} r^b \mu^b(\phi) d\phi \quad \text{and} \quad \bar{r}^a = \int_{\phi^u}^{\infty} r^a \mu^u(\phi) d\phi \tag{A4}$$

Using expressions (4), (7), and (14), solve for $\bar{r}^b$ and $\bar{r}^a$. That is,

$$\bar{r}^b = w\sigma\kappa_1 f \quad \text{and} \quad \bar{r}^a = w\sigma\kappa_1 f \lambda^c b \tag{A5}$$

where $\kappa_1 = k/(k - (\sigma - 1)) > 0$. Consequently,

$$\bar{\pi} = wf(\kappa_1 - 1)(1 + \theta\lambda^c b) \tag{A6}$$

Using expressions (15), (16), and (A6), implies that

$$f^e M^e = M^b(\kappa_1 - 1)(1 + \theta\lambda^c b) \tag{A7}$$

Second, average variable labor demand in (18) is given by the following:

$$\bar{l}^b = \int_{\phi^b}^{\infty} \frac{q^b}{\phi} \mu^b(\phi) d\phi \quad \text{and} \quad \bar{l}^a = \int_{\phi^u}^{\infty} \frac{q^a}{\phi(1+\delta)} \mu^u(\phi) d\phi \tag{A8}$$

Using expressions (4), (7), and (14), solve for $\bar{l}^b$ and $\bar{l}^a$. That is,

$$\bar{l}^b = (\sigma - 1)\kappa_1 f \quad \text{and} \quad \bar{l}^a = (\sigma - 1)\kappa_1 f \lambda^c b \tag{A9}$$

Using (17), (A7), and (A9), in (18) solves for M^b. That is,

$$M^b = \frac{L}{\sigma\kappa_1 F} \tag{A10}$$

as desired.

Proof of Corollary 1

Using expression (19) and (A6) implies that

$$\phi^b = \left(\frac{F(\kappa - 1)}{\eta f^e} \right)^{\frac{1}{k}} \tag{A11}$$

which implies that

$$\frac{\partial\phi^b/\phi^b}{\partial\eta/\eta} = \frac{1}{k}\left(\frac{\partial F/F}{\partial\eta/\eta} - 1 \right) \tag{A12}$$

Finally, relating (A12) and (22) produces the desired result.

Proof of Result 2

The decomposition in (26) follows from the definition of $\bar{q}$ given in (24). Using expressions (4), (7), and (14), solve for $\bar{q}^b$ and $\bar{q}^a$. That is,

$$\bar{q}^b = \phi^b(\sigma - 1)\left(\frac{k}{k-\sigma}\right) f \quad \text{and} \quad \bar{q}^a = \phi^u(\sigma - 1)\left(\frac{k}{k-\sigma}\right)((1+\delta)^\sigma - 1)\left(\frac{bf}{\Lambda}\right) \tag{A13}$$

Differentiation of (A13) implies that

$$\frac{\partial\bar{q}^b/\bar{q}^b}{\partial\eta/\eta} = \frac{\partial\phi^b/\phi^b}{\partial\eta/\eta} \quad \text{and} \quad \frac{\partial\bar{q}^a/\bar{q}^a}{\partial\eta/\eta} = \frac{\partial\phi^u/\phi^u}{\partial\eta/\eta} + \epsilon_{b\eta} \tag{A14}$$

Using (A12) and the definition of F implies that

$$\frac{\partial\phi^b/\phi^b}{\partial\eta/\eta} = -\frac{1}{k}\left[\left(\frac{k}{\sigma-1} - 1\right)\left(\frac{\theta\lambda^c b}{1+\theta\lambda^c b}\right)\epsilon_{b\eta} + 1\right] \tag{A15}$$

And using (12) and (A14) implies that

$$\frac{\partial\phi^u/\phi^u}{\partial\eta/\eta} = -\frac{1}{k}\left(\left[\left(\frac{k}{\sigma-1} - 1\right)\left(\frac{\theta\lambda^c b}{1+\theta\lambda^c b}\right) + \left(\frac{k}{\sigma-1}\right)\right]\epsilon_{b\eta} + 1\right) \tag{A16}$$

Using expression (A15) in (A14) implies that

$$\frac{\bar{q}^b}{\bar{q}}\frac{\partial\bar{q}^b/\bar{q}^b}{\partial\eta/\eta} = -\left(1 - \frac{\theta\bar{q}^a}{\bar{q}}\right)\frac{1}{k}\left[\left(\frac{k}{\sigma-1} - 1\right)\left(\frac{\theta\lambda^c b}{1+\theta\lambda^c b}\right)\epsilon_{b\eta} + 1\right] \tag{A17}$$

Using expression (A16) in (A14) implies that

$$\frac{\theta\bar{q}^a}{\bar{q}}\left(\frac{\partial\theta/\theta}{\partial\eta/\eta} + \frac{\partial\bar{q}^a/\bar{q}^a}{\partial\eta/\eta}\right) =$$

$$-\frac{\theta\bar{q}^a}{\bar{q}}\left[\left(\frac{1}{k}\left(\frac{k}{\sigma-1} - 1\right)\left(\frac{\theta\lambda^c b}{1+\theta\lambda^c b}\right) + \left(\frac{k-\sigma}{\sigma-1}\right)\right)\epsilon_{b\eta} + \frac{1}{k}\right] \tag{A18}$$

Using expressions (A17) and (A18) in (26) produces equation (27). Finally, (28) follows from (A13), as well as (12) and (17).

Proof of Result 3

The decomposition in (29) follows from the definition of $\bar{z}$ given in (27). Using expressions (4), (7), and (14), solve for $\bar{z}^b$ and $\bar{z}^a$. That is,

$$\bar{z}^b = (\phi^b)^{1-\alpha}(\sigma-1)\kappa_2 f \quad \text{and} \quad \bar{z}^a = (\phi^u)^{1-\alpha}(\sigma-1)\kappa_2(\Gamma-1)\left(\frac{bf}{\Lambda}\right) \tag{A19}$$

where $\kappa_2 = k/(k-(\sigma-1)+\alpha)$. Differentiation of (A19) implies that

$$\frac{\partial \bar{z}^b/\bar{z}^b}{\partial \eta/\eta} = (1-\alpha)\frac{\partial \phi^b/\phi^b}{\partial \eta/\eta} \quad \text{and} \quad \frac{\partial \bar{z}^a/\bar{z}^a}{\partial \eta/\eta} = (1-\alpha)\frac{\partial \phi^u/\phi^u}{\partial \eta/\eta} + \epsilon_{b\eta} \tag{A20}$$

Using expression (A15) in (A20) implies that

$$\frac{\bar{z}^b}{\bar{z}}\frac{\partial \bar{z}^b/\bar{z}^b}{\partial \eta/\eta} = -\left(1-\frac{\theta\bar{z}^a}{\bar{z}}\right)\left(\frac{1-\alpha}{k}\right)\left[\left(\frac{k}{\sigma-1}-1\right)\left(\frac{\theta\lambda^c b}{1+\theta\lambda^c b}\right)\epsilon_{b\eta}+1\right] \tag{A21}$$

Using expression (A16) in (A20) implies that

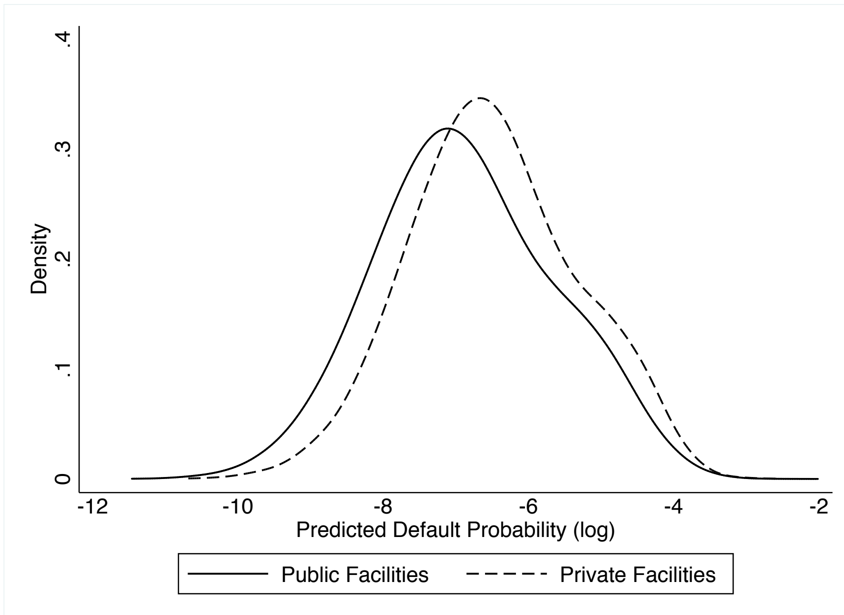
$$\frac{\theta\bar{z}^a}{\bar{z}}\left(\frac{\partial\theta/\theta}{\partial\eta/\eta}+\frac{\partial \bar{z}^a/\bar{z}^a}{\partial \eta/\eta}\right) =$$

$$-\frac{\theta\bar{z}^a}{\bar{z}}\left[\left(\left(\frac{1-\alpha}{k}\right)\left(\frac{k}{\sigma-1}-1\right)\left(\frac{\theta\lambda^c b}{1+\theta\lambda^c b}\right)+\left(\frac{k-\sigma+\alpha}{\sigma-1}\right)\right)\epsilon_{b\eta}+\left(\frac{1-\alpha}{k}\right)\right] \tag{A22}$$

Using expressions (A21) and (A22) in (29) produces equation (30). Finally, (31) follows from (A19), as well as (12) and (17).

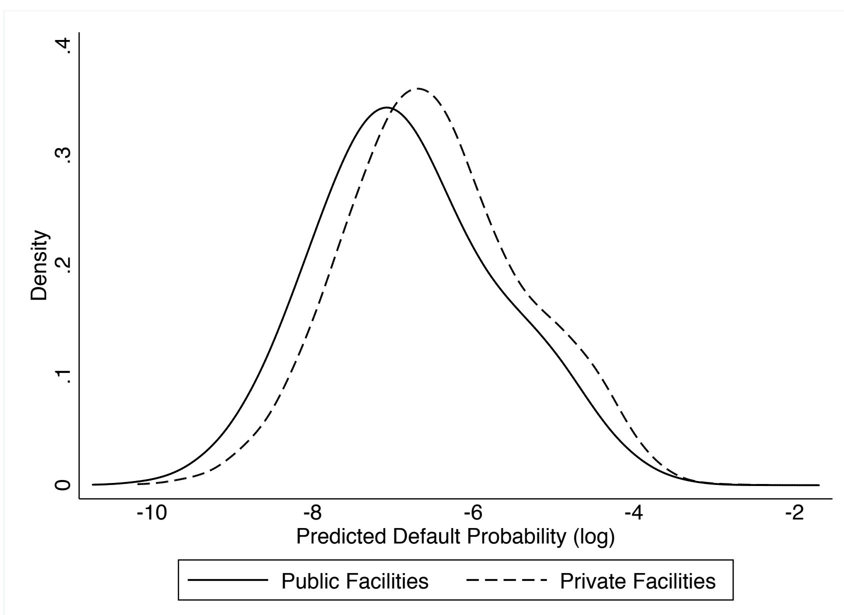
B Tables and Figures Appendix

Figure A1: Kernel Density of Predicted Default Probabilities for Public and Private Facilities



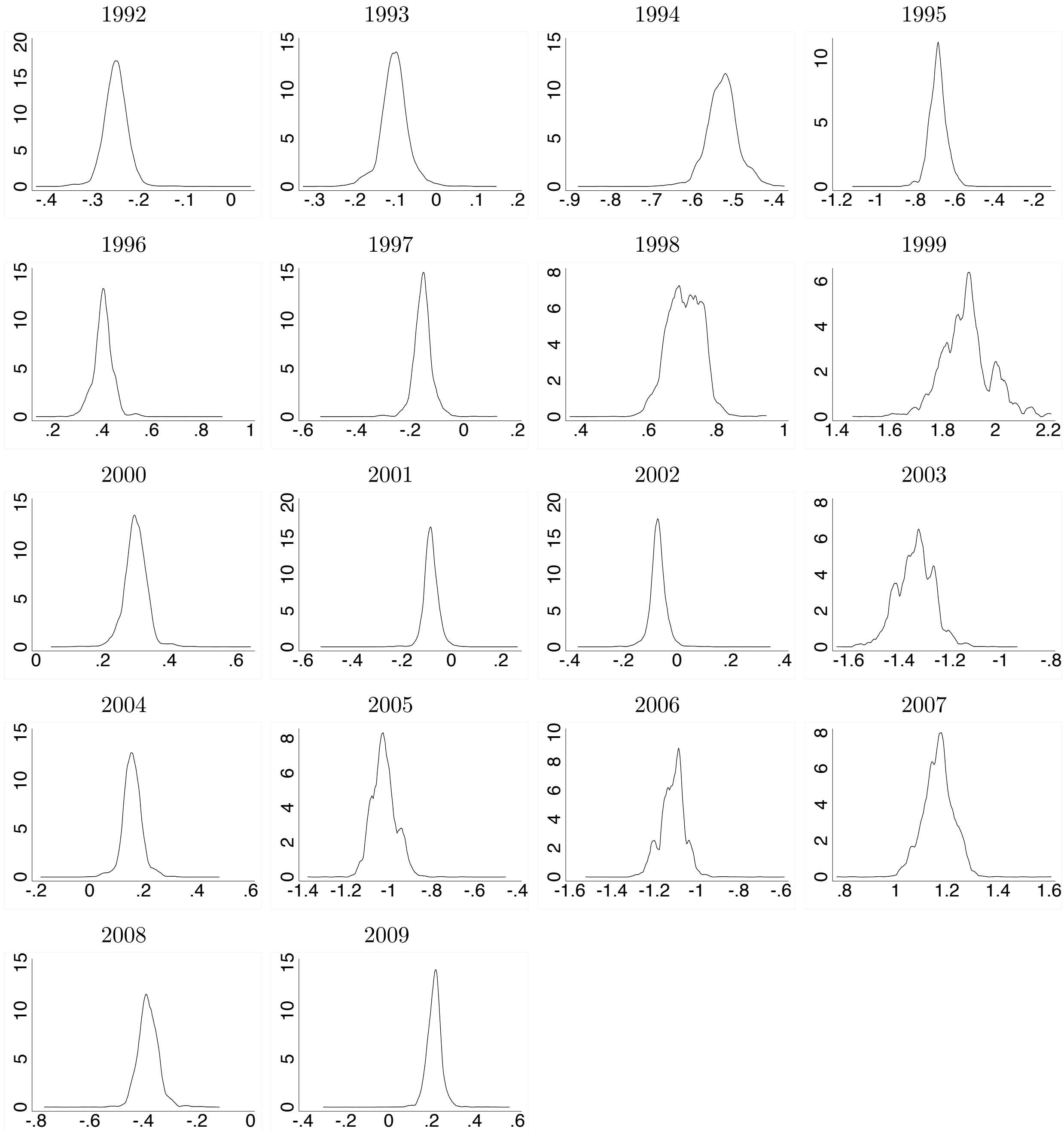
NOTE.—Predicted probabilities are generated from the model estimated in Table 2, column 2.

Figure A2: Kernel Density of Predicted Default Probabilities for Public and Private Facilities



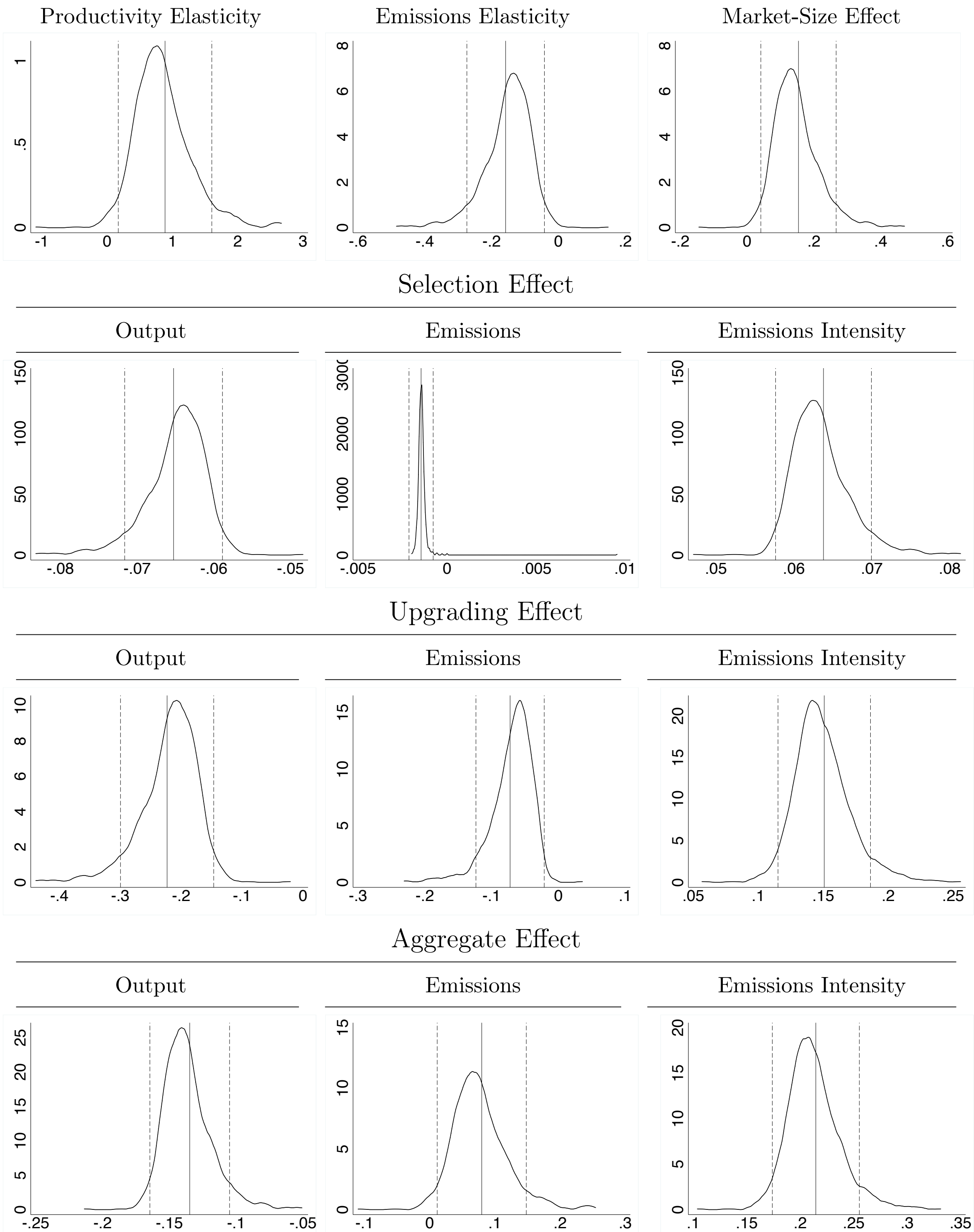
NOTE.—Predicted probabilities are generated from the logit model estimated in Table 2, column 4.

Figure A3: Industry Default Risk Shocks



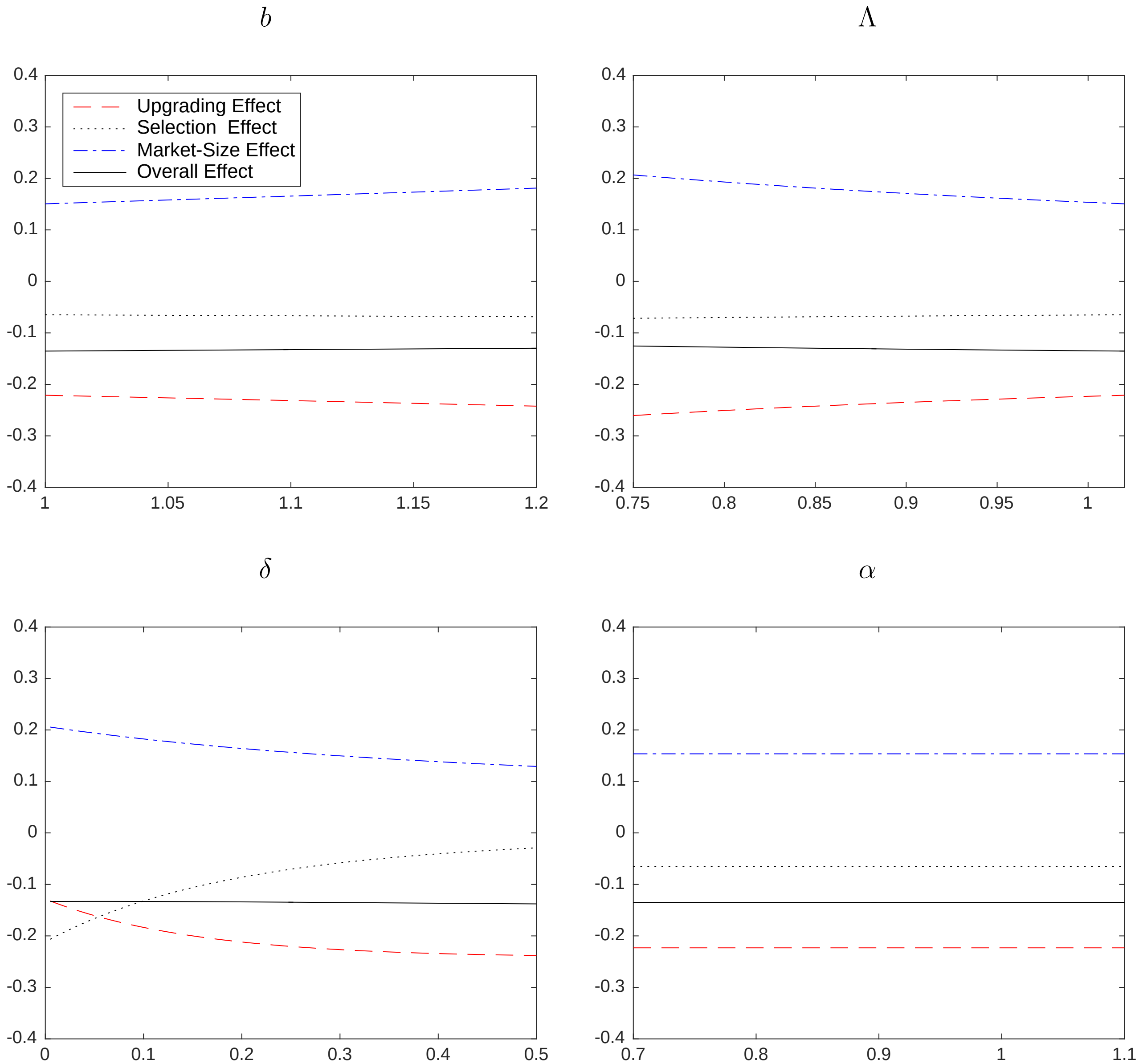
NOTE.—The kernel density distributions are the changes in log Default Risk by industry averaged over all establishments in the sample.

Figure A4: Numerical Model Simulation Results



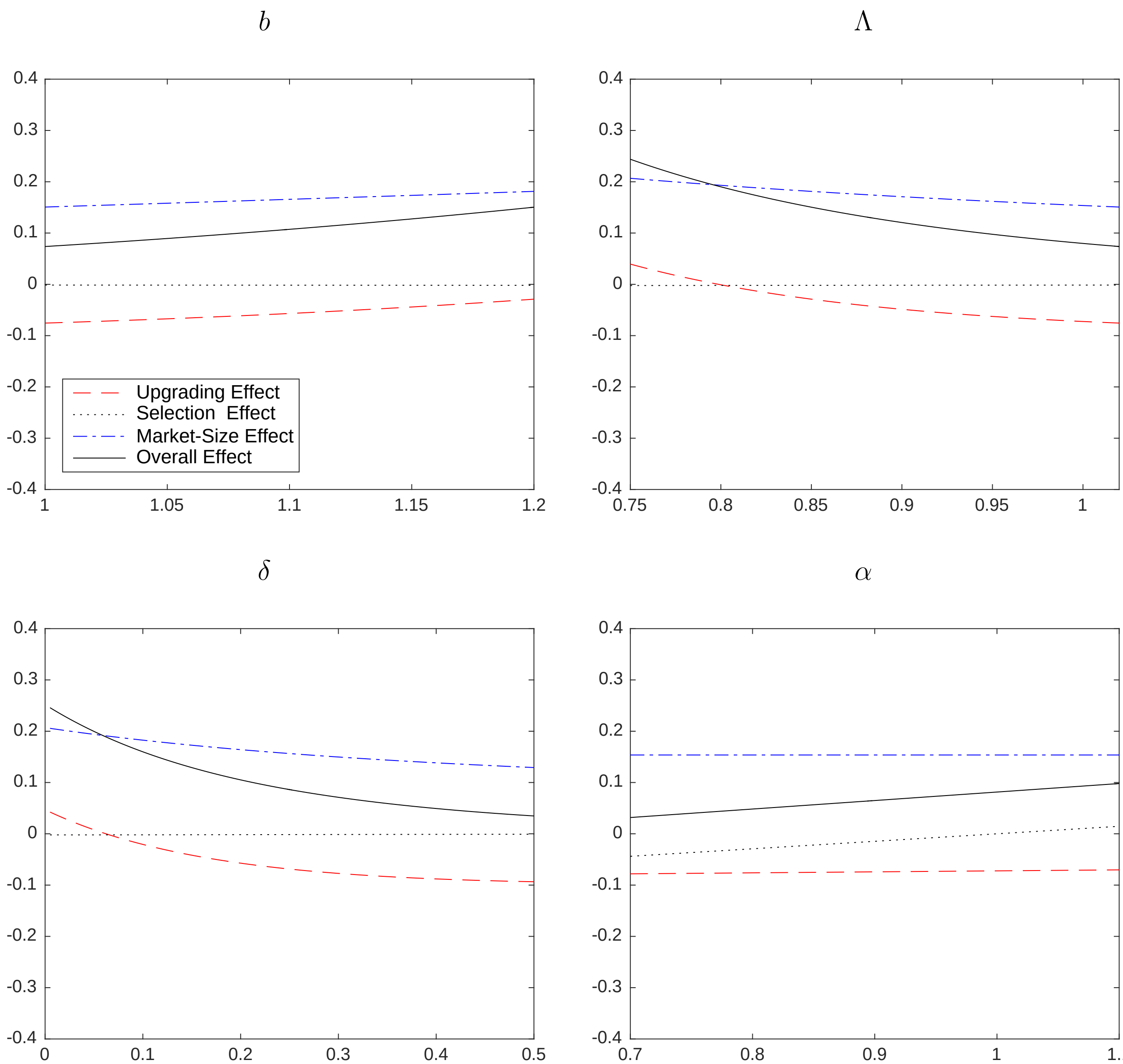
NOTE.—The kernel density distributions are estimated using the two-step bootstrap procedure explained in Section 3.5.2, wherein 1,000 random samples of establishments are drawn with replacement.

Figure A5: Sensitivity Analysis: Output Effects



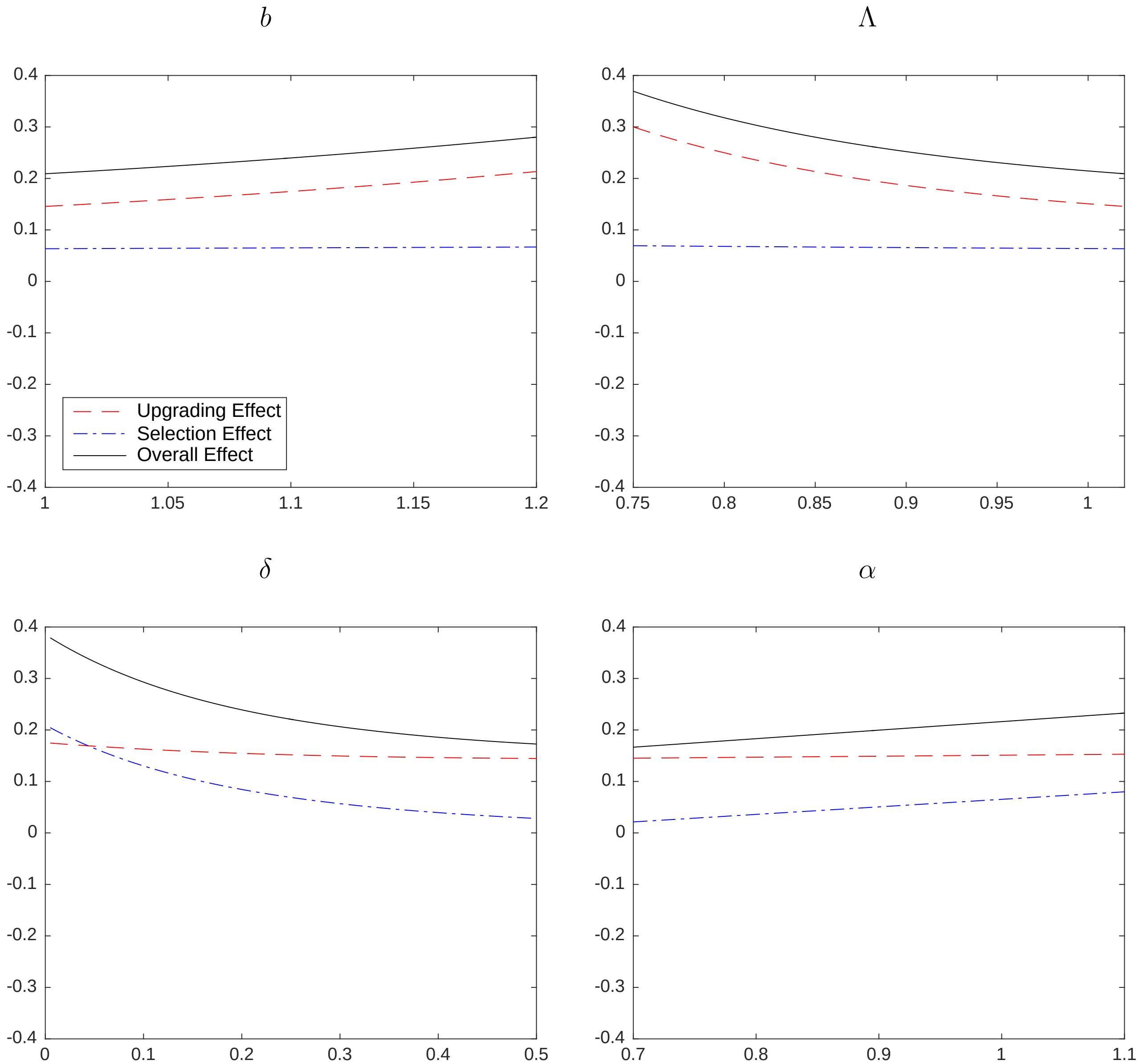
NOTE.—-The above figures plot the various components of the Overall Output Effect (Market-Size, Upgrading, and Selection, Effects) over various parameter values, holding the values of the other parameters constant ($b = 1.02$, $\Lambda = 1$, $\delta = 0.27$, and $\alpha = 0.99$).

Figure A6: Sensitivity Analysis: Emissions Effects



NOTE.—The above figures plot the various components of the Overall Emissions Effect (Market-Size, Upgrading, and Selection, Effects) over various parameter values, holding the values of the other parameters constant ($b = 1.02$, $\Lambda = 1$, $\delta = 0.27$, and $\alpha = 0.99$).

Figure A7: Sensitivity Analysis: Emissions-Intensity Effects



NOTE.—The above figures plot the various components of the Overall Emissions Intensity Effect (Upgrading and Selection, Effects) over various parameter values, holding the values of the other parameters constant ($b = 1.02$, $\Lambda = 1$, $\delta = 0.27$, and $\alpha = 0.99$).

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