MATERIALS PRICES AND PRODUCTIVITY

Enghin Atalay
University of Chicago

Abstract
There is substantial within-industry variation in the prices that plants pay for their material inputs. Using plant-level data from the US Census Bureau, I explore the consequences and sources of this variation in materials prices. For a sample of industries with relatively homogeneous products, the standard deviation of plant-level productivity would be 7% smaller if all plants faced the same materials prices. Moreover, plant-level materials prices are persistent, spatially correlated, and positively associated with the probability of exit. The contribution of entry and exit to aggregate productivity growth is smaller for productivity measures that are purged of materials price variation. After documenting these patterns, I discuss three potential sources of materials price variation: geography, differences in suppliers' marginal costs, and within-supplier markup differences. Together, these variables explain 15% of the variation of materials prices. (JEL: E23, L16, L60)

1. Introduction

There is substantial within-industry variation in the prices that establishments pay for their material inputs, even in industries that use and produce homogeneous inputs and outputs. This paper assesses the implications and sources of this variation in materials prices. When input prices differ across plants, plants may have lower marginal costs not only because they are able to produce more efficiently, but also because they are able to purchase intermediate inputs at relatively low prices.

Accounting for the variation in materials prices[1] provides new answers to two long-standing questions: First, why are within-industry differences in plants' measured productivities so large? Second, what is the role of reallocation—via the entry

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E-mail: atalay@uchicago.edu

1. Throughout this paper, I use the terms "intermediate inputs" and "materials" interchangeably.

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of relatively productive plants and the exit of unproductive plants—on industry productivity growth?

Large, persistent, within-industry productivity differences are ubiquitous. Syverson (2004a), for example, estimates that, in the average four-digit manufacturing industry, the 90th percentile plant has a total factor productivity that is approximately 90% higher than the 10th percentile plant. Given the importance that a plant's productivity has for its growth and survival, as well as the strong relationship between countries' GDPs and the average productivities of their firms, several papers have tried to explain why some plants are productive while others are not. This literature has argued that relatively productive plants are more likely to employ high-quality inputs (Fox and Smeets 2011), patent (Balasubramanian and Sivadasan 2011), enter export or import markets (Bernard and Jensen 1999; Eslava et al. 2004, 2013), and follow best-practice management techniques (Bloom and Van Reenen 2010). In addition, productivity dispersion is larger in markets with less-intense competition (Syverson 2004b) and in countries with larger factor misallocations (Hsieh and Klenow 2009).

In the cited studies, plants' productivities are calculated as the ratio of outputs to inputs. Usually, data on input and output prices are not collected, meaning that—in most cases—real revenues are the measure of establishment outputs, while real input expenditures are the measure of establishment inputs.[2] With these productivity measures, an establishment's measured productivity will depend on conditions in output and factor markets. Potentially, an establishment's measured productivity could have no relationship with how efficient it is in transforming inputs into outputs.

The potential confounding effects of input and output price variation in productivity estimation are already well known. Both Katayama, Lu, and Tybout (2009) and Gorodnichenko (2010) argue, in detail, why plant-level measured productivities may have little to do with plants' technical efficiencies. These papers propose structural estimators of establishments' cost and revenue functions, exploiting information derived from the solutions to their cost minimization and/or profit maximization problems. Quantifying the extent to which input price variation confounds the measurement of plants' technical efficiencies is one of the main contributions of my paper.

A second long-standing question (previously addressed by Baily, Hulten, and Campbell 1992; Griliches and Regev 1995; Foster, Haltiwanger, and Krizan 2001; Foster, Haltiwanger, and Syverson 2008) concerns the extent to which industry productivity growth is driven by the intra-industry reallocation of factors towards

2. Four partial exceptions are Syverson (2004b), Eslava et al. (2004, 2013), and Ornaghi (2006). Syverson (2004b) utilizes establishment-level output price data, but does not use establishment-level intermediate input price data. Ornaghi (2006), however, has data on materials prices. His analysis focuses on the estimation of input elasticities, instead of the distribution of plant-level productivities, which is the focus here. Perhaps closest to the current paper, Eslava et al. (2004, 2013) use plant-level input and output price data from Colombia to test the hypothesis that a trade liberalization stiffens the competitive environment, forces low productivity plants to exit, and thus increases aggregate productivity.

Among these papers, only Syverson (2004b) restricts the sample to homogeneous-output industries. So, some of the variation in quantity total factor productivity in Eslava et al. (2004, 2013) will be a result of differences in output or input quality.

more efficient producers. Foster et al. (2008) carefully argue that (conventional) revenue-based productivity measures understate the importance of reallocation and firm turnover to industry productivity growth: Since entrants charge exceptionally low prices, measures that embody output price differences will understate entrants' productivity advantages. In Foster et al. (2008), as well as other papers that study reallocation and industry productivity growth, all plants in an industry are assumed to pay the same prices for their intermediate inputs. By considering the differences—across entrants, incumbents, exiting plants, and survivors—in plants' materials prices, the current paper provides a more complete depiction of the contribution of turnover to aggregate productivity growth.

The current paper also relates to and complements Kugler and Verhoogen (2012) and Manova and Zhang (2012). In these papers, plants' input/output prices proxy for the quality of the products that the plants use and produce. Kugler and Verhoogen construct a model in which input quality and plant technical efficiency are complementary in production. As a result, the authors are able to explain the observed positive relationships between a plant's size and the prices of its inputs and outputs. Manova and Zhang document that exporters sell their products at higher prices in markets that are larger, richer, more distant, and less remote. The authors argue that exporters vary the quality of their goods across the markets to which they export. Unlike these papers, I focus on industries with insubstantial quality variation, with the goal of isolating other sources of materials price variation.

By exploiting plant-level materials price—and output price—data, I am able compare the following three productivity measures: Revenue total factor productivity (*TFPR*) is computed using industry-level price indices for both plants' outputs and intermediate inputs. Quantity productivity (*TPFQ*) again uses industry-level price indices for intermediate inputs, but relies on plant-level output prices. Finally, technical efficiency (which I denote Φ) uses both plant-level materials and output prices.

Comparisons of the three productivity measures, as provided in this paper, are of interest for the following two reasons. First, differences across the productivity measures highlight the relevance of different models of heterogeneous-plant industry dynamics. If dispersion in (commonly-used) revenue productivity is mostly driven by technical efficiency, models examining learning-by-doing, innovation, and management practices may be particularly relevant. However, if differences in productivity measures derive from (input or output) price dispersion, models of market structure would be more salient.

Second, the different productivity measures may be more or less germane to different applications. Under some conditions, for example, the dispersion of revenue productivity is a sufficient statistic for the welfare costs of barriers to reallocation; see Hsieh and Klenow (2009). However, the distribution of technical efficiency may better summarize how far along an industry is in the adoption of a new technology.[3]

3. To give an example, Collard-Wexler and De Loecker (2013) examine the distribution of technical efficiency in their chronicle of minimills' displacement of vertically integrated producers in the US steel industry.

In Section 2, I introduce the two plant-level datasets—the Census of Manufacturers and the Commodity Flow Survey—employed in this paper, as well as the set of industries that comprise my sample. Building on Foster, Haltiwanger, and Syverson (2008), I restrict my sample to the few industries—such as gasoline, ready-mix concrete, and corrugated boxes—for which plants' output prices and materials prices can be computed and meaningfully compared across establishments, and for which prices do not primarily reflect differences in input or output quality.

Price variation in factor and output markets is substantial, even in industries that produce commodity-like products. In the benchmark sample, the within-product-year standard deviation of the logarithm of materials prices is 12%. I establish in Section 3.1 that *TFPQ* is negatively related to materials prices: the correlation between the logarithm of *TFPQ* and materials prices is −37%. In Section 3.2, I compute the fraction of *TFPQ* dispersion that is due to differences in materials prices: the standard deviation would be 7% lower, and the 75/25 ratio would be 10% lower, in a counterfactual world in which all plants face the same materials prices. To give context, 7% to 10% is larger than the fraction of productivity dispersion explained by the competitive environment (Syverson 2004b), and at least as large as the fraction explained by differences in labor quality (Fox and Smeets 2011).

As I demonstrate in Sections 3.3 and 3.4, plant-level intermediate input prices are persistent, spatially correlated, and related to the probability of exit from the industry. The one-year autocorrelation of the logarithm of plants' materials prices is 80%, comparable to the autocorrelation of the logarithms of *TFPR*, *TFPQ*, or output prices. In addition, intermediate input prices are 1.4% higher for plants that are about to exit. Following from the negative correlations between quantity productivity and input/output prices, the productivity advantage of surviving plants (compared to exiting plants) is highest when using *TPFQ*, and lower when using either *TFPR* or Φ, as the productivity measure. Concomitantly, the contribution of net entry to aggregate productivity growth is smaller for productivity measures that embody plants' output prices (i.e., *TFPR*, but not *TFPQ* or Φ), but larger for productivity measures that embody input prices (i.e., *TFPR* and *TFPQ*, but not Φ).

In Section 4, I offer three potential explanations for within-industry differences in materials prices. First, plants in particular geographic regions enjoy particularly low input prices due, for example, to the abundance of primary materials with which the intermediate input is produced. Second, plants pay relatively little for their intermediate inputs when their suppliers are exceptionally productive: productive upstream plants pass some of their low marginal costs through to their buyers. Also, even after accounting for transportation costs, suppliers tend to charge different prices for their outputs across different destinations. These within-supplier differences are a third source of price variation in intermediate goods markets. For a pooled sample of ready-mix concrete and corrugated box manufacturers, these three sources reduce the unexplained materials price variation by 15%. Both the across-supplier component (i.e., low marginal cost suppliers charge, on average, low prices) and the within-supplier component (i.e., a given supplier charges different prices to different downstream plants) are important factors for explaining the variation in materials prices.

Section 5 concludes. Two robustness checks, discussing the potential confounding effects of output quality variation (Appendix A.1) and input quality variation (Appendix A.2) are included in the Appendix.

Additional robustness checks (Appendices A.3–A.13), a more detailed description of the construction of the sample (Appendix B), and bootstrapped confidence intervals (Appendix C) can be found in the Online Appendix.

2. Data and Definitions

The purpose of this section is to introduce the data sources, data sample, and price and productivity measures that will be used in the remainder of the paper. I describe the Census of Manufacturers and the Commodity Flow Survey in Section 2.1, and then the benchmark sample in Section 2.2. I define plants' materials prices, output prices, and productivities in Sections 2.3 and 2.4, and finally, in Section 2.5, I briefly discuss the relationships among these price and productivity measures.

2.1. Data Sources

The main data sources are the Commodity Flow Survey and the Census of Manufacturers, both of which are collected and maintained by the US Census Bureau.

The Census of Manufacturers contains information on manufacturing establishments' productive characteristics: employment of production and nonproduction workers, measured in hours; the book value of building and machine capital; and expenditures on electricity. Of particular importance for the current paper, for certain industries, establishments with five or more employees list both the quantity and the value of each of the products they produce (at the seven-digit level), and the quantity and value of each of the materials they consume (at the six-digit level).[4] The Census of Manufacturers is conducted every five years, in years ending in "2" or "7". For this paper, I use the Census of Manufacturers from 1972 to 1997.

The Commodity Flow Survey allows me to impute buyer–supplier relationships, as I do in Section 4.1. Like the Census of Manufacturers, the Commodity Flow Survey is conducted every five years, in years ending in "2" or "7", although it did not begin until 1993. Surveyed establishments are asked to list 20–40 shipments that they make each quarter.[5] Each observation includes information on: the weight and value of the shipment; a five-digit code, specifying the commodity that was shipped; the method of transport (air, truck, rail, courier service, and so forth); the destination zip

4. To give the reader an idea of the scope of a seven-digit product, ready-mix concrete (3273000) is one of the larger product groups, while one of the smaller product groups is self-rising family white flour (2044126). For 1992, http://www.census.gov/prod/2/manmin/mc92-r-1.pdf contains a description of the product codes.

5. In 1993, approximately 60,000 (out of the 350,000 existing manufacturing plants) were surveyed in the Commodity Flow Survey, while in 1997 approximately 30,000 plants were surveyed.

code;[6] and the identity of the sending establishment. Unfortunately, the identity of the receiving establishment is not recorded, meaning that buyers and suppliers cannot be linked directly; I describe, in Section 4.1, the algorithm used to impute the buyer of each shipment. In Section 4, I employ the 1993 and 1997 Commodity Flow Surveys.

2.2. Sample

Similar to Roberts and Supina (1996, 2000) and Foster, Haltiwanger, and Syverson (2008), the analysis centers around industries for which outputs and inputs are relatively homogeneous. In industries with heterogeneous inputs or outputs, differences in quality may be a primary source of the variation in the prices that different firms charge. I would like, as much as possible, to rule out quality as a source of input or output price variation. An additional restriction is that both the inputs and outputs should be measured in units that are comparable across establishments.[7]

The ten industries (alternatively referred to as "products") that comprise the main sample are corrugated boxes (with the years 1972–1987 and 1992–1997 analyzed separately), ground coffee, ready-mix concrete, white wheat flour, gasoline, bulk milk, packaged milk, raw cane sugar, and carded cotton yarn; see Table 1.[8,9] Approximately one-third of the 10,503 plant-year observations are from plants that manufacture ready-mix concrete. However, when observations are weighed by their real revenues, the gasoline industry is the most prominent: Approximately three-quarters of the total revenues are earned by plants from this industry.

To be in the benchmark sample, the manufacturers must also fill out the materials and production supplements. These supplemental forms, which the Census sends out to larger establishments, are necessary to compute the unit values of manufacturers' outputs and materials purchases.

Thus, there are two sources of sample selection. First, I have chosen industries based on the characteristics of the outputs produced and inputs purchased. These industries tend to use materials particularly intensely. Since the scope for price differences to cause measured productivity dispersion increases with the intensity

6. There are roughly 45,000 zip codes in the United States, meaning that the average zip code contains approximately eight manufacturing plants.

7. This second restriction rules out industries like oak, hardwood rough lumber (seven-digit product code = 2421163). For this industry, output is measured in units of board feet, but different plants manufacture lumber with different thickness. For this reason, it is difficult to compare different plants' output prices, productivities, or other plant-level characteristics.

8. A problem similar to the one described in footnote 7 exists for the post-1992 corrugated-box industry. Beginning in 1992, the units of output switch from thousands of pounds to thousands of square feet. I detail my response to this potential problem in Online Appendix B.1.

9. Corrugated boxes, raw cane sugar, gasoline, ground coffee, and ready-mix concrete are included in both the current paper and Foster, Haltiwanger, and Syverson (2008). I could not include carbon black, block ice, or processed ice, as there were insufficiently many plants that filled out both the production and materials supplements. I do not include hardwood flooring or plywood, the last two industries that Foster, Haltiwanger, and Syverson (2008) include. Large output price dispersions seem to indicate that the outputs of these industries are not sufficiently homogeneous.

TABLE 1. Description of the ten industries in the benchmark sample.

Sample	Units of output	Material inputs	N
Boxes, year≤1987	Short tons	Paper/paperboard (90%)	1,820
Boxes, year≥1992	Square feet	Paper/paperboard (89%)	646
Ground coffee	1,000 pounds	Green coffee beans (80%)	300
Ready-mix concrete	1,000 cubic yards	Cement (53%) Sand/gravel (28%)	3708
White wheat flour	50-pound sacks	Wheat (90%)	503
Gasoline	1,000 barrels	Crude petroleum (84%)	692
Milk, bulk	1,000 pounds	Unprocessed whole milk (88%)	127
Milk, packaged	1,000 quarts	Unprocessed whole milk (72%)	2,099
Raw cane sugar	Short tons	Sugar cane (93%)	177
Carded cotton yarn	1,000 pounds	Cotton fibers (80%) Polyester tow (10%)	431
Pooled	–	–	10,503

Notes: The percentages that appear in the "Material inputs" column are the fraction of materials expenditures that go to each particular material input. The "Material inputs" column shows the inputs that represent greater than 6% of the average plant's total material purchases.

of intermediate input usage (see equation (8)), it is likely that the decline in total factor productivity dispersion is larger for the ten industries in my sample than for the broader manufacturing sector.

Second, the plants in the benchmark sample tend to be larger, relative to the other plants from their respective industries. The average plant in my sample employs roughly five times more employees and has revenues that are four times larger than the average plant in their respective industry. (For more details, see Online Appendix B.1.) Since the probability of exit tends to decrease with size, the plants in my benchmark sample are relatively more likely to survive: Plants in the benchmark sample have a five-year survival rate of 86%, compared to the average survival rate for plants in their corresponding four-digit Standard Industrial Classification (SIC) industries, 72%.

These sample selection issues limit the generalizability of the results given in Sections 3 and 4. However, by sacrificing generality, I am able to isolate the effect of differences in materials prices on intra-industry productivity dispersion.

2.3. *Assumptions*

I make five assumptions regarding plants' production technologies and the way in which intermediate inputs, labor, capital, and electricity are supplied. The aim of these assumptions is to highlight the importance of price dispersion in the measurement of plant-level productivities. Towards this goal, I will, as much as possible, adhere to conventional assumptions made in the literature on plant-level production function estimation. The key assumption that I will relax is that all plants within an industry pay the same unit price for their intermediate inputs. Relaxing this assumption potentially has a significant effect on productivity measurement, as intermediate inputs represent roughly 60% of input expenditures in the median manufacturing industry.

ASSUMPTION 1. *Plants within an industry have constant-returns-to-scale Cobb–Douglas production functions, with labor, capital, electricity, and materials as the inputs. Furthermore, factor shares are common across all plants within an industry-year combination.*

There are three components to the first assumption: a unitary elasticity of substitution, common factor shares within an industry, and constant returns to scale. The unitary elasticity of substitution is common in studies of plants' production functions, mainly for convenience. However, several authors have estimated an elasticity of substitution between labor and capital that is less than 1 (e.g., Raval 2011). For the objects of interest, the Cobb–Douglas assumption seems to have little effect on the dispersion of measured productivity. I show, in Online Appendix A.3, that the results of Section 3 are robust to complementarities among material inputs and other inputs.

The other parts of Assumption 1 are also rather innocuous. In Syverson (2004a), the relationships between within-industry productivity dispersion and other industry characteristics are robust to using plant-specific factor shares when estimating plants' TFPs. Related to the constant-returns-to-scale component of Assumption 1, Syverson (2004b) estimates that the returns to scale are indistinguishable from 1 for plants in the ready-mix concrete industry, the industry that contains roughly one-third of the plants in my sample.[10]

ASSUMPTION 2. *The unit input costs of capital, labor, and electricity are the same for all plants within an industry-year combination. In addition, the unit prices of all inputs are constant in the amount purchased.*

Data limitations necessitate the assumption that all plants face the same costs for a unit of capital services. The assumption that electricity costs are the same across plants within an industry can be relaxed, without changing any of the results of Section 3.[11,12]

10. Baily, Hulten, and Campbell (1992) estimate returns to scale for a broader set of industries and find the same result.

11. Davis, Grim, and Haltiwanger (2008) compute plant-level energy prices and show that there is substantial variation, within industries, in the cost of a kilowatt-hour of electricity. In an unreported robustness exercise, I check that the results of Section 3 are virtually identical after relaxing the assumption that all plants face the same electricity prices, the reason being that the expenditure share of energy is small (on average, 2.5%) for plants in the benchmark sample.

12. Differences in labor quality, across plants, may muddle the interpretation of plants' productivities. Using hours worked as the measure of labor means that plants with exceptionally skilled workers would appear to be highly productive. If workers' wages reflect differences in skill (as opposed to, for example, workers' bargaining power), it would be preferable to measure labor inputs by the wages paid by each plant. In an unreported robustness check, I reproduce Tables 2 and 3 using the wage bill, instead of hours worked, as the measure of labor inputs. The results are virtually identical when using this different measure of labor inputs.

Assumptions 3–5 deal with the fact that plants may produce multiple outputs and purchase multiple intermediate inputs.

ASSUMPTION 3. *The fraction of each input employed in producing a particular product equals the plant's share of revenue coming from that product.*

The need for Assumption 3, an assumption also made by Foster, Haltiwanger, and Syverson (2008), stems from a limitation of the dataset. In particular, for plants that produce multiple goods, it is impossible to know exactly how much of each input is used in the production of each output. I make the simplest possible assumption, and assume that each input is allocated in proportion to the plant's sales of each product. For example, for a hypothetical plant that employs L units of labor and sells Y_g dollars of good g, for $g \in \{1, \ldots, G\}$, the amount of labor used in the production of g is

$$L \frac{Y_g}{\sum_{\hat{g}=1}^{G} Y_{\hat{g}}}. \tag{1}$$

Similar to Foster et al., I argue that the dispersion of productivity is robust to the way in which inputs are allocated to outputs, mainly because the plants in my sample tend to be heavily specialized in the goods they manufacture.

In addition to Assumptions 1–3, which are common in papers that estimate plant-level productivities, I make two assumptions on the substitutability among different material inputs. Together, Assumptions 4 and 5 will allow me to compute plant-specific materials prices from the data at hand. While restrictive, they are much less so than the common assumption that all plants face the same intermediate input prices.

ASSUMPTION 4. *If multiple intermediate inputs are observed, the elasticity of substitution between the materials is* 0.

This assumption is pertinent only for the two industries, plants producing ready-mix concrete or yarn, for which I observe multiple material inputs being employed. I show, in Online Appendix A.4, that the level of productivity dispersion is extremely robust to moderate levels of substitutability among the different material inputs.

ASSUMPTION 5. *The elasticity of substitution, between plants' "priced" and "nonpriced" materials is* 1. *In addition, the elasticity of substitution between "nonpriced" materials and capital, labor, and electricity is also* 1.

Here, "priced materials" are the materials that most plants in the industry purchase. For instance, in the case of yarn manufacturers, cotton fibers and polyester tow are the "priced materials". The nonpriced materials are purchased by only a few plants in the industry. Again, turning to the yarn industry, approximately 10% of the expenditures on intermediate inputs go to purchases of materials other than cotton fibers (see the

"Material inputs" column of Table 1). Some of these yarn-producing plants purchase silk fibers; others purchase nylon tow. Since only a few plants purchase these materials, it is difficult to ascertain if plants are purchasing these inputs relatively cheaply or expensively. I treat the "nonpriced" materials as if they were any other input for which I do not observe unit prices, such as capital, and assume that there is a unitary elasticity of substitution between "nonpriced" materials and "priced" materials, labor, capital, and electricity.

2.4. Definitions

In this section, I define plants' materials and output prices, as well as the three plant-level productivity measures: *TFPQ*, *TFPR*, and Φ. The first two productivity measures are exactly as in Foster, Haltiwanger, and Syverson (2008). The productivity measure that is new to this paper, Φ, aims to isolate plants' abilities to transform inputs into outputs. In particular, Φ should not reflect plants' abilities to sell their output at a relatively high price, or to purchase their intermediate inputs at a relatively low price.

I begin by defining plants' input and output prices. The price P_{ijt}^{out} that plant i charges for product j in year t is simply the ratio of revenues Y_{ijt} to physical quantity shipped Q_{ijt}:

$$P_{ijt}^{out} \equiv \frac{Y_{ijt}}{Q_{ijt}}. \tag{2}$$

Before defining plant-level input prices, I introduce some notation. Let M_{ijt} be the expenditure on materials of plant i in the production of product j in year t. Plant i's purchases consist of "nonpriced" materials, which I denote using M_{ijt}^0, and "priced" materials, which I denote using M_{ijt}^1 (and M_{ijt}^2 if j is produced using two material inputs). Let s_{jt}^{κ} denote the average fraction—across plants in my sample in industry j and year t—of materials expenditures that is spent on material κ.[13] Finally, let S_{jt} denote the average fraction of materials expenditures, in industry j and year t, that go to "priced" materials.[14]

For plants in industries that use only one type of "priced" material (i.e., all industries except for ready-mix concrete and yarn), the input price equals the ratio of materials expenditures (M_{ijt}^1) to the physical quantity consumed (N_{ijt}^1) of the lone priced material:

$$P_{ijt}^{in} \equiv \frac{M_{ijt}^1}{N_{ijt}^1}. \tag{3}$$

13. For example, for $j =$ concrete and $\kappa =$ cement, s_{jt}^{κ} would be approximately 0.53, with slight variation across years.

14. Continuing with the example from the previous footnote, S_{jt} would be approximately 0.81 $(= 0.28 + 0.53)$ for ready-mix concrete manufacturers.

To construct plant-level materials prices for ready-mix concrete and yarn manufacturers, I begin by defining a unit of the intermediate input bundle as follows:

$$N_{ijt} \equiv \min\left\{ \frac{N_{ijt}^{1}}{\bar{N}_{jt}^{1}} \div \left(\frac{s_{jt}^{1}}{S_{jt}}\right), \frac{N_{ijt}^{2}}{\bar{N}_{jt}^{2}} \div \left(\frac{s_{jt}^{2}}{S_{jt}}\right) \right\}$$
$$= \lim_{\varrho \to 0} \left(\left(\left(\frac{s_{jt}^{1}}{S_{jt}}\right)^{\frac{1}{\varrho}} \quad \frac{N_{ijt}^{1}}{\bar{N}_{jt}^{1}} \right)^{\frac{\varrho-1}{\varrho}} + \quad \frac{s_{jt}^{2}}{S_{jt}} \right)^{\frac{1}{\varrho}} \quad \frac{N_{ijt}^{2}}{\bar{N}_{jt}^{2}} \Bigg)^{\frac{\varrho-1}{\varrho}} \Bigg)^{\frac{\varrho}{\varrho-1}}. \tag{4}$$

In equation (4), N_{ijt} is the number of units of the intermediate input bundle purchased by plant i in industry j and year t. Because the units of N_{ijt} have no natural interpretation, it is necessary to normalize by the average input utilization of each of the intermediate goods, $\bar{N}_{jt}^{1}$ and $\bar{N}_{jt}^{2}$, in the given industry-year.[15] Assumption 4 pins down how the two different materials are combined to form the composite intermediate input; relaxing Assumption 4 would involve allowing $\varrho > 0$.

Let P_{1ijt}^{in} and P_{2ijt}^{in} be the price that plant i of industry j pays for materials 1 and 2 in year t, and let $\bar{P}_{1jt}^{in}$ and $\bar{P}_{2jt}^{in}$ be the corresponding industry-year averages. Then, the materials bundle's ideal price index equals the value-weighted average of the individual inputs' prices:

$$P_{ijt}^{in} \equiv \frac{s_{jt}^{1}}{S_{jt}} \frac{P_{1ijt}^{in}}{\bar{P}_{1jt}^{in}} + \frac{s_{jt}^{2}}{S_{jt}} \frac{P_{2ijt}^{in}}{\bar{P}_{2jt}^{in}}. \tag{5}$$

Having defined plant-level materials and output prices, I can now compute plant-level productivities. For each plant, i, producing in industry j and year t, define its total factor productivity quantity (*TFPQ*) as the ratio between the physical quantity it produces and the inputs it utilizes in the production of this product:[16]

$$TFPQ_{ijt} \equiv Q_{ijt} \left(L_{ijt}\right)^{-\lambda_{jt}} \left(K_{ijt}\right)^{-\kappa_{jt}} \left(E_{ijt}\right)^{-\epsilon_{jt}} \left(M_{ijt}\right)^{-\sigma_{jt}}. \tag{6}$$

In equation (6), L_{ijt}, K_{ijt}, and E_{ijt} denote the amount of labor, capital, and energy used in the production of product j. As in Foster, Haltiwanger, and Syverson (2008),

15. Klump, McAdam, and William (2012) comprises a discussion of the necessity of normalizing CES production functions when $\varrho \neq 1$. (When $\varrho = 1$, the units can be factored out into a multiplicative constant.)

16. Ideally, I would compare the estimates generated by equations (6)–(8) to those computed using other estimation methodologies. Unfortunately, like Foster, Haltiwanger, and Syverson (2008), I am unable to compute plant-level productivities using the methods outlined in Olley and Pakes (1996), Blundell and Bond (2000), and Ackerberg, Caves, and Frazer (2006). These methods generally require annual observations, while information on quantities of output produced or intermediate inputs purchased exist only for years in which the Census of Manufacturers is conducted. Most likely, my results would not change if other productivity measures were used. Van Biesebroeck (2008) reports that, unlike estimates of input elasticities, which are sensitive to the estimation methodology, plant-level productivity estimates are highly correlated across different estimation methodologies.

In Online Appendix A.5, I re-estimate plants' productivities, using the index number approach outlined in Caves, Christensen, and Diewert (1982). The main results of Section 3 are essentially unchanged.

labor is stated in terms of hours, and capital is computed by summing plants' reported book values of equipment and structures. Note that, because of Assumption 1, the factor elasticities, λ_{jt}, κ_{jt}, ϵ_{jt} and σ_{jt}, are the same for all plants within an industry-year pair. In addition, $\lambda_{jt} + \kappa_{jt} + \epsilon_{jt} + \sigma_{jt} = 1$ for all j, t pairs. To emphasize, since $M_{ijt} = P^{in}_{ijt} N_{ijt}$, low materials prices are associated with high $TFPQ_{ijt}$.

The industry-year specific cost shares in equation (6) are computed as in Foster, Haltiwanger, and Syverson (2008): I use industry-year level cost shares from the NBER Productivity database as estimates of the production function factor shares. Capital service expenditures are set equal to the value of the stock of capital multiplied by capital rental rates (from unpublished data constructed by the Bureau of Labor Statistics).

Revenue total factor productivity (*TFPR*) captures a plant's ability to transform a given bundle of inputs into revenue. As equation (7) makes clear, plants will have a high *TFPR* for one of two reasons: Either they have high *TFPQ*, or they sell their output at a particularly high price:

$$\begin{aligned} TFPR_{ijt} &\equiv Y_{ijt} \left(L_{ijt}\right)^{-\lambda_{jt}} \left(K_{ijt}\right)^{-\kappa_{jt}} \left(E_{ijt}\right)^{-\epsilon_{jt}} \left(M_{ijt}\right)^{-\sigma_{jt}} \\ &= TFPQ_{ijt} P^{out}_{ijt}. \end{aligned} \tag{7}$$

Finally, when computing plants' technical efficiencies (Φ_{ijt}), I purge the materials price from measured productivity:

$$\begin{aligned} \Phi_{ijt} &\equiv Q_{ijt} \left(L_{ijt}\right)^{-\lambda_{jt}} \left(K_{ijt}\right)^{-\kappa_{jt}} \left(E_{ijt}\right)^{-\epsilon_{jt}} \left(M^{0}_{ijt}\right)^{-\sigma_{jt}(1-S_{jt})} \left(N_{ijt}\right)^{-\sigma_{jt} S_{jt}} \\ &= Q_{ijt} \left(L_{ijt}\right)^{-\lambda_{jt}} \left(K_{ijt}\right)^{-\kappa_{jt}} \left(E_{ijt}\right)^{-\epsilon_{jt}} \left(M_{ijt}\right)^{-\sigma_{jt}} \left(P^{in}_{ijt}\right)^{\sigma_{jt} S_{jt}} \\ &= TFPQ_{ijt} \left(P^{in}_{ijt}\right)^{\sigma_{jt} S_{jt}}. \end{aligned} \tag{8}$$

The equality of the first and second lines of equation (8) follows from Assumption 5, namely the unitary elasticity of substitution between "priced" and "nonpriced" materials. The equality of the second and third lines follows from the definition of *TFPQ*. Equation (8) states that plants will have high $TFPQ_{ijt}$ for one of two reasons: either the plant is technically efficient (Φ_{ijt} is large), or materials prices are low (P^{in}_{ijt} is low).[17,18]

17. Of course, there may be within-industry differences in the factor market conditions for labor, capital, and electricity. Because of Assumption 2, these differences would be incorrectly labeled as differences in technical efficiencies.

18. To the extent that plants invest in finding suppliers that will charge a low price, stripping out materials price variation may do more harm than good. Following Foster, Haltiwanger, and Syverson (2008), I examine the relationship between plants' input prices and the share of workers that are not engaged in actual production. These workers are, potentially, the ones that are searching for new, low-cost suppliers. If this hypothesis is correct, plants that have a higher share of nonproduction workers will have lower-than-average materials prices. In the data, this turns out not to be the case. The correlation between a plant's (log) non-production worker share and its p^{in} equals -0.00. Foster, Haltiwanger, and Syverson document a similar result: A higher nonproduction worker share is very weakly positively correlated with

TABLE 2. Correlations and standard deviations of plant-level characteristics.

	p^{in}	p^{out}	*tfpq*	φ	*tfpr*
p^{out}	0.231**				
tfpq	–0.369**	–0.551**			
φ	0.127**	–0.469**	0.873**		
tfpr	–0.232**	0.219**	0.616**	0.694**	
Std. dev.	0.117	0.119	0.161	0.151	0.137

Notes: Observations are weighed by plants' real revenues. Correlations for each of the ten industries are presented in Online Appendix A.6, while correlations that give plant-year observations equal weight are given in Online Appendix A.8. $N = 10{,}503$.
**Correlation is significantly different from 0 at the 5% level (see Online Appendix C for details).

Note that Assumptions 1 and 2 imply that *TFPQ* is inversely proportional to marginal costs.[19] Given this, I will use the terms "low quantity productivity" and "high marginal cost" interchangeably.

So that I can compare observations across industries and years, all quantities will be stated relative to the mean for that industry-year. I use lower-case letters to denote the percentage deviation of a variable from its industry-year average. For any plant-level statistic X_{ijt} define

$$x_{ijt} \equiv \log(X_{ijt}) - \frac{\sum_{k:k\in i\text{'s industry in year t}} \log X_{kjt}}{\|\{k : k \in i\text{'s industry in year } t\}\|} \tag{9}$$

2.5. Relationships Between Prices and Productivity Measures

Before proceeding to the empirical analysis, I provide expressions for the relationships among the different productivity measures and plant-level prices.[20] I will take φ_{ijt} and p_{ijt}^{in} as given and use equations (6)–(9) to characterize the signs of the relationships between the plant-level productivity measures and input prices. In general, φ_{ijt} and p_{ijt}^{in} emerge from the interactions between plant i's choices (on how much to produce, how much of each input to purchase, how much effort to spend searching for low-cost inputs, etc.) and conditions in factor and output markets. For this discussion, it suffices to leave these decisions and interactions unmodeled.

In this section, I assume that $\text{Cov}(\varphi, p^{in}) \approx 0$. That is, in the observed sample, there is no relationship between plants' technical efficiencies and the prices at which they purchase intermediate inputs. As Table 2 will demonstrate, there is actually a weak

higher output prices. While this is a crude calculation, it suggests that plants' investments are not a driving source of materials price variation.

19. Solving the cost minimization problem of a plant with a constant-returns Cobb–Douglas production technology yields the following expression for its marginal cost: $MC_{ijt} \propto (\Phi_{ijt})^{-1} (P_{ijt}^{in})^{\sigma_{jt} S_{jt}} = TFPQ^{-1}$. The constant of proportionality is a function of the industry-year specific unit costs of labor, capital, and electricity.

20. The exposition of this section is due, in large part, to an anonymous referee, to whom I am deeply grateful.

positive relationship between materials prices and technical efficiencies. Ignoring this positive relationship, for the moment, yields simple expressions for the relationships of interest. In conjunction with the definitions given in equations (6)–(9), this section's assumption yields

$$\mathrm{Cov}(\mathit{tfpq}, \varphi) = \mathrm{Var}(\varphi) > 0 \tag{10}$$

$$\mathrm{Cov}(\mathit{tfpq}, p^{in}) = -\sigma S \,\mathrm{Var}(p^{in}) < 0 \tag{11}$$

$$\mathrm{Var}(\mathit{tfpq}) - \mathrm{Var}(\varphi) = (\sigma S)^2\, \mathrm{Var}(p^{in}) > 0. \tag{12}$$

Equation (10) states that plants with high technical efficiencies also have higher-than-average quantity productivities. Moreover, plants that purchase their inputs cheaply have high *tfpq*'s (low marginal costs). Finally, *tfpq* is more dispersed than φ. To provide some intuition for the sign of equation (12), notice that *tfpq* is the difference of φ and p^{in}. As long as the relationship between technical efficiency and input prices is not too strong, which, for now I am assuming, the variance of *tfpq* will have to be larger than the variance of φ.

There are other relationships of interest, among plants' output prices, revenue productivities, and quantity productivities. A simple model generating predictions over these relationships can be found in Foster, Haltiwanger, and Syverson (2008). Their set-up yields the following predictions: Plants with low marginal costs (high *tfpq*) will have higher-than-average markups, but lower-than-average output prices. Thus, p^{out} will be positively correlated with *tfpr*, but negatively correlated with *tfpq*. I check these predictions, in addition to the more novel predictions given in equations (10)–(12), in the following section.

3. Implications of Materials Price Dispersion

In this section, I explore some of the implications of price dispersion in intermediate input markets. In Section 3.1, I document that materials price dispersion is substantial and provide correlations among plant-level statistics. In Section 3.2, I estimate that 7% to 10% of the variation in *tfpq* is attributable to differences in the materials prices that plants face. In Section 3.3, I argue that the price that plants face when purchasing their materials is persistent across time and correlated across space. In Section 3.4, I show that materials prices are higher for plants that are about to exit. Finally, in Section 3.5, I compute the contribution, towards aggregate productivity growth, of the entry of relatively productive plants and the exit of relatively unproductive plants.

3.1. Descriptive Statistics

Table 2 contains summary statistics for the plant-level productivities and input/output prices. All plant-level variables are de-meaned by industry-year according to equation (9).

The first takeaway from Table 2 is that within-industry price dispersion is substantial. For the benchmark sample which, again, consists of plants that produce commodity-like products, the within-industry standard deviations of plant-level materials and output prices are approximately 12%. These dispersions are of similar magnitude to the within-industry variation in plant productivities.

What is more, the observed correlations in Table 2 match the predictions made in Section 2.5. The correlation coefficients between *tfpq*, *tfpr*, and p^{out} are similar to those computed in Foster, Haltiwanger, and Syverson (2008). Plants with higher *tfpq* pass on some of their lower marginal costs to their consumers (generating a low p^{out}). In addition, *tfpq* and *tfpr* are positively correlated, as are *tfpr* and p^{out}.

The variables that are new to this study are φ and p^{in}, log technical efficiencies and log materials prices. First, plant-level materials prices, p^{in}, are negatively correlated with *tfpq* and *tfpr*. Plants that purchase inputs cheaply appear to be more productive according to the conventional measures. At the same time, *tfpq* and φ are highly correlated with one another, while the correlation between φ and *tfpr* is similar to the correlation between *tfpr* and *tfpq*.

Materials prices are positively correlated with output prices and technical efficiencies. There are several possible explanations for these positive relationships. First, the correlations may reflect any differences in input and output quality that still remain (despite my best efforts to choose a sample of industries with outputs and material inputs that are comparable across plants). If (a) inputs vary in quality, (b) these quality differences are reflected by differences in materials prices, and (c) high-quality inputs allow a plant to produce more units of a given product using a given bundle of inputs (measured in physical units), then we will observe a positive correlation between φ and p^{in}. Quality variation may also explain why p^{out} and p^{in} are correlated with one another, to the extent that inputs vary considerably in quality and consumers value products that are produced using high-quality material inputs.

A second possible explanation is that a selection mechanism, one on plant survival, may be causing us to observe a positive relationship between p^{out}/φ and p^{in}: If plants' survival depends on their profitability being above some cutoff, plants will be able to tolerate poor conditions in input markets if they are able to sell their output expensively or if they are particularly technically efficient.

Finally, independent of quality differences or selection, the positive correlation between input and output prices may be due to imperfections in output markets, where high materials prices can at least partially be passed through to the establishments' customers.

3.2. Implications for Productivity Dispersion

In this section, I compare the dispersions of the distributions of *tfpq* and φ. In so doing, I provide a measure of the fraction of *tfpq* dispersion that can be explained by differences in intermediate input prices. The main finding, that the dispersion of *tfpq* exceeds the dispersion of φ, is the prediction of equation (12).

Pooling across the ten industries in the sample, the standard deviation of φ is 16.3% $\left(= e^{0.151}\right)$, while the standard deviation of *tfpq* is 17.5%, which is 7% larger than the standard deviation of φ. So, by eliminating the effect of differences in materials prices, the observed distribution of productivities would be approximately 7% lower; the 95% confidence interval of the difference between the standard deviations of *tfpq* and φ is [0.2%, 10.4%]. Table 3 includes two other measures of dispersion, the 90/10 ratio and the 75/25 ratio. The difference between the dispersions of *tfpq* and φ is somewhat greater with these two alternate measures: 9% for the 90/10 ratio and 10% for the 75/25 ratio.

The difference between *tfpq* and φ varies across industries, particularly for the industries with small sample sizes. For coffee, *tfpq* is 17% to 30%more dispersed than φ, while φ actually displays more dispersion than *tfpq* for the smallest-sample industry, raw cane sugar.

Even though I have chosen industries based on the homogeneity of the inputs and outputs, it is likely that at least some of the variation in materials and output prices is due to differences in quality. Variation in input/output quality attenuates the negative correlation between *tfpq* and p^{in} (see Appendices A.1 and A.2, where I study samples with more pronounced input/output quality variation). High-quality material inputs, for example, will allow establishments to produce and sell more using a given measured quantity of material inputs. To the extent that high-quality intermediate inputs are purchased at higher unit prices, this will induce a positive relationship between φ and p^{in}. As a result, then, within-industry variation in quality will lead to a downward bias in the measured difference between the dispersion of *tfpq* and the dispersion of φ.[21] In other words, the 7% to 10% decline in dispersion most likely under-represents the actual fraction of *tfpq* dispersion that is due to differences in materials prices.

Measurement error has the potential to bias the correlations given in Table 2 and the dispersions given in Tables 3 and 4. Because P^{in}_{ijt} is constructed by taking the ratio of M_{ijt} and N_{ijt}, any measurement error in N_{ijt} will induce spurious positive correlation between p^{in} and φ. Similarly, because plant-specific output prices (P^{out}_{ijt}) are computed by taking the ratio of revenues (Y_{ijt}) to quantities produced (Q_{ijt}), measurement error in Q_{ijt} will tend to engender negative correlations between p^{out} and *tfpq*/φ. In turn, measurement error in N_{ijt} and Q_{ijt} has the potential to bias the dispersions of *tfpq* and φ. I explore the magnitude of these biases in Online Appendix A.7. The main takeaway from Online Appendix A.7 is that measurement error will also lead me to understate the difference between the dispersion of *tfpq* and the dispersion of φ.

With these caveats in mind, I now relate the 7% to 10% decline in dispersion to dispersion declines reported in two other papers. First, Syverson (2004b) hypothesizes that, in markets for which competitive forces are exceptionally strong, low-productivity plants are more likely to exit the industry, in turn leading to a more compressed productivity distribution. Within the ready-mix concrete industry, Syverson characterizes areas with high densities of construction activity

21. Since $\mathrm{Var}(tfpq) = \mathrm{Var}(\varphi) + (\sigma S)^2\mathrm{Var}(p^{in}) - 2\sigma S\,\mathrm{Cov}(\varphi, p^{in})$, any positive correlation between φ and p^{in} will lead to a decline in the dispersion of *tfpq* relative to that of φ.

TABLE 3. Dispersion of *tfpq* and φ.

Sample	Dispersion of *tfpq*			Dispersion of φ			Percentage decrease		
	90/10	75/25	SD	90/10	75/25	SD	90/10	75/25	SD
Boxes, year≤1987	0.380	0.179	0.168	0.366	0.177	0.166	3.7%**	1.0%	1.6%
Boxes, year≥1992	0.566	0.293	0.225	0.526	0.276	0.211	7.9%**	6.2%**	6.7%**
Coffee	0.709	0.326	0.266	0.562	0.277	0.229	30.1%**	19.5%**	17.4%**
Concrete	0.521	0.251	0.224	0.486	0.236	0.215	7.4%**	6.6%**	4.4%**
Flour	0.360	0.190	0.142	0.349	0.158	0.148	3.2%	23.2%**	–4.1%
Gasoline	0.300	0.145	0.132	0.280	0.133	0.122	7.6%	9.5%	8.1%
Milk, bulk	0.597	0.285	0.252	0.531	0.267	0.229	13.1%	7.2%	10.3%
Milk, packaged	0.535	0.261	0.227	0.502	0.248	0.218	6.7%**	5.3%**	4.1%**
Sugar	0.588	0.297	0.280	0.766	0.340	0.319	–20.7%	–11.9%	–11.5%**
Yarn	0.581	0.275	0.256	0.633	0.310	0.252	–8.0%	–10.8%	1.5%
Pooled: weighted	0.351	0.164	0.161	0.324	0.151	0.151	8.8%**	9.7%	6.9%**
Pooled: unweighted	0.527	0.253	0.227	0.493	0.238	0.219	7.2%**	6.5%**	3.9%**

Notes: Except for the final row, observations are weighed by plants' real revenues. See Online Appendix A.8 for the unweighted computations, broken out by industry.[22]
** Significant at 5% (see Online Appendix C for details).

TABLE 4. Dispersion of *tfpr* and *tfpq*.

Revenue-weighted?	Dispersion of *tfpr*			Dispersion of *tfpq*			Percentage increase		
	90/10	75/25	SD	90/10	75/25	SD	90/10	75/25	SD
Yes	0.306	0.147	0.137	0.351	0.164	0.161	16.0%**	12.9%	18.5%**
No	0.380	0.178	0.176	0.527	0.253	0.227	47.3%**	53.0%**	33.7%**

Note: $N = 10{,}503$.
** Significant at 5% (see Online Appendix C for details).

as highly competitive markets, and finds that this demand density index explains approximately 2% of the cross-market variation in the dispersion of measured productivity. In a second example, Fox and Smeets (2011) compute the fraction of measured productivity dispersion that can be explained by differences in worker quality. While Fox and Smeets' application of a value-added production function muddles a comparison of magnitudes, it is likely that materials price variation is at least as important—in terms of reducing measured productivity dispersions—as labor-quality variation.[23]

22. Due to Census rules regarding data confidentiality, I am prohibited from reporting the actual quantiles of any empirical distribution. The quantiles (but not the standard deviations, which are not subject to this regulation) are computed in a two-step process. First, using a kernel density estimator, I produce a smoothed version of the empirical cumulative distribution function of the variable of interest. I then report the quantile of this smoothed distribution. The decrease in productivity dispersion—between *tfpq* and φ—is not substantially affected by this smoothing procedure. I employ the same two-step procedure in the calculations of Tables 4, A.2, A.5, A.8, and A.15.

23. Within four manufacturing industries, Fox and Smeets (2011) report a 14% decline in the 90/10 ratio of measured productivities, after including rich controls for worker quality. (The wage bill alone reduces the

TABLE 5. Persistence of plant-level characteristics.

	Revenue-weighted?	*tfpq*	*tfpr*	p^{out}	φ	p^{in}	y	q	n
β	No	0.351**	0.306**	0.432**	0.299**	0.309**	0.895**	0.901**	0.889**
S.E.	No	(0.022)	(0.024)	(0.024)	(0.023)	(0.025)	(0.010)	(0.009)	(0.010)
$\beta^{1/5}$	No	0.811	0.789	0.846	0.786	0.791	0.978	0.979	0.977
β	Yes	0.175	0.201	0.305**	0.185**	0.326**	0.868**	0.868**	0.885**
S.E.	Yes	(0.092)	(0.106)	(0.040)	(0.083)	(0.047)	(0.045)	(0.051)	(0.028)
$\beta^{1/5}$	Yes	0.706	0.726	0.789	0.713	0.799	0.972	0.972	0.976

Note: $N = 4{,}310$.
**Significant at 5%.

While price dispersion in intermediate input markets tends to reduce the dispersion of measured productivity (i.e., the dispersion of *tfpq* is greater than that of φ), price dispersion in output markets has the opposite effect on the dispersion of measured productivity (i.e., the dispersion *tfpr* is smaller than that of *tfpq*). The latter relationship, which Foster, Haltiwanger, and Syverson (2008) also document, stems from the strong negative correlation between p^{out} and *tfpq*: The standard deviation of revenue productivity, which is 14.7% in the revenue-weighted calculations, is approximately 19% smaller than the standard deviation of quantity productivity. In this sense, φ and *tfpr* are closer to each other than one might presume. The similarity of these two productivity measures is intuitive; it stems from the positive correlation between input and output prices. The countervailing effects—as in this case, on the standard deviation of measured productivity—of factor price dispersion and output price dispersion will be a recurring finding in the remainder of this section.

3.3. Serial and Spatial Correlation

A long stream of research, beginning with Baily, Hulten, and Campbell (1992), has documented the persistence of plant-level characteristics. Using regressions of the form

$$x_{i,j,t+5} = \alpha + \beta x_{ijt} + \varepsilon_{ijt}, \tag{13}$$

Foster, Haltiwanger, and Syverson (2008) compute the one- and five-year autocorrelation coefficients for different plant-level statistics. They compute that plant-level productivities and output prices have a one-year autocorrelation coefficient of approximately 70% to 80%. I replicate these findings in Table 5. The novel components

90/10 ratio by almost as much, 13%.) However, as Gandhi, Navarro, and Rivers (2012, p. 1) argue, value-added production functions cause one to overstate productivity dispersion and to infer "fundamentally different patterns of productivity heterogeneity".

I compute the decline in measured productivity dispersion accrued by replacing hours with wages as the measure of labor inputs, still using, as I have throughout the paper, a gross output production function. For the ten industries in my benchmark sample, the 90/10 ratio declines by 2.4% if observations are revenue weighted, and 6.6% if observations are given equal weight.

TABLE 6. Spatial correlation of materials prices.

Sample	β	S.E.	Adjusted-R^2
Boxes, year≤1987	0.884	0.080	0.063
Boxes, year≥1992	0.693	0.120	0.048
Coffee	0.051	0.080	–0.002
Concrete	0.913	0.028	0.222
Flour	0.266	0.091	0.015
Gasoline	0.721	0.056	0.193
Milk, bulk	0.139	0.118	0.003
Milk, packaged	0.826	0.041	0.160
Sugar	0.193	0.183	0.001
Yarn	–0.377	0.308	0.001
Pooled	0.577	0.016	0.107

Notes: The dependent variable is p^{in}_{ijt}, and the independent variable is the (revenue-weighted) average of the $p^{in}_{i'jt}$ for the plants that are within a 250-mile radius of plant i in industry j and year t. Observations are revenue weighted. See Online Appendix A.8 for the unweighted version of this table.

of Table 5 appear in the final five columns. I find that the persistence of φ is similar to that of the two other plant-level productivity measures, and that the persistence of p^{in} is similar to the persistence of p^{out}. Measures of plant size—revenues and physical quantities of outputs and intermediate inputs—exhibit significantly more persistence relative to the productivity and price measures.

There are at least three potential explanations as to why materials price variation is so persistent. A first possibility is that the price variation reflects residual, persistent, within-industry differences in the quality of plants' inputs. Again, while this possibility should not completely be discounted, I have selected industries with little quality variation to mitigate its role in my analysis. Second, persistence of materials price variation might result from long-term buyer–supplier relationships, a possibility I explore in Sections 4.2 and 4.3. A third possibility, which I also revisit in Section 4.2, is that geographical forces generate persistent within-industry variation in materials prices.

To examine this final possibility, I measure the extent to which materials prices are spatially correlated.[24] In particular, I run a regression on the benchmark sample of 10,503 plant-year observations. In this regression, the dependent variable is the materials price for plant i in year t, p^{in}_{ijt}. The sole independent variable is the revenue-weighted average of the materials prices of the other plants that are located within 250 miles of plant i. (I find similar results using a range of alternate cutoffs.) Table 6 indicates that 11% of materials price variation is explained by the materials prices of nearby plants. Materials prices for gasoline refiners and concrete manufacturers exhibit the strongest spatial correlation, while the materials prices of bulk milk, yarn, coffee, and sugar manufacturers are not spatially correlated.

24. Geographical price variation could potentially reflect differences in demand for high-quality inputs, across locations. See Appendix A.2 for a discussion of the ready-mix concrete industry, an industry for which this might be the case.

TABLE 7. Comparison of plant-level statistics and entry/exit status.

Coefficient on:	Revenue-weighted?	*tfpq*	φ	*tfpr*	y	p^{in}	p^{out}
Entry	No	0.017**	0.020**	0.015**	–0.456**	0.005	–0.002
Entry	No	(0.008)	(0.007)	(0.006)	(0.032)	(0.006)	(0.006)
Entry	Yes	0.009	–0.004	–0.005	–0.698**	–0.019	–0.014
Entry	Yes	(0.025)	(0.023)	(0.022)	(0.092)	(0.015)	(0.016)
Exit	No	–0.025**	–0.016**	–0.020**	–0.534**	0.014**	0.005
Exit	No	(0.007)	(0.007)	(0.006)	(0.031)	(0.005)	(0.006)
Exit	Yes	–0.051**	–0.042**	–0.039	–0.609**	0.013	0.012
Exit	Yes	(0.018)	(0.016)	(0.020)	(0.131)	(0.012)	(0.012)

Notes: In the first four rows, each cell gives the coefficient estimate, or standard error, of β_1 in equation (14). In the final four rows, each cell gives the coefficient estimate, or standard error, of β_2 in equation (15). $N = 10{,}503$.
**Significant at 5%.

3.4. Characteristics of Entering and Exiting Plants

In this section, I compare the prices and productivity measures of entering plants with incumbent plants and exiting plants with surviving plants. Table 7 presents the main results of this section, the results of the regressions defined by equations (14) and (15):[25]

$$x_{ijt} = \alpha_{jt} + \beta_1 \mathbb{I}\{i \in \text{plants that enter between years } t-5 \text{ and } t\} + \varepsilon_{ijt} \tag{14}$$

$$x_{ijt} = \zeta_{jt} + \beta_2 \mathbb{I}\{i \in \text{plants that exit between years } t \text{ and } t+5\} + \varepsilon_{ijt}. \tag{15}$$

Like Foster, Haltiwanger, and Syverson (2008), I find that entrants/exiting plants are significantly smaller than the average plant in a given industry-year, and that exiting plants have significantly lower φ, *tfpq*, and *tfpr*. The productivity advantage of entrants (and productivity disadvantage of exiting plants) is larger for quantity productivity than it is for revenue productivity: Removing the output-price component of revenue productivity tends to increase the difference between surviving and exiting plants' productivities.

In addition to these already-known empirical regularities, I find that exiting plants pay approximately 1.4% (1.3% for the revenue-weighted calculations) more per unit of the intermediate input than the surviving plants in their industry-year. The positive relationship between materials prices and the probability of exit reinforces my assumption of insubstantial quality variation in the benchmark sample: High materials prices are a burden to bear, not a marker of high-quality type, as in, for example, Kugler and Verhoogen (2012).

Comparing the first two columns of Table 7, the productivity advantage of surviving plants is larger for *tfpq* than it is for φ: Removing the materials-price component of

25. To emphasize, exit (and entry) are defined on the basis of true exit and entry from the overall population of establishments, not simply exit (or entry) from the benchmark sample.

quantity productivity marginally decreases the measured difference between surviving and exiting plants' productivities.

The results in Table 7 indicate that the productivity advantage of entrants (compared to incumbents) and surviving plants (compared to exiting plants) is highest when using *tfpq* as the productivity measure. In other words, controlling for output prices but not materials prices tends to make entrants (survivors) appear relatively more productive than incumbents (exiting plants). The next section considers the magnitude and significance of the differences, across the three productivity measures, of the contribution of reallocation—via plants' entry and exit—on industry productivity growth.

3.5. Decompositions of Industry Productivity Growth

In this section, I compute the fraction of aggregate productivity growth that occurs via the *net entry effect*: the exit of relatively unproductive plants and the entry of relatively productive plants. The extent to which reallocation across plants explains aggregate productivity growth has been extensively studied (e.g., Baily, Hulten, and Campbell 1992; Griliches and Regev 1995; Foster, Haltiwanger, and Krizan 2001; and Foster, Haltiwanger, and Syverson 2008). Of these analyses, I am most closely following Foster et al. (2008), who compute the net entry effect when either *tfpr* or *tfpq* is used as the measure of plant productivity. Because entrants charge lower prices than incumbents, the net entry effect is smaller when revenue productivity measures are used instead of quantity productivity measures. The authors conclude that, "in terms of understanding the barriers to allocative efficiency . . . revenue based productivity decompositions may focus too much attention on continuing businesses and not enough on the role of entering businesses" (p. 419). In what follows, I show that accounting for materials prices partially reverses this finding.

Like Foster, Haltiwanger, and Syverson (2008), I use the following growth decomposition, due to Baily, Hulten, and Campbell (1992) and Foster, Haltiwanger, and Krizan (2001):

$$\begin{aligned}\Delta\overline{tfp}_t = &\sum_{i\in\mathcal{C}}\theta_{i,t-1}\Delta tfp_{it} + \sum_{i\in\mathcal{C}}\left(tfp_{i,t-1} - \overline{tfp}_{t-1}\right)\Delta\theta_{it} + \sum_{i\in\mathcal{C}}\Delta tfp_{it}\Delta\theta_{it}\\ &+ \underbrace{\sum_{i\in\mathcal{N}}\theta_{it}\left(tfp_{it} - \overline{tfp}_{t-1}\right)}_{\text{Entry Effect}} - \underbrace{\sum_{i\in\mathcal{X}}\theta_{i,t-1}\left(tfp_{i,t-1} - \overline{tfp}_{t-1}\right)}_{\text{Exit Effect}}. \qquad (16)\end{aligned}$$

where θ_{it} denotes the revenue share of plant i, within its industry, in year t; $\overline{tfp}_t$ gives the revenue-weighted average (log) productivity in year t; Δ is the difference operator; and $\mathcal{C}$, $\mathcal{N}$, and $\mathcal{X}$ are the sets of continuing, entering, and exiting plants. The decomposition highlights the different sources of industry productivity growth, including the Entry Effect, the Exit Effect, and the sum of the two effects (the Net

TABLE 8. Aggregate productivity growth decompositions.

Productivity measure	Total	Entry	Exit	Net entry	Total	Entry	Exit	Net entry
tfpr	–1.60	–0.08	0.08	0.00	1.30	0.23	0.12	0.35
tfpq	–1.60	–0.06	0.15	0.09	1.30	0.32	0.12	0.44
φ	–1.60	–0.09	0.13	0.04	1.30	0.25*	0.14	0.39

Notes: All values are given as percentages, over five-year horizons. In the first four columns, industries are assigned importance according to their total revenues. In the last four columns, industries are assigned importance according to the number of plants.
*The value is significantly different from the corresponding value that uses *tfpq* as the measure of plant productivity (see Online Appendix C for details).

Entry Effect).[26] The magnitudes of these three effects will depend on the productivity measure—either *tfpr*, *tfpq*, or φ—used in equation (16).

The results of the industry decompositions are given in Table 8. I decompose the productivity growth—over five-year intervals—separately for each of the ten industries in the benchmark sample. The values are the averages over these ten industries. In the first four columns, industries with larger revenues (primarily gasoline manufacturing) are given more weight while, in the last four columns, industries' weights are determined by the number of plants in the industry. The main takeaway from the table is that the Net Entry term is larger for quantity productivity (*tfpq*) than it is for either revenue productivity (*tfpr*) or technical efficiency (φ). Consistent with Foster, Haltiwanger, and Syverson (2008), Table 8 indicates that the contribution of net entry to aggregate productivity is larger when output prices are accounted for. At the same time, accounting for materials prices reduces the measured contribution of net entry to industry productivity growth. These patterns are robust to the decomposition method and the relative weights given to different industries.[27]

For completeness' sake, I assess the statistical significance of the differences, across the productivity measures, of the importance of the Entry, Exit, or Net Entry terms. When industries are weighed by the number of plants, the Entry Effect is significantly greater when φ—instead of *tfpq*—is used as the productivity measure. Other differences are not statistically significant.

To summarize, the conventional productivity measures, *tfpq* and *tfpr*, reflect within-industry differences in materials prices. Because exiting plants face relatively high

26. Since a large number of plants enter and exit my benchmark sample without actually entering or exiting their industries, I will be unable to distinguish between the sources of aggregate productivity growth that are listed in the first line of equation (16).

27. Foster, Haltiwanger, and Syverson (2008) consider a second growth decomposition, due to Griliches and Regev (1995). I show, in Online Appendix A.9, that this alternate decomposition method yields results very similar to those presented in Table 8.

One problem with the productivity growth decompositions originates from the over-representation of large plants in the benchmark sample. Because of this, entering and exiting plants are under-represented in the benchmark sample, and the decompositions understate the role of net entry as a source of aggregate productivity growth. In Online Appendix A.10, I show that the qualitative patterns of this section (in particular, the difference in the size of the Net Entry Effect between the three productivity measures) hold after correcting for the under-representation of entering and exiting plants.

materials prices, and because (large) entrants pay relatively low prices, the difference between the productivity of exiting and surviving plants (and between entrants and incumbents) is larger for productivity measures that embody plants' materials prices. As a result, the contribution of reallocation, via entry and exit, is smaller for the productivity measure φ that is cleansed of materials prices. These differences, however, are small and only of marginal statistical significance.

4. Sources of Materials Price Dispersion

I discuss three explanations for the observed within-industry dispersion of intermediate input prices. The sources of materials price dispersion have implications for the social benefits generated by each plant. Plants that pay low materials prices by taking advantage of monopsonistic power are not providing any societal benefit: Low materials prices are a transfer of profits from supplier to buyer. However, if plants pay low materials prices because their suppliers are exceptionally productive, low materials prices represent a positive impact on social welfare. The fraction of these welfare benefits that accrue to consumers will depend, in turn, on the degree to which lower input prices are passed on to final consumers.

To calculate the relative importance of these different sources of materials price dispersion, I need to impute, for each manufacturer, the identities of its suppliers. I outline, in Section 4.1, the algorithm that I use to impute buyer-supplier relationships. In Section 4.2, I compute the fraction of dispersion in *tfpq* and p^{in} that can be explained by plants' geographic locations, their suppliers' marginal costs, and within-supplier deviations. A positive correlation between plants' materials prices and their suppliers' marginal costs stimulates the following question: If plants with low marginal cost suppliers pay less for their inputs, and if having low materials prices is so advantageous, then what prevents plants from purchasing their materials from the low marginal cost suppliers? In Section 4.3, I argue that buyer–supplier relationships are persistent, suggesting that there is some inertial force that inhibits all plants from switching to low marginal cost suppliers.[28]

4.1. Imputation of Buyer–Supplier Relationships

To impute buyer–supplier relationships, I use the algorithm introduced by Atalay, Hortaçsu, and Syverson (2013). The algorithm generates a list of establishments that could potentially receive any shipment that is observed in the Commodity Flow Survey. Consider a hypothetical shipment of commodity c made by establishment h to zip code z. The establishments, i, that could potentially receive this shipment are those who are located in z and are members of an industry that use c. For example, the potential recipients of a shipment of Portland cement to z would be all plants in that zip

28. Foster, Haltiwanger, and Syverson (2008) provide additional anecdotal evidence for the importance of relationship capital; see footnotes 23 and 24 of their paper.

code that are engaged in road construction, concrete brick manufacturing, ready-mix concrete manufacturing, or wholesaling of brick, stone, and related materials. If there are multiple potential recipients of the shipment, and one of these establishments is owned by the same firm as the sending establishment, then I assume that the shipment is received by the same-firm establishment.[29] Otherwise, I assign each potential recipient, i, to be downstream of plant h.[30]

In order to compute suppliers' marginal costs, I require the upstream industry to also be part of the manufacturing sector. Of the ten industries in the benchmark sample, only two—ready-mix concrete and corrugated boxes—have a main input that is produced by a manufacturer. The industries with establishments that could potentially receive Portland cement (STCC = 32411) are road construction firms (SIC = 1610–1619), concrete brick and block manufacturers (SIC = 3271), ready-mix concrete manufacturers (SIC = 3273), and wholesalers of brick, stone, and related materials (SIC = 5032).[31,32] For paper and paperboard manufacturers, I look for shipments in the Commodity Flow Survey for which the commodity code is that of paperboard (STCC = 26311 in 1993, SCTG = 27319–27320 in 1997), which are also sent to zip codes that contain establishments in either the corrugated and solid fiber boxes (SIC = 2653) industry or the folding paperboard boxes (SIC = 2657) industry. Finally, I drop shipments for which the unit price is greater than four times, or less than one-fourth, the average for the industry-year.

For within-firm shipments, surveyed establishments do not report the actual market value of the transaction. Instead, the establishments are asked to estimate what the value of the shipment would have been had it been sold to some other firm. Since it is unclear what these values actually represent, I remove downstream establishments who receive a substantial fraction, 15% or more, of the relevant input from other plants from the same firm.[33]

29. Atalay, Hortaçsu, and Syverson (2013) make the same assumption. This assumption is motivated by the finding that establishment h is much more likely to ship to zip codes that contain an establishment from the same firm. The results of the current section are not sensitive to this assumption.

30. Assigning all potential recipients, i, to be downstream of plant h likely overcounts the number of buyer–supplier relationships. In an unreported robustness check, I reproduce the analysis of Section 4.2, weighing observations by the inverse of the number of potential recipients in the destination zip code. I find that the results are essentially unchanged.

31. The commodity code used in the 1993 Commodity Flow Survey is the Standard Transportation Commodity Code (STCC). A list of STCC codes can be found in pages 117 to 167 of "Reference Guide for the 2008 Surface Transportation Board Carload Waybill Sample", published by Railinc. Since 1997, the Commodity Flow Survey has used the Standard Classification of Transported Goods (SCTG) classification of commodity codes. Documentation related to SCTG codes can be found on the Census web page.

32. Productivity data for cement and ready-mix concrete manufacturers are unavailable in 1997. So, for cement and concrete manufacturers, I only look at buyer–supplier relationships in the 1993 Commodity Flow Survey.

33. While varying the 15% cutoff down to 0% or up to 25% does not affect this section's results, the relationship between input prices and supplier productivity begins to disappear once the cutoff exceeds 25 or 30%.

Bernard, Jensen, and Schott (2006) show that reported prices on cross-border shipments, for which the sender and receiver are part of the same firm, are manipulated to take advantage of the different tax

4.2. *Sources of Materials Price Dispersion*

The purpose of this section is to describe and assess the quantitative importance of the three potential sources of materials price variation.

I begin with some notation. Let χ_{hit} denote the total mass (in thousands of pounds) of shipments sent by plant h to plant i in year t, and let ω_{hit} denote the total value (in thousands of real dollars) of shipments sent by plant h to plant i in year t. Then, the free on board (f.o.b.)[34] price that plant h charges plant i is simply the ratio of the value to the price:

$$P_{hit}^{CFS} \equiv \frac{\omega_{hit}}{\chi_{hit}}. \tag{17}$$

The "CFS" superscript denotes prices computed using the Commodity Flow Survey data (as opposed to the prices that are computed in Section 3, using data from the Census of Manufacturers).[35]

For each downstream plant i, input prices are defined by taking the value-weighted average over all plants, h, that I observe i purchasing from:

$$P_{it}^{in,CFS} \equiv \frac{\sum_{h\in\Gamma(i)} \omega_{hit} P_{hit}^{CFS}}{\sum_{h\in\Gamma(i)} \omega_{hit}}. \tag{18}$$

In equation (18), and throughout the remainder of this section, $\Gamma(i)$ refers to the suppliers of plant i, excluding the establishments that are in the same firm as plant i. Note that, because it does not include freight charges, $P_{it}^{in,CFS}$ will be less than what plants pay for their intermediate inputs. I define a second plant-level input price, which includes freight charges:

$$\tilde{P}_{it}^{in,CFS} \equiv \frac{\sum_{h\in\Gamma(i)} \omega_{hit} \left(P_{hit}^{CFS} + \tau_{hit}\right)}{\sum_{h\in\Gamma(i)} \omega_{hit}}. \tag{19}$$

I estimate transportation costs τ_{hit} from the mileage of the shipment and the mode of transport.[36,37]

policies of the destination and source countries. Even though such an incentive to mis-report does not exist in the Commodity Flow Survey data, I argue that one should not put too much weight on input prices of the plants that buy a substantial fraction of their inputs from within the firm.

34. Unlike the (cost, insurance, and freight) c.i.f. price, the f.o.b. price does not include freight or insurance charges.

35. The Commodity Flow Survey has, up to now, been an unexploited source of data on plants' output prices. With this in mind, I compare plants' output prices, derived from the Commodity Flow Survey to the prices derived from the better-known Census of Manufacturers. For the 66 cement manufacturers in this section's sample, the correlation between $p_h^{out,CFS}$ and p_h^{out} is 39%. For the 162 paperboard manufacturers, the correlation between the two plant-level output prices is 60%.

36. The Bureau of Transportation Statistics collects information on ton-mile freight charges for shipments sent along different transport modes; see US Department of Transportation (2009). Since the Commodity Flow Survey contains information on the weight of each shipment, as well as the distance that the shipment traveled, it is straightforward to estimate the shipment freight charge.

37. For the corrugated-box manufacturing industry, I relate $\tilde{p}_{it}^{in,CFS}$ and p_{it}^{in}. (Remember that p_{it}^{in} cannot be computed in 1992 or 1997 for ready-mix concrete manufacturers.) The strength of this relationship,

TABLE 9. Relationship between materials prices and nearby limestone production.

Nearby limestone employment	–0.043** (0.005)	–0.138** (0.012)	–0.232** (0.028)
(Nearby limestone employment)^2		0.047** (0.005)	0.159** (0.028)
(Nearby limestone employment)^3			–0.031** (0.007)
Adjusted-R^2	0.034	0.056	0.060

Notes: Observations are revenue weighted. $N = 3{,}708$.
**Significant at 5%.

Similar to the analysis of Section 3, all plant-level statistics are stated as the percentage deviation relative to the average value for the industry-year. Again, these deviations are written using lower-case letters.

Geography. Geography is the first of the three sources of materials price variation. As discussed in Section 3.3, of the ten industries in the benchmark sample, concrete is the industry with the strongest spatial correlation in materials prices, while the corrugated-box industry displays relatively weak spatial correlation. Cement prices tend to be lower in areas with an abundance of limestone, namely in the Appalachian and Great Lakes regions.[38] To assess the relationship between concrete plants' materials prices and their proximity to limestone production, I regress—for the 3,708 concrete plant-year observations in the benchmark sample—p_{ijt}^{in} against a cubic polynomial of nearby employment in the limestone industry. The coefficient estimates given in the final column of Table 9 imply that the materials price of concrete plants is roughly 10% higher for plants that are in the 75th percentile of the limestone proximity index, relative to plants in the 25th percentile.

Suppliers' Marginal Costs. Even within geographical areas, there is heterogeneity in plants' suppliers' marginal costs. For any concrete or corrugated-box manufacturer i that is identified by the algorithm outlined in Section 4.1, I compute average supplier productivity $\overline{TFPQ}_{it}$ as follows:

$$\overline{TFPQ}_{it} \equiv \frac{\sum_{h\in\Gamma(i)} \omega_{hit} TFPQ_{ht}}{\sum_{h\in\Gamma(i)} \omega_{hit}}. \tag{20}$$

between the materials prices computed from the two data sources, indicates the success (or lack thereof) of the imputation procedure outlined in Section 4.1. The correlation between $\tilde{p}_{it}^{in,CFS}$ and p_{it}^{in} is 22%, meaning that I am mismeasuring many buyer–supplier relationships, but that the imputation algorithm yields a viable dataset.

38. In 1997, 48% of limestone shipment value originated from eight states—Alabama, Kentucky, Illinois, Indiana, Ohio, Pennsylvania, Tennessee, and West Virginia— which represent roughly 24% of the US population. See http://www.census.gov/prod/ec97/97n2123b.pdf for the state-by-state data on limestone production.

The dispersion of $\overline{tfpq}_{it}$ (the percentage deviation of $\overline{TFPQ}_{it}$ from its industry-year average) is substantial. For plants in the ready-mix-concrete (box-making) industry, the standard deviation of $\overline{tfpq}_{it}$ is 41% (26%). After including year by geographic division fixed effects, the standard deviation of $\overline{tfpq}_{it}$ is 36% for the ready-mix concrete industry, and 25% for the corrugated box industry.[39]

Within-Supplier Price Differences. A third explanation for price variation lies in differences in the relative bargaining power of the suppliers and buyers of any given material input, yielding variation in the prices that suppliers charge, for the same good, across destinations. Define a supplier's average output price $P_{ht}^{out,CFS}$ as a value-weighted average of the prices that it charges in its Commodity Flow Survey shipments. For each buyer–supplier relationship, I define the *within-supplier price deviation* ψ_{hit} as

$${}_{hit} \equiv \log \left. \frac{P_{hit}^{CFS}}{P_{ht}^{out,CFS}} \right), \tag{21}$$

where ${}_{hit}$ is the price that i pays for h's output, relative to the other plants that buy intermediate inputs from h; ${}_{hit}$ is positive provided plant i purchases its material inputs from h at a higher price than $P_{ht}^{out,CFS}$, the average output price of supplier, h.

Figure 1 decomposes the price distribution into two separate components. Any buyer–supplier-specific price p_{hit}^{CFS} is the sum of the supplier's average output prices $p_{ht}^{out,CFS}$ and the within-supplier price deviation ψ_{hit}. The price p_{hit}^{CFS} that a supplier charges a buyer for intermediate inputs can be, mechanically, high for one of two reasons: either the supplier has a high average price $p_{ht}^{out,CFS}$ or the supplier charges i a higher price than its other customers (i.e., ψ_{hit} is large).[40] For my sample of cement and paperboard manufacturers, the distributions of p_{hit}^{CFS}, ψ_{hit}, and $p_{ht}^{out,CFS}$ are depicted in Figure 1. The standard deviation of p_{hit}^{CFS} is 25%, which is 30% larger than the standard deviation of suppliers' average output prices ($SD(p_{ht}^{out,CFS}) = 19\%$), and 50% larger than the standard deviation of the within-supplier deviations ($SD(\psi_{hit}) = 16\%$).[41]

The *average within-supplier price deviation* ψ_{it} measures the extent to which plant i pays its supplier a higher materials price than the other customers of its suppliers. It

39. There are nine Census-defined divisions within the United States. See http://www.census.gov/geo/www/us_regdiv.pdf for a correspondence between states and divisions.

40. Price discriminatory behavior, which would result from differences in buyers' and suppliers' bargaining positions, is a first explanation for these within-supplier price differences. In addition, some of the within-supplier variation in materials prices may potentially be due to the time at which plant i receives its shipments from plant h. In Online Appendix A.11, I argue that, at least for this small sample of concrete and box manufacturers, the timing of shipments is not a primary source of materials price variation.

41. Figure 1 looks similar, whether one uses the sample of cement manufacturers, the sample of paperboard manufacturers, or the pooled sample of paperboard and cement manufacturers. See Online Appendix A.12.

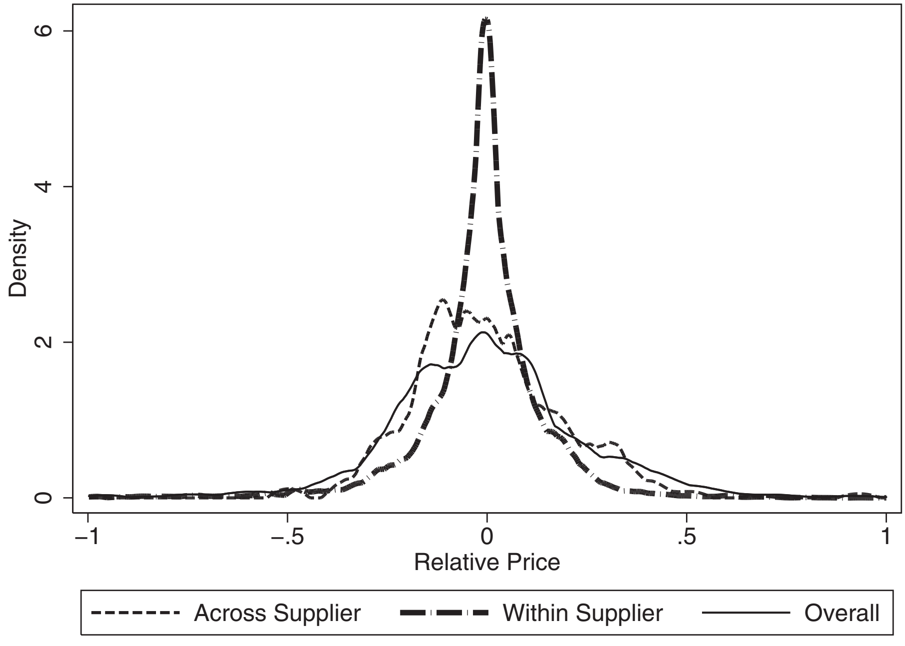

FIGURE 1. Value-weighted price distributions. The sample includes all shipments sent by the cement and paperboard manufacturers that comprised the sample of the regression defined by equation (23).

is a weighted average, over i's suppliers, of the ${}_{hit}$:

$$\psi_{it} \equiv \frac{\sum_{h\in\Gamma(i)} \omega_{hit}\psi_{hit}}{\sum_{h\in\Gamma(i)} \omega_{hit}} = \frac{\sum_{h\in\Gamma(i)} \omega_{hit}\left(p_{hit} - p_{ht}^{out,CFS}\right)}{\sum_{h\in\Gamma(i)} \omega_{hit}}. \tag{22}$$

Regression Results. Using these definitions, I can now compare the price that a plant pays for its material inputs to differences in geography (summarized by division fixed effects), differences in suppliers' marginal costs, and within-supplier price differences:[42]

$$\tilde{p}_{it}^{in,CFS} = \beta_{\text{division}} + \beta_1 \overline{tfpq}_{it} + \beta_2 \psi_{it} + \varepsilon_{it}. \tag{23}$$

The results are presented in Table 10. A 10% increase in the marginal cost of plants' suppliers corresponds to a 2.0% to 2.5% increase in plants' materials prices. The estimated effect of supplier productivity on materials prices is somewhat stronger for boxes than it is for ready-mix concrete. Including fixed effects for the geographic region of the downstream plant has almost no effect on the estimate of β_1.[43] Finally,

42. Using $p_{it}^{in,CFS}$ instead of $\tilde{p}_{it}^{in,CFS}$ as the dependent variable of the regression corresponding to equation (23) generates a similar estimate of β_1.

43. It is possible that division fixed effects are too coarse to sufficiently control for the geographic variation in materials prices. Online Appendix A.13 presents evidence that this is not the case.

TABLE 10. Regression results.

Sample	Boxes			Concrete			Pooled		
$\overline{tfpq}_{it}$	−0.267**	−0.257**	−0.233**	−0.201**	−0.210	−0.146	−0.253**	−0.243**	−0.212**
	(0.059)	(0.057)	(0.056)	(0.092)	(0.110)	(0.105)	(0.050)	(0.048)	(0.047)
$_{it}$			0.340**			0.691**			0.406**
			(0.111)			(0.165)			(0.118)
N	190	190	190	131	131	131	321	321	321
Adjusted-R^2	0.129	0.133	0.223	0.046	0.091	0.511	0.107	0.117	0.263
Division F.E.?	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Notes: This table presents coefficient estimates and robust standard errors, from the regressions defined by equation (23). The dependent variable in this regression is $\tilde{p}_{it}^{in,CFS}$. Observations are assigned weights according to the revenues of plant i.
**Significant at 5%.

TABLE 11. Unexplained materials price variation.

Sample	Include division fixed effects ?	No	Yes	No	Yes	No	Yes	No	Yes
	Include $\overline{tfpq}_{it}$?	No	No	Yes	Yes	No	No	Yes	Yes
	Include ψ_{it}?	No	No	No	No	Yes	Yes	Yes	Yes
	Sample size								
Boxes	190	0.187	0.180	0.174*	0.170*	0.175*	0.169*	0.164*	0.160*
Concrete	131	0.359	0.338	0.349	0.330	0.268*	0.247*	0.262*	0.241*
Pooled	321	0.209	0.204	0.197*	0.194*	0.189*	0.185*	0.180*	0.177*

Notes: Each cell gives the real-revenue-weighted standard deviation of the residuals in a particular regression; the full specification is given in equation (23). Across the columns of the table, different combinations of independent variables are included in the regressions.
*The decline in dispersion is significantly more than the decline that would occur from simply including "fake" random variables on the right-hand side of equation (23). See Online Appendix C for details.

the coefficient estimate β_2 on the average within-supplier deviation term is positive and significant. Note that a mechanical relationship between ψ_{it} and $\tilde{p}_{it}^{in,CFS}$ exists, as higher-than-average-priced shipments will generate a large value for $\tilde{p}_{it}^{in,CFS}$ (see equation (19)) and a large value of ψ_{it} (see equation (22)). Measurement error in P_{hit}^{CFS}, for example, will skew the coefficient estimate of β_2 towards 1.

Each cell in Table 11 presents the unexplained variation—measured as the (revenue-weighted) standard deviation of the residuals—when $\tilde{p}_{it}^{in,CFS}$ is regressed on different combinations of the right-hand side variables of equation (23). Comparing the first and second columns of Table 11, I calculate that the inclusion of division fixed effects reduces the unexplained variation of materials prices by approximately 2%. The inclusion of suppliers' productivities reduces the unexplained variation by approximately 6%, while the two sets of variables jointly reduce the unexplained price variation by 7%. Finally, the full combination of right-hand-side variables—including the average within-supplier deviation—reduces the unexplained variation of $\tilde{p}_{it}^{in,CFS}$ by 15%. To summarize, both within-supplier and between-supplier explanatory factors are significant and quantitatively important when accounting for the dispersion in downstream plants' materials prices.[44] These findings indicate that while purely geographical considerations—such as spatial differences in resource abundance—drive some of the differences in materials prices, the factor market's competitive environment is also of primary significance.

4.3. Persistence of Relationships

Buyer–supplier relationships are persistent across time, suggesting that there is some force that inhibits intermediate inputs purchasers from switching suppliers. Whether this inhibiting force reflects some extra profitability that is conferred by repeated interaction, or some idiosyncratic match-specific productivity, it prevents all buyers from switching to the lowest-cost intermediate goods suppliers.

To provide some empirical evidence for the persistence of buyer–supplier relationships, I explore the shipments sent by cement and paperboard manufacturers in the 1993 and 1997 Commodity Flow Surveys. As before, the Commodity Flow Survey does not identify the downstream buyer. Instead, I proxy for the identity of the downstream buyer using the destination zip code. I run a conditional logit regression, described by equation (24); the dependent variable equals 1 if the cement/paperboard plant i ships to zip code z in 1997. The explanatory variable of interest is an indicator, which equals 1 if the plant shipped to the zip code in 1993. Destination zip code-level fixed effects, supplier fixed effects, and the log distance between i and z are additional explanatory variables:

$$\begin{aligned}\mathbb{I}\{i \rightarrow z \text{ in } 1997\} = \beta_z + \beta_i + \beta_3 \log(\text{distance } i \rightarrow z) + \beta_4 \mathbb{I}\{i \rightarrow z \text{ in } 1993\} \\ + \beta_5 \mathbb{I}\{\text{plant of i's firm is located in } z \text{ in } 1997\} + \varepsilon_{iz}. \qquad (24)\end{aligned}$$

The results are presented in Table 12. Both cement and paperboard suppliers' decisions on which destinations to ship to are persistent across time. If plant i sells to zip code z in 1993, the probability that i will sell to z in 1997 is much larger, approximately 6 to 8 times larger for cement manufacturers, and 10 to 14 times larger for paperboard manufacturers.

There are two distinct interpretations of the positive estimate on β_4, the coefficient on the persistence of buyer–supplier relationships (see, for example, Dubé, Hitsch, and Rossi 2010). In the first interpretation, an establishment's profitability of working with a counterparty increases from having transacted with that counterparty in the past. Kellogg (2011), for instance, documents that oil production companies and drillers become more productive as they gain experience working with one another. According

44. Regarding the statistical significance of the results, note that any set of variables—for example, a random variable drawn from a standard normal distribution, or a set of twelve dummy variables that sum up to 1—will necessarily explain some positive fraction of the variation in $\tilde{p}_i^{in,CFS}$. In Online Appendix C, I test whether the decline in dispersion is significantly greater than what would be expected from including different combinations of "fake" random variables on the right-hand side of equation (23).

TABLE 12. Persistence of buyer–supplier relationships.

Sample	Cement	Cement	Cement	Paperboard	Paperboard	Paperboard
Log mileage	–2.835	–2.594	–2.593	–1.025	–0.867	–0.881
	(0.050)	(0.050)	(0.051)	(0.024)	0.026	(0.026)
Did the plant sell to the zip code in 1993?		2.075	2.009		2.988	2.661
		(0.105)	(0.105)		(0.067)	(0.069)
N	106,795	106,795	106,795	75,360	75,360	75,360
Number of zip codes	2,015	2,015	2,015	1,256	1,256	1,256
Number of plants	53	53	53	60	60	60
Pseudo-R^2	0.687	0.713	0.718	0.148	0.257	0.290
Unconditional probability of shipping to zip code z	0.021	0.021	0.021	0.030	0.030	0.030
Include control for firm presence in z?	No	No	Yes	No	No	Yes

Notes: This table presents coefficient estimates and standard errors, from the regression defined by equation (24). The sample is comprised of cement and paperboard plants that were included in the sample of Regression (23). For a zip code to be in the sample, at least one plant in the sample must have shipped to the zip code in 1997.[45]

to the second interpretation, some establishments happen to find it more profitable to work with certain counterparties for idiosyncratic reasons, other than geographic proximity. The estimate of the persistence term β_4 will be positive provided these idiosyncratic factors display some persistence. Unfortunately, the data that I have at hand do not permit me to distinguish between these two interpretations. Either interpretation, however, is consistent with downstream establishments that decide to remain matched with high marginal cost suppliers.

5. Conclusion

In this paper, I have studied the consequences and sources of materials price dispersion. Variation in materials prices explains a substantial fraction of the variation in plants' marginal costs, revenue total factor productivities, and probabilities of survival. Moreover, one reason why some plants have low materials prices is that they have access to suppliers with low marginal costs.

The paper's results suggest that establishments' survival and growth prospects are directly related to those of their customers and/or suppliers. In future work, I hope to investigate the relationship between establishments' growth and the growth rates of their counterparties. Such an investigation will be an important building block

45. In addition, I restrict the sample to establishments that were sampled in both the 1993 and 1997 Commodity Flow Surveys. Secondly, in order to comply with Census disclosure rules, I restrict the sample to plants that are members of firms f such that the following three criteria hold: (a) there exists at least one i, z pair for which plant i (owned by f) shipped to z in 1993, but not in 1997; (b) there exists at least one i, z pair for which plant i shipped to z in 1997, but not in 1993; and (c) there exists at least one i, z pair for which i shipped to z in both 1993 and 1997. The coefficient estimates are similar when the sample is constructed without this second restriction.

in understanding the propensity with which shocks to a small set of firms have the potential to cascade throughout the economy and produce aggregate fluctuations.

Appendix: Robustness Checks and Other Calculations

A.1. Industries with Heterogeneous Quality Outputs

In this section, I reproduce the empirical analysis of Sections 3.1–3.3 for a set of industries that display substantial output quality variation. The four industries that I choose for this exercise are cucumber pickles, sausages, softwood cut stock, and wine. Details on the construction of the sample can be found in Online Appendix B.2.

Correlations among plant-level characteristics are presented in Table A.1. Compared to the benchmark sample, the standard deviations of most plant-level characteristics are larger, while the correlations among the different productivity measures are, in general, weaker. While the correlation between *tfpr* and p^{in} is negative (−0.232) and significant in the benchmark sample, in the Quality Variation sample there is essentially no relationship between input prices and revenue productivity. Within the Quality Variation sample, high materials prices reflect high-quality inputs, which in turn lead to greater profitability. (There is still the countervailing relationship—as for the benchmark sample—where high materials prices reflect unfavorable factor market conditions, potentially lowering profitability.)

The dispersions of *tfpq* and φ are given in Table A.2. For the pooled sample, the dispersions of the two distributions are essentially the same. Looking across the four industries, there is a significant decline in productivity dispersion for one of the industries, softwood cut stock, and no difference for the other three industries.

In Table A.3, I present regression results, in which I regress plants' materials prices against the materials prices of nearby plants (those within 250 miles, in the same industry-year). The fraction of materials price variation that is explained by neighbors' average materials prices is essentially 0 for each of the four industries in the Quality Variation sample.

In summation, output quality variation has the potential to severely attenuate the difference between the dispersions of φ and *tfpq*. To the extent that any quality variation

TABLE A.1. Correlations and standard deviations of plant-level characteristics.

	p^{in}	p^{out}	*tfpq*	φ	*tfpr*
p^{out}	0.284**				
tfpq	–0.273**	–0.808**			
φ	0.254**	–0.659**	0.858**		
tfpr	0.024	0.329**	0.305**	0.290**	
Std. Dev.	0.318	0.385	0.380	0.380	0.237

Notes: Observations are revenue weighted. $N = 1{,}256$.
**Correlation is significantly different from 0, at the 5% level (see Online Appendix C for details).

TABLE A.2. Dispersion of *tfpq* and φ.

Sample	Dispersion of *tfpq* 90/10	75/25	SD	Dispersion of φ 90/10	75/25	SD	Percentage decline 90/10	75/25	SD	N
Pickles	0.891	0.446	0.344	0.881	0.412	0.339	1.2%	8.6%	1.3%	145
Sausages	0.727	0.399	0.295	0.747	0.366	0.301	−2.7%	9.5%	−2.0%	621
Softwood	1.571	0.818	0.547	1.316	0.697	0.477	21.4%**	18.9%	16.0%**	160
Wine	1.314	0.696	0.479	1.268	0.726	0.481	3.6%	−4.0%	−0.5%	330
Pooled	0.948	0.494	0.380	0.977	0.486	0.380	−2.9%	1.7%	0.0%	1256

Notes: Observations are revenue weighted.
**The difference between *tfpq* and φ is significant at the 5% level (see Online Appendix C for details).

TABLE A.3. Spatial correlation of materials prices.

Sample	β	S.E.	Adjusted-R^2
Pickles	0.124	0.130	–0.001
Sausages	0.038	0.075	–0.001
Softwood	–0.165	0.137	0.003
Wine	–0.456	0.195	0.013
Pooled	–0.017	0.064	–0.001

Notes: The dependent variable is p_{ijt}^{in}, and the independent variable is the (revenue-weighted) average of the $p_{i'jt}^{in}$ for the plants that are within a 250-mile radius of plant i in industry j and year t. Observations are revenue weighted.

exists in the benchmark sample, the difference between the dispersions of φ and *tfpq*, as reported in Table 3, may be downwardly biased.

A.2. Variation in Input Quality

One of the main assumptions of the empirical analysis is that variation in input quality is not an important source of variation of input prices. I have chosen industries to try to minimize the role of input quality differentiation. There is one specific industry, ready-mix concrete, for which there is reason to suspect that input quality differences could be contaminating some of the results. In this section, I explain why input quality varies across plants, and then determine how big an effect input quality variation has on the observed relationships between input prices and different productivity measures.

Portland cement, the main intermediate input used in the production of ready-mix concrete, comes in four types, labeled type I, II, III, or IV.[46] Type-I and II cement account for over 90% of the expenditures on cement, with the majority of sales coming from type-I cement (US Department of Interior 1989). In areas where the soil has

46. The standards for the different types of Portland cement are set by the American Society for Testing and Materials (ASTM). See the ASTM web page for more information on the distinguishing features of different types of Portland cement: http://www.astm.org/Standards/C150.htm.

TABLE A.4. Correlations between plant-level characteristics.

Sample	p^{in}, *tfpq*	p^{in}, φ	p^{in}, p^{out}	p^{in}, *tfpr*	φ, *tfpq*	*tfpq*, *tfpr*	*tfpq*, p^{out}	N
Entire United States	–0.306**	0.120**	0.276**	–0.127**	0.908**	0.741**	–0.476**	3708
Divisions 1–7	–0.341**	0.089**	0.251**	–0.180**	0.906**	0.750**	–0.430**	3049
Divisions 8–9	–0.351**	0.066	0.360**	–0.105	0.911**	0.688**	–0.597**	659

Notes: Observations are revenue weighted.
**The correlation is significantly different from 0, at the 5% level.

high sulfate concentrations, type-II cement may be preferable to the less expensive type-I cement, since ready-mix concrete produced using type-I cement is susceptible to *sulfate attack* (cracking or loss of strength in the presence of sulfate). Since high sulfate concentrations exist only in the soil of parts of the western third of the United States, one should observe type-I and type-II cement consumed in the western United States, and only type-I cement consumed in the remainder of the United States.[47]

Given this geographic difference in soil composition, I split the sample of ready-mix concrete plants into two subsamples: plants residing in Census divisions 1–7, and plants located in Census divisions 8–9.[48] The dispersion of p^{in} is larger in divisions 8–9 (20.0%, versus 17.0% for divisions 1–7), as some ready-mix concrete plants purchase the low-price type-I cement, while others must purchase the high-price type-II cement. In contrast, in the eastern United States, virtually all ready-mix concrete plants purchase type-I cement, leading to a more compressed p^{in} distribution. For both subsamples, *tfpq* and p^{in} are inversely related to one another, with the negative relationship between *tfpq* and p^{in} somewhat stronger in the eastern United States; see Table A.4. These geographic differences are consistent with greater cement quality variation in the western United States.

In Table A.5, I compute the dispersion of *tfpq* and φ for the ready-mix concrete subsamples. The decline in dispersion is larger for each of the two subsamples than it is for the pooled sample of 3,708 ready-mix concrete plants.

In Table A.6, I assess the spatial correlation of materials prices, separately for plants in the eastern and western United States. Materials prices are strongly spatially correlated, within each of the two parts of the United States. Thus, it does not seem as if the spatial correlation of cement prices is primarily due to higher-than-average input quality in the western United States.

In summation, there is almost no variation in the quality of cement purchased by ready-mix concrete plants in the eastern two-thirds of the United States. For this subsample, the difference between the standard deviation of *tfpq* and the standard

47. Cement type is not recorded in the Census of Manufacturers materials file. I confirm, using the Census of Manufacturers production file, that only type-I cement is produced by plants in the eastern two-thirds of the United States, while both types I and II are produced in the western United States.

48. Census division 8 is made up of Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming, while Census division 9 includes Alaska, California, Hawaii, Oregon, and Washington.

TABLE A.5. Dispersion of *tfpq* and φ.

Sample	Dispersion of *tfpq*			Dispersion of φ			Percentage decline			
	90/10	75/25	SD	90/10	75/25	SD	90/10	75/25	SD	N
Entire United States	0.521	0.251	0.224	0.486	0.236	0.215	7.4%**	6.6%**	4.4%**	3708
Divisions 1–7	0.486	0.238	0.211	0.439	0.222	0.199	11.3%**	7.7%**	6.2%**	3049
Divisions 8–9	0.611	0.296	0.255	0.570	0.253	0.239	7.4%	18.3%**	6.9%**	659

**The difference between *tfpq* and φ is significant at the 5% level.

TABLE A.6. Spatial correlation of materials prices.

Sample	β	S.E.	Adjusted-R^2
Entire United States	0.913	0.028	0.222
Divisions 1–7	0.936	0.033	0.210
Divisions 8–9	0.812	0.068	0.177

Notes: The dependent variable is p^{in}_{ijt}, and the independent variable is the (revenue-weighted) average of the $p^{in}_{i'jt}$ for the plants that are within a 250-mile radius of plant i in industry j and year t. Observations are revenue weighted.

deviation of φ is 2 to 3 percentage points larger than the differences that are reported in Table 3. So, a moderate amount of materials quality variation would probably cause me to somewhat under-report the fraction of productivity dispersion that is due to differences in factor market conditions.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Online Appendix
Replication

ONLINE APPENDIX FOR "MATERIALS PRICES AND PRODUCTIVITY"

Enghin Atalay
University of Chicago

Appendix A: Robustness Checks and Other Calculations

A.3. Substitution Between Material Inputs and Other Inputs

The empirical analysis of Section 3 invokes the assumption that the elasticity of substitution, $\hat{\varrho}$, between material inputs and all other inputs equals 1 (see Assumption 1). In reality, material inputs are likely to be complements to other inputs. In this subsection, I analyze how the dispersion of φ differs under different assumptions on $\hat{\varrho}$.

Consider a plant with technical efficiency Φ_{ijt}. Assume that, for plant i, the price of a unit of the "priced" intermediate input is P_{ijt}^{in}, and let the corresponding industry-year average be $\bar{P}_{jt}^{in}$. The prices of the other inputs are assumed to be the same for all plants in the industry-year (see Assumption 2). With an elasticity of substitution of $\hat{\varrho}$, plant i's marginal cost equals:

$$MC_{ijt} = \frac{1}{\Phi_{ijt}} \left[S_{jt} \cdot \sigma_{jt} \cdot \left(\frac{P_{ijt}^{in}}{\bar{P}_{jt}^{in}} \right)^{1-\hat{\varrho}} + 1 - S_{jt} \cdot \sigma_{jt} \right]^{\frac{1}{1-\hat{\varrho}}} \qquad \text{(A.1)}$$

As in Section 3, $\sigma_{jt} \cdot S_{jt}$ refers to the expenditure share of "priced" materials. Equation (A.1) states that plants' marginal costs are determined by their technical efficiencies (Φ_{ijt}) and the composite price that they face for intermediate inputs and other inputs. The elasticity, $\hat{\varrho}$, dictates how the prices of intermediate inputs and other inputs are combined. As $\hat{\varrho}$ decreases, a larger weight is allotted to the input with a higher relative price.

E-mail: atalay@uchicago.edu

	$\hat{\varrho}$	0.2	0.4	0.6	0.8	1.0
Revenue-	Yes	0.1507	0.1507	0.1507	0.1507	0.1506
weighted?	No	0.2193	0.2192	0.2192	0.2191	0.2191

TABLE A.7. Dispersion of φ, as computed using equations (9) and (A.2).
Notes: The dispersion of φ, when $\hat{\varrho} = \mathbf{1.0}$, equals the value given in the final two rows of Table 3. N=10,503.

Re-arranging equation (A.1) yields the following expression for Φ_{ijt} in terms of $TFPQ_{ijt}$ and P_{ijt}^{in}:

$$\Phi_{ijt} = TFPQ_{ijt} \left[S_{jt} \cdot \sigma_{jt} \cdot \left(\frac{P_{ijt}^{in}}{\bar{P}_{jt}^{in}} \right)^{1-\hat{\varrho}} + 1 - S_{jt} \cdot \sigma_{jt} \right]^{\frac{1}{1-\hat{\varrho}}} \tag{A.2}$$

For the pooled benchmark sample, I use equation (A.2) to compute the standard deviation of φ_{ijt}, for $\hat{\varrho} \in \{0.2, 0.4, .0.6, 0.8, 1.0\}$. These results, which are presented in Table A.7, illustrate that the dispersion of φ is robust to changes in the elasticity of substitution, even as $\hat{\varrho}$ approaches 0. Varying the elasticity of substitution, $\hat{\varrho}$, only has a noticeable effect on the measured technical efficiency for plants that have very small or very large values of $P_{ijt}^{in} \div \bar{P}_{jt}^{in}$. Since most plants have materials prices that are close to the industry average, $\hat{\varrho}$ does not substantially alter the measured dispersion of φ.

A.4. Substitution Across Material Inputs

Throughout the body of the paper, I assume that the elasticity of substitution between different material inputs—for industries that use multiple material inputs—is 0 (see Assumption 4). For plants that produce ready-mix concrete, I assess the importance of the assumption that plants may not substitute across different material inputs.

When the elasticity of substitution between gravel/sand and cement is constant (but not necessarily 0), the price of a bundle of material inputs equals:

$$P_{ijt}^{in} \equiv \left[\frac{s_{jt}^{Gravel}}{s_{jt}^{Gravel} + s_{jt}^{Cement}} \cdot \left(\frac{P_{Gravel,ijt}^{in}}{\bar{P}_{Gravel,jt}^{in}} \right)^{1-\varrho} + \frac{s_{jt}^{Cement}}{s_{jt}^{Gravel} + s_{jt}^{Cement}} \cdot \left(\frac{P_{Cement,ijt}^{in}}{\bar{P}_{Cement,jt}^{in}} \right)^{1-\varrho} \right]^{\frac{1}{1-\varrho}} \tag{A.3}$$

In equation (A.3), s_{jt}^{Gravel} refers to the share of materials expenditures that go to gravel, $P_{Gravel,ijt}^{in}$ is the price that plant i pays per 1000 pounds of gravel in year t, $\bar{P}_{Gravel,ijt}^{in}$ is the geometric average of the price paid by all ready-mix concrete producing plants in year t, and ϱ is the elasticity of substitution between cement and sand/gravel. In the baseline analysis, I had set $\varrho = 0$.

Using equation (A.3), I compute ready-mix concrete plants' materials prices. I then re-compute Φ_{ijt}, using equation (8), and φ_{ijt}, using equation (9). The dispersion of φ is given in Table A.8. As ϱ increases, the price of a bundle of intermediate

Sample	Revenue-weighted?	90/10	SD	90/10	SD	90/10	SD	N
ϱ		0.1	0.1	0.3	0.3	0.5	0.5	
Concrete	No	0.5223	0.2302	0.5223	0.2302	0.5222	0.2303	3708
	Yes	0.4864	0.2151	0.4863	0.2151	0.4862	0.2151	3708
Pooled	No	0.4930	0.2190	0.4929	0.2190	0.4928	0.2191	10,503
	Yes	0.3240	0.1506	0.3240	0.1506	0.3240	0.1506	10,503

TABLE A.8. Dispersion of φ, as computed using equations (8), (9), and (A.3).

inputs decreases for plants that have exceptionally cheap input prices for one of the two intermediate inputs. Also, as ϱ increases, the relative price of the bundle increases for plants that pay roughly the same relative price for the two intermediate inputs. It turns out that, in combination, these two effects have almost no impact on the overall dispersion of φ.

A.5. An Alternative Measure of Plant Productivity

In this subsection, I re-compute Table 3 using the productivity measure discussed in Caves, Christensen, and Diewert (1982) (hereafter, CCD). Unlike the current paper, which uses a Cobb-Douglas productivity measure, CCD assume that plants' production technologies take the (more flexible) translog form. Moreover, the parameters of this production function are allowed to vary across the plants within an industry. A third difference, between the current paper and CCD, is that the latter paper invokes the assumption that plants (flexibly) choose inputs to minimize costs.

The set-up in Caves, Christensen, and Diewert (1982) yields the following comparison of plants' productivities (see equation (33) of that paper):[1]

$$\Phi_{ijt}^{CCD} \equiv Q_{ijt} \cdot \left(L_{ijt}\right)^{-\frac{\lambda_{jt}+\lambda_{ijt}}{2}} \cdot \left(K_{ijt}\right)^{-\frac{\kappa_{jt}+\kappa_{ijt}}{2}} \cdot \left(E_{ijt}\right)^{-\frac{\varepsilon_{jt}+\varepsilon_{ijt}}{2}} \cdot \left(N_{ijt}\right)^{-\frac{\sigma_{jt}+\sigma_{ijt}}{2}} . \tag{A.4}$$

In equation (A.4), $\lambda_{jt}, \kappa_{jt}, \varepsilon_{jt}$, and σ_{jt} are the industry average cost shares of labor, capital, electricity, and materials (as in Section 2.4), while λ_{ijt}, κ_{ijt}, ε_{ijt}, and σ_{ijt} are the corresponding plant-specific cost shares. The other two productivity measures are defined as follows:

$$\begin{aligned} TFPQ_{ijt}^{CCD} &= \Phi_{ijt} \cdot \left(P_{ijt}^{in}\right)^{-\frac{\sigma_{jt}+\sigma_{ijt}}{2}} \\ TFPR_{ijt}^{CCD} &= TFPQ_{ijt}^{CCD} \cdot P_{ijt}^{out} \end{aligned}$$

Table A.9 recomputes the within-industry productivity dispersions, using the CCD approach for computing plants' productivities. Here, too, the main results of

1. Unfortunately, I can't apply the CCD methodology exactly. In that paper, the authors assume that each plant produces every relevant output and uses every relevant input. To give an example, when comparing plants in the ready-mix concrete industry, if there are some plants that manufacture concrete bricks (a product distinct from ready-mix concrete), then all plants must produce at least some concrete bricks. This assumption turns out to be violated in the data. For this reason, I deflate input purchases in the manner described by equation (1).

Revenue-weighted?	Dispersion of $tfpq^{CCD}$ 90/10	75/25	SD	Dispersion of φ^{CCD} 90/10	75/25	SD	Percent Decline 90/10	75/25	SD
Yes	0.438	0.203	0.188	0.391	0.193	0.177	12.8%*	5.7%	6.4%*
No	0.521	0.249	0.229	0.489	0.234	0.219	6.7%*	6.5%*	4.5%*

TABLE A.9. Dispersion of $tfpq$ and φ.
Notes: In the final three columns, stars indicate that the difference between $tfpq$ and φ is statistically significant, at the 5% level (see Web Appendix C for details).

Table 3 survive. The difference in the dispersion of $tfpq$ and φ ranges between 4.5% and 12.8%, and is statistically different from 0 for five of the six measures. Thus, the different methodology—due to CCD—yields very similar conclusions regarding the dispersion of measured productivity that is attributable to materials price variation.

A.6. More Correlations

Table A.10 presents correlations among plant-level characteristics for each of the 10 industries in the benchmark sample.

For several of the correlations, the subsample of raw cane sugar manufacturing plants is anomalous. For this industry, plants' marginal costs are unrelated to their materials prices. Moreover, the correlation between input prices and technical efficiencies is much stronger (48%) than for other subsamples. These patterns are somewhat puzzling. Most likely, either there is substantial measurement error in the physical units that cane sugar refiners use, or there is significant quality heterogeneity among the raw cane sugar manufacturers.

Except for the raw cane sugar industry, correlations among plant-level characteristics are qualitatively similar across the different industries in the benchmark sample. The correlation between materials prices and quantity productivities is moderately negative for the nine other industries, while the correlation between quantity productivities and output prices is strongly negative (ranging between −37% and −88%). Finally, the three productivity measures are always highly correlated with one another, with the correlation between φ and $tfpq$ being larger than the correlation between $tfpq$ and $tfpr$.

A.7. Measurement Error

As discussed in Section 3.2, measurement error in the quantities that a plant consumes or produces has the potential to bias the correlations among plant-level characteristics. In this subsection, I assess the importance of measurement error.

To do so, I perform an exercise in which I add a randomly-generated disturbance to plant-level input and output quantities, and then re-compute the plant-level productivity measures. In particular, for each of the $10,503$ plant-year observations in the benchmark sample, I take two draws from a standard normal distribution. Use υ_{ijt} and ϖ_{ijt} to refer to these randomly-generated numbers for plant i, in industry j, and year t. I apply these randomly-generated numbers to the physical quantities of input and output purchases, yielding "contaminated" physical quantity

Sample	$p^{in}, tfpq$	p^{in}, φ	p^{in}, p^{out}	$p^{in}, tfpr$	$\varphi, tfpq$	$tfpq, tfpr$	$tfpq, p^{out}$
Boxes, Yr.≤'87	-0.286*	0.226*	0.280*	-0.042	0.868*	0.418*	-0.797*
Boxes, Yr.≥'92	-0.352*	0.089	0.286*	-0.086*	0.901*	0.116*	-0.877*
Coffee	-0.485*	0.030	0.343*	-0.227	0.855*	0.592*	-0.584*
Concrete	-0.306*	0.120*	0.276*	-0.127*	0.908*	0.740*	-0.476*
Flour	-0.394*	0.468*	0.312*	-0.011	0.628*	0.128	-0.722*
Gasoline	-0.395*	0.141*	0.171*	-0.310*	0.854*	0.824*	-0.368*
Milk, Bulk	-0.424*	-0.149	0.410*	-0.072	0.958*	0.444*	-0.770*
Milk, Packaged	-0.281*	0.049	0.225*	-0.104*	0.945*	0.435*	-0.754*
Sugar	-0.034	0.481*	0.237*	0.100	0.860*	0.858*	-0.466*
Yarn	-0.301*	0.197	0.211*	-0.174*	0.875*	0.491*	-0.763*
Pooled	-0.369*	0.127*	0.231*	-0.232*	0.873*	0.694*	-0.551*

TABLE A.10. Correlations among plant-level characteristics.
Notes: Stars indicate that the correlation is significantly different from 0, at the 5% level (see Web Appendix C for details).

measures:

$$\hat{q}_{ijt} = q_{ijt} + \vartheta \cdot \upsilon_{ijt} \tag{A.5}$$
$$\hat{n}_{ijt} = n_{ijt} + \vartheta \cdot \varpi_{ijt} \tag{A.6}$$

In equations (A.5)-(A.6), and throughout the rest of this subsection, $\hat{x}$ will refer to the version of any plant-level characteristic, x, that is imbued with extra measurement error. ϑ is a parameter that characterizes the amount extra measurement error.

The definitions of plants' input prices, output prices, and productivity measures follow from equations (A.5)-(A.6), in combination with equations (3)-(8):

$$\hat{p}^{out}_{ijt} = p^{out}_{ijt} - \vartheta \cdot \upsilon_{ijt} \tag{A.7}$$
$$\hat{p}^{in}_{ijt} = p^{in}_{ijt} - \vartheta \cdot \varpi_{ijt} \tag{A.8}$$
$$\widehat{tfpq}_{ijt} = tfpq_{ijt} + \vartheta \cdot \upsilon_{ijt} \tag{A.9}$$
$$\hat{\varphi}_{ijt} = \varphi_{ijt} + \vartheta \cdot \upsilon_{ijt} - S_{jt} \cdot \sigma_{jt} \cdot \vartheta \cdot \varpi_{ijt} \tag{A.10}$$

In this exercise, no extra measurement error is applied to the revenue productivity measure ($tfpr$), because both q_{ijt} and n_{ijt} are absent in the computation of this variable.

Correlations among the contaminated plant-level characteristics are presented in Table A.11. Table A.12 displays the standard deviations of $\hat{\varphi}$, $\widehat{tfpq}$, $\widehat{p^{in}}$, and $\widehat{p^{out}}$, in addition to the 5-year autocorrelation coefficients of $\hat{\varphi}$, $\widehat{tfpq}$, $\widehat{p^{in}}$, and $\widehat{p^{out}}$. The takeaways from Tables A.11 and A.12 are that measurement error in input and output quantities magnifies the correlation between input prices and technical efficiency, and between output prices and quantity productivity. Second, measurement error attenuates the correlation between input prices and quantity productivity, and between input prices and revenue productivity. Third, measurement error increases the dispersions of quantity productivity and technical efficiency, with a larger increase in the dispersion of the technical efficiency term. (Since the technical efficiency term is computed using both input and output quantities, it is more sensitive to measurement

ϑ	$\widehat{p^{in}}, \widehat{tfpq}$	$\widehat{p^{in}}, \widehat{\varphi}$	$\widehat{p^{in}}, \widehat{p^{out}}$	$\widehat{p^{in}}, tfpr$	$\widehat{\varphi}, \widehat{tfpq}$	$\widehat{tfpq}, tfpr$	$\widehat{tfpq}, \widehat{p^{out}}$
0.01	-0.366	0.128	0.226	-0.234	0.874	0.694	-0.553
0.02	-0.360	0.135	0.218	-0.234	0.874	0.691	-0.558
0.03	-0.350	0.147	0.207	-0.232	0.873	0.687	-0.568
0.04	-0.337	0.163	0.195	-0.229	0.872	0.680	-0.580
0.05	-0.323	0.182	0.182	-0.225	0.870	0.671	-0.595
0.06	-0.306	0.203	0.168	-0.220	0.868	0.660	-0.612
0.07	-0.289	0.226	0.155	-0.215	0.865	0.648	-0.631
0.08	-0.271	0.249	0.141	-0.208	0.863	0.635	-0.650
0.09	-0.254	0.272	0.128	-0.202	0.860	0.621	-0.669
0.10	-0.237	0.294	0.116	-0.195	0.857	0.607	-0.688

TABLE A.11. Biases generated by measurement error.
Notes: The table presents correlations among plant-level characteristics. In a given row, the standard deviation of the extra measurement error is given by ϑ. In the calculations, observations are weighed by real revenues.

	Std. Dev.				Persistence			
ϑ	$\widehat{tfpq}$	$\widehat{\varphi}$	$\widehat{p^{out}}$	$\widehat{p^{in}}$	$\widehat{tfpq}$	$\widehat{\varphi}$	$\widehat{p^{in}}$	$\widehat{p^{out}}$
0.01	0.161	0.151	0.117	0.119	0.180	0.186	0.320	0.305
0.02	0.162	0.152	0.117	0.120	0.184	0.185	0.308	0.300
0.03	0.163	0.155	0.119	0.121	0.187	0.182	0.290	0.292
0.04	0.165	0.158	0.121	0.124	0.189	0.177	0.268	0.281
0.05	0.168	0.162	0.124	0.127	0.189	0.170	0.244	0.268
0.06	0.171	0.166	0.128	0.131	0.189	0.163	0.217	0.254
0.07	0.174	0.172	0.132	0.135	0.187	0.154	0.191	0.239
0.08	0.178	0.177	0.136	0.140	0.185	0.146	0.165	0.224
0.09	0.182	0.184	0.142	0.145	0.182	0.137	0.141	0.210
0.10	0.187	0.191	0.147	0.151	0.178	0.128	0.118	0.197

TABLE A.12. Biases generated by measurement error.
Notes: The first four columns give the standard deviations of quantity productivity, technical efficiency, input prices, and output prices, while the final four columns present the 5-year autocorrelation coefficients of the same variables. In a given row, the standard deviation of the extra measurement error is given by ϑ. In the calculations, observations are weighed by real revenues.

error.) Finally, measurement error reduces the estimated persistence of the plant-level input prices, output prices, and productivity measures.

A.8. Unweighted Results

In this subsection, I present the unweighted versions of Tables 2, 3, 6, A.2, A.3, and A.10. In the benchmark calculations, observations are revenue weighted. To preview the main results, all of the main conclusions of Section 3 are robust to the weighting scheme.

The first two tables, Tables A.13 and A.14, give the correlations among plant-level statistics. Overall, the correlation between p^{in} and p^{out} is somewhat larger, while the correlation between p^{in} and $tfpq$ is somewhat closer to 0, compared to the correlations contained in Tables 2 and A.10.

	p^{in}	p^{out}	$tfpq$	φ	$tfpr$
p^{out}	0.278*				
$tfpq$	-0.303*	-0.653*			
φ	0.141*	-0.549*	0.899*		
$tfpr$	-0.098*	0.212*	0.601*	0.581*	
Std. Dev.	0.167	0.186	0.227	0.219	0.176

TABLE A.13. Correlations and standard deviations of plant-level characteristics.
Notes: Correlations give equal weight to all plant-year observations. Stars indicate that the correlation is significantly different from 0, at the 5% level (see Web Appendix C for details). Also, see Table 2 for the real-revenue-weighted version of this table. N=10,503.

Sample	$p^{in}, tfpq$	p^{in}, φ	p^{in}, p^{out}	$p^{in}, tfpr$	$\varphi, tfpq$	$tfpq, tfpr$	$tfpq, p^{out}$
Boxes, Yr.≤'87	-0.406*	0.153*	0.404*	-0.061*	0.841*	0.425*	-0.824*
Boxes, Yr.≥'92	-0.428*	0.142*	0.366*	-0.070	0.834*	0.127*	-0.873*
Coffee	-0.293*	0.227*	0.300*	-0.027	0.862*	0.517*	-0.645*
Concrete	-0.271*	0.107*	0.234*	-0.132*	0.928*	0.776*	-0.458*
Flour	-0.344*	0.454*	0.256*	-0.073	0.681*	0.254*	-0.715*
Gasoline	-0.353*	0.203*	0.125*	-0.305*	0.844*	0.840*	-0.396*
Milk, Bulk	-0.280*	0.033	0.382*	0.079	0.950*	0.522*	-0.789*
Milk, Packaged	-0.282*	0.054*	0.237*	-0.095*	0.943*	0.456*	-0.753*
Sugar	0.055	0.459*	0.116	0.118	0.912*	0.889*	-0.405*
Yarn	-0.354*	0.117	0.297*	-0.135*	0.887*	0.455*	-0.788*
Pooled-Benchmark	-0.303*	0.141*	0.278*	-0.098*	0.899*	0.601*	-0.653*

TABLE A.14. Correlations among plant-level characteristics.
Notes: Correlations give equal weight to all plant-year observations. Stars indicate that the correlation is significantly different from 0, at the 5% level (see Web Appendix C for details). See Table A.10 for the real-revenue-weighted version of this table.

Compared to the revenue-weighted calculations, the unweighted dispersions of $tfpr$, $tfpq$, and φ are larger (see the first eleven rows of Table A.15 for the benchmark sample, and the final five rows for the Quality Variation sample). The larger dispersions have two sources. First, revenue weighting gives more importance to high revenue-per-plant industries. Since gasoline, which by far has the largest average revenues among the industries in the benchmark sample, has more compressed $tfpr$, $tfpq$, and φ distributions, assigning weights by revenue causes the pooled dispersion to be larger in the unweighted calculations. Second, the unweighted calculations give relatively more weight, within industries, to the low productivity, low employment plants, again causing unweighted dispersions to be larger than the weighted dispersions.

For the pooled benchmark sample, the decline in dispersion is smaller when observations given equal weight. For example, compared to the 8.8% decline that is given in Table 3, the 90/10 ratio of $tfpq$ is only 7.2% larger than the 90/10 ratio of φ. The difference, between the unweighted and weighted calculations, is due to differences in the weight that particular industries get. When observations are given equal weight, the ready-mix concrete industry (which had a particularly small decline in productivity dispersion) is relatively more important in the calculations. On the other hand, when observations are revenue weighted, the gasoline industry (which has a slightly larger than average decline in productivity dispersion) is relatively more

	Dispersion of $tfpq$			Dispersion of φ			Percent Decline		
Sample	90/10	75/25	SD	90/10	75/25	SD	90/10	75/25	SD
Boxes, Year≤'87	0.475	0.204	0.199	0.409	0.196	0.185	17.3%*	4.1%*	8.1%*
Boxes, Year≥'92	0.617	0.318	0.242	0.548	0.278	0.221	13.4%*	15.7%*	10.1%*
Coffee	0.635	0.321	0.257	0.569	0.272	0.249	12.3%*	19.6%*	3.3%
Concrete	0.558	0.275	0.238	0.522	0.260	0.230	7.1%*	5.8%*	3.4%*
Flour	0.404	0.205	0.163	0.396	0.176	0.172	2.0%	17.9%*	-5.3%
Gasoline	0.309	0.151	0.147	0.296	0.137	0.141	4.6%	10.7%	4.8%
Milk, Bulk	0.809	0.306	0.316	0.681	0.322	0.303	20.6%*	-4.8%	4.4%
Milk, Packaged	0.564	0.284	0.235	0.531	0.262	0.226	6.5%*	8.9%*	4.2%*
Sugar	0.692	0.330	0.313	0.807	0.352	0.352	-13.2%*	-6.3%	-10.6%*
Yarn	0.620	0.310	0.262	0.629	0.312	0.248	-1.4%	-0.6%	5.6%*
Pooled-Benchmark	0.527	0.253	0.227	0.493	0.238	0.219	7.2%*	6.5%*	3.9%*
Pickles	0.890	0.441	0.346	0.962	0.471	0.368	-7.3%	-6.2%	-5.8%
Sausages	0.800	0.409	0.316	0.730	0.358	0.308	10.0%*	15.3%*	2.5%
Softwood	1.379	0.675	0.490	1.310	0.651	0.489	5.4%	3.6%	0.2%
Wine	1.407	0.735	0.502	1.444	0.779	0.536	-2.6%	-5.4%	-6.1%
Pooled-Quality	1.028	0.500	0.400	1.021	0.477	0.410	0.7%	4.8%	-2.5%

TABLE A.15. Dispersion of $tfpq$ and φ.
Notes: All observations are given equal weight. In the final three columns, stars indicate that he difference between $tfpq$ and φ is statistically significant, at the 5% level (see Web Appendix C for details).

Sample	β	$s.e.$	Adjusted R^2
Boxes, Yr.≤'87	0.693	0.116	0.019
Boxes, Yr.≥'92	0.538	0.182	0.012
Coffee	-0.137	0.092	0.004
Concrete	0.854	0.030	0.184
Flour	0.254	0.093	0.013
Gasoline	0.618	0.058	0.138
Milk, Bulk	0.322	0.152	0.027
Milk, Packaged	0.821	0.041	0.160
Sugar	0.081	0.191	-0.005
Yarn	0.024	0.339	-0.002
Pooled-Benchmark	0.606	0.021	0.072
Pickles	-0.038	0.196	-0.007
Sausages	0.006	0.086	-0.002
Softwood	-0.273	0.137	0.018
Wine	0.313	0.150	0.010
Pooled-Quality	0.027	0.061	-0.001

TABLE A.16. Spatial correlation of materials prices.
Notes: The dependent variable is p_{ijt}^{in}, and the independent variable is the (revenue-weighted) average of the $p_{i'jt}^{in}$ for the plants that are within a 250-mile radius of plant i in industry j and year t. Observations are given equal weight. See Tables 6 and A.3 for the real-revenue-weighted version of this table.

important in the calculations. Note that, weighing observations by revenue does not cause the within-industry declines in dispersion to be systematically larger or smaller. For the sample of industries with substantial variation in output quality, there are no systematic differences between the weighted and unweighted calculations (compare Table A.2 and the final five rows of Table A.15).

Finally, Table A.16 presents the unweighted versions of Tables 6 and A.3.

Productivity Measure	Total	Entry	Exit	Net Entry	Total	Entry	Exit	Net Entry
$tfpr$	-1.60	-0.05	0.12	0.08	1.30	0.16	0.22	0.38
$tfpq$	-1.60	-0.02	0.19	0.16	1.30	0.25	0.22	0.47
φ	-1.60	-0.05	0.17	0.12	1.30	0.17*	0.24	0.41

TABLE A.17. Aggregate productivity growth decompositions.
Notes: All values are given as percentages, over five-year horizons. In the first four columns, industries are assigned importance according to their total revenues. In the last four columns, industries are assigned importance according to the number of plants. Stars indicate that the value given in the cell is significantly different than the corresponding value that uses $tfpq$ as the measure of plant productivity. See Web Appendix C for details.

A.9. An Alternative Growth Decomposition

In this subsection, I reproduce the analysis of Section 3.5, using the decomposition method of Griliches and Regev (1995). Relative to the Foster, Haltiwanger, and Krizan (2001) decomposition, the Griliches and Regev (1995) decomposition replaces $\overline{tfp}_{t-1}$ with $\frac{1}{2}\overline{tfp}_{t-1} + \frac{1}{2}\overline{tfp}_t$ in the "Entry Effect" and "Exit Effect" terms:

$$\Delta\overline{tfp}_t = \sum_{i\in\mathcal{C}} \frac{1}{2}\left(\theta_{i,t-1} + \theta_{i,t}\right)\cdot \Delta tfp_{it} + \sum_{i\in\mathcal{C}} \frac{1}{2}\left(tfp_{i,t} + tfp_{i,t-1} - \overline{tfp}_{t-1} - \overline{tfp}_t\right)\cdot \Delta\theta_{it}$$

$$+ \underbrace{\sum_{i\in\mathcal{N}} \theta_{it}\cdot\left(tfp_{it} - \frac{1}{2}\overline{tfp}_{t-1} - \frac{1}{2}\overline{tfp}_t\right)}_{\text{Entry Effect}} \underbrace{- \sum_{i\in\mathcal{X}} \theta_{i,t-1}\cdot\left(tfp_{i,t-1} - \frac{1}{2}\overline{tfp}_{t-1} - \frac{1}{2}\overline{tfp}_t\right)}_{\text{Exit Effect}} \tag{A.11}$$

The results of the alternate decomposition are given in Table A.17. The magnitudes of the "Net Entry" effect are robust to the decomposition method.

A.10. Correcting for Sample Selection in Decompositions of Industry Productivity Growth

As mentioned in Section 2.2, plants in the benchmark sample tend to exit and enter less frequently, compared to plants from their corresponding industries. As a result, the productivity decompositions of Section 3.5 may underrepresent the role of entry and exit in generating aggregate productivity growth. In this subsection, I try to account for this sample selection problem.

Table A.18 presents the aggregate productivity growth decompositions, corrected for the underrepresentation of entering and exiting plants in the benchmark sample. For each industry in my benchmark sample, I compute the corrected Entry (Exit) Effects by dividing by the ratio of the revenue-weighted fraction of entrants (exiting plants) in the overall sample to the revenue-weighted fraction of entrants (exiting plants) in the benchmark sample. The correction that I make will magnify the share of entrants/exiting plants to the extent that entrants/exiting plants are underrepresented in the benchmark sample. Specifically, the corrected Entry and Exit Effects are given by:

$$\text{Entry Effect}_{FHK} = \frac{\Pr\{i \in \mathcal{N} \mid i \in \text{overall sample}\}}{\Pr\{i \in \mathcal{N} \mid i \in \text{benchmark sample}\}} \cdot \sum_{i \in \mathcal{N} \cap \text{benchmark}} \theta_{i,t-1} \cdot (tfp_{it} - \overline{tfp}_{t-1}) \tag{A.12}$$

$$\text{Exit Effect}_{FHK} = -\frac{\Pr\{i \in \mathcal{X} \mid i \in \text{overall sample}\}}{\Pr\{i \in \mathcal{X} \mid i \in \text{benchmark sample}\}} \cdot \sum_{i \in \mathcal{X} \cap \text{benchmark}} \theta_{i,t-1} \cdot (tfp_{i,t-1} - \overline{tfp}_{t-1}) \tag{A.13}$$

$$\text{Entry Effect}_{GR} = \frac{\Pr\{i \in \mathcal{N} \mid i \in \text{overall sample}\}}{\Pr\{i \in \mathcal{N} \mid i \in \text{benchmark sample}\}} \cdot \sum_{i \in \mathcal{N} \cap \text{benchmark}} \theta_{it} \cdot \left(tfp_{it} - \frac{1}{2}\overline{tfp}_{t-1} - \frac{1}{2}\overline{tfp}_{t} \right) \tag{A.14}$$

$$\text{Exit Effect}_{GR} = -\frac{\Pr\{i \in \mathcal{X} \mid i \in \text{overall sample}\}}{\Pr\{i \in \mathcal{X} \mid i \in \text{benchmark sample}\}} \cdot \sum_{i \in \mathcal{X} \cap \text{benchmark}} \theta_{i,t-1} \cdot \left(tfp_{i,t-1} - \frac{1}{2}\overline{tfp}_{t-1} - \frac{1}{2}\overline{tfp}_{t} \right) \tag{A.15}$$

In equations (A.12)-(A.15), FHK denotes the decomposition method of Foster, Haltiwanger, and Krizan (2001), while GR denotes the decomposition method of Griliches and Regev (1995).

As in Table 8, I average over the industries in the benchmark sample to arrive at the aggregate Entry Effect, Exit Effect, and Net Entry Effect. The Net Entry Effect is less than 0.1 percentage points larger after correcting for the underrepresentation of entering and exiting plants in the benchmark sample. As in Table 8, the only statistically significant difference among the three productivity measures is that the role of entry, which is lager when $tfpq$, instead of φ, is used as the productivity measure.

A.11. Within-Supplier Price Deviations and Shipment Timing

Some of the cross-buyer, within-supplier variation in input prices is potentially due to differences in the timing of shipments. I run two regressions to explore the within-supplier variation in input prices. In the first regression, the dependent variable is the logarithm of the difference between the shipment price and the supplier's average price;[2] the independent variables are indicator variables for the quarter of the shipment. In the second regression, I average the left- and right-hand side variables from the first

2. Note the dependent variable is not quite the same as ψ_{hit}, as this latter variable combines all of the shipments made by h to i in year t.

Productivity Measure	Weight Industries By:	Total	Entry	Exit	Net Entry	Entry	Exit	Net Entry
$tfpr$	Real Revenues	-1.60	-0.06	0.11	0.04	-0.06	0.17	0.11
$tfpq$	Real Revenues	-1.60	-0.08	0.20	0.12	-0.07	0.26	0.19
φ	Real Revenues	-1.60	-0.12	0.17	0.05	-0.11	0.23	0.12
$tfpr$	# of Plants	1.30	0.30	0.17	0.47	0.20	0.28	0.49
$tfpq$	# of Plants	1.30	0.40	0.15	0.54	0.30	0.26	0.56
φ	# of Plants	1.30	0.27*	0.18	0.45	0.18*	0.29	0.47
Decomposition Method			Foster et. al			Griliches and Regev		

TABLE A.18. Aggregate productivity growth decompositions.
Notes: See equations (A.12)-(A.15). All values are percentages, over five-year intervals. When $tfpr$ or φ is the productivity measure, stars indicate that the value given in the cell is significantly different than the corresponding value that uses $tfpq$ as the measure of plant productivity. See Web Appendix C for a detailed description of the bootstrapping procedure.

Sample	Concrete	Boxes	Pooled
Quarter 2	0.030	-0.014	-0.011
	(0.019)	(0.038)	(0.035)
Quarter 3	0.031	0.019	0.019
	(0.036)	(0.028)	(0.026)
Quarter 4	0.033	0.041	0.040
	(0.030)	(0.024)	(0.023)
Constant	-0.150	0.003	-0.142
	(0.020)	(0.020)	(0.019)
Adjusted R^2	0.005	0.008	0.029
N	520	1375	1895

TABLE A.19. Regression of shipment price (relative to the average for the supplier), against indicator variables of the quarter of the shipment.
Notes: All observations are weighed by the value of the shipment.

Sample	Concrete	Boxes	Pooled
Quarter 2	0.245	-0.033	0.002
	(0.215)	(0.058)	(0.058)
Quarter 3	0.114	0.011	0.020
	(0.228)	(0.057)	(0.059)
Quarter 4	0.232	0.031	0.058
	(0.202)	(0.045)	(0.048)
Constant	-0.331	0.000	-0.200
	(0.193)	(0.029)	(0.073)
Adjusted R^2	0.072	0.012	0.080
N	131	190	321

TABLE A.20. Regression of ψ_{it} against the fraction of shipment value that i receives in quarter 2, 3, and 4.
Notes: Observations are weighed by the revenues of plant i.

regression. In particular, I regress ψ_{it} against the fraction of shipment-value received by plant i in quarter 2, in quarter 3, and in quarter 4. The results of these regressions are given in Tables A.19 and A.20. For concrete, within-supplier deviations are smaller (though not significantly so) for shipments made in the first quarter. Overall, shipment timing explains only a small fraction of the dispersion in materials prices.

Sample	Boxes			Concrete			Pooled		
$\overline{tfpq}_{it}$	-0.267*	-0.255*	-0.230*	-0.195*	-0.211	-0.138	-0.253*	-0.243*	-0.211*
	(0.059)	(0.058)	(0.056)	(0.092)	(0.112)	(0.106)	(0.050)	(0.048)	(0.047)
ψ_{it}			0.342*			0.698*			0.407*
			(0.112)			(0.163)			(0.118)
$\bar{p}_{it}^{in,local}$	0.010	0.019	0.022	0.095	-0.010	0.064	0.005	0.008	0.011
	(0.029)	(0.029)	(0.029)	(0.088)	(0.100)	(0.082)	(0.020)	(0.019)	(0.020)
N	190	190	190	131	131	131	321	321	321
Adjusted R^2	0.125	0.130	0.222	0.050	0.083	0.511	0.105	0.115	0.262
Division F.E.?	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

TABLE A.21. Regression results.

Notes: This table presents the coefficient estimates and robust standard errors, from the regressions defined by equation (23), with the addition of $\bar{p}_{it}^{in,local}$ as an explanatory variable. The dependent variable in these regressions is $\tilde{p}_{it}^{in,CFS}$. Stars indicate significance at the 5% level.

A.12. Figure 1, for Different Subsamples

Figure 1 decomposes the price distribution of Commodity Flow Survey cement and paper shipments into two separate components. In the figure, cement shipments from 1992, paper shipments from 1992, and paper shipments from 1997 are pooled together. Figure 2 reproduces the decomposition of Figure 1, separately for each of these three subsamples.

The main qualitative results of Figure 1 abide for each of the three subsamples. The within-supplier price distribution is less disperse, compared to the across-supplier distribution. The distributions are (roughly) unimodal, with the mean and the mode close to one another.

Of the two industries, the price distributions for paper are more disperse. For the two paper subsamples, the price distributions are very similar across the two years.

A.13. Including Local Prices in the Regression Defined by Equation (23)

One concern, regarding the regression corresponding to equation (23) is that division fixed effects may not sufficiently control for the geographic forces that generate variation in p_{it}^{in}. Unfortunately, since there are so few observations in the sample of corrugated box and concrete manufacturers, I cannot include fixed effects of greater geographic detail. Instead, I include—on the right-hand side of equation (23)—the average materials price paid by plants that are close to plant i. In particular, I define $\bar{p}_{it}^{in,local}$ as the logarithm of the average (value-weighted) price paid by all of the establishments, other than i, that are located less than 50 miles from plant i. Materials prices are spatially correlated for concrete, but not for boxes (i.e., p_{it}^{in} is correlated to $\bar{p}_{it}^{in,local}$ only for the subsample of concrete manufacturers), consistent with the results of Section 3.3.

Regressions of plants' materials prices on suppliers' marginal costs are given in Table A.21. The estimated coefficient corresponding to $\bar{p}_{it}^{in,local}$ is not significantly greater than 0, and tends to be somewhat larger for the subsample of ready-mix concrete

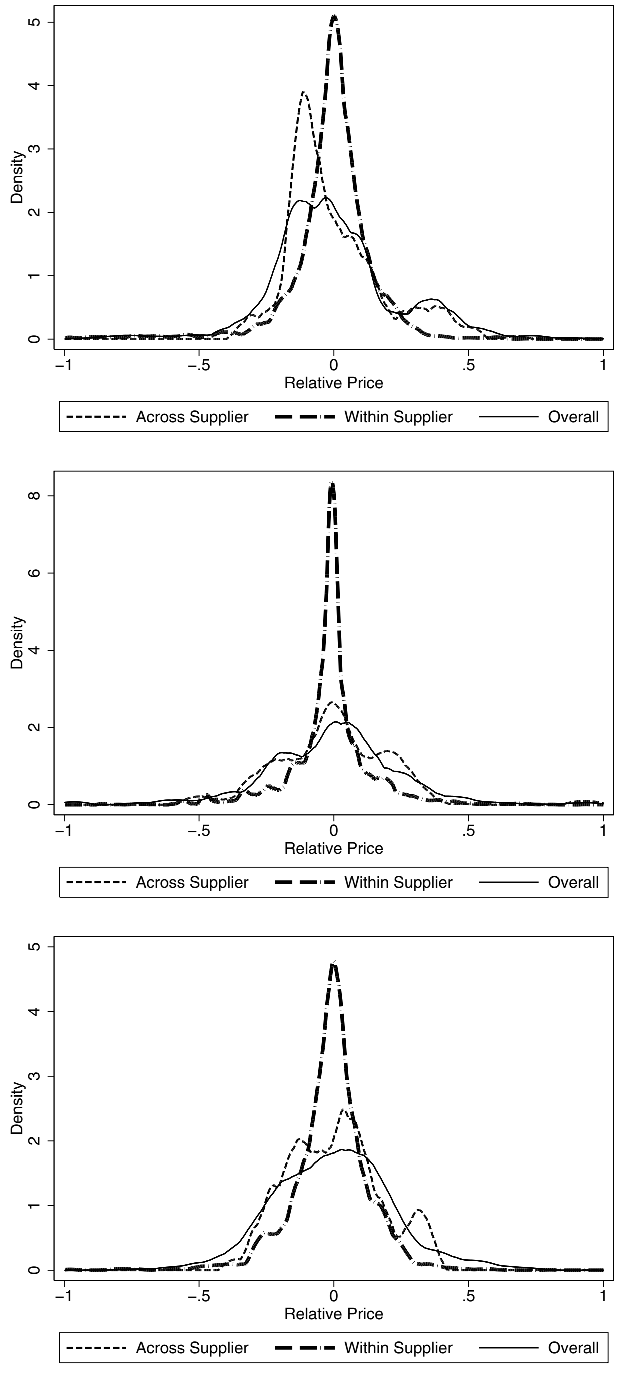

Figure A.1. Value-weighted price distributions. The sample includes all shipments sent by the cement and paperboard manufacturers that comprise the sample of the regressions defined by equation (23). The top panel includes the sample of paperboard manufacturers, from 1992; the middle panel includes the sample of cement manufacturers, from 1992; and, the bottom panel includes the sample of paperboard manufacturers, from 1997.

manufacturers. Importantly, the coefficient estimates of the $\overline{tfpq}_{it}$ and ψ_{it} terms are unchanged after including $\bar{p}_{it}^{in,local}$ as an explanatory variable.

Appendix B: Construction of the Sample

B.1. Benchmark Sample

The benchmark sample consists of 10 industries (collections of 7-digit products) for which both inputs and outputs display minimal levels of quality differentiation. The construction of the sample consists of plants for which the following five conditions hold. First, I discard any plants that have missing data on labor inputs, capital stocks, electricity bills, or materials bills. Second, I discard any plants that do not fill out either the Census of Manufacturers Materials Supplement (containing information on purchases of intermediate inputs) or the Census of Manufacturers Productivity Supplement (containing information on products produced). Third, I throw out plants that have imputed values for quantities of materials purchased or products produced.[3] Fourth, I require that the plants in the benchmark sample earn at least half of their revenues from one of the 10 main industries. Fifth, I discard any plant that has an output price (defined by p^{out}, as in equation (2)), an input price (defined by p^{in}, as in equation (3) or (5)), or a quantity total factor productivity (defined by $tfpq$, as in equation (6)) that is more than 3 units away than the average for that industry-year.

Industries are defined as the collection of 7-digit products in the following manner.

Coffee consists of two 7-digit products, whole bean coffee (2095111) and ground coffee (2095115). The units of output are thousands of pounds.

Ready-mix concrete consists of the single 7-digit product (3273000). In 1972 and 1977 some concrete plants were producing a product with a code of 3273011. The units of output are thousands of cubic yards. Production data do not exist for 1997; materials data do not exist for 1992 or 1997. Because of this, for the analysis in Section 3, the sample period for ready mix concrete is 1972–1987. The sample period for the analysis of Section 4, in which I use the Commodity Flow Survey but not the Census

3. White, Reiter, and Petrin (2012) argue that, because of survey nonresponse, on average, 40% of the non-administrative record plants in the Census of Manufacturers have imputed data. Moreover, because the Census uses industry averages to impute missing values for shipments, materials purchases, or other variables, the imputation method causes a downward bias in estimated within-industry productivity dispersions. The imputation method also biases the measured relationships among plant-level characteristics. With this in mind, I have chosen to exclude all plants with imputed data on the quantities of materials purchases or goods shipped. (Unfortunately, imputed-data flags for other variables—employment, electricity purchases, etc...—exist only beginning in 2002. However, using data from 2002, I have checked that there are very few observations with a) non-imputed quantities of materials/output and b) imputed values for other relevant variables. For 2002, I have also checked that the difference—between the three productivity measures—is robust to the inclusion/exclusion of observations that have imputed values for the "other" variables.) Then, at least for my selected sample, I will be able to accurately measure within-industry dispersions of prices and productivities.

of Manufacturers' materials data, is 1992. In addition to the five criteria listed in the first paragraph of this subsection, I require ready-mix concrete plants to have positive purchases of both cement and sand/gravel.

White wheat flour is the combination of the 10 7-digit products: white flour, shipped for export (2041105 and 2041107); bakers' and institutional white bread-type flours (2041111 and 2041113); bakers' and institutional soft wheat flour (2041115 and 2041117); family white flour, other than self-rising (2041121 and 2041123); self-rising family white flour (2044126); and flour shipped to blenders or other processors (2041128 and 2041129). The units of white wheat flour are 50-pound sacks.

Gasoline is comprised of the following three 7-digit products: motor gasoline (2911131), distillate fuel oil (2911412), and No. 4 type light fuel oil (2911414). The units of output are thousands of barrels.

Bulk milk is the combination of fluid whole milk, bulk sales (2026112) and fluid skim milk, bulk sales (2026115). The units of bulk milk are thousands of pounds.

Packaged milk consists of the following three 7-digit products: fluid whole milk (2026212), low fat milk (2026223), and skim milk (2026225). The units of output are thousands of quarts.

Sugar consists of the single 7-digit product, raw cane sugar (2061011). The units of output are short tons.

Yarn is comprised of the two 7-digit products, spun gray (2281110) and yarn, spun and finished in the same establishment (2281187). The units of output are thousands of pounds.

Corrugated boxes is a combination of nine 7-digit products, with products being classified by their end use. These end uses are containers of food and beverages (2653012); carry-out boxes for retail food (2653014); containers of paper and allied products (2653013); containers of glass, clay, and stone products (2653015); containers of metal products, machinery, equipment, and supplies (2653016); containers of electrical machinery, equipment, supplies, and appliances (2653018); containers of chemicals and drugs, including paints, varnishes, cosmetics, and soaps (2653021); containers of lumber and wood products, including furniture (2653022); all other end uses not specified (2653030). From 1972 to 1987, the units of output for corrugated boxes were thousands of pounds. From 1992 on, the units of output for corrugated boxes have been thousands of square feet.

Measuring corrugated boxes in terms of area, instead of mass, is somewhat problematic. Boxes' densities depend on their final use. In particular, the densities of boxes are lower for those that are used as containers of food, beverages, paper and allied products, glass, clay, stone, or metal, while the densities are higher for boxes that are used as containers of machinery, electronics, chemicals, lumber, and other products. Since the total cost of producing corrugated boxes seems to be more closely related to the mass—instead of surface area—of the amount produced, measured quantity total factor productivity for low density box manufacturers began to exceed, in 1992, the measured quantity total factor productivity of high density boxes.

To mitigate the impact of this measurement problem, I de-meaned, according to equation (9), plant-level statistics separately for the high-density (those plants that

	Employment		Total Value of Shipments		N		Main
Sample	Benchmark	Main Ind.	Benchmark	Main Ind.	Benchmark	Main Ind.	Ind.
Boxes, Yr.≤'87	5.399	3.998	9.426	8.404	1820	7742	2653
Boxes, Yr.≥'92	5.559	3.998	9.799	8.404	646	7742	2653
Coffee	4.906	3.484	9.920	8.736	300	874	2095
Concrete	3.547	2.350	7.682	6.827	3708	20,956	3273
Flour	4.763	3.010	9.854	7.942	503	2073	2041
Gasoline	6.554	4.867	12.977	11.157	692	1706	2911
Milk, Bulk	3.950	3.441	9.082	8.023	127	7661	2026
Milk, Packaged	5.119	3.441	9.465	8.023	2099	7661	2026
Sugar	5.708	4.901	10.000	9.301	177	301	2061
Yarn	5.942	4.749	9.508	8.645	431	2233	2281
Pooled	4.740	3.128	9.119	7.689	10,503	43,546	

TABLE B.1. Descriptive statistics for the benchmark sample, and for the 4-digit SIC of which each product is a member.
Notes: Variables are stated in logs. The final column refers to the 4-digit SIC of which the product is a member.

produced output with a product code between 2653016 and 2653030) and low-density (those plants that produced output with a product code between 2653012 and 2653015) box manufacturers.[4]

In Table B.1, I provide some descriptive statistics of the benchmark sample. The average log employment for plants is 3.93 (i.e., roughly $51 \approx e^{3.93}$ employees work in the average plant.) Plants that produce ready-mix concrete are one-third the size of the average benchmark-sample plant, while plants engaged in gasoline production employ approximately 6.1 ($\approx e^{5.74-3.93}$) times as many workers as the average plant.

Compared to the universe of plants that are in the same 4-digit SIC industry, the plants in the benchmark sample employ 5.0 ($\approx e^{4.74-3.13}$) times as many employees and have revenues that are 4.2 ($\approx e^{9.12-7.68}$) times larger. The difference is due to the Census Bureau's survey methodology: the largest plants tend to receive the survey questionnaires on the products they produce or the materials they consume.

For a particular intermediate input to be included in the analysis, expenditures of the material input must make up at least 6% of total materials expenditures for that product group. As the cutoff expenditure share decreases, additional intermediate inputs are included in the analysis. Setting the cutoff too low results in the inclusion of intermediate inputs that are purchased only by a few plants, hindering cross-plant comparisons of materials prices. Setting the cutoff too high means that important components of plants' materials prices are ignored. The 6% cutoff seems like a good compromise between these two considerations.

4. Dropping the "Boxes, Year≥1992" subsample does not change any of the results from Section 3. I find it worth the trouble to keep the "Boxes, Year≥1992" subsample, since corrugated box manufacturers purchase one of their main inputs–namely, paperboard–from the manufacturing sector, and thus can be included in the analysis of Section 4.

In some instances, I combine groups of similar 6-digit products to form a given "material input."[5] For example, I combine material 131111 (domestic crude petroleum) and 131112 (foreign crude petroleum). The presumption when deciding to combine two materials is that the manufacturer is indifferent between the two 6-digit products. The way in which I combined these 6-digit products is given below.

Green coffee beans (017921) are the sole material input used in the production of ground/whole bean coffee.

In the production of ready-mix concrete, the two materials are cement (which was coded as 324101 in 1982 and 1992 and 324102 in other years) and sand/gravel aggregate (144201).

For white wheat flour, the sole material input is wheat (011111).

In the production of gasoline, I have combined foreign and domestic crude petroleum into one material input.

For milk (either bulk or packaged), the sole material input is unpasteurized whole milk (024111).

In the production of raw cane sugar, the sole material input is sugar cane (013321).

In the production of yarn, the two materials are raw cotton fibers (013101) and a combination of polyester staple and tow (282425) and acrylic staple and tow (282426).

Finally, in 1992-1997, the sole material input used in the production of corrugated boxes is coded 260003 ("Paper and Paperboard"). In 1987, the material input "Paper/Paperboard" is the combination of 262104 ("Paper, Cellulosic Wadding") and 262108 ("Paper"). Earlier than this, "Paper/Paperboard" is the combination of materials 262102, 262103, and 262105.

B.2. Quality Variation Sample

Industries are defined as the collection of 7-digit products in the following manner:

Pickles are a combination of four products: dill pickles (2035211), sour pickles (2035213), sweet pickles (2035215), and refrigerated pickles (2035219). The units of output are thousands of gallons.

Sausages are a combination of six products: fresh sausage (2011711 and 2013711); dry or semi-dry sausages (2011717 and 2013717); and frankfurters (2011721 and 2013721). The units of output are thousands of pounds.

Softwood cut stock is a combination of two product groups: furniture cut stock (2421711) and industrial cut stock (2421751). The units of output are thousands of board feet.

5. For 1992 and 1997, a description of the 6-digit material codes can be found by downloading MC92F7.dbf from the following Census web page: ftp://ftp2.census.gov/econ1992/MC92/.

Sample	Units of Output	Material Inputs	N
Pickles	1000 Gallons	Cucumbers (43%) Glass Containers (28%)	145
Sausages	1000 Pounds	Fresh and Frozen Pork (34%) Fresh and Frozen Beef (30%) Meat, Unknown Species (13%)	621
Softwood Cut Stock	1000 Board Feet	Softwood Dressed Lumber (75%) Softwood Logs (8%) Hardwood Dressed Lumber (8%)	160
Wine	1000 Gallons	Fresh Grapes (41%) Purchased Wines (23%) Glass Containers (19%)	330
Pooled	-	-	1256

TABLE B.2. Description of the four industries comprising the Quality Variation sample. The Material Inputs column gives the inputs that represent greater than 6% of the average plants' total material purchases. The percentages that appear in the Material Inputs column are the fraction of materials expenditures that go to each particular material input.

Wine is a combination of the following three products: white grape wine (2084012), red grape wine (2084014), and rosé grape wine (2084016). The units of output are thousands of gallons.

As with the benchmark sample, materials that make up more than 6% of materials expenditures are included as "priced" materials. A summary of the characteristics of the Quality Variation sample are given in Table B.2.

Appendix C: Details of the Bootstrapping Exercises

The purpose of this section is to describe, and give the results of, the four bootstrapping exercises that are employed in Sections 3 and 4. The four bootstrapping exercises are used to determine a) whether the correlations among certain plant-level statistics are significantly different from 0, b) whether the dispersion of $tfpq$ is different from that of φ or $tfpr$, c) whether the Entry/Exit/Net Entry Effects (as in equations (16) and (A.11)) are significantly different when $tfpq$ is used instead of φ or $tfpr$, and d) whether the declines in dispersion that are reported in Table 11 are significantly more than would be expected by simply adding independent variables. Below, I explain how each of the bootstrapping exercises is performed, and give the resulting confidence intervals.

To determine whether specific correlations among plant-level statistics are different from 0, I take 1000 bootstrapped samples, from the benchmark sample of 10,503 plant-year observations (or 1256 observations in the case of the Quality Variation sample). In each bootstrapped sample, the number of plants taken from each industry-year is the same as in the benchmark sample. After sampling, I de-mean, as

Sample	$p^{in}, tfpq$	p^{in}, φ	p^{in}, p^{out}	$p^{in}, tfpr$	$\varphi, tfpq$	$tfpq, tfpr$	$tfpq, p^{out}$
Boxes, Yr.≤'87	-0.36,-0.21	0.14,0.31	0.21,0.35	-0.10,0.02	0.83,0.90	0.37,0.48	-0.83,-0.76
Boxes, Yr.≥'92	-0.43,-0.27	0.00,0.18	0.20,0.37	-0.16,-0.01	0.88,0.92	0.03,0.20	-0.90,-0.85
Coffee	-0.69,-0.20	-0.20,0.29	0.10,0.57	-0.48,0.16	0.77,0.92	0.38,0.74	-0.73,-0.41
Concrete	-0.36,-0.26	0.07,0.17	0.23,0.33	-0.18,-0.08	0.89,0.92	0.71,0.77	-0.52,-0.43
Flour	-0.48,-0.31	0.34,0.57	0.18,0.43	-0.18,0.15	0.54,0.72	0.00,0.27	-0.78,-0.66
Gasoline	-0.48,-0.31	0.02,0.26	0.06,0.26	-0.40,-0.21	0.82,0.89	0.77,0.87	-0.48,-0.27
Milk, Bulk	-0.68,-0.13	-0.44,0.14	0.06,0.70	-0.25,0.08	0.93,0.98	0.26,0.67	-0.89,-0.56
Milk, Packaged	-0.33,-0.23	-0.02,0.11	0.17,0.28	-0.17,-0.04	0.93,0.95	0.37,0.49	-0.80,-0.69
Sugar	-0.22,0.14	0.32,0.61	0.03,0.40	-0.08,0.28	0.78,0.92	0.76,0.93	-0.58,-0.32
Yarn	-0.45,-0.17	-0.05,0.40	0.08,0.36	-0.29,-0.05	0.82,0.92	0.36,0.61	-0.84,-0.67
Pooled-Bench.	-0.42,-0.31	0.05,0.20	0.18,0.28	-0.30,-0.16	0.85,0.89	0.65,0.74	-0.60,-0.50
Pickles	-0.41,0.05	-0.14,0.35	-0.13,0.31	-0.35,0.11	0.93,0.97	0.29,0.60	-0.84,-0.61
Sausages	-0.33,-0.04	0.12,0.39	0.06,0.35	-0.09,0.19	0.87,0.92	0.10,0.44	-0.84,-0.73
Softwood	-0.66,-0.23	-0.32,0.19	0.22,0.66	-0.35,0.05	0.87,0.94	0.15,0.56	-0.97,-0.89
Wine	-0.47,-0.12	0.08,0.50	0.11,0.52	-0.23,0.34	0.71,0.86	0.00,0.48	-0.89,-0.69
Pooled-Quality	-0.38,-0.17	0.14,0.36	0.16,0.41	-0.14,0.19	0.82,0.89	0.16,0.42	-0.86,-0.75

TABLE C.1. Confidence intervals of correlations among plant-level characteristics.

Benchmark Sample:				
	p^{in}	p^{out}	$tfpq$	φ
p^{out}	0.180, 0.279			
$tfpq$	-0.424,-0.314	-0.599,-0.504		
φ	0.054,0.200	-0.518,-0.422	0.852,0.890	
$tfpr$	-0.303,-0.163	0.149,0.284	0.652,0.736	0.568,0.660
Output Quality Variation Sample:				
	p^{in}	p^{out}	$tfpq$	φ
p^{out}	0.160,0.407			
$tfpq$	-0.385,-0.166	-0.858,-0.165		
φ	0.137,0.363	-0.733,-0.560	0.819,0.888	
$tfpr$	-0.143,0.180	0.241,0.423	0.157,0.418	0.189,0.404

TABLE C.2. Confidence intervals of correlations among plant-level characteristics.

in equation (9), and then compute the weighted and unweighted correlations. The 95% confidence intervals are provided in Tables C.1, and C.2.[6]

I follow a similar procedure to determine whether $tfpq$ is significantly more disperse than $tfpr$ or φ: For each (out of 1000) bootstrapped sample, I de-mean plant-level statistics, as in equation (9), and then compute dispersions (the standard deviations, the 90/10 ratios, and the 75/25 ratios) of $tfpq$, $tfpr$, and φ. I then take the ratio of the dispersion of $tfpq$ and the dispersion of either $tfpr$ or φ. The 95% confidence intervals are provided in Table C.3. In most cases, the left endpoint of the confidence interval is greater than 1, meaning that $tfpq$ is significantly more disperse than both $tpfr$ and φ. For the benchmark, pooled sample, $tfpq$ is significantly more disperse than φ, except when observations are revenue weighted and the interquartile range is the measure of dispersion.

6. Throughout this section, the confidence intervals correspond to the revenue-weighted calculations. Confidence intervals corresponding to the unweighted calculations are available upon request.

	Ratio of dispersion of $tfpq$ to dispersion of φ			Ratio of dispersion of $tfpq$ to dispersion of $tfpr$		
Sample	90/10	75/25	SD	90/10	75/25	SD
Boxes,Yr.≤'87	1.002,1.078	0.972,1.058	1.002,1.060	1.573,1.757	1.427,1.908	1.654,2.098
Boxes,Yr.≥'92	1.022,1.146	1.008,1.123	1.022,1.117	2.534,4.309	2.517,3.853	2.024,3.230
Coffee	1.018,1.783	1.012,1.671	1.018,1.406	0.894,2.182	0.903,2.016	0.947,1.590
Concrete	1.037,1.118	1.015,1.126	1.037,1.069	1.047,1.176	1.026,1.165	1.072,1.154
Flour	0.927,1.180	1.040,1.438	0.927,1.059	1.079,1.892	1.232,1.637	0.992,1.463
Gasoline	0.976,1.170	0.974,1.227	0.976,1.145	0.931,1.146	0.911,1.137	0.980,1.125
Milk, Bulk	0.970,1.401	0.854,1.498	0.970,1.273	0.977,6.031	0.795,4.583	1.166,3.287
Milk, Packaged	1.036,1.110	1.009,1.113	1.036,1.062	1.485,2.072	1.562,1.942	1.375,1.863
Sugar	0.710,1.018	0.689,1.233	0.710,0.962	0.931,1.364	0.834,1.443	1.030,1.275
Yarn	0.824,1.028	0.770,1.027	0.824,1.109	1.220,2.101	1.118,2.017	1.341,2.239
Pooled: Weighted	1.002,1.168	0.996,1.200	1.002,1.104	1.066,1.227	0.984,1.281	1.123,1.249
Pooled: Unweighted	1.056,1.091	1.050,1.093	1.028,1.050	1.415,1.515	1.474,1.600	1.303,1.374

TABLE C.3. Confidence intervals.
Notes: The confidence intervals are of a) the ratio of the dispersion of $tfpq$ to the dispersion of $tfpr$–given in the left three columns–and b) the ratio of the dispersion of $tfpq$ to the dispersion of φ–given in the right three columns.

	Ratio of dispersion of $tfpq$ to dispersion of φ			Ratio of dispersion of $tfpq$ to dispersion of $tfpr$		
Sample	90/10	75/25	SD	90/10	75/25	SD
Pooled: Weighted	1.024,1.156	0.975,1.184	1.007,1.083	0.969,1.102	0.932,1.105	1.006,1.092
Pooled: Unweighted	1.068,1.109	1.054,1.106	1.037,1.060	1.107,1.172	1.078,1.150	1.122,1.173

TABLE C.4. Confidence intervals.
Notes: The confidence intervals are of a) the ratio of the dispersion of $tfpq$ to the dispersion of $tfpr$–given in the left three columns–and b) the ratio of the dispersion of $tfpq$ to the dispersion of φ–given in the right three columns.

Table C.4 presents the confidence intervals, related to the Caves, Christensen, and Diewert (1982) robustness check of Web Appendix A.5. As in the benchmark calculations, $tfpq$ is significantly more disperse than φ, except when observations are revenue weighted and the interquartile range is the measure of dispersion. Revenue productivity is less disperse than quantity productivity for two of the three measures of dispersion, in the weighted calculations, and one of the three measures of dispersion, when observations are assigned equal weights. Other differences are not statistically significant.

And again, I follow a similar procedure to determine whether the Entry/Exit/Net Entry Effects (as in equations (16) and (A.11)) are significantly different when $tfpq$ is used instead of φ or $tfpr$. Again, I take 1000 bootstrapped samples, where, in each bootstrapped sample, the number of plants taken from each industry-year is the same as in the benchmark sample. For each bootstrapped sample, I compute the Entry, Exit, and Net Entry Effects, by plugging in $tfpq$, $tfpr$, and φ into

Measure	Weight Industries By:	Entry	Exit	Net Entry	Entry	Exit	Net Entry
$tfpr$	Revenues	-0.06,0.11	-0.05,0.19	-0.07,0.23	-0.06,0.11	-0.06,0.19	-0.07,0.24
φ	Revenues	-0.02,0.09	-0.06,0.10	-0.05,0.14	-0.02,0.09	-0.07,0.10	-0.05,0.13
$tfpr$	Plants	-0.05,0.23	-0.12,0.13	-0.09,0.28	-0.04,0.23	-0.12,0.13	-0.09,0.28
φ	Plants	0.00,0.16	-0.09,0.05	-0.05,0.15	0.01,0.15	-0.10,0.06	-0.04,0.15
Decomposition Method		Foster, Haltiwanger, and Krizan			Griliches and Regev		

TABLE C.5. Confidence intervals.
Notes: The confidence intervals are of the difference, when $tfpq$, instead of $tfpr/\varphi$, is used as the measure of plant productivity, of the Entry Effect, Exit Effect, and Net Entry Effect. These three effects are defined in equations (16) and (A.11).

Include Division Fixed Effects?		No	Yes	No	Yes
Include $\overline{tfpq}_{it}$?		No	No	Yes	Yes
Sample Size	Sample				
131	Concrete		0.292,0.354	0.342,0.359	0.288,0.352
190	Boxes		0.175,0.185	0.184,0.187	0.175,0.185
321	Pooled		0.200,0.208	0.206,0.209	0.199,0.207
131	Concrete	0.333,0.359	0.286,0.352	0.327,0.359	0.284,0.351
190	Boxes	0.184,0.187	0.174,0.185	0.182,0.187	0.174,0.185
321	Pooled	0.206,0.209	0.199,0.208	0.205,0.209	0.195,0.207

TABLE C.6. Confidence intervals.
Notes: The first three rows present the confidence intervals related to the specifications that exclude ψ_{it} as an explanatory variable. The final three rows give the confidence intervals related to the specifications that include ψ_{it}.

equations (16) and (A.11). I then compute the difference between the Entry/Exit/Net Entry Effects when $tfpq$ is used instead of $tfpr$ (or φ).

Table C.5 gives the resulting confidence intervals. In the first and the third rows, 0 lies within each and every confidence interval: The Entry/Exit/Net Entry Effects are not significantly different for revenue productivity versus quantity productivity. On the other hand, when industries are weighed by the number of plants, the Entry Effect is significantly greater when $tfpq$, instead of φ, is used as the measure of productivity.

I follow a somewhat different procedure to determine whether the estimated dispersion declines, as reported in Table 11 are significantly more than would be expected by simply adding independent variables. I implement the following algorithm 1000 times:

From the sample of plant-year observations, I construct a new variable, $\mathcal{P}\left(\tilde{p}_{it}^{in,CFS}\right)$, which is constructed by randomly permuting $\tilde{p}_{it}^{in,CFS}$ among the observations from a given industry-year. I then regress $\mathcal{P}\left(\tilde{p}_{it}^{in,CFS}\right)$ against all the combinations of right-hand side variables of the regression given in equation (23). Following these regressions, I compute the revenue-weighted standard deviations of the residuals. These residuals are stored, for each iteration.

The 95% confidence intervals are presented in Table C.6. The first three rows present the confidence intervals related to the specifications that exclude ψ_{it} as an explanatory variable. The final three rows give the confidence intervals related to the specifications that include ψ_{it}. To make things concrete, consider the values given in the first row and penultimate column. To construct these two values, I repeatedly regress random permutations of $\mathcal{P}\left(\tilde{p}_{it}^{in,CFS}\right)$ against $\overline{tfpq}_{it}$, and then store the standard deviation of the residuals from each regression. The smaller value equals the 2.5-percentile standard deviation, and the larger value equals the 97.5-percentile standard deviation.

Additional References

White, T. Kirk, Jerome P. Reiter, and Amil Petrin (2012). "Plant-level Productivity and Imputation of Missing Data in U.S. Census Manufacturing Data." NBER Working Paper No. 17816.