

Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?*

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Abstract

There is considerable evidence that producer-level churning contributes substantially to aggregate (industry) productivity growth, as more productive businesses displace less productive ones. However, this research has been limited by the fact that producer-level prices are typically unobserved; thus within-industry price differences are embodied in productivity measures. If prices reflect idiosyncratic demand or market power shifts, high “productivity” businesses may not be particularly efficient, and the literature’s findings might be better interpreted as evidence of entering businesses displacing less *profitable*, but not necessarily less productive, exiting businesses. In this paper, we investigate the nature of selection and productivity growth using data from industries where we observe producer-level quantities and prices separately. We show there are important differences between revenue and physical productivity. A key dissimilarity is that physical productivity is inversely correlated with plant-level prices while revenue productivity is positively correlated with prices. This implies that previous work linking (revenue-based) productivity to survival has confounded the separate and opposing effects of technical efficiency and demand on survival, understating the true impacts of both. We further show that young producers charge lower prices than incumbents, and as such the literature understates the productivity advantage of new producers and the contribution of entry to aggregate productivity growth.

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1. Introduction

A robust finding of the large and growing literature using business-level microdata is that within-industry reallocation and its associated firm turnover shape changes in industry aggregates. The effect of this churning process on aggregate productivity has received particular theoretical and empirical attention.

Models of such selection mechanisms characterize industries as collections of heterogeneous-productivity producers and link producers' productivity levels to their performance and survival in the industry (see, for example, Jovanovic (1982), Hopenhayn (1992), Ericson and Pakes (1995), Melitz (2003), and Asplund and Nocke (2006)). The important mechanism driving aggregate productivity movements in these models is the reallocation of market shares to more efficient producers, either through market share shifts among incumbents or through entry and exit. Low productivity plants are less likely to survive and thrive than their more efficient counterparts, creating selection-driven aggregate (industry) productivity increases. Hence the theories point to the productivity-survival link as a crucial driver of productivity growth.

The related empirical literature has documented this mechanism as a robust feature of industry dynamics.¹ Businesses' measured productivity levels are persistent and vary significantly within industries, suggesting that productivity "types" among producers have an inherent idiosyncratic element. Reallocation, entry, and exit rates are large. Businesses with higher measured productivity levels tend to grow faster and are more likely to survive than their less productive industry cohorts. These signs all point to a selection mechanism being at work.

In reality, however, the productivity-survival link is a simplification. Selection is on profitability, not productivity (though the two are likely correlated). Productivity is only one of several possible idiosyncratic factors that determine profits, however. Other idiosyncratic factors may affect survival as well.²

Given the empirical findings discussed above on the importance of productivity to survival, does this theoretical simplification matter? There is reason to believe it may. A limitation of empirical research with business microdata is that establishment-level prices are

¹ Bartelsman and Doms (2000) review much of this literature.

² While the models cited above and their literature counterparts *do* actually construct their selection mechanism on profits, productivity is the only idiosyncratic producer characteristic. Thus producer profits are a positive monotonic function of productivity, and selection on profits is equivalent to selection on productivity.

typically unobserved. Previous studies have had to measure establishment output as revenue divided by a common industry-level deflator.³ Therefore within-industry price differences are embodied in output and productivity measures. If prices reflect idiosyncratic demand shifts or market power variation rather than quality or production efficiency differences, a reasonable supposition for many industries, then high “productivity” businesses may not be particularly technologically efficient.⁴ If this is the case, the empirical literature documents the importance of selection on profits, but not necessarily productivity. Therefore the connection between productivity and survival probability, reallocation, and industry dynamics may be overstated, and the impact of demand-side influences on survival understated.

In this paper, we attempt to measure the separate influences of idiosyncratic productivity and demand on selection. We can explore this bifurcation systematically because, unlike most of the previous empirical work on the subject, we are able to observe both producers’ physical outputs and prices. We can then directly measure physical efficiency (the quantity of physical units of output produced per unit of input) as well as estimate idiosyncratic demand shocks at the business level. We use these measures to look at the independent contributions of technology and demand heterogeneity on producer dynamics and within-industry reallocation.

Our empirical strategy is to focus on establishments producing physically homogeneous products. Avoiding large quality variation in producers’ physical outputs—the dimension along which we have direct quantity measures—allows us to highlight the quantity-versus-revenue distinction that is otherwise confounded in the literature. For example, one might reasonably consider two plants’ outputs of 1000 cubic feet of ready-mixed concrete as equivalent. And if these plants require the same inputs to produce this much output, it seems reasonable to think of them as being equally technically efficient. Note that this equivalence does not necessarily imply that these producers operate in an undifferentiated product market. Prices could vary within industries because, for instance, geographic demand variations or webs of history-laden

³ Syverson (2004), which uses physical output data as we do in this study, is an exception to this. In addition, in a series of papers using Colombian data, Eslava et al. (2004, 2005a, 2005b) use plant-level output and input price data in a manner similar to that used here. The focus of the latter papers is in the impact of market reform on firm dynamics, but at the core the findings for Colombia are consistent with the findings reported here.

⁴ Input price variation is another possible business-specific profitability influence that could also show up in productivity measures. Businesses enjoying idiosyncratically low input prices will look as though they are hiring fewer inputs per unit output. While we abstract from the effects of input price variation here, Katayama, Lu, and Tybout (2003) and Gorodnichenko (2005) argue factor prices are potentially important. We see this area as a possible expansion point for future work.

relationships between particular consumers and producers that create producer-specific demand shifts. (We discuss in detail in Section 3.3 what factors might explain price/demand variations across producers in our sample.) The output equivalence in this example is meaningful not due to the complete absence of differentiation, but rather because there is no differentiation along the dimension in which we measure output—the physical unit.⁵ We have chosen our sample industries based on the notion that a consumer should be roughly indifferent between unlabeled units of the industry output. This upfront effort to obtain homogeneity aside, we will consider below, in light of the evidence, whether the patterns we observe are consistent with this supposedly small quality variation.

The specific products that we investigate are corrugated and solid fiber boxes (henceforth referred to as boxes), white pan bread (bread), carbon black, roasted coffee beans (coffee), ready-mixed concrete (concrete), oak flooring (flooring), motor gasoline (gasoline), block ice, processed ice, hardwood plywood (plywood), and raw cane sugar (sugar). Producers of these products make outputs that are among the most physically homogeneous in the manufacturing sector. In addition to product homogeneity, the set of producers is large enough to exhibit sufficiently rich within-industry reallocation and turnover.⁶

We are not the first to note the possible difficulties involved in using revenue-based output and productivity measures when using microdata. Abbott (1992) documents the extent of price dispersion within broad industries and outlines possible implications for measurement of aggregates. Klette and Griliches (1996) and Mairesse and Jaumandreu (2005) consider how intra-industry price fluctuations can affect production function and productivity estimates. Melitz (2000), De Loecker (2005) and Gorodnichenko (2005) have extended these analyses to accommodate multi-product producers and factor price variation. Katayama, Lu, and Tybout (2003), whose theme perhaps most closely matches that of this paper, demonstrate that revenue-

⁵ If prices varied instead primarily due to quality differences within a unit of physical output, then the sorts of comparisons above would be less meaningful. Asserting output equivalence between, say, two automobile assemblers producing 1000 cars each, is dubious since there is considerable scope for quality variation even within the unit of output measurement (one car).

⁶ Seven of our products are in the group of thirteen products that Roberts and Supina (1996, 2000) use in their studies of establishment-level price variation. We could not use all thirteen products due to data availability issues. The four products that we study that are not used in the Roberts and Supina studies are carbon black, block ice, processed ice, and raw cane sugar. There are also homogeneous-output industries with large numbers of businesses outside of the manufacturing sector. Unfortunately, the microdata for these other sectors lacks the detailed production information necessary for this study.

based output and expenditure-based input measures can lead to productivity mismeasurement and incorrect interpretations about how heterogeneous producers respond to shocks and associated welfare implications. Each of these papers forwards an alternative method of empirical inference that attempts to avoid the difficulties inherent in productivity analysis when business-level price data is unavailable.

This paper shares an obvious common thread with this earlier work. It departs in that, rather than using alternative estimation strategies to try separating confounded demand-side impacts from technological efficiency, we have the unusual opportunity to compute physical productivity using the data at hand. We can therefore directly compare revenue-based productivity measures with measures of physical efficiency, and show precisely the impacts of each on selection dynamics and industry evolution. We can further use our business-level price observations to estimate the influence of idiosyncratic demand elements on survival. We do not mean to imply that having to econometrically infer true technological productivity is a weakness of the earlier research. Indeed, the thrust of those papers was to seek alternate inference methods, given that revenue-based output measures are so ubiquitous. We instead seek to take advantage of observing both “standard” microdata and the much more rare quantity data in order to determine definitively (at least for our sample industries) the differences between revenue-based and physical output measures. The hope is, of course, that our findings for a small subset of industries offer insight into these links in the broader economy.

To preview our findings, we find that the large and persistent within-industry dispersion observed in revenue-based productivity measures is also present in prices and physical-quantity-based productivity measures. Interestingly, physical productivity is actually more dispersed than revenue-based productivity even though the former is a component of the latter. This pattern reflects the fact that, while the two productivity measures are highly correlated with each other, physical productivity is negatively correlated with establishment-level prices while revenue productivity is positively correlated with prices. The negative physical productivity-price correlation is consistent with equilibria where producers are price setters and more efficient businesses find it optimal to pass along their cost savings through lower prices.

We exploit the observed variation in prices, physical output and physical productivity to estimate plants’ idiosyncratic demand levels. Our physical productivity measures provide a unique and powerful instrument for price to overcome the typical simultaneity bias in demand

estimation. The demand estimates allow us to decompose plant-level price variation into two components, one reflecting movements along the demand curve due to differences in physical efficiency, the other reflecting producers' idiosyncratic demand shift.

With regard to industry evolution, we find that exiting businesses have lower productivity levels—either revenue based or physical quantity based—than incumbents, though the gap is larger in magnitude for revenue productivity. Entering businesses, on the other hand, have higher physical productivity levels than incumbents, but their revenue-based productivity advantage is much less pronounced and sometimes nonexistent. Similar patterns are seen when we compare young businesses to their more mature competitors. For all of these findings, the key source of discrepancies between the estimated effects of revenue and physical productivity is that young businesses charge lower prices than incumbents. This also suggests that the current literature understates the contribution of entry to aggregate productivity growth.

We bring these pieces together to explore the determinants of market selection. As in the existing literature, we find that plants with lower revenue productivity are more likely to exit. When we decompose revenue productivity into physical productivity and prices, though, we find that both independently affect survival and the magnitudes of their individual effects are larger than their combined effect through revenue productivity measures. That is, while low prices and low physical productivity are both associated with higher probabilities of exit in isolation, the marginal effect of each is substantially enhanced by controlling for the other. When we further decompose prices into technology and demand fundamentals, our analysis shows that producers facing lower demand shocks are more likely to exit. In fact, our estimates suggest that demand variations across producers are the dominant factor in determining survival.

The paper proceeds as follows. The next section provides the theoretical motivation for the paper by highlighting the multi-dimensional nature of selection with a simple model of imperfect competition among producers that differ not only in their cost/productivity levels, but also in the idiosyncratic demand conditions they face. Section 3 describes the data and measurement issues involved in our empirical study. Basic empirical facts about productivity and price distributions in our industries are then discussed in Section 4, and the central results regarding selection dynamics are presented in Section 5. Section 6 describes robustness checks of our empirical results, and Section 7 concludes.

2. Theoretical Motivation

We construct a model that shows how idiosyncratic technology and demand factors can jointly determine producers' long-run survival prospects in industry equilibrium. While simple, the model has the advantages of having an analytically tractable equilibrium and a straightforward selection mechanism. To further enhance the presentation's clarity, we assume a specific demand system for industry products. It is important to note, however, that the qualitative characteristics of the results can be obtained using other demand structures.

An industry is comprised of a continuum of producers of measure N . Producers are indexed by i (I is the set of industry producers), each making a distinct variety of the industry product. Demand for the industry's product is embodied in the representative industry consumer's preferences over varieties, which is given by

$$\begin{aligned}
 U &= y + \int_{i \in I} (\alpha + \delta_i) q_i di - \frac{1}{2} \eta \left(\int_{i \in I} q_i di \right)^2 - \frac{1}{2} \gamma \int_{i \in I} q_i^2 di \\
 &= y + \alpha \int_{i \in I} q_i di - \frac{1}{2} \left(\eta + \frac{\gamma}{N} \right) \left(\int_{i \in I} q_i di \right)^2 + \int_{i \in I} \delta_i q_i di - \frac{1}{2} \gamma \int_{i \in I} (q_i - \bar{q})^2 di
 \end{aligned} \tag{1}$$

where y is the quantity of a numeraire good, $\alpha > 0$, $\eta > 0$, and $\gamma \geq 0$.⁷ The variable δ_i is a variety-specific, mean-zero taste shifter; q_i is the quantity of good i consumed; and $\bar{q} = N^{-1} \int q_i di$. Utility is thus a quadratic in total consumption of the industry's output, plus a term capturing idiosyncratic tastes for particular varieties, minus a term increasing in the variance of consumption across varieties. This last term introduces an incentive to equate consumption levels of different varieties. The parameter γ embodies the extent to which varieties are substitutable for one another; a higher γ imposes a greater utility loss from consuming idiosyncratically large or small quantities of particular q_i , limiting consumer responses to price differences among industry producers. As $\gamma \rightarrow 0$, substitutability becomes perfect: only the total taste-adjusted quantity of industry varieties consumed affects utility.⁸ The parameters α and η shift overall demand for the industry's output relative to the numeraire, and

⁷ This demand system is a modified version of the one used in a different context by Melitz and Ottaviano (2005).

⁸ A decrease in γ has another effect: it raises the utility of any given bundle of industry goods and therefore draws in expenditure into the industry from the numeraire. While this will impact certain equilibrium elements such as the average price level and number of industry producers, it does not impact any of the qualitative implications we draw on below. We thank a referee for bringing this second effect to our attention.

δ_i shifts demand for particular goods relative to the level of α .

The technology is a single-input production function

$$q_i = \omega_i x_i, \quad (2)$$

where x_i is the input and ω_i is producer-specific productivity. The input can be purchased at a price w_i , which we allow to also be specific to producers. Therefore producers' total costs are $C_i(q_i) = (w_i/\omega_i)q_i$ with marginal costs equal to w_i/ω_i . Hence there is within-industry variation in demand (δ_i), productivity (ω_i), and factor prices (w_i).

These demand and supply fundamentals imply (see Foster, Haltiwanger, and Syverson 2005) that a producer's profit-maximizing price is

$$p_i = \frac{1}{2} \frac{\gamma}{\eta N + \gamma} \alpha - \frac{1}{2} \frac{\eta N}{\eta N + \gamma} \bar{\delta} + \frac{1}{2} \frac{\eta N}{\eta N + \gamma} \bar{p} + \frac{1}{2} \delta_i + \frac{1}{2} \frac{w_i}{\omega_i} \quad (3)$$

and maximized profits are

$$\pi_i = \frac{1}{4\gamma} \left(\frac{\gamma}{\eta N + \gamma} \alpha - \frac{\eta N}{\eta N + \gamma} \bar{\delta} + \frac{\eta N}{\eta N + \gamma} \bar{p} + \delta_i - \frac{w_i}{\omega_i} \right)^2, \quad (4)$$

where \bar{p} and $\bar{\delta}$ are the average price and quality weight among industry producers ($\bar{\delta}$ need not be zero in equilibrium). Prices and profits are intuitively increasing in the overall level of demand for the industry's output, the average price of industry competitors, and demand for the specific producer's variety (measured by δ_i). They are decreasing in the average quality level of the producer's competitors. Higher marginal costs lead to higher prices and lower profits.⁹

We can compute the deviation of any particular producer's price from the industry average by taking the mean of (3) across producers and subtracting it from (3). This gives

$$p_i - \bar{p} = \frac{1}{2} (\delta_i - \bar{\delta}) + \frac{1}{2} \left(\frac{w_i}{\omega_i} - \overline{\left(\frac{w}{\omega} \right)} \right), \quad (5)$$

where $\overline{(w/\omega)}$ is the average marginal cost in equilibrium. Note that *both* higher-demand and higher-cost (those facing high input prices or the less efficient) producers charge higher prices.

We will see this dual influence acting in our empirical work below.

⁹ The derivation does not account for the fact that, since marginal utility for any particular good is bounded at $\alpha + \delta_i$ (see (1)), some goods may not be purchased at the price given by (3). However, one can show that any producer operating in equilibrium (i.e., satisfying $q_i > 0$ and $\pi_i \geq 0$) has an optimal price given by (3) that is below this marginal utility bound. See Foster, Haltiwanger, and Syverson (2005).

Define the “profitability index” of a particular producer as follows:

$$\phi_i \equiv \delta_i - \frac{w_i}{\omega_i}. \quad (6)$$

Note that this index captures both idiosyncratic demand for producer i 's product and its own marginal cost. Expression (4) implies a critical value of this index, ϕ^* , where producers with $\phi_i < \phi^*$ will not find operations profitable.¹⁰ If we set (4) equal to zero and then solve to obtain ϕ^* explicitly, we can substitute ϕ^* and (6) back into (4) to obtain a simple expression for a producer's operating profits in terms of its own and the cutoff profitability levels:

$$\pi_i = \frac{1}{4\gamma} (\phi_i - \phi^*)^2. \quad (7)$$

A large pool of ex-ante identical potential entrants decides whether to enter the industry as follows. They first choose whether to pay a sunk entry cost s in order to receive demand, productivity, and input price draws from a joint distribution with probability density function $f(\delta, \omega, w)$. The marginal distributions of δ, ω , and w are defined respectively over $[-\delta_e, \delta_e]$, $[\omega_l, \omega_u]$, and $[0, w_u]$, where $\delta_e < \alpha$ and $\omega_l > 0$. (Values $\delta_e, \omega_l, \omega_u$, and w_u are otherwise arbitrary, and while the marginal distribution of δ need not be symmetric, we assume here for simplicity that it is.) If they choose to receive draws, they determine after observing them whether to begin production and earn the corresponding operating profits (7). Clearly, only potential entrants with draws yielding a profitability index that offers nonnegative operating profits ($\phi_i \geq \phi^*$) will choose to produce in equilibrium. Hence the expected value of paying s is the expected value of (7) over $f(\delta, \omega, w)$, conditional on drawing $\phi_i \geq \phi^*$. This expected value is obviously affected by the cutoff cost level ϕ^* . A free-entry condition pins down this value: ϕ^* must set the net expected value of entry into the industry V^e equal to zero. Thus ϕ^* satisfies

$$V^e = \int_0^{w_u} \int_{\omega_l}^{\omega_u} \int_{-\delta_e}^{\delta_e} \frac{1}{4\gamma} (\phi_i - \phi^*)^2 f(\delta, \omega, w) d\delta d\omega dw - s = 0. \quad (8)$$

This expression summarizes the industry equilibrium. (The equilibrium mass of producers N is determined by $\alpha, \eta, \gamma, \overline{(w/\omega)}$, and ϕ^* , and can be solved for by substituting the \bar{p} implied by (3) into the explicit expression for ϕ^* .) It combines the two conditions that all

¹⁰ Note that while the quadratic form of the profit function (4) implies positive profits for $\phi_i < \phi^*$, this would also imply that $q_i < 0$.

producers make nonnegative operating profits and that entry occurs until the expected value of taking demand, efficiency, and factor price draws is zero. Notice that the equilibrium requires producers to obtain a combination of idiosyncratic draws high enough to meet the profitability threshold. The particular value of this threshold is affected by the distributions of the demand, efficiency, and factor price draws as well as industry-wide demand and technology parameters, as discussed below. Hence the model points to idiosyncratic technology and demand factors *jointly* determining the likelihood of survivorship in the industry.¹¹

2.1. Productivity Measures

We now derive from the model the productivity measures corresponding to those discussed in the Introduction. The first measure, which we call physical productivity (TFPQ), is based on quantities of physical output:

$$TFPQ_i = \frac{q_i}{x_i} = \frac{\omega_i x_i}{x_i} = \omega_i.$$

Notice that $TFPQ_i$ equals the producer's "true" technical efficiency level ω_i .

The second productivity measure, which we call revenue productivity (TFPR), is based on producer revenue:

$$TFPR_i = \frac{p_i q_i}{x_i} = p_i \omega_i = \frac{1}{2} \frac{\gamma \alpha}{\eta N + \gamma} \omega_i + \frac{1}{2} \frac{\eta N}{\eta N + \gamma} (\bar{p} - \bar{\delta}) \omega_i + \frac{1}{2} \delta_i \omega_i + \frac{1}{2} w_i.$$

Empirical work with micro data typically uses revenue-based productivity measures. As can be seen, while it is positively correlated with true productivity ω_i , $TFPR_i$ confounds idiosyncratic demand and factor price effects with efficiency differences. Producers can have high TFPR levels because they are efficient, but this can also be driven by high producer-specific demand.¹²

¹¹ As a two-stage entry and production model, our framework abstracts from dynamics. It can thus be interpreted as highlighting selection effects across long-run industry equilibria. However, embedding our model into a fully dynamic framework like that in Asplund and Nocke (2006) would be conceptually straightforward (albeit space-consuming). An additional implication that Asplund-Nocke-type dynamics would make explicit is that the quantitative impact of profitability components on survival depend on the persistence of their plant-level stochastic processes. That is, a given change in (say) plant-level demand will have a larger effect on a plant's survival the greater is the persistence of the idiosyncratic demand process. We will see this feature in the empirical work below.

¹² In practice, comprehensive *input* quantity data are rarely available, so expenditures are used instead (i.e., total inputs are measured as $w_i x_i$). This would imply that TFPQ reflects plants' idiosyncratic cost components, both technological fundamentals and factor prices, while TFPR still confounds these supply-side factors with demand-side effects.

2.2. Comparative Statics

The model yields implications about the relationship between exogenous parameters and ϕ^* , the equilibrium cutoff profitability level. From these we can draw connections between changes in industry-wide demand or technology parameters and survivorship.

Using the implicit function theorem on (8) yields two comparative statics of interest: $d\phi^*/d\gamma < 0$ and $d\phi^*/ds < 0$. The first indicates that a decrease in substitutability (an increase in γ) leads to a lower cutoff profitability cost level. This is intuitive; lower substitution possibilities for consumers protect producers with less appealing products or higher costs from being driven out of business by high-demand and/or low-cost competitors. The second is that a higher sunk entry cost s makes it easier for relatively unprofitable (low-demand and/or high-cost) producers to survive in equilibrium. Higher entry costs reduce the number of potential entrants who buy profitability draws, lowering the highest order statistics of draws among potential entrants that end up producing in equilibrium.

2.3. Discussion

The model offers several insights that we test in the data. First, selection and survival in industry equilibrium can depend on both producer-specific technology and demand factors. Second, shifts in aggregate industry conditions interact with idiosyncratic factors to determine the margins along which selection occurs (i.e., as ϕ^* shifts). Whether such shifts “bite” harder on, say, the demand or technical efficiency margin depends on the joint density of the producer-specific draws $f(\delta, \omega, w)$. This question is one area of focus for the empirical work below. Third, the producer-specific deviation from average industry price is positively correlated with idiosyncratic demand and negatively correlated with true productivity. And finally, revenue-based TFP measures are positively correlated with true productivity, but they also confound idiosyncratic demand with efficiency factors.

3. Data and Measurement Issues

We explore the demand-efficiency-survival links using establishment-level data for producers of eleven manufacturing products. The data is from the Census of Manufactures (CM). The CM is conducted quinquennially in years ending in ‘2’ and ‘7’ and covers the universe of manufacturing plants. We select census years 1977, 1982, 1987, 1992, and 1997 for our

sample based upon the availability and quality of physical output data in the CM.¹³ The CM collects information on plants' annual value of shipments by seven-digit SIC product category and, when feasible, shipments in physical units. The CM also contains production worker and nonproduction worker employment, production worker hours, book values of equipment and structures, cost of materials, and cost of energy usage.

The unit of observation in our sample is the establishment ("plant"). Our product definitions are built up from the seven-digit SIC product classification system. Some of our eleven products are the only seven-digit product in their respective four-digit SIC industry, and thus the product defines the industry. This is true of, for example, ready-mixed concrete. Others are single seven-digit products that are parts of industries that make multiple products. Raw cane sugar, for instance, is one seven-digit product produced by the four-digit sugar and confectionary products industry. Finally, some of our eleven products are combinations of seven-digit products within the same four-digit industry. For example, the product we call boxes is actually comprised of roughly ten seven-digit products.¹⁴

We calculate unit prices for each producer using their reported revenue and physical output.¹⁵ These prices are then adjusted to a common 1987 basis using the revenue-weighted geometric mean of the product price across all of the plants producing the product in our sample. In the analysis that follows, we use the log of this real price.

We also compute three total factor productivity (TFP) values for each plant. Each measure follows the typical index form

$$t\hat{p}_{it} = y_{it} - \alpha_l l_{it} - \alpha_k k_{it} - \alpha_m m_{it} - \alpha_e e_{it}, \quad (9)$$

¹³ A problem with CMs prior to our sample is that it is more difficult to identify balancing product codes (these are used to make sure the sum of the plant's product-specific shipment values equals the plant's separately reported total value of shipments). A related problem is that there are erratic time series patterns in the number of establishments reporting physical quantities. Given our focus on entry and exit, we chose to focus on the data in 1977 and beyond.

¹⁴ The exact definition of the eleven products can be found in the Appendix. In cases where we combine products, we base the decision on our impression of the available physical quantity metric's ability to capture output variations across the seven-digit products without introducing serious measurement problems due to product differentiation. In boxes, for instance, the several seven-digit products differ in their final demand sector; e.g., classifications include "boxes for glass, clay, and stone products," and "boxes for lumber and wood products, including furniture," and "boxes for electrical machinery, equipment, supplies, and appliances." While there may be some slight variations in the physical attributes of these different types of boxes, we presume that short tons (our physical output measure) of these box types are comparable among one another. That is, a plant making 1000 tons of furniture boxes has the same output as one making 1000 tons of appliance boxes.

¹⁵ The reported revenues and physical quantities are annual aggregates, so the unit price is an annual average. This is equivalent to a quantity-weighted average of all transaction prices charged by the plant during the year.

where the lower-case letters indicate logarithms of establishment-level TFP, gross output, labor hours, capital stocks, materials, and energy inputs, and α_j ($j = \{l, k, m, e\}$) are the factor elasticities for the corresponding inputs.¹⁶ Labor inputs are measured in hours, capital as plants' reported book values of equipment and structures deflated to 1987 dollars, and materials and energy inputs are the reported expenditures on each deflated using the corresponding input price indices from the NBER Productivity Database. Because we use expenditures to compute materials and energy use, idiosyncratic establishment-level variation in input prices will be captured here as high measured inputs and in turn low measured productivity. For many purposes, this does not pose a problem (we discuss this further below), because the implications of being high cost are the same as being of low productivity.¹⁷ To measure the input elasticities α_j , we use industries' average cost shares over our sample. Labor, materials, and energy cost shares are computed from reported expenditures in the CM, while capital cost shares are constructed as reported equipment and building stocks multiplied by their respective capital rental rates for each plant's corresponding two-digit industry. Further details on the construction of input measures and elasticities are in the Appendix.¹⁸

¹⁶ An implicit assumption in this index is constant returns to scale. If the scale elasticity were instead different from one, each of the input elasticities α_j should be multiplied by the scale elasticity. Syverson (2004) actually estimates a physical production function for ready-mixed concrete plants and finds constant returns to scale (the estimated scale elasticity is 0.996). On this basis, we are confident of our constant returns assumption for the most prominent product/industry in our sample. In further explorations of the influence of the assumed scale elasticities, we found our results robust to modest departures from unitary scale elasticities, and assuming decreasing returns of any degree served only to reinforce the survival effect of higher productivity. We did see sensitivity when increasing returns were assumed to be large enough (around 1.1 or above). This is because assuming high enough scale elasticities can make the correlation between TFP and plant size negative. Since large plants are more likely to survive, as will be seen below, our estimates of the survival effect of productivity shrink in magnitude, and in extreme cases can actually imply higher productivity plants are more likely to exit. We are not particularly concerned about this sensitivity, however. First, there are the concrete results described above. In addition, the empirical literature on plant-level production function estimation supports the assumption of constant returns to scale (or if anything decreasing returns to scale) – see, e.g., Baily, Hulten and Campbell (1992) and Olley and Pakes (1996). Second, many researchers have found a positive correlation between plant size and productivity using various methods of TFP measurement. Third, regardless what the scale elasticity is, equilibrium selection tends to create a positive correlation between plant size and TFP. This suggests the negative correlation that we found is likely to be an artifact of imposing a large degree of increasing returns that is not suggested by observed input and output patterns.

¹⁷ Dunne and Roberts (1992) and Roberts and Supina (1996, 2000) use CM materials price data and find that plants facing high materials prices charge high output prices. Syverson (forthcoming) finds that there is also a relationship between the dispersion of local materials and output price distributions. We do not use the materials data here because our focus is on industry evolution, and the number of plants for which materials prices are available is considerably more limited than our current sample. Idiosyncratic variation in labor costs may be especially difficult to disentangle as wage variation across plants undoubtedly reflects skill mix differences across plants.

¹⁸ There are a number of alternative means of measuring factor elasticities. One is to estimate factor elasticities using either an instrumental variables procedure or the proxy methods developed by Olley and Pakes (1996) or Levinsohn and Petrin (2003). These latter methods are best suited to annual panel data, however. Moreover,

The difference between our three TFP indices lies in the log output measure y_i . The first index, physical productivity (TFPQ), uses the physical output data described above.¹⁹ As we noted earlier, TFPQ variation reflects dispersion in physical efficiency and possibly factor input prices; it essentially reflects a producer's average cost per unit. The next two indices are revenue-based measures of productivity. They differ in their nominal revenue measure and the price deflator used to construct real revenue. We call one index traditional TFP (TFPT), since it corresponds to the standard revenue-based output measure used in the literature. This index measures output as the dollar value of shipments adjusted for inventory changes, deflated by the four-digit industry-level shipments deflator from the NBER Productivity Database. The final TFP index measures output as the deflated nominal revenue from product sales, where the deflator is the revenue-weighted geometric mean price across all plants making that product in our sample. We call this index revenue-based productivity (TFPR). TFPR is an internally consistent measure that satisfies the simple identity that it equals the sum of TFPQ (already in logged terms) and logged plant level prices. Thus one can interpret much of our analysis below as decomposing TFPR into its two components: physical efficiency and prices.²⁰

interpreting their estimates as factor elasticities is appropriate only if plants are price takers, because idiosyncratic demand shocks make the proxies functions of both technology and demand shocks, thereby inducing a possible omitted variable bias. Put simply, proxy methods require a one-to-one mapping between plant-level productivity and the observable used to proxy for productivity. This mapping breaks down if other unobservable plant-level factors besides productivity drive changes in the observable proxy. Of course, this possibility is the very point of our paper. While it would be interesting to explore the robustness of our findings to alternative factor elasticities, the findings of Van Biesebroeck (2004), who finds high TFP correlations across various measurement alternatives, suggest this is unlikely to be a first-order issue. Further, Syverson (2004) finds similar robustness among producer TFP measures for one of our products, ready-mixed concrete, with a specification and approach that incorporates the presence of idiosyncratic demand shocks.

¹⁹ Given that producers of the products in focus also sometimes make other products, some adjustment to this physical quantity is made as described below.

²⁰ The differences in nominal revenue concepts between TFPR and TFPT deserve further comment. TFPR uses the nominal product-level revenue that is collected during the process of measuring physical output. TFPT instead uses a closely related measure called the "total value of shipments," which potentially includes additional revenue streams such as that from contract work. Moreover, TFPT output adjusts for inventory changes. In practice, we will see that TFPT and TFPR are highly correlated at the micro level. But the identities between revenue productivity, physical productivity, and prices—which play an important role in interpretation of our results below—only hold using TFPR as the revenue-based productivity measure. We include TFPT analysis because it is the measure that most researchers using microdata (and the U.S. Economic Census in particular) have used. Finally, as noted before, our products do not always fully cover the four-digit industries from which they are drawn. For most purposes this is not a concern for measurement and analysis of prices, since we control for product-year interactions in our empirical work below. However, as will become clear, the discrepancy between the price deflators for products and industries causes measurement difficulties for the analysis of aggregate (industry/product) effects.

3.1. Rules for Inclusion in the Sample

While the Economic Census data we use is very rich, it still has limitations that make necessary three restrictions on the set of producers included in our sample. First, we exclude plants in a small number of product-years for which physical output data are not available due to Census decisions to not collect it or obvious recording problems. Second, we exclude establishments whose production information appears to be imputed (imputes are not always identifiable in the CM) or suffering from gross reporting errors. Third, we impose a product specialization criterion: a plant must obtain at least 50% of its revenue from sales of our product of interest. This restriction reduces measurement problems in computing physical TFP. Because plants' factor inputs are not reported separately by product but rather at the plant level, we must for multi-product plants apportion the share of inputs used to make our product of interest. Operationally, we make this adjustment by dividing the plant's reported output of the product of interest by that product's share of plant sales. This restriction is not very binding in seven of our products whose establishments are on average quite specialized. Bread, flooring, gasoline, and block ice producers are less specialized, however, so care must be taken in interpreting our sample as being representative of all producers of those products. We test below the sensitivity of our results to the inclusion of less specialized producers.²¹ Characteristics of the final sample can be seen in Table A.1.

Details of these specific restrictions as well as how we identify affected establishments are in the Appendix.

3.2. Properties of the Sample

Applying the rules described above yields a pooled sample of 17,669 establishment-year observations over five census years. Table 1 shows summary statistics for core variables. We focus on correlations and standard deviations. We remove product-year fixed effects from these summary statistics—and control for them in all of our empirical exercises—so cross-product

²¹ This input-adjustment method in effect assumes inputs are used proportionately to each product's revenue share. For example, a plant producing 1000 cubic yards of ready-mixed concrete accounting for 80% of its shipment revenues will have the same physical TFP value as a completely specialized plant producing 1250 cubic yards of concrete, assuming they employ the same measured inputs. Without adjusting the output, the first plant would appear less productive because the inputs it uses its other products would be instead attributed entirely to ready-mixed production. The average share of our sample plants' values of shipments accounted for by the corresponding product is given in parentheses: boxes (93), bread (39), carbon black (96), coffee (86), concrete (92), flooring (46), gasoline (49), block ice (37), processed ice (76), plywood (64), and sugar (90).

heterogeneity or aggregate intertemporal movements do not drive our results.

The table shows summary statistics for our three measures of log output (traditional, revenue, and physical, as described above), our price measure, our three total factor productivity measures (corresponding to each output measure), and log plant capital. The first point to note is the very high correlation in the output measures. This partly reflects the enormous dispersion in the size of businesses within industries, as evidenced by the output measures' large standard deviations. Put simply, a large business is a large business regardless of the details of output measurement. The second point to note is that the productivity measures are also highly correlated and exhibit substantial dispersion within product-years, with standard deviations exceeding 20 log points. Interestingly, physical productivity TFPQ has higher dispersion than the internally consistent revenue-based productivity TFPR. Since the former is, along with logged price, a component of the latter, this might at first seem surprising. However, notice that physical productivity and prices are strongly inversely correlated. Thus, even though there is substantial price dispersion across producers in the same industry, the negative covariance between prices and physical productivity results in revenue productivity being less dispersed than physical productivity.

The inverse correlation between physical productivity and prices is consistent with more efficient businesses having lower marginal costs and in turn charging lower prices, a common implication of models of imperfect competition and our model above. Note that this effect might also be reflecting input price variation. High input price plants will have low TFPQ values because their materials and energy expenditures will be larger than those of their industry counterparts.

We note that the negative correlation between physical productivity and prices bolsters our strategy of focusing on homogenous products to reduce the effects of quality variation. While this correlation is consistent with price variation reflecting demand shifts across producers, it is far from obvious that physical productivity and prices would be negatively correlated if price variation simply reflected output quality differences.

It is also interesting that, again as predicted by the model, revenue productivity and prices are positively correlated. By construction, revenue productivity combines both prices and physical productivity. As such, one component of revenue productivity is positively correlated with prices while the other is negatively correlated. We shall return to this point below.

In what follows, we often present results on both an unweighted and a real revenue-weighted basis. The unweighted results treat all observations equally, while the weighted results give a greater influence to high-revenue plants. Since most of the empirical exercises that follow use the pooled sample, it is useful to know the influence that individual products have in the sample. (Although we always control for a full set of product-year interactions, so it is within product-year variation that we are exploiting.) In terms of general sample properties, concrete dominates the sample in terms of the number of establishments, while gasoline dominates the sample in terms of the share of real revenue. Table A.1 contains more details.

3.3. Idiosyncratic Demand: Concept and Measurement

This paper seeks to separate the influences of idiosyncratic technology and demand— influences that previous studies have had to lump together due to data limitations—and explore the contribution of each to plant survival and productivity growth. In this vein, we compute the technology component (physical efficiency) as described above. In this section, we describe how we use the other component of revenue-based productivity, price, to estimate plants’ idiosyncratic demand levels. We use these demand estimates along with our physical productivity measures extensively in our analysis below.

Before describing the empirical methodology, it is useful to discuss what the price and demand variations within our sample products embody. As noted, we construct our sample from producers of goods that, to our best judgment, are physically homogeneous. The purpose of doing so is to make physical productivity (i.e., the number of units of the good produced per unit of input) a measure of technical efficiency that is directly comparable across plants producing a given product. It also means that the across-producer price variation and the plant-specific demand measures we estimate from these prices reflect factors other than vertical quality differentials among producers’ physical products.

What might these other factors be? For products with high enough transport costs, these factors could reflect demand idiosyncrasies across local markets.²² Producers in markets that

²² According to the 1977 Commodity Transport Survey—the last survey for which detailed product-level shipment distance data are reported—six of our products saw a majority of their shipments sent less than 100 miles (the shortest distance category for which tabulations are available) from the plant. Over 99 percent of ice products and 95 percent of ready-mixed concrete production was shipped to buyers within this distance. For boxes, bread, and gasoline, the shares were 63, 62, and 53 percent, respectively.

happen to be facing particularly high demand (or, to a lesser extent, those producers in high-demand areas *within* markets) are likely able to set higher prices or sell more at a given price than those in low-demand markets. High-demand producers are also more apt to survive even if they are no more physically efficient than their low-demand industry cohorts. This is the demand-based survival benefit we wish to separate from physical productivity's survival benefit. Notice that local demand idiosyncrasies imply producers of such products have some degree of market power despite producing what are, from a physical standpoint, commodities. Importantly, however, this market power is driven by horizontal product differentiation. Consumers will have different preference orderings over producers' locations. Also, differentiation is not tied to the physical product which we measure (e.g., cubic yards of concrete or tons of ice). Most construction contractors, for example, would be indifferent between—and in fact be unable to discern—two unlabeled truckloads of ready-mixed concrete. This allows us to be confident that physical output and productivity measures are comparable across producers and economically meaningful from the standpoint of technical efficiency.

Even for producers of national-market products in our sample, there are probable sources of other, non-spatial horizontal differentiation. Leading candidate sources of this differentiation are the often complex and history-laden collection of relationships between suppliers and their customers. Long-run buyer-supplier ties, whether driven primarily by business or personal bonds, are likely pervasive across industries. While it is of course very difficult to quantify these relationships, there is some anecdotal evidence of their importance in our industries. For instance, while press accounts describe carbon black as "...a typical commodity business wherein there is very limited scope for value addition" (Krishnakumar, 2001), major producer Cabot Corporation states in its 2005 annual report that, "Under appropriate circumstances, we have pursued a strategy of entering into annual and long-term supply contracts (those with a term longer than one year) with certain customers" (Cabot Corporation, 2006). In its 2005 annual report, Imperial Sugar comments on "...the harsh realities of operating in a commodity business," but also states that "...the majority of our sales [are made] to industrial customers under fixed price, forward sales contracts," though typically with terms of one year or less (Imperial Sugar, 2006). Both of these examples suggest that non-spatial product differentiation exists even among producers of physically identical commodities. Customers do not perceive all producers as symmetric—hence their willingness to enter into what are likely multiple-

transaction contracts with certain producers.²³ Moreover, these examples reflect producer-consumer relationships that are actually contracted over. We suspect, though of course cannot show definitively, that non-contractual “relationship capital” of this sort is as much or even more important in our industries.²⁴ Such differentiation is conceptually identical to the spatial demand idiosyncrasies described above, as long as such contracts (explicit or implicit) reflect horizontal preference variation across consumers rather than vertical differentiation—for example, a tire firm contracts with Cabot because of some match-specific factor (perhaps a past history with this supplier has built relationship capital), rather than Cabot’s carbon black and bundled products being considered superior by all possible consumers. Therefore, just as with the spatially differentiated industries, the idiosyncratic price and demand variation across producers reflects the strength of particular producers’ horizontal demand differentials.

To measure such idiosyncratic demand elements, we begin by estimating the following demand system separately for each of our eleven products:

$$\ln q_{it} = \alpha_o + \alpha_1 \ln p_{it} + \sum \alpha_t YEAR_t + \alpha_2 \ln(INCOME_{mt}) + \eta_{it}, \quad (10)$$

where q_{it} is the physical output of plant i in year t , p_{it} is the plant’s price, and η_{it} is a plant-year

²³ Such relationship-driven differentiation can also exist alongside the spatial demand idiosyncrasies in the more local industries discussed above. For example, the president of National Portland Cement Company testified in a FTC investigation that acquiring (i.e., forward integrating into) an existing ready-mixed concrete business is easier than building one from scratch. His stated reasoning was, “The ready-mixed business, as we analyze it, is a very personal type of business and the operators develop personal relationships with contractors over many, many years. To go in and go through developing those relationships on the part of a newcomer would assure you that you are going to lose money for 3, 4, 5 years.” (U.S. FTC, 1966)

²⁴ Some striking examples of the strength and persistence of consumers’ relationships with particular producers can be found in Bronnenberg, Dhar, and Dubé (2005). They document large and persistent geographic variation in preferences for specific brands of what are physically very similar consumer package goods (including, incidentally, ground coffee, though they look at retail sales while we focus on manufacturers). They find that this variation can be tied to being the first mover into the particular market, even if the initial entry episode took place more than a century prior. One caveat that should be kept in mind with regard to relationship capital is that if producers spend current productive resources to build it, this might be thought of as revenue-enhancing, even though it could lower the producer’s TFPQ (but raising the price it can charge in exchange). We obtained a rough measure of the possible magnitude of such activities by looking at the correlation between a plant’s nonproduction worker share (i.e., the fraction of its employees classified as nonproduction workers according to the Census Bureau’s definition) and the plant’s TFPQ and price. This is based on the notion that “relationship-building” activity would primarily be conducted by nonproduction workers. We found nonproduction workers’ share is positively correlated with prices and negatively correlated with physical productivity. This is consistent with relationship-building activity trading off physical efficiency for a higher price. However, these correlations were quite weak, with absolute magnitudes of 0.01. Further, there was also indication that any active cultivation captured by these measures might not be yielding net gains for the producer: nonproduction worker intensity and TFPR were negatively correlated. In short, we are assuming in the present analysis that the sources of demand variation across plants are essentially exogenous (or at least unrelated to current measured input choices). This evidence on the relationship of key measures to the nonproduction worker share suggests this assumption is not unreasonable.

specific disturbance term. We also control for a set of demand shifters, including a set of year dummies ($YEAR_t$), which adjust for any economy-wide variation in the demand for the product, as well as the average income in the plant's local market m . We define local markets using the Bureau of Economic Analysis' Economic Areas (EAs).²⁵

Of course, estimating (10) using ordinary least squares (OLS) methods could lead to positively biased estimates of the price elasticity α_1 , because producers may optimally respond to demand shocks in η_{it} by raising prices. This would create a positive correlation between the error term and p_{it} . A solution to this is to instrument for p_{it} using supply-side (cost) influences on prices. While such instruments can sometimes be hard to come by in practice, we believe we have very suitable instruments at hand: namely, plants' TFPQ levels. As discussed previously, these embody producers' idiosyncratic technologies (physical production costs). As such, they should have explanatory power over prices. The large negative correlation between TFPQ and prices shown above indicates that this is the case. Further, it is unlikely they will be correlated with any short-run plant-specific demand shocks embodied in η_{it} . Hence they appear quite suitable as instruments for plant prices.²⁶

Our demand estimates are shown in Table 2. The first two columns provide the main results using plants' physical productivity levels as instrumental variables (IV) for their prices,

²⁵ EAs are collections of counties usually, but not always, centered on Metropolitan Statistical Areas. Counties are selected for inclusion in a given EA based upon their MSA status, commuting patterns, and newspaper circulation configurations, subject to the condition that EAs contain only contiguous counties. EA boundaries do not have to coincide with state boundaries. The roughly 3200 U.S. counties are grouped into 172 EAs that are mutually exclusive and exhaustive of the land area of the United States. See U.S. Bureau of Economic Analysis (1995) for detailed information. A small percentage of establishments in the CM switch counties over time (either due to data errors or, more rarely, changes in county limits). Since $INCOME_{mt}$ is merged into our dataset using county level information, we edit such county-switchers in our sample so that they remain in a fixed county over time.

²⁶ There are two potential problems with using TFPQ as an instrument. The first is that selection on profitability can lead to a correlation between TFPQ and demand at the plant level, even if the innovations to both series are orthogonal as assumed. This is because producers with a higher TFPQ draws can tolerate lower demand draws (and vice versa) while still remaining profitable. Hence producers that chose in the previous period to continue operations into the current period—i.e., the continuing plants—will tend to have negatively correlated lagged TFPQ and lagged demand levels. (This is unlikely to be a problem for entering plants, however, since profitability-based selection has not yet had time to act.) To address this issue, we estimated product demand curves using an alternative instrument for price that is based only upon innovations to TFPQ. A second potential problem is measurement error. We compute prices by dividing reported revenue by quantity and any measurement error in physical quantities will overstate the negative correlation between prices and TFPQ. Since the first stage of the IV estimation regresses plants' prices on their TFP levels, measurement error would yield biased estimates of the fitted prices used in the second stage, possibly leading in turn to biased price elasticities and idiosyncratic demand measures. We employ another alternative specification to deal with measurement error. In both cases (described in detail in the Appendix) we found the patterns of elasticities, demand shocks, and the results that depend upon demand shocks in Tables 3-6 to be quite robust. Hence it does not appear that either concern is driving our demand estimation results.

and the second two columns provide OLS estimates for reference purposes.

Focusing on the IV estimation cases, we find that all estimated price elasticities are negative, and for all but carbon black, they exceed one in absolute value. Elasticities range from -5.93 for concrete to -0.52 for carbon black. These estimates are reassuring since price-setting producers should be operating in the elastic portion of their demand curves. (Carbon black's inelastic point estimate may arise in part because the small number of producers yields imprecise estimates; in fact, we cannot reject that carbon black producers face elastic demand.)

Additionally reassuring for our demand estimation strategy is that all products (again except for carbon black) have more elastic IV demand estimates than in the OLS estimations. This is consistent with the theorized simultaneity bias present in the OLS results as well as the ability of TFPQ to instrument for endogenous prices. The table also shows for the IV results the Shea-corrected first-stage R^2 of price on TFPQ.²⁷ In all cases these show that physical productivity is a relevant instrument. The coefficient on local income is positive and significant for most but not all products.

We exploit the residuals from these demand function estimations in the analysis of market selection below. Specifically, the producer-specific demand measure we use is the residual from the IV demand estimation, along with the estimated contribution of local income added back in. One way of thinking about this measure is that it is the output variation across plants due to shifts in the demand curve rather than movements along the demand curve. Alternatively, it is a measure of output variation that is by construction orthogonal to physical productivity TFPQ. (Some correlation may remain in the constructed demand measures because while the demand function residuals themselves are orthogonal to TFPQ, the local market income component that is added back in may be related to average TFPQ levels. However, as we will see below this correlation is small.) It is also worth noting that although we have variation in elasticities across products, we do not exploit those in our analysis. The reason is that all of our subsequent analysis controls for a complete set of product-year interactions, and thus we are abstracting from all between-product variation.

Our measure of producer-specific demand is positively correlated with revenue productivity (correlations of 0.23 with TFPT and 0.28 with TFPR) and prices (correlation of 0.34) but, as discussed above, virtually uncorrelated with physical productivity (0.01). The

²⁷ This uses Shea's (1997) correction for a multivariate regression in which the instruments are highly collinear.

standard deviation of demand shocks is quite large (1.16), reflecting the large dispersion in output across producers of the same product. As noted, the interesting aspect of this measure is that it captures the variation in output after taking into account productivity variations and the movements along the demand curve associated with these.

4. Basic Facts about Dynamics

In this section, we provide additional basic facts about the plant-level distributions of total factor productivity, prices, and demand shocks using our pooled sample to set the stage for our analysis of selection in Section 5. We first examine the persistence of plants' productivity, prices, and demand levels. We next characterize the entry and exit dynamics of our sample.

4.1. Persistence

Preceding work (e.g., Supina and Roberts (1996); Baily, Hulten, and Campbell (1992); and Foster, Haltiwanger and Krizan (2002)) has found that, conditional on survival, there is substantial persistence in revenue productivity and prices. The findings from our sample reported in Table 3 are consistent with this earlier research.

The table shows the coefficients on the respective lagged dependent variables in simple autoregressive regressions of each measure on its own lag (five years earlier). We report the regression coefficients and standard errors in the first two columns and provide as a reference the implied one-year persistence rates in the next two columns. We find that producer-level revenue productivity measures and output prices are highly persistent in our sample as well, with implied annual autocorrelation values of roughly 0.75 to 0.80.

We also characterize (for the first time in the literature, to our knowledge) the persistence in physical productivity and demand shocks. Interestingly, we find that physical productivity exhibits persistence of similar magnitude to that for revenue productivity. Demand shocks are even more persistent. All variables are more persistent in the weighted results, implying that larger establishments have more persistent idiosyncratic characteristics.²⁸

While all of the fundamentals exhibit substantial persistence, the finding that demand shocks are substantially more persistent than physical productivity shocks has potentially

²⁸ We always use real revenue rather than physical-quantity weights for the weighted results to avoid comparability/aggregation problems across products.

important implications for market selection. The persistence of a current shock to profitability is critical for the impact on the expected present discounted value of profits, and as such, the impact on market selection.

4.2. Establishment Turnover

Our focus on the determinants of selection naturally compels us to measure the rate of establishment turnover in our sample. The entry rate in year t is defined simply as the number of entering establishments between $t-k$ ($k = 5$ here given use of Economic Censuses) and t as a fraction of the total number of establishments in year t . The exit rate in t is the fraction of establishments in year $t-k$ that exit between $t-k$ and t .

Table A.2 in the Appendix contains the detailed results that we summarize here. There is substantial entry and exit of establishments for all products.²⁹ Our pooled sample has an entry rate of 22.3 percent and an exit rate of 19.6 percent. These high turnover rates are in accordance with earlier findings in the business microdata literature (e.g., Dunne, Roberts, and Samuelson (1988)). There are significant differences in turnover across products. Entry rates vary from a low of 3.9 percent for sugar to a high of 26.6 percent for concrete (these are pooled over all available years of data). The range of exit rates for products is narrower, the lowest being 9.0 percent for gasoline and the highest 27.7 percent for processed ice. Some products appear to be in a period of retrenchment or consolidation. Sugar, for example, has a very low entry rate (3.9 percent) but a high exit rate (17.0 percent). Other products appear to simply have a high degree of churning. For example, concrete and both types of ice products all have entry rates and exit rates that exceed 20 percent.

Having established that our sample shows significant entry and exit of establishments, we turn now to our analysis of selection dynamics.

5. Selection Dynamics

²⁹ We use the universe Census files to define entry and exit. Thus we do not introduce spurious turnover simply through imposing our sample selection criteria (only those plants with physical quantity data, etc.). One possible remaining concern is that our criteria create sample selection problems particularly with respect to the implied effects of idiosyncratic technology and demand on plant turnover. We have found, however, that plant turnover rates are similar for both the universe of plants and our sample of plants. Readers preferring to be more cautious can interpret our results as being representative of these effects for the set of plants with physical output data available, which tend to be the larger producers in an industry.

The primary focus of our analysis is the connection between entry and exit dynamics and productivity, prices, and demand. As emphasized in the theoretical model in Section 2, the working hypothesis is that market selection is driven by both technology and demand factors. This implies that the connections drawn between revenue TFP and entry and exit in the existing literature may be misleading with regard to the importance of market selection for productivity growth. That is, revenue TFP dynamics may not accurately reflect physical TFP dynamics. This section characterizes the relations between entry and exit and the evolution of producers' idiosyncratic technology and demand levels.

5.1. Evolution of Key Distributions

We begin with some simple descriptive statistics on the differences in means between continuing, entering and exiting establishments. We compute these differences in means by regressing each of the key business-level measures (productivity, prices, and demand shocks) on entry and exit dummies and a complete set of product-by-year fixed effects. The entry dummy for year t equals one if the establishment enters the product group between $t-k$ and t , and the exit dummy equals one in year t if the establishment exits sometime between t and $t+k$. The product-year interactions capture the evolution of continuing establishments (hereafter denoted incumbents). The coefficient on the entry (exit) dummy thus measures the average difference between the productivity/price/demand of entering (exiting) establishments and incumbent producers of the respective products.

The outcome of this exercise is reported in Table 4. For the unweighted results, we find that exiting establishments have lower revenue productivity (TFPR and TFPT), physical productivity (TFPQ), prices, and demand shocks than incumbents. All these differences save for prices are statistically significant. In contrast, entering establishments have significantly higher TFPQ and TFPR (but not TFPT) than incumbents as well as lower prices (although not significantly) and demand (highly significant). The finding that there is no significant difference between entrants and incumbents in TFPT levels is common in the literature. When we weight observations by revenue, similar patterns hold, but the magnitudes of differences between incumbents, entrants, and exiters are larger. In particular, entering businesses have significantly lower prices (about 4 percent on average) on a quantity-weighted basis than incumbents. The larger magnitude of the effects with weighting suggests that these differences will be important

for aggregate dynamics.

These results already hint that caution needs to be used in interpreting entry and exit effects on revenue-based productivity patterns. Specifically, the finding that entrants have lower prices and demand shocks than incumbents means revenue-based productivity measures understate the true technological productivity of entrants. In the weighted results of Table 4, this shows up as a substantial difference in entrants' revenue and physical productivity measures.

This finding is particularly important for vintage and learning models of productivity dynamics. Many theories imply that entrants should be more efficient than incumbents because of vintage technology/capital effects. However, a potentially offsetting factor is that learning-by-doing or start-up costs keep entrants from immediately reaching their production frontier. The earlier literature's common finding, obtained using traditional measures of revenue productivity, that there is not much productivity difference between entrants and incumbents (and in many studies, entrants are found to have lower productivity than incumbents) has been taken as evidence of the dominance of learning or start-up costs over vintage effects. Our analysis here, however, suggests this view should be tempered. Part of the reason for the lower revenue-based productivity levels of entrants comes from the fact that entrants charge lower prices than incumbents, not because they are less technologically efficient. In fact, we find that entrants do have significantly higher physical TFP levels than incumbents, but this advantage is clouded in revenue productivity. We explore this empirical pattern a bit further here by comparing the dynamics of prices, productivity and demand shocks for young producers to those of more mature plants in the following analysis.

We start by categorizing each establishment in our sample according to their age (which is determined based upon their existence in Census of Manufacturers from 1963 to 1997). We classify as "young" those establishments that first appeared in the census prior to the current time period (i.e., those plants that were entrants in the previous census). Likewise, establishments first appearing two censuses back are "medium" aged, and finally establishments that first appeared three or more censuses prior to the current are classified as "old." We then estimate a similar specification to the entering-exiting-incumbent producer comparison above, but now also include dummies for young and medium plants as well as entry and exit dummies:

$$x_{it} = \beta_o + \beta_1 Exit_{it} + \beta_2 Entry_{it} + \beta_3 Young_{it} + \beta_4 Medium_{it} + \sum_{IT} \beta_{IT} IndYear_{IT} + u_{it}, \quad (11)$$

where x_{it} is an establishment-specific measure (i.e., TFP, price, or demand). As before, we

include a full set of product-year dummies $IndYear_{it}$. Thus the specification does not confound age with time effects; the establishment age coefficients reflect average differences across producers of different ages within product-years.

The results of our age effects estimation are reported in Table 5. In interpreting the results (particularly when comparing them with Table 4) it is important to note that the omitted reference group in Table 5 is only old plants, while the reference group in Table 4 includes all incumbents. The most striking patterns in Table 5 are for the weighted results, although many of the general patterns also hold for the unweighted results. Entering plants in the weighted results have a physical productivity advantage relative to old incumbents, but young and medium-aged plants do not. For revenue productivity (either TFPT or TFPR), entrants have no productivity advantage relative to old incumbents, and young and medium age plants have significantly lower productivity. The source of these contrasts can be seen in the price results: plants' prices rise (relative to older plants in the industry) with plant age. Thus the decomposition of revenue productivity into its price and physical productivity components reveals quite different life cycle patterns over the first 15 years of a plant's existence that are concealed if one only looks at the evolution of revenue productivity.³⁰

5.2. Selection

We now turn to the main focus of our analysis: the determinants of selection. We explore the role of physical productivity, prices, and demand shocks on plant survival both in isolation and jointly, testing if each has a significant impact on plants' exit decisions. We also compare these findings to those obtained in the literature using the traditional revenue productivity measure (TFPT). This allows us to quantify the degree to which previous empirical work potentially misinterpreted the contribution of the productivity-survival link to aggregate productivity growth.

³⁰ The patterns of plants' idiosyncratic demands are also interesting. New plants start with significantly lower average demands than older plants, and this gap closes very slowly. Even plants 10-15 years old have idiosyncratic demand values that imply their quantities produced are roughly 20-25 percent lower than that of old plants charging the same price. There are several plausible explanations for this. New producers in spatial industries might get less appealing locations. Entrants may want to resolve residual uncertainty about their idiosyncratic profitability before making costly investments to expand capacity. Consumers may establish match-specific relationship capital with producers, as discussed in Section 3.3, that young firms need time to build up; see Fishman and Rob (2003) for a model of such a process. These explanations might also be partly related to the fact that new firms charge lower prices. While we do not take a stand on any particular explanation here, we do see exploring these results more deeply as an interesting avenue for future work.

Table 6 presents the results of probit exit regressions, where we regress an indicator for plant survival (equal to one if the plant survives to the next CM) on our measures of producers' idiosyncratic technology and demand.³¹ We also estimate a version of each specification that includes the plant's logged capital stock; these are shown in the bottom half of the table. Including the capital stock in the specification has a benefit of allowing the short- and long-run components of plant survival to be separately measured. As Olley and Pakes (1996) discuss, a plant's capital stock reflects persistent components of survival because it embodies accumulated effects of the plant's past profitability draws—a series of good draws (high demands or low costs) should lead in equilibrium to higher investment and a large plant, and bad draws lead to smaller plants (or exit). The TFP, price, and demand coefficients in the specifications that include capital capture the shorter-run survival effects that are orthogonal to those embodied in the plant's capital stock. All specifications in the table use the pooled sample and again include a full set of product-year interactions as controls.³²

The first five columns present the marginal effects (evaluated at the median) of each of our main variables of interest in isolation. We find that establishments with lower TFP (by any measure), prices, or demand shocks are more likely to exit when each of these variables is considered in isolation. These results are statistically significant except for the impact of prices. The summary statistics in Table 1 and Section 3.3 and the coefficients in the upper part of Table 6 imply that a one standard deviation increase each in TFPT, TFPR, TFPQ, price, and demand correspond respectively to declines in exit probabilities of 1.5, 1.4, 1.0, 0.4 and 5.0 percentage points. Given that the mean five-year exit rate for our sample is around 20 percent, most of these are nontrivial effects. The specifications controlling for plant capital show similar results. The implied survival effects of the TFP measures fall insignificantly. More of a drop is seen in the effect of demand shocks, where the magnitude of the coefficient falls by one-third. This is not

³¹ Specifications using a simple linear probability model yield qualitatively similar results.

³² We do not estimate weighted specifications here. In the exercises above, weighted results could be interpreted as comparing output-weighted average attributes across plants of various categories. The present specification predicts how plants' average exit probabilities vary with their attributes. One might then be tempted, as we were in an earlier version, to interpret weighted versions of this specification as predicting exit probabilities of particular units of revenue. However, exit is inherently a plant-level process. Units of revenue can only exit in plant-level clusters, making weighted exit probability results hard to meaningfully interpret. Thus we do not report them. It *is* the case, though, that the size of exiting plants relative to incumbents affects the evolution of industry-level productivity aggregates. This will be accounted for below in Section 5.3. All this said, we have estimated weighted selection equations and found the results were largely comparable to the unweighted results, with the exception of the highly-specialized-producer subsample used in the robustness exercises below, where the weighted results indicated considerably weaker connections between plant attributes and survival.

unexpected; recall that our demand measure is a plant-specific demand shifter. High-quantity plants within an industry tend to be large plants with more capital (note the correlation between plant output and logged capital seen in Table 1). Interestingly, however, despite their correlation, both capital and our demand measure have statistically significant impacts on survival. The estimated marginal survival impact of capital is notably stable across the other specifications. A capital coefficient of -0.023 means moving one standard deviation up the logged capital distribution lowers the exit probability 2.6 percentage points.

The two richer specifications in columns 6 and 7 simultaneously include physical TFP and producers' prices or idiosyncratic demand measures in the specification. When TFPQ and prices are jointly controlled for in column 6, both higher TFPQ and higher prices are associated with a lower likelihood of exit. Moreover, the magnitudes of both marginal effects increase substantially relative to the case when each variable is considered in isolation (the impact of price more than triples). One standard deviation increases in TFPQ and prices reduce exit probabilities by 1.6 and 1.2 percentage points, respectively. The larger magnitudes for both price and physical productivity effects in this case make sense given the negative covariance between prices and TFPQ. If high-cost/low-productivity plants are high-price plants, then when we include only one of these plant-level measures, there is an implied omitted variable bias that obscures each measure's true effect. Put differently, the key point here is that controlling for both price and productivity effects enables us to separately identify the cost/productivity and demand effects that influence survival probabilities in opposite directions. Prices will in general reflect both demand and cost/productivity factors; higher prices are related to higher survival rates when they reflect idiosyncratic demand, but lower survival rates if they reflect higher costs/lower productivity. Once we control for TFPQ, however, the variation in prices isolates demand effects, raising the estimated survival impact of prices.

We obtain similar results when TFPQ and demand effects are included simultaneously, confirming the predictions of the model. Both higher TFPQ and higher demand are associated with a significantly lower exit probability. A one standard deviation increase in TFPQ corresponds with a 1.2 percent decline in the probability of exit. The earlier estimate of the survival-enhancing impact of higher demand is invariant to controlling for TFPQ because our demand measure is orthogonal to physical productivity. The larger response of exit to demand than to physical productivity shocks reflects both the greater volatility of demand shocks and the

greater marginal effect of a demand shock. The latter presumably reflects, among other things, the greater persistence of demand shocks documented above.

In sum, the decomposition of revenue productivity into physical productivity, price, and demand effects unmask important features of selection. Moreover, it is important to control for both price and productivity effects simultaneously. The unconditional relationship between physical productivity and survival understates the true impact of physical productivity because price effects are omitted. Likewise, unconditional relationship between prices and survival understates the true impacts of prices.

As expected, we find demand shocks are very important in accounting for the likelihood of survival. Indeed, even controlling for overall plant size using its capital stock, a one standard deviation increase in demand shocks accounts for a decrease in the likelihood of exit that is over three times larger than the decrease in the likelihood of exit from a one standard deviation in physical productivity. It is difficult to avoid the interpretation that demand effects are a predominant determinant of survival.

Given the importance of demand shocks, investigating the source of their variation is of interest but beyond the scope of the current analysis. Since they are a residual measure, they may capture many different factors. In our model, they embody the idiosyncratic variation in demand denoted by δ . Empirically, they may reflect geographic variations in product demand, differences in “relationship capital” in firm-consumer matches (see the discussion in Section 3.3), or perhaps quality differences that remain despite our product selection strategy (though see the discussion above about quality variation and the negative correlation between prices and physical productivity). In addition, since we permit elasticities to vary across products but not within products, the demand shocks may reflect differences in markups across producers of the same product.³³

³³ We have explored the possibility that elasticities vary across plants in the data and the sensitivity of the estimated survival impact of demand shocks to this variation. We allowed flexibility in our estimated demand specification based on an observable difference across plants: specifically, whether or not they are a part of a multi-unit firm (a firm that owns more than one plant). We estimated separate demand functions, keeping the isoelastic formulation above, for an industry’s multi-unit and single-unit plants. The results, which we do not report here for space reasons, indicate that for most industries (but not all: concrete and flooring are exceptions), multi-unit plants face more elastic demand than do single-unit plants, though these differences are not always statistically significant. When we use the plant-level demand shocks from this more flexible demand specification in the survival regressions, however, we find very little difference from the results here. This suggests that the specific reasons why plants’ elasticities vary along the multi-/single-unit dimension, while beyond the scope of our present effort but

5.3. Implications for Aggregate Productivity Growth

To gauge the implications of our findings for aggregate (product- or industry-level) productivity growth, we decompose across-CM changes in products' real revenue-weighted average TFPT, TFPR and TFPQ. The existing literature (see, e.g., Aw, Chen and Roberts (2001), Baily, Hulten, and Campbell (1992), Bartelsman and Doms (2000), and Foster, Haltiwanger, and Krizan (2001, 2002)) has found that an important fraction of productivity growth is accounted for by reallocation effects, and net entry in particular.

To explore these issues in this context, we use our alternative productivity measures to calculate the relative contributions of within-plant growth, reallocation between incumbents, and entry and exit to aggregate productivity growth. There is some debate in the literature about the appropriate form of such calculations; accordingly, we explore two alternative decompositions. The first is a modified version of the Baily, Hulten, and Campbell (1992) decomposition derived by Foster, Haltiwanger, and Krizan (2001) (hereafter FHK). It is given as follows (this decomposition is referred to as BHC/FHK in Table 7):

$$\begin{aligned} \Delta TFP_t = & \sum_{i \in C} \theta_{i,t-1} \Delta tfp_{it} + \sum_{i \in C} (tfp_{i,t-1} - TFP_{t-1}) \Delta \theta_{it} + \sum_{i \in C} \Delta tfp_{it} \Delta \theta_{it} \\ & + \sum_{i \in N} \theta_{it} (tfp_{it} - TFP_{t-1}) - \sum_{i \in X} \theta_{i,t-1} (tfp_{i,t-1} - TFP_{t-1}) \end{aligned} \quad (12)$$

where TFP_t is the output-share-weighted average productivity (either physical or revenue TFP) in period t across all producers of a product, tfp_{it} is the productivity for establishment i in t , and θ_{it} is the activity share for plant i for a given product. The sets C , N , and X respectively represent the set of continuing, entering, and exiting establishments. This decomposition has five terms that embody the contributions of various components to aggregate productivity growth. In the order of their inclusion in (12), these are the within-establishment effect, the between-establishment effect, the cross effect, the entry effect, and the exit effect (the difference between the final two is often called the net entry effect). We apply this decomposition separately by product, and then average the results across products using the aggregate product revenue as weights to obtain the results reported in Table 7.

A closely related decomposition by Griliches and Regev (1995) (and modified by FHK to

an interesting point for future research, are not distorting the results using idiosyncratic demand estimates from a less flexible specification.

accommodate entry/exit appropriately) is given by (referred to as GR in Table 7):

$$\begin{aligned} \Delta TFP_t = & \sum_{i \in C} \bar{\theta}_i \Delta tfp_{it} + \sum_{i \in C} (\bar{tfp}_i - \overline{TFP}) \Delta \theta_{it} \\ & + \sum_{i \in N} \theta_{it} (tfp_{it} - \overline{TFP}) - \sum_{i \in X} \theta_{it-1} (tfp_{it-1} - \overline{TFP}) \end{aligned} \quad (13)$$

In this decomposition, the bars over a variable indicate the average of the variable across $t-1$ and t . As such, this decomposition includes a within term based upon the growth rate of continuing plants' TFP weighted by average shares across the previous and current periods, a between term based upon changes in shares weighted by average TFP deviations, and entry and exit terms deviated from overall time averages. As noted by Diewert and Fox (2005), the within term in this decomposition is a Divisia index of continuing plants' TFP growth. While this nicely links the within term to the index number literature, FHK note the decomposition is more difficult to interpret in the context of reallocation dynamics. The BHC/FHK within term allows one to conduct the interesting counterfactual exercise of holding shares at their initial levels so as to measure what productivity growth would have been in the absence of any reallocation. The GR decomposition does not permit the same counterfactual exercise because the within term confounds changes in productivity and changes in shares. As will become clear, however, the main results of this section are not sensitive to the choice of decomposition.

An open question is the choice of activity weights, θ_{it} . We use plants' real revenue shares for the given product-year. This takes advantage of a basic and important identity emphasized by Melitz (2003). He notes that industry productivity, defined as the weighted average of plant-level productivity, is the same whether plant-level revenue productivity or physical productivity is used as long as (i) the same revenue weights are used, and (ii) the industry price deflator for revenue based productivity is the appropriate geometric mean of the plant-level prices. This identity holds because upon aggregation, the weighted average of plant-level prices in the numerator of aggregate revenue-based productivity cancels with the deflator's weighted average price in the denominator. Importantly, this identity will *not* in general hold for TFPT, as this productivity measure uses the industry-level PPI as the price deflator. The PPI is a geometric mean, but it is drawn from a different establishment survey conducted by the Bureau of Labor Statistics with different plant-level weights.

We apply the above decompositions to all five-year changes available for each product

and report the averages of each term across products and time periods. (We weight the averages with time-invariant product real revenue weights, so the results are not impacted by changing product mixes over time.) Table 7 reports the results. The first row of each panel reports the decomposition of aggregate TFPT growth, the second row TFPR growth, and the third row TFPQ growth. Observe first that the identity noted above holds for TFPR and TFPQ (aggregate productivity growth in each is the same), but TFPT yields quite different aggregate patterns due to deflator differences and the inclusion of non-production activities in the traditional output measure. As such, we report TFPT for completeness but focus our attention on TFPR and TFPQ given that they are the internally consistent measures at the aggregate level.

Decompositions of both TFPR and TFPQ imply a substantial within-plant contribution to five-year productivity growth. About 3.4 to 4.0 of the 5.1 percent aggregate productivity growth comes from productivity growth within surviving plants, depending upon the decomposition. Regardless of the decomposition used, though, TFPR growth has a substantially smaller entry component than TFPQ. This is consistent with the plant-level price variation discussed above. Specifically, entering plants charge appreciably lower prices (especially on a size-weighted basis, and the decompositions here are weighted by construction), so they have significantly lower measured revenue productivity levels at entry. This in turn causes revenue-based methods to substantially understate the contribution of net entry to aggregate productivity growth. In this case, the understatement is by one-third: in both decompositions, using TFPQ implies that net entry's contribution to productivity growth is about 1.35 percentage points of the 5.1 percent total, while using TFPR implies it is only 0.9 percentage points of the total.

Since both TFPR and TFPQ yield the same overall aggregate productivity growth, the understatement of entry's contribution must yield an overstatement in some other term. Under FHK, this shows up in the contribution of the cross term, which is positive when businesses experiencing productivity growth also gain market share. This is not surprising because we have seen that producers tend to raise prices as they age, thereby (all else equal) driving up both their revenue productivity and market share simultaneously. Under the GR decomposition, this shows up in a combination of larger within and between terms under TFPR than TFPQ. This pattern is also consistent with businesses that are increasing prices and revenue shares, because share changes in this decomposition contribute to both the within and between terms.

The large differences we find between TFPQ and TFPR in terms of the contribution of

net entry to aggregate productivity growth are important in thinking about how reallocation dynamics drive productivity growth. Some theories of industry dynamics emphasize entry and exit of businesses in the creative destruction process, while others emphasize within-plant adjustment and growth or the reallocation of activity across continuing businesses. The frictions relevant for these alternative types of adjustment and reallocation are likely to be quite different. For continuing businesses, the frictions impinging upon within plant adjustment and reallocation likely involve adjustment costs, as it is costly to adjust technology as well as the mix and scale of factors, and limited product substitutability due to product differentiation (in spatial terms, physical attributes, or otherwise). For entering businesses, these same frictions likely apply, but entry costs are obviously a distinguishing feature. The point to emphasize is that in terms of understanding the barriers to allocative efficiency, these findings suggest that revenue based productivity decompositions may focus too much attention on continuing businesses and not enough on the role of entering businesses.

6. Robustness Checks

In this section we briefly describe exercises we conducted to see if the results above are robust to our empirical modeling assumptions.

6.1. Quality Variation versus Spatial Differentiation

We focus on producers of physically homogeneous goods to make quantity comparisons meaningful and minimize price variations due to quality differences across producers' outputs. If this sample selection strategy does in fact avoid quality differences (at least in the physical product) in our sample, then the observed price and demand variation above, as well as the finite price elasticities we estimate, must be due to horizontal differentiation. As discussed in Section 3.3., in industries where transport costs are important, spatial separation is a readily identifiable source of such horizontal differentiation. And while there are other plausible sources of horizontal differentiation in national-market industries, their importance is more difficult to quantify. One might then be concerned that some price variation in our non-spatial industries still reflects quality variation not purged by our product selection process.

To see if this might be driving our key findings, we redo the empirical exercises above using only those products that have sufficiently "local" markets. We define these as products for

which the majority of their shipments were within the shortest distance category in the 1977 Commodity Transport Survey: less than 100 miles. These include block and processed ice, concrete, boxes, bread, and gasoline. These products have a readily identifiable source of horizontal differentiation that can explain price and demand differences among their producers.

We find very little difference between the results above and those from the local-market-product-only subsample. This is perhaps not surprising, since these industries account for a large majority of the establishment-years in our sample: 16,666 of 17,669 observations. Table 8 shows results obtained from this subsample regarding the determinants of selection and the BHC decomposition of industry-level productivity growth (these are analogous to the results shown in Table 6 and the upper part of Table 7 for the full sample). We report just these results because of space limitations and the extensive similarity between the earlier results and those from this local-market-product subsample. Indeed, the only notable quantitative difference from the full-sample findings is a weaker though still negative price-survival correlation in the restricted sample.

6.2. Specialization

We impose a specialization criterion for inclusion in our sample: plants must derive at least 50 percent of their revenue from one of our products of interest. This reduces measurement problems involved in dealing with multi-product firms. Apportioning reported plant-level input usage across different products made by the plant, a necessary step to compute TFPQ, is less likely to result in quantity mismeasurement when producers are specialized in our products of interest. (See the discussion in Section 3.1.) Still, the 50 percent criterion is arbitrary and still leaves some room for inaccuracies, particularly in products like bread and flooring whose producers are not typically specialized. Therefore we check our results to sensitivity to this cutoff by repeating the empirical exercises on a set of highly specialized producers: those earning over 90 percent of their revenue from one of our products. This more stringent selection criterion yields a subsample of 14,310 plant-year observations, a 19 percent reduction from our full sample. The subsample's industry composition differs because average plant specialization rates vary across the industries that make our products. For example, we lose about half of our flooring plants, 80 percent of our bread-making plants, and almost all of our gasoline manufacturers (in other words, very few refineries obtain over 90 percent of their revenue from

gasoline).

Despite these differences in the sample, the estimates we obtain using highly specialized plants track our main results above closely. This is especially so for the unweighted results, where there are no qualitative or even quantitative differences of note. The weighted results regarding prices are more sensitive to the minimum specialization criterion. In particular, the price gap between entrants and incumbents seen in the full sample is not as large. In Table 9 we again report results corresponding to those in Tables 6 and 7 for the specialized producer subsample. (Again space constraints and similarities between these and the earlier results cause us to limit reported output.) The coefficients in Panel A closely match those in Table 6, and for that matter, those in Panel A of Table 8. And despite the smaller price differences of entrants in the weighted results, revenue-based productivity decompositions still understate the contribution of entry to industry productivity growth, as can be seen in Panel B.

7. Conclusion

The paper has explored the contributions of plant-level technology and demand fundamentals to survival and selection-based productivity growth. We construct a simple differentiated products model that shows market selection should be driven by both demand and efficiency (productivity) factors. Much of the recent empirical literature on productivity has focused on the latter effect by effectively assuming away within-sector demand dispersion.

Using a sample of approximately 18,000 establishment-level observations of producers of eleven homogenous products, we go on to empirically characterize the nature of selection. Our ability to measure producer-level prices allows us to, unlike the previous literature, measure technical efficiency and producer-specific demand separately. This in turn allows us to measure the separate impact of each on plant survival.

We find that the producer heterogeneity assumed in the model is present in the data. Productivity (both revenue- and physical-quantity-based measures) and prices exhibit substantial and persistent dispersion across establishments within narrowly defined product classes. Interestingly, quantity-based productivity measures exhibit greater dispersion than revenue-based measures. This pattern reflects the fact that, while the two productivity measures are highly correlated with each other (not surprising since the physical productivity is a component of revenue productivity), physical productivity is negatively correlated with establishment-level

prices while revenue productivity is positively correlated with prices.

We exploit this variation to estimate plants' idiosyncratic demand levels. Our physical productivity measure provides a unique instrument for price to avoid the typical simultaneity bias in demand estimation. The demand estimates decompose plant-level price variation into two components, one reflecting movements along the demand curve due to differences in physical efficiency, and the other reflecting producers' idiosyncratic demand levels.

Turning to selection more directly, we find exiting businesses have lower prices and lower productivity (either revenue based or physical quantity based) than incumbents or entrants. Consistent with the earlier literature, we also find that there is at best weak evidence of a productivity advantage of entrants relative to incumbents when revenue-based productivity measures are used. However, we show that this results in part because entering businesses also have lower prices than incumbents. Therefore revenue-based measures understate entrants' productivity advantages. Indeed, we show that entrants are more physically productive than incumbents. This productivity understatement is also seen not just for entrants but for young businesses in general relative to mature incumbents, because young businesses charge lower prices than their older competitors.

Plants with lower productivity levels (revenue- or quantity-based), lower prices, and lower idiosyncratic demand are more likely to exit. Decomposing and controlling for both price and productivity effects simultaneously shows that both factors are important for survival. Moreover, the contribution of each is much larger when controlled for simultaneously than when considered in isolation, because the negative covariance between prices and physical productivity yields an omitted variable bias when the effect of each is considered in isolation. While physical productivity is an important factor in determining survival, the dominant factor determining survival is demand variation across producers. A basic message of this paper is that recognizing the contribution of and further investigation into the determinants of these demand factors is an important area for future research.

Finally, decompositions of aggregate (product-level) productivity growth using the alternative productivity measures suggest that the existing literature may understate the contribution of entry to aggregate productivity growth and overstate the contribution of continuing business. This misattribution is again driven by the relationship between prices and continuing and entering businesses, diminishing entrants' true impact on productivity levels.

Our findings provide both good and “bad” news for the existing literature on productivity dynamics and reallocation. The good news is that revenue-based and physical productivity are highly correlated, and that price and physical productivity measures work in the same direction in accounting for survival (i.e., low price and low physical productivity businesses are more likely to exit). The “bad” news is that the interactions between prices and physical productivity are rich enough to make it important to decompose revenue productivity into its price and physical productivity components, something that cannot be easily done with most producer microdata.

Where do we go from here? Our findings suggest that the recent literature’s efforts to address the role of demand factors (at least indirectly) in productivity dynamics should have a high priority. One possible item for this research agenda is to use those few data samples where plant-level prices are observed directly to evaluate the various methods that have been proposed for addressing these issues. Another direction for future research is to further develop theoretical and empirical models that can account for the role of demand factors and price variation across continuing, entering and exiting plants. It seems to us that an important issue to explore in this context is the striking finding here that entering businesses tend to charge lower prices. As we have noted, this finding is important for understanding the contribution of net entry to aggregate productivity dynamics, but it is also quite interesting in and of itself.

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Table 1. Summary Statistics for Output, Price, and Productivity Measures

Correlations								
Variables	Trad'l. Output	Revenue Output	Physical Output	Price	Trad'l. TFP	Revenue TFP	Physical TFP	Capital
Traditional Output	1.00							
Revenue Output	0.99	1.00						
Physical Output	0.98	0.99	1.00					
Price	-0.03	-0.03	-0.19	1.00				
Traditional TFP	0.19	0.18	0.15	0.13	1.00			
Revenue TFP	0.17	0.21	0.18	0.16	0.86	1.00		
Physical TFP	0.17	0.20	0.28	-0.54	0.64	0.75	1.00	
Capital	0.86	0.85	0.84	-0.04	0.00	-0.00	0.03	1.00
Standard Deviations								
Standard Deviations	1.03	1.03	1.05	0.18	0.21	0.22	0.26	1.14

Note: This table shows correlations and standard deviations for plant-level variables for our pooled sample of 17,669 plant-year observations. We remove product-year fixed effects from each variable before computing the statistics. All variables are in logs. See the text for definitions of the variables.

Table 2. Estimating Price Elasticities by Product

Product	IV Estimation		OLS Estimation	
	Price Coefficient (α_1)	Income Coefficient (α_2)	Price Coefficient (α_1)	Income Coefficient (α_2)
Boxes	-3.02 <i>0.17</i> [0.61]	-0.03 <i>0.02</i>	-2.19 <i>0.12</i>	-0.03 <i>0.02</i>
Bread	-3.09 <i>0.42</i> [0.33]	0.12 <i>0.05</i>	-0.89 <i>0.15</i>	0.07 <i>0.04</i>
Carbon Black	-0.52 <i>0.38</i> [0.50]	-0.21 <i>0.11</i>	-0.57 <i>0.21</i>	-0.21 <i>0.11</i>
Coffee	-3.63 <i>0.98</i> [0.41]	0.22 <i>0.14</i>	-1.03 <i>0.32</i>	0.20 <i>0.13</i>
Concrete	-5.93 <i>0.36</i> [0.10]	0.13 <i>0.01</i>	-0.83 <i>0.09</i>	0.15 <i>0.01</i>
Hardwood Flooring	-1.67 <i>0.48</i> [0.61]	-0.20 <i>0.18</i>	-0.87 <i>0.47</i>	-0.24 <i>0.18</i>
Gasoline	-1.42 <i>2.72</i> [0.20]	0.23 <i>0.07</i>	-0.16 <i>0.80</i>	0.23 <i>0.07</i>
Block Ice	-2.05 <i>0.46</i> [0.32]	0.00 <i>0.11</i>	-0.63 <i>0.20</i>	0.16 <i>0.07</i>
Processed Ice	-1.48 <i>0.27</i> [0.37]	0.18 <i>0.03</i>	-0.70 <i>0.13</i>	0.16 <i>0.03</i>
Plywood	-1.21 <i>0.14</i> [0.89]	-0.23 <i>0.10</i>	-1.19 <i>0.13</i>	-0.23 <i>0.10</i>
Sugar	-2.52 <i>1.01</i> [0.15]	0.76 <i>0.13</i>	-1.04 <i>0.55</i>	0.72 <i>0.12</i>

Note: This table shows the results of estimating demand isoelastic curves separately for each product (shown by row). Two specifications are estimated for each product, one using IV methods and one using OLS for comparison. All regressions also include year fixed effects. Sample sizes by product are shown in Table A.1. Standard errors, clustered by plant, are in italics. Where applicable, Shea-corrected first-stage R^2 are listed in brackets. See text for details.

Table 3. Persistence of Productivity, Prices and Demand Shocks

Dependent Variable	Five-Year Horizon		Implied One-Year Persistence Rates	
	Unweighted Regression	Weighted Regression	Unweighted Regression	Weighted Regression
Traditional TFP	0.249 <i>0.017</i>	0.316 <i>0.042</i>	0.757	0.794
Revenue TFP	0.277 <i>0.021</i>	0.316 <i>0.042</i>	0.774	0.794
Physical TFP	0.312 <i>0.019</i>	0.358 <i>0.049</i>	0.792	0.814
Price	0.365 <i>0.025</i>	0.384 <i>0.066</i>	0.817	0.826
Demand Shock	0.619 <i>0.013</i>	0.843 <i>0.021</i>	0.909	0.966

Note: This table reports the results of regressing a plant's current TFP, price, or idiosyncratic demand (shown by row) on its value in the previous Census of Manufacture (five years prior). Reported coefficients are those on the lagged variable. The sample includes continuing establishments only, N = 7812. Weighted regressions are weighted by revenue. The implied one-year persistence rates are the autocorrelation coefficients for annual data that would yield the same persistence over a five-year period as is implied by the regressions; i.e., they are the estimated coefficients to the one-fifth power. Standard errors, clustered by plant, are in italics.

Table 4. Evolution of Revenue Productivity, Physical Productivity, Prices and Demand Shocks

Variable	Unweighted Regression		Weighted Regression	
	Exit Dummy	Entry Dummy	Exit Dummy	Entry Dummy
Traditional TFP	-0.0209 <i>0.0042</i>	0.0014 <i>0.0040</i>	-0.0164 <i>0.0126</i>	-0.0032 <i>0.0188</i>
Revenue TFP	-0.0218 <i>0.0044</i>	0.0110 <i>0.0042</i>	-0.0197 <i>0.0135</i>	-0.0005 <i>0.0183</i>
Physical TFP	-0.0186 <i>0.0050</i>	0.0125 <i>0.0047</i>	-0.0142 <i>0.0144</i>	0.0383 <i>0.0177</i>
Price	-0.0033 <i>0.0031</i>	-0.0015 <i>0.0028</i>	-0.0055 <i>0.0080</i>	-0.0388 <i>0.0141</i>
Demand Shock	-0.3586 <i>0.0228</i>	-0.3976 <i>0.0224</i>	-0.5903 <i>0.0968</i>	-0.2188 <i>0.1278</i>

Note: This table shows the coefficients on indicator variables for exiting and entering plants (shown by column) when we regress plant-level productivity, price, and demand values (shown by row) on these indicators and a full set of product-year fixed effects. The sample is our pooled sample of 17,314 plant-year observations (355 observations from the main sample are excluded because we cannot determine exiting plants in the 1997 CM, the final year of observation). Weighted regressions are weighted by revenue. Standard errors, clustered by plant, are in italics.

Table 5. Evolution of Productivity, Price and Demand with Age Effects

Variable	Plant Age Dummies			
	Exit	Entry	Young	Medium
Unweighted Regressions				
Traditional TFP	-0.0211 <i>0.0042</i>	0.0044 <i>0.0044</i>	0.0074 <i>0.0048</i>	0.0061 <i>0.0048</i>
Revenue TFP	-0.0220 <i>0.0044</i>	0.0133 <i>0.0047</i>	0.0075 <i>0.0051</i>	0.0028 <i>0.0053</i>
Physical TFP	-0.0186 <i>0.0050</i>	0.0128 <i>0.0053</i>	0.0046 <i>0.0058</i>	-0.0039 <i>0.0062</i>
Price	-0.0034 <i>0.0031</i>	0.0005 <i>0.0034</i>	0.0029 <i>0.0038</i>	0.0067 <i>0.0042</i>
Demand Shock	-0.3466 <i>0.0227</i>	-0.5557 <i>0.0264</i>	-0.3985 <i>0.0263</i>	-0.3183 <i>0.0267</i>
Weighted Regressions				
Traditional TFP	-0.0156 <i>0.0127</i>	-0.0068 <i>0.0203</i>	-0.0156 <i>0.0171</i>	-0.0234 <i>0.0132</i>
Revenue TFP	-0.0191 <i>0.0136</i>	-0.0038 <i>0.0200</i>	-0.0180 <i>0.0198</i>	-0.0165 <i>0.0131</i>
Physical TFP	-0.0142 <i>0.0144</i>	0.0383 <i>0.0186</i>	0.0056 <i>0.0142</i>	-0.0050 <i>0.0135</i>
Price	-0.0049 <i>0.0079</i>	-0.0421 <i>0.0147</i>	-0.0236 <i>0.0114</i>	-0.0114 <i>0.0096</i>
Demand Shock	-0.5790 <i>0.0972</i>	-0.2785 <i>0.1459</i>	-0.3133 <i>0.1695</i>	-0.3164 <i>0.1197</i>

Note: This table shows the coefficients on indicator variables for exiting, entering, and continuing plants of two age cohorts (shown by column; “young” establishments first appeared in the census five years ago, “medium” establishments first appeared in the census ten years ago) when we regress plant-level productivity, price, and demand values (shown by row) on these indicators and a full set of product-year fixed effects. The excluded group includes plants that appeared three or more censuses prior. The sample is our pooled sample of 17,314 plant-year observations (355 observations from the main sample are excluded because we cannot determine exiting plants in the 1997 CM, the final year of observation). Weighted regressions are weighted by revenue. Standard errors, clustered by plant, are in italics.

Table 6. Selection on Productivity or Profitability?

Specification:	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Traditional TFP	-0.073 <i>0.015</i>						
Revenue TFP		-0.063 <i>0.014</i>					
Physical TFP			-0.040 <i>0.012</i>			-0.062 <i>0.014</i>	-0.034 <i>0.012</i>
Prices				-0.021 <i>0.018</i>		-0.069 <i>0.021</i>	
Demand Shock					-0.047 <i>0.003</i>		-0.047 <i>0.003</i>
Controlling for Plant Capital Stock							
Traditional TFP	-0.069 <i>0.015</i>						
Revenue TFP		-0.061 <i>0.013</i>					
Physical TFP			-0.035 <i>0.012</i>			-0.059 <i>0.014</i>	-0.034 <i>0.012</i>
Prices				-0.030 <i>0.018</i>		-0.076 <i>0.021</i>	
Demand Shock					-0.030 <i>0.004</i>		-0.029 <i>0.004</i>
Capital Stock	-0.046 <i>0.003</i>	-0.046 <i>0.003</i>	-0.046 <i>0.003</i>	-0.046 <i>0.003</i>	-0.023 <i>0.004</i>	-0.046 <i>0.003</i>	-0.023 <i>0.004</i>

Note: These results are from various probits of plant exit by the next census (shown by column) on plant-level productivity, price, demand, and capital stock measures (shown by row) as well as a full set of product-year fixed effects. The sample is our pooled sample of 17,314 plant-year observations (355 observations from the main sample are excluded because we cannot determine exiting plants in the 1997 CM, the final year of observation). Standard errors, clustered by plant, are in italics.

Table 7. Decomposition of Industry Productivity Growth over Five-Year Horizons

Productivity Measure	Total Growth	Components of Decomposition (BHC/FHK)					
		Within	Between	Cross	Entry	Exit	Net Entry
Traditional	2.30	0.82	-0.38	1.16	0.55	0.16	0.70
Revenue	5.13	3.34	-0.52	1.39	0.73	0.19	0.93
Physical	5.13	3.44	-0.41	0.76	1.23	0.12	1.35
		Components of Decomposition (GR)					
		Within	Between		Entry	Exit	Net Entry
Traditional	2.30	1.40	0.18		0.44	0.27	0.72
Revenue	5.13	4.03	0.16		0.55	0.39	0.94
Physical	5.13	3.82	-0.05		1.04	0.32	1.36

Note: This table shows decompositions of industry level productivity growth for three different productivity measures (shown by row) using equations (12) and (13) in text. The column labeled “Total Growth” reflects the weighted average five-year productivity growth for the industry. The remaining columns reflect the individual terms in the decomposition. Weights used in decompositions are revenue weights. Average industry revenues across the sample are used to calculate the results for the average industry. See text for details.

Table 8. Robustness Check: Local-Market Products Only

A. Selection on Productivity or Profitability?

Specification:	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Traditional TFP	-0.076 <i>0.016</i>						
Revenue TFP		-0.067 <i>0.014</i>					
Physical TFP			-0.055 <i>0.013</i>			-0.069 <i>0.014</i>	-0.048 <i>0.013</i>
Prices				-0.002 <i>0.020</i>		-0.052 <i>0.023</i>	
Demand Shock					-0.046 <i>0.003</i>		-0.046 <i>0.003</i>
Controlling for Plant Capital Stock							
Traditional TFP	-0.072 <i>0.016</i>						
Revenue TFP		-0.064 <i>0.014</i>					
Physical TFP			-0.049 <i>0.013</i>			-0.065 <i>0.014</i>	-0.048 <i>0.013</i>
Prices				-0.014 <i>0.020</i>		-0.061 <i>0.023</i>	
Demand Shock					-0.028 <i>0.004</i>		-0.028 <i>0.004</i>
Capital Stock	-0.045 <i>0.003</i>	-0.046 <i>0.003</i>	-0.045 <i>0.003</i>	-0.046 <i>0.003</i>	-0.024 <i>0.004</i>	-0.046 <i>0.003</i>	-0.024 <i>0.004</i>

B. Decomposition of Industry Productivity Growth over Five-Year Horizons

Productivity Measure	Total Growth	Components of Decomposition (BHC/FHK)					
		Within	Between	Cross	Entry	Exit	Net Entry
Traditional	0.84	-0.43	-0.34	0.91	0.58	0.11	0.69
Revenue	4.01	2.39	-0.45	1.12	0.80	0.15	0.95
Physical	4.01	2.37	-0.33	0.57	1.29	0.11	1.40

Note: See notes to Table 6 for Panel A and notes to Table 7 for Panel B.

Table 9. Robustness Check: Highly Specialized Producers Only

A. Selection on Productivity or Profitability?

Specification:	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Traditional TFP	-0.089 <i>0.018</i>						
Revenue TFP		-0.071 <i>0.017</i>					
Physical TFP			-0.048 <i>0.014</i>			-0.071 <i>0.017</i>	-0.040 <i>0.014</i>
Prices				-0.018 <i>0.021</i>		-0.072 <i>0.025</i>	
Demand Shock					-0.047 <i>0.003</i>		-0.047 <i>0.003</i>
Controlling for Plant Capital Stock							
Traditional TFP	-0.085 <i>0.018</i>						
Revenue TFP		-0.069 <i>0.016</i>					
Physical TFP			-0.042 <i>0.014</i>			-0.067 <i>0.017</i>	-0.040 <i>0.014</i>
Prices				-0.029 <i>0.021</i>		-0.081 <i>0.025</i>	
Demand Shock					-0.031 <i>0.004</i>		-0.031 <i>0.004</i>
Capital Stock	-0.045 <i>0.003</i>	-0.045 <i>0.003</i>	-0.045 <i>0.003</i>	-0.045 <i>0.003</i>	-0.021 <i>0.004</i>	-0.045 <i>0.003</i>	-0.021 <i>0.004</i>

B. Decomposition of Industry Productivity Growth over Five-Year Horizons

Productivity Measure	Total Growth	Components of Decomposition (BHC/FHK)					
		Within	Between	Cross	Entry	Exit	Net Entry
Traditional	5.87	3.36	-0.42	2.23	0.44	0.25	0.69
Revenue	6.90	3.98	-0.76	2.77	0.66	0.22	0.87
Physical	6.90	4.67	-0.97	1.76	1.13	0.27	1.40

Note: See notes to Table 6 for Panel A and notes to Table 7 for Panel B.

Appendix

A.1. Defining Our Products

As background to how we define our products, it is first necessary to understand the product coding scheme that Census uses. There are three types of codes that we highlight. First, Census codes flags products from administrative records (AR) sources. We exclude all of these AR products from our analysis. (Including in our measures of PPSR since it is obviously not possible to assign these AR products to a single 7-digit code.) Second, Census uses balancing codes to correct cases in which the sum of the total value of shipments of reported individual products does not sum to the reported total value of shipments. Census identified these balancing codes using special suffixes for the product codes in every census year except in 1987. Where balancing codes are identified, they have been deleted. Finally, Census collects data on receipts for contract work, miscellaneous receipts, and resales of products. These products are excluded from our calculations of PPSR (again, because it is obviously not possible to assign these AR products to a single 7-digit code). As a final exclusion, we did not include any products in that have a negative value since these are presumably balancing codes. The precise definitions of our eleven products are listed below (with 7-digit product codes in parentheses).

Boxes is defined as the sum of boxes classified by their end use and boxes classified by their materials. Boxes classified by end use are: food and beverages (2653012), paper and allied products (2653013), carryout boxes for retail food (2653014 category starts in 1987) glass, clay, and stone products (2653015), metal products, machinery, equipment, and supplies except electrical (2653016), electrical machinery, equipment, supplies, and appliances (2653018), chemicals and drugs, including paints, varnishes, cosmetics, and soap (2653021), lumber and wood products, including furniture (2653029), and all other ends uses not specified above (2653029 in 1977 and 1982, 2653030 in 1987). Boxes classified by their materials are: solid fiber (2653051), corrugated paperboard in sheets and rolls, lined and unlined (2653067), and corrugated and solid fiber pallets, pads and partitions (2653068). The physical data for boxes is measured in short tons.

Bread is defined as one 7-digit product, white pan bread (2051111), until 1992 when it was split into two products white pan bread, except frozen (2051121) and frozen white pan bread (2051122). The physical data for bread is measured in thousands of pounds.

Carbon Black is defined as one 7-digit product, carbon black (2895011 in 1977, 2895000 thereafter). The physical data for carbon black is measured in thousands of pounds.

Coffee is the sum of whole bean (2095111), ground and extended yield (2095117 and 2095118 in 1982 and 2095115 thereafter), and ground coffee mixtures (2095121). The physical data for coffee is measured in thousands of pounds.

Concrete is defined as one 7-digit product, ready-mix concrete (3273000), over our entire sample. Some of the products coded as 3273000 in 1987 were in fact census balancing codes and thus were deleted from our sample. The physical data for concrete is measured in thousands of cubic yards.

Flooring is defined as one 7-digit product, hardwood oak flooring (2426111), over our entire sample. The physical data for flooring is measured in thousands of board feet.

Gasoline is defined as one 7-digit product, motor gasoline (2911131), over our entire sample. The physical data for gasoline is measured in thousands of barrels.

Block Ice is defined as one 7-digit product, can or block ice (2097011), over our entire sample. The physical data for block ice is measured in short tons.

Processed Ice is defined as one 7-digit product, cubed, crushed, or other processed ice (2097051), over our entire sample. The physical data for processed ice is measured in short tons.

Plywood is defined as one 7-digit product, hardwood plywood (2435100), over 1977-1987. Starting in 1992, plywood is the sum of veneer core (2435101), particleboard core (2435105), medium density fiberboard core

(2435107), and other core (2435147). The physical data for plywood is measured in thousands of square feet surface measure.

Sugar is defined as one 7-digit product, raw cane sugar (2061011), over our entire sample. The physical data for sugar is measured in short tons.

A.2. Measurement of input levels and input elasticities in the TFP indexes.

This section reports details on the measurement of input levels and elasticities in the TFP measures described in Section 3.

Labor inputs are measured as plants' reported production-worker hours adjusted using the method of Baily, Hulten and Campbell (1992). This involves multiplying the production-worker hours by the ratio of total payroll to payroll for production workers. Prior work has shown this measure to be highly correlated with Davis and Haltiwanger's (1991) more direct imputation of nonproduction workers, which multiplies a plant's number of nonproduction workers by the average annual hours for nonproduction workers in the corresponding two-digit industry calculated from the CPS. Capital inputs are plants' reported book values for their structure and equipment capital stocks deflated to 1987 levels using sector-specific deflators from the Bureau of Economic Analysis. The method is detailed in Foster, Haltiwanger and Krizan (2001). Materials and energy inputs are simply plants' reported expenditures on each deflated using the corresponding input price indices from the NBER Productivity Database.

To compute the industry-level cost shares that we use to measure the input elasticities α_j , we use the materials and energy expenditures along with payments to labor to measure the costs of these three inputs. We construct the cost of capital by multiplying real capital stock value by the capital rental rates for the plant's respective two-digit industry. These rental rates are from unpublished data constructed and used by the Bureau of Labor Statistics in computing their Multifactor Productivity series. Formulas, related methodology, and data sources are described in U.S. Bureau of Labor Statistics (1983) and Harper, Berndt, and Wood (1989).

A.3. Rules for Inclusion in the Sample

We detail here our sample inclusion criterion discussed in Section 3.1.

Census reports physical product data for only a subset of the 11,000 products reported in the Census of Manufactures. While we use only products for which physical output is reported, the collection of this data has changed over time for two of our products. (See Table A.1.) Census did not collect physical output for ready-mix concrete in 1997, and the unit of measurement for boxes changed over our sample period in a way that makes the 1992 and 1997 data incomparable to the earlier periods. Additionally, there are recording flaws in the 1992 quantity data for processed ice that make using it unfeasible.

The Census Bureau relies on administrative record data for very small establishments (typically with less than five employees). In these cases all production data except total revenues and the number of employees are imputed, and production operations are classified only up to the four-digit industry level. Since our unit of analysis is more detailed than the four-digit industry, we cannot determine whether a particular administrative record establishment actually produces the product of interest. For these reasons, we exclude administrative records cases from our sample. While about one-third of CM establishments are administrative records, their output and employment shares are much less because they are such small plants.

We also exclude establishments whose data appear to be imputed or suffer from reporting or recording errors. The Census Bureau imputes physical quantities when product-level data are not fully reported. Unfortunately, imputed data are not explicitly identified. To distinguish and remove imputed product-level data from the sample, we use techniques similar to those employed by Roberts and Supina (1996, 2000). To minimize the influence of reporting and recording errors, we also remove a small number of plants reporting physical quantities that imply prices greater than ten times or less than one-tenth the median price in a given year. In order to maintain the same sample over all exercises, we delete observations that are missing any one of the main regression variables. We also delete observations when the plant's labor or materials cost share is less than one-tenth of the corresponding industry's average cost share for that year, or when the cost share is more than one. Finally, we still find a relatively small number of obvious outliers in physical quantity measures, so we trim the one-percent tails of the physical productivity (TFPQ) distribution.

Our product specialization criterion requires that plants obtain at least 50% of their revenue from our product of interest. The text discusses the measurement reasons for imposing this restriction as well as describing a robustness check with respect to this product specialization cutoff.

A.4. Characteristics of Establishments by Product

In this section we briefly characterize some of the relevant properties of the establishments that produce our products. Table A.1 shows characteristics of the sample by product. The first five columns show the number of establishments in our sample by year for each product. The second to last column shows the real revenue shares of each product. Real revenue is the weight used in our weighted regressions. Concrete clearly dominates our sample in terms of the number of establishments while gasoline dominates in terms of the revenue share. The table's last column shows mean logged income (income is taken from Census reports for the county in which the plant is located) for each product in our sample. Concrete has the highest mean log income while carbon black has the lowest.

Table A.2 shows the entry and exit rates by product for the data pooled over all available years. Entry rates range from a low of 3.9 for sugar to a high of 26.6 for concrete, while exit rates range from a low of 9.0 for gasoline and to a high of 27.7 for processed ice. Some products appear to be in a period of retrenchment or consolidation. Sugar for example, has a very low entry rate (3.9) but a high exit rate (17.0). The number of plants in the sugar and confectionary products industry (SIC 2061) has fallen from 66 in 1977 to 39 in 1997. Other products appear to simply have a high degree of churning. For example, concrete and both types of ice products all have entry rates and exit rates that exceed 20 percent. The number of establishments in ready-mixed concrete (SIC 3273) industry increases over our sample period, while the number of establishments in the block and processed ice industry (SIC 2097) falls somewhat over our sample, from 675 establishments in 1977 to 582 establishments in 1997.

A.5. Robustness of Demand Estimates

There are two potential problems with using TFPQ as an instrument. We have explored both and found our results to be robust. We briefly describe these potential issues here.

The first regards how selection on profitability impacts the assumption that TFPQ is uncorrelated with demand shocks at the plant level. This assumption, which is necessary for TFPQ to be a valid instrument in the demand estimation, strikes us as quite reasonable for *innovations* to the dynamic plant-level TFPQ and demand processes. Hence for entering plants, which get their initial idiosyncratic productivity and demand levels as draws from the respective innovation processes, the assumption of no correlation is likely to hold. However, TFPQ and demand levels may be correlated for *continuing* plants (those operating in both the current and previous periods) because of selection. Here is why. A producer continues operation if it is profitable, which depends on idiosyncratic productivity and demand. Since a producer with a higher TFPQ draw can tolerate lower demand draws (and vice versa) while remaining profitable, those producers that chose in the previous period to continue operations into the current period—i.e., the continuing plants—will tend to have negatively correlated lagged TFPQ and lagged demand levels. The correlation arises in the lagged values because the plants' decisions to continue operating into the current period were conditioned on that information. But because both of these processes are persistent, their current values could be correlated as well, making the orthogonality assumption necessary for consistent demand elasticity estimation questionable.

To explore the sensitivity of our results to this issue, we estimated product demand curves (10) using an alternative instrument for price that is based only upon innovations to TFPQ. For entrants, this was simply the observed level of TFPQ (after taking out product-year fixed effects). For continuers, on the other hand, we regressed the plants' current TFPQ levels on their lagged values (again including product-year fixed effects), and used the residual from this to instrument for price. In this way, we use the innovation to producers' productivity levels—information that was plausibly not included in their decision in the previous period to continue operations, but that should affect current costs—to gain exogenous variation in current prices. (The fact that we only observe plants every five years makes necessary some assumptions of timing here. The first is that the period when plants have received their idiosyncratic profitability draws but have yet to decide whether to exit, which is instantaneous in our two-stage model, can in reality actually correspond to a period of a few years. The entering plants in our sample are assumed to be in this stage. The second is that the TFPQ innovation does not impact producers' exit decisions in intercensal years.)

When we use this alternative TFPQ-innovation-based instrument, we find that the pattern of elasticities and even more importantly the pattern of demand shocks to be very robust. We also find the results that depend upon demand shocks in Tables 3-6 to be virtually unaffected. These results are available upon request.

A second potential problem is measurement error. We compute prices by dividing reported revenue by quantity and any measurement error in physical quantities will overstate the negative correlation between prices and TFPQ. Since the first stage of the IV estimation regresses plants' prices on their TFP levels, measurement error would yield biased estimates of the fitted prices used in the second stage, possibly leading in turn to biased price elasticities and idiosyncratic demand measures. To address this concern, we estimated a specification that should be

robust to measurement error, implemented as follows. Rather than using current plant TFP directly as an instrument, we use a “fitted” value constructed as a projection of current TFP on several values expected to be correlated with plant productivity but orthogonal to measurement error. These include the plant’s lagged TFP, lead TFP, the average TFP of the *other* plants in the same industry owned by the plant’s firm (these three variables are used as available, depending on the plant), a set of birth-cohort-by-industry dummies, and a set of “survival-cohort”-by-industry dummies denoting how many more CMs a plant exists before exiting (or if it survives until the end of our sample).

All of these variables should have predictive power over a plant’s current TFP level but be orthogonal to classical measurement error in quantity. Lag and lead TFP values are relevant to current TFP because of productivity persistence, the average TFP of other plants owned by the same firm because of management-driven productivity spillovers or assortative matching of plants, and the birth and survival cohort indicators because of age-specific productivity evolutions and because future survival is determined by current productivity. Second, besides this fitted TFP value, we also include the local average wage as an instrument in the first stage. This factor price is of course an additional cost shifter for the plant.

As with the other robustness check above, the results of this alternative demand estimation procedure yield demand estimates that closely track those obtained in our benchmark specification. Moreover, the subsequent results using the estimated demand shocks from this alternative estimation are very similar to those reported in the paper. Again, we do not report these here for space reasons.

In considering these two robustness checks, we note that they employ essentially opposite strategies: one uses the transitory variation in TFPQ while the other uses the permanent component. We are reassured by the fact that the results are robust to using either component of TFPQ variation. If either potential problem was a major driver of our results, we would expect the demand estimates to be quite sensitive to these distinctions.

Table A.1: Characteristics of the Sample by Product

Product	Number of Observations					Real Revenue Share (%)	Mean (log) Income
	1977	1982	1987	1992	1997		
Boxes	936	905	1045	NA	NA	7.9	17.4
Bread	195	142	110	92	92	2.4	17.0
Carbon Black	31	23	22	21	18	0.7	16.2
Coffee	61	84	79	77	77	4.7	18.0
Concrete	2184	3316	3236	3427	NA	7.0	17.1
Hardwood Flooring	8	10	16	25	24	0.2	16.7
Gasoline	99	99	94	95	71	75.0	17.1
Block Ice	40	43	26	23	10	0.0	16.9
Processed Ice	87	155	144	NA	NA	0.1	16.8
Plywood	71	68	42	42	37	0.6	16.5
Sugar	40	36	30	35	26	1.3	16.6

Note: This table shows the number of establishments in our sample by product and year, as well as each product's share of total real revenue in the sample (pooled across all years). Mean log income, used in our demand estimation procedure, is for plants' corresponding Economic Areas (see text for details) based on data pooled over all years.

Table A.2: Entry and Exit Rates by Product

Products	Entry Rates	Exit Rates
All Products	22.3	19.6
By Product:		
Boxes	12.4	12.2
Bread	7.6	18.9
Carbon Black	4.8	13.4
Coffee	9.1	15.6
Concrete	26.6	21.8
Hardwood Flooring	18.7	11.9
Gasoline	4.2	9.0
Block Ice	24.5	26.5
Processed Ice	23.1	27.7
Plywood	7.4	10.3
Sugar	3.9	17.0

Note: This table shows the plant entry and exit rates (averaged across all years in the sample). Entry (exit) is determined by plants' first (last) appearance in a CM. See text for details. Entry rates for gasoline reflect a small number (less than five) births in the 1987, 1992, and 1997 CMs, even though the Energy Information Administration reports no new refineries were built during that period. It is not clear why there is a discrepancy in the Census data, but for the sake of consistency and given the low entry rate in the industry overall, we defined these new plants as entrants.