

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

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We investigate the nature of selection and productivity growth in industries where we observe producer-level quantities and prices separately. We show there are important differences between revenue and physical productivity. Because physical productivity is inversely correlated with price while revenue productivity is positively correlated with price, previous work linking (revenue-based) productivity to survival confounded the separate and opposing effects of technical efficiency and demand on survival, understating the true impacts of both. Further, we find that young producers charge lower prices than incumbents. Thus the literature understates new producers' productivity advantages and entry's contribution to aggregate productivity growth. (JEL D24, L11, L25)

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, Boyan Jovanovic (1982), Hugo A. Hopenhayn (1992), Richard Ericson and Ariel Pakes (1995), Marc J. Melitz (2003), and Marcus Asplund and Volker 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

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

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 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 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 relationships between particular consumers and producers that create producer-specific demand shifts. (We discuss in detail in Section IIC what factors might explain price/demand variations across producers in our sample.) The output equivalence in this example is meaningful not due

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.

³ Syverson (2004), who 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, Marcela Eslava, Haltiwanger, Adriana Kugler, and Maurice Kugler (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, Hajime Katayama, Shihua Lu, and James Tybout (2003) and Yuriy Gorodnichenko (2005) argue factor prices are potentially important. We see this area as a possible expansion point for future work.

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. Thomas A. Abbott (1992) documents the extent of price dispersion within broad industries and outlines possible implications for measurement of aggregates. Tor J. Klette and Zvi Griliches (1996) and Jacques Mairesse and Jordi Jaumandreu (2005) consider how intra-industry price fluctuations can affect production function and productivity estimates. Melitz (2000), Jan 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-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 body of 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.

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 Mark J. Roberts and Dylan 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.

To preview our findings, we note 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 II 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 III, and the central results regarding selection dynamics are presented in Section IV. Section V describes robustness checks of our empirical results, and Section VI concludes.

I. 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

$$(1) \quad U = y + \int_{i \in I} (\alpha + \delta_i) q_i di - \frac{1}{2} \eta \left(\int_{i \in I} q_i di \right)^2 - \frac{1}{2} \gamma \int_{i \in I} q_i^2 di$$

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

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

The technology is a single-input production function

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

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 also allow to 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

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

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

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.

and maximized profits are

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

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

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

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.

Define the "profitability index" of a particular producer as follows:

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

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:

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

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 δ_e , ω_l , ω_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 $f(\delta, \omega, w)$,

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).

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

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

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

This expression summarizes the industry equilibrium. (The equilibrium mass of producers N is determined by α , η , γ , (w/ω) , 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 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, discussed below. Hence the model points to idiosyncratic technology and demand factors *jointly* determining the likelihood of survivorship in the industry.¹¹

A. 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:

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

Empirical work with micro data typically uses revenue-based productivity measures. 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.

B. 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.

C. 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.

II. 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 standard industrial classification (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

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.

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

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

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 those of low productivity.¹⁷ To measure the input elasticities α_j , we use

¹⁴ The exact definition of the eleven products can be found in the Web Appendix (<http://www.aeaweb.org/articles.php?doi=10.1257/aer.98.1.394>). 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.

¹⁶ An implicit assumption in this index is constant returns to scale. If the scale elasticity were 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., Martin N. Baily, Charles Hulten and David Campbell (1992) and G. Steven 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 of 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 Timothy 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 (2007) 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

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 can be found in the Web Appendix.¹⁸

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 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

A. 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

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 James Levinsohn and Amil Petrin (2003). These latter methods are best suited to annual panel data, however. Moreover, 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 Johannes 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.

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								
	1.03	1.03	1.05	0.18	0.21	0.22	0.26	1.14

Notes: 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.

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 percent 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, for multi-product plants, we must 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 A1 in the Web Appendix.

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

B. 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

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 percent 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 to make 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).

statistics—and control for them in all of our empirical exercises—so cross-product 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 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, it is also the case within product-year variation that we are exploiting.) Regarding 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 A1 in the Web Appendix contains more details.

C. 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. We describe here 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 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" (B. 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, 2005, p. 15). 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 Company, 2005, 3 and 11). 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

²² According to the 1977 Commodity Transportation Survey (US Census Bureau 1981)—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.

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

producer-consumer relationships that are actually contracted over. We suspect, though of course cannot show definitively, that noncontractual “relationship capital” of this sort is as, 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:

$$(10) \quad \ln q_{it} = \alpha_o + \alpha_1 \ln p_{it} + \sum_t \alpha_t \text{YEAR}_t + \alpha_2 \ln (\text{INCOME}_{mt}) + \eta_{it},$$

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 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

Federal Trade Commission (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.” (US FTC, 1966)

²⁴ Some striking examples of the strength and persistence of consumers’ relationships with particular producers can be found in Bart J. Bronnenberg, Sanjay K. Dhar, and Jean-Pierre 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.

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 3,200 US counties are grouped into 172 EAs that are mutually exclusive and exhaustive of the land area of the United States. See US 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.

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, 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 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.

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 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 TFPQ 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 Web 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.

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

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 (0.17) [0.61]	−0.03 (0.02)	−2.19 (0.12)	−0.03 (0.02)
Bread	−3.09 (0.42) [0.33]	0.12 (0.05)	−0.89 (0.15)	0.07 (0.04)
Carbon black	−0.52 (0.38) [0.50]	−0.21 (0.11)	−0.57 (0.21)	−0.21 (0.11)
Coffee	−3.63 (0.98) [0.41]	0.22 (0.14)	−1.03 (0.32)	0.20 (0.13)
Concrete	−5.93 (0.36) [0.10]	0.13 (0.01)	−0.83 (0.09)	0.15 (0.01)
Hardwood flooring	−1.67 (0.48) [0.61]	−0.20 (0.18)	−0.87 (0.47)	−0.24 (0.18)
Gasoline	−1.42 (2.72) [0.20]	0.23 (0.07)	−0.16 (0.80)	0.23 (0.07)
Block ice	−2.05 (0.46) [0.32]	0.00 (0.11)	−0.63 (0.20)	0.16 (0.07)
Processed ice	−1.48 (0.27) [0.37]	0.18 (0.03)	−0.70 (0.13)	0.16 (0.03)
Plywood	−1.21 (0.14) [0.89]	−0.23 (0.10)	−1.19 (0.13)	−0.23 (0.10)
Sugar	−2.52 (1.01) [0.15]	0.76 (0.13)	−1.04 (0.55)	0.72 (0.12)

Notes: 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 A1 in the Web Appendix. Standard errors, clustered by plant, are in parentheses. Where applicable, Shea-corrected first-stage R^2 are listed in brackets. See text for details.

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 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.

III. 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 IV. We first examine the persistence of plants' productivity, prices, and demand levels. We next characterize the entry and exit dynamics of our sample.

A. Persistence

Preceding work (e.g., Baily, Hulten, and Campbell (1992); Roberts and Supina (1996); and Foster, Haltiwanger and C. J. Krizan (2006)) 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.

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 (0.017)	0.316 (0.042)	0.757	0.794
Revenue TFP	0.277 (0.021)	0.316 (0.042)	0.774	0.794
Physical TFP	0.312 (0.019)	0.358 (0.049)	0.792	0.814
Price	0.365 (0.025)	0.384 (0.066)	0.817	0.826
Demand shock	0.619 (0.013)	0.843 (0.021)	0.909	0.966

Notes: 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 Manufactures (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 parentheses.

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 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.

B. 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 .

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

Table A2 in the Web 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 Larry 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.

IV. Selection Dynamics

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 I, 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.

A. 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

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.

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 (0.0042)	0.0014 (0.0040)	−0.0164 (0.0126)	−0.0032 (0.0188)
Revenue TFP	−0.0218 (0.0044)	0.0110 (0.0042)	−0.0197 (0.0135)	−0.0005 (0.0183)
Physical TFP	−0.0186 (0.0050)	0.0125 (0.0047)	−0.0142 (0.0144)	0.0383 (0.0177)
Price	−0.0033 (0.0031)	−0.0015 (0.0028)	−0.0055 (0.0080)	−0.0388 (0.0141)
Demand shock	−0.3586 (0.0228)	−0.3976 (0.0224)	−0.5903 (0.0968)	−0.2188 (0.1278)

Notes: 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 parentheses.

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 exitters 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

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 (0.0042)	0.0044 (0.0044)	0.0074 (0.0048)	0.0061 (0.0048)
Revenue TFP	−0.0220 (0.0044)	0.0133 (0.0047)	0.0075 (0.0051)	0.0028 (0.0053)
Physical TFP	−0.0186 (0.0050)	0.0128 (0.0053)	0.0046 (0.0058)	−0.0039 (0.0062)
Price	−0.0034 (0.0031)	0.0005 (0.0034)	0.0029 (0.0038)	0.0067 (0.0042)
Demand shock	−0.3466 (0.0227)	−0.5557 (0.0264)	−0.3985 (0.0263)	−0.3183 (0.0267)
Weighted regressions				
Traditional TFP	−0.0156 (0.0127)	−0.0068 (0.0203)	−0.0156 (0.0171)	−0.0234 (0.0132)
Revenue TFP	−0.0191 (0.0136)	−0.0038 (0.0200)	−0.0180 (0.0198)	−0.0165 (0.0131)
Physical TFP	−0.0142 (0.0144)	0.0383 (0.0186)	0.0056 (0.0142)	−0.0050 (0.0135)
Price	−0.0049 (0.0079)	−0.0421 (0.0147)	−0.0236 (0.0114)	−0.0114 (0.0096)
Demand shock	−0.5790 (0.0972)	−0.2785 (0.1459)	−0.3133 (0.1695)	−0.3164 (0.1197)

Notes: 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 parentheses.

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:

$$(11) \quad x_{it} = \beta_o + \beta_1 \text{Exit}_{it} + \beta_2 \text{Entry}_{it} + \beta_3 \text{Young}_{it} + \beta_4 \text{Medium}_{it} + \sum_{IT} \beta_{IT} \text{IndYear}_{IT} + u_{it},$$

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 looks only at the evolution of revenue productivity.³⁰

B. 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.

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 IIC, and the coefficients in the upper part of Table 6,

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 IIC, that young firms need time to build; see Arthur Fishman and Rafael 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.

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 IV.C. 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.

TABLE 6—SELECTION ON PRODUCTIVITY OR PROFITABILITY?

Specification:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Traditional TFP	−0.073 (0.015)						
Revenue TFP		−0.063 (0.014)					
Physical TFP			−0.040 (0.012)			−0.062 (0.014)	−0.034 (0.012)
Prices				−0.021 (0.018)		−0.069 (0.021)	
Demand shock					−0.047 (0.003)		−0.047 (0.003)
Controlling for plant capital stock							
Traditional TFP	−0.069 (0.015)						
Revenue TFP		−0.061 (0.013)					
Physical TFP			−0.035 (0.012)			−0.059 (0.014)	−0.034 (0.012)
Prices				−0.030 (0.018)		−0.076 (0.021)	
Demand shock					−0.030 (0.004)		−0.029 (0.004)
Capital stock	−0.046 (0.003)	−0.046 (0.003)	−0.046 (0.003)	−0.046 (0.003)	−0.023 (0.004)	−0.046 (0.003)	−0.023 (0.004)

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 parentheses.

imply that a one-standard-deviation increase each in TFPT, TFPR, TFPQ, price, and demand corresponds 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 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 shown 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 that 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 increase 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 IIC), or perhaps quality differences that remain despite our product selection strategy (see, however, 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

C. 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., Baily, Hulten, and Campbell (1992); Bartelsman and Doms (2000); Bee Yan Aw, Xiaomin Chen and Roberts (2001); and Foster, Haltiwanger, and Krizan (2001, 2006)) 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) (hereafter BHC) 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):

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

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 Haim Regev (1995) (and modified by FHK to accommodate entry/exit appropriately, hereafter referred to as GR) is given by:

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

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 Erwin Diewert and Kevin Fox (forthcoming), the within term in this decomposition is a Divisia index of continuing plants' TFP growth. While this links nicely 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

dimension, while beyond the scope of our present effort but an interesting point for future research, are not distorting the results using idiosyncratic demand estimates from a less flexible specification.

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

Notes: 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.

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.

The choice of activity weights, θ_{it} , is an open question. 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 BHC/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.

V. Robustness Checks

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

A. *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 II.C, 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/FHK 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.

B. 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 II.A.) 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 for 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.

VI. 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.

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 (0.016)						
Revenue TFP		−0.067 (0.014)					
Physical TFP			−0.055 (0.013)			−0.069 (0.014)	−0.048 (0.013)
Prices				−0.002 (0.020)		−0.052 (0.023)	
Demand shock					−0.046 (0.003)		−0.046 (0.003)
Controlling for plant capital stock							
Traditional TFP	−0.072 (0.016)						
Revenue TFP		−0.064 (0.014)					
Physical TFP			−0.049 (0.013)			−0.065 (0.014)	−0.048 (0.013)
Prices				−0.014 (0.020)		−0.061 (0.023)	
Demand shock					−0.028 (0.004)		−0.028 (0.004)
Capital stock	−0.045 (0.003)	−0.046 (0.003)	−0.045 (0.003)	−0.046 (0.003)	−0.024 (0.004)	−0.046 (0.003)	−0.024 (0.004)

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.

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

TABLE 9—ROBUSTNESS CHECK: HIGHLY SPECIALIZED PRODUCERS ONLY

<i>A. Selection on productivity or profitability?</i>							
Specification:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Traditional TFP	−0.089 (0.018)						
Revenue TFP		−0.071 (0.017)					
Physical TFP			−0.048 (0.014)			−0.071 (0.017)	−0.040 (0.014)
Prices				−0.018 (0.021)		−0.072 (0.025)	
Demand shock					−0.047 (0.003)		−0.047 (0.003)
Controlling for plant capital stock							
Traditional TFP	−0.085 (0.018)						
Revenue TFP		−0.069 (0.016)					
Physical TFP			−0.042 (0.014)			−0.067 (0.017)	−0.040 (0.014)
Prices				−0.029 (0.021)		−0.081 (0.025)	
Demand shock					−0.031 (0.004)		−0.031 (0.004)
Capital stock	−0.045 (0.003)	−0.045 (0.003)	−0.045 (0.003)	−0.045 (0.003)	−0.021 (0.004)	−0.045 (0.003)	−0.021 (0.004)
<i>B. Decomposition of industry productivity growth over five-year horizons</i>							
Productivity measure	Total growth	Within	Components of decomposition (BHC/FHK)				
			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.

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.

REFERENCES

- Abbott, Thomas A, III.** 1992. "Price Dispersion in U.S. Manufacturing: Implications for the Aggregation of Products and Firms." US Census Bureau Working Paper 92-93.
- Asplund, Marcus, and Volker Nocke.** 2006. "Firm Turnover in Imperfectly Competitive Markets." *Review of Economic Studies*, 73(2): 295-327.
- Aw, Bee Yan, Xiaomin Chen, and Mark J. Roberts.** 2001. "Firm-Level Evidence on Productivity Differentials and Turnover in Taiwanese Manufacturing." *Journal of Development Economics*, 66(1): 51-86.
- Baily, Martin Neil, Charles Hulten, and David Campbell.** 1992. "Productivity Dynamics in Manufacturing Plants." *Brookings Papers on Economic Activity, Microeconomics*: 187-249.
- Bartelsman, Eric J., and Mark Doms.** 2000. "Understanding Productivity: Lessons from Longitudinal Microdata." *Journal of Economic Literature*, 38(3): 569-94.
- Bronnenberg, Bart J., Sanjay K. Dhar, and Jean-Pierre Dubé.** 2005. "Market Structure and the Geographic Distribution of Brand Shares in Consumer Package Goods Industries." http://faculty.chicagogsb.edu/jean-pierre.dube/research/papers/cpg_sept_1_2005.pdf.
- Cabot Corporation.** 2005. *2005 Annual Report*. Boston, MA.
- Davis, Steve J., and John Haltiwanger.** 1991. "Wage Dispersion between and within U.S. Manufacturing Plants, 1963-86." *Brookings Papers on Economic Activity, Microeconomics*: 115-80.
- De Loecker, Jan.** 2005. "Product Differentiation, Multi-Product Firms and Structural Estimation of Productivity." <http://www.econ.kuleuven.be/econometrie/abstracts/abstract0506/DELOECKER.pdf>.
- Diewert, Erwin, and Kevin Fox.** Forthcoming. "On Measuring the Contribution of Entering and Exiting Firms to Aggregate Productivity Growth." In *Price and Productivity Measurement*, ed. W. Erwin

- Diewert, Bert M. Balk, Dennis Fixler, Kevin Fox, and Alice O. Nakamura. Manchester: Trafford Press.
- Dunne, Timothy, and Mark J. Roberts.** 1992. "Costs, Demand, and Imperfect Competition as Determinants of Plant-Level Output Prices." In *Empirical Studies in Industrial Organization: Essays in Honor of Leonard W. Weiss*, ed. David Audretsch and John Siegfried, 13–34. Norwell: Kluwer Academic Publishers.
- Dunne, Timothy, Mark J. Roberts, and Larry Samuelson.** 1988. "Patterns of Firm Entry and Exit in U.S. Manufacturing Industries." *RAND Journal of Economics*, 19(4): 495–515.
- Ericson, Richard, and Ariel Pakes.** 1995. "Markov-Perfect Industry Dynamics: A Framework for Empirical Work." *Review of Economic Studies*, 62(1): 53–82.
- Eslava, Marcela, John Haltiwanger, Adriana Kugler, and Maurice Kugler.** 2004. "The Effects of Structural Reforms on Productivity and Profitability Enhancing Reallocation: Evidence from Colombia." *Journal of Development Economics*, 75(2): 333–71.
- Eslava, Marcela, John Haltiwanger, Adriana Kugler, and Maurice Kugler.** 2005a. "Employment and Capital Adjustments After Factor Market Deregulation." http://www.banrep.gov.co/documentos/conferencias/2006/ac_ehkk_060105.pdf.
- Eslava, Marcela, John Haltiwanger, Adriana Kugler, and Maurice Kugler.** 2005b. "Plant Survival, Market Fundamentals and Trade Liberalization." <https://www.imf.org/external/np/res/seminars/2005/arc/pdf/esla.pdf>.
- Fishman, Arthur, and Rafael Rob.** 2003. "Consumer Inertia, Firm Growth and Industry Dynamics." *Journal of Economic Theory*, 109(1): 24–38.
- Foster, Lucia, John Haltiwanger, and C. J. Krizan.** 2001. "Aggregate Productivity Growth: Lessons from Microeconomic Evidence." In *New Development in Productivity Analysis*, ed. Edward Dean, Michael Harper, and Charles Hulten, 303–63. Chicago: University of Chicago Press.
- Foster, Lucia, John Haltiwanger, and C. J. Krizan.** 2006. "Market Selection, Reallocation, and Restructuring in the U.S. Retail Trade Sector in the 1990s." *Review of Economics and Statistics*, 88(4): 748–58.
- Foster, Lucia, John Haltiwanger, and Chad Syverson.** 2005. "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" National Bureau of Economic Research Working Paper 11555.
- Griliches, Zvi, and Haim Regev.** 1995. "Firm Productivity in Israeli Industry: 1979–1988." *Journal of Econometrics*, 65(1): 175–203.
- Gorodnichenko, Yuriy.** 2005. "What Do We Estimate in Production Function Regressions? Critique and New Approaches." http://www.ces.census.gov/docs/caed/abstracts/abs_83_Yuriy_Gorodnichenko.pdf.
- Harper, Michael J., Ernst R. Berndt, and David O. Wood.** 1989. "Rates of Return and Capital Aggregation Using Alternative Rental Prices." In *Technology and Capital Formation*, ed. Dale W. Jorgenson and Ralph Landau, 331–72. Cambridge, MA: MIT Press.
- Hopenhayn, Hugo A.** 1992. "Entry, Exit, and Firm Dynamics in Long Run Equilibrium." *Econometrica*, 60(5): 1127–50.
- Imperial Sugar Company.** 2005. *2005 Annual Report*. Sugar Land, Texas.
- Johnson, Kenneth P.** 1995. "Redefinition of the BEA Economic Areas." *Survey of Current Business*, 75(2): 75–81.
- Jovanovic, Boyan.** 1982. "Selection and the Evolution of Industry." *Econometrica*, 50(3): 649–70.
- Katayama, Haijime, Shihua Lu, and James Tybout.** 2003. "Why Plant-Level Productivity Studies Are Often Misleading, and an Alternative Approach to Interference." National Bureau of Economic Research Working Paper 9617.
- Klette, Tor Jakob, and Zvi Griliches.** 1996. "The Inconsistency of Common Scale Estimators when Output Prices Are Unobserved and Endogenous." *Journal of Applied Econometrics*, 11(4): 343–61.
- Krishnakumar, B.** 2001. "All Grey for Carbon Black." *Business Line's Investment World*, Jan. 7. <http://www.blonnet.com/iw/2001/01/07/stories/0507e051.htm>.
- Levinsohn, James, and Amil Petrin.** 2003. "Estimating Production Functions Using Inputs to Control for Unobservables." *Review of Economic Studies*, 70(2): 317–41.
- Mairesse, Jacques, and Jordi Jaumandreu.** 2005. "Panel-Data Estimates of the Production Function and the Revenue Function: What Difference Does It Make?" *Scandinavian Journal of Economics*, 107(4): 651–72.
- Melitz, Marc J.** 2000. "Estimating Firm-Level Productivity in Differentiated Product Industries." <http://post.economics.harvard.edu/faculty/melitz/papers/prodest.pdf>.
- Melitz, Marc J.** 2003. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity." *Econometrica*, 71(6): 1695–1725.
- Melitz, Marc J., and Gianmarco I. P. Ottaviano.** Forthcoming. "Market Size, Trade, and Productivity." *Review of Economic Studies*.

- Olley, G. Steven, and Ariel Pakes.** 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica*, 64(6): 1263–97.
- Roberts, Mark J, and Dylan Supina.** 2000. "Output Price and Markup Dispersion in Micro Data: The Roles of Producer Heterogeneity and Noise." In *Advances in Applied Microeconomics*, Vol. 9, *Industrial Organization*, ed. Michael R. Baye, 1–36. Greenwich: JAI Press.
- Roberts, Mark J, and Dylan Supina.** 1996. "Output Price, Markups, and Producer Size." *European Economic Review*, 40(3–5): 909–21.
- Shea, John.** 1997. "Instrument Relevance in Multivariate Linear Models: A Simple Measure." *Review of Economics and Statistics*, 79(2): 348–52.
- Syverson, Chad.** 2004. "Market Structure and Productivity: A Concrete Example." *Journal of Political Economy*, 112(6): 1181–1222.
- Syverson, Chad.** 2007. "Prices, Spatial Competition and Heterogeneous Producers: An Empirical Test." *Journal of Industrial Economics*, 55(2): 197–222.
- US Bureau of Labor Statistics.** 1983. "Trends in Multifactor Productivity: 1948–81." Bulletin 2178. Washington, DC: Government Printing Office.
- US Bureau of the Census.** 1981. "Commodity Transportation Survey." 1977 *Census of Transportation*, TC77–CS. Washington D.C.: Government Printing Office.
- U.S. Federal Trade Commission.** 1966. *Economic Report on Mergers and Vertical Integration in the Cement Industry*.
- Van Biesebroeck, Johannes.** 2004. "Robustness of Productivity Estimates" National Bureau of Economic Research Working Paper 10303.

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4. Hyunbae Chun, Jung-Wook Kim, Randall Morck. 2016. Productivity growth and stock returns: firm- and aggregate-level analyses. *Applied Economics* **48**:38, 3644-3664. [[CrossRef](#)]
5. Amitabh Chandra, Amy Finkelstein, Adam Sacarny, Chad Syverson. 2016. Health Care Exceptionalism? Performance and Allocation in the US Health Care Sector. *American Economic Review* **106**:8, 2110-2144. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
6. Colin J. Hottman, Stephen J. Redding, David E. Weinstein. 2016. Quantifying the Sources of Firm Heterogeneity. *The Quarterly Journal of Economics* **131**:3, 1291-1364. [[CrossRef](#)]
7. Andrea Pozzi, Fabiano Schivardi. 2016. Demand or productivity: what determines firm growth?. *The RAND Journal of Economics* **47**:3, 608-630. [[CrossRef](#)]
8. Mehmet Ugur, Eshref Trushin, Edna Solomon, Francesco Guidi. 2016. R&D and productivity in OECD firms and industries: A hierarchical meta-regression analysis. *Research Policy* . [[CrossRef](#)]
9. Pekka Ilmakunnas, Mika Maliranta. 2016. How does the age structure of worker flows affect firm performance?. *Journal of Productivity Analysis* **46**:1, 43-62. [[CrossRef](#)]
10. Xiaoyong Dai, Liwei Cheng. 2016. Market distortions and aggregate productivity: Evidence from Chinese energy enterprises. *Energy Policy* **95**, 304-313. [[CrossRef](#)]
11. Keith Barnatchez, Robert Lester. 2016. THE RELATIONSHIP BETWEEN ECONOMIC FREEDOM AND ECONOMIC DYNAMISM. *Contemporary Economic Policy* . [[CrossRef](#)]
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13. Arne Bigsten, Mulu Gebreeyesus, Måns Söderbom. 2016. Tariffs and Firm Performance in Ethiopia. *The Journal of Development Studies* **52**:7, 986-1001. [[CrossRef](#)]
14. Justin R. Pierce, Peter K. Schott. 2016. The Surprisingly Swift Decline of US Manufacturing Employment. *American Economic Review* **106**:7, 1632-1662. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
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18. Ryan A. Decker, John Haltiwanger, Ron S. Jarmin, Javier Miranda. 2016. Where has all the skewness gone? The decline in high-growth (young) firms in the U.S. *European Economic Review* **86**, 4-23. [[CrossRef](#)]

19. Johan M. Kuhn, Nikolaj Malchow-Møller, Anders Sørensen. 2016. Job creation and job types – New evidence from Danish entrepreneurs. *European Economic Review* **86**, 161-187. [[CrossRef](#)]
20. Wen Chen, Robert Inklaar. 2016. Productivity spillovers of organization capital. *Journal of Productivity Analysis* **45**:3, 229-245. [[CrossRef](#)]
21. Michel Dumont, Glenn Rayp, Marijn Vershelde, Bruno Merlevede. 2016. The contribution of start-ups and young firms to industry-level efficiency growth. *Applied Economics* 1-16. [[CrossRef](#)]
22. Renu Agarwal, Roy Green, Neeru Agarwal, Krithika Randhawa. 2016. Management practices in Australian healthcare: can NSW public hospitals do better?. *Journal of Health Organization and Management* **30**:3, 331-353. [[CrossRef](#)]
23. Clemens Ohlert. 2016. Establishment heterogeneity, rent sharing and the rise of wage inequality in Germany. *International Journal of Manpower* **37**:2, 210-228. [[CrossRef](#)]
24. Amitabh Chandra, Amy Finkelstein, Adam Sacarny, Chad Syverson. 2016. Productivity Dispersion in Medicine and Manufacturing. *American Economic Review* **106**:5, 99-103. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
25. Alan Spearot. 2016. Unpacking the Long-Run Effects of Tariff Shocks: New Structural Implications from Firm Heterogeneity Models. *American Economic Journal: Microeconomics* **8**:2, 128-167. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
26. Lucia Foster, Cheryl Grim, John Haltiwanger, Zoltan Wolf. 2016. Firm-Level Dispersion in Productivity: Is the Devil in the Details?. *American Economic Review* **106**:5, 95-98. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
27. Adelheid Holl. 2016. Highways and productivity in manufacturing firms. *Journal of Urban Economics* **93**, 131-151. [[CrossRef](#)]
28. Paul L. E. Grieco, Shengyu Li, Hongsong Zhang. 2016. PRODUCTION FUNCTION ESTIMATION WITH UNOBSERVED INPUT PRICE DISPERSION. *International Economic Review* **57**:2, 665-690. [[CrossRef](#)]
29. Wim Naudé. 2016. Entrepreneurship and the Reallocation of African Farmers. *Agrekon* **55**:1-2, 1-33. [[CrossRef](#)]
30. Sai Ding, Alessandra Guariglia, Richard Harris. 2016. The determinants of productivity in Chinese large and medium-sized industrial firms, 1998–2007. *Journal of Productivity Analysis* **45**:2, 131-155. [[CrossRef](#)]
31. Zheng Jiang, Huimin Shi. 2016. The selection of firms based on productivity: different roles of entry and overhead cost. *Economic Modelling* **54**, 537-544. [[CrossRef](#)]
32. Ruhul Salim, Shamsul Arifeen Khan Mamun, Kamrul Hassan. 2016. Role of communication technologies in broadacre agriculture in Australia: an empirical analysis using panel data. *Australian Journal of Agricultural and Resource Economics* **60**:2, 243-264. [[CrossRef](#)]
33. J. David Brown, Gustavo A. Crespi, Leonardo Iacovone, Luca Marcolin. Productivity Convergence at the Firm Level: New Evidence from the Americas 117-186. [[CrossRef](#)]
34. Ramana Nanda, Matthew Rhodes-Kropf. 2016. Financing Risk and Innovation. *Management Science* . [[CrossRef](#)]
35. Renu Agarwal, Roy Green, Neeru Agarwal, Krithika Randhawa. 2016. Benchmarking management practices in Australian public healthcare. *Journal of Health Organization and Management* **30**:1, 31-56. [[CrossRef](#)]
36. Ralf R. Meisenzahl. 2016. Can Financing Constraints Explain the Evolution of the Firm Size Distribution?. *Review of Industrial Organization* **48**:2, 123-147. [[CrossRef](#)]
37. Gabriel Natividad. 2016. Quotas, Productivity, and Prices: The Case of Anchovy Fishing. *Journal of Economics & Management Strategy* **25**:1, 220-257. [[CrossRef](#)]

38. Robert M. Adams, Jacob Gramlich. 2016. Where Are All the New Banks? The Role of Regulatory Burden in New Bank Formation. *Review of Industrial Organization* **48**:2, 181-208. [[CrossRef](#)]
39. Nkechi S. Owoo, Wim Naudé. 2016. Spatial Proximity and Firm Performance: Evidence from Non-Farm Rural Enterprises in Ethiopia and Nigeria. *Regional Studies* 1-13. [[CrossRef](#)]
40. Manuel Guisado-González, Mercedes Vila-Alonso, Manuel Guisado-Tato. 2016. Radical innovation, incremental innovation and training: Analysis of complementarity. *Technology in Society* **44**, 48-54. [[CrossRef](#)]
41. Marijn Verschelde, Michel Dumont, Glenn Rayp, Bruno Merlevede. 2016. Semiparametric stochastic metafrontier efficiency of European manufacturing firms. *Journal of Productivity Analysis* **45**:1, 53-69. [[CrossRef](#)]
42. Mykola Ryzhenkov. 2016. Resource misallocation and manufacturing productivity: The case of Ukraine. *Journal of Comparative Economics* **44**:1, 41-55. [[CrossRef](#)]
43. Cui Hu, Faqin Lin, Xiaosong Wang. 2016. Learning from exporting in China. *Economics of Transition* n/a-n/a. [[CrossRef](#)]
44. Kim P. Huynh, Robert J. Petrunia. 2016. Post-Entry Struggle for Life and Pre-Exit Shadow of Death from a Financial Perspective. *International Journal of the Economics of Business* **23**:1, 1-18. [[CrossRef](#)]
45. Lucia Foster, John Haltiwanger, Chad Syverson. 2016. The Slow Growth of New Plants: Learning about Demand?. *Economica* **83**:329, 91-129. [[CrossRef](#)]
46. Flora Bellone, Patrick Musso, Lionel Nesta, Frederic Warzynski. 2016. International trade and firm-level markups when location and quality matter. *Journal of Economic Geography* **16**:1, 67-91. [[CrossRef](#)]
47. Mika Maliranta, Niku Määttä. 2015. An Augmented Static Olley-Pakes Productivity Decomposition with Entry and Exit: Measurement and Interpretation. *Economica* **82**, 1372-1416. [[CrossRef](#)]
48. Sara Calligaris. 2015. Misallocation and Total Factor Productivity in Italy: Evidence from Firm-Level Data. *LABOUR* **29**:4, 367-393. [[CrossRef](#)]
49. Yu Sheng, Thomas Jackson, Peter Gooday. 2015. Resource reallocation and its contribution to productivity growth in Australian broadacre agriculture. *Australian Journal of Agricultural and Resource Economics* n/a-n/a. [[CrossRef](#)]
50. Peter Scott, Nicolas Ziebarth. 2015. The Determinants of Plant Survival in the U.S. Radio Equipment Industry During the Great Depression. *The Journal of Economic History* **75**:04, 1097-1127. [[CrossRef](#)]
51. Hirokazu Ishise. 2015. Capital heterogeneity as a source of comparative advantage: Putty-clay technology in a ricardian model. *Journal of International Economics* . [[CrossRef](#)]
52. Yoonsoo Lee, Toshihiko Mukoyama. 2015. Productivity and employment dynamics of US manufacturing plants. *Economics Letters* **136**, 190-193. [[CrossRef](#)]
53. Costas Arkolakis. 2015. A Unified Theory of Firm Selection and Growth. *The Quarterly Journal of Economics* qjv039. [[CrossRef](#)]
54. Nicolas L. Ziebarth. 2015. The Great Depression Through the Eyes of the Census of Manufactures. *Historical Methods: A Journal of Quantitative and Interdisciplinary History* **48**:4, 185-194. [[CrossRef](#)]
55. Cecília Hornok, Balázs Muraközy. 2015. Magyar vállalatok haszonkulcsai. *Közgazdasági Szemle* **62**:10, 1048-1069. [[CrossRef](#)]
56. Guido Buenstorf. 2015. Schumpeterian incumbents and industry evolution. *Journal of Evolutionary Economics* . [[CrossRef](#)]
57. P.M. Picard. 2015. Trade, economic geography and the choice of product quality. *Regional Science and Urban Economics* **54**, 18-27. [[CrossRef](#)]

58. Natina Yaduma, Allan Williams, Andrew Lockwood, Sangwon Park. 2015. Performance, labour flexibility and migrant workers in hotels: An establishment and departmental level analysis. *International Journal of Hospitality Management* **50**, 94-104. [[CrossRef](#)]
59. Denis Medvedev, Ana María Oviedo. 2015. Informality and Profitability: Evidence from a New Firm Survey in Ecuador. *The Journal of Development Studies* 1-16. [[CrossRef](#)]
60. Can Tian. 2015. Riskiness, endogenous productivity dispersion and business cycles. *Journal of Economic Dynamics and Control* **57**, 227-249. [[CrossRef](#)]
61. John Haltiwanger. 2015. Job Creation, Job Destruction, and Productivity Growth: The Role of Young Businesses. *Annual Review of Economics* **7**:1, 341-358. [[CrossRef](#)]
62. Antoine Gervais. 2015. Product quality and firm heterogeneity in international trade. *Canadian Journal of Economics/Revue canadienne d'économique* **48**:3, 1152-1174. [[CrossRef](#)]
63. Serguey Braguinsky, Atsushi Ohyama, Tetsuji Okazaki, Chad Syverson. 2015. Acquisitions, Productivity, and Profitability: Evidence from the Japanese Cotton Spinning Industry. *American Economic Review* **105**:7, 2086-2119. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
64. Daniel P. Murphy. 2015. How can government spending stimulate consumption?. *Review of Economic Dynamics* **18**:3, 551-574. [[CrossRef](#)]
65. Ying Ge, Huiwen Lai, Susan Chun Zhu. 2015. Multinational price premium. *Journal of Development Economics* **115**, 181-199. [[CrossRef](#)]
66. Kaiji Chen, Alfonso Irarrazabal. 2015. The role of allocative efficiency in a decade of recovery. *Review of Economic Dynamics* **18**:3, 523-550. [[CrossRef](#)]
67. Yoonsoo Lee, Toshihiko Mukoyama. 2015. Entry and exit of manufacturing plants over the business cycle. *European Economic Review* **77**, 20-27. [[CrossRef](#)]
68. Guying Laura Wu. 2015. Investment Frictions and the Aggregate Output Loss in China. *Oxford Bulletin of Economics and Statistics* **77**:3, 437-465. [[CrossRef](#)]
69. Marc J. Melitz, Sašo Polanec. 2015. Dynamic Olley-Pakes productivity decomposition with entry and exit. *The RAND Journal of Economics* **46**:2, 362-375. [[CrossRef](#)]
70. X. Yu, G. Dosi, J. Lei, A. Nuvolari. 2015. Institutional change and productivity growth in China's manufacturing: the microeconomics of knowledge accumulation and "creative restructuring". *Industrial and Corporate Change* **24**:3, 565-602. [[CrossRef](#)]
71. Michele Battisti, Filippo Belloc, Massimo Del Gatto. 2015. Unbundling Technology Adoption and tfp at the Firm Level: Do Intangibles Matter?. *Journal of Economics & Management Strategy* **24**:2, 390-414. [[CrossRef](#)]
72. Mikael Carlsson, Julián Messina, Oskar Nordström Skans. 2015. Wage Adjustment and Productivity Shocks. *The Economic Journal* n/a-n/a. [[CrossRef](#)]
73. X. Liu, H. Li. 2015. Financial constraints and the productivity-survival link: evidence from China's firm-level data. *Industrial and Corporate Change* . [[CrossRef](#)]
74. Sabien Dobbelaere, Kozo Kiyota, Jacques Mairesse. 2015. Product and labor market imperfections and scale economies: Micro-evidence on France, Japan and the Netherlands. *Journal of Comparative Economics* **43**:2, 290-322. [[CrossRef](#)]
75. Ivan Cherkashin, Svetlana Demidova, Hiau Looi Kee, Kala Krishna. 2015. Firm heterogeneity and costly trade: A new estimation strategy and policy experiments. *Journal of International Economics* **96**:1, 18-36. [[CrossRef](#)]
76. Iris Mihai. 2015. Economic Productivity Flip-Flop in the Danube Countries. *Procedia - Social and Behavioral Sciences* **183**, 11-20. [[CrossRef](#)]

77. Florin Maican, Matilda Orth. 2015. A dynamic analysis of entry regulations and productivity in retail trade. *International Journal of Industrial Organization* **40**, 67-80. [[CrossRef](#)]
78. Nicolas Petrosky-Nadeau, Etienne Wasmer. 2015. Macroeconomic dynamics in a model of goods, labor, and credit market frictions. *Journal of Monetary Economics* **72**, 97-113. [[CrossRef](#)]
79. Ejaz Ghani, Arti Grover Goswami, William R. Kerr. 2015. Highway to Success: The Impact of the Golden Quadrilateral Project for the Location and Performance of Indian Manufacturing. *The Economic Journal* n/a-n/a. [[CrossRef](#)]
80. S. Board, M. Meyer-Ter-Vehn. 2015. Relational Contracts in Competitive Labour Markets. *The Review of Economic Studies* **82**:2, 490-534. [[CrossRef](#)]
81. N. Bloom, C. Propper, S. Seiler, J. Van Reenen. 2015. The Impact of Competition on Management Quality: Evidence from Public Hospitals. *The Review of Economic Studies* **82**:2, 457-489. [[CrossRef](#)]
82. Olga A. Timoshenko. 2015. Product switching in a model of learning. *Journal of International Economics* **95**:2, 233-249. [[CrossRef](#)]
83. Gustavo Lannelongue, Javier Gonzalez-Benito, Oscar Gonzalez-Benito. 2015. Input, Output, and Environmental Management Productivity: Effects on Firm Performance. *Business Strategy and the Environment* **24**:3, 145-158. [[CrossRef](#)]
84. Alexis Antoniadis. 2015. Heterogeneous Firms, Quality, and Trade. *Journal of International Economics* **95**:2, 263-273. [[CrossRef](#)]
85. Carlos Casacuberta, Néstor Gandelman. 2015. Productivity, Exit, and Crisis in the Manufacturing and Service Sectors. *The Developing Economies* **53**:1, 27-43. [[CrossRef](#)]
86. Nune Hovhannisyan, Wolfgang Keller. 2015. International business travel: an engine of innovation?. *Journal of Economic Growth* **20**:1, 75-104. [[CrossRef](#)]
87. XAVIER GIROUD, HOLGER M. MUELLER. 2015. Capital and Labor Reallocation within Firms. *The Journal of Finance* n/a-n/a. [[CrossRef](#)]
88. Chia -Yen Lee, Andrew L. Johnson. 2015. Measuring Efficiency in Imperfectly Competitive Markets: An Example of Rational Inefficiency. *Journal of Optimization Theory and Applications* **164**:2, 702-722. [[CrossRef](#)]
89. Bert M. Balk. 2015. Measuring and relating aggregate and subaggregate total factor productivity change without neoclassical assumptions. *Statistica Neerlandica* **69**:1, 21-48. [[CrossRef](#)]
90. G. Duranton. 2015. Growing through Cities in Developing Countries. *The World Bank Research Observer* **30**:1, 39-73. [[CrossRef](#)]
91. Fariha Kamal. 2015. Origin of Foreign Direct Investment and Firm Performance: Evidence from Foreign Acquisitions of Chinese Domestic Firms. *The World Economy* **38**:2, 286-314. [[CrossRef](#)]
92. N. Bloom, J. Liang, J. Roberts, Z. J. Ying. 2015. Does Working from Home Work? Evidence from a Chinese Experiment. *The Quarterly Journal of Economics* **130**:1, 165-218. [[CrossRef](#)]
93. Allan Collard-Wexler, Jan De Loecker. 2015. Reallocation and Technology: Evidence from the US Steel Industry. *American Economic Review* **105**:1, 131-171. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
94. Atanas Hristov. 2015. The high sensitivity of employment to agency costs: The relevance of wage rigidity. *Journal of Macroeconomics* **45**, 137. [[CrossRef](#)]
95. Anna Belova, Wayne B. Gray, Joshua Linn, Richard D. Morgenstern, William Pizer. 2015. Estimating the Job Impacts of Environmental Regulation. *Journal of Benefit-Cost Analysis* **6**:02, 325-340. [[CrossRef](#)]
96. 2015. *Journal of Macroeconomics* **45**. . [[CrossRef](#)]

97. T. Weng, T. Vukina, X. Zheng. 2015. Productivity or Demand: Determinants of Plant Survival and Ownership Change in the U.S. Poultry Industry. *Applied Economic Perspectives and Policy* 37:1, 151. [[CrossRef](#)]
98. Era Dabla-Norris, Si Guo, Vikram Haksar, Minsuk Kim, Kalpana Kochhar, Kevin Wiseman, Aleksandra Zdzienicka. 2015. The New Normal: A Sector-level Perspective on Productivity Trends in Advanced Economies. *Staff Discussion Notes* 15:3, 1. [[CrossRef](#)]
99. Rui Castro, Gian Luca Clementi, Yoonsoo Lee. 2015. Cross Sectoral Variation in the Volatility of Plant Level Idiosyncratic Shocks. *The Journal of Industrial Economics* 63:1, 1. [[CrossRef](#)]
100. Olivier Charlot, Franck Malherbet, Cristina Terra. 2015. Informality in developing economies: Regulation and fiscal policies. *Journal of Economic Dynamics and Control* 51, 1. [[CrossRef](#)]
101. Rita K Almeida, Reyes Aterido. 2015. Investing in formal on-the-job training: are SMEs lagging much behind?. *IZA Journal of Labor & Development* 4:1. . [[CrossRef](#)]
102. Margo Liik, Jaan Masso, Kadri Ukrainski. 2014. The contribution of R&D to production efficiency in OECD countries: econometric analysis of industry-level panel data. *Baltic Journal of Economics* 14:1-2, 78-100. [[CrossRef](#)]
103. Talan B. İşcan. 2014. Allocative inefficiency and sectoral allocation of labor: Evidence from U.S. agriculture. *Economic Modelling* 43, 305-320. [[CrossRef](#)]
104. Allan Collard-Wexler. 2014. Mergers and Sunk Costs: An Application to the Ready-Mix Concrete Industry. *American Economic Journal: Microeconomics* 6:4, 407-447. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
105. Jacob Rubæk Holm. 2014. The significance of structural transformation to productivity growth. *Journal of Evolutionary Economics* 24:5, 1009-1036. [[CrossRef](#)]
106. Kristian Behrens, Giordano Mion, Yasusada Murata, Jens Südekum. 2014. TRADE, WAGES, AND PRODUCTIVITY. *International Economic Review* 55:4, 1305-1348. [[CrossRef](#)]
107. Ina Charlotte Jäkel. 2014. Import-push or export-pull? An industry-level analysis of the impact of trade on firm exit. *Empirica* 41:4, 747-775. [[CrossRef](#)]
108. Bruce A. Blonigen, Lionel Fontagné, Nicholas Sly, Farid Toubal. 2014. Cherries for sale: The incidence and timing of cross-border M&A. *Journal of International Economics* 94:2, 341-357. [[CrossRef](#)]
109. R. Basile, S. de Nardis, C. Pappalardo. 2014. Firm heterogeneity and regional business cycles differentials. *Journal of Economic Geography* 14:6, 1087-1115. [[CrossRef](#)]
110. Pilar Beneito, María Engracia Rochina-Barrachina, Amparo Sanchis. 2014. Learning through experience in Research & Development: An empirical analysis with Spanish firms. *Technological Forecasting and Social Change* 88, 290-305. [[CrossRef](#)]
111. Mitsukuni Nishida, Amil Petrin, Sašo Polanec. 2014. Exploring reallocation's apparent weak contribution to growth. *Journal of Productivity Analysis* 42:2, 187-210. [[CrossRef](#)]
112. Dennis O. Kundisch, Neeraj Mittal, Barrie R. Nault. 2014. Research Commentary —Using Income Accounting as the Theoretical Basis for Measuring IT Productivity. *Information Systems Research* 25:3, 449-467. [[CrossRef](#)]
113. Chris Vickers, Nicolas L. Ziebarth. 2014. Did the National Industrial Recovery Act Foster Collusion? Evidence from the Macaroni Industry. *The Journal of Economic History* 74:03, 831-862. [[CrossRef](#)]
114. Ryan Decker, John Haltiwanger, Ron Jarmin, Javier Miranda. 2014. The Role of Entrepreneurship in US Job Creation and Economic Dynamism. *Journal of Economic Perspectives* 28:3, 3-24. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
115. Elena Golovko, Giovanni Valentini. 2014. Selective Learning-by-Exporting: Firm Size and Product Versus Process Innovation. *Global Strategy Journal* 4:3, 161-180. [[CrossRef](#)]

116. Nicholas Bloom, Renata Lemos, Raffaella Sadun, Daniela Scur, John Van Reenen. 2014. JEEA-FBBVA LECTURE 2013 : THE NEW EMPIRICAL ECONOMICS OF MANAGEMENT. *Journal of the European Economic Association* **12**:4, 835-876. [[CrossRef](#)]
117. Jan De Loecker, Pinelopi Koujianou Goldberg. 2014. Firm Performance in a Global Market. *Annual Review of Economics* **6**:1, 201-227. [[CrossRef](#)]
118. C.-T. Hsieh, P. J. Klenow. 2014. The Life Cycle of Plants in India and Mexico. *The Quarterly Journal of Economics* **129**:3, 1035-1084. [[CrossRef](#)]
119. Keith W. Glaister. 2014. The contribution of management to economic growth: a review. *Prometheus* **32**:3, 227-244. [[CrossRef](#)]
120. Francesco Lippi, Fabiano Schivardi. 2014. Corporate control and executive selection. *Quantitative Economics* **5**:2, 417-456. [[CrossRef](#)]
121. Joel Rodrigue, Omolola Soumonni. 2014. Deforestation, foreign demand and export dynamics in Indonesia. *Journal of International Economics* **93**:2, 316-338. [[CrossRef](#)]
122. Umut Kılınç. 2014. How to measure competition in an economy in transition. *Economics of Transition* **22**:3, 397-432. [[CrossRef](#)]
123. Pierre Blanchard, Jean-Pierre Huiban, Claude Mathieu. 2014. The shadow of death model revisited with an application to French firms. *Applied Economics* **46**:16, 1883-1893. [[CrossRef](#)]
124. Álvaro Escribano, Rodolfo Stucchi. 2014. Does recession drive convergence in firms' productivity? Evidence from Spanish manufacturing firms. *Journal of Productivity Analysis* **41**:3, 339-349. [[CrossRef](#)]
125. John R. Baldwin, Amélie Lafrance. 2014. Firm Turnover and Productivity Growth in Canadian Manufacturing and Services Industries, 2000 to 2007. *Journal of Industry, Competition and Trade* **14**:2, 173-205. [[CrossRef](#)]
126. Jens J. Krüger. 2014. Intrasectoral structural change and aggregate productivity development: robust stochastic nonparametric frontier function estimates. *Empirical Economics* **46**:4, 1545-1572. [[CrossRef](#)]
127. Pekka Ilmakunnas, Hannu Piekola. 2014. Intangible investment in people and productivity. *Journal of Productivity Analysis* **41**:3, 443-456. [[CrossRef](#)]
128. Enghin Atalay. 2014. MATERIALS PRICES AND PRODUCTIVITY. *Journal of the European Economic Association* **12**:3, 575-611. [[CrossRef](#)]
129. Kristina McElheran. 2014. Delegation in Multi-Establishment Firms: Evidence from I.T. Purchasing. *Journal of Economics & Management Strategy* **23**:2, 225-258. [[CrossRef](#)]
130. Marian Rizov, Xufei Zhang. 2014. Regional disparities and productivity in China: Evidence from manufacturing micro data. *Papers in Regional Science* **93**:2, 321-339. [[CrossRef](#)]
131. Horst Raff, Joachim Wagner. 2014. Foreign Ownership and the Extensive Margins of Exports: Evidence for Manufacturing Enterprises in Germany. *The World Economy* **37**:5, 579-591. [[CrossRef](#)]
132. Albert Guangzhou Hu, Zhengning Liu. 2014. Trade Liberalization and Firm Productivity: Evidence from Chinese Manufacturing Industries. *Review of International Economics* n/a-n/a. [[CrossRef](#)]
133. Francesco Di Comite, Jacques-François Thisse, Hylke Vandenbussche. 2014. Verti-zontal differentiation in export markets. *Journal of International Economics* **93**:1, 50-66. [[CrossRef](#)]
134. Julien Martin, Isabelle Mejean. 2014. Low-wage country competition and the quality content of high-wage country exports. *Journal of International Economics* **93**:1, 140-152. [[CrossRef](#)]
135. Enghin Atalay, Ali Hortaçsu, Chad Syverson. 2014. Vertical Integration and Input Flows. *American Economic Review* **104**:4, 1120-1148. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
136. Esben Sloth Andersen, Jacob Rubæk Holm. 2014. The signs of change in economic evolution. *Journal of Evolutionary Economics* **24**:2, 291-316. [[CrossRef](#)]

137. C. Gaigne, L. Le Mener. 2014. Agricultural Prices, Selection, and the Evolution of the Food Industry. *American Journal of Agricultural Economics* **96**:3, 884-902. [[CrossRef](#)]
138. Bee Yan Aw, Yi Lee. 2014. A model of demand, productivity and foreign location decision among Taiwanese firms. *Journal of International Economics* **92**:2, 304-316. [[CrossRef](#)]
139. Ferran Vendrell-Herrero, José L. González-Pernía, Iñaki Peña-Legazkue. 2014. "Do incentives matter to promote high technology-driven entrepreneurial activity?". *International Entrepreneurship and Management Journal* **10**:1, 43-66. [[CrossRef](#)]
140. Kristiaan Kerstens, Ignace Van de Woestyne. 2014. Comparing Malmquist and Hicks-Moorsteen productivity indices: Exploring the impact of unbalanced vs. balanced panel data. *European Journal of Operational Research* **233**:3, 749-758. [[CrossRef](#)]
141. Gabriel Natividad. 2014. Integration and Productivity: Satellite-Tracked Evidence. *Management Science* 140220085922009. [[CrossRef](#)]
142. B. S. Javorcik, Y. Li. 2014. Global Retail Chains and the Supplying Industries: Evidence from Romania. *CESifo Economic Studies* . [[CrossRef](#)]
143. Umut Kilinç. 2014. Estimating entrants' productivity when prices are unobserved. *Economic Modelling* **38**, 640-647. [[CrossRef](#)]
144. Burak R. Uras. 2014. Corporate financial structure, misallocation and total factor productivity. *Journal of Banking & Finance* **39**, 177-191. [[CrossRef](#)]
145. Joachim Wagner. 2014. Exports, foreign direct investments and productivity: are services firms different?. *The Service Industries Journal* **34**:1, 24-37. [[CrossRef](#)]
146. David Powell, Joachim Wagner. 2014. The exporter productivity premium along the productivity distribution: evidence from quantile regression with nonadditive firm fixed effects. *Review of World Economics* **150**:4, 763. [[CrossRef](#)]
147. Ann E. Harrison, Justin Yifu Lin, Lixin Colin Xu. 2014. Explaining Africa's (Dis)advantage. *World Development* . [[CrossRef](#)]
148. Takahiro Fukunishi, Herinjatovo Aimé Ramiarison The Export-Oriented Garment Industry in Madagascar: Implications of Foreign Direct Investment for the Local Economy 135-173. [[CrossRef](#)]
149. P. Nightingale, A. Coad. 2013. Muppets and gazelles: political and methodological biases in entrepreneurship research. *Industrial and Corporate Change* . [[CrossRef](#)]
150. F. Kamal, M. E. Lovely. 2013. Labor Allocation in China: Implicit Taxation of the Heterogeneous Non-State Sector. *CESifo Economic Studies* **59**:4, 731-758. [[CrossRef](#)]
151. M. Vivarelli. 2013. Is entrepreneurship necessarily good? Microeconomic evidence from developed and developing countries. *Industrial and Corporate Change* **22**:6, 1453-1495. [[CrossRef](#)]
152. Sanjay K. Chugh. 2013. Costly external finance and labor market dynamics. *Journal of Economic Dynamics and Control* **37**:12, 2882-2912. [[CrossRef](#)]
153. Matthias Bürker, Chiara Franco, G. Alfredo Minerva. 2013. Foreign ownership, firm performance, and the geography of civic capital. *Regional Science and Urban Economics* **43**:6, 964-984. [[CrossRef](#)]
154. Philipp Ehrl. 2013. Agglomeration economies with consistent productivity estimates. *Regional Science and Urban Economics* **43**:5, 751-763. [[CrossRef](#)]
155. Juan Carlos Hallak, Jagadeesh Sivadasan. 2013. Product and process productivity: Implications for quality choice and conditional exporter premia. *Journal of International Economics* **91**:1, 53-67. [[CrossRef](#)]
156. D. Card, J. Heining, P. Kline. 2013. Workplace Heterogeneity and the Rise of West German Wage Inequality. *The Quarterly Journal of Economics* **128**:3, 967-1015. [[CrossRef](#)]

157. Sea-Jin Chang, Brian Wu. 2013. Institutional barriers and industry dynamics. *Strategic Management Journal* n/a-n/a. [[CrossRef](#)]
158. Valerie Smeets, Frederic Warzynski. 2013. Estimating productivity with multi-product firms, pricing heterogeneity and the role of international trade. *Journal of International Economics* **90**:2, 237-244. [[CrossRef](#)]
159. Ramana Nanda, Matthew Rhodes-Kropf. 2013. Investment cycles and startup innovation. *Journal of Financial Economics* . [[CrossRef](#)]
160. Beata S. Javorcik, Yue Li. 2013. Do the biggest aisles serve a brighter future? Global retail chains and their implications for Romania. *Journal of International Economics* **90**:2, 348-363. [[CrossRef](#)]
161. C. Bontemps, Z. Bouamra-Mechemache, M. Simioni. 2013. Quality labels and firm survival: some first empirical evidence. *European Review of Agricultural Economics* **40**:3, 413-439. [[CrossRef](#)]
162. De-Chih Liu. 2013. The evolution of excess job reallocation in the U.S. *Journal of Macroeconomics* **36**, 188-206. [[CrossRef](#)]
163. Ari Hyytinen, Mika Maliranta. 2013. Firm lifecycles and evolution of industry productivity. *Research Policy* **42**:5, 1080-1098. [[CrossRef](#)]
164. Masato Nishiwaki, Hyoeg Ug Kwon. 2013. Are Losers Picked? An Empirical Analysis of Capacity Divestment and Production Reallocation in the Japanese Cement Industry. *The Journal of Industrial Economics* **61**:2, 430-467. [[CrossRef](#)]
165. Kaiji Chen, Zheng Song. 2013. Financial frictions on capital allocation: A transmission mechanism of TFP fluctuations. *Journal of Monetary Economics* . [[CrossRef](#)]
166. Richard Harris, John Moffat. 2013. The Direct Contribution of FDI to Productivity Growth in Britain, 1997-2008. *The World Economy* **36**:6, 713-736. [[CrossRef](#)]
167. Sascha Rexhäuser, Christian Rammer. 2013. Environmental Innovations and Firm Profitability: Unmasking the Porter Hypothesis. *Environmental and Resource Economics* . [[CrossRef](#)]
168. X. Giroud. 2013. Proximity and Investment: Evidence from Plant-Level Data. *The Quarterly Journal of Economics* **128**:2, 861-915. [[CrossRef](#)]
169. Alan C. Spearot. 2013. MARKET ACCESS, INVESTMENT, AND HETEROGENEOUS FIRMS*. *International Economic Review* **54**:2, 601-627. [[CrossRef](#)]
170. Federico Cingano, Paolo Pinotti. 2013. POLITICIANS AT WORK: THE PRIVATE RETURNS AND SOCIAL COSTS OF POLITICAL CONNECTIONS. *Journal of the European Economic Association* **11**:2, 433-465. [[CrossRef](#)]
171. Fang Cai, Yang Lu. 2013. Population Change and Resulting Slowdown in Potential GDP Growth in China. *China & World Economy* **21**:2, 1-14. [[CrossRef](#)]
172. Magnus Lofstrom, Timothy Bates, Simon C. Parker. 2013. Why are some people more likely to become small-businesses owners than others: Entrepreneurship entry and industry-specific barriers. *Journal of Business Venturing* . [[CrossRef](#)]
173. Jan Boone, Jan C. Ours, Henry Wiel. 2013. When is the Price Cost Margin a Safe Way to Measure Changes in Competition?. *De Economist* **161**:1, 45-67. [[CrossRef](#)]
174. G. Moscarini, F. Postel-Vinay. 2013. Stochastic Search Equilibrium. *The Review of Economic Studies* . [[CrossRef](#)]
175. U. Doraszelski, J. Jaumandreu. 2013. R&D and Productivity: Estimating Endogenous Productivity. *The Review of Economic Studies* . [[CrossRef](#)]
176. Eric Bartelsman,, John Haltiwanger,, Stefano Scarpetta. 2013. Cross-Country Differences in Productivity: The Role of Allocation and Selection. *American Economic Review* **103**:1, 305-334. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]

177. Gaaitzen J. de Vries. 2013. Productivity in a Distorted Market: The Case of Brazil's Retail Sector. *Review of Income and Wealth* n/a-n/a. [[CrossRef](#)]
178. Nicolas L. Ziebarth. 2013. Identifying the Effects of Bank Failures from a Natural Experiment in Mississippi during the Great Depression. *American Economic Journal: Macroeconomics* 5:1, 81-101. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
179. Emin Dinlersoz, Henry R Hyatt, Sang V Nguyen. 2013. The plant life-cycle of the average wage of employees in U.S. manufacturing. *IZA Journal of Labor Economics* 2:1, 7. [[CrossRef](#)]
180. Diego Restuccia, Richard Rogerson. 2013. Misallocation and productivity. *Review of Economic Dynamics* 16:1, 1-10. [[CrossRef](#)]
181. C. Newman, J. Rand, F. Tarp. 2013. Industry Switching in Developing Countries. *The World Bank Economic Review* 27:2, 357-388. [[CrossRef](#)]
182. Albert Bollard, Peter J. Klenow, Gunjan Sharma. 2013. India's mysterious manufacturing miracle. *Review of Economic Dynamics* 16:1, 59-85. [[CrossRef](#)]
183. Nicolas L. Ziebarth. 2013. Are China and India backward? Evidence from the 19th century U.S. Census of Manufactures. *Review of Economic Dynamics* 16:1, 86-99. [[CrossRef](#)]
184. Sabien Dobbelaere, Jacques Mairesse. 2013. Panel data estimates of the production function and product and labor market imperfections. *Journal of Applied Econometrics* 28:1, 1-46. [[CrossRef](#)]
185. Marcela Eslava, John Haltiwanger, Adriana Kugler, Maurice Kugler. 2013. Trade and market selection: Evidence from manufacturing plants in Colombia. *Review of Economic Dynamics* 16:1, 135-158. [[CrossRef](#)]
186. M. C. Levenstein. 2012. Escape from Equilibrium: Thinking Historically about Firm Responses to Competition. *Enterprise and Society* 13:4, 710-728. [[CrossRef](#)]
187. Yi-Chen Lin, Tai-Hsin Huang. 2012. Creative destruction over the business cycle: a stochastic frontier analysis. *Journal of Productivity Analysis* 38:3, 285-302. [[CrossRef](#)]
188. Giulio Bottazzi, Angelo Secchi. 2012. Productivity, profitability and growth: The empirics of firm dynamics. *Structural Change and Economic Dynamics* 23:4, 325-328. [[CrossRef](#)]
189. Måns Söderbom, Qian Weng. 2012. Multi-product firms, product mix changes and upgrading: Evidence from China's state-owned forest areas. *China Economic Review* 23:4, 801-818. [[CrossRef](#)]
190. Rosario Crinò, Paolo Epifani. 2012. Productivity, Quality and Export Behaviour*. *The Economic Journal* 122:565, 1206-1243. [[CrossRef](#)]
191. Margaret C. Levenstein. 2012. Escape from Equilibrium: Thinking Historically about Firm Responses to Competition. *Enterprise and Society* 13:04, 710-728. [[CrossRef](#)]
192. Pierre M. Picard, Toshihiro Okubo. 2012. Firms' locations under demand heterogeneity. *Regional Science and Urban Economics* 42:6, 961-974. [[CrossRef](#)]
193. Joachim Wagner. 2012. Exports, Imports and Profitability: First Evidence for Manufacturing Enterprises. *Open Economies Review* 23:5, 747-765. [[CrossRef](#)]
194. Giovanni Dosi, Marco Grazzi, Chiara Tomasi, Alessandro Zeli. 2012. Turbulence underneath the big calm? The micro-evidence behind Italian productivity dynamics. *Small Business Economics* 39:4, 1043-1067. [[CrossRef](#)]
195. Jan De Loecker,, Frederic Warzynski. 2012. Markups and Firm-Level Export Status. *American Economic Review* 102:6, 2437-2471. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
196. Giuseppe Moscarini,, Fabien Postel-Vinay. 2012. The Contribution of Large and Small Employers to Job Creation in Times of High and Low Unemployment. *American Economic Review* 102:6, 2509-2539. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]

197. Cristina Arellano, Yan Bai, Jing Zhang. 2012. Firm dynamics and financial development. *Journal of Monetary Economics* **59**:6, 533-549. [[CrossRef](#)]
198. N. Bloom, R. Sadun, J. Van Reenen. 2012. The Organization of Firms Across Countries. *The Quarterly Journal of Economics* . [[CrossRef](#)]
199. Emek Basker, Shawn Klimek, Pham Hoang Van. 2012. Supersize It: The Growth of Retail Chains and the Rise of the “Big-Box” Store. *Journal of Economics & Management Strategy* **21**:3, 541-582. [[CrossRef](#)]
200. Joachim Wagner. 2012. The Post-entry Performance of Cohorts of Export Starters in German Manufacturing Industries#. *International Journal of the Economics of Business* **19**:2, 169-193. [[CrossRef](#)]
201. Svetlana Demidova, Hiau Looi Kee, Kala Krishna. 2012. Do trade policy differences induce sorting? Theory and evidence from Bangladeshi apparel exporters. *Journal of International Economics* **87**:2, 247-261. [[CrossRef](#)]
202. Marian Rizov, Arie Oskam, Paul Walsh. 2012. Is there a limit to agglomeration? Evidence from productivity of Dutch firms. *Regional Science and Urban Economics* **42**:4, 595-606. [[CrossRef](#)]
203. Alan C. Spearot. 2012. Variable Demand Elasticities and Tariff Liberalization. *Journal of International Economics* . [[CrossRef](#)]
204. Gregory Corcos, Massimo Del Gatto, Giordano Mion, Gianmarco I.P. Ottaviano. 2012. Productivity and Firm Selection: Quantifying the ‘New’ Gains from Trade*. *The Economic Journal* **122**:561, 754-798. [[CrossRef](#)]
205. Matilde Bombardini, Christopher J. Kurz, Peter M. Morrow. 2012. Ricardian trade and the impact of domestic competition on export performance. *Canadian Journal of Economics/Revue canadienne d'économie* **45**:2, 585-612. [[CrossRef](#)]
206. Murat Şeker. 2012. Importing, Exporting, and Innovation in Developing Countries. *Review of International Economics* **20**:2, 299-314. [[CrossRef](#)]
207. Emin M. Dinlersoz,, Mehmet Yorukoglu. 2012. Information and Industry Dynamics. *American Economic Review* **102**:2, 884-913. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
208. George Kenyon, Brian D. Neureuther. 2012. An Adaptive Model for Assessing Supply Chain Risk. *Journal of Marketing Channels* **19**:2, 156-170. [[CrossRef](#)]
209. Alan C. Spearot. 2012. Firm Heterogeneity, New Investment and Acquisitions. *The Journal of Industrial Economics* **60**:1, 1-45. [[CrossRef](#)]
210. Nicholas Bloom,, Raffaella Sadun,, John Van Reenen. 2012. Americans Do IT Better: US Multinationals and the Productivity Miracle. *American Economic Review* **102**:1, 167-201. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
211. Nicholas Bloom, Christos Genakos, Raffaella Sadun, John Van Reenen. 2012. Management Practices Across Firms and Countries. *The Academy of Management Perspectives (AMP)* **26**:1, 12-33. [[CrossRef](#)]
212. Sasan Bakhtiari. 2012. Markets and the non-monotonic relation between productivity and establishment size. *Canadian Journal of Economics/Revue canadienne d'économie* **45**:1, 345-372. [[CrossRef](#)]
213. Joachim Wagner. 2012. International trade and firm performance: a survey of empirical studies since 2006. *Review of World Economics* . [[CrossRef](#)]
214. John Haltiwanger. 2012. Job Creation and Firm Dynamics in the United States. *Innovation Policy and the Economy* **12**:1, 17-38. [[CrossRef](#)]
215. M. Kugler, E. Verhoogen. 2012. Prices, Plant Size, and Product Quality. *The Review of Economic Studies* **79**:1, 307-339. [[CrossRef](#)]

216. Cai Fang, Zhao Wen. When Demographic Dividend Disappears: Growth Sustainability of China 75-90. [\[CrossRef\]](#)
217. IZAK ATIYAS. 2011. FIRM-LEVEL DATA IN THE MENA REGION: RESEARCH QUESTIONS, DATA REQUIREMENTS AND POSSIBILITIES. *Middle East Development Journal* **03**:02, 159-190. [\[CrossRef\]](#)
218. Vincenzo Verardi, Joachim Wagner. 2011. Productivity Premia for German Manufacturing Firms Exporting to the Euro-Area and Beyond: First Evidence from Robust Fixed Effects Estimations. *The World Economy* no-no. [\[CrossRef\]](#)
219. M. Crozet, K. Head, T. Mayer. 2011. Quality Sorting and Trade: Firm-level Evidence for French Wine. *The Review of Economic Studies* . [\[CrossRef\]](#)
220. Jeremy T. Fox, Valérie Smeets. 2011. DOES INPUT QUALITY DRIVE MEASURED DIFFERENCES IN FIRM PRODUCTIVITY?*. *International Economic Review* **52**:4, 961-989. [\[CrossRef\]](#)
221. A. Costinot, D. Donaldson, I. Komunjer. 2011. What Goods Do Countries Trade? A Quantitative Exploration of Ricardo's Ideas. *The Review of Economic Studies* . [\[CrossRef\]](#)
222. ALEXANDRE JANIAK, PAULO SANTOS MONTEIRO. 2011. Inflation and Welfare in Long-Run Equilibrium with Firm Dynamics. *Journal of Money, Credit and Banking* **43**:5, 795-834. [\[CrossRef\]](#)
223. A. B. Bernard, S. J. Redding, P. K. Schott. 2011. Multiproduct Firms and Trade Liberalization. *The Quarterly Journal of Economics* . [\[CrossRef\]](#)
224. Justin R. Pierce. 2011. Plant-level responses to antidumping duties: Evidence from U.S. manufacturers. *Journal of International Economics* . [\[CrossRef\]](#)
225. Chad Syverson. 2011. What Determines Productivity?.. *Journal of Economic Literature* **49**:2, 326-365. [\[Abstract\]](#) [\[View PDF article\]](#) [\[PDF with links\]](#)
226. Chien-Ming Chen, Joe Zhu. 2011. Efficient Resource Allocation via Efficiency Bootstraps: An Application to R&D Project Budgeting. *Operations Research* **59**:3, 729-741. [\[CrossRef\]](#)
227. Joachim Wagner. 2011. One-third Codetermination at Company Supervisory Boards and Firm Performance in German Manufacturing Industries: First Direct Evidence from a New Type of Enterprise Data. *Schmollers Jahrbuch* **131**:1, 91-106. [\[CrossRef\]](#)
228. Susan Houseman,, Christopher Kurz,, Paul Lengermann,, Benjamin Mandel. 2011. Offshoring Bias in U.S. Manufacturing. *Journal of Economic Perspectives* **25**:2, 111-132. [\[Abstract\]](#) [\[View PDF article\]](#) [\[PDF with links\]](#)
229. Kyoji Fukao, Tomohiko Inui, Keiko Ito, Young Gak Kim, Tangjun Yuan. 2011. An international comparison of the TFP levels and the productivity convergence of Japanese, Korean, Taiwanese and Chinese listed firms. *Journal of Chinese Economic and Business Studies* **9**:2, 127-150. [\[CrossRef\]](#)
230. John Van Reenen. 2011. Does competition raise productivity through improving management quality?.. *International Journal of Industrial Organization* **29**:3, 306-316. [\[CrossRef\]](#)
231. Marian Rizov, Patrick Paul Walsh. 2011. Is There a Rural-Urban Divide? Location and Productivity of UK Manufacturing. *Regional Studies* **45**:5, 641-656. [\[CrossRef\]](#)
232. Krisztina Demeter, Attila Chikán, Zsolt Matyusz. 2011. Labour productivity change: Drivers, business impact and macroeconomic moderators. *International Journal of Production Economics* **131**:1, 215-223. [\[CrossRef\]](#)
233. Pekka Ilmakunnas, Seija Ilmakunnas. 2011. Diversity at the Workplace: Whom Does it Benefit?. *De Economist* . [\[CrossRef\]](#)
234. M. Joffe. 2011. The root cause of economic growth under capitalism. *Cambridge Journal of Economics* . [\[CrossRef\]](#)

235. Natarajan Balasubramanian. 2011. New Plant Venture Performance Differences Among Incumbent, Diversifying, and Entrepreneurial Firms: The Impact of Industry Learning Intensity. *Management Science* 57:3, 549-565. [[CrossRef](#)]
236. Loren Brandt, Johannes Van Biesebroeck, Yifan Zhang. 2011. Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing. *Journal of Development Economics* . [[CrossRef](#)]
237. Paula Bustos. 2011. Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms. *American Economic Review* 101:1, 304-340. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
238. Natarajan Balasubramanian, Jagadeesh Sivadasan. 2011. What Happens When Firms Patent? New Evidence from U.S. Economic Census Data. *Review of Economics and Statistics* 93:1, 126-146. [[CrossRef](#)]
239. Gunnar Breustedt, Hendrik Habermann. 2011. The Incidence of EU Per-Hectare Payments on Farmland Rental Rates: A Spatial Econometric Analysis of German Farm-Level Data. *Journal of Agricultural Economics* 62:1, 225-243. [[CrossRef](#)]
240. Masayuki Morikawa. 2011. Economies of Density and Productivity in Service Industries: An Analysis of Personal Service Industries Based on Establishment-Level Data. *Review of Economics and Statistics* 93:1, 179-192. [[CrossRef](#)]
241. J. R. Baldwin, W. Gu. 2011. Firm dynamics and productivity growth: a comparison of the retail trade and manufacturing sectors. *Industrial and Corporate Change* . [[CrossRef](#)]
242. Aekapol Chongvilaivan. 2011. Learning by exporting and high-tech capital deepening in Singapore manufacturing industries, 1974-2006. *Applied Economics* 1-18. [[CrossRef](#)]
243. Bruno Cassiman, Elena Golovko. 2011. Innovation and internationalization through exports. *Journal of International Business Studies* 42:1, 56-75. [[CrossRef](#)]
244. Nicholas Bloom, John Van Reenen. Human Resource Management and Productivity 1697-1767. [[CrossRef](#)]
245. A. Bassanini. 2010. Inside the perpetual-motion machine: cross-country comparable evidence on job and worker flows at the industry and firm level. *Industrial and Corporate Change* 19:6, 2097-2134. [[CrossRef](#)]
246. G. Dosi, S. Lechevalier, A. Secchi. 2010. Introduction: Interfirm heterogeneity--nature, sources and consequences for industrial dynamics. *Industrial and Corporate Change* 19:6, 1867-1890. [[CrossRef](#)]
247. G. Faggio, K. G. Salvanes, J. Van Reenen. 2010. The evolution of inequality in productivity and wages: panel data evidence. *Industrial and Corporate Change* 19:6, 1919-1951. [[CrossRef](#)]
248. G. Bottazzi, G. Dosi, N. Jacoby, A. Secchi, F. Tamagni. 2010. Corporate performances and market selection: some comparative evidence. *Industrial and Corporate Change* 19:6, 1953-1996. [[CrossRef](#)]
249. Shuyun May Li. 2010. Costly external finance, reallocation, and aggregate productivity. *Journal of Productivity Analysis* . [[CrossRef](#)]
250. Jonathan Temple. 2010. Aggregate production functions, growth economics, and the part-time tyranny of the identity: a reply to Felipe and McCombie. *International Review of Applied Economics* 24:6, 685-692. [[CrossRef](#)]
251. Toshihiro Okubo, Pierre M. Picard, Jacques-François Thisse. 2010. The spatial selection of heterogeneous firms#. *Journal of International Economics* 82:2, 230-237. [[CrossRef](#)]
252. Nicholas Bloom, Raffaella Sadun, John Van Reenen. 2010. Recent Advances in the Empirics of Organizational Economics. *Annual Review of Economics* 2:1, 105-137. [[CrossRef](#)]
253. Ilke Van Beveren. 2010. TOTAL FACTOR PRODUCTIVITY ESTIMATION: A PRACTICAL REVIEW. *Journal of Economic Surveys* no-no. [[CrossRef](#)]

254. Susanne Prantl. 2010. The impact of firm entry regulation on long-living entrants. *Small Business Economics* . [[CrossRef](#)]
255. EMI NAKAMURA, DAWIT ZEROM. 2010. Accounting for Incomplete Pass-Through. *Review of Economic Studies* **77**:3, 1192-1230. [[CrossRef](#)]
256. Nicholas Bloom,, John Van Reenen. 2010. New Approaches to Surveying Organizations. *American Economic Review* **100**:2, 105-109. [[Citation](#)] [[View PDF article](#)] [[PDF with links](#)]
257. Marcela Eslava, John Haltiwanger, Adriana Kugler, Maurice Kugler. 2010. Factor Adjustments after Deregulation: Panel Evidence from Colombian Plants. *Review of Economics and Statistics* **92**:2, 378-391. [[CrossRef](#)]
258. Massimo Del Gatto, Adriana Di Liberto, Carmelo Petraglia. 2010. MEASURING PRODUCTIVITY. *Journal of Economic Surveys* no-no. [[CrossRef](#)]
259. Andrew B. Bernard,, Stephen J. Redding,, Peter K. Schott. 2010. Multiple-Product Firms and Product Switching. *American Economic Review* **100**:1, 70-97. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
260. Helmut Fryges, Joachim Wagner. 2010. Exports and Profitability: First Evidence for German Manufacturing Firms. *World Economy* **33**:3, 399-423. [[CrossRef](#)]
261. Nicholas Bloom,, John Van Reenen,. 2010. Why Do Management Practices Differ across Firms and Countries?. *Journal of Economic Perspectives* **24**:1, 203-224. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
262. Joachim Wagner. 2010. Entry, Exit and Productivity: Empirical Results for German Manufacturing Industries. *German Economic Review* **11**:1, 78-85. [[CrossRef](#)]
263. Evan Rawley. 2010. Diversification, coordination costs, and organizational rigidity: evidence from microdata. *Strategic Management Journal* n/a-n/a. [[CrossRef](#)]
264. Charles R. HultenGrowth Accounting* 987-1031. [[CrossRef](#)]
265. Wolfgang KellerInternational Trade, Foreign Direct Investment, and Technology Spillovers 793-829. [[CrossRef](#)]
266. Thibault Fally, Rodrigo Paillacar, Cristina Terra. 2010. Economic geography and wages in Brazil: Evidence from micro-data. *Journal of Development Economics* **91**:1, 155-168. [[CrossRef](#)]
267. Giovanni Dosi, Richard R. NelsonTechnical Change and Industrial Dynamics as Evolutionary Processes 51-127. [[CrossRef](#)]
268. Natalia Ramondo. 2009. Foreign Plants and Industry Productivity: Evidence from Chile. *Scandinavian Journal of Economics* **111**:4, 789-809. [[CrossRef](#)]
269. Andrew B. Bernard, Stephen J. Redding, Peter K. Schott. 2009. Products and Productivity*. *Scandinavian Journal of Economics* **111**:4, 681-709. [[CrossRef](#)]
270. Dongsoo Kim, Feng Liu, Anthony Yezer. 2009. Do inter-city differences in intra-city wage differentials have any interesting implications?. *Journal of Urban Economics* **66**:3, 203-209. [[CrossRef](#)]
271. Helen Simpson. 2009. PRODUCTIVITY IN PUBLIC SERVICES. *Journal of Economic Surveys* **23**:2, 250-276. [[CrossRef](#)]
272. Min Ouyang. 2009. The scarring effect of recessions#. *Journal of Monetary Economics* **56**:2, 184-199. [[CrossRef](#)]
273. Joshua Linn. 2008. Energy Prices and the Adoption of Energy-Saving Technology*. *The Economic Journal* **118**:533, 1986-2012. [[CrossRef](#)]
274. G. Bottazzi, A. Secchi, F. Tamagni. 2008. Productivity, profitability and financial performance. *Industrial and Corporate Change* **17**:4, 711-751. [[CrossRef](#)]