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Aggregate Productivity Growth
Lessons from Microeconomic Evidence

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8.1 Overview

Recent research using establishment- and firm-level data has raised a variety of conceptual and measurement questions regarding our understanding of aggregate productivity growth.[1] Several key related findings are of interest. First, there is large-scale, ongoing reallocation of outputs and inputs across individual producers. Second, the pace of this reallocation varies over time (both secularly and cyclically) and across sectors. Third, much of this reallocation reflects within- rather than between-sector reallocation. Fourth, there are large differentials in the levels and the rates of growth of productivity across establishments within the same sector. The rapid pace of output and input reallocation along with differences in productivity levels and growth rates are the necessary ingredients for the pace of reallocation to play an important role in aggregate (i.e., industry) productivity growth. However, our review of the existing studies

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1. Empirical papers of relevance that focus on the connection between micro- and aggregate productivity growth include: (a) for the United States: Baily, Hulten, and Campbell (1992), Baily, Bartelsman, and Haltiwanger (1996, forthcoming), Bartelsman and Dhrymes (1998), Dwyer (1998, 1997), Haltiwanger (1997), and Olley and Pakes (1996); (b) for other countries: Tybout (1996), Aw, Chen, and Roberts (1997), Liu and Tybout (1996), and Griliches and Regev (1995).

indicates that the measured contribution of such reallocation effects varies over time and across sectors and is sensitive to measurement methodology. An important objective of this paper is to sort out the role of these different factors so that we can understand the nature and the magnitude of the contribution of reallocation to aggregate productivity growth.

These recent empirical findings have been developed in parallel with an emerging theoretical literature that seeks to account for the heterogeneous fortunes across individual producers and to explore the role of such micro-heterogeneity in aggregate productivity growth. This theoretical strand combined with the literature concerning the role of reallocation forms the theoretical underpinning of this paper. Of course, the idea that productivity growth in a market economy invariably involves restructuring and reallocation across producers is not new. For example, Schumpeter (1942, 83) coined the term "creative destruction," which he described as follows:

> The fundamental impulse that keeps the capital engine in motion comes from the new consumers' goods, the new methods of production and transportation, the new markets . . . [The process] incessantly revolutionizes from within, incessantly destroying the old one, incessantly creating a new one. This process of Creative Destruction is the essential fact of capitalism.

However, what is new in the emerging empirical literature is the growing availability of longitudinal establishment-level data that permit characterization and analysis of the reallocation across individual producers within narrowly defined sectors and, in turn, the connection of this reallocation to aggregate productivity growth.

In this paper, we seek to synthesize and extend this emerging literature on the connection between micro- and aggregate productivity growth dynamics. We focus primarily on the empirical findings and we find, as will become clear, that the measured quantitative contribution of reallocation to aggregate productivity growth varies significantly across studies. Our objective is to understand the sources of the differences in results across studies. We pursue this objective in two ways. First, we compare the results carefully across studies, taking note of differences on a variety of dimensions including country, sectoral coverage, time period, frequency, and measurement methodology. Second, we exploit establishment-level data for the U.S. manufacturing sector as well as for a few selected service sector industries to conduct our own independent investigation of the relevant issues. The inclusion of service sector results is of particular interest since the existing literature has focused almost exclusively on manufacturing industries.

The paper proceeds as follows. In section 8.2, we provide a summary of theories that can account for the observed heterogeneous fortunes across establishments in the same narrowly defined sector. In addition, we consider the related theoretical literature on creative destruction models of growth. This brief discussion of theoretical underpinnings is of considerable help in putting the results on the relationship between micro- and macroproductivity growth into perspective. In section 8.3, we present a review and synthesis of the recent literature. As already noted above, there are significant differences in the quantitative findings across studies. Section 8.4 presents a discussion of key measurement and methodological questions that can potentially account for these differences. In section 8.5, we present a sensitivity and robustness analysis of alternative measurement methodologies using establishment-level data for the U.S. manufacturing sector. Section 8.6 presents new evidence on the relationship between micro and aggregate productivity behavior using selected service sector industries. Section 8.7 provides concluding remarks.

8.2 Theoretical Underpinnings

This section draws together theories and evidence related to the reasons for cross-sectional heterogeneity in plant-level and firm-level outcomes. A pervasive empirical finding in the recent literature is that within-sector differences dwarf between-sector differences in behavior. For example, Haltiwanger 1999, table 1, shows that four-digit industry effects account for less than 10 percent of the cross-sectional heterogeneity in output, employment, capital equipment, capital structures, and productivity growth rates across establishments.

The magnitude of within-sector heterogeneity implies that idiosyncratic factors dominate the determination of which plants create and destroy jobs and which plants achieve rapid productivity growth or suffer productivity declines. An examination of the literature suggests that the following may account for plant-level heterogeneity: uncertainty; plant-level differences in managerial ability, capital vintage, location, and disturbances; and diffusion of knowledge. Starting with the first of these, one likely reason for heterogeneity in plant-level outcomes is the considerable uncertainty that surrounds the development, adoption, distribution, marketing and regulation of new products and production techniques. Uncertainty about the demand for new products or the cost-effectiveness of alternative technologies encourages firms to experiment with different technologies, goods, and production facilities (Roberts and Weitzman 1981). Experimentation, in turn, generates differences in outcomes (Jovanovic 1982; Ericson and Pakes 1992). Even when incentives for experimentation are absent, uncertainty about future cost or demand conditions encourages firms to differentiate their choice of current products and technology so as to position themselves optimally for possible future circumstances (Lambson, 1991).

Another possible reason is that differences in entrepreneurial and managerial ability lead to differences in job and productivity growth rates among firms and plants. These differences include the ability to identify and develop new products, to organize production activity, to motivate workers, and to adapt to changing circumstances. There seems little doubt that these and other ability differences among managers generate much of the observed heterogeneity in plant-level outcomes. Business magazines, newspapers, and academic case studies (e.g., Dial and Murphy 1995) regularly portray the decisions and actions of particular management teams or individuals as crucial determinants of success or failure. High levels of compensation, often heavily skewed toward various forms of incentive pay (Murphy 1999), also suggest that senior managers play key roles in business performance, including productivity and job growth outcomes.[2] A related idea is that it takes time for new businesses to learn about their own abilities.

Other factors that drive heterogeneity in plant-level productivity, output, and input growth outcomes involve plant- and firm-specific location and disturbances. For example, energy costs and labor costs vary across locations, as do the timing of changes in factor costs. Cost differences induce different employment and investment decisions among otherwise similar plants and firms. These decisions, in addition, influence the size and type of labor force and capital stock that a business carries into the future. Thus, current differences in cost and demand conditions induce contemporaneous heterogeneity in plant-level job and productivity growth, and they also cause businesses to differentiate themselves in ways that lead to heterogeneous responses to common shocks in the future. The role of plant-specific shocks to technology, factor costs, and product demand in accounting for the pace of job reallocation has been explored in Hopenhayn (1992), Hopenhayn and Rogerson (1993), and Campbell (1998).

Slow diffusion of information about technology, distribution channels, marketing strategies, and consumer tastes is another important source of plant-level heterogeneity in productivity and job growth. Nasbeth and Ray (1974) and Rogers (1983) document multiyear lags in the diffusion of knowledge about new technologies among firms producing related products. Mansfield, Schwartz, and Wagner (1981) and Pakes and Schankerman (1984) provide evidence of long imitation and product development lags.[3]

Part of the differences across plants may reflect the vintage of the in-

2. Many economic analyses attribute a key role to managerial ability in the organization of firms and production units. Lucas (1977), for example, provides an early and influential formal treatment.

3. Knowledge diffusion plays a key role in many theories of firm-level dynamics, industrial evolution, economic growth and international trade. See, for example, Grossman and Helpman (1991), Jovanovic and Rob (1989), and Jovanovic and MacDonald (1994).

stalled capital.[4] Suppose, for example, that new technology can be adopted only by new plants. Under this view, entering, technologically sophisticated plants displace older, outmoded plants and gross output and input flows reflect a process of creative destruction. A related idea is that it may not be the vintage of the capital but rather the vintage of the manager or the organizational structure that induces plant-level heterogeneity (see, e.g., Nelson and Winter 1982).

These models of plant-level heterogeneity are closely related to the theoretical growth models emphasizing the role of creative destruction. Creative destruction models of economic growth stress that the process of adopting new products and new processes inherently involves the destruction of old products and processes. Creative destruction manifests itself in many forms. An important paper that formalizes these ideas is Aghion and Howitt (1992). They consider a model of endogenous growth where endogenous innovations yield creative destruction. Specifically, the creator of a new innovation gets some monopoly rents until the next innovation comes along, at which point the knowledge underlying the rents becomes obsolete. The incentives for investment in R&D and thus growth are impacted by this process of creative destruction.[5]

An alternative but related type of creative destruction growth model mentioned above as a source of plant-level heterogeneity is the vintage capital model. One form of these models (Caballero and Hammour 1994; Campbell 1998) emphasizes the potential role of entry and exit. If new technology can be adopted only by new establishments, growth occurs only via entry and exit, and this requires output and input reallocation. An alternative view is that new technology is embodied in new capital (e.g., Cooper, Haltiwanger, and Power 1999), but that existing plants can adopt new technology by retooling. Under this latter view, both within-plant and between-plant job reallocation may be induced in the retooling process. If, for example, there is skill-biased technical change, the adoption of new technology through retooling will yield a change in the desired mix

4. See Aghion and Howitt (1992), Caballero and Hammour (1994, 1996), Campbell (1998), Stein (1997), Cooley, Greenwood, and Yorukoglu (1997), and Chari and Hopenhayn (1991).

5. Growth may be more or less than optimal since there are effects that work in opposite directions. On the one hand, appropriability and intertemporal spillover effects make growth slower than optimal. The appropriability effect derives from the fact that, in the Aghion and Howitt (1992) model, research on new innovations requires skilled labor as does the production of the intermediate goods where new innovations are implemented. A fixed supply of skilled labor implies that skilled labor earns part of the returns from new innovations. The inability of the research firms to capture all of the value from the innovations reduces their incentives to conduct research. The intertemporal spillover effect derives from the fact that current and future innovators derive benefits (i.e., knowledge) from past innovations but do not compensate past innovators for this benefit. The fact that private research firms do not internalize the destruction of rents generated by their innovation works in the opposite direction. This business-stealing effect can actually yield a too-high growth rate. Aghion and Howitt (1992) also find, however, that the business-stealing effect also tends to make innovations too small.

of skilled workers at an establishment. In addition, there may be an impact on the overall desired level of employment at the establishment.

In all of these creative destruction models, the reallocation of outputs and inputs across producers plays a critical role in economic growth. In these models, stifling reallocation in turn stifles growth. It is important to emphasize, however, that there are many forces that may cause growth and the pace of reallocation to deviate from optimal outcomes. As mentioned above in the context of Aghion and Howitt (1992), a generic problem is that agents (firms, innovators, workers) do not internalize the impact of their actions on others. In an analogous manner, Caballero and Hammour (1996) emphasize that the sunkness of investment in new capital implies potential ex post holdup problems that yield several harmful side effects. They explore the hold-up problem generated by worker-firm bargaining over wages after the firm's investment in specific capital.[6] A related point is that, even though reallocation may be vital for growth, there are clearly losers in the process. The losers include the owners of the outmoded businesses that fail as well as the displaced workers.

8.3 Review of Existing Empirical Evidence

The theoretical literature on creative destruction as well as the underlying theories of heterogeneity characterize technological change as a noisy, complex process with considerable experimentation (in terms of entry and retooling) and failure (in terms of contraction and exit) playing integral roles. In this section, we review the evidence from the recent empirical literature that has developed in parallel with the theoretical literature. We conduct this review in two parts: First, we provide a brief review of the micropatterns of output, input, and productivity growth; second, we consider the aggregate implications of these micropatterns. Our review of micropatterns is brief since we regard the results discussed in this section as well established, and excellent recent survey articles by Bartelsman and Doms (2000) and Caves (1998) cover much of the same material in more detail. Moreover, it is the aggregate consequences of these micropatterns that are more open to debate and, as we make clear, a number of measurement issues generate the variation that is found across studies on this dimension.

8.3.1 Brief Review of Key Micropatterns

We begin our review by briefly summarizing a few key patterns that have become well established in this literature. Virtually all of the findings refer to manufacturing; they are as follows.

6. Indeed, Blanchard and Kremer (1997) argue that for transition economies, such holdup problems are potentially severe enough that the restructuring process is better described as "disruptive destruction" rather than creative destruction.

Large-scale reallocation of outputs and inputs within sectors. The rate of within-sector reallocation of output and inputs is of great magnitude. Davis and Haltiwanger (1999) summarize much of the recent literature on gross job flows; they note that in the United States, more than one in ten jobs is created in a given year and more than one in ten jobs is destroyed every year. Similar patterns hold for many other market economies. Much of this reallocation reflects reallocation within narrowly defined sectors. For example, Davis and Haltiwanger (1999) report that across a variety of studies, only about 10 percent of reallocation reflects shifts of employment opportunities across four-digit industries.

Entry and exit play a significant role in this process of reallocation. For annual changes, Davis, Haltiwanger, and Schuh (1996) report that about 20 percent of job destruction and 15 percent of job creation is accounted for by entry and exit. For five-year changes, Baldwin, Dunne, and Haltiwanger (1995) report that about 40 percent of creation and destruction are accounted for by entry and exit, respectively.[7]

Persistent differences in levels of productivity. There are large and persistent differences in productivity across plants in the same industry (see Bartelsman and Doms 2000 for an excellent discussion). In analyzing persistence, many studies report transition matrices of plants in the relative productivity distribution within narrowly defined industries (see, e.g., Baily, Hulten, and Campbell 1992 and Bartelsman and Dhrymes 1998). These transition matrices exhibit large diagonal and near-diagonal elements, indicating that plants that are high in the distribution in one period tend to stay high in the distribution in subsequent periods. In contrast, establishment-level productivity growth *rates* exhibit an important transitory component. Baily, Hulten, and Campbell (1992) and Dwyer (1998) present strong evidence of regression to the mean effects in productivity growth regressions.

Low productivity helps predict exit. Many studies (e.g., Baily, Hulten, and Campbell 1992; Olley and Pakes 1996; Dwyer 1998) find that the productivity level helps predict exit. Low-productivity plants are more likely to exit even after controlling for other factors such as establishment size and age. A related set of findings is that observable plant characteristics are positively correlated with productivity, including size, age, wages, adoption of advanced technologies, and exporting (see, e.g., Baily, Hulten, and Campbell 1992; Doms, Dunne, and Troske 1996; Olley and Pakes 1996; Bernard and Jensen 1999). It has been more difficult to find correlates of changes

7. The calculations in Baldwin, Dunne, and Haltiwanger (1995) are an updated version of earlier calculations by Dunne, Roberts, and Samuelson (1989). The five-year gross flows and the shares accounted for by entry and exit are somewhat lower in the later work for equivalent periods, reflecting the improvement in longitudinal linkages in the Census of Manufacturers over time.

in productivity. For example, Doms, Dunne, and Troske (1996) find that plants that have adopted advanced technologies are more likely to be high-productivity plants, but that the change in productivity is only weakly related to the adoption of such advanced technologies.

8.3.2 Reallocation and Aggregate Productivity Growth

Empirical analysis of the implications of the pace of reallocation and restructuring for productivity dynamics has been recently provided by Baily, Hulten, and Campbell (1992), Olley and Pakes (1996), Bartelsman and Dhrymes (1998), Dwyer (1998, 1997) and Haltiwanger (1997), using plant-level manufacturing data from the United States; Aw, Chen, and Roberts (1997) using firm-level data from Taiwan; Tybout (1996) and Liu and Tybout (1996) using data from Colombia, Chile, and Morocco; and Griliches and Regev (1995) using data from Israel.[8] Virtually all of the studies consider some form of decomposition of an index of industry-level productivity:

$$P_{it} = \sum_{e \in I} s_{et} p_{et} \quad (1)$$

where P_{it} is the index of industry productivity, s_{et} is the share of plant e in industry i (e.g., output share), and p_{et} is an index of plant-level productivity.

Using plant-level data, the industry index and its components can be constructed for measures of labor and multifactor productivity. Many studies have decomposed the time series changes in aggregate (i.e., industry-level) productivity into components that reflect a within component (holding shares fixed in some manner) and other effects that reflect the reallocation of the shares across plants, including the impact of entry and exit. Table 8.1 presents a summary of results from a variety of studies using different countries, time periods, frequency of measured changes, productivity concepts (i.e., multifactor vs. labor), and measurement methodologies.[9] The differences along these many dimensions make fine comparisons difficult so our objective in considering the alternative studies is to consider broad patterns. In the next section, we consider methodological issues in detail and then conduct our own sensitivity analysis. For now, we attempt to compare studies on dimensions that are relatively easy to compare.

One core aspect that is roughly comparable across studies is the contribution of the within plant contribution to aggregate productivity growth.

8. Baldwin (1995) presents some related analysis of the contribution of plant turnover to productivity growth for Canada, but his methodology differs sufficiently from the rest of the literature that it is not easy to integrate his work into this discussion.

9. In the case of Taiwan, a simple average (or simple median) of the industry-level results reported in the Aw, Chen, and Roberts (1997) paper is presented.

Table 8.1 A Comparison of Decompositions of Aggregate Productivity Growth

Country	Frequency	Sample Period	Sectoral Coverage	Weight Used to Calculate Within Plant Changes[a]	Average Fraction from Within Plant Changes	Fraction of Activity[b] from Entrants (t)	Fraction of Activity from Exits ($t-k$)	Relative Productivity of Births (t) to Deaths ($t-k$)	Study
				A. Multifactor Productivity Decompositions					
U.S.	Five-year	1972–87	Selected manufacturing industries (23)	Output ($t-k$)	0.37	n.a.	n.a.	n.a.	Baily, Hulten, and Campbell (1992)
U.S.	Five-year	1977–87	All manufacturing industries	Output ($t-k$)	0.23	0.08	0.10	1.05	Haltiwanger (1997)
U.S.	Ten-year	1977–87	All manufacturing industries	Output ($t-k$)	0.54	0.16	0.21	1.11	Haltiwanger (1997)
Taiwan[c]	Five-year	1981–91	Selected manufacturing industries (9)	Output (average of [$t-k$] and t)	0.94 (Median = 0.63)	n.a.	n.a.	n.a.	Aw, Chen, and Roberts (1997)
Colombia	Annual	1978–86	Selected manufacturing industries (5)	Input index[d] (average of [$t-k$] and t)	1.00	n.a.	0.05	1.05	Liu and Tybout (1996)
				B. Labor Productivity Growth Decompositions					
U.S.	Ten-year	1977–87	All manufacturing industries	Employment ($t-k$)	0.79	0.26	0.28	1.42	Baily, Bartelsman, and Haltiwanger (1996)
U.S.	Annual	1972–88	All manufacturing industries	Manhours ($t-k$)	1.20	0.01	0.02	1.03	Baily, Bartelsman, and Haltiwanger (forthcoming)
Israel	Three-Year	1979–88	All manufacturing industries	Employment (average of [$t-k$] and t)	0.83	0.08	0.06	1.20	Griliches and Regev (1995)

Note: n.a. = not available.

[a] Within contribution is measured as the weighted sum of plant-level productivity growth as a fraction of aggregate index of productivity growth. In all cases, output above refers to gross output.

[b] Activity is measured in the same units as weight (e.g., employment or output).

[c] Simple average (and simple median) of industry-based results reported.

[d] The input index is a geometric mean of inputs using estimated factor elasticities.

Even for this measure, there are differences in the methodology along a number of dimensions. These include whether the measure of productivity is multifactor or labor, whether the share is based on output or employment weights, and whether the share is based on the initial share at the base period or the average share (averaged over base and end period).

The fraction of within-plant contribution to multifactor productivity growth ranges from 0.23 to 1.00 across studies, while the fraction of the within-plant contribution to labor productivity growth ranges from 0.79 to 1.20 across studies. It is obviously difficult to draw conclusions even in broad terms about whether the within-plant contribution is large or small. The variation across countries may reflect a variety of factors. Nevertheless, careful examination of the individual studies indicates that this variation is due in part to there being considerable sensitivity to time period, frequency, and cross-industry variation.

To shed light on the sensitivity to business cycles and industry, table 8.2 presents a few selected results from different time periods and industries from the Baily, Hulten, and Campbell (1992) and Haltiwanger (1997) studies. For the 1977–82 period, the within-plant contribution for manufacturing in general is negative for both studies reflecting the fact that, while there is modest overall productivity growth over this period, its source is not the within-plant component. In contrast, for the 1982–87 period, the within-plant contribution is large and positive during a period of robust productivity growth. This apparent sensitivity to the business cycle (1982 was during a severe slump in U.S. manufacturing) is interesting in its own right. These results suggest that overall productivity is less procyclical than within-plant productivity. The inference is that reallocation effects tend to generate a countercyclical "bias," and thus recessions are times when the share of activity accounted for by less productive plants decreases either through contraction or exit.[10] The more general point in the current context is that the within-plant contribution varies substantially with the cycle.

Table 8.2 also shows that the results tend to vary dramatically by detailed industry. Steel mills (Standard Industrial Classification [SIC] 3312, blast furnaces) exhibit tremendous cyclicality in the behavior of productivity, while telecommunications equipment (SIC 3661, telephone and telegraph equipment) does not. Moreover, the fraction accounted for by within-plant changes is large and stable for telecommunications and very large and variable for steel mills.

Given the discussion of theoretical underpinnings in section 8.2 an obvious question is the contribution of plant entry and exit to these aggregate productivity dynamics. While many studies consider this issue, the precise measurement of the contribution of net entry and exit is quite sensitive to

10. Baily, Bartelsman, and Haltiwanger (forthcoming) provide a more extensive analysis of the role of reallocation for the cyclical behavior of productivity.

Table 8.2 **Sensitivity of Decomposition Results to Business Cycle and Sector (five-year frequency)**

Sectoral Coverage	1977–82 Multifactor Productivity Growth	1977–82 Fraction from Within Plant Changes	1982–87 Multifactor Productivity Growth	1982–87 Fraction from Within Plant Changes	Study
All manufacturing industries	2.43	−0.12	8.26	0.58	Haltiwanger (1997)
Selected manufacturing industries (23)	2.39	−0.46	15.63	0.87	Baily, Hulten, and Campbell (1992)
Blast furnaces (SIC = 3312)	−3.66	2.15	18.30	1.06	Baily, Hulten, and Campbell (1992)
Telephone and telegraph equipment (SIC = 3661)	14.58	0.78	13.19	0.86	Baily, Hulten, and Campbell (1992)

Notes: Weight for within calculation from both studies is initial gross output share for the plant in each industry. Results aggregated across industries are based upon weighted average with weight for this purpose equal to the average of nominal gross output for the industry.

the decomposition methodology that is used. This sensitivity, in turn, makes cross-study comparisons of the contribution of net entry especially difficult. Nevertheless, some aspects of the underlying roles of entry and exit can be directly compared across studies.

Returning to table 8.1, we see that one important factor is the horizon over which the productivity growth is measured. By construction, the share of activity accounted for by exits in the base year and entrants in the end year are increasing in the horizon over which the base and end year are measured. At an annual frequency, we observe that the share of employment accounted for by exits in the U.S. in the year $t - 1$ is only 0.02 and by entrants in year t is only 0.01. In contrast, at a ten-year horizon, the share of employment accounted for by plants in the United States in year $t - 10$ that ultimately exit over the ten years is 0.28 while the share of employment accounted for by plants in year t that entered over the ten years is 0.26. These results imply that the contribution of any differences in productivity between entering and exiting plants will be greater for changes measured over a longer horizon.

The influence of the horizon also is likely to impact the observed productivity differences between exiting plants in the base year and entering plants in the end year via selection and learning effects. That is, one-year-old plants are likely to have on average a lower productivity than ten-year-old plants because of selection and learning effects. Many studies (e.g., Olley and Pakes 1996; Liu and Tybout 1996; Aw, Chen, and Roberts 1997) present results suggesting that selection and learning effects play an important role. The results in table 8.1 reflect this in that the relative productivity of entering plants in the end year to exiting plants in the base year is increasing for changes measured over a longer horizon.[11]

Putting these results on entry and exit together helps account for the finding that studies that focus on high frequency variation (e.g., Baily, Bartelsman, and Haltiwanger forthcoming and Griliches and Regev 1995) tend to find a small contribution of net entry to aggregate productivity growth while studies over a longer horizon find a large role for net entry (e.g., Baily, Bartelsman, and Haltiwanger 1996; Haltiwanger 1997; and Aw, Chen, and Roberts 1997). We return to this theme in subsequent sections.

Overall, however, the fact remains that it is difficult to assess the contribution of reallocation to productivity growth by a simple comparison of results across studies. Obviously, part of the reason for this is that the results across studies are from different countries, time periods, frequencies, and sectoral coverage. Indeed, exploiting the variation along these

11. Although the earlier vintage arguments suggest that it may be that younger plants should have higher productivity. While such vintage effects may be present, the evidence clearly suggests that the impact of selection and learning effects dominate.

dimensions would be useful to shed light on the factors that yield variation in the contribution of reallocation to productivity growth. However, part of the reason for the differences across studies reflects differences in the decomposition methodology across studies. To disentangle these differences, we conduct our own analysis and consider in detail the sensitivity of results to alternative measurement methodologies. We now turn our attention to this sensitivity analysis.

8.4 Measurement and Methodological Issues

8.4.1 Alternative Decomposition Methodologies

To illustrate the sensitivity to measurement methodology, we consider two alternative decomposition methodologies. The first decomposition method (denoted method 1 in what follows) we consider is a modified version of that used by Baily, Hulten, and Campbell (1992) and is given by[12]

$$\text{(2)} \qquad \Delta P_{it} = \sum_{e\in C} s_{et-1}\Delta p_{et} + \sum_{e\in C}(p_{et-1} - P_{it-1})\Delta s_{et} + \sum_{e\in C}\Delta p_{et}\Delta s_{et} + \sum_{e\in N} s_{et}(p_{et} - P_{it-1}) - \sum_{e\in X} s_{et-1}(p_{et-1} - P_{it-1})$$

where C denotes continuing plants, N denotes entering plants, and X denotes exiting plants. The first term in this decomposition represents a within plant component based on plant-level changes, weighted by initial shares in the industry. The second term represents a between-plant component that reflects changing shares, weighted by the deviation of initial plant productivity from the initial industry index. The third term represents a cross (i.e., covariance-type) term. The last two terms represent the contribution of entering and exiting plants, respectively.

In this decomposition, the between-plant term and the entry and exit terms involve deviations of plant-level productivity from the initial industry index. For a continuing plant, this implies that an increase in its share contributes positively to the between-plant component only if the plant has higher productivity than average initial productivity for the industry. Similarly, an exiting plant contributes positively only if the plant exhibits

12. The first term in this decomposition (the "within component") is identical to that in Baily, Hulten, and Campbell (1992). They essentially combined the second two terms by calculating a term based upon the sum of changes in shares of activity weighted by ending period productivity. In addition, they did not deviate the terms in the between and net entry terms from initial levels. As Haltiwanger (1997) points out, this implies that even if all plants have the same productivity in both beginning and end periods, the between component and the net entry component in the Baily, Hulten, and Campbell decomposition will, in general, be nonzero. See Haltiwanger (1997) for further discussion.

productivity lower than the initial average, and an entering plant contributes positively only if the plant has higher productivity than the initial average.

This decomposition differs somewhat from others that have appeared in the literature in some subtle but important ways. Key distinguishing features of the decomposition used here are: (a) an integrated treatment of entry/exit and continuing plants; (b) separating-out within and between effects from cross/covariance effects. Some of the decompositions that appear in the literature are more difficult to interpret because they do not separate out cross/covariance effects. For example, some measure the within effect as the change in productivity weighted by average shares (in t and $t - k$—see method 2 below). While the latter method yields a seemingly cleaner decomposition, it also allows the within effect to reflect partially the reallocation effects, since it incorporates the share in period t. Another problem is in the treatment of net entry. Virtually all of the decompositions in the literature that consider net entry measure the contribution of net entry via the simple difference between the weighted average of entrants and exiting plants productivity. Even if there are no differences in productivity between entering and exiting plants, this commonly used method yields the inference that net entry contributes positively to an increase (decrease) in productivity growth if the share of entrants is greater (less than) the share of exiting plants. There are related (and offsetting) problems in the treatment of the contribution of continuing plants.

While this first method is our preferred decomposition, measurement error considerations suggest an alternative decomposition closely related to that used by Griliches and Regev (1995). Consider, in particular, the following alternative decomposition (denoted method 2 in the remainder of this paper):

$$\Delta P_{it} = \sum_{e \in C} \bar{s}_e \Delta p_{et} + \sum_{e \in C} (\bar{p}_e - \bar{P}_i) \Delta s_{et} + \sum_{e \in N} s_{et}(p_{et} - \bar{P}_i) - \sum_{e \in X} s_{et-1}(p_{et-1} - \bar{P}_i) \tag{3}$$

where a bar over a variable indicates the average of the variable over the base and end years. In this decomposition, the first term is interpretable as a within effect that is measured as the weighted sum of productivity with the weights equal to the average (across time) shares. The second is interpretable as a between effect where the changes in the shares are indexed by the deviations of the average plant-level productivity from the overall industry average. In a like manner, the net entry terms are such that entry contributes positively as long as entering plants are higher than the overall average and exiting plants are lower than the overall average.

This second decomposition method is a modification of the standard within/between decomposition that is often used for balanced panels. The disadvantage of this method is that the measured within effect will now reflect in part cross/covariance effects (as will the measured between effect). However, this second method is apt to be less sensitive to measurement error in outputs or inputs relative to the first method as shown in equation (2). Suppose, for example, we are considering labor productivity (e.g., output per man-hour) and that there is random measurement error in measured man-hours. Measurement error of this type will imply that plants in a given period with spuriously high measured man-hours will have spuriously low measured productivity. Such measurement error will yield a negative covariance between changes in productivity and changes in shares (measured in terms of man-hours) and a spuriously high within-plant effect under method 1. In a similar manner, consider the decomposition of multifactor productivity (MFP) using output weights. Random measurement error in output will yield a positive covariance between productivity changes and changes in shares and a spuriously low within-plant effect under method 1. In contrast, the measured within effect from method 2 will be less sensitive to random measurement error in output or inputs since the averaging across time of the shares will mitigate the influence of measurement error.[13]

An alternative cross-sectional decomposition methodology utilized by Olley and Pakes (1996) is of interest as well. Consider the following cross-sectional decomposition of productivity for an industry in period t (denoted method 3 in what follows):

$$P_{it} = \bar{p} + \sum_{e}(s_{et} - \bar{s})(p_{et} - \bar{p}) \tag{4}$$

where in this case a bar over a variable represents the *cross-sectional* (unweighted) mean across all plants in the same industry. The second term in this decomposition provides insights into whether activity (e.g., output or employment, depending on how shares are measured) is disproportionately located at high-productivity plants. In addition, by examining the time series pattern of each of the terms in this decomposition we can learn whether the cross-sectional allocation of activity has become more or less productivity enhancing over time. One advantage of this cross-sectional approach is that the cross-sectional differences in productivity are more persistent and less dominated by measurement error and transitory shocks. A related advantage is that this cross-sectional decomposition does not rely on accurately measuring entry and exit. Both of these problems potentially plague the time series decompositions using method 1 or method 2 (although method 2 has some advantages in terms of measure-

13. This discussion focuses on simple classical measurement error. There may be other forms of nonrandom measurement error that are important in this context.

ment error). Of course, examining the time series patterns of the cross-sectional decomposition does not permit characterizing the role of entry and exit.

Clearly each of these techniques has notable strengths and weaknesses. Given the measurement concerns we have raised and given the independent interest in each of these alternative methodologies, we present results from each of the three methods in the analysis that follows.

8.4.2 Measurement of Output, Inputs, and Productivity Using the Census of Manufactures

In the next section, we present evidence applying the alternative decomposition methodologies using plant-level data from the Census of Manufactures. A number of different but related versions of the decompositions are considered. First, we consider the decomposition of industry-level MFP where the shares (s_{et}) are measured using plant-level gross output. This weighting methodology is common in the recent literature investigating such MFP decompositions (see, e.g., Baily, Hulten, and Campbell 1992; Bartelsman and Dhrymes 1994; Olley and Pakes 1996; Aw, Chen, and Roberts 1997). Next, we consider a decomposition of industry-level labor productivity using both gross output and employment share weights. For labor productivity, the seemingly appropriate weight is employment (or man-hours) since this will yield a tight measurement link between most measures of labor productivity using industry-level data and industry-based measures built up from plant-level data. Both the Griliches and Regev (1995) and Baily, Bartelsman, and Haltiwanger (1996) papers use employment weights in this context. However, as we shall see, using gross output weights as an alternative provides useful insights into the relationship between multifactor and labor productivity decompositions and, in so doing, on the role of reallocation in productivity growth.

The index of plant-level multifactor productivity (MFP_{et}) used here is similar to that used by Baily, Hulten, and Campbell (1992). The index is measured as follows:

$$\ln \mathrm{MFP}_{et} = \ln Q_{et} - \alpha_K \ln K_{et} - \alpha_L \ln L_{et} - \alpha_M \ln M_{et},$$

where Q_{et} is real gross output, L_{et} is labor input (total hours), K_{et} is real capital (in practice separate terms are included for structures and equipment), and M_{et} is real materials. Outputs and inputs are measured in constant (1987) dollars. Factor elasticities are measured via industry cost shares. The index of plant-level labor productivity is measured as the difference between log gross output and log labor input.[14] Using this mea-

14. We also performed the labor productivity analysis using value added per unit of labor. The results using this alternative measure in terms of the decompositions and relative productivity are very similar to those we report in the subsequent sections.

surement methodology with equation (1) yields industry-level growth rates in productivity that correspond closely to industry-level growth rates constructed using industry-level data.

The Census of Manufactures (CM) plant-level data used in the analysis include information on shipments, inventories, book values of equipment and structures, employment of production and nonproduction workers, total hours of production workers, and cost of materials and energy usage. For the most part, the measurement methodology closely follows that of Baily, Hulten, and Campbell (1992). The details of the measurement of output and inputs are provided in the appendix.

8.5 Results for the U.S. Manufacturing Sector

We begin by characterizing results on the U.S. manufacturing sector over the 1977 to 1987 period. We focus on this interval since it comes close to reflecting changes on a peak-to-peak basis. In the second subsection, we consider various five-year intervals which tend to be dominated more by cyclical variation in productivity. In the third subsection, we look at net entry in more detail. The last subsection summarizes the results.

8.5.1 Ten-year changes: Basic Decompositions

Table 8.3 presents estimates of the gross expansion and contraction rates of employment, output and capital (structures and equipment) over the 1977–87 period. The rates of output and input expansion (contraction) are measured as the weighted average of the growth rates of expanding (contracting) plants including the contribution of entering (exiting) plants using the methodology of Davis, Haltiwanger, and Schuh (1996).[15] The pace of gross output and input expansion and contraction is extremely large over the ten-year horizon. Expanding plants yielded a gross rate of expansion of more than 40 percent of outputs and inputs and contracting plants yielded a gross rate of contraction in excess of 30 percent of outputs and inputs. Net growth rate of output is higher than that of inputs (especially employment) reflecting the productivity growth over this period. A large fraction of the output and input gross creation from expanding plants came from entry and a large fraction of the output and input gross destruction came from exit.

Table 8.3 also includes the fraction of excess reallocation within four-digit industries in each of these industries. Excess reallocation is the sum of gross expansion and contraction rates less the absolute value of net

15. This methodology entails defining plant-level growth rates as the change divided by the average of the base and end-year variable. The advantage of this growth rate measure is that it is symmetric for positive and negative changes and allows for an integrated treatment of entering and exiting plants.

Table 8.3 **Gross Reallocation of Employment, Output, Equipment, and Structures (ten-year changes from 1977–87)**

Measure	Creation (Expansion) Rate	Share of Creation (Expansion) Due to Entrants	Destruction (Contraction) Rate	Share of Destruction (Contraction) Due to Exits	Fraction of Excess Reallocation within 4-Digit Industry
Real gross output	49.4	0.44	34.4	0.61	0.80
Employment	39.4	0.58	45.8	0.62	0.75
Capital equipment	46.1	0.42	37.1	0.51	0.71
Capital structures	44.9	0.44	48.4	0.42	0.69

Source: Tabulations from the CM.

Note: See text for details of construction of output, equipment, and structures measures.

change for the sector. Thus, excess reallocation reflects the gross reallocation (expansion plus contraction) that is in excess of that required to accommodate the net expansion of the sector. Following Davis, Haltiwanger, and Schuh (1996; see pages 52 and 53 for a description of the methodology), excess reallocation rates at the total manufacturing level can be decomposed into within- and between-sector effects. The far right column of table 8.3 indicates that most of the excess reallocation at the total manufacturing level reflects excess reallocation within four-digit industries. Thus, the implied large shifts in the allocation of employment, output, and capital are primarily among producers in the same four-digit industry.

The large within-sector reallocation rates motivate our analysis of productivity decompositions at the four-digit level. We apply the decompositions in equations (2) and (3) at the four-digit level. In most of our results, we report the results for the average industry. Following Baily, Hulten, and Campbell (1992), the weights used to average across industries are average nominal gross output, averaged over the beginning and ending years of the period over which the change is measured. The same industry weights are used to aggregate the industry results across all of the decompositions. The motivation for this is that the focus here is on within-industry decompositions and thus the results do not reflect changing industry composition.[16]

Consider first the decomposition of industry-level *multifactor* productivity reported in table 8.4 for the 1977–87 period. For method 1, the within-plant component accounts for about half of average industry productivity growth, the between-plant component is negative but relatively small, and the cross term is positive and large accounting for about a third of the average industry change. Net entry accounts for 26 percent of the average industry change. For method 2, the within component accounts for 65 percent of average industry productivity growth, the between component 10 percent, and net entry 25 percent.[17] The comparison across methods for MFP suggests that the impact of net entry is robust across methods but that inferences regarding the contribution of reallocation among continuing plants vary widely across methods. We return to considering the reasons for this below after we consider the labor productivity decompositions.

The decompositions of *labor* productivity are reported in table 8.4 as

16. Change in aggregate productivity from between-industry reallocation is an interesting topic in its own right, but the conceptual and measurement issues are potentially quite different. Our focus is on the noisy and complex process of industry growth with individual businesses in the same industry that are trying to find the best ways to produce and sell their goods and services given their own potentially idiosyncratic conditions. The resulting entry/exit as well as contraction and expansion of businesses in the same industry reflects the evolution of the idiosyncratic decisions and fortunes across businesses.

17. We look at method 3 at the end of this subsection.

Table 8.4 Decomposition of Multifactor and Labor Productivity Growth, 1977–87

Measure	Weight	Overall Growth	Within Share	Between Share	Cross Share	Net Entry Share
		A. Method 1				
Multifactor productivity	Gross output	10.24	0.48	−0.08	0.34	0.26
Labor productivity (per hour)	Gross output	25.56	0.45	−0.13	0.37	0.31
	Man-hours	21.32	0.77	0.08	−0.14	0.29
(per worker)	Employment	23.02	0.74	0.08	−0.11	0.29
		B. Method 2				
Multifactor productivity	Gross output	10.24	0.65	0.10	—	0.25
Labor productivity (per hour)	Gross output	25.56	0.64	0.06	—	0.31
	Man-hours	21.32	0.70	0.00	—	0.30
(per worker)	Employment	23.02	0.69	0.01	—	0.30

Source: Tabulations from the CM.
Note: Long dash = not applicable.

well. For labor productivity at the establishment level we consider two alternatives: output per man-hour and output per worker. In general, the results are very similar between these alternatives. To aggregate across establishments in the same industry, we consider two alternatives as well: output weights and labor input weights. When we use output weights, we only report the results for output per man-hour since the results are very similar to those for output per worker. In the discussion that follows we focus on the distinction between those results that use output weights and those that use labor weights (either employment or manhours).

Interestingly, whether one uses labor or output shares yields approximately the same overall average industry growth in labor productivity over this period. In addition, the contribution of net entry is quite similar whether labor or output shares are used or whether method 1 or method 2 is used. Thus, in either case, reallocation plays an important role (at least in an accounting sense) in labor productivity growth via net entry.

The biggest difference between the results using output and employment weights is associated with the continuing plants for method 1. The decomposition of labor productivity using gross output share weights looks very similar to the multifactor productivity decomposition in that the respective roles of within, between, and cross effects are quite similar. When labor shares are used as weights as opposed to output shares, the within-plant component of labor productivity growth is much larger. In addition, with labor weights, there is relatively little contribution from the between and covariance terms. This finding of a large within-plant contribution for labor productivity using labor weights is similar to the findings in Griliches and Regev (1995) and Baily, Bartelsman, and Haltiwanger (1996). The implication from the labor weighted results is that, for continuing plants, much of the increase in labor productivity would have occurred even if labor shares had been held constant at their initial levels.

For method 2, the differences between the results using labor or output weights are substantially diminished. Indeed, under method 2, the results using alternative productivity measures (multifactor or labor) or alternative weights (output, man-hours, or employment) are very similar. These results suggest that more than 60 percent of average industry productivity growth can be accounted for by within-plant effects, less than 10 percent by between-plant effects, and more than 25 percent by net entry.

An obvious question is what underlies the differences between method 1 and method 2? To shed light on the differences in results across methods, table 8.5 presents simple correlations of the plant-level growth rates in multifactor productivity, labor productivity, output, employment, equipment and structures. These correlations are based upon the 1977–87 changes for continuing plants. Multifactor productivity and labor productivity growth are strongly positively correlated. Not surprisingly, output growth and input growth are highly positively correlated (especially output and employment growth). Nevertheless, while output growth is strongly positively correlated with both multifactor and labor productivity growth, employment and capital growth are virtually uncorrelated with multifactor productivity growth. There is a positive correlation between capital growth and labor productivity growth and an even stronger positive correlation between capital intensity growth (the growth in capital per unit of labor) and labor productivity growth. The negative correlation between labor productivity growth and labor input growth underlie the negative cross terms in the decompositions of labor productivity using employment or man-hours weights. In an analogous manner, the positive correlations between productivity (multifactor or labor) growth and output growth underlie the positive cross terms in the decompositions using output weights.

A number of factors are at work in generating these patterns; analyzing these factors will help us disentangle the differences in the results between methods 1 and 2. The first potential factor is measurement error, the second factor concerns changes in factor intensities. As discussed in section 8.4, measurement error will generate a downward bias in the correlation between productivity growth and employment growth and an upward bias in the correlation between productivity growth and output growth. Likewise, measurement error will yield a spuriously low (high) within plant share for multifactor (labor) productivity growth using method 1. The patterns in tables 8.4 and 8.5 are consistent with such influences of measurement error. Moreover, the seemingly consistent results across productivity

Table 8.5 **Correlation between Plant-Level Productivity, Output, and Input Growth, 1977–87 (continuing plants)**

	Multifactor Productivity	Labor Productivity (per hour)	Labor Productivity (per worker)	Output	Employment	Manhours	Capital Equipment	Capital Structures
Multifactor productivity	1.00							
Labor productivity								
(per hour)	0.41	1.00						
(per worker)	0.38	0.93	1.00					
Output	0.24	0.47	0.52	1.00				
Employment	−0.03	−0.17	−0.17	0.76	1.00			
Man-hours	−0.04	−0.22	−0.12	0.75	0.96	1.00		
Capital equipment	−0.06	0.16	0.18	0.55	0.49	0.49	1.00	
Capital structures	−0.07	0.15	0.17	0.52	0.46	0.46	0.76	1.00
Capital intensity	−0.03	0.34	0.30	0.06	−0.16	−0.19	0.71	0.63

Source: Tabulations from the CM.

measures using method 2 suggests that method 2 is effective in mitigating these measurement error problems. Recall that method 2 uses averages across time to generate the appropriate aggregation "weights" for the changes in productivity and changes in activity shares and this averaging will tend to mitigate problems from measurement error.

While it is tempting to conclude that measurement error is driving the differences between methods 1 and 2 and thus method 2 should be preferred, there are alternative explanations of the observed patterns. First, the differences between methods 1 and 2 are systematic for alternative measures of productivity. In particular, the results for labor productivity per hour are very similar to those using labor productivity per worker. Since employment and shipments are measured relatively well (in comparison to, say, hours), the latter productivity measure should be the least affected by measurement error but we do not see a different pattern for this measure. In addition, and perhaps more importantly, there are a number of reasons that the patterns of labor productivity and multifactor productivity should be different. We now consider these issues briefly.

Recall that table 8.5 shows a strong positive correlation between labor productivity growth and capital intensity growth. Moreover, there is a positive correlation between plants with initially high labor shares and growth in capital intensity (their correlation is 0.14). These patterns suggest that changes in capital intensity may be associated with the large within-plant contribution for labor productivity under method 1. That is, plants with large changes in capital intensity also exhibited large changes in labor productivity and had large initial labor shares. These factors together contribute to a large within-plant share under method 1 for labor productivity. Note as well that changes in capital intensity need not be tightly linked to changes in MFP, which is indeed the case as seen in table 8.5. Viewed from this perspective, method 2 may be masking some important differences in the patterns of labor and multifactor productivity. Recall that the conceptual problem with method 2 is that the within term confounds changes in plant-level productivity with changes in shares of activity. The within-plant component for labor productivity is lessened because the change in labor productivity is aggregated using average instead of initial labor shares and thus mitigates the relationship between changes in capital intensity and labor productivity (and initial shares).

To help differentiate between the measurement error and productivity-enhancing changes in factor intensities, it is useful to consider evidence for some individual industries. Consider, for example, the steel industry (SIC 3312). As documented in Davis, Haltiwanger, and Schuh (1996), the steel industry underwent tremendous restructuring over the 1970s and the 1980s. A large part of this restructuring involved the shifting from integrated mills to mini-mills. While substantial entry and exit played a major role, the restructuring of the industry also involved the retooling of many continuing plants. Baily, Bartelsman, and Haltiwanger (1996) present evidence that continuing plants in the steel industry downsized significantly over this period of time and exhibited substantial productivity gains (i.e., there is a large negative covariance between employment changes and labor productivity changes among the continuing plants in the steel industry). As reported in Davis, Haltiwanger, and Schuh (1996), the average worker employed at a steel mill worked at a plant with 7,000 workers in 1980 and only 4,000 workers by 1985. Moreover, this downsizing was associated with large subsequent productivity gains in the steel industry (see, e.g., figure 5.8 in Davis, Haltiwanger, and Schuh 1996). These patterns are reflected in the decompositions we have generated underlying table 8.4. For SIC 3312, for example, we find that growth in labor productivity per hour is 29.7 for the 1977–87 period and the within component using method 1 accounts for 93 percent. Consistent with the view that the downsizing was productivity enhancing in this industry we find a negative cross term of 23 percent. In addition, capital intensity growth in the steel industry is positively correlated with changes in labor productivity at the plant level, with a correlation of 0.26. Taken together, these patterns paint a picture of many plants changing their factor intensities in dramatic ways and this in turn being reflected in the growth in labor productivity.[18]

As the discussion of the steel industry illustrates, the patterns we observe in the cross terms in the decompositions for method 1 using alternative weights are potentially driven by part of a within-plant restructuring process that yields substantial productivity gains. More generally, these results suggest that the connection between measured reallocation of inputs, outputs, and productivity growth is quite complex. Plants are often changing the mix of inputs at the same time they change the scale of production. Some technological innovations (e.g., mini-mills) may lead to substantial downsizing by plants that adopt the new technology. Alternatively, technological innovations may take the form of cost savings or product quality enhancements that enable successfully adopting plants to increase their market share with accompanying expansion.

Results using the cross-sectional decomposition (method 3) are reported in table 8.6. We conducted this decomposition separately for every four-digit industry using MFP with output weights, labor productivity per hour using man-hour weights, and labor productivity per worker using employment weights. The reported results are the average industry results where the weighted average across industries uses the same industry weights as those used in table 8.4. There is a positive second term for all productivity measures for all years indicating that plants with higher productivity have higher output and labor shares in their industry. For each of the measures,

18. It is worth noting, as well, that the within component using method 1 accounts for 87 percent of the growth in MFP in this industry.

Table 8.6 **Cross-Sectional Decompositions of Productivity, by Year**

		1977			1987		
Measure	Weight	Overall	$\bar{p}$	Cross	Overall	$\bar{p}$	Cross
Multifactor productivity	Gross output	1.62	1.57	0.05	1.73	1.67	0.06
Labor productivity							
(per hour)	Man-hours	4.12	4.01	0.11	4.37	4.21	0.15
(per worker)	Employment	4.80	4.67	0.13	5.06	4.90	0.16

Source: Tabulations from the CM.

the overall productivity increases between 1977 and 1987. The decomposition reveals that this reflects both an increase in the unweighted mean productivity across plants and an increase in the cross term for the average industry. This latter finding indicates that the reallocation of both outputs and labor inputs between 1977 and 1987 has been productivity enhancing.

8.5.2 Five-Year Changes: 1977–82, 1982–87, and 1987–92

For the five-year changes in industry-level productivity, we consider a subset of the exercises considered in the prior section. In particular, we consider the time series decompositions using methods 1 and 2 for the five-year changes measured from 1977 to 1982, 1982 to 1987, and 1987 to 1992. The productivity measures we consider are MFP using gross output weights in the decompositions and labor productivity per hour using man-hour weights in the decompositions.

The results of these decompositions are reported in table 8.7. Cyclical variation in productivity growth plays a dominant role in the overall patterns. Productivity growth is especially modest in the 1977–82 period and very strong in the 1982–87 period. Using method 1, the multifactor productivity and labor productivity decompositions yield quite different stories, especially for the periods that are roughly coincident with cyclical downturns. For example, for the 1977–82 period, the within share is actually negative for the multifactor productivity decomposition while the within share is above one for the labor productivity decomposition. Associated with these dramatically different within plant contributions are very different cross terms. For the MFP decomposition, the cross term is positive and relatively large (above 1) and for the labor productivity decomposition, the cross term is negative and relatively large (above 1 in absolute magnitude).

In contrast, method 2 yields results that are much less erratic across multifactor and labor productivity and across the alternative subperiods. Even here, however, the contribution of within-plant changes to MFP

Table 8.7 **Decomposition of Multifacator and Labor Productivity Growth over Subperiods**

Years	Measure	Weight	Overall Growth	Within Share	Between Share	Cross Share	Net Entry Share
			A. Method 1				
1977–82	Multifactor productivity	Gross output	2.70	−0.09	−0.33	1.16	0.25
	Labor productivity	Man-hours	2.54	1.22	0.85	−1.27	0.20
1982–87	Multifactor productivity	Gross output	7.32	0.52	−0.18	0.51	0.14
	Labor productivity	Man-hours	18.67	0.83	0.13	−0.15	0.19
1987–92	Multifactor productivity	Gross output	3.30	−0.06	−0.39	1.10	0.35
	Labor productivity	Man-hours	7.17	0.94	0.33	−0.49	0.21
			B. Method 2				
1977–82	Multifactor productivity	Gross output	2.70	0.49	0.26	—	0.25
	Labor productivity	Man-hours	2.54	0.59	0.21	—	0.20
1982–87	Multifactor productivity	Gross output	7.32	0.78	0.08	—	0.14
	Labor productivity	Man-hours	18.67	0.75	0.03	—	0.21
1987–92	Multifactor productivity	Gross output	3.30	0.49	0.17	—	0.34
	Labor productivity	Man-hours	7.17	0.70	0.08	—	0.22

Source: Tabulations from the CM.

Notes: Labor productivity is per hour. Long dash = not applicable.

Table 8.8 **Correlation between Plant-Level Productivity, Output, and Input Growth for Subperiods (continuing plants)**

	1977–82	1982–87	1987–92
A. Multifactor Productivity			
Output	0.29	0.23	0.24
Man-hours	−0.07	−0.08	−0.07
Capital intensity	0.07	−0.00	−0.08
Labor productivity (per hour)	0.45	0.41	0.40
B. Labor Productivity (per hour)			
Output	0.52	0.50	0.53
Man-hours	−0.25	−0.26	−0.27
Capital intensity	0.38	0.39	0.29

Source: Tabulations from the CM.

ranges from about 50 percent in cyclical downturns to about 80 percent in cyclical upturns.

What underlies these very different patterns? Table 8.8 sheds light on this issue by characterizing the simple correlations for continuing establishments. The correlation between productivity growth (either multifactor or labor) and output growth is large and positive while the correlation between labor productivity and man-hours growth is large and negative. These correlations and the implied patterns in the decompositions likely reflect a variety of cyclical phenomena and associated measurement problems. For example, cyclical changes in factor utilization will yield spurious changes in measured productivity to the extent that the changes in utilization are poorly measured.

In short, the high-frequency results are difficult to characterize since the contribution of various components is sensitive to decomposition methodology, the measurement of multifactor versus labor productivity, and to time period. However, a couple of patterns are robust. First, the contribution of net entry is robust to the alternative measurement methods. Second, while the contribution of net entry is sensitive to time period, the pattern is regular in the sense that the contribution of net entry is greater in cyclical downturns.[19] Third, using the method more robust to measure-

19. It is useful to note that the large contribution of net entry to productivity growth in 1977–82 and 1987–92 is not due to an especially large share of activity accounted for by entering and exiting plants, but rather by a large gap in productivity between entering and exiting plants relative to the overall growth in productivity. For example, for the 1987–92 period, the share of output of exiting plants in 1987 is only 0.13 and the share of output of entering plants in 1992 is only 0.12. However, the difference in productivity between entering and exiting plants is about 7 percent, which is substantially greater than the 3.3 percent overall growth in productivity over this time period.

ment error problems (method 2), the contribution of reallocation amongst continuing plants is also greater in cyclical downturns. Putting these pieces together yields the interesting inference that the contribution of reallocation to productivity growth tends to be greater during cyclical downturns.

8.5.3 The Role of Entry and Exit

As noted in the previous subsections, a robust result is the contribution of net entry. Whether we examine ten-year or five-year changes, net entry plays an important role in accounting for aggregate productivity growth. We begin our detailed examination of the roles of entry and exit by returning to the ten-year changes for 1977–87. The material under heading A of table 8.9 provides information about some of the underlying determinants of the role of net entry by reporting output and labor shares of entering and exiting plants and the weighted average of productivity levels for continuing, entering and exiting plants. The reported productivity indexes are relative to the weighted average for continuing plants in 1977. Entering plants tend to be smaller than exiting plants, as reflected in the generally smaller output and employment shares of entrants (relative to exiting plants). Entering plants in period t (here 1987) tend to have higher productivity than the level of productivity in period $t - k$ (here 1977) for exiting and continuing plants, but entrants exhibit slightly lower productivity than continuing plants in period t. Exiting plants from period $t - k$ tend to have lower productivity than continuing plants in period $t - k$.

One insight that emerges from comparing heading A of table 8.9 to the results of table 8.4 is that the contribution of entering plants displacing exiting plants to productivity growth is disproportionate relative to the respective contribution of entry and exit in accounting for activity. For example, the contribution of net entry to MFP is 25 percent while the share of output accounted for by exiting plants is 22 percent and the share of activity accounted for by entering plants is 21 percent. Similar patterns of disproportionality are observed for labor productivity. The disproportionate contribution of net entry reflects the fact that the gap in productivity between entering and exiting plants is larger than the gap across time among continuing plants. This finding is important because it indicates that the contribution of net entry is not simply an accounting result. That is, if entry and exit were just random and uncorrelated with productivity, then the contribution of net entry would simply reflect the share of activity accounted for by entering and exiting plants.

It is, of course, limiting to simply compare the relative productivity of entering plants in 1987 with exiting plants in 1977. The differences reflect many factors, including overall productivity growth and selection and learning effects. To begin shedding light on these issues, heading B of table 8.9 considers the relative productivity of the entering plants in 1987 based upon a cross classification of the year of entry. Given the availability of

Table 8.9 **Relative Productivity for Continuers, Exiters, and Entrants, 1977–87**

A. Output Shares and Relative Productivity

		Shares		Relative Productivity			
Measure	Weight	Exiting Plants ($t-k$)	Entering Plants (t)	Exiting Plants ($t-k$)	Entering Plants (t)	Continuing Plants ($t-k$)	Continuing Plants (t)
Multifactor productivity	Gross output	0.22	0.21	0.96	1.09	1.00	1.10
Labor productivity							
(per hour)	Man-hours	0.25	0.21	0.83	1.11	1.00	1.20
(per worker)	Employment	0.25	0.21	0.82	1.11	1.00	1.21

B. Relative Productivity of Plants in 1987 for Entrants by Entry Cohort

		Plants that entered between:	
Measure	Weight	1978–82	1983–87
Multifactor productivity	Gross output	1.10	1.07
Labor productivity			
(per hour)	Man-hours	1.16	1.04
(per worker)	Employment	1.16	1.05

Source: Tabulations from the CM.

economic census data in 1982, entry age can be measured for all entering establishments in terms of census cohorts (i.e., 1978–82 or 1983–87). For multifactor productivity, we find that in 1987 the relative productivity of the older cohort is higher (1.10) than the younger cohort (1.07). For labor productivity using man-hours or employment, a similar pattern is observed. These findings are consistent with the predicted impact of selection and learning effects but still are inadequate for understanding the underpinnings of the contribution of net entry. Following methodology used by Aw, Chen, and Roberts (1997), we can make a bit more progress in distinguishing between alternative factors using some simple regression analysis to which we now turn.

Table 8.10 presents regression results using the pooled 1977–87 data. Heading A of table 8.10 considers a simple regression of the (log) of productivity on a set of dummies indicating whether the plant exited in 1977 or entered in 1987; a year effect to control for average differences in productivity across the two years; and four-digit industry dummies (not reported).[20] The omitted group is continuing plants in 1977 so the coefficients can be interpreted accordingly. This first set of results simply confirms earlier results but helps in quantifying statistical significance: Exiting plants have significantly lower productivity (multifactor and labor) than continuing plants; plants in 1987 have significantly higher productivity (multifactor and labor) than plants in 1977; and entering plants in 1987 have lower *labor* productivity than the continuing plants in 1987. Note, however, that according to these regressions there is no statistical difference between continuing plants and entering plants in terms of MFP in 1987. Also reported in heading A is the *F*-test on the difference between entering and exiting plants, which is highly significant for all measures even after having controlled for year effects.

Heading B of table 8.10 is the regression analogue of heading B of table 8.9. Essentially the same specification as in the upper panel is used except that here we classify entering plants based on whether they entered between 1977 and 1982 or 1982 and 1987. The results indicate that there are significant differences between the cohorts of plants. The plants that en-

20. By pooling the data across industries, we are pursuing a slightly different approach than in prior decomposition exercises where we calculated the decomposition for each industry and then took the weighted average of the four-digit results. However, by controlling for four-digit effects and using analogous weights to those used in the decomposition exercises, these results are close to being the regression analogues of earlier tables. The results using unweighted regressions are qualitatively similar to those reported here with similar significance levels for the various tests on coefficients. Moreover, for MFP, the magnitudes of the coefficients are very similar using unweighted results. We suspect that this is because the typical entering and exiting plant is smaller and less capital intensive than the typical continuing plant. Since there is a positive relationship among size, capital intensity, and labor productivity, this will yield larger differences in average productivity levels among continuing, entering, and exiting plants using weighted as opposed to unweighted regressions.

Table 8.10 **Regression Results Concerning Net Entry, 1977–87**

A. Differences Between Continuing, Entering, and Exiting Plants

Measure	Exit Dummy in 1977 (β)	Entry Dummy in 1987 (δ)	1987 Year Effect	*F*-test on $\beta = \delta$ (*p*-value)
Multifactor productivity	−0.019	0.003	0.098	0.0001
	(0.002)	(0.002)	(0.001)	
Labor productivity				
(per hour)	−0.150	−0.075	0.191	0.0001
	(0.003)	(0.003)	(0.002)	
(per worker)	−0.162	−0.086	0.208	0.0001
	(0.003)	(0.003)	(0.002)	

B. Regression Results Distinguishing between Entering Cohorts

Measure	Entry Dummy in 1987 Interacted with Dummy for 1977–82 Cohort (η)	Entry Dummy in 1987 Interacted with Dummy for 1982–87 Cohort (μ)	*F*-test on $\eta = \mu$ (*p*-value)
Multifactor productivity	0.016	−0.010	0.0001
	(0.002)	(0.002)	
Labor productivity			
(per hour)	−0.020	−0.123	0.0001
	(0.004)	(0.004)	
(per worker)	−0.032	−0.132	0.0001
	(0.004)	(0.004)	

Notes: Results under heading A are based upon regression of pooled 1977 and 1987 data with dependent variable the measure of productivity (in logs) and the explanatory variables including four-digit industry effects, year effects, an exit dummy in 1977, and an entry dummy in 1987. The results under heading B use the same specification but interact the entry dummy with entering cohort dummies. Under heading B, the exit dummy and year effect dummy are not shown as they are the same as under heading A. All results are weighted regressions with gross output weights in regressions using multifactor productivity, hours weights in labor productivity per hour regressions, and employment weights in labor productivity per worker regressions. Standard errors in parentheses.

tered earlier have significantly higher productivity (multifactor or labor) than plants that entered later.

Heading B of table 8.10 still does not permit disentangling selection and learning effects. In table 8.11, we report results that shed some light on these different effects.[21] In table 8.11, we use a similar pooled specification with year effects, entry dummy, exit dummy, and four-digit effects. However, in this case we consider additional information about plants that entered between 1972 and 1977. By dividing this entering cohort into exiters and survivors, we can characterize selection and learning effects. In particular, we make three comparisons using this information. First, for exits, we distinguish among exits those who entered between 1972 and 1977 and those who did not (comparing α and γ). Second, we distinguish among the entering cohort those that exit and those that survive to 1987 (comparing α and θ). Finally, for the surviving 1972–77 cohort, we also examine productivity in 1977 (the entering year) and productivity ten years later (comparing θ and λ).

Plants that entered between 1972 and 1977 and then exited are significantly less productive in 1977 than continuing incumbents in 1977 (who are not from that entering cohort) whether productivity is measured in terms of multifactor or labor productivity ($\alpha < 0$). Of exiting plants, those that entered between 1972 and 1977 are less productive in 1977 than other exiting plants ($\alpha < \gamma$), although the results are not statistically significant for MFP. The exiting plants from this entering cohort are also less productive in 1977 than the surviving members of this cohort ($\alpha < \theta$), although the differences are not statistically significant for the MFP measure even at the 10 percent level. The latter findings are broadly consistent with selection effects since it is the less productive plants from the entering cohort that exit (although again this is not always highly significant).

Even the surviving members of the entering 1972–77 cohort are less productive than incumbents ($\theta < 0$). However, for the entering cohort, we observe significant increases in productivity over the ten years ($\theta < \lambda$), even though we are controlling for overall year effects. This pattern is consistent with learning effects playing an important role.

To conclude this section, we consider similar regression exercises for the five-year changes from 1977 to 1982, 1982 to 1987, and 1987 to 1992.[22] Tables 8.12 and 8.13 report regression results for these five-year intervals. Interestingly, the patterns for the five-year changes regarding the differ-

21. This specification is quite similar to various specifications considered in Aw, Chen, and Roberts (1997). Our results are qualitatively consistent with theirs in the sense that we find that both learning and selection effects contribute significantly to the observed plant-level productivity differentials.

22. All specifications include four-digit industry effects, year effects, and entry and exit dummies. Table 8.13 is analogous to table 8.11; we decompose some of these effects allowing for potentially different behavior of the most recent entering cohort.

Table 8.11 **Regression Results Distinguishing between Selection and Learning Effects Using 1972–77 Entering Cohort**

Measure	Exit Dummy in 1977 for Entering Cohort (α)	Exit Dummy in 1977 for Other Exiting Plants (γ)	Survival Dummy in 1987 for Entering Cohort (θ)	Survival Dummy in 1987 for Entering Cohort (λ)	F-test on $\alpha = \gamma$ (p-value)	F-test on $\alpha = \theta$ (p-value)	F-test on $\theta = \lambda$ (p-value)
Multifactor productivity	−0.024	−0.019	−0.017	0.018	0.238	0.184	0.0001
	(0.004)	(0.002)	(0.003)	(0.003)			
Labor productivity							
(per hour)	−0.182	−0.149	−0.058	−0.016	0.0001	0.0001	0.0001
	(0.007)	(0.003)	(0.006)	(0.005)			
(per worker)	−0.215	−0.158	−0.072	−0.017	0.0001	0.0001	0.0001
	(0.007)	(0.003)	(0.006)	(0.005)			

Source: Tabulations from the CM.

Notes: Results are based upon regression of pooled 1977 and 1987 data with dependent variable the measure of productivity and the explanatory variables including four-digit industry effects, year effects, an entry dummy in 1987, the exit dummy interacted with whether the plant is in the 1972–77 entering cohort, and a surviving dummy for the 1972–77 entering cohort interacted with the year effects. All results are weighted regressions with gross output weights in regressions using multifactor productivity, hours weights in labor productivity per hour regressions, and employment weights in labor productivity per worker regressions. Standard errors in parentheses.

Table 8.12 **Regression Results on Differences between Continuing, Entering, and Exiting Plants**

Measure	Exit Dummy in Beginning Year (β)	Entry Dummy in Ending Year (δ)	End Year Effect	F-test on $\gamma = \delta$ (p-value)
		A. 1977–82		
Multifactor productivity	−0.047	0.005	0.021	0.0001
	(0.002)	(0.002)	(0.001)	
Labor productivity				
(per hour)	−0.164	−0.140	0.022	0.0001
	(0.004)	(0.004)	(0.002)	
(per worker)	−0.187	−0.131	−0.009	0.0001
	(0.004)	(0.004)	(0.002)	
		B. 1982–87		
Multifactor productivity	−0.017	−0.005	0.071	0.0002
	(0.002)	(0.002)	(0.001)	
Labor productivity				
(per hour)	−0.193	−0.121	0.169	0.0001
	(0.004)	(0.004)	(0.002)	
(per worker)	−0.204	−0.130	0.211	0.0001
	(0.004)	(0.004)	(0.002)	
		C. 1987–92		
Multifactor productivity	−0.056	0.009	0.025	0.0001
	(0.002)	(0.002)	(0.001)	
Labor productivity				
(per hour)	−0.179	−0.140	0.064	0.0001
	(0.004)	(0.004)	(0.002)	
(per worker)	−0.192	−0.126	0.083	0.0001
	(0.004)	(0.004)	(0.002)	

Note: Standard errors in parentheses.

ences between entering and exiting plants and the role of selection and learning effects mimic those for the ten-year changes. In table 8.12, we observe that entering plants have higher productivity than exiting plants even while controlling for year effects. In table 8.13, we examine the behavior of the entering cohorts for each of the five-year changes.[23] With one exception, for plants that exit the plants that are in the entering cohort have lower productivity than other plants ($\alpha < \gamma$). For the entering cohort, the productivity level in the year of entry is lower for those that immediately exit than those that survive ($\alpha < \theta$). For those that survive in the entering cohort, we observe significant increases in productivity even after controlling for average increases in productivity amongst all plants via year

23. That is, for the 1977–82 changes we consider the 1972–77 entering cohort; for the 1982–87 changes we consider the 1977–82 entering cohort; and for the 1987–92 changes we consider the 1982–87 entering cohort.

Table 8.13 Regression Results Distinguishing between Selection and Learning Effects Using Entering Cohort

Measure	Exit Dummy in Start for Entering (α)	Exit Dummy in Start for Other Exiting (γ)	Survival Dummy in Start for Entering (θ)	Survival Dummy in End for Entering (λ)	F-test on $\alpha = \gamma$ (p-value)	F-test on $\alpha = \theta$ (p-value)	F-test on $\theta = \lambda$ (p-value)
A. 1977–82 (start = 1977, end = 1982)							
Multifactor productivity	−0.050	−0.047	−0.011	0.023	0.662	0.0001	0.0001
	(0.005)	(0.003)	(0.003)	(0.003)			
Labor productivity							
(per hour)	−0.190	−0.164	−0.069	−0.035	0.005	0.0001	0.0001
	(0.008)	(0.005)	(0.005)	(0.005)			
(per worker)	−0.231	−0.184	−0.089	−0.032	0.0001	0.0001	0.0001
	(0.008)	(0.005)	(0.005)	(0.005)			
B. 1982–87 (start = 1982, end = 1987)							
Multifactor productivity	−0.039	−0.014	−0.017	0.001	0.0001	0.0001	0.0001
	(0.005)	(0.002)	(0.003)	(0.003)			
Labor productivity							
(per hour)	−0.306	−0.175	−0.063	−0.045	0.0001	0.0001	0.019
	(0.008)	(0.004)	(0.006)	(0.005)			
(per worker)	−0.313	−0.186	−0.061	−0.052	0.0001	0.0001	0.216
	(0.008)	(0.004)	(0.006)	(0.005)			
C. 1987–92 (start = 1987, end = 1992)							
Multifactor productivity	−0.049	−0.060	−0.017	0.043	0.048	0.0001	0.0001
	(0.005)	(0.003)	(0.003)	(0.003)			
Labor productivity							
(per hour)	−0.254	−0.170	−0.097	−0.057	0.0001	0.0001	0.0001
	(0.008)	(0.004)	(0.005)	(0.005)			
(per worker)	−0.274	−0.183	−0.101	−0.050	0.0001	0.0001	0.0001
	(0.007)	(0.004)	(0.005)	(0.005)			

Note: Standard errors in parentheses.

effects ($\theta < \lambda$). One interesting feature of these results is that the differences reflecting both selection and learning effects are highly significant for both multifactor and labor productivity measures.

In sum, we find that net entry contributes disproportionately to productivity growth. The disproportionate contribution is associated with less productive exiting plants being displaced by more productive entering plants. New entrants tend to be less productive than surviving incumbents but exhibit substantial productivity growth. The latter reflects both selection effects (the less productive amongst the entrants exit) and learning effects.

8.5.4 Summing Up the Results for Manufacturing

To sum up the results from this sensitivity analysis, our results suggest that reallocation plays a significant role in the changes in productivity growth at the industry level. While measurement error problems cloud the results somewhat, two aspects of the results point clearly in this direction. First, our time series decompositions show a large contribution from the replacement of less productive exiting plants with more productive entering plants when productivity changes are measured over five- or ten-year horizons. A key feature of these findings is that the contribution of net entry is disproportionate—that is, the contribution of net entry to productivity growth exceeds that which would be predicted by simply examining the share of activity accounted for entering and exiting plants. Second, the cross-sectional decompositions, which are less subject to measurement error problems, uniformly show that the reallocation of both output and labor inputs has been productivity enhancing over this same period.

Nevertheless, an important conclusion of this sensitivity analysis is that the quantitative contribution of reallocation to the aggregate change in productivity is sensitive to the decomposition methodology that is employed. Using a method that characterizes the within-plant contribution in terms of the weighted average of changes in plant multifactor (labor, when using labor weights) productivity using fixed initial weights yields a substantially lower (higher) within-plant contribution than an alternative method that uses the average time series share of activity as weights. The former method (method 1) arguably yields cleaner conceptual interpretations but is also more subject to measurement error. The latter method (method 2) yields results that are more consistent across multifactor and labor productivity measures. Examining the detailed components of the decompositions across multifactor and labor productivity measures yields results consistent with measurement error interpretations and, on this basis, favors method 2, which mitigates measurement error problems. However, some aspects of the patterns (in particular, the strong correlation between within-plant changes in labor productivity and capital intensity) suggest that there are likely important and systematic differences in the contribution of reallocation to labor and multifactor productivity.

8.6 Productivity and Reallocation in the Service Sector

8.6.1 Overview and Measurement Issues

All of the studies we have reviewed, as well as our analysis of the sensitivity of the results to alternative methodologies, have been based on productivity decompositions using manufacturing data. In this section, we consider the same issues in the context of changes in productivity in a service sector industry. We restrict our attention here to a small number of four-digit industries that account for the three-digit industry automotive repair shops (SIC 753). Our focus on this three-digit industry is motivated by several factors. First, since this is one of the first studies to exploit the Census of Service Industries establishment-level data at the Bureau of the Census, we wanted to conduct a study on a relatively small number of four-digit industries to permit careful attention to measurement issues.[24] Second, for this specific three-digit industry, we can apply procedures for measuring plant-level labor productivity (here measured as gross output per worker) in a manner that is directly comparable to official BLS methods. That is, for this specific industry, BLS generates four-digit output per worker measures by using gross revenue from the Census of Service Industries and then deflating the four-digit revenue using an appropriate four-digit deflator derived from the Consumer Price Index.[25] By obtaining the appropriate deflators, we can mimic BLS procedures here, which is especially important given our concerns about measurement issues.

A third reason that we selected this specific three-digit industry is that this industry has been subject to rapid technological change. Over the last decade or so, the automotive repair industry has experienced significant changes in the nature and complexity in both the automobiles that are being serviced and in the equipment used to do the servicing. According to Automotive Body Repair News (ABRN; 1997), " . . . vehicles are becoming more electronic and require more expensive diagnostic tools for successful troubleshooting." For example, ABRN reports that the percentage of automobiles with electronic transmissions has increased from 20 percent in 1990 to 80 percent in 1995 and is expected to increase to 95 percent by the year 2000. According to ABRN, "this growth in automotive electronics has not only changed the vehicle, it has altered significantly the technical requirements of the individuals who service" the automobiles.

Recent improvements in automobiles and in the manner in which they are repaired may interfere with our measurement of changes in output per worker. It is possible that we may not accurately characterize productivity changes in the industry because of changes in the quality of both the out-

24. Given that these data have not been widely used, the results reported here should be viewed as exploratory and interpreted with appropriate caution.

25. See the paper by Dean and Kunze (1992) on service sector productivity measurement.

puts and the inputs. While we recognize that this pervasive concern may be especially problematic in the service sector, we believe that these problems will be somewhat mitigated by several factors unique to this context. First, our (admittedly limited) research on changes in this industry indicate that process innovations dominate product innovations. That is, while both the parts and processes to repair automobiles have undergone substantial improvement, we believe that the improvements in repair technology are more important for our purposes. For example, some of the largest changes have taken place in the field of troubleshooting and have provided mechanics with the ability to diagnose repair problems more accurately and more quickly. Such improvements in diagnostics are appropriately reflected in our (and the official BLS) output per worker measures since establishments that are better at diagnosis will exhibit higher measured output per worker. Second, our focus is on the decomposition of productivity changes rather than the overall change itself. Mismeasured quality change will undoubtedly imply that the overall change in mismeasured, but it is less clear how it will distort the inferences about the contribution of reallocation to the overall change.

We conduct our analysis by exploiting the Census of Service Industries establishment-level data from 1987 and 1992. The Census of Service Industries data contain information on gross revenue and employment as well as a host of establishment-level identifiers. The data on gross revenue are deflated with an appropriate four-digit deflator to generate a measure of real gross output (in 1987 dollars). Combining the data on real gross output with the employment data allows us to generate measures of labor productivity that are fully comparable to those presented in section 8.5. A discussion of the method used to link establishments in the Census of Service Industries can be found in the appendix.

Before proceeding to our analysis of the microdata, it is useful to consider the official BLS productivity series for SIC 753. Figure 8.1 plots the index for output per worker produced by BLS. As is evident from the figure, this industry exhibits substantial cyclicality in labor productivity. This cyclicality likely influences our analysis since we focus on the Census of Service Industries microdata from 1987 to 1992. Figure 8.1 indicates that while recovery had begun in 1992 and 1992 labor productivity exceeds 1987 labor productivity, labor productivity was below the cyclical peak it had reached in 1989. Recall from the discussion in sections 8.3 and 8.4 that the role of reallocation in productivity growth appears to be cyclically sensitive for studies using manufacturing data. We need to keep the impact of cyclicality in mind, therefore, when considering the determinants of industry-wide productivity growth.

8.6.2 Decompositions of Industry Productivity Changes

We now turn our attention to an analysis of the decomposition of aggregate productivity growth for the automobile repair industry. To begin,

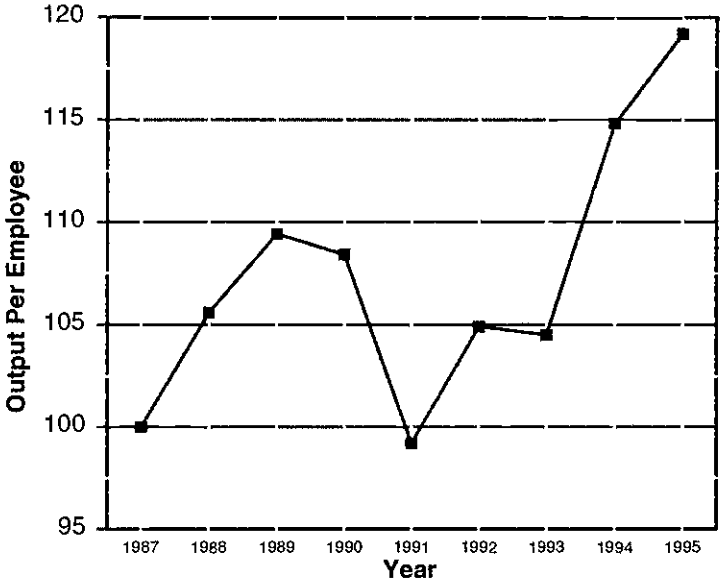

Fig. 8.1 Automotive repair shops (SIC 753; BLS productivity calculations)

table 8.14 presents gross expansion and contraction rates for employment and output for the overall three-digit industry and the underlying four-digit industries. The gross flows of employment and output are quite large in this industry with five-year gross expansion and contraction rates of approximately 50 percent. The implied five-year excess reallocation rates for each industry are often above 80 percent. These rates are quite large relative to the ten-year gross rates for manufacturing reported in table 8.3. Indeed, for manufacturing, five-year gross employment expansion and contraction rates are typically less than 30 percent (see, e.g., Dunne, Roberts, and Samuelson 1989 and Baldwin, Dunne, and Haltiwanger 1995). Thus, taken at face value, these rates suggest tremendous churning among automotive repair shops.[26]

In a related manner, the share of expansion accounted for by entrants and the share of contraction accounted for by exits are both extremely large. The entry and exit shares exceed 50 percent for all industries and in

26. Given the magnitude of establishment births and deaths on employment flows and productivity, and the newness of these data, we considered it prudent to try to find benchmarks for business failure from sources outside the Census Bureau. We contacted BABCOX Publications, publishers of several automobile service periodicals. BABCOX provides its publications free of charge to all companies in, among others, SIC 7532 (top, body, and upholstery repair shops and paint shops), and they believe that their mailing list includes almost all of the individual establishments in the industry. They find that about 10 percent of the businesses on their mailing list disappear each year. Over a five-year period, therefore, their attrition rate is similar to what we find.

Table 8.14 Gross Reallocation of Employment and Output for Automobile Repair Shops

Industry	Creation (Expansion) Rate	Share of Creation (Expansion) Due to Entrants	Destruction (Contraction) Rate	Share of Destruction (Contraction) Due to Exits	Excess Reallocation Within Industry
	A. Five-Year Changes from 1987–92, Employment				
Automobile repair shops (SIC = 753)	50.9	75.8	44.2	63.5	88.4
Top, body, and upholstery repair shops and paint shops (SIC = 7532)	44.2	69.3	42.9	59.1	85.8
Auto exhaust system repair shops (SIC = 7533)	46.0	69.5	37.1	55.3	74.2
Tire retreading and repair shops (SIC = 7534)	53.2	79.0	57.5	82.1	106.4
Automotive glass replacement shops (SIC = 7536)	60.3	79.6	38.9	51.7	77.8
Automotive transmission repair shops (SIC = 7537)	38.9	70.4	46.1	61.4	77.8
General automotive repair shops (SIC = 7538)	58.3	80.0	45.3	67.4	90.6
Automotive repair shops not elsewhere classified (SIC = 7539)	43.6	76.2	43.9	61.8	87.2

	B. Five-Year Changes from 1987–92, Output				
Automobile repair shops (SIC = 753)	51.8	75.8	40.3	61.3	80.6
Top, body, and upholstery repair shops and paint shops (SIC = 7532)	44.7	68.8	38.5	57.1	77.0
Auto exhaust system repair shops (SIC = 7533)	45.2	71.2	31.9	55.7	63.8
Tire retreading and repair shops (SIC = 7534)	53.6	79.7	51.2	80.3	102.4
Automotive glass replacement shops (SIC = 7536)	59.9	79.8	38.7	45.3	77.4
Automotive transmission repair shops (SIC = 7537)	37.9	74.5	42.7	57.5	75.8
General automotive repair shops (SIC = 7538)	59.9	79.3	41.2	65.4	82.4
Automotive repair shops not elsewhere classfied (SIC = 7539)	42.8	78.3	43.4	59.3	85.6

Source: Tabulations from Censuses of Service Industries.

some cases exceed 80 percent. To provide some perspective, Baldwin, Dunne, and Haltiwanger (1995) report that roughly 40 percent of five-year gross job flows in U.S. manufacturing are accounted for by entrants and exits.

Table 8.15 presents the gross contraction and expansion rates by establishment-size class along with information regarding the distribution of establishments by size class. The vast majority of automotive repair shops are very small, with fewer than ten employees. This helps account for the rapid pace of output and employment reallocation and the dominant role of entrants and exits. Many studies (see the survey in Davis and Haltiwanger 1999) have shown that the pace of reallocation as well as entry/exit rates are sharply decreasing functions of employer size.

Table 8.16 presents the decomposition of labor productivity (per worker) growth using method 1 (heading A) and method 2 (heading B) described in section 8.4. The components in these tables are reported directly (essentially the terms in equations [2] and [3]) rather than as shares of the total as in prior tables. We present them in this form to avoid confusion. The components exhibit considerable variation in both sign and magnitude so the shares of the total often exceed one.

For the overall three-digit industry, we find that the gain in productivity across the five-year period is approximately 2.4 percent. This is lower than the BLS estimate in figure 8.1 of approximately 4.9 percent. There are several possible explanations for this difference. First, our data on revenue and employment come exclusively from the economic censuses. While, according to Dean and Kunze (1992), BLS gets its employment data from a variety of sources including BLS's Establishment Survey, IRS's Statistics of Income, and the Census Bureau's Current Population Survey.[27] Furthermore, BLS attempts to adjust their industry output to account for businesses without payroll (e.g., sole proprietorships). By contrast, the economic census data we use cover only establishments with paid employees.

Next, note from table 8.16 that net entry plays a very large role regardless of the method used. Indeed, productivity growth from net entry actually exceeds the overall industry growth. Thus, the overall contribution of continuing establishments is negative. On the other hand, the decomposition of the effects of continuing establishments differs substantially across methods 1 and 2. The reason for this is that there is an extremely large negative cross effect with method 1. With method 1, the within and between effects are typically positive. In contrast, under method 2, the within effect is uniformly negative and the between effect is typically positive.

27. A joint BEA, BLS, and Bureau of the Census project currently underway is comparing the establishment data gathered by BLS and Census. One of its goals is to examine how mixing employment and revenue data from the two agencies may affect statistics such as industry productivity measurements.

Table 8.15 **Gross Reallocation of Employment and Output by Size Class for Automobile Repair Shops**

Establishment Average Employment	Number of Establishments	Average Number of Employees	Creation (Expansion) Rate	Share of Creation (Expansion) Due to Entrants	Destruction (Contraction) Rate	Share of Destruction (Contraction) Due to Exits	Net Job Flow Rate of Size Class	Net Output Flow Rate of Size Class
A. Five-Year Changes from 1987–92, Employment								
1–4	123,378	224,309	71.7	85.2	53.3	77.1	18.4	
5–9	22,163	145,528	36.5	63.1	36.5	51.3	0.0	
10–19	6,683	86,647	28.0	52.0	33.1	40.2	−5.1	
20–49	1,236	33,230	32.6	56.0	39.9	40.5	−7.3	
50+	88	7,624	54.6	65.3	66.6	61.9	−12.0	
B. Five-Year Changes from 1987–92, Output								
1–4	123,378	224,309	73.9	84.5	47.0	75.5		26.9
5–9	22,163	145,528	35.3	64.1	35.2	48.7		0.1
10–19	6,683	86,647	27.5	52.4	32.4	38.9		−4.9
20–49	1,236	33,230	34.3	52.1	34.9	40.5		−0.6
50+	88	7,624	44.1	58.8	50.8	54.5		−6.7

Source: Tabulations from Censuses of Service Industries.

Table 8.16 Decomposition of Labor Productivity Growth, 1987–92

Industry	Average Number of Employees	Overall Growth	Within Effect	Between Effect	Cross Effect	Total Continuer Effect	Net Entry Effect
				A. Method 1			
Auto repair shops (SIC = 753)	497,336	2.43	2.41	4.58	−7.29	−0.30	2.73
Top, body, and upholstery repair shops and paint shops (SIC = 7532)	163,302	4.16	3.24	5.81	−8.13	0.92	3.24
Auto exhaust system repair shops (SIC = 7533)	22,112	3.47	5.72	4.02	−9.80	−0.06	3.54
Tire retreading and repair shops (SIC = 7534)	12,874	−1.34	−2.99	5.23	−2.78	−0.54	−0.81
Automotive glass replacement shops (SIC = 7536)	19,816	−3.55	−0.43	1.50	−4.57	−3.50	−0.05
Automotive transmission repair shops (SIC = 7537)	24,507	0.79	1.26	4.93	−8.35	−2.16	2.96
General automotive repair shops (SIC = 7538)	213,768	2.36	2.38	3.90	−6.79	−0.51	2.87
Automotive repair shops not elsewhere classified (SIC = 7539)	40,956	−1.22	1.36	4.85	−7.67	−1.46	0.24

	B. Method 2						
Automobile repair shops (SIC = 753)	497,336	2.43	−1.24	1.01	—	−0.23	2.66
Top, body, and upholstery repair shops and paint shops (SIC = 7532)	163,302	4.16	−0.82	1.84	—	1.02	3.15
Auto exhaust system repair shops (SIC = 7533)	22,112	3.47	0.81	−0.73	—	0.08	3.39
Tire retreading and repair shops (SIC = 7534)	12,874	−1.34	−4.37	3.85	—	−0.52	−0.81
Automotive glass replacement shops (SIC = 7536)	19,816	−3.55	−2.72	−1.16	—	−3.88	0.33
Automotive transmission repair shops (SIC = 7537)	24,507	0.79	−2.92	0.76	—	−2.16	2.95
General automotive repair shops (SIC = 7538)	213,768	2.36	−1.02	0.59	—	−0.43	2.79
Automotive repair shops not elsewhere classfied (SIC = 7539)	40,956	−1.22	−2.48	0.99	—	−1.49	0.28

Source: Tabulations from Censuses of Service Industries.

Correlations for continuing establishments are reported in table 8.17. Underlying the cross terms in table 8.16 are the large positive correlation between labor productivity growth and output growth and the large negative correlation between labor productivity growth and employment growth.

Since the time series decompositions are sensitive to measurement error problems and longitudinal linkage problems, it is useful to also examine the Olley-Pakes style cross-sectional decompositions. Table 8.18 reports these cross-sectional decompositions for 1987 and 1992. The cross term for all industries is positive, indicating that the share of employment is greater at establishments with larger productivity. The relative importance of the cross term is especially large for the overall three-digit industry and also for its biggest single four-digit industry, general automotive repair shops (SIC 7538). In addition, for the overall three-digit industry as well as for general automotive repair shops there is an increase in the cross term, reflecting the fact that the reallocation of employment over this time has been productivity enhancing.

8.6.3 The Role of Entry and Exit

The results in the prior section indicate that in an accounting sense essentially all (indeed more than all) of the productivity growth in these industries comes from net entry. Table 8.19 illustrates the underlying determinants of the contribution of net entry. Several features of table 8.19 stand out. First, the shares of employment accounted for by exiting plants in 1987 and by entering plants in 1992 are very large. Second, continuing plants exhibit little overall change in productivity. Third, entering plants in 1992 actually have somewhat lower productivity than the incumbents had in 1987 but they have much larger productivity than the exiting plants had in 1987. Thus, the greatest impact comes from the large exodus of low-productivity plants.

In an analogous manner to the regression exercises in section 8.4, table 8.20 characterizes the differences between entering and exiting plants more formally. The specification includes year effects, four-digit industry effects (not shown), and entry and exit dummies. Even after controlling for year effects (and thus overall trends in productivity growth in the industry), exiting plants have significantly lower productivity than continuing plants, entering plants have significantly lower productivity than continuing plants, and entering plants have significantly higher productivity than exiting plants.

8.6.4 Summary of Service Sector Results

Since the Census of Service Industries microdata have not been widely used, this analysis and the findings should be viewed as exploratory. Nevertheless, taken at face value the results are quite interesting and clearly call

Table 8.17 Correlation among Plant-Level Productivity, Output, and Input Growth, 1987–92 (continuing plants; SIC = 753)

	Change in Labor Productivity (per worker)	Change in Output	Change in Employment	Employment in 1987	Employment in 1992
Change in labor productivity (per worker)	1				
Change in output	0.51	1			
Change in employment	−0.39	0.60	1		
Employment in 1987	0.06	−0.18	−0.24	1	
Employment in 1992	−0.10	0.11	0.21	0.72	1

Source: Tabulations from Census of Service Industries.

Table 8.18 Cross-Sectional Decompositions of Productivity, by Year

Industry	Year	Overall	P-Bar	Cross
Automotive repair shops (SIC = 753)	1987	3.92	3.69	0.23
	1992	3.95	3.69	0.25
Top, body, and upholstery repair	1987	3.75	3.68	0.07
shops and paint shops (SIC = 7532)	1992	3.77	3.69	0.08
Auto exhaust system repair shops	1987	3.96	3.95	0.01
(SIC = 7533)	1992	4.02	4.02	0.00
Tire retreading and repair shops	1987	3.96	3.95	0.01
(SIC = 7534)	1992	3.91	3.90	0.01
Automotive glass replacement shops	1987	3.95	3.95	0.01
(SIC = 7536)	1992	3.96	3.95	0.01
Automotive transmission repair shops	1987	3.67	3.66	0.01
(SIC = 7537)	1992	3.70	3.70	0.01
General automotive repair shops	1987	3.76	3.65	0.11
(SIC = 7538)	1992	3.77	3.63	0.13
Automotive repair shops not	1987	3.71	3.69	0.02
elsewhere classified (SIC = 7539)	1992	3.75	3.74	0.01

Source: Tabulations from Censuses of Service Industries.

for further analysis. First, there is tremendous reallocation of activity across these service establishments with much of this reallocation generated by entry and exit. Second, the productivity growth in the industry is dominated by entry and exit effects. The primary source of productivity growth between 1987 and 1992 for the automobile repair shop industry is accounted for by the exit of very low–productivity plants.

8.7 Concluding Remarks

In this study we have focused on the contribution of the reallocation of activity across individual producers in accounting for aggregate productivity growth. A growing body of empirical analysis reveals striking patterns in the behavior of establishment-level reallocation and productivity. First, there is a large ongoing pace of reallocation of outputs and inputs across establishments. Second, the pace of reallocation varies secularly, cyclically, and by industry. Third, there are large and persistent productivity differentials across establishments in the same industry. Fourth, entering plants tend to have higher productivity than exiting plants. Large productivity differentials and substantial reallocation are the necessary ingredients for an important role for reallocation in aggregate productivity growth. Nevertheless, a review of existing studies yields a wide range of findings regarding the contribution of reallocation to aggregate productivity growth.

In both our review of existing studies and our own sensitivity analysis, we find that the variation across studies reflects a number of factors. First, the contribution of reallocation varies over time (i.e., is cyclically sensitive)

Table 8.19 Employment Shares and Relative Labor Productivity, 1987–92

	Shares		Relative Productivity			
Industry	Exiting Plants ($t-k$)	Entering Plants (t)	Exiting Plants ($t-k$)	Entering Plants (t)	Continuing Plants ($t-k$)	Continuing Plants (t)
Automotive repair shops (SIC = 753)	0.39	0.32	0.84	0.93	1.00	1.00
Top, body, and upholstery repair shops and paint shops (SIC = 7532)	0.27	0.32	0.80	0.92	1.00	1.02
Auto exhaust system repair shops (SIC = 7533)	0.22	0.31	0.81	0.96	1.00	1.00
Tire retreading and repair shops (SIC = 7534)	0.49	0.48	0.86	0.85	1.00	0.99
Automotive glass replacement shops (SIC = 7536)	0.23	0.44	0.78	0.86	1.00	0.96
Automotive transmission repair shops (SIC = 7537)	0.28	0.30	0.80	0.90	1.00	0.97
General automotive repair shops (SIC = 7538)	0.38	0.45	0.86	0.94	1.00	1.00
Automotive repair shops not elsewhere classified (SIC = 7539)	0.30	0.35	0.90	0.92	1.00	0.98

Source: Tabulations from Censuses of Service Industries.

Table 8.20 Regression Results on Differences among Continuing, Entering, and Exiting Plants

Measure	Exit Dummy in Beginning Year (β)	Entry Dummy in Ending Year (δ)	End Year Effect	*F*-test on β = δ (*p*-value)
1987–92 for SIC = 753				
Labor productivity	−0.153	−0.068	0.001	0.0001
(weighted by employment)	(0.004)	(0.003)	(0.003)	

Source: Tabulations from Censuses of Service Industries.
Note: Standard errors in parentheses.

and across industries. Second, the details of the decomposition methodology matter. Our findings suggest that measurement error interacts with the alternative decomposition methodologies in ways that affect the final results. Third, the contribution of net entry depends critically on the horizon over which the changes are measured. Small shares of the role of entrants and exits in high-frequency data (e.g., annual) make for a relatively small role of entrants and exits using high frequency changes. However, intermediate and longer run (e.g., five- and ten-year) changes yield a large role for net entry. Part of this is virtually by construction since the share of activity accounted for by entry and exit will inherently increase the longer the horizon over which changes are measured. Nevertheless, a robust finding is that the impact of net entry is disproportionate since entering plants tend to displace less productive exiting plants, even after controlling for overall average growth in productivity. The gap between the productivity of entering and exiting plants also increases in the horizon over which the changes are measured since a longer horizon yields greater differentials from selection and learning effects. Our findings confirm and extend others in the literature that indicate that both learning and selection effects are important in this context.

A novel aspect of our analysis is that we have extended the analysis of the role of reallocation in aggregate productivity growth to a selected set of service sector industries. Our analysis considers the four-digit industries that form the three-digit automobile repair shop sector. This sector has been experiencing dramatic changes over the last decade because of the greater technological sophistication of new automobiles and the accompanying advances in the equipment used to service them. We found tremendous churning in this industry with extremely high rates of entry and exit. Moreover, we found that productivity growth in the industry is dominated by entry and exit. In an accounting sense, the primary source of productivity growth in this industry over the 1987–92 period is the exit of very low–productivity plants. While these results should be viewed as exploratory given the limited use to date of the nonmanufacturing establishment data at Census, the results are quite striking and clearly call for further analysis.

While the precise quantitative contribution of reallocation varies along a number of systematic dimensions and is sensitive to measurement methodology, a reading of the literature and our own analysis of manufacturing and service sector industries clearly yield the conclusion that an understanding of the dynamics of *aggregate* productivity growth requires tracking the dynamics of *microeconomic* productivity growth. Indeed, the fact that the contribution of reallocation varies across sectors and time makes it that much more important to relate aggregate and microeconomic productivity dynamics.

Given this conclusion, a natural question is what the implications are for the existing official productivity measures from the Bureau of Labor

Statistics. Our findings of the importance of reallocation effects have implications for the *interpretation* of aggregate productivity measures rather than suggesting another potential source of *measurement* problems in the official aggregate productivity statistics per se. There are a number of well-recognized measurement challenges confronting the developers of the official statistics and there have been a number of associated proposals for improvements in the measurement of these statistics. These challenges include accounting for changes in quality in inputs and output, important technical issues on the ideal choice of an index, and the difficult conceptual and measurement problems in measuring output in the service sector. While there is a substantial literature on these topics, addressing these challenges requires further research as well as enhanced resources for data collection.[28] A related literature, of which our paper is a part, takes a different tack by focusing on the relationship between microeconomic productivity dynamics and aggregate productivity growth while taking the measurement methodology of aggregate productivity as given. Our results suggest that interpreting and understanding changes in the official aggregate productivity measures across time and across sectors would be significantly enhanced by relating the aggregate measures to the underlying microeconomic evidence.

Rather than a call for additional data, the implied recommendation of our work is a change in the collection and processing of data that would readily permit relating the aggregate and the microstatistics. Put differently, our results suggest that a comprehensive and integrated approach to the collection and processing of data on establishments is important. Ideally, we would like to measure outputs, inputs, and associated prices of outputs and inputs at the establishment level in a way that permits the analysis of aggregate productivity growth in the manner discussed in this paper. Current practices at statistical agencies are far from this ideal with many of the components collected by different surveys with different units of observation (e.g., establishments vs. companies) and indeed by different statistical agencies. Pursuing the approach advocated in this paper requires overcoming the legal data-sharing limitations that are currently part of the U.S. statistical system.

There are a large number of open conceptual and measurement issues that deserve further attention in pursuing the connection between micro- and aggregate productivity dynamics. One issue that we and most of the literature neglect is the role of within-sector price dispersion and related issues of product differentiation. Following the literature, we use four-digit deflators for shipments and materials in the construction of our productiv-

28. As examples of this extensive literature, see the following previous NBER Studies in Income and Wealth conference volumes: Griliches (1992), Berndt and Triplett (1990), Kendrick and Vaccara (1980).

ity measures. However, a limited number of studies (e.g., Roberts and Supina 1997) find considerable price dispersion across establishments even within narrow seven-digit product classes. If the price dispersion reflects quality differences across the products produced by different establishments, then the common procedures in the literature are such that measured productivity differences across establishments will reflect such quality differences. A related and more serious problem is the extent to which price dispersion reflects product differentiation implying that we need both a richer characterization of market structure and the information on this market structure to proceed appropriately.

Another problem is that much that we have discussed in this paper is simply accounting. To understand the role of reallocation in productivity growth, we need to provide better connections between the theoretical underpinnings in section 8.2 and the variety of empirical results summarized in the succeeding sections. For one thing, we need to come to grips with the determinants of heterogeneity across producers. There is no shortage of candidate hypotheses, but currently this heterogeneity is mostly a residual with several claimants. For another, we need to develop the theoretical structure and accompanying empirical analysis to understand the connection between output and input reallocation. The results to date suggest that this connection is quite complex, with restructuring and technological change yielding changes in the scale and mix of factors that are not well understood. A related problem is that there is accumulating evidence that the adjustment process of many of these factors is quite lumpy, so the dynamics are quite complicated. Developing the conceptual models of heterogeneity in behavior, reallocation, and lumpy adjustment at the micro level and, in turn, considering the aggregate implications, should be a high priority.

Appendix

Measuring Output and Inputs in the Manufacturing Sector

The Census of Manufactures (CM) plant-level data includes value of shipments, inventories, book values of equipment and structures, employment of production and nonproduction workers, total hours of production workers, and cost of materials and energy usage. Real gross output is measured as shipments adjusted for inventories, deflated by the four-digit output deflator for the industry in which the plant is classified. All output and materials deflators used are from the four-digit NBER Productivity Database (Bartelsman and Gray, 1996, recently updated by Bartelsman, Becker and Gray). Labor input is measured by total hours for production workers plus an imputed value for the total hours for nonproduction workers. The latter imputation is obtained by multiplying the number of nonproduction workers at the plant (a collected data item) times the average annual hours per worker for a nonproduction worker from the Current Population Survey. We construct the latter at the 2-digit industry level for each year and match this information to the CM by year and industry. The methodology for constructing this hours variable is discussed at length in Davis and Haltiwanger (1999).

We have also used an alternative estimate of total hours, like that in Baily, Hulten and Campbell (1992), which is total hours for production hours multiplied by the ratio of total payroll for all workers plus payments for contract work to payroll for production workers. The multiplication factor acts as a means for accounting for both hours of nonproduction and contract workers. The correlation between these alternative hours measures is 0.95 at the plant level. Moreover, the results for the aggregate decompositions and other exercises are very similar using the alternative measures. However, we did find that the use of this ratio adjusted hours measure yielded somewhat more erratic results in comparing results using only Annual Survey of Manufactures (ASM) cases to all Census of Manufactures (CM) cases. In particular, we found substantial differences in results between those generated from the full CM and the ASM when considering decompositions of labor productivity per hour. We did not have this type of deviation for any of the other measures (e.g., multifactor productivity and labor productivity per worker) including the CPS-based hours method.

Materials input is measured as the cost of materials deflated by the 4-digit materials deflator. Capital stocks for equipment and structures are measured from the book values deflated by capital stock deflators (where the latter is measured as the ratio of the current dollar book value to the constant dollar value for the two-digit industry from Bureau of Economic Analysis data). Energy input is measured as the cost of energy usage, deflated by the Gray-Bartelsman energy-price deflator. The factor elasticities are measured as the industry average cost shares, averaged over the beginning and ending year of the period of growth. Industry cost shares are generated by combining industry-level data from the NBER Productivity Database with the Bureau of Labor Statistics (BLS) capital rental prices.

The CM does not include data on purchased services (other than that measured through contract work) on a systematic basis (there is increased information on purchased services over time). Baily, Hulten, and Campbell used a crude estimate of purchased services based on the two-digit ratio of purchased services-to-materials usage available from the Bureau of Labor Statistics KLEMS data. They applied the two-digit ratio from the aggregate KLEMS data to the plant level data on materials. Because they reported that this adjustment did not matter much and it is at best a crude adjustment that will not provide much help in decomposing productivity growth *within four-digit* industries, this adjustment was not incorporated in the analysis.[29]

The data used are from the mail universe of the CM for 1977 and 1987. In the CM, very small plants (typically fewer than five employees) are excluded from the mail universe and denoted administrative record cases. Payroll and employment information on such very small establishments are available from administrative records (i.e., the Standard Statistical Establishment List) but the remainder of their data are imputed. Such administrative record cases are excluded from the analysis. In addition to the usual problems in using book-value data, for plants that were not in the Annual Survey of Manufactures (about 50,000–70,000 plants) but in the mail universe of the CM, book-value data are imputed in years other than 1987. We investigated this issue (and like Baily, Hulten, and Campbell) found little sensitivity on this dimension. This partly reflects the relatively small capital shares in total factor costs when materials are included. Nevertheless, for the exercises presented in section V, we considered results using both the full CM (less administrative records) and results generated from the ASM plants. Note that to do this properly, we used the CM files to identify entering, exiting and continuing plants and then considered the ASM subsample of each of those files and applied appropriate ASM sample weights. We only report the results for the full CM since the results are quite similar using the full CM and the ASM only cases. Part of the preference for the full CM in this context is that net entry plays an important role and the measure of the aggregate contribution of entry and exit is likely to be more reliable using the full CM.

Linking Establishments over Time for the Services Sector

Our first step in using the Census of Service Industries establishment-level data is to employ a flag used by the Census Bureau in their tabulation of the non-manufacturing censuses to identify observations containing inappropriate data (for example, out-of-scope establishments). These observations are excluded from tabulations for official Census publications and we eliminated them from our analysis as well. In addition, we excluded a small number of observations with duplicate permanent plant numbers (PPN) in each year that could not be matched with alternative matching routines. Our initial files closely approximated both the number of establishments and total employment contained in official Census Bureau publications.

The biggest challenge that we face in using the Census of Service Industries data for this effort is linking the establishment data over time and measuring the contribution of entry and exit to employment changes and productivity growth. To accomplish this, we match the micro data files

29. Siegel and Griliches (1992) also find a relatively modest role for purchased services in their study of manufacturing productivity growth.

using PPNs that the Bureau of the Census assigns to establishments. In principle, PPNs are supposed to remain fixed even during changes in organization or ownership. However, the actual assignment of PPNs is far from perfect. During the construction of the Longitudinal Research Database (LRD) which encompasses the CM and ASM, many PPN linkage problems were detected through analyses of the data by many different individuals (see the appendix of Davis, Haltiwanger and Schuh (1996) for more discussion on PPN linkage problems in the LRD).

Since the service sector data have not previously been linked together over time or analyzed in this manner, it is undoubtedly the case that initial attempts at linking the data that rely only on PPNs will leave a greater number of longitudinal linkage problems than remain in the LRD. Therefore, we took an additional step to improve the matches and used additional identifiers on the files (i.e., Census File Numbers and Employer Identification Numbers). Unfortunately, even after this step, an exploratory analysis of births and deaths for a specific zip code shows that a small but important fraction of the births and deaths reflected changes in ownership for an establishment that continued to operate at the same location in the same industry.

To overcome the remaining linkage problems, we use the name and address information in the files and a sophisticated matching software (Automatch) to improve the matches. Most data processing software takes a very literal approach to this sort of information, thus limiting its value for matching purposes. For example, if an establishment's name is 'K Auto Mart Inc.' in one file and has the exact same name in the other, the two records will match. However, if in the second year the establishment's name is 'K Auto Mart Incorporated' it will not match the previous record if linked using conventional software because the two entries are not exactly the same. Clearly, abbreviations, misspellings, and accidental concatenations can substantially reduce the usefulness of these fields for matching purposes if literal matches are required. However, the software we used is designed to recognize many alternative specifications for the same name and address. That is, it can recognize that abbreviations such as "St" that frequently appear in addresses may stand for "Saint" as in "St James Street" or "Street" as in "Saint James St." The software assigns probability-based weights to the set of potential matches and the user determines the cut-off value of the weights that gives him the best set of 'valid' matches.[30]

Heading A of table 8A.1 shows that by using this technique we are able to reduce the number of unmatched establishments in the 1987 file by

30. Two types of errors are unavoidable in this process. First, some "true" matches will not be made and some "false" matches will be. Our review of the individual records indicates that the overall error rate is, nevertheless, substantially diminished.

Table 8A.1 **Results of Using Automatch to Improve Longitudinal Linkages**

A. Summary Statistics

	Continuers Based on Original Linkages	Additional Continuers after Improved Linkages	Exits after Improved Linkages	Entrants after Improved Linkages
Number of establishments	59,011	9,447	44,281	61,649
Employment mean: 1987	5.2	5.1	3.7	
Employment mean: 1992	5.0	4.8		3.4

B. Impact on Gross Employment Flows

	Original Matched Files	File after Matching Name/Address	Change	Percentage Change
Employment at births	231,094	192,016	−39,078	−16.9
Employment at deaths	179,111	139,408	−39,703	−22.2
Job creation rate	56.2	50.9	−5.3	−9.4
Job destruction rate	49.3	44.2	−5.1	−10.3
Percent of creation from entry	82.6	75.8	−6.8	−8.2
Percent of destruction from exits	73	63.5	−9.5	−13.0
Net employment growth rate	6.9	6.7	−0.2	−2.9

Source: Tabulations from Censuses of Service Industries.

about 17.6% and the number of unmatched establishments in the 1992 file by about 13.3%. Notice also that the mean size (employment) of the additional matched establishments is much closer to that of the original matched cases than it is to the remaining unmatched establishments. Heading B of table 8A.1 shows the effects of the additional matches on the five-year gross employment flows statistics. Both the positive and negative flows are about 10% lower after using Automatch than when the only plant identifier numbers are used. This percentage decrease is less than the percent decrease in the number of unmatched establishments since matched establishments often generate positive or negative job flows, though obviously of a lesser magnitude than those generated by spurious entrants and exits. Overall, we consider the application of the matching software to be successful and this bodes well for future longitudinal database development using the non-manufacturing establishment data at Census.

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Comment Mark J. Roberts

Over the last decade economists have gained access to the firm- or plant-level data collected as part of the economic censuses conducted in many developed and developing countries. This has given rise to a large empirical literature on the patterns of producer dynamics that now spans the fields of industrial organization, macro, labor, and development economics. Two broad conclusions emerge from these studies. First, there is extensive heterogeneity across producers in virtually every dimension examined, but particularly in size and productivity. This heterogeneity exists across producers within the same industry and is not a purely transitory or measurement error phenomenon; rather, the micro-level differences can persist for long periods of time. Second, the entry, growth, and exit processes often generate large gross flows of employment or output among producers within the same industry, even when there is little net change in the total employment or output of the industry.

These findings raise the obvious question, to what extent does the underlying heterogeneity drive the patterns of producer turnover? In response, empirical studies for a number of countries have focused on the correlation between productivity and firm transitions in or out of operation. They have often used an accounting framework to ask if the aggregate or industry productivity changes we observe over time result from widespread changes in productivity at the micro level or from changes in the mix of producers—that is, the entry and expansion of higher productivity producers and the decline and exit of less efficient ones.

The paper by Foster, Haltiwanger, and Krizan covers three topics in

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this literature. First, the authors ask how differences in methodology alter the conclusions about the micro sources of aggregate productivity change in the U.S. manufacturing sector. They focus on the decisions that researchers must make concerning the measure of productivity (single factor or multifactor productivity), the way plants or firms are weighted to construct the productivity aggregate (output or input weights), and the time series decomposition of the aggregate into within-plant and between-plant movements in the components. Second, they use the microdata for U.S. manufacturing and compare the average productivity of entering, exiting, and continuing cohorts of plants to see if there are systematic differences that reflect market selection forces. Third, they provide one of the first analyses of the micro sources of industry productivity growth for a service sector industry, in this case the U.S. automobile repair industry. This service sector is interesting because it is characterized by very high rates of producer turnover and large micro-level differences in productivity, particularly between entering and exiting plants, that, together, are an important contributing factor to industry productivity change.

Decomposing Aggregate Productivity Change

I will begin with a discussion of some of the methodological issues raised in section 8.4 of their paper. Aggregate productivity is defined as a share-weighted sum of plant productivity levels. The aggregate can change over time as the productivity of individual plants changes, labeled the within-plant component; as the share weights shift among continuing plants, the between-plant component; or as entry and exit occur, the net entry component. For plants that continue in operation for several years, movements in their productivity and share weights are correlated over time, and the authors argue that it is useful to isolate this correlation from the within, between, and net entry components. The decomposition of aggregate productivity change, which they label "method 1," does this by breaking out a covariance term between the change in a plant's productivity and the change in its share weight. The authors label this the cross share. They compare this decomposition with one they label method 2, which is essentially the decomposition developed by Griliches and Regev (1995). In this second approach, the within-plant effect is constructed by weighting the change in plant productivity by the plant's average share in the beginning and ending period, rather than the beginning period share used in method 1. Comovements in the weights and productivity are thus both captured in the within-plant component. A similar distinction is made with the between-plant component of the two decompositions. The use of the method 1 decomposition represents a useful extension of the methods developed by Baily, Hulten, and Campbell (1992) and Griliches and Regev (1995) because it addresses the question of whether the plants that are improving their productivity are also responsible for an increasing or decreasing share of the resources that are reflected in the weights. If the shares are measured using plant output, we would expect that market competition, which reallocates production toward the least cost producers, would generate a positive cross share. This is what the authors find (the first two rows of table 8.4), and we see that productivity improvement in the continuing plants, evaluated at both their initial output shares and recognizing the contemporaneous increase in their market share, is a major source of aggregate productivity change.

The authors' comparison of decomposition methods 1 and 2 illustrates that real care in interpretation is needed. Terms that are superficially similar to the casual reader, and are often labeled the same, are not measuring the same resource flows. The different methods are related, however, and the terms can be sorted out. From the decompositions in table 8.4 we see that the within share in method 2 is equal to the within share in method 1 plus one-half the cross share. This holds as an identity. The other half of the method 1 cross share is allocated into both the between share and net entry share in method 2. In their particular application it is virtually all allocated to the between share, which leaves the net entry share with the same role regardless of decomposition method. I believe that the important question in the choice of decomposition method 1 or 2 is whether it is useful to measure the covariance term separately. I believe it is useful because the comovement of productivity and resource shares is a unique and potentially important source of dynamic adjustment.

Single versus Multifactor Productivity

One of the major differences revealed by the methodological comparisons in table 8.4 is the difference in the overall growth rates of multifactor and labor productivity. The authors calculate that between 1977 and 1987 the U.S. manufacturing labor productivity grew by 21.32 to 25.56 percent, depending on the measurement method, whereas TFP grew by 10.24 percent. This difference largely reflects differences in the growth rate of nonlabor inputs. The U.S. Bureau of Labor Statistics multifactor productivity calculations show that between 1977 and 1987 capital input in manufacturing grew 32.8 percent, and material input grew 9.9 percent, whereas labor hours declined by 2.4 percent. The substantial amount of input substitution that is reflected in these large changes in the capital-labor and material-labor ratios leads to the much higher growth in labor productivity and is a familiar argument for using measures of multifactor productivity instead of labor productivity.

Aggregating Plant Productivity

The second place where the methodology clearly has an effect on the results and their interpretation is the choice of aggregation weights. When plants are aggregated using their share of output, we observe a positive correlation between productivity growth, regardless of whether it is multifactor or labor productivity, and the change in the shares. Plants with rising productivity are accounting for a rising share of industry output, which generates the *positive* cross share observed in the first two rows of table 8.4. In contrast, when plant labor productivity is aggregated using the share of labor input as weights (rows 3 and 4 of the table) we observe a *negative* cross share and a larger within-plant share. This implies that plants that are increasing their (labor) productivity are reducing their share of industry labor input. The authors suggest that a combination of measurement error and changing input intensities is the likely explanation.

Transitory measurement errors in output can certainly produce the observed positive correlation between changes in output shares and changes in productivity. A plant with higher-than-normal output in year t as a result of measurement error will show a spurious increase in both productivity and market share between years $t - 1$ and t. The changes will both be negative from year t to year $t + 1$ as the plant's output returns to normal levels. Similarly, measurement errors in labor input can produce the negative correlation between changes in labor input shares and changes in labor productivity. What works against this measurement error explanation is the ten-year period over which the changes are calculated. As the time period increases, the effect of uncorrelated, transitory measurement errors on the output or employment levels should diminish, and the permanent, or at least long-term, changes in output and inputs should become more prominent. Thus the correlations between the change in productivity and the change in the aggregation weights are more likely to reflect long-term changes in plant size and production efficiency. Over a ten-year period, particularly one characterized by as much restructuring as the 1977–87 period for U.S. manufacturing, it is likely that changes in productivity and shares reflect more fundamental long-term changes in a plant's capital intensity and size. Plants that substitute capital and materials for labor over this decade would have large increases in labor productivity and could have large increases in TFP and their output share, while reducing their share of manufacturing labor use. (The latter depends on whether an increase in labor demand due to increases in size outweighs the substitution effect.) Input substitution is able to explain the signs of the cross shares and the differences in overall labor and TFP growth that we observe. It is also an important reason for the patterns that the authors cite for the steel industry.

In table 8.4, Foster, Haltiwanger, and Krizan provide a detailed comparison of the effect of using alternative productivity measures and aggregation weights on the sources of aggregate productivity change. It is still necessary for the researcher to choose among the methods, and here the economic theory of index numbers can provide some guidance. Diewert

(1980, section 8.5.3) shows that a change in industry productivity, which is defined as a proportional shift in the industry variable profit function over time, equals a weighted sum of the shifts in individual plant, or firm, variable profit functions. The appropriate weight for each micro unit in a competitive industry is their share of industry revenue, which is equivalent to their share of industry output. The construction of multifactor productivity indexes at the micro level and their aggregation with output weights, as the authors do in the first row of table 8.4, can be justified by this argument.

Index Numbers for Plant Productivity

An additional methodological issue concerns the measurement of multifactor productivity for the micro units. Diewert (1976) has established the linkages between the form of the index number used to measure productivity and the form of the underlying production function. His work provides the justification for superlative productivity indexes, such as the Tornqvist, which aggregate inputs using time varying input cost shares as weights, because they are consistent with more general production functions than are fixed weight input indexes. The multifactor productivity index used by Foster, Haltiwanger, and Krizan recognizes differences in input and output levels across producers but weights all inputs with their industry-level cost shares, thus not allowing any variation in factor prices or the marginal products of inputs across micro units.

The multilateral Tornqvist index numbers developed by Caves, Christensen, and Diewert (1982) provide a general basis for measuring productivity in microlevel panel data sets in a way that is consistent with general production functions. The productivity indexes they develop express the output and input levels of each micro observation as a deviation from a single reference point, the geometric mean of the output and input levels over all observations in the data. The use of this single reference point makes the index free of the units in which output and input are measured and preserves the transitivity of comparisons among observations. In the productivity index, the inputs for each micro observation are aggregated using information on the input cost shares for the micro unit, which will capture the effect of factor price differences across micro units on the input bundle used, and the average input cost shares across all observations. This blending of the microlevel and industry-level cost shares as input weights has the advantage of recognizing the substantial variation in input mix at the micro level while providing some smoothing of the weights across units. The use of microlevel input cost shares does raise the additional practical issue of how much of the observed factor price and input share variation is real and how much is due to measurement errors in the microdata. I do not believe this issue has been addressed in the productivity literature, and it is a difficult one to answer with the data that is typically collected in plant-level surveys or censuses conducted by most government statistical agencies.

Overall, a good methodological basis for microlevel productivity measurement and aggregation is provided by the economic theory of index numbers. The measurement of TFP at the micro level using a Tornqvist index number formula and aggregation to the industry or sector level using the plant's share of industry or sector output as a weight can be justified on fairly general grounds. This can provide a common starting point for the type of productivity measurements made by Foster, Haltiwanger, and Krizan, and by related papers in the literature. The disaggregation of changes in aggregate productivity into within-plant, between-plant, covariance, and entry-exit components using a decomposition like the authors' method 1 is a useful next step in accounting for the productivity changes at the micro level and for how they contribute to the aggregate growth.

The Importance of Entry and Exit

In the U.S. manufacturing data the authors find (first row of table 8.4) that continuing plant productivity gains, reallocation of market shares toward higher productivity plants, and turnover all contributed to the manufacturing sector gains over the 1977–87 period. Although not always defined in the same way, within-plant productivity improvements have virtually always been found in this literature to be an important source of aggregate productivity movements. The finding by Foster, Haltiwanger, and Krizan that entry and exit are a significant source of U.S. manufacturing productivity gain over the 1977–87 period is not true of many of the other studies using this type of accounting decomposition. As the authors point out, the time period over which entry and exit are measured is likely to be a key factor in their productivity contribution. What also appears to be important is the magnitude of demand or cost shocks that occur during the period. This paper covers a time period that includes one of the largest recessions experienced by the manufacturing sector. The two other papers that find an important role for entry and exit also covered time periods of major structural adjustments. Olley and Pakes (1996) study the U.S. telecommunications industry around the time of deregulation, and Aw, Chen, and Roberts (1997) study the Taiwanese manufacturing sector during the decade of the 1980s, a time period when real manufacturing output grew at an annual rate of 6.5 percent and the annual rate of net firm entry was 7.7 percent. Time periods that include substantial demand or supply shocks appear to generate a significant role for producer turnover to contribute to aggregate productivity movements.

Foster, Haltiwanger, and Krizan also document the average productivity differences among cohorts of entering, exiting, and continuing plants. A useful theoretical basis for these comparisons is provided by recent models of industry dynamics (Jovanovic 1982; Hopenhayn 1992; Ericson and Pakes 1995). These models begin with the assumption that producers differ in their productivity and are subject to idiosyncratic shocks or uncertainty about their efficiency. Differences in the evolution of their productivity over time, in turn, lead producers to make different decisions regarding entry, growth, and exit. As a result they provide a useful framework for organizing microlevel data on plant productivity and turnover.

A number of the empirical regularities reported by the authors in this paper are consistent with predictions that follow from these theoretical models. The models predict that exit will be concentrated among the least productive producers at each point in time. This occurs because a plant's current productivity is a determinant of its likely future productivity. Low-productivity plants are less likely to experience increases in future productivity and more likely to experience low future profit levels that will induce them to exit. As reported in table 8.11, the authors find that in 1977 the plants that do not survive until 1987 are less productive than the ones that do survive until 1987. They have, on average, TFP levels that are 1.9 percent below the survivors if they are old plants (entered prior to 1972) and 2.4 percent below if they are young plants (entered between 1972 and 1977). Also, if we just focus on the cohort of plants that first appear in the data in 1977, the ones that do not survive until 1987 are, on average, 0.7 percent less productive than the cohort members that do survive. The labor productivity differentials between exiting and surviving plants are even more substantial, likely reflecting the fact that exiting plants tend to be less capital intensive than survivors. The exiting plants have labor productivity (output per hour) levels that, depending on their age, are an average of 18.2 percent or 14.9 percent lower than survivors. Within the 1977 entry cohort the exiting plants are 12.4 percent less productive than the survivors.

On the entry side, the theoretical model by Hopenhayn (1992) predicts that under stable market demand the productivity distribution of older cohorts will stochastically dominate the productivity distribution of an entering cohort. This occurs because of market selection. Older plants will have had more opportunities to experience productivity levels low enough to induce exit, and thus as a cohort ages it will be increasingly composed of only the higher productivity members. The numbers presented in the lower half of table 8.10 are consistent with this. In 1987, plants that were zero to five years old were less productive, on average, than plants six to ten years old. However, this pattern is not very strong when comparing the whole group of new plants in 1987 with the whole group of incumbents. In this case there is no difference between the average TFP of entrants and incumbents (table 8.9, row 1).

One possible reason for this weak pattern is that the model predictions are based on assumptions of stable market demand and that entering plants have no knowledge of their individual productivity prior to entry. If instead there are cyclical movements in demand and producers have some knowledge of their likely productivity prior to entry, then the composition of the entering cohort would change over time. Only the highest productivity entrants would find it profitable to enter in low demand periods, and the average productivity of the entering cohort would move countercyclically. One result of the 1982 recession could be a relatively productive group of entrants that are first observed in 1987. Running counter to this trend would be the exit of large numbers of low-productivity incumbents during the recession, which would tend to raise the productivity of the older cohorts in the years following the recession. Further refinements of the comparison between the productivity of new and old cohorts may be useful in sorting out one pathway by which cyclical shocks can affect aggregate productivity.

In the paper the authors emphasize the broad conclusion that net entry plays a significant role in aggregate productivity growth in the period 1977–87. This is a combination of the facts that in 1977 the plants that were not going to survive were less productive than was the group of survivors, and that in 1987 the entrants were similar (or slightly lower) in productivity than were the incumbents in that year. As a result, the productivity difference between the entering group in 1987 and the exiting group in 1977 is larger than the productivity differential across the two years for the continuing plants. This productivity differential between entering and exiting plants plays a larger role in the automobile repair industry, which the authors analyze in the last section of the paper. In this case, the productivity of incumbent plants changes very little over time so that most industry productivity growth is due to the replacement of low-productivity exiting plants by higher productivity entrants.

The Role of Sunk Entry and Exit Costs

The theoretical models of industry evolution also suggest one reason that entry and exit play a larger role in the service industries. Hopenhayn (1992) demonstrates that the amount of producer turnover will be positively related to the magnitude of sunk entry or exit costs. If these costs are not too large, industry equilibrium will involve simultaneous offsetting flows of entering and exiting producers, and changes in the level of entry costs will affect the magnitude of these flows. An increase in the entry cost raises the level of discounted profits needed to make entry profitable, thus discouraging entry. An increase in these costs also lowers the minimum productivity level needed for incumbents to survive, thus lowering the amount of exit. High entry costs choke off both entry and exit. This can lead to a useful across-industry comparison. The authors find that plant turnover in the automobile repair service industry is very high when compared with the typical manufacturing sector. If service sector industries have lower entry costs because the scale of operation is smaller and the technology less capital intensive, for example, then we would expect higher rates of producer turnover and smaller productivity differentials to exist across producers.

Sunk entry costs may also be one reason why the results in the existing literature, which covers a very diverse group of countries, industries, and time periods, are so difficult to reconcile. If entry costs or other lump-sum costs of adjustment are important, then the level of current demand and cost are not sufficient to explain a plant's decision to be in operation. Demand conditions that generate profits sufficient to keep current producers in operation may not be sufficient to induce entry. Consider two time periods with the same level of demand. When entry costs are large, small demand fluctuations between the two periods will lead to little entry or exit. In contrast, if the intervening period is characterized by a large demand increase followed by a large decline in demand, this can cause a permanent increase in the number of producers or hysteresis in market structure. The magnitude of entry and exit flows will depend on the entire path of demand (or cost) shocks, not just the level at the beginning and end of the period of analysis, and the dependence on the path of demand will increase with the level of entry costs. Even comparing across two business cycle peaks is not sufficient to control for the role of demand changes in determining entry and exit. This suggests that attempts to reconcile the diverse findings on the sources of aggregate productivity growth, and particularly the role of entry and exit as a contributing factor, will need to separate industries, countries, or time periods by the importance of entry costs and the pattern of demand or cost shocks that are present over longer periods of time.

In this paper the authors have made substantial progress on a number of outstanding issues in the literature linking microlevel adjustments and aggregate productivity change. They have clarified several methodological issues that should help standardize the approach used by researchers in future work. They have also laid out a set of stylized facts for manufacturing that can be used as a basis for future comparisons and have extended the literature to the service sector. I completely agree with their assessment that developing a better understanding of the role of heterogeneity, reallocation, and lumpy adjustment at the micro level should be a top research priority for those interested in understanding firm dynamics and its implications for aggregate growth.

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