NBER WORKING PAPER SERIES

THE LINK BETWEEN AGGREGATE AND MICRO PRODUCTIVITY GROWTH: EVIDENCE FROM RETAIL TRADE

Lucia Foster
John Haltiwanger
C.J. Krizan

Working Paper 9120
http://www.nber.org/papers/w9120

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2002

We thank Jeffrey Campbell; Michael Harper; Thomas Holmes; and the participants at seminars and workshops at the Bureau of the Census, George Washington University, the University of Chicago, the NBER Summer Institute, the NBER Productivity Group, CEPR, and CAED for many helpful comments on earlier drafts of this paper. We thank Brian Friedman of the Bureau of Labor Statistics for providing us with BLS' industry-level data. The analysis and results presented in this paper are attributable to the authors and do not necessarily reflect concurrence by the Center for Economic Studies, the Bureau of the Census, or The Bank of Spain. This paper has undergone a more limited review by the Census Bureau than its official publications. It has been screened to insure that no confidential data are revealed. The views expressed herein are those of the authors and not necessarily those of the National Bureau of Economic Research.

The Link Between Aggregate and Micro Productivity Growth:
Evidence from Retail Trade
Lucia Foster, John Haltiwanger and C.J. Krizan
NBER Working Paper No. 9120
August 2002
JEL No. D24, J24, O47

ABSTRACT

Understanding the nature and magnitude of resource reallocation, particularly as it relates to productivity growth, is important both because it affects how we model and interpret aggregate productivity dynamics, and also because market structure and institutions may affect the reallocation's magnitude and efficiency. Most evidence to date on the connection between reallocation and productivity dynamics for the U.S. and other countries comes from a single industry: manufacturing. Building upon a unique establishment-level data set of U.S. retail trade businesses, we provide some of the first evidence on the connection between reallocation and productivity dynamics in a non-manufacturing sector. Retail trade is a particularly appropriate subject for such a study since this large industry lies at the heart of many recent technological advances, such as E-commerce and advanced inventory controls. Our results show that virtually all of the productivity growth in the U.S. retail trade sector over the 1990s is accounted for by more productive entering establishments displacing much less productive exiting establishments. Interestingly, much of the between-establishment reallocation is a within, rather than between-firm phenomenon.

Lucia Foster
Center for Economic Studies
Bureau of Census
Washington, DC 20233
lucia.s.foster@census.gov

John Haltiwanger
Department of Economics
University of Maryland
College Park, MD 20742
and NBER
halt@glue.umd.edu

C.J. Krizan
The Bank of Spain
Madrid, Spain
krizan@bde.es

1. Introduction

What is the connection between productivity growth and the ongoing reallocation of outputs and inputs in a market economy? There are many different dimensions to the answer to this question. Aggregate productivity growth might, as in the simple neoclassical growth model, be driven by common technology shocks and the ongoing high pace of reallocation observed in market economies might primarily reflect idiosyncratic shocks that largely cancel out in the aggregate. Under this view, the dynamics of technological change and productivity growth can be modeled and studied by examining the changes that occur at the average (or representative) establishment. Alternatively, the reallocation process may be intertwined with the dynamics of technological change. It may be the case that adopting new production processes and introducing new products is a noisy and complex process involving trial and error, uncertainty, and irreversibilities at particular establishments. Under this view, the dynamics of technological changes and productivity growth will be closely connected to the reallocation of production inputs and output across establishments rather than via changes within establishments. Moreover, the reallocation may occur at the margins of establishment entry and exit. If technological change does occur predominantly through the reallocation process then the costs of technological change must be modeled in terms of these reallocation dynamics. Under this latter case, distortions in market structure, institutions, and government policies that impact the reallocation process in turn impact the level and growth in productivity. Thus it may be that understanding differences in the level and growth in productivity across countries, regions, sectors and time requires understanding the differences in the reallocation dynamics induced by these factors.

A growing empirical literature exploiting longitudinal business-level data to explore the connection between reallocation and productivity dynamics has emerged in the last decade.[1] This body

[1] Papers that have focused on the connection between micro and aggregate productivity growth include: (a) for the United States: Baily, Hulten and Campbell (1992), Baily, Bartelsman and

of work has shown that a substantial fraction of aggregate productivity growth is associated with the reallocation of outputs and inputs from less productive to more productive individual microeconomic units. Moreover, entry and exit of establishments play an important role in this reallocation. In the U.S., roughly thirty percent of productivity growth (measured as either multifactor or labor productivity) over a ten-year horizon is accounted for by more productive entering plants displacing less productive exiting plants.[2] While we have learned much from this work for both the U.S. and other countries, much of the analysis has focused on one sector: manufacturing. In this paper, we explore the connection between reallocation and productivity dynamics using newly constructed longitudinal establishment data for the retail trade sector in the United States.

An investigation of the retail trade sector in this context is interesting in its own right and poses a host of new measurement and conceptual questions. According to official Bureau of Labor Statistics (BLS) productivity statistics, retail trade as a whole experienced moderate overall labor productivity growth during the last decade. The BLS labor productivity statistics for retail trade are based upon a measure of gross output (essentially real gross sales) per hour. While some questions can be raised about this as a measure of productivity (which we discuss below), we also adopt this measure. Changes in this measure at the industry or retail establishment level potentially reflect changes in technology, industry structure, and consumer demand preferences. In retail trade, an obviously important factor in determining the relative success of an establishment is the location of the establishment. The Census

---

Haltiwanger (1996, 1997), Bartelsman and Dhrymes (1998), Dwyer (1998, 1997), Foster, Haltiwanger and Krizan (2001), and Olley and Pakes (1996); (b) for other countries: Aw, Chen and Roberts (2001), Disney, Haskel, and Heden (2000), Liu and Tybout (1996), Griliches and Regev (1995), Roberts and Tybout (1996), and Tybout (1996). Bartelsman and Doms (2000) provide an excellent review of the literature.

[2] Foster, Haltiwanger, Krizan (2001) looked at automobile repair shops in addition to the manufacturing sector. They found that reallocation effects via net entry account for virtually all of the (labor) productivity gains in one industry in the service sector. This finding raises questions about the nature of the reallocation dynamics and their connection to productivity for sectors outside of manufacturing.

data on U.S. retail trade businesses reflects individual physical locations and thus we are able to track the activity and performance at each and every retail location in the country. Accordingly, our measures of reallocation and the contribution of this reallocation to productivity growth provide a measure of how the shifting of activity across locations is related to productivity growth in the U.S. retail trade industry.

The structure of the retail trade industry has changed substantially in the last decade and the information technology revolution has played an important role in this change. Adoption of systems which electronically link cash registers to scanners and credit card processing machines have allowed establishments to increase services and sales without increasing personnel (Sieling (2001)). Widespread adoption of electronic scanners has meant that managers are able to change prices relatively costlessly ("high-low" pricing where a price alternates between its regular level and its sale level) and to track more easily the success of their pricing strategies for individual items (Nakumura (1998)). Further, these scanners allow for improved inventory and sales tracking. Computerization has allowed large retailers to adopt "lean retailing" practices of closely tracking of inventory levels which allows these stores to keep low levels of inventories (Levinsohn and Petropolous (2001)). The McKinsey Global Institute (2001) attributes much of the drive to adopt new technologies and organization practices in retail trade to the influence of one company, Wal-Mart. McKinsey finds that the competitive pressure of Wal-Mart encouraged other retailers to adopt its technological and organizational best practices. This influence was felt throughout the retail trade sector because Wal-Mart competes with retailers across many categories including general merchandise stores, drug stores, apparel stores, and grocery stores (Basker (2001)). The retail trade sector has also become more concentrated over time, with the four-firm concentration ratio increasing from 5.2 percent in 1987 to 6.8 percent in 1992 and increasing further in 1997. Finally, Sieling *et al* (2001) note that consumer spending patterns shifted towards mass merchandising stores in some industries while favoring speciality shops in other industries.

In our analysis, we track the entry and exit of establishments in the retail trade sector over the course of the 1990s. We investigate the contribution to industry-level productivity growth of continuing establishments versus the entry and exit of establishments. We are able to link establishments to their parent firms and thus are able to examine the contribution of entering establishments of existing firms and of new firms as well as the related contribution of exits of establishments from continuing firms and from exiting firms. As part of this analysis of entry and exit, we attempt to disentangle the influences of selection and learning-by-doing effects on net entry.

Underlying the overall productivity growth in retail trade are very different experiences in individual retail trade industries. We examine three industries in detail in order to highlight the different industry stories that are otherwise hidden by our focus on the average industry in the sector. The industries are Department Stores, Miscellaneous General Merchandise Stores, and Catalog and Mail-Order Houses. These three industries all experienced robust productivity growth in the 1990s but this growth was the result of very different underlying processes. While there is much anecdotal evidence that these industries have undergone substantial restructuring, the official BLS statistics can only provide the aggregate picture. Quantifying and understanding the nature of and the contribution of this restructuring and reallocation to productivity growth requires consistent measurement of the establishment data underlying the industry statistics. This is the type of data that we exploit in this paper and, accordingly, we can directly address these issues.

The paper proceeds as follows. In Section 2 we discuss the conceptual underpinnings that motivate our empirical analysis and the decomposition methodology we use to relate reallocation and productivity growth. The data used for our empirical analysis are described in Section 3. In Section 4 we examine some basic features of the productivity distribution of establishments (such as heterogeneity and persistence). Our empirical decomposition of industry level productivity growth into within establishment and reallocation effects is shown in Section 5. The results of this decomposition lead us to focus, in

Section 6, on the role of selection and learning effects on the observed micro dynamics of productivity. In Section 7 we focus on a few selected industries in order to give a further sense of the underlying heterogeneity of experiences in retail trade. We provide concluding remarks in Section 8.

2. Conceptual Underpinnings

2.1 Related Literature

A pervasive empirical finding in the recent literature is that within-sector differences dwarf between-sector differences in behavior across businesses on a variety of dimensions. For example, Haltiwanger (1997) 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 in U.S. manufacturing. The magnitude of within-sector heterogeneity implies that idiosyncratic factors dominate the determination of which establishments create and destroy jobs and which establishments achieve rapid productivity growth or suffer productivity declines. An examination of the theoretical literature suggests that many factors may account for such establishment-level heterogeneity including: uncertainty; establishment-level differences in managerial/entrepreneurial ability, capital vintage, location and disturbances; learning about all of these factors; and diffusion of knowledge. Bartelsman and Doms (2000) and Foster, Haltiwanger and Krizan (2001) provide surveys of the literature concerning these factors.

For our purposes, we are interested in the connection between micro and macro (in this case industry-level) productivity dynamics. Even though there is enormous micro-level heterogeneity and associated reallocation, it is possible that the reallocation is not very important for industry-level productivity dynamics. One reason is that there is undoubtedly substantial canceling out of the idiosyncratic shocks in the aggregation from micro-level to industry-level changes. Put differently, industry-level productivity dynamics may be primarily driven by industry-level productivity shocks that are common to all businesses in the industry.

Alternatively, there are classes of models where the process of reallocation plays a vital role in productivity growth. In the creative destruction models of Aghion and Howitt (1994) and Caballero and Hammour (1994), new technology can be adopted only by new establishments. Faster technological growth increases the pace of creative destruction in this class of models and is associated with an increased gap between the productivity levels of entering and exiting plants. Such models can be enhanced with uncertainty, learning, and diffusion effects as in Jovanovic (1982), Jovanovic and MacDonald (1994), and Ericson and Pakes (1995). Uncertainty about initial type for entrants as well uncertainty about new innovations at existing businesses can generate increased churning that is closely connected to the process of productivity growth. Such uncertainty is motivated by the inevitable trial and error process of implementing new ways of doing business at a particular location and or for new products and processes. The trial and error process suggests that both selection and learning effects are potentially important for aggregate (industry-level) productivity dynamics. Our primary objective is to quantify the extent of the entry and exit dynamics within industries in the retail trade sector and in turn to quantify the contribution of associated selection and learning effects associated with this reallocation process.

While the working hypothesis is that the reallocation should be productivity enhancing, both the magnitude and the sign of this relationship should be viewed as open empirical questions. It may be that the magnitude of the effect is small if technological change primarily involves within-plant upgrading of technologies. It may also be the case that the reallocation reflects inefficiencies and as such is not productivity enhancing. Market imperfections in product, capital, or labor markets can distort the reallocation process so that the timing, magnitude, and or nature of reallocation is not productivity enhancing (see, e.g., Caballero and Hammour (2000)). While there is a presumption that the U.S. has generally well-functioning markets (at least relative to the rest of the world), it is not difficult to imagine that there are sectors or times in the U.S. during which a variety of market distortions play an important role. One possibility is that capital markets are especially imperfect for small and young businesses. Following this line of argument, the churning among small and young businesses may reflect such capital market imperfections. To the extent that this is the case, this will affect the link between reallocation and productivity growth. Since we focus on the retail trade sector, which is dominated by small businesses (and evidently young businesses, as we find enormous rates of entry and exit), these issues may be of particular relevance.

2.2 The Accounting Relationship Between Aggregate Productivity Growth and Reallocation

Much of the recent literature begins with basic accounting decompositions of aggregate productivity growth into within-establishment and reallocation effects. Virtually all of the studies in the literature consider some form of decomposition of an index of industry-level productivity:

$$LP_{it} = \sum_{e \in i} s_{et} LP_{et} \tag{1}$$

where LP_{it} is the index of *industry* productivity, s_{et} is the share of plant e in industry i (e.g., output or input share), and LP_{et} is an index of *plant-level* productivity. The decomposition considers the roles of changing shares versus changing productivity at the micro level in a manner that permits an integrated treatment of the contribution of entering and exiting establishments.

An examination of the literature reveals that there are alternate decompositions in use and that the choice of the decomposition can impact the results significantly.[3] We believe that our version has the most direct economic interpretation of the terms in the decomposition. Our decomposition is:

[3] See Foster, Haltiwanger, and Krizan (2001) for a discussion of the alternate decomposition methodologies.

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

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 term (i.e., covariance-type) that tells us whether businesses with large positive productivity changes are more likely to have decreased employment and vice-versa. The last two terms represent the contribution of entering and exiting plants, respectively.

In this decomposition, the between-plant, 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 productivity lower than the initial average, and an entering plant contributes positively only if the plant has higher productivity than the initial average.[4]

Relating this decomposition to the discussion in Section 2.1, if industry-level productivity growth

[4] Our decomposition is a modified version of that used by Baily, Hulten, and Campbell (1992). The first term in our 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.

is primarily driven by common shocks (or analogously common adoption of some new technology) then the within effect should dominate. Alternatively, if implementing new technology can only be accomplished via entry then the net entry terms should dominate. Reallocation among continuing plants may contribute positively to industry growth to the extent that the implementation of new technology at continuing plants involves experimentation and associated reallocation. Note as well that idiosyncratic shocks will tend to generate offsetting between and cross terms for continuing plants.

The decomposition of aggregate productivity growth into these components is interesting but only the first step. As will become clear below, we pursue a number of exercises to explore the factors underlying the respective contributions of continuing versus entering and exiting establishments to aggregate (industry level) productivity growth.

2.3 The Interaction Between Conceptual and Measurement Issues

The measure of labor productivity that is commonly used for retail trade is real sales per worker or real sales per hour. Before proceeding with the details of the measurement and subsequent analysis of this measure, it is useful to consider the potential sources of variation between and within establishments in this measure. For this purpose, we sketch a simple descriptive model that focuses on the measurement issues and then relate it to the above discussion of the literature.

Suppose establishment *e* in period *t* has output given by:

$$Q_{et} = A_{et}(L_{et} - f_e)^{\theta} \tag{3}$$

where Q_{et} is output, A_{et} reflects a variety of factors (discussed below) that impact labor productivity, L_{et} is the labor input, f_e is overhead labor, and θ is a positive parameter ($\theta<1$).[5] We want to think of A_{et} broadly

[5] This simple production function should be interpreted as having maximized out the other variable factors (e.g., intermediate inputs, which in the case of retail include the goods sold) and treating the fixed and quasi-fixed factors (e.g., location, capital) as contributing to the shift factor A. That is, suppose the primitive production function specifies output as a function of capital, materials (in this case including the goods sold), and labor. Suppose we treat capital as fixed and thus just include the

as incorporating many potential factors including the level of productivity associated with the installed technology , technology shocks, and fixed and quasi-fixed factors like location and capital (both tangible and intangible). Location is obviously important in retail trade and so it is useful to think about A_{et} as reflecting the myriad factors which impact the efficiency of a particular location as a place in which to operate a retail establishment. The presence of such fixed and quasi-fixed factors justifies the assumption that $\theta<1$.

One of the key assumptions made here is the presence of overhead labor. This assumption is not novel, the specification of the production function here is identical to that of Aghion and Howitt (1994), but we believe it is especially applicable in the current context. For retail trade establishments in particular, some workers must be present even if no transactions are actually occurring. Put simply, some workers must be present to open up the doors in the morning and to be available during business hours to conduct transactions regardless of whether any transactions are occurring. Moreover, since the typical retail establishment is quite small (more on this below), the role of overhead labor is arguably especially important in retail trade.

Labor productivity is thus given by:

$$LP_{et} = \frac{A_{et}(L_{et} - f_e)^{\theta}}{L_{et}} \qquad \textbf{(4)}$$

contribution of capital as a shift factor absorbed in A. Moreover, treating materials as a variable factor of production and using the first order condition for materials we can substitute out for materials. All shift variables that impact materials (e.g., the cost of materials) are also absorbed in A. Note that A is a combination of technology, cost, and fixed factors. Note also that θ will reflect the underlying labor share and other terms after substituting out for optimal materials.

Suppose at least initially we assume that all establishments in the same industry are price takers.[6] If establishments can adjust labor costlessly and continuously, establishment specific differences in A_{et} will be reflected in both differences in size and in labor productivity (given the presence of overhead labor). That is, optimal frictionless employment is given by:

$$L_{et} = f_e + (\frac{p_t A_{et}\theta}{w_t})^{\frac{1}{1-\theta}} \qquad \textbf{(5)}$$

where p_t is the price of the output and w_t is the wage (both presumed to be the same for businesses in the same industry for now). Within the same industry, establishments with larger values of A_{et} will have larger employment. Labor productivity with optimal frictionless employment will be given by:

$$LP_{et} = \frac{(\frac{p_t\theta}{w_t})^{\frac{\theta}{1-\theta}}}{(\frac{p_t\theta}{w_t})^{\frac{1}{1-\theta}} + f_e A_{et}^{\frac{1}{\theta-1}}} \qquad \textbf{(6)}$$

The presence of overhead labor implies that establishments with higher A_{et} will have higher productivity (that is differences in A_{et} will not simply be reflected in differences in size even with employment at its frictionless level).

There may be a variety of frictions that prevent businesses from being at the optimal frictionless employment such as adjustment costs. Thus, at any given point in time, we are likely to see greater dispersion in productivity than suggested by equation (4). In turn, some adjustments will be induced by the departure from optimal frictionless employment. As such, even from this simple descriptive model,

[6] The implications of product price differences across establishments in the same industry are discussed in Section 2.4. As we note, many of the implications we emphasize carry over to this case.

some predictions emerge linking reallocation to productivity differences for continuing businesses. Businesses with high productivity will increase employment and businesses with low productivity will decrease employment. In addition, for such continuing businesses, there will be a negative covariance between changes in employment and changes in labor productivity given the decreasing returns ($\theta<1$).

The connection between reallocation and aggregate productivity growth is likely to be closely connected to entry and exit dynamics in this environment. To consider entry and exit dynamics, we need to think about the incentives on both margins and their respective interaction. Businesses will exit when the value of continuing operations at the existing location is negative. On the flip side, businesses will enter until the expected discounted value of profits equals the cost of entry (assumed positive). The presence of the fixed costs of production (as captured here via overhead labor) implies that low productivity plants will exit. New businesses will have incentives to enter to replace the exiting businesses. The precise incentives for entry depend upon assumptions about the nature of shocks, uncertainty, and the growth and adoption of new technologies. One obvious way to obtain a clear prediction regarding the contribution of entry and exit to aggregate growth is to assume that only entering businesses have access to the latest technology as in Aghion and Howitt (1994) and Caballero and Hammour (1994).[7]

As noted in the discussion in earlier sections, this type of vintage model could be enhanced by assuming uncertainty about type/ability at entry so that even though new businesses are the only ones who have access to the latest technology, some businesses may be more capable of implementing the new technology than others. In addition, there may be learning-by-doing associated with the new technology.

[7] In an Aghion and Howitt (1994) or Caballero and Hammour (1994) environment, the growth in the productivity of the leading edge technology implies that the production real wage (wages divided by the industry output price) will be growing over time. New businesses will enter to take advantage of the new more productive technology. Existing businesses will contract and eventually exit (e.g., when they hit zero value) as they age since they face ever increasing real wages over time but no access to the leading technology.

Uncertainty about types and learning can imply that, even though new businesses have access to the latest technology, entering businesses do not have higher average productivity than incumbents. Some of the new businesses will not be very good at implementing the new technology and fail. Even successful new businesses may take time to learn how to implement the new technology. Such selection and learning effects for any wave of entrants can enhance the connection between reallocation and productivity growth.

A modification of the view that new technology can only be implemented by new businesses is the view that new technology is embodied in capital that is quasi-fixed (which in principle could be either tangible physical capital or intangible organizational capital). This closely related view implies that reallocation across existing businesses may be closely linked to aggregate industry growth. Consider a new technology that will lead ultimately to industry-level productivity growth. Analogous to the impact of uncertainty on new businesses, if there is uncertainty about type/ability regarding the adoption of new technology by existing businesses then only some businesses may be successful in implementing the new technology. As such, resources will be reallocated to those who successfully implement and away from those who implement poorly. Thus, it may be that each new wave of innovations and implementation unleashes reallocation dynamics among existing businesses that are productivity enhancing.

In short, this simple description of plant-level labor productivity helps illustrate the potential connections between industry-level productivity growth and reallocation. As should be clear, industry-level productivity growth could reflect common technology shocks (or analogously common adoption of new technologies) that are shared by all businesses in the sector so that reallocation dynamics are not particularly important. Alternatively, reallocation dynamics may be vital for productivity growth if, for example, new technologies can only be implemented by new businesses and or implementation of new technologies is inherently a noisy one with much trial and error (and associated success and failure). In the empirical analysis that follows, we will quantify the extent of and contribution of such reallocation dynamics to industry-level productivity growth.

2.4 An Interesting Complicating Factor: Idiosyncratic Prices

An interesting and related complicating factor in theory and practice in measuring establishment-level productivity is that establishments may have different output prices. Such price differences may reflect differences in product quality which we want to include in our measured differences in productivity across businesses. However, product price differences may also reflect some degree of market power and, if so, idiosyncratic demand and technology shocks will be associated with variation in prices. This may be especially appropriate in retail as one might think of the location of the product yielding a differentiated product market structure. To consider this idea in this context, suppose that the establishment-specific demand is given as follows:

$$p_{et} = \delta_{et} Q_{et}^{-\eta} \tag{7}$$

where p_{et} is the price of output, δ_{et} is a demand shock, and η is a positive parameter (where η<1 will be assumed consistent with the related product differentiation models such as that of Melitz (2000)). Such establishment-specific demand factors complicate not only matters conceptually but also practically since establishment-level prices are not readily available. Measured labor productivity for an establishment in an industry is typically establishment-level revenue deflated with an industry-level deflator divided by labor input. Under this specification, measured labor productivity (at frictionless employment) is given by:

$$LP_{et} = \frac{\left(\frac{\alpha}{w_t}\right)^{\frac{\alpha}{1-\alpha}}}{p_t\left(\frac{\alpha}{w_t}\right)^{\frac{1}{1-\alpha}} + p_t f_e \delta_{et}^{\frac{1}{\alpha-1}} A_{et}^{\frac{1-\eta}{\alpha-1}}} \qquad \textbf{(8)}$$

Actual labor productivity is given by:

$$(Actual)LP_{et} = \frac{\delta_{et}^{\frac{\theta-1}{1-\alpha}} A_{et}^{\frac{\eta}{1-\alpha}} \left(\frac{\alpha}{w_t}\right)^{\frac{\theta}{1-\alpha}}}{\left(\frac{\alpha}{w_t}\right)^{\frac{1}{1-\alpha}} + f_e \delta_{et}^{\frac{1}{\alpha-1}} A_{et}^{\frac{1-\eta}{\alpha-1}}} \qquad \textbf{(9)}$$

where $\alpha=\theta(1-\eta)$.

Comparing and contrasting equations (8) and (9) (and equation (6) in the prior section) is useful. Both actual and measured labor productivity will reflect differences in efficiencies and demand shocks (even with fully flexible labor). As in the prior section, the primary reason that there are persistent differences in measured and actual productivity across plants is the presence of overhead labor. Businesses with higher efficiencies and greater demand will be larger which (over some range) raises productivity in the presence of overhead labor.[8]

It is apparent from equations (8) and (9) that actual and measured productivity are closely related.

[8] Interestingly, in the absence of overhead labor, idiosyncratic differences in demand and technology will yield differences in actual productivity but not measured productivity. This is because the establishment is not setting the value of marginal product of labor equal to the wage but rather the marginal revenue product equal to the wage. As such, demand and technology changes induce changes in labor demand that in turn generate fluctuations in output per unit of labor even without overhead labor. However, since firms set the marginal revenue product of labor equal to the wage, in the absence of overhead labor there will be no differences (in the long run) in measured productivity across firms.

In order to gauge the precise relationship between actual and measured productivity we did a simple calibration exercise. We attempted to choose parameters that seem reasonable and match some of the characteristics of the data for this purpose. The parameters we had to choose include θ, η, f_e, w, and the mean and variances of the demand and technology shocks (we assumed the two types of idiosyncratic shocks are uncorrelated). We let η=0.2 implying an elasticity of -5 and a markup of 25 percent and θ=0.67 where both are within ranges of parameter estimates in the literature (see, e.g., Betancourt and Gautschi (1993) and Betancourt and Mlanoski (1999)). Recall that θ is the parameter that emerges after optimizing out the other variable factors of production. If we assume that the labor share of gross output is 0.4 and the intermediate input share is 0.5 then with an η of 0.2 we obtain θ=0.67. We selected the remaining parameters to match two of the features of the data (for details about the data see the subsequent sections): the average size of a retail establishment is 13.8 employees and the interquartile range of log measured productivity is 0.57. To accomplish this, we set $f_e = 5$ and the standard deviations of the (log of) demand and technology shocks equal to each other at 0.2. For this exercise, we used three states for both of the shocks with a simple uniform distribution. The resulting series for the nine possible outcomes (three demand x three technology states) are plotted in Figure 1. In a crude fashion, one can think of each of the points representing a different establishment outcome depending upon the state of demand and state of technology at the establishment. The correlation between the actual and measured productivity is quite high at 0.80 (the correlation is between log actual and log measured to stay consistent with our analysis). A couple of features of the two series are interesting to note. First, measured productivity is more highly correlated with demand shocks than actual productivity (0.80 versus 0.15) and measured productivity is less highly correlated with technology shocks than actual productivity (0.61 versus 0.97). Second, the standard deviations of the two series are virtually identical (0.44 for log measured or actual productivity).[9]

The first conclusion of this section, therefore, is that the presence of overhead labor yields a close connection between measured and actual labor productivity even in the presence of idiosyncratic prices. For our purposes, it is also important to emphasize that the distribution of measured labor productivity is likely to exhibit similar dynamics to those described in Section 2.2. That is, frictions in the adjustment of employment will imply differences in measured labor productivity that in turn yield incentives for adjusting employment. Businesses with high measured productivity will expand and businesses with low measured productivity will contract. In addition, businesses with low measured productivity will be more likely to exit as they will be unable to cover their fixed costs. The connection between micro and industry level productivity dynamics is likely to be similar in this context as well. For example, if new technology can be implemented only by new businesses, then measured industry productivity growth will be associated with entering businesses displacing lower measured productivity exiting businesses. Thus, many of the inferences to be drawn from our analysis based upon the homogenous price case still apply in this more complicated environment.

To conclude this section, it is worth emphasizing a point made by Melitz (2000). If BLS does have the appropriate market-share weights across firms, then its price index at the industry level is correct

[9] These patterns are mildly sensitive to parameter variation. For example, the correlation between measured and actual productivity (ρ) takes on the following values for different parameter choices: when θ=0.5 then ρ= 0.78, when η=0.1 (thereby increasing the elasticity) then ρ=0.62, when f_e =3 then ρ=0.69, when the variance of demand shocks=0 then ρ=0.999, and when the variance of technology shocks=0 then ρ=0.94. In short, for the case we examine and these reasonably large departures from the base case, actual and measured productivity are highly correlated. While these are relatively crude calibrations, these findings provide some degree of confidence that our measured productivity is providing information about the true variation in productivity. In this environment, the measurement error is not random and measured productivity is likely to be a better predictor of entry and exit than actual productivity because it is more closely related to profits (in this example, measured productivity has a correlation of 0.9 with profits and actual productivity has a correlation of 0.7). It is worth emphasizing that these conclusions depend critically on the presence of at least some overhead labor. As is clear from equation (7), in the absence of overhead labor there would be no differences across businesses in measured productivity (with frictionless labor).

and the official BLS productivity measure would be correct even if there are differences in prices across firms.[10] In what follows, we show that our industry-level measures correspond closely to those of BLS. This implies that components of our decomposition (2) aggregate to the correct measure of industry level productivity growth even in the presence of idiosyncratic prices.

Putting the pieces together provides a reasonable degree of confidence about the measurement and methodology used here. With homogenous prices within narrowly defined sectors as in Section 2.3, the measures at the micro and industry level are correct. With heterogenous prices within narrowly defined sectors, if these differences reflect differences in quality across producers then our measurement is correct. Regardless, our industry level measure of productivity growth is still correct and therefore the components of our decompositions still aggregate to the correct measure. Moreover, even with heterogeneous prices, we have shown that the connection between measured and actual productivity at the micro level is still likely to be strong. Perhaps even more importantly, the observed dynamics of measured productivity at the micro level should exhibit the same types of patterns (e.g., reflecting adjustment dynamics, learning and selection effects) that we hypothesized in Section 2.3 .

3. Data Issues

The empirical analysis in this paper uses data from the Census of Retail Trade (CRT). Every five years (those ending in ‘2' and ‘7’), the Census conducts a survey of retail trade establishments. The survey

---

[10] It is worth noting that official BLS productivity statistics at the industry-level also suffer from some aspects of these biases induced by within-industry product differentiation to the extent that the product differentiation occurs within the most disaggregated product classes underlying BLS gross output series. We note in this regard that BLS has used data at the merchandise line level to construct their gross output indices and thus may be less subject to these biases at the industry level. Since our industry-level productivity measures that use only 4-digit industry deflators (rather than merchandise line deflators) align closely with BLS series, this suggests that either these biases are small and or they occur mostly within merchandise lines.

questionnaire is mailed out to all large and medium-sized firms and generally all firms that operate multiple establishments; most very small firms are excused from answering the questionnaire. The data for these very small firms come from two sources: a Census sample of these very small firms and administrative records from other federal agencies. We use both reported data and administrative data in our empirical exercises because there is no reason to suppose that the administrative records data are inferior to the reported data for the variables being used in this study.[11]

The CRT contains data on establishments concerning the kind of business, physical location, sales in dollars, annual and first quarter payroll, and employment for the pay period including March 12th. In addition, the mail segment of the CRT includes some industry-specific data and sometimes other special interest data. For our purposes, the relevant point is that while it is possible to construct measures of labor productivity, it is not possible to measure multifactor productivity. The index of establishment-level labor productivity used here is similar to that used in the literature and is given by:

$$lnLP_{et} = lnQ_{et} - lnL_{et}, \qquad \textbf{(10)}$$

where Q_{et} is real gross output and L_{et} is labor input (total hours) for establishment e at time t. We are constrained by the data to use sales as our measure of nominal output. A preferable measure of output for the retail trade sector might be gross margins (total sales less the cost of goods sold). However, it is worth noting that this is the same measure of output used by the BLS in their measures of productivity for the retail trade sector.[12] We deflate sales using BLS' four-digit industry deflators (see the Data Appendix for

[11] These administrative records cases accounted for about 10 percent of total sales in 1987, 1992, and 1997. See the Data Appendix for the precise categories of administrative records cases by year. The percent of administrative cases for 1997 is based on the North American Industrial Classification System (NAICS) version of the retail trade sector.

[12] The output statistics that the Bureau of Economic Analysis (BEA) produces (as opposed to BLS) use a gross margins adjustment. However, as noted by Triplett and Bosworth (2001) the BLS sales based and BEA gross margin based measures are very similar. The reason is that the gross margin adjustment that is applied does not vary much over time and is at a high level of aggregation. Part of the

more details about data from BLS). In measuring the labor input, we again face data constraints because the CRT does not collect hours information. Instead, we construct manhours at the establishment level by multiplying establishment employment by the industry average of hours as measured by BLS.[13]

Our empirical exercises use data from 1987, 1992, and 1997 since these are the years for which we are able to link establishments over time (see the Data Appendix for discussions regarding the creation of the longitudinal links). There are approximately 1.5 million establishments in the retail trade sector employing close to 20 million workers and generating close to $2 trillion in sales on average for these three census years.[14] We focus on productivity dynamics for 1987-97 period and for the two five-year subperiods (1987-92 and 1992-97). Using the two five-year periods allows us to study the dynamics of an entering cohort. In particular, we are able to track the behavior of establishments that enter between 1987 and 1992 by examining their behavior in both 1992 and 1997 (including the possibility that the establishment does not survive until 1997).

Since the CRT data have not been extensively used and our methodology is based on aggregating micro data, it is helpful to compare the productivity measures based on the Census data to those officially published by the Bureau of Labor Statistics. The Data Appendix describes this comparison detail. In short, we find that our overall average productivity growth rates are quite similar and that the correlation between the BLS and Census industry-level productivity growth rates is quite high (0.80).

Before proceeding it is important to emphasize that the unit of observation in the analysis is primarily the establishment. An establishment is defined as a physical location at which economic activity

---

reason for this is that detailed data on gross margins (e.g., at a merchandise line level) are not collected.

[13] The adjustment for hours is obviously crude at best. This adjustment should be interpreted as a means of controlling for detailed industry and time variation in hours per worker. We have conducted all our analyses without this adjustment (so our measure of labor productivity is output per worker) and we obtain very similar results. We find that we match the BLS levels and trends by industry somewhat better by incorporating the hours adjustment.

[14] All of the empirical work in this paper is based on the retail trade sector as defined by Standard Industrial Classification (SIC) system.

is occurring. We can also link the establishments in our data to their parent firms. In the analysis that follows, we find it helpful at times to distinguish between entering establishments of new firms (typically single-unit entrants) and entering establishments of continuing firms. In a like manner, we distinguish between exiting establishments of exiting firms (again, typically single-units) and exiting establishments that belong to continuing firms.

4. Characteristics of the Productivity Distribution

In this section, we present basic facts about the shape and evolution of the distribution of productivity across businesses. We begin by simply characterizing the differences in labor productivity across businesses in the same narrowly defined industry. For this purpose, we examine the percentiles of the labor productivity distribution across businesses after removing four-digit industry fixed effects. The measure we use for this purpose is the log of output per hour at the businesses and we consider the hours-weighted distribution of this measure.[15] By construction (since the four-digit effects have been removed), the distribution has a zero mean. The standard deviation and the interquartile range of this distribution are very large and stable: the standard deviation is about 0.54 and the interquartile range is about 0.57 for all three years. It is striking that within the same industry some businesses are so much more productive than others and that this dispersion is quite stable over this time period. The latter of course does not mean that individual businesses are stable within this distribution. Indeed, much of our analysis is devoted towards examining the churning of businesses within this distribution including the role of entry and exit.

We begin our analysis of the dynamics of establishment-level productivity by examining the transition of individual businesses in the overall distribution of productivity over the 1987-97 period. In each of the years under consideration, we classify establishments into quintiles of the hours-weighted

[15] We have also examined this distribution for output per worker and find very similar results.

labor productivity distribution. We can thus look forwards or backwards in terms of where the establishments in 1987 end up or where the establishments in 1997 came from. Since we have removed four-digit industry effects from each year, the quintiles should be interpreted as capturing relative productivity *within* the four-digit industry.

The transition matrix is shown in Table 1. The most striking feature of Table 1 is the large role of births and deaths. For any quintile in 1987, the most likely outcome (row percentage) is death. For any quintile in 1997, the most likely origin (column percentage) is birth. Interestingly, births arrive uniformly throughout the productivity distribution. In contrast, deaths are concentrated in the businesses with low productivity in 1987. For example, 70.3 percent of businesses in the *lowest* quintile in 1987 did not survive until 1997, while in contrast, only 39.2 percent of businesses in the *highest* quintile in 1987 did not survive until 1997. While the latter probability of death is large in absolute terms it is much smaller than the probability of death for the least productive businesses.

Conditional on survival, substantial persistence is exhibited by individual businesses in terms of the relative productivity rankings. Businesses in the top quintile in 1987 had a 26.5 percent chance of staying in the top quintile in 1997 but only a 4.9 percent chance of moving to the bottom quintile. Likewise businesses in the lowest quintile in 1987 had a 12.8 percent chance of staying in the lowest quintile in 1997 but only a 2.8 percent chance of moving to the highest quintile.

Comparing these results with analogous results for U.S. manufacturing establishments reported in Baily, Hulten and Campbell (1992), reveals a number of similarities but also a number of differences. Baily, Hulten and Campbell (1992) find a higher degree of persistence (see their Table 3) but part of this reflects much lower turnover of businesses in manufacturing as opposed to retail trade. That is, conditional on survival, the persistence rates are not so different between manufacturing and retail trade. The large difference, however, is that survival is much less likely in retail trade and it is closely linked to productivity.

It is evident from Table 1 that there is considerable turnover of businesses and associated reallocation of jobs. To examine these issues more directly, Table 2 presents estimates of the gross expansion and contraction rates of employment over the 1987-97 period (and the subperiods 1987-92 and 1992-97).[16] The rates of 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).[17] The pace of gross input expansion and contraction is extremely large over the ten-year horizon. Expanding plants yielded a gross rate of expansion of 69.2 percent of inputs and contracting plants yielded a gross rate of contraction of 54.6 percent of inputs over 1987-97. The importance of entry and exit are evident in the lower panel of the table, where one sees that 84 percent of the input gross creation from expanding plants came from entry of establishments and 82 percent of the input gross destruction came from exit of establishments over the ten-year period.

Table 2 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 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)[18] excess reallocation rates for the entire retail trade sector can be decomposed into within and between sector effects. The far right column of the upper panel

---

[16] We have also looked at the gross reallocation rates for real output. The reallocation patterns for real output are qualitatively similar to the patterns that we report here concerning employment. The net growth rate of output is higher than that of inputs (especially employment) reflecting the productivity growth over this period.

[17] 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.

[18] See pages 52 and 53 for a description of the methodology.

of Table 2 indicates that most of the excess reallocation at the retail trade level reflects excess reallocation within four-digit industries. Thus, the implied large shifts in the allocation of employment are primarily among producers in the same four-digit industry. This finding is especially noteworthy since there are large differences in the net growth rates across four-digit industries – however, apparently, these are dwarfed by the pace of reallocation within the four-digit industries.

Given the very large rates of establishment entry and exit, it is of interest to know how much of the entry and exit of establishments reflects entry and exit of *firms* as opposed to entry and exit of *establishments* for continuing firms.[19] The lower panel of Table 2 shows the share of total creation from new establishments due to new firms and the share of total destruction from exiting establishments due to exiting firms. The share of job creation due to establishment entry from new firms is greater than half, but establishment entry from continuing firms is clearly an important contributing factor. On the exit side, exiting firms account for three-quarters of the job destruction from exiting establishments, but again exiting establishments of continuing firms play a non-trivial role. We can quantify the overall contribution of reallocation across establishments within firms by decomposing excess reallocation into within-firm and between-firm components. For this purpose, we consider not only the reallocation due to entry and exit but also reallocation among continuing establishments. The last column of the lower panel of Table 2 shows that roughly 20 percent of excess reallocation is due to the reallocation of employment across establishments within firms.[20]

---

[19] Jarmin, Klimek, and Miranda (2001) focus on *firm* entry and exit in retail trade and find that the entry and exit rates of firms are substantially larger in retail trade than in manufacturing. However, they include firm diversification in their definition of entry and so their results are not directly comparable to ours.

[20] We use the same form of the decomposition used to decompose excess into within- and between-industry components. That is, we measure within-firm excess reallocation for each firm as the sum of within-firm creation and destruction less the absolute value of the net growth rate of the firm. We aggregate this across firms with appropriate employment or output weights. We measure the between-firm component as the sum of the deviations of each firm's absolute net growth rate and the overall absolute net growth rate. See Davis, Haltiwanger and Schuh (1996) for further details of this

Table 2 also shows the analogous results for the subperiods 1987-92 and 1992-97. The rates of expansion exceed 40 percent for inputs and the rates of contraction exceed 35 percent in both subperiods. The implied cumulative change from the two five-year horizons is larger than the actual ten-year change reflecting the fact that some of the five-year changes reflect transitory movements. The shares of expansion accounted for by births and the shares of destruction accounted for by deaths are extremely high (accounting for around three-quarters for both for each subperiod).

We have also calculated the gross contraction and expansion rates by establishment size class (defined as the average of beginning and ending year employment). The pace of reallocation and excess reallocation fall systematically with the size of the business in all years. For example, the excess reallocation rate for 1987-97 is roughly 170 percent for the smallest size class (1-4 employees) but is only roughly 60 percent for the largest size class (over 50 employees). Part of this difference is driven by the extremely large entry and exit rates for small businesses – we observe a very high fraction of creation accounted for by entrants (about 96 percent) and an analogously high fraction of destruction accounted for by exits (roughly 96 percent) for the smallest establishments for 1987-97. As with reallocation rates, these fractions fall for the largest size classes. For the largest size class of establishments, births account for only about 73 percent of the jobs created and deaths account for only about 55 percent of jobs destroyed. The two subperiods show similar patterns. Interestingly, net growth rates are actually increasing functions of the size of the establishment. For each of the three time periods, the smallest establishment class has negative net growth, while the largest establishment class has positive net job growth rate and the highest net growth of all the size groups. Since the majority of workers in retail trade work for employers with fewer than 50 employees, these patterns help account for the rapid pace of output

methodology. Doms, Jarmin, and Klimek (2001) decompose employment changes into those accounted for by continuing firms and by net entry of firms. Since they decompose net employment and use a different definition of firm, their results are not directly comparable to ours. In their paper they explore the role of information technology investment on the growth and productivity dynamics of firms.

and employment reallocation and the dominant role of entrants and exits seen in earlier results. Many studies (see the survey in Davis and Haltiwanger (1999)) have shown that the pace of reallocation as well as entry and exit rates are sharply decreasing functions of employer size.

Finally, we also measured the gross contraction and expansion rates by two-digit industry. The pace of reallocation also varies substantially across the two-digit industries. Apparel and furniture stores, for example, have especially high paces of job reallocation with gross creation and destruction rates roughly between 50-80 percent and excess reallocation about 100 percent. Industries with relatively low rates of job reallocation include general merchandise stores and food stores. General merchandise has particularly low creation and destruction rates (roughly 30-50 percent) and excess reallocation rates (about 50-80 percent).[21] In all industries, entry and exit play a very large role with about three quarters of creation (destruction) accounted for by entry (exit) over a ten-year horizon.

Overall, retail trade is a sector that has exhibited tremendous turbulence. There are substantial differences in the net growth rates across two-digit industries but these are dwarfed by the gross rates of reallocation. The large differences between net and gross rates helps account for the finding in Table 2 that much of the reallocation is within as opposed to between industries. Comparing the results here with those reported in Foster, Haltiwanger and Krizan (2001) reveals that retail trade gross flows are about 50 percent larger than those in manufacturing with a higher share of the flows accounted for by entry and exit. A key factor here is that retail trade is a sector dominated by small businesses both in terms of number of establishments and numbers of workers at those establishments. Moreover, we find that the smallest establishments within retail trade exhibit disproportionately large reallocation and associated entry and exit rates. We also find that much of the establishment entry and exit is associated with firm

[21] We look at some of the four-digit industries within this major industry group in Section 7. We find that the creation and destruction rates look very different for two of the major industries in this group, Miscellaneous General Merchandise Stores and Department Stores.

entry and exit but a non-trivial fraction is accounted for by entry and exit of establishments among continuing firms. Finally, and quite importantly, we find that virtually all of the reallocation is a within-industry phenomenon. As such, the standard approach of measuring change and growth at the four-digit level will miss much of the action and it is impossible with such data to capture the contribution of reallocation to productivity growth.

5. Productivity Decompositions

The large differences in productivity across businesses in the same sector and the large within-sector reallocation rates motivate our analysis of productivity decompositions at the four-digit level. We apply the decomposition in equation (2) at the four-digit level. For this purpose, we use the labor input (total hours) share weights. For labor productivity, the seemingly appropriate weight is employment (or 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. 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 nominal gross output by industry averaged over the beginning and ending years of the period for which the change is measured. The same industry weights are used to aggregate the industry results across all of the decompositions because the focus is on within-industry decompositions. By using the same weights, the results do not reflect changing industry composition.

The decompositions of labor productivity are reported in the upper panel of Table 3.[22] For all

[22] We have conducted all of the analysis in the paper on productivity decompositions and associated regressions using output per worker as an alternative measure. In general, the results are very similar between these two alternatives. In addition, due to concerns about the data, we also performed

time periods, we find that reallocation effects account for the majority of changes in labor productivity. That is, the within-establishment contribution is substantially less than half for each of the five-year changes and less than 20 percent for the ten-year change. In considering the role of reallocation effects, the contribution of net entry is enormous accounting for virtually all of the overall change in all three time periods. Moreover, the between-establishment contribution is positive and significant as well. The within, between, and net entry effects add up to more than the total because the cross term among continuing establishments reduces labor productivity over these periods. The sign of the cross term reflects a negative covariance between labor productivity and employment changes. The offsetting nature of the between and cross terms is consistent with the view that idiosyncratic productivity shocks induce changes in size and that such changes in size in turn induce productivity changes given within-establishment decreasing returns. The negative cross term is also consistent with the view that downsizing has been productivity enhancing over this period for continuing establishments. Putting all of this together suggests that the average establishment exhibited modest productivity growth over the period, reallocation played a dominant role primarily due to net entry but also because output and employment were reallocated towards establishments who had higher than average productivity at the beginning of the period, and establishments that downsized tended to exhibit increases in productivity (the negative cross term).

To shed further light on these results, the lower panel of Table 3 presents components of the net entry term. As can be seen, the large positive contribution of the net entry term is primarily due to a very large contribution from exit although there is a relatively modest positive contribution from entry. Interestingly, the positive contribution of entry is mostly coming from entering establishments of existing firms -- the contribution of entering establishments from new firms is positive over the 10-year horizon but negative for the five-year horizons. In contrast, the large contribution of exit is mostly coming from

---

these decompositions excluding establishments in the computer store industry. The results of the decompositions are qualitatively similar to those using establishments in all industries.

exiting establishments of exiting firms. Note that the contribution of net entry to productivity is disproportionate to net entry's size in terms of employment (not shown in the table).

This disproportionate contribution of net entry can be understood by examining the relative productivities of entering versus exiting establishments. To shed further light on the role of net entry, we ranked groups of establishments in terms of their productivity relative to continuing establishments in 1987. We find the following rank ordering of productivity (the numbers in parentheses show the productivity of the group as a percent of that for the baseline group): continuing establishments in 1997 (101%), continuing establishments in 1987 (100%), entering establishments (95%), and exiting establishments (78%). Focusing on the net entry groups, we further find the following ranking (again relative to 1987 continuers): new establishments of existing firms (111%), new establishments of new firms (93%), exiting establishments of continuing firms (89%), and exiting establishments of exiting firms (75%).

Before proceeding to the next section, it is worthwhile to compare the findings presented here for retail trade with the prior literature that focuses on manufacturing. The primary difference is that in manufacturing net entry was part of the story while in retail trade it appears to be almost the entire story. The retail trade industry would have exhibited no (or even negative) productivity growth without the contribution of net entry.

6. Learning and Selection Effects

The results reported in Section 5 make clear that entry and exit dynamics dominate the productivity growth for the retail trade sector. By exploring the differences in productivity dynamics between incumbents, entrants and exiting establishments in more detail, we can provide a richer picture of the role of learning (by doing) and selection effects that underlie these dynamics. We use the term "learning" effects broadly in this context to include any "learning" about how best to run the business at the specific location. An example might be learning how to more efficiently serve customers at the specific location of the retail establishment. As such, we are using learning as a short-hand for learning-by-doing. The selection effects we identify also inherently involve a form of learning as well. That is, as discussed in Section 2 businesses may be uncertain about their efficiency, learn about their relative efficiencies over time, and those that learn they are poor performers exit.

We begin by considering a simple regression of (the log of) productivity on a set of dummies indicating whether the establishment exited in 1987 (YRDEA87), entered in 1997 (YRBIR97), a year effect to control for average differences in productivity across the two years (YR97), and four-digit industry dummies (not reported) using the pooled data .[23] The omitted group is continuing establishments in 1987 so the coefficients can be interpreted accordingly.[24] The specification is given by:

$$P_{et} = \psi + \beta * YRDEA87_{et} + \delta * YRBIR97_{et} + \phi_i \sum_{i=1}^{63} Industry_{iet} + \upsilon * YR97_{et} + \epsilon_{et} \quad \textbf{(11)}$$

The results of this regression, shown in the upper panel of Table 4, confirm earlier results and help quantify statistical significance: exiting establishments have significantly lower productivity than continuing establishments, establishments in 1997 have significantly higher productivity than establishments in 1987, and entering establishments in 1997 have lower labor productivity than continuing

[23] 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.

[24] Care must be taken when interpreting the coefficient on the entry dummy (δ). This coefficient shows how entering establishments compare to incumbents *abstracting* from the overall growth. In order to compare births in 1997 to the incumbents in 1987, one must also consider the year effects (i.e., look at $\delta+\nu$). Thus entering establishments in 1997 are more productive than incumbents in 1987 ($\delta+\nu>0$), but less productive than incumbents in 1997 ($\delta<0$).

establishments in 1997. Also reported in the upper panel is the F-test on the difference between entering and exiting establishments which is highly significant, even after controlling for year effects. We also examine the significance of net entry for the five-year changes using analogous regression specifications. Interestingly, the patterns for the five-year changes regarding the differences between entering and exiting establishments are similar to those for the ten-year period. In particular, we observe that entering establishments have higher productivity than exiting establishments even while controlling for year effects ($\delta>\beta$). There are differences across the periods as the average continuing establishment exhibited productivity declines in 1987-92 ($\nu<0$) but modest productivity gains in 1992-97 ($\nu>0$). We know from Table 3 that both periods exhibited overall productivity gains. As is clear from Table 4, this comes overwhelmingly from the contribution of net entry and in particular from the exit of the least productive establishments.

The lower panel of Table 4 shows results where the impact of entry and exit is decomposed between continuing and entering and exiting firms. The rank ordering described in Section 5 emerges clearly. The least productive are the exiting establishments from exiting firms while the most productive (even after controlling for year effects) are entering establishments of continuing firms. It is also clear there are large differences in productivity between establishment entrants that are new firms versus those that are continuing firms and between establishment exits that are exiting firms and establishment exits that are part of continuing firms.[25] An interesting implication is that continuing firms have a higher productivity threshold for exit for an individual establishment than do non-continuing firms.[26]

---

[25] It may at first appear that there is a productivity premium to an establishment for being associated with a continuing firm. However, in unreported results we have found that for continuing establishments those that have switched their firm affiliation are on average substantially more productive. The causality for this latter finding may run in both directions.

[26] Since the non-continuing firms are dominated by single unit establishments, this finding may be related to the finding in Holmes and Schmitz (1992) that owner-managed businesses are less likely to exit than other businesses.

We next examine the dynamics of entering cohorts. We use essentially the same specification as above except now we classify entering establishments based on whether they entered between 1987-92 (YRBOLD97) or 1992-97 (YRBYNG97):

$$P_{et} = \psi + \beta * YRDEA87_{et} + \eta * YRBOLD97_{et} + \mu * YRBYNG97_{et} + \phi_i \sum_{i=1}^{63} Industry_{iet} + \upsilon * YR97_{et} + \epsilon_{et} \quad \textbf{(12)}$$

The results shown in the upper panel of Table 5 indicate that there are significant differences between the cohorts of establishments. Establishments that entered earlier have significantly higher productivity than establishments that entered later ($\eta>\mu$). These cohort effects could be driven by selection and or learning effects. The results could reflect that the entrants from 1987- 92 who make it to 1997 are more productive entrants (selection), or that the earlier entrants had more time to learn than the later entrants (learning).[27] We attempt to disentangle these effects later in the paper.

We also decompose these cohort effects into effects for new and continuing firms and show these results in the lower panel of Table 5. We find that for both cohorts, entrants from continuing firms have very high productivity relative to both incumbents in 1997 ($\eta^c>0$ and $\mu^c>0$) and other entrants ($\eta^c>\eta^b$ and $\mu^c>\mu^b$). On the other hand, establishment entrants that are new firms actually have lower productivity than incumbents in 1997 ($\eta^b<0$ and $\mu^b<0$). Thus we find that a continuing versus new firm effect plays a role here. However, interestingly, for either new or continuing firms, we find that the entrants from the earlier cohort have higher productivity than the entrants from the latter cohort holding the firm status constant ($\eta^c>\mu^c$ and $\eta^b>\mu^b$). Thus, selection and or learning effects seem to be playing a role for establishments of a new cohort whether the establishment is part of a continuing firm or is a new firm.

[27] Aw, Chen, and Roberts (2001) perform a related cohort analysis (but for Taiwanese manufacturers). They compare the productivity of the following pairs of groups: surviving and exiting firms of the same entry cohort, entrants and incumbents in the same year, entering firms in a cohort with recent exiters, and productivity of incumbents at the start date and at the end date.

The results from these two sets of regressions make clear the role of entry and exit but do not permit disentangling selection and learning effects. We shed some light on learning and selection effects via regressions that use additional information about establishments that entered between 1987-92. By dividing this entering cohort into exiters and survivors, we can characterize selection and learning effects. Thus in our specification we have dummies for those from the entering cohort who then die (ENTDEA), all other deaths (OTHDEA), and entering cohort that survive (SURV92 and SURV97) in addition to the usual birth, year, and industry dummies. The specification is given by:

$$P_{et} = \psi + \alpha * ENTDEA_{et} + \gamma * OTHDEA_{et} + \delta * YRBIR97_{et} + \theta * SURV92_{et} + \lambda * SURV97_{et} + \phi_i \sum_{i=1}^{63} Industry_{iet} + \upsilon * YR97_{et} + \epsilon_{et} \qquad \textbf{(13)}$$

Using this specification, we make three comparisons. First, for exits, we distinguish among exits in the 1992-97 period between those who entered during 1987-92 and those who did not (comparing α and γ). Second, among the entering cohort we distinguish between those that exit and those that survive to 1997 (comparing α and θ). Finally, for the surviving 1987-92 cohort, we also examine productivity in 1992 and productivity five years later (comparing θ and λ). The results are shown in Table 6.

Establishments that entered between 1987-92 and then exited are significantly less productive in 1992 than continuing incumbents in 1992 (who are not from that entering cohort, i.e., $\alpha<0$). Of exiting establishments, those that entered between 1987-92 are less productive in 1992 than other exiting establishments ($\alpha<\gamma$). The exiting establishments from this entering cohort are also less productive in 1992 than the surviving members of this cohort ($\alpha<\theta$). The latter findings are broadly consistent with selection effects since it is the less productive establishments from the entering cohort that exit .

The surviving members of the entering 1987-92 cohort are actually more productive than incumbents ($\theta>0$) even upon entry. Moreover, for the entering cohort, we observe significant increases in productivity over the five years ($\theta<\lambda$), even though we control for overall year effects. This pattern is consistent with learning effects playing an important role. It is noteworthy that once we have separately accounted for the learning of the entering cohort, there is essentially no productivity growth for incumbents between 1992 and 1997 who also were present in 1987 (ν=0). Put differently, much of the productivity growth from 1992 to 1997 is accounted for by the combination of the exit of the least productive establishments and the learning amongst the cohort of establishments that entered between 1987 and 1992.

We further decompose these selection and learning effects by controlling for new versus continuing firms in the lower panel of Table 6. We find that the establishments that exit from a recent cohort that are part of a new firm at entry have very low productivity (α^b is very low). Thus, the selection effects we have detected primarily reflect exit of establishments that are new firms. In contrast, we find that entering establishments of continuing firms have high productivity upon entry and exhibit substantial productivity growth after entry (θ^c is very high and $\theta^c < \lambda^c$). Thus, the learning effects for survivors appear to come primarily from new establishments in continuing firms. For surviving entering establishments of new firms, we find virtually no productivity growth ($\theta^b = \lambda^b$).

In sum, we find that net entry contributes disproportionately to productivity growth. The disproportionate contribution is associated with less productive exiting establishments being displaced by more productive entering establishments. 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. The selection effects are especially important for the exit of establishments from the entering cohort of new firms. The learning effects are driven entirely by the growth in productivity in the early years of entering establishments of continuing firms.

7. Results for Selected Industries

In all of the results presented thus far, we have controlled for four-digit industry effects but have reported the effects for the "average" retail trade industry. There is undoubtedly considerable heterogeneity in the technology, cost and demand variation across industries. In this section, we explore the results for three selected industries: Department Stores, Miscellaneous General Merchandise Stores (hereafter General Stores) and Catalog and Mail-Order Houses (hereafter Catalog Houses). We selected these three industries because they exhibited especially robust productivity growth over this period of time and anecdotal and descriptive evidence suggests that they experienced substantial structural change over this period of time. Before turning to the empirical exercises, we next briefly describe these industries.

The Department Stores industry has approximately 11,000 establishments generating 200 billion dollars in sales on average over the census years in this study. The industry has a relatively small and declining number of firms. There are less than 300 firms in any of the years under consideration. The industry has become more concentrated over the time period: the four-firm concentration of sales rose from 44 percent in 1987 to 53 percent in 1992 and continued to increase in 1997.[28] Sieling *et al* (2001) note that the Department Stores industry has shifted towards larger mass merchandise stores over this period and that this type of operation often has increased use of self-service operations.

The General Stores industry includes warehouse clubs, catalog showrooms, and similar discount houses. There are approximately 12,000 establishments in this industry generating 50 billion dollars in sales on average over the years in our study. The industry contains a relatively large number of firms, more than 5,000 in each of the three years, but the number of firms has been falling over time. The General Stores industry has also become more concentrated over time: the four-firm concentration of sales rose from 36 percent in 1987 to 58 percent in 1992 and rose further in 1997. The information technology revolution has played an important role in this industry through the management of inventories. These

[28] The concentration ratios for 1997 have been suppressed for disclosure reasons.

stores depend upon high volume of sales as they offer low prices on a wide range of goods and management of inventories is especially critical for these businesses. Sieling *et al* (2001) attribute much of the productivity growth in General Stores to advances in computer technologies. Dumas (1997) notes that warehouse clubs in particular exhibited rapid growth and changes in size, merchandise mix, and services provided.

Over the years of our study, the Catalog Houses industry had on average approximately 8,000 establishments generating 40 billion dollars in sales. In contrast to the other two industries, the number of firms has increased over the time period (from about 6,000 to 9,000) and the concentration has remained relatively low and constant over the period in question (the firm-four concentration of sales is about 16 percent). This industry is of particular interest as new e-commerce retail businesses would be classified in this industry over this period of time (although the amount of this might be limited by 1997). More generally, the IT revolution could potentially substantially change business practices in this industry via changes in telecommunications and computer technologies. Sieling *et al* (2001) site a study which finds that 95 percent of all catalog companies also sold on the internet.

The gross reallocation rates of employment over 1987-97 for these three industries are shown in Table 7. All three industries exhibited dramatic net growth in employment (21 percent for Department Stores, 25 percent for General Stores, and 50 percent for Catalog Houses). Moreover, large gross flows account for the net growth in all three industries. In both General Stores and Catalog Houses the employment creation rates are above 75 percent and the corresponding destruction rates are about 50 percent. The creation and destruction rates are lower for Department Stores, at about 55 percent and 35 percent respectively. Entry and exit dominate the gross flows in all three industries: shares of creation due to entrants range from 72 percent to 83 percent and shares of destruction due to exits range from 63 percent to 90 percent. These three industries exhibit substantially larger net flows than the average industry in retail trade (compare to Table 2). Moreover, General Stores and Catalog Houses have larger gross flows than the average industry.

The contribution of continuing versus non-continuing firms to net entry differs across industries. For the Department Stores and General Stores industries, a large fraction of the job creation from new establishments comes from continuing firms. For Catalog Houses, a much smaller fraction of the job creation from new establishments comes from continuing firms. This difference across industries in the importance of new firms may partially reflect differences in their structures. Single unit firms comprise a much larger fraction of sales and employment in Catalog Houses than in the other two industries. In General Stores and Catalog Houses, much of the job destruction from exiting establishments is associated with exiting firms. Exiting firms are not as important for Department Stores.

The decompositions of labor productivity per hour for 1987-97 are shown in Table 8. For Department Stores, overall productivity growth is strong (18 percent) and is accounted for equally by within establishment productivity contributions (56 percent) and net entry contributions (59 percent). The importance of the within share contrasts sharply with the other two industries, particularly for General Stores. Combined with the relatively lower creation and destruction rates for the Department Stores industry, this suggests that the reallocation of workers across establishments is not as important for productivity growth in Department Stores as it is for other retail trade industries. Notice also that Department Stores have the lowest productivity growth of the three industries. The contributions of entry and exit in terms of the impact of continuing and non-continuing firms are also shown in Table 8. Most of the contribution from births for Department Stores is due to births into continuing firms, while the contribution from exits are evenly divided between continuing and exiting firms.

For the General Stores industry, overall productivity growth is large and positive (23 percent) but the within-establishment contribution is substantially negative (-46 percent). Thus, more than all of the productivity growth in this industry is accounted for by reallocation, and in particular by net entry. Net entry accounts for 142 percent of the change in productivity. Combining the productivity and reallocation results, it is apparent that this industry exhibited huge between-establishment restructuring and that this restructuring had an enormous productivity payoff. While much of the restructuring is between establishments, it does not appear to be between firms on the creation side. The positive contribution of births is entirely from *continuing* firms, establishment births into new firms contribute negatively to productivity growth. The positive contribution of exits is due largely to exiting firms.

For Catalog Houses, the story is substantially different. For this industry, overall productivity growth is again very large and positive (39 percent) over 1987-97. However, while most of the increase in productivity is due to reallocation effects via net entry, about 30 percent is a within-establishment effect. In this industry, there is apparently substantial within and between establishment restructuring and both had substantial productivity payoffs. In marked contrast to the other two industries, the contribution of births is largest for births into *new* firms. Finally, the contribution from deaths for Catalog Houses is all from exiting firms since exits from continuing firms contribute negatively.

As before, we ranked groups of establishments in terms of their productivity relative to continuing establishments in 1987. Department Stores and Catalog Houses have the same rank ordering as the average industry: productivity relative to 1987 incumbents is higher for 1997 incumbents, higher for entrants, and lower for exiters. In contrast, for General Stores productivity relative to 1987 incumbents is *lower* for 1997 incumbents, slightly higher for entrants, and very much lower for exiters. In sum, the results suggest that productivity growth in Department Stores is largely a within establishment phenomenon; in General Stores exits, particularly of establishments of exiting firms, are important; while in Catalog Houses births, especially of those establishments in new firms, are important.

The results of the net entry regressions are shown in Table 9 (the specification is given by equation (8)). Entering establishments have substantially higher productivity than exiting establishments even after controlling for average overall growth in productivity ($\delta>\beta$). In addition, for all three industries, entering establishments in 1997 are more productive than 1987 incumbents ($\delta+\nu>0$). For

Department Stores entering establishments in 1997 are less productive than 1997 incumbents ($\delta<0$) as was true for the average industry in retail trade, but for the General Stores and Catalog Houses industries entrants are *more* productive than incumbents in 1997 ($\delta>0$). In the General Stores and Catalog House industries, and to a lesser extent in the Department Stores industry, establishment entrants to continuing firms are more productive than entrants to new firms ($\delta^c > \delta^b$). In all three industries, establishment exits from exiting firms are the least productive establishments with productivity lower than that of establishments exiting from continuing firms ($\beta^c > \beta^d$).

The cohort regressions results are reported in Table 10 (the specification is given by equation (9)). The results show that older entrants have higher productivity than younger entrants for all three industries ($\eta > \mu$). Again, we attempt to disentangle the selection and learning effects that could account for this pattern. The selection and learning regression results are shown in Table 11 (the specification is given by equation (10)). For all three industries, as with the average industry results, establishments that entered between 1987-92 and then exited are significantly less productive in 1992 than continuing incumbents in 1992 ($\alpha<0$) and are also less productive in 1992 than the surviving members of this cohort ($\alpha<\theta$). The latter finding is broadly consistent with selection effects since it is the less productive establishments from the entering cohort that exit. However, the relationship between exiting establishments that entered between 1987-92 in 1992 and other exiting establishments (α and γ) for these three industries differs from the average. In these three industries, there is either no significant difference between the two groups (as for Department Stores and Catalog Houses) or the exiting establishments from the 1987-92 cohort are more productive in 1992 than other exiting establishments ($\alpha>\gamma$).

As with the industry average, the surviving members of the entering 1987-92 cohort are actually more productive than incumbents ($\theta>0$) even upon entry. However, we find evidence of learning effects ($\theta<\lambda$) only for General Stores. For General Stores those that survived from the entering cohort exhibited an 18 point log increase in productivity from 1992 to 1997 relative to other surviving incumbents. This latter post-entry growth effect holds (roughly) for entrants from both continuing and new firms. The finding of significant learning effects for surviving entrants of new firms contrasts with the findings we report for the average industry in the prior section (where learning effects are confined to entrants of continuing firms). Recall that for the industry average, once we separately account for the learning of the entering cohort, there is essentially no productivity growth for incumbents between 1992 and 1997 who also were present in 1987 ($\nu=0$). This is not the case for the three industries: Department Stores and Catalog Houses show positive productivity growth for incumbents ($\nu>0$) while General Stores shows negative productivity growth for incumbents ($\nu<0$).

In many ways, these three industries are more dramatic versions of what we observed for retail trade as a whole. Perhaps the most interesting aspect of these industry-specific results is that we observe substantial differences in the importance of the within-establishment contribution. All of the industries exhibit rapid productivity growth with net entry playing a very large role. However, in one case the within component is almost as large as the net entry component (Department Stores), in another case it is about half as large as the net entry component (Catalog Houses), and in the third case the within contribution is actually negative (General Stores). The most natural interpretation is that continuing establishments in the Department Stores and Catalog Houses industry were able to find ways to improve their productivity internally while continuing establishments in the General Stores apparently were not able to reinvent themselves in such a positive manner. Interestingly, in this latter industry, net entry more than compensated for the poor performance of continuing businesses. We only found evidence of strong learning effects in General Stores. Moreover, it was especially entry of establishments from continuing businesses and exiting establishments from exiting businesses that generated the large impact of net entry.

8. Concluding Remarks

The evidence that we have presented in this paper suggests that aggregate productivity dynamics in retail trade are driven by the reallocation of inputs and outputs from less productive to more productive establishments. Specifically, our main findings can be summarized as follows. Retail trade businesses exhibit continuous large scale reallocation of output and labor across establishments within the same narrowly defined industries. Much of the reallocation is accounted for by entry and exit of establishments but a substantial fraction of the between establishment reallocation is due to within firm reallocation. We also find that retail trade businesses in the same four-digit industry exhibit tremendous productivity differences and for continuing businesses these differences are highly persistent. We find that new establishments enter at roughly equal rates across the distribution of labor productivity, but exiting establishments disproportionately are from the lowest percentiles of the labor productivity distribution.

When we decompose industry-level productivity growth into reallocation and within-establishment effects we find that net entry accounts for virtually all of the labor productivity growth in retail trade. Exiting establishments are substantially less productive than incumbents (about 25 percent) and entering establishments exhibit about the same productivity as incumbents at the point of entry. Further investigation from tracking cohorts of entrants shows that these entry and exit dynamics are closely linked. For any new cohort, many of the new establishments fail and those that fail are substantially less productive than incumbents. For successful entrants, we find that they exhibit more rapid productivity growth in the first five years after entry than incumbents over that same period of time suggesting learning by doing. Moreover we find that there are distinct differences in the dynamics of entry and exit of establishments from continuing firms and from non-continuing firms. Exiting establishments from exiting firms exhibit extremely low productivity, while entering establishments from continuing firms exhibit very high productivity.

Finally, having provided a broad picture of the link between aggregate and micro productivity dynamics in the retail trade sector by focusing on the average industry, we narrow our focus to concentrate on three industries in the sector. We find that the sources of productivity growth differ greatly across the industries. In some industries within-establishment effects make an important positive contribution, but in others the within-establishment effects are negative. In addition, while selection effects (especially those from entering cohorts) are evident in all three industries that we study, learning (by doing) effects are only evident in one of the industries.

Broadly speaking, these findings show that reallocation effects dominate productivity growth in retail trade. Compared to the results for U.S. manufacturing in the existing literature, in retail trade net entry is virtually the entire story while in U.S. manufacturing net entry accounts for only about one third of the story. Indeed, in an accounting sense, without churning retail trade would not have exhibited any productivity growth. The clear message that emerges is that in the U.S. retail trade sector new ways of doing business are introduced and successfully contribute to productivity growth via entry and exit. Within-establishment restructuring does not contribute much to productivity growth for the overall sector but we did find some detailed industries where the within-establishment contribution is substantially greater. We do find that within-firm restructuring does contribute substantially but as noted above it is the within-firm interacting with the between-firm restructuring that is especially important (i.e., entrants from continuing firms versus exits from exiting firms). While these findings are interesting, they raise many questions that deserve further attention. For one, it would be of interest to document the precise nature of the organizational and structural changes that are driving the enormous pace of entry and exit in the retail trade sector. We have found that in industries where the descriptive evidence suggests substantial restructuring we observe such restructuring and that it contributes substantially to overall productivity growth. A natural next step is to link the establishment-level productivity and employment dynamics that we have been exploiting here with observable indicators of the types of technological changes (broadly speaking) that are observed across establishments. There is some scope to do this with the Census of

Retail Trade data since there is much information about the types of establishments that we have not yet exploited.

While the churning appears to be productivity enhancing for the entire retail trade sector, it would be of interest to explore whether this finding holds up for all industries and for all types of businesses. Market imperfections such as imperfect capital markets can distort the reallocation process. It may be that such market imperfections are more important for small businesses so it would be of interest to focus attention on the role of churning for small businesses. In addition, the smallest retail establishments are often single establishments with an owner/manager. The dynamics of such owner-managed businesses may be very different as we know for example that the presence of an owner-manager at an establishment yields a lower probability of exit (see, e.g., Holmes and Schmitz (1992)). Examining the connection between churning and productivity growth for such owner-managed businesses is another area for future work.

Finally, lurking underneath all of this analysis are difficult measurement and conceptual issues in terms of measuring productivity at the micro and industry level in retail trade. The official statistical agency measures of productivity in the retail trade sector are primarily measures based upon sales per worker. In a like manner, the micro based measures we use here primarily reflect sales per worker. Under strong assumptions, these measures correspond to (or are highly correlated with) what we are really interested in: some measure of value-added per hour in the retail trade sector at the micro and aggregate levels. Some of the measurement difficulties are shared at the micro and industry level (e.g., inadequate measures of gross margins) but some of the measurement problems are more severe at the micro level so that measurement error at the micro level is likely non-trivial. We believe that the measurement difficulties at the micro level deserve much further attention and as such our results should be viewed with appropriate caution and seen as exploratory. However, it is worth noting that it may be that the measurement error at the micro level implies that we have understated the contribution of net entry to productivity growth in retail trade. If we interpret the micro measurement error as classical then such classical measurement error will lower the estimated differentials we have detected across entering and exiting establishments and, in turn, imply that we have understated the contribution of net entry to aggregate industry growth.

References

Aghion, Philippe and Peter Howitt, "Growth and Unemployment," *Review of Economic Studies,* July 1994, 477-494.

Aw, Bee Yan, Xiaomin Chen, and Mark Roberts. "Firm-Level Evidence on Productivity Differentials and Turnover in Taiwanese Manufacturing," *Journal of Development Economics*, October 2001.

Basker, Emek (2001), "Competition, Efficiency, and Employment: Labor-Market Effects of Wal-Mart Expansion," Mimeo, MIT.

Baily, Martin Neil, Eric J. Bartelsman and John Haltiwanger. " Downsizing and Productivity Growth: Myth or Reality?" *Small Business Economics*, 8, 1996, 259-278.

Baily, Martin Neil, Eric J. Bartelsman and John Haltiwanger. "Labor Productivity: Structural Change and Cyclical Dynamics," NBER Working Paper No. 5503, revised 1997.

Baily, Martin Neil, Charles Hulten and David Campbell. "Productivity Dynamics in Manufacturing Establishments," *Brookings Papers on Economic Activity: Microeconomics,* 1992, 187-249.

Bartelsman, Eric J. and Mark Doms. "Understanding Productivity: Lessons from Longitudinal Microdata," *Journal of Economic Literature*, 2000, 38, 569-594

Bartelsman, Eric J., and Phoebus J. Dhrymes. "Productivity Dynamics: U.S. Manufacturing Plants, 1972-86," *Journal of Productivity Analysis,* 9(1), 5-34, 1998.

Betancourt, Roger, and David Gautschi. "The Outputs of Retail Activities: Concepts, Measurement and Evidence from U.S. Census Data," *Review of Economics and Statistics*, 75, 1993, 294-301.

Betancourt, Roger and Margaret Malanoski. "An Estimable Model of Supermarket Behavior: Prices, Distribution Services and Some Effects of Competition," mimeo, January 1999.

Bureau of the Census. *History of the 1987 Economic Census*, Washington: U.S. Government Printing Office, 1992.

Bureau of the Census. *History of the 1992 Economic Census*, Washington: U.S. Government Printing Office, 1996.

Bureau of the Census. *1997 Economic Census, Retail Trade, Geographic Area Series*, 2000.

Bureau of Labor Statistics. *BLS Handbook of Methods*, Bulletin 2490, Washington: U.S. Government Printing Office, 1997.

Caballero, Ricardo, and Mohamad Hammour. "The Cleansing Effect of Recessions," *American Economic Review*, 84(5), 1350-1368.

Caballero, Ricardo, and Mohamad Hammour. "Creative Destruction and Development: Institutions, Crises, and Restructuring", Working Paper, 2000.

Davis, Steven J., and John Haltiwanger. "Gross Job Flows," in Orley Ashenfelter and David Card (eds.), *Handbook of Labor Economics*, 1999.

Davis, Steven J., John C. Haltiwanger and Scott Schuh. *Job Creation and Destruction*, Cambridge: MIT Press, 1996.

Disney, Richard, Jonathan Haskel, and Yvla Heden. "Restructuring and Productivity Growth in U.K. Manufacturing," mimeo, 2000.

Doms, Mark, Ron Jarmin, and Shawn Klimek. "IT Investment and Firm Performance in Retail Trade," mimeo, 2001.

Dwyer, Douglas. "Technology Locks, Creative Destruction, and Non-Convergence in Productivity Levels" *Review of Economic Dynamics*, 1(2), 430-73, 1998.

Dwyer, Douglas. "Productivity Races I: Are Some Productivity Measures Better Than Others?" Center for Economic Studies Working Paper, CES 97-2, 1997.

Dumas, Mark W. "Productivity Trends in Two Retail Trade Industries, 1987-95," *Monthly Labor Review*, July 1997, 35-39.

Ericson, Richard and Ariel Pakes. "Markov Perfect Industry Dynamics: A Framework for Empirical Work," *Review of Economic Studies*, Vol 62(1), 1995, 53-82.

Foster, Lucia, Haltiwanger, John, and C.J. Krizan. "Aggregate Productivity Growth: Lessons from Microeconomic Evidence," in *New Developments in Productivity Analysis*, editors: Edward Dean, Michael Harper and Charles Hulten, Chicago: University of Chicago Press, 2001.

Griliches, Zvi, and Haim Regev. "Productivity and Firm Turnover in Israeli Industry: 1979-1988,"*Journal of Econometrics*, 65, 1995, 175-203.

Haltiwanger, John. "Measuring and Analyzing Aggregate Fluctuations: The Importance of Building from Microeconomic Evidence, " *Federal Reserve Bank of St. Louis Economic Review*, January/February, 1997.

Holmes, Thomas and James Schmitz. "Managerial Tenure, Business Age And Small Business Dynamics," *Center for Economic Studies Working Paper* No. 92-11, 1992.

Jarmin, Ronald, Shawn Klimek, and Javier Miranda. "Firm Entry and Exit in the U.S. Retail Sector, 1977-1997," mimeo, December 2001.

Jovanovic, Boyan. "Selection and the Evolution of Industry," *Econometrica*, 50(3), 1982, 649-670.

Jovanovic, Boyan and Glenn MacDonald, "Competitive Diffusion," *Journal of Political Economy*, 98, 1994, 24-52.

Klette, Tor and Zvi Griliches. "The Inconsistency of Common Scale Estimators when Output Prices are Unobserved and Exogenous," *Journal of Applied Econometrics*, 11(4), 1996, 343-61.

Liu, Lili, and James R. Tybout. "Productivity Growth in Chile and Columbia: The Role of Entry, Exit and Learning," in Roberts and Tybout (eds.), *Industrial Evolution in Developing Countries: Micro Patterns of Turnover, Productivity and Market Structure*, New York: Oxford University Press for the World Bank, 1996, 73-103.

McKinsey Global Institute (2001), *U.S. Productivity Growth 1995-2000*. Washington, D.C.: McKinsey Global Institute, October.

Melitz, Mark, "Estimating Firm-Level Productivity in Differentiated Product Industries," working paper, 2000.

Nakamura, Leonard, "The Measurement of Retail Output and the Retail Revolution," *Federal Reserve Bank of Philadelphia, Working Paper 98-5,* March 1998.

Olley, G. Steven, and Ariel Pakes. "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 64(6), 1996, 1263-1297.

Roberts, Mark and James Tybout. "Producer Turnover and Productivity Growth in Developing Countries," *World Bank Research Observer*, 12(1), 1-18, February 1997.

Sieling, Mark, Brian Friedman, and Mark Dumas, "Labor Productivity in the Retail Trade Industry, 1987-99," *Monthly Labor Review*, December 2001, pp. 3-14.

Triplett, Jack and Barry Bosworth. "Productivity in the Services Sector," in *Services in the International Economy,* editor Robert M. Stern, University of Michigan Press, 2001.

Tybout, James R. "Heterogeneity and Productivity Growth: Assessing the Evidence" in Roberts and Tybout (eds.), *Industrial Evolution in Developing Countries: Micro Patterns of Turnover, Productivity, and Market Structure*, New York: Oxford University Press for the World Bank, 1996, 43-72.

Data Appendix

A.1 Administrative Records in the Census of Retail Trade

The Census Bureau relies on administrative records to gather data on nonemployers and selected small establishments. The definition of selected small establishments varies by year. In general the selected small establishments are business firms with paid employees and with payrolls below a specified cutoff. Although the cutoff varies by kind of business, the small-employer segment generally includes firms with one to three paid employees. This group usually represents about 10 percent of total retail sales. See Bureau of the Census (1992, 1996, 2000) for further discussion.

A.2 Bureau of Labor Statistics Data

For all of the four-digit industry indices that we are using from BLS, there are 24 four-digit industries that do not meet BLS standards for publication. The BLS deflators that we use are industry implicit price deflators. "In the case of retail trade industries, the industry price index is developed by combining current-year consumer price indexes with weights based in sales for each category of merchandise in census years (Bureau of Labor Statistics (1997), p.105).[29] "

The BLS employee hours index is for "all employees"which includes the self-employed and unpaid family workers (except for industries 5311 and 5511 which are all paid employees). The index of hours is created by dividing a measure of total hours in the industry in each year by the hours for the base year. Total hours are measured for each industry as the industry's annual employment times the industry's average weekly hours times 52.

A.3 Creating Longitudinal Links

One of the first tasks in preparing the micro data is to link each establishment's data over time. These links allow us to measure establishment births and deaths and to measure productivity growth over time. In theory these linkages can take place via the unique permanent establishment number (PPN) that is assigned to each establishment. In practice there are often problems with the PPNs that cause links to be incorrectly severed. We improve our links by using additional identifiers on the files and sophisticated matching software which uses the name and address information from the business establishment list that Census maintains.[30]

Another data issue concerns the existence of active establishments with zero total employment. Roughly speaking, an active establishment is one with positive payroll over the current year. It is not surprising to find active establishments with zero employment since employment is measured only for the pay period including March 12th. Since we use total employment (or employment times hours) in the denominator of our productivity measure and employment (or employment times hours) weights to

[29] Concerning the BLS price index, Nakamura (1998) discusses the price mismeasurement in retail trade introduced by the adoption of electronic scanners which allow establishments to switch prices (as for sales promotions) relatively costlessly. In this case, the establishment's measured price is higher than the actual price paid by consumers, resulting in an upwardly biased price index.

[30] An additional problem with relying on the PPN for links is the existence of duplicate PPNs in a given census year. This is a relatively small problem: the duplicate PPN establishments account for only 0.5 percent of establishments in 1987, 0.06 percent in 1992, and 0.01 percent in 1997. These duplicate PPNs do not appear to be predominantly in any one of the industries within retail trade. We drop these duplicate PPNs from our analysis.

aggregate, these observations would be dropped and or contribute nothing to aggregate in year with zero employment. A concern about this is that the loss of an observation can potentially cause a false birth or death if the establishment has positive employment in the other years. Since we are interested in births and deaths it is important that we avoid creating false births and deaths. For this reason, we delete establishments that have positive payroll but zero total employment in any of the three years in our analysis. Approximately 13 percent of the total three year sample is dropped using this rule. Of these observations that are dropped using the zero employment rule, the majority have zero employment or missing employment in all three years under consideration and thus would be dropped from all three years even with a less strict rule. The reason for this is that "true" entry and exit are so large that a substantial fraction of those establishments who have one observation of positive payroll and zero employment are not in the Census in other years. In fact, 68 percent of these dropped observations have missing employment in the other two years under consideration (recall one year must have zero employment to be in this group). In any event, we believe that this methodology yields a more conservative estimate of the contribution of entry and exit to the reallocation and productivity dynamics -- that is, if anything we are undercounting the contribution of entry and exit. [31]

A.4 Comparing Our Data to BLS' Data

Since the CRT data have not been extensively used and our methodology is based on aggregating up micro data, it is helpful to compare the productivity measures based on the Census data to those officially published by the Bureau of Labor Statistics. The BLS creates a labor productivity per hours index for each of the 64 four-digit industries in retail trade. It is not practical for us to attempt to replicate BLS' index numbers since BLS uses a Tornqvist index which would require us to use merchandise line data. Instead of attempting to replicate their methodology, we compare growth rates of the BLS series and our series at the industry and retail trade levels.

To create our measure of labor productivity growth, we create establishment-level productivity growth series which we aggregate up to the four-digit level using the manhours weights and then to the retail trade level using gross average nominal output weights by industry. For the BLS measure, we calculate the four-digit growth rate by taking the log difference of their four-digit productivity by hours index over the appropriate year pairs. We aggregate this from the four-digit industry level to the retail trade level using the same weights as for the Census measure so that we may concentrate on the within industry differences in these measures. At the time in which we did the empirical analysis, BLS data contained some known problem industries, we also calculated these measures excluding the industries which BLS designated as problematic. As is evident from Table A, the two measures of productivity growth are roughly similar across all three sets of years. The correlations at the industry level for 1987-97 are 0.80 for all industries and 0.81 for the subset of industries that meet BLS' standards for publication. The five-year aggregate growth rates implied by the Census data are higher for 1987-92 (about 5 percent versus about 4 percent) than the BLS growth rates, but are lower for 1992-97 (about 6 percent versus about 9 percent). Interestingly, the growth rates over the ten-year horizon are also reasonably close (especially for the BLS published industries).

---

[31] These establishments could be seasonal establishments with sales/payroll activity at other times of year. They could be late year births or early year deaths (prior to March 12). We suspect that this latter case is more prevalent and this implies we may be undercounting the contribution of entry and exit to our analysis.

Table 1: Matrix of Relative Productivity in 1987 and 1997							
Establish-ment Group	Quintile 1 (1997)	Quintile 2 (1997)	Quintile 3 (1997)	Quintile 4 (1997)	Quintile 5 (1997)	Deaths	Row Total
Quintile 1 (1987)	12.8 11.0	6.5 5.6	4.2 3.6	3.4 2.9	2.8 2.3	70.3 28.0	11.9
Quintile 2 (1987)	11.6 10.1	15.3 13.3	10.2 8.9	6.7 5.7	4.1 3.4	52.1 20.9	12.0
Quintile 3 (1987)	8.3 7.4	15.0 13.4	16.1 14.2	11.8 10.3	6.3 5.3	42.5 17.4	12.2
Quintile 4 (1987)	6.6 6.0	10.7 9.7	15.2 13.7	17.3 15.3	10.9 9.3	39.3 16.3	12.5
Quintile 5 (1987)	4.9 4.7	6.4 6.2	8.3 7.9	14.8 13.9	26.5 23.9	39.2 17.4	13.2
Births	22.0 60.9	18.7 51.8	18.8 51.8	19.1 51.9	21.4 55.9		38.2
Column Total	13.8	13.8	13.9	14.0	14.6	29.9	100.0

Notes: Weighted by hours. Quintile 1 is the lowest productivity, quintile 5 is the highest. The top number in each cell is the row percentage (shows where the establishments that were in a given quintile in 1987 are in 1997). The bottom number in each cell is the column percentage (shows where the establishments in a given quintile in 1997 came from).

Source: Tabulations from the Census of Retail Trade

Table 2 : Gross Reallocation of Employment					
Panel A: Gross Reallocation Rates					
Years	Creation Rate	Destruction Rate	Net Flows	Excess Reallocation	Fraction of Excess Reallocation Within Four-digit Industry
1987-92	45.0	42.7	2.2	85.5	0.94
1992-97	48.7	36.3	12.4	72.5	0.97
1987-97	69.2	54.6	14.6	109.2	0.96
Panel B: Shares					
Years	Share of Creation Due to Entrants	Share of Entry Induced Creation from New Firms	Share of Destruction Due to Exits	Share of Exit Induced Destruction from Exiting Firms	Fraction of Excess Reallocation Within Firms
1987-92	0.77	0.61	0.70	0.73	0.20
1992-97	0.73	0.58	0.72	0.71	0.21
1987-97	0.84	0.60	0.82	0.75	0.18
Source: Tabulations from the Census of Retail Trade					

Table 3: Decomposition of Labor Productivity Growth

Panel A: Decomposition

Years	Overall Growth	Within Share	Between Share	Cross Share	Net Entry Share
1987-92	5.00	0.07	0.79	-1.14	1.28
1992-97	6.48	0.35	0.63	-0.97	0.99
1987-97	11.43	0.16	0.24	-0.39	0.98

Panel B: Details on the Net Entry Share

Years	Establishment Birth Contribution			Establishment Death Contribution		
	Total	Cont. Firm	New Firm	Total	Cont. Firm	Exiting Firm
1987-92	0.25	0.36	-0.11	1.03	0.15	0.88
1992-97	0.17	0.25	-0.08	0.82	0.13	0.69
1987-97	0.54	0.37	0.17	0.45	0.03	0.42

Source: Tabulations from the Census of Retail Trade

Table 4: Net Entry Regression Results

Panel A: Differences Between Continuing, Entering and Exiting Establishments

Years	Exit Dummy in Beginning Year (β)	Entry Dummy in Ending Year (δ)	End Year Effect (ν)	F-test on $\beta=\delta$ (p-value)
1987-92	-0.266 (0.001)	-0.021 (0.001)	-0.019 (0.001)	0.0001
1992-97	-0.302 (0.001)	-0.057 (0.001)	0.006 (0.001)	0.0001
1987-97	-0.228 (0.001)	-0.001 (0.001)	0.011 (0.001)	0.0001

Panel B: Entering and Exiting Establishments and Firm Status

Years	Exiting Establishments		Entering Establishments		F-tests concerning Firms (p-value)	
	Cont. Firm (β^c)	Exiting Firm (β^e)	Cont. Firm (δ^c)	New Firm (δ^b)	Exiting Estabs. $\beta^c=\beta^e$	Entering Estabs. $\delta^c=\delta^b$
1987-92	-0.171 (0.002)	-0.302 (0.001)	0.098 (0.001)	-0.106 (0.001)	0.0001	0.0001
1992-97	-0.206 (0.002)	-0.343 (0.001)	0.033 (0.001)	-0.133 (0.001)	0.0001	0.0001
1987-97	-0.135 (0.002)	-0.261 (0.001)	0.089 (0.001)	-0.068 (0.001)	0.0001	0.0001

Note: Results in panel A are based upon regression of pooled 1987 and 1997 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 1987 and an entry dummy in 1997. The results in panel B use the same specification but interact the entry and exit dummies with firm status dummies. In panel B, the exit dummy and year effect dummy are not shown as they are the same as in panel A. All results are weighted regressions with manhours weights. Standard errors in parentheses.

Source: Calculations from the Census of Retail Trade

Table 5: Entering Cohorts Regression Results					
Panel A: Distinguishing Between Entering Cohorts					
Entry Dummy in 1997 interacted with Dummy for 1987-92 Cohort (η)		Entry Dummy in 1997 interacted with Dummy for 1992-97 Cohort (μ)		F-test on $\eta = \mu$ (p-value)	
0.041 (0.001)		-0.033 (0.001)		0.0001	
Panel B: Entering Cohorts and Firm Status					
Entry Dummy in 1997 interacted with Dummy for 1987-92 Cohort (η) interacted with:		Entry Dummy in 1997 interacted with Dummy for 1992-97 Cohort (μ) interacted with:		F-tests concerning Firms (p-value)	
Cont. Firm (η^c)	New Firm (η^b)	Cont. Firm (μ^c)	New Firm (μ^b)	Exiting Estabs. $\eta^c = \eta^b$	Entering Estabs. $\mu^c = \mu^b$
0.136 (0.002)	-0.036 (0.002)	0.049 (0.002)	-0.090 (0.001)	0.0001	0.0001

Notes: Results in panel A are based upon regression of pooled 1987 and 1997 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 1987 and an entry dummy in 1997. The results in panel B use the same specification but interact the entry dummies with firm status dummies. In panel B, the exit dummy and year effect dummy are not shown as they are the same as in panel A. All results are weighted regressions with manhours weights. Standard errors in parentheses.

Source: Calculations from the Census of Retail Trade

Table 6: Selection and Learning Effects Regression Results

Panel A: Selection and Learning Effects

Exit Dummy in 1992 for Entering Cohort (α)	Exit Dummy in 1992 for Other Exiting Plants (γ)	Survival Dummy in 1992 for Entering Cohort (θ)	Survival Dummy in 1997 for Entering Cohort (λ)	1997 Year Effect (ν)	F-tests (p-values reported) on:		
					$\alpha = \gamma$	$\alpha = \theta$	$\theta = \lambda$
-0.324 (0.002)	-0.274 (0.001)	0.029 (0.001)	0.049 (0.001)	-0.000 (0.001)	0.0001	0.0001	0.0001

Panel B: Selection and Learning Effects and Firm Status

Exit Dummy in 1992 for Entering Cohort interacted with:		Exit Dummy in 1992 for Other Exiting Plants interacted with:		Survival Dummy in 1992 for Entering Cohort interacted with:		Survival Dummy in 1997 for Entering Cohort interacted with:	
Cont. Firm (α^c)	New Firm (α^b)	Cont. Firm (γ^c)	Exiting Firm (γ^e)	Cont. Firm (θ^c)	New Firm (θ^b)	Cont. Firm (λ^c)	New Firm (λ^b)
-0.216 (0.003)	-0.365 (0.002)	-0.208 (0.002)	-0.307 (0.002)	0.099 (0.002)	-0.037 (0.002)	0.145 (0.002)	-0.037 (0.002)

Notes: Results are based upon regression of pooled 1992 and 1997 data with dependent variable the measure of productivity. The explanatory variables include four-digit industry effects, year effects, an entry dummy in 1997, the exit dummy interacted with whether the plant is in the 87-92 entering cohort, and a surviving dummy for the 87-92 entering cohort interacted with the year effects. All results are weighted regressions with manhours weights. Note that the results in the lower panel also include the year effect and it is the same as in panel A. Standard errors in parentheses.

Source: Tabulations from the Census of Retail Trade.

Table 7: Gross Reallocation of Employment for Selected Industries, 1987-97

Panel A: Gross Reallocation Rates

Industry	Creation Rate	Destruction Rate	Net Flows	Excess Reallocation
Department Stores	56.4	35.0	21.4	70.0
General Stores	79.1	54.5	24.6	109.1
Catalog Houses	100.0	50.2	49.8	100.4

Panel B: Shares

Industry	Share of Creation Due to Entrants	Share of Entry Induced Creation from New Firms	Share of Destruction Due to Exits	Share of Exit Induced Destruction from Exiting Firms	Fraction of Excess Reallocation Within Firms
Department Stores	0.79	0.04	0.63	0.36	0.48
General Stores	0.83	0.21	0.85	0.61	0.15
Catalog Houses	0.72	0.79	0.90	0.59	0.14

Source: Tabulations from the Census of Retail Trade

Table 8: Decomposition of Labor Productivity Growth for Selected Industries, 1987-97						
Panel A: Decomposition						
Industry	Overall Growth	Within Share	Between Share	Cross Share	Net Entry Share	
Department Stores	18.4	0.56	0.06	-0.21	0.59	
General Stores	22.9	-0.46	0.17	-0.13	1.42	
Catalog Houses	39.3	0.30	0.19	-0.15	0.65	
Panel B: Details on the Net Entry Share						
Industry	Establishment Birth Contribution			Establishment Death Contribution		
	Total	Cont. Firm	New Firm	Total	Cont. Firm	Exiting Firm
Department Stores	0.39	0.38	0.01	0.20	0.10	0.10
General Stores	0.85	0.95	-0.09	0.57	0.09	0.48
Catalog Houses	0.64	0.21	0.43	0.02	-0.10	0.12
Source: Tabulations from the Census of Retail Trade						

Table 9: Net Entry Regression Results for Selected Industries

Panel A: Differences Between Continuing, Entering and Exiting Establishments

Industry	Exit Dummy in Beginning Year (β)	Entry Dummy in Ending Year (δ)	End Year Effect (ν)	F-test on $\beta=\delta$ (p-value)
Department Stores	-0.198 (0.007)	-0.015 (0.006)	0.141 (0.005)	0.0001
General Stores	-0.527 (0.015)	0.236 (0.015)	-0.209 (0.016)	0.0001
Catalog Houses	-0.025 (0.020)	0.093 (0.020)	0.325 (0.022)	0.0001

Panel B: Entering and Exiting Establishments and Firm Status

Industry	Exiting Establishments		Entering Establishments		F-tests concerning Firms (p-value)	
	Cont. Firm (β^c)	Exiting Firm (β^e)	Cont. Firm (δ^c)	New Firm (δ^b)	Exiting Estabs. $\beta^c=\beta^e$	Entering Estabs. $\delta^c=\delta^b$
Department Stores	-0.167 (0.008)	-0.256 (0.010)	-0.012 (0.006)	-0.085 (0.024)	0.0001	0.0024
General Stores	-0.390 (0.019)	-0.617 (0.016)	0.363 (0.015)	-0.255 (0.023)	0.0001	0.0001
Catalog Houses	0.144 (0.025)	-0.142 (0.023)	0.348 (0.032)	0.026 (0.021)	0.0001	0.0001

Note: Results in panel A are based upon regression of pooled 1987 and 1997 data with dependent variable the measure of productivity (in logs) and the explanatory variables including year effects, an exit dummy in 1987 and an entry dummy in 1997. The results in panel B use the same specification but interact the entry and exit dummies with firm status dummies. In panel B, the exit dummy and year effect dummy are not shown as they are the same as in panel A. All results are weighted regressions with manhours weights. Standard errors in parentheses.

Source: Calculations from the Census of Retail Trade

Table 10: Entering Cohorts Regression Results for Selected Industries						
Panel A: Distinguishing Between Entering Cohorts						
Industry	Entry Dummy in 1997 interacted with Dummy for 1987-92 Cohort (η)		Entry Dummy in 1997 interacted with Dummy for 1992-97 Cohort (μ)		F-test on $\eta = \mu$ (p-value)	
Dept Stores	0.023 (0.007)		-0.054 (0.007)		0.0001	
General Stores	0.400 (0.017)		0.072 (0.017)		0.0001	
Catalog Houses	0.320 (0.025)		-0.082 (0.023)		0.0001	
Panel B: Entering Cohorts and Firm Status						
Industry	Entry Dummy in 1997 interacted with Dummy for 1987-92 Cohort (η) interacted with:		Entry Dummy in 1997 interacted with Dummy for 1992-97 Cohort (μ) interacted with:		F-tests concerning Firms (p-value)	
	Cont. Firm (η^c)	New Firm (η^e)	Cont. Firm (μ^c)	New Firm (μ^b)	Exiting Estabs. $\eta^c = \eta^e$	Entering Estabs. $\mu^c = \mu^b$
Dept Stores	0.024 (0.007)	-0.025 (0.033)	-0.050 (0.008)	-0.145 (0.033)	0.1454	0.0051
General Stores	0.478 (0.018)	-0.107 (0.037)	0.224 (0.019)	-0.327 (0.027)	0.0001	0.0001
Catalog Houses	0.652 (0.043)	0.223 (0.027)	0.069 (0.042)	-0.118 (0.024)	0.0001	0.0001

Notes: Results in panel A are based upon regression of pooled 1987 and 1997 data with dependent variable the measure of productivity (in logs) and the explanatory variables including year effects, an exit dummy in 1987 and an entry dummy in 1997. The results in panel B use the same specification but interact the entry dummies with firm status dummies. In panel B, the exit dummy and year effect dummy are not shown as they are the same as in panel A. All results are weighted regressions with manhours weights. Standard errors in parentheses.

Source: Calculations from the Census of Retail Trade

Table 11: Selection and Learning Effects Regression Results for Selected Industries

Panel A: Selection and Learning Effects

Industry	Exit Dummy in 1992 for Entering Cohort (α)	Exit Dummy in 1992 for Other Exiting Plants (γ)	Survival Dummy in 1992 for Entering Cohort (θ)	Survival Dummy in 1997 for Entering Cohort (λ)	1997 Year Effect (ν)	F-tests (p-values reported) on:		
						$\alpha = \gamma$	$\alpha = \theta$	$\theta = \lambda$
Dept Stores	-0.273 (0.026)	-0.326 (0.009)	0.029 (0.007)	0.024 (0.007)	0.138 (0.005)	0.0539	0.0001	0.6002
General Stores	-0.416 (0.026)	-0.589 (0.024)	0.245 (0.019)	0.424 (0.019)	-0.278 (0.018)	0.0001	0.0001	0.0001
Catalog Houses	-0.378 (0.028)	-0.392 (0.028)	0.295 (0.027)	0.329 (0.025)	0.218 (0.022)	0.6770	0.0001	0.3531

Panel B: Selection and Learning Effects and Firm Status

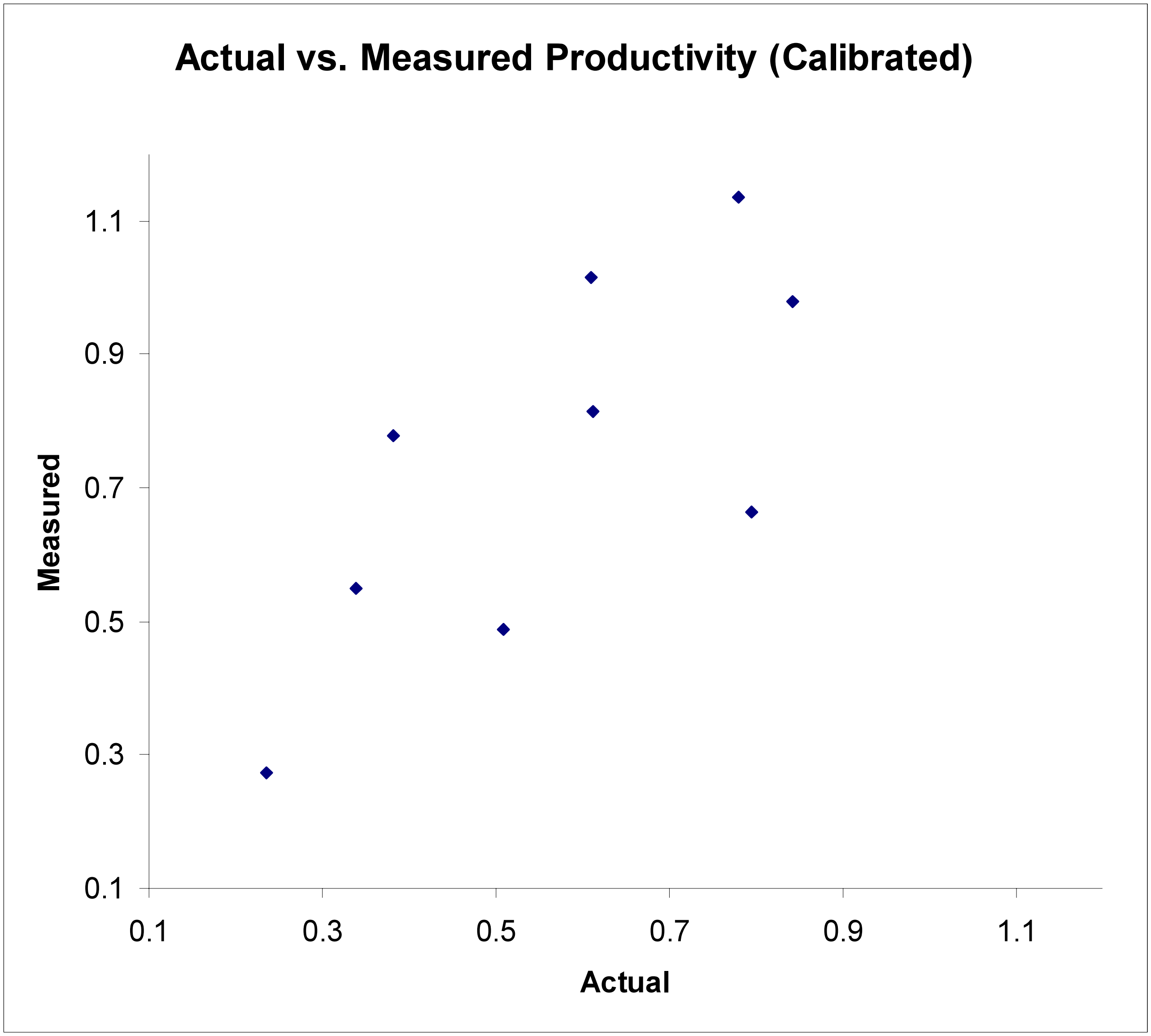
Industry	Exit Dummy in 1992 for Entering Cohort interacted with:		Exit Dummy in 1992 for Other Exiting Plants interacted with:		Survival Dummy in 1992 for Entering Cohort interacted with:		Survival Dummy in 1997 for Entering Cohort interacted with:	
	Cont. Firm (α^c)	New Firm (α^b)	Cont. Firm (γ^c)	Exiting Firm (γ^e)	Cont. Firm (θ^c)	New Firm (θ^b)	Cont. Firm (λ^c)	New Firm (λ^b)
Dept Stores	-0.314 (0.028)	-0.003 (0.071)	-0.342 (0.011)	-0.292 (0.016)	0.029 (0.007)	0.022 (0.037)	0.025 (0.007)	-0.044 (0.042)
General Stores	-0.195 (0.030)	-0.877 (0.041)	-0.510 (0.031)	-0.657 (0.029)	0.334 (0.019)	-0.345 (0.039)	0.508 (0.019)	-0.158 (0.041)
Catalog Houses	-0.320 (0.040)	-0.414 (0.033)	-0.135 (0.037)	-0.625 (0.036)	0.620 (0.037)	0.076 (0.031)	0.719 (0.036)	0.116 (0.029)

Notes: Results are based upon regression of pooled 1992 and 1997 data with dependent variable the measure of productivity. The explanatory variables include year effects, an entry dummy in 1997, the exit dummy interacted with whether the plant is in the 87-92 entering cohort, and a surviving dummy for the 87-92 entering cohort interacted with the year effects. Note that the results in the lower panel also include the year effect and it is the same as in panel A All results are weighted regressions with manhours weights. Standard errors in parentheses.

Source: Tabulations from the Census of Retail Trade.

Table A: Comparison of Labor Productivity Per Hour Growth Measures				
Years	Sample	Census	BLS	Correlation at Industry-Level
1987-92	All Industries	5.00	4.35	0.64
	Published Industries	4.78	4.01	0.78
1992-97	All Industries	6.48	9.37	0.75
	Published Industries	5.67	8.33	0.68
1987-97	All Industries	11.43	14.10	0.80
	Published Industries	10.30	12.45	0.81
Sources: Calculations using the Census of Retail Trade and BLS industry productivity. Published Industries refers to the 40 four-digit industries that met BLS' standards for publication.				

Figure 1


Actual vs. Measured Productivity (Calibrated)
Measured
1.1
0.9
0.7
0.5
0.3
0.1
0.1
0.3
0.5
0.7
0.9
1.1
Actual