Wages, Productivity, and the Dynamic Interaction of Businesses and Workers

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ABSTRACT

This paper exploits a new matched universal and longitudinal employer-employee database at the US Census Bureau to empirically investigate the link between firms’ choice of worker mix and the implied relationships between productivity and wages. We particularly focus on the decision making process of new firms and examine the role of both learning and selection.

Our key empirical results are:

(i) We find substantial and persistent differences in earnings per worker, output per worker, and worker mix across businesses within narrowly defined industries, which remain even after controlling for other observable characteristics.

(ii) Within narrowly defined industries, mature businesses locate along an upward sloping productivity/worker skill profile and a closely related upward sloping earnings per worker/worker skill profile.

(iii) We find that new businesses exhibit even greater heterogeneity in earnings and productivity than do mature businesses, but that they adjust their worker mix in a manner consistent with selection and learning effects. As firms age, businesses that have made “errors” with their worker mix (and on other dimensions) either exit or adjust their worker skill mix in the direction of the profiles of mature businesses.

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1. Introduction

Research exploiting new longitudinal business datasets has shown that firms in narrowly defined industries exhibit very different outcomes in terms of productivity, wages, growth, and survival. These firms also exhibit very different choices in terms of technology, organizational structure, size, and factor mix. It is apparent that there is much heterogeneity and persistence in the ways firms produce and do business, and that learning and selection effects play large roles in these processes. In this paper we use a unique new database with longitudinal information on both firms and their workforce to find that this heterogeneity and persistence in productivity both extends to and is related to firm workforce composition. We propose a framework where the underlying source of these different outcomes is differences in firms’ endowment of key factors such as technology, capital, organizational structure, and the ability of managers. New firms that make mistakes in recognizing their initial endowment either adjust their workforce as they learn about their capabilities or exit through a competitive selection mechanism.

This study follows in the footsteps of recent studies using longitudinal business data and the much larger and more established literature using worker level data. While the former contributes to understanding the nature and sources of firm heterogeneity and the latter to understanding worker heterogeneity, this paper contributes to the gap in knowledge about the connections between the two – and hence a key piece of the story underlying the interactions of workers and firms. Casual observation suggests that these interactions are important: similar firms, even when faced with similar markets, make very different choices of workers. For example, visits to various individual businesses will reveal different types of workers at each, and repeat visits will confirm that although the workers may have changed, the age, gender, and education level of the replacement workers are similar. Recent empirical evidence using longitudinal matched employer-employee data confirms this anecdotal impression: in their sample of long-lived large firms, Haltiwanger, Lane, and Spletzer
(1999) found that employers choose very different types of workforces and productivity levels, even within relatively narrow industries, and these choices are quite persistent over time.

Figure 1 illustrates this heterogeneity and persistence in workforce mix, productivity, and earnings per worker. Using a sample of long-lived single establishments in Maryland, the upper left panel of this figure plots the proportion of the workplace that is female for each firm in 1986 against the same proportion for the same firm in 1996, the upper right panel plots the proportion of the workplace that is highly educated for each firm in 1986 against the same proportion for the same firm in 1996, the lower left panel of this figure plots the productivity in 1986 against the productivity for the same firm in 1996, and the lower right panel plots the analogous relationship for earnings per worker. The data show quite dramatic heterogeneity and persistence in firm personnel practices and firm outcomes. That is, firms not only choose widely different workforces (the percent female and percent highly educated range from 0% to 100%) but the result that workforce composition, productivity, and earnings per worker are very similar a decade later suggests that these firms are choosing their workforces quite deliberately.

Such a deliberate choice of worker mix is likely to be complementary to other choices of the firm, such as technology and organizational practice, and to other intrinsic characteristics of the business, such as managerial or entrepreneurial ability. Consideration of these relationships leads one to think about the complex matching and sorting processes that must underlie the connection between firm and worker outcomes. In particular, it raises questions about the relationship between wages, productivity, and worker mix, and the way in which firms – particularly new firms - make such widely

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1 A description of the data underlying Figure 1 is provided in section 6. Note that 4-digit effects have been removed from the observations underlying Figure 1. We find similar patterns of heterogeneity and persistence for other measures of worker characteristics including other categories of education, age and foreign born.

2 For all cases, we present a 10 percent random sample of our data. For percent highly educated, we only show the range from 0 to 0.4 since the mean is relatively low. In all cases, the persistence is measured as the first order AR coefficient from a regression of the 96 value on the 86 value -- for percent female, the AR1 coefficient is 0.82; for highly educated the coefficient is 0.45; for productivity the coefficient is 0.47, for earnings the coefficient is 0.45.
differing choices. This raises other issues about the role of learning and selection in this process. In this paper we both propose a framework where the underlying source of different outcomes in both workforce composition and productivity is differences in firms’ endowment of key factors such as technology, capital, organizational structure, and the ability of managers, and we investigate the implications of the model using a new longitudinal matched employer-employee dataset.

Our key empirical results are:

i. We find substantial and persistent differences in earnings per worker, output per worker, and worker mix across businesses within narrowly defined industries, which remain even after controlling for other observable characteristics.

ii. Within narrowly defined industries, mature businesses locate along an upward sloping productivity/worker skill profile and a closely related upward sloping earnings per worker/worker skill profile.

iii. We find that new businesses exhibit even greater heterogeneity in earnings and productivity than do mature businesses but they adjust their worker mix in a manner consistent with selection and learning effects. “Mistake” prone firms either exit or adjust their worker mix in a direction consistent with the profiles of mature businesses. Evidence for these selection and learning effects is seen in the following three specific results:

iii.1. Firms that initially find themselves above the mature business productivity/skill mix profile (and thus have a positive initial productivity “surprise”) increase their skill mix while firms that find themselves below the mature business productivity/skill mix profile (a negative “surprise”) adjust their skill mix downwards over time.

iii.2. The dispersion in “errors” (deviations from the mature business productivity/skill mix profile) about the skill mix made by firms decreases as they age.

iii.3. New businesses are more likely to exit if they have a negative surprise and are low skilled.
This paper is organized as follows. We first set the stage by describing how our approach draws on the previous literature and explore some of the implications of Figure 1 a bit more. We then develop a descriptive model that synthesizes a number of these ideas. We follow this by describing the construction of a linked employer employee dataset, which we use to empirically test our key hypotheses. We conclude by summarizing our contribution.

2. Background

The framework presented here views the choice of worker mix as part of the experimentation of how best to create and run a business. It is clear from the emerging literature using linked employer-employee data that worker heterogeneity and firm heterogeneity are closely linked. Our earlier work (as well as that of others) suggest firms ultimately locate along a productivity/earnings/skill locus with some firms being high productivity, high wage, and high skill firms while others are low productivity, low wage, and low skill firms. In the current paper, we provide further analysis of the connection between productivity, earnings, and worker mix and, in particular, focus on the learning and selection dynamics of new businesses and the role of worker mix in these dynamics. Prior to beginning our own analysis, it is useful to review briefly key strands of the theoretical and empirical literature on firm dynamics that provide background and additional motivation for our analysis.

First, firm performance and behavior, even within quite narrowly defined industries, is quite heterogeneous. Davis, Haltiwanger, and Schuh (1996) document the large magnitude of job creation and destruction and the dominance of idiosyncratic factors in accounting for the observed large pace of job reallocation. Spletzer (2000) reports that forty percent of new businesses die within three years of their birth, and more than half of all jobs destroyed in a three-year period are due to the death of establishments. In addition to growth and survival, firm heterogeneity in wages and productivity has been documented by Abowd, Kramarz, and Margolis (1999), Foster, Haltiwanger, and Krizan (1998), and Dunne, Foster, Haltiwanger, and Troske (2000), amongst others.
Second, complementarities in the firm's production process can lead to a choice of worker skill mix that varies across firms. Kremer's (1993) model of production as a series of tasks where quantity cannot be substituted for quality provides insights into how workers of similar skill will match together in firms. Empirical evidence that worker skill is positively correlated across occupations within establishments is provided by Lane, Salmon, and Spletzer (1999). Milgrom and Roberts (1990) discuss the business strategy of exploiting complementarities and the resulting clustering of marketing, production, and organization. Ichniowski, Shaw, and Prennushi (1997) find that innovative employment practices tend to be complements, and these human resource policies are important determinants of productivity. Bresnahan, Brynjolfsson, and Hitt (1999) describe how information technology is complementary with the organization of work, including the demand for workers of various skill levels. Similarly, Booth and Zoega (2001) suggest that workforce heterogeneity may be a direct consequence of the complexity of the production process. Bingley and Westergaard-Nielsen (2001) find a strong relationship between firm personnel policy and economic performance.

Third, there is considerable persistence in outcomes such as wages and productivity across mature businesses. Baily, Hulten, and Campbell (1992) particularly note this with regard to productivity, and Doms, Dunne, and Troske (1997) with regard to wages. In addition, there is considerable persistence in measures of choice of technology, factor mix, and worker mix across mature businesses -- see Doms, Dunne, and Troske (1997) and Haltiwanger, Lane, and Spletzer (1999). There is some evidence that this is deliberate – Piekkola (2000), for example, suggests that firms substitute high wages for monitoring costs.

Fourth, the idea that learning and selection dynamics are important for firm dynamics and heterogeneity across firms is most notably attributable to Jovanovic (1982), but also by Ericson and Pakes (1995). In this vein, Jovanovic develops the notion that firms learn about their nature after they enter, firms that learn they have a good match (on potentially many dimensions) survive and bad matches die. Consistent with the learning and selection models, Evans (1987), Audretsch and
Mahmood (1995), and Dunne, Roberts, and Samuelson (1989) find that establishment specific characteristics such as size and age are important contributors to the success or failure of manufacturing establishments. Burgess, Lane, and Stevens (2000) find that firms both at the beginning and end of their lifecycle have much higher turnover rates than mature and successful firms do, and Lane, Isaac, and Stevens (1996) suggest that this contributes to firm exit. Foster, Haltiwanger, and Krizan (1998) note that a common finding in the emerging literature is that low productivity is an excellent predictor of exit.

The evidence of tremendous heterogeneity in outcomes such as productivity, employment, and wages (both in levels and growth rates) across businesses in the same narrowly defined industries is at the core of this burgeoning literature. In the next section, we provide some further analysis of the nature of this heterogeneity. We think this analysis is interesting in its own right but also helps in thinking about the connections between productivity, earnings, and worker mix.

3. The Sources of Firm Heterogeneity

The motivating force for this paper was presented in Figure 1, which showed that businesses in the same year exhibit widely different productivity, wages, and worker mixes – and that these differences are persistent. What might drive this? The most obvious argument is that this persistence and heterogeneity reflects different production techniques: different industries, quite naturally, require different levels of capital intensity, or organizational structure, and that this is reflected in the workforce composition. In this view, if we hone in closely enough to industry characteristics, the observed persistence and heterogeneity should be reduced: firms within very narrowly defined industries should choose roughly similar methods of production and consequently workforces. Figure 1 goes a long way in this direction by controlling for 4-digit effects but it may be that even narrower classification is required for this purpose.
In fact, we have a unique opportunity to examine this, because we can link our analytical dataset (described in detail in section 6 below) to internal Census files with detailed firm level responses to the quinquennial economic Censuses in 1987 and 1992. In Figures 2 and 3, we recreate the relationship described in Figure 1 for two detailed five-digit industries: restaurants and plumbing businesses. For each of these industries, we examine the heterogeneity and persistence for all businesses, and then businesses that fit into a very narrow set of what one might think of as observable dimensions of differences across firms.

For the restaurant industry we present eight panels of firm level scatter plots on the relationship between variables on worker mix, earnings and productivity for the firm in 1987 against the corresponding variable in 1992. The left column of panels present these relationships for the entire restaurant industry in the state of Maryland; the right-hand column for the subset of restaurants that have table service, that are in metropolitan areas in the state, and where the average customer spends the same amount (within a $5 range). By restricting our attention in the right panels to the narrow set of restaurants on several dimensions, we think we have come fairly close to finding firms with observationally equivalent sets of characteristics.

In the left panels of Figure 2, looking at the entire restaurant industry, it is “surprising” (although this mimics the results that controlled for 4-digit industry) to find considerable heterogeneity and persistence in the measures of worker mix, earnings, and productivity within a relatively narrow five digit industry. As noted, this “surprising” result may simply reflect observable differences in products and services provided – that is for the restaurant industry, some datapoints are for the fast food restaurants while others are expensive, fancy restaurants. The right panels of Figure 2 depict the same scatter plots focusing on the businesses with seemingly very similar observable characteristics. The

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3 We chose these industries both because of an abundance of data points and because the questions asked of firms in these industries were particularly well suited to our analytical purpose.
striking finding is there remains substantial heterogeneity and persistence in earnings, productivity, and worker mix even within as narrow a group as can be defined using detailed survey data.\footnote{4}

We repeat this same exercise for plumbing businesses in Figure 3. On the left hand column we recreate Figure 1 for all firms in the industry. On the right column we subset the firms to include those in the top decile of capital expenditures and capital assets. Again, despite controlling for these observable differences, we still find similar patterns – substantial heterogeneity and persistence across businesses not only in the same narrowly defined industry but also controlling for various detailed characteristics of the business.

Our interpretation of these findings of large residual heterogeneity and persistence is that they are prima facie evidence that there are some inherently unobservable (or difficult to measure) dimensions of firm heterogeneity. Indeed, this would mirror the prior research surveyed in Section 2, which documented substantial differences in capital intensities as well as propensities to adopt advanced technologies, organizational and human resource practices across business even in the same 4-digit industries. In our view, these differences are likely to reflect, at least in part, inherently difficult to measure characteristics such as managerial ability or related organizational practices.\footnote{6}

\section*{4. Theoretical Underpinnings – Learning and Selection}

\footnote{4}{The autocorrelation coefficients from simple linear regression fit through these points are positive and significant for all of the plots in Figure 2 and 3.}
\footnote{5}{One issue for restaurants in particular but potentially all of our industries is that gender discrimination may have an important role in accounting for differences in the patterns across firms (see, e.g., Neumark (1996) who found evidence of gender discrimination especially in high price, table service restaurants). We clearly recognize that the gender differences across businesses may reflect many factors but use it as a useful and important control for differences in the worker mix across businesses. Consistent with the emerging literature, we find that earnings and productivity differences across businesses are partly accounted for by gender differences across businesses.}
\footnote{6}{It is important to emphasize that all of the results to be presented in this paper control for 4-digit industry, which is a basic control for observable differences across businesses. There may well be, of course, other important observable dimensions of firm heterogeneity. As such, we believe that it would be a fruitful path for future research to explore on an industry-by-industry basis other observable dimensions of differences across businesses.}
The preceding section described differences in productivity levels, workforce composition, and earnings for long-lived, mature businesses. In order to understand these different outcomes, we argue in this paper that the heterogeneity in each of these is a manifestation of an underlying quasi-fixed heterogeneity in firm type. This also explains the persistence in outcomes: since firm type is quasi-fixed, the manifestation of type should not change quickly. In the model we sketch in this section, we make three key assumptions about differences across firms. First, we assume that there are some underlying differences in firm type, labeled “k”. Second, we assume that firms of different types have incentives to use different mixes of workers through the nature of the interaction between firm type and the productivity of different types of workers. Third, since some aspects of firm type are arguably initially unobservable even to the firm itself, newly born firms learn and evolve towards their “long run” type (or potentially exit as discussed below). In what follows, we first focus on the nature of the connection between firm type and worker mix. We then consider the role of uncertainty, the effect of this on the learning of surviving firms, the associated belief distribution in this learning, and the consequences for the choice of worker mix. After discussing the optimal choice of worker mix for surviving firms, we discuss the factors that determine selection.

4A. The link between firm type and worker mix

We draw heavily on the literature in sketching a simple model here to motivate and help interpret the empirical exercises we consider in section 8. The model focuses on the choice of worker mix and abstracts from scale effects by taking the size of businesses as given and focusing on the determinants of output per worker and the mix of workers by worker type within a business.\footnote{It is worth noting, of course, that many of the same factors that influence mix also affect scale. For example, Lucas (1977) develops a model of the size distribution of employment that depends upon heterogeneity in the managerial ability across businesses. The latter is part of what we have mind as “k” in the analysis that follows. In the Lucas (1977) model, the most productive entrepreneurs employ more workers but do not capture the entire market because of diseconomies of control – even the most productive individual can only effectively control a limited size operation. While this is outside the scope of our model, this argument is implicitly important in our context as well in that it provides one potential explanation for why the high and low “k” firms can operate simultaneously.}
We begin by assuming that the observed firm heterogeneity fundamentally reflects some variation in business type – the idiosyncratic ability of managers, the firm's organizational practices or policies, or the choice of productive inputs such as technology, physical capital, or organizational capital. In what follows, we refer to this type as “k” with high “k” firms inherently more productive. For now, it is useful to think of k as fixed but in practice it is better to think of k as changing either slowly or, even better, infrequently (as when a firm adopts a technology through an investment spike - see, for example, Cooper, Haltiwanger, and Power (1999)). Following the learning literature, we also argue that firms are not likely to be fully aware of their type at birth, and initially “guess” their type to be K. Since k is not directly observable to the firm, but output is, firms have to revise their priors each period based upon observations of their output. However, a firm’s ability to extract information on its type is clouded to some extent by unobservable profit (i.e., productivity, demand, and cost) shocks.

Furthermore, assume that output per worker is given by \( \theta f(k,s) \) (suppressing time subscripts), where \( \theta \) is initially assumed to be a random (i.i.d.) profit shock, s is skill mix, f is increasing in its arguments and the cross partial between k and s is positive (i.e., there is k-skill complementarity). Firms observe total output each period after decisions for the period are made, but do not observe k or \( \theta \) directly. The observation of output implies there is learning over time about true k.

We specify two components of wages: one a function of skill and one reflecting the ability of workers in a firm to extract rents (and or more generally internal labor market considerations that might generate firm specific components to wages – in what follows we use “rent sharing” as a catch all label for such effects). Specifically, wages are given by \( w(s) = \omega(s) + \delta \Pi \), where \( \omega(s) \) is the reservation wage for workers of skill s (with \( \omega' > 0 \)), and \( \delta \Pi \) is the rent sharing premium such that \( \delta < 1 \) and \( \Pi \) is the surplus in the period (see below). In principle, we permit \( \delta \) to vary over time (e.g.,
over the life cycle of the firm) and to be idiosyncratic and stochastic. This permits the evolution of firm paysetting structures over the lifecycle, and a concomitant change in the earnings profile of the business. Clearly this is a simplistic approach, since wage differentials might vary with worker characteristics and hence δ might not only vary with time but also with s. However, we include this simple possibility to point out the potential empirical relevance of the nature of the firm-specific components of wage determination and to recognize that a richer examination of this component should be a high priority for future research.

In this setting, expected profits in a given period are given by (normalizing the output price to one for now):

\[ \text{E}[(1-\delta)\{\theta f(k,s) - \omega(s) - F\} | K], \]  

(1)

where F represents fixed costs of operating in each period and K represents the belief about type in each period. In our simple model, firms will learn about their type and update K each period based upon prior observations. Then they will either decide to shut down (selection) or decide to continue to operate. If the latter, they will choose s, and generate their output.

This generates several concrete predictions. First, in the absence of uncertainty and rent-sharing, the choice of s each period will satisfy \( \theta \partial f(k,s)/\partial s = \omega'(s) \) and k-skill complementarity implies that firms with higher k will have higher s and higher wages. Second, the slope of the wage and productivity profiles should be the same for given k. In this simple case, systematic firm productivity differentials, wage differentials, and workforce composition differences are entirely driven by differences in k.

The intuition of this result can be seen in figure 4, where we have graphed the productivity profiles for firms with three different values of k (k_3 > k_2 > k_1). For any given skill level s, firms that

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8 The assumption that \( \theta \) is i.i.d. is not critical and likely unrealistic – we assume this for now to make some of the simple illustrative analysis easier to present.
are type $k_3$ are the most productive, firms that are type $k_1$ are the least productive, and firms that are
type $k_2$ are in between. Expanding this simple three firm example to a continuum of $k$, the points of
tangency where marginal productivity equals marginal wages sketch out the equilibrium line of
observed productivity/skill combinations (for simplicity in drawing the figure, we have assumed that
wages are linear in skills). If we interpret skill on the horizontal axis as an index of observable worker
characteristics, this line can be thought of a possible underlying theoretical justification for the
statistically significant productivity/skill relationship found for long-lived large firms by Haltiwanger,
Lane, and Spletzer (1999).\footnote{10}

4B. The role of uncertainty about type and the implications for learning

In the more general case, with uncertainty about firm type, the skill mix $s$ will be chosen so that
$E[\theta f(k,s)/\partial s | K] = \omega'(s)$. We still obtain the result that firms with higher $K$ choose higher $s$ and have
higher wages. However, as is obvious from the first order condition, uncertainty about $k$ implies that
the slopes of the wage and productivity profiles need not be the same, even for firms with the same $k$.
Figure 5 provides a visual interpretation of this. Suppose we have three firms in an entering cohort,

\footnote{9 We assume conditions are such that expected profits are a strictly concave function of $s$. In many of our
eamples, we assume $f$ is strictly concave in $s$ and $\omega$ is linear in $s$.}

\footnote{10 It is worth noting that there are a number of potential reasons why high “$k$” and low “$k$” firms can both exist
in the same market. If $k$ is managerial ability, economies of scope as in Lucas (1977) can limit the size of the
business. If $k$ is type of technology adopted, then costs of adopting and learning new skills may mean that there
is heterogeneity in technologies being used as in Cooper, Haltiwanger and Power (1999) or Caselli (1999). It
might also be that we want to think about $k$ as the persistent component of idiosyncratic technology or cost
shocks as in Hopenhayn (1992) or Hopenhayn and Rogerson (1993). Such idiosyncratic technology and cost
shocks might relate to the location of production or the specific technology adopted (and thus be related to some
of these other factors as well). It is the case that the equilibrating forces act somewhat differently across these
different possibilities. As noted above, in Lucas (1977) the differences in managerial ability and the economies
of scope yield differences in the size of businesses (and thus determine the equilibrium size distribution). In
Caselli (1999), there is some general capital that is perfectly mobile and thus sites that have adopted the latest
technology have not only better capital but also more capital. In Hopenhayn and Rogerson (1992), labor is the
only input considered, labor is subject to adjustment costs and is subject to decreasing returns and there are entry
costs (therefore the mass of entrants does not take over the market nor does any individual business). These
different models and associated equilibrating forces have implications for the dispersion of productivity across
businesses. Although it is beyond the scope of this paper to specify fully the nature of the factors generating the
productivity dispersion and the associated equilibrating forces, mapping the observed patterns and evolution of
dispersion in productivity (and earnings) across businesses to the specific implications of these alternative
models is an important area for future research.}
each of which has the same k, but each of which initially believes it has a different type $K_3 > K_2 > K_1$. At birth, then, they choose different skill levels based upon their belief about K. However, because productivity is determined by actual type as well as the skill mix of workers, the optimistic firm's realization of productivity is less than anticipated. Similarly, the pessimistic firm's realized productivity is greater than expected. Only firm 2 is at a point on the long-run (no uncertainty) productivity/skill locus. Firms 1 and 3 then adjust their skill level along the productivity curve, so that eventually they end up with a workforce composition appropriate to their type (and in this case the three firms with the same k would end up with the same workforce compositions and the same productivity level).

While the specific quantitative implications from Figure 5 depend upon the precise assumptions about the initial distribution of beliefs, there are a few key aspects of the implications illustrated that do not depend assumptions regarding initial beliefs. For one, Figure 5 helps illustrate the more general prediction that businesses will learn that they have made mistakes about their type and will adjust their mix of workers in a systematic fashion: overestimates of type result in decreased s; underestimates result in increased s.11 A second key related prediction that does not depend upon the initial distribution of beliefs is that the deviations from the long run profile should be reduced over time. In the limit, only the idiosyncratic productivity shocks should generate deviations in the long run. It is on these two predictions that we focus in the empirical analysis that follows. Before proceeding to that analysis, we discuss briefly predictions regarding the selection dynamics that accompany the learning dynamics we have been discussing.

4C. Selection

On the selection side, we draw heavily on the implications from the existing literature on selection as we have little to add (theoretically) except for some modest refinements. Following

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11 It should be clear that even if firms had the same initial belief, firms with negative errors (overly optimistic) will decrease their skill mix while firms with positive errors (overly pessimistic) will increase their skill mix.
Jovanovic (1982) and Dunne, Roberts, and Samuelson (1989), we suppose that entering firms face the uncertainty about type that we have already outlined, entry costs, and a fixed cost of operating in every period (denoted F in the prior section). In this environment, only firms with sufficiently high expected $k$ will enter. The marginal entering firm will have zero expected discounted profits taking into account the costs of entry. However, given the learning as well as the fixed costs of operating each period, some firms will learn that they have negative expected profits and exit. The firms that are more likely to exit are those with low $k$ since they will be closer to the marginal firm.

In terms of observable implications, low $k$ firms will tend to have both lower productivity and lower “$s$”. Putting these pieces together, we get some modest refinements of the typical predictions of the selection literature. The standard prediction is that low productivity firms are more likely to exit and this reflects the fact that low productivity firms are more likely (on average) to have learned through experience of producing that they are expected negative profit firms. Our refinement is that we should see that such marginal firms have also selected a low “$s$” and thus we should see that low “$s$” predicts exit. Errors should also provide information: firms that deviate from the long run profile in the negative direction should also be more likely to exit since this yields information about the learning about type. That is, a negative error indicates that the firm is more likely to have overestimated rather than underestimated its type and such firms will revise their expected type downwards and be more likely to exit.

To sum up, like the standard selection model, firms that learn they are low productivity firms are more likely to exit. Our focus on the choice of worker mix suggests the following refinements. First, the choice of mix will be correlated with $k$ and productivity and thus should help predict exit. Second,

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12 In a formal model of entry and exit, we might also want to guarantee some exit of mature businesses. The latter could be generated from there being some probability of any given production site becoming sufficiently unproductive (e.g., as in Davis and Haltiwanger (1990) or Ericson and Pakes (1995)) that it should exit. In terms of the model sketched above, this could be captured by assuming that there is a component of the profit shock $\theta$ that has this feature.
the component of productivity that is not predicted by worker mix may also have some additional power to predict exit as this indicates the direction of learning.

5. Empirical Specifications and Tests

The above theoretical discussion generates testable hypotheses about selection and the evolution of productivity and worker mix as a cohort of businesses enters and ages. We have specific predictions about the evolution of productivity as firms age and the role of changes in the worker mix in this evolution. To test the predictions of the theory we start with a simple decomposition of productivity given by:

\[ y_{it} = X_{it} \bar{\beta} + v_{it} . \]  

Here \( y_{it} \) is a measure of an outcome such as output per worker, \( X_{it} \) is a vector of worker characteristics, and \( \bar{\beta} \) represents a set of time invariant coefficient estimates representing the long run productivity profiles discussed above. The error term in this simple decomposition, \( v_{it} \), can be interpreted as representing deviations from the long run profile.

An open question is how to determine \( \bar{\beta} \). We use the estimated coefficients from a balanced panel of mature businesses to generate the “fixed” \( \beta \)’s (the \( \bar{\beta} \) in the above equation). The motivation for this -- influenced largely by Figures 4 and 5 and our initial empirical work in Haltiwanger, Lane, and Spletzer (1999) -- is that mature businesses have presumably learned their type and thus the estimated coefficients will not reflect errors in type.

Using this simple decomposition, we examine the predictions of the theory for entering cohorts of firms. The theory predicts that firms that overestimate their type will decrease their skill mix while firms that underestimate their type will increase their skill mix. Second, the theory predicts that the dispersion in the errors will be reduced as the cohort ages (and learns). These predictions can be tested
for entering cohorts of businesses by examining the relationship between changes in the skill mix and initial errors made upon entry. To be specific, we construct a measure of predicted productivity using the long run $\beta$’s and the actual skill mix chosen by each entering business. The difference between actual and predicted productivity yields a measure of the “error” made by the entering business (this measure of the error is captured as $\nu_e$ in equation (2)). A similar measure of the wage “error” is also constructed. We use these constructed errors in two ways. First, we examine the changes in the skill mix for entering businesses as a function of the initial error. Second, we examine the change in the dispersion of the errors as an entering business ages.

Finally, on the selection side, the theory predicts that firms with observed initial low productivity are more likely to fail. It could be that the firm had expectations that it was a marginal firm with a low $k$ and therefore had also chosen a low $s$ and therefore worker mix should help predict exit. Alternatively, the low observed productivity could be a surprise (and thus show up in the error term) that indicates the firm overestimated its type and through learning the firm is more likely to exit. We can test these predictions by examining the probability of exit as a function of initial productivity as well as the magnitude and sign of the errors made in $k$. The measure of the errors is constructed in the manner discussed above.

Before proceeding, we note that in the following empirical analysis our focus is on the evolution of productivity differences across businesses and the relationship of these differences to choices about worker mix. However, we also consider the relationship between earnings per worker and worker mix in some exercises for two reasons. First, the slope of the productivity-skill profile will be related to the slope of the earnings-skill profile and thus we seek to examine this relationship. Second, firm-specific differences in earnings may be related to firm specific differences in productivity since there may be rent sharing occurring. Thus, for example, the prediction for a fall in the dispersion of productivity as a cohort ages may carry over to a prediction of a fall in the dispersion of earnings.
6. **Longitudinal Linked Employer-Employee Data**

In order to address these questions, we need a dataset that links workers to their employers, provides information on the characteristics of both, and follows both over time. We use three sources of data to create our longitudinal linked employer-employee dataset. Firm characteristics are obtained from the Standard Statistical Establishment List (SSEL), which is the U.S. Census Bureau's sampling frame for businesses in the United States. Demographic characteristics of individuals are obtained from administrative records at the U.S. Census Bureau. The bridge between the workers and the firms is the Unemployment Insurance (UI) wage records from the state of Maryland.

Every quarter, all employers subject to state Unemployment Insurance (UI) laws are required to submit quarterly contribution reports detailing their monthly employment and quarterly wages to the State Employment Security Agencies. The employer also provides quarterly wages for every employee. These data on individual employees are known as the wage records, and are used by the states to manage their unemployment insurance program. The UI wage records have been used by many previous authors for research into worker flows, job flows, and the earnings effects of labor reallocation -- see, for example, Jacobson, Lalonde, and Sullivan (1993), Anderson and Meyer (1994), Lane, Miranda, Spletzer, and Burgess (1999), and Burgess, Lane, and Stevens (2000). In this paper, we use wage records from the state of Maryland from the second quarter of 1985 through the third quarter of 1997. This dataset consists of 108,254,142 observations on 5,006,622 workers and 262,062 employers.

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13 We should note that our linked employer-employee dataset has been created under strict protocols within the confidential firewalls at the U.S. Census Bureau. Following Census Bureau policy, the resulting micro analytic database can be used only for statistical purposes, and the output from such statistical analysis is carefully reviewed to ensure the confidentiality of individual households and businesses.
The main advantage of the UI wage records is their coverage of essentially a universe of workers and employers. Another advantage of the wage records data is the ability to construct longitudinal linkages for both individuals and employers. We have linked the UI wage records across quarters, using the employer as the unit of analysis. To ensure that we do not falsely define businesses that are involved in ownership changes as births and deaths, we use information on worker flows to distinguish administrative changes in employer identification numbers from true births and deaths.

Perhaps the main drawback to the UI wage records data is the lack of even the most basic demographic information on workers. We overcome this by linking the UI microdata to administrative data residing at the Census Bureau that contains information such as date of birth, place of birth, and gender. We are also particularly interested in the educational composition of the workforce. We were able to directly obtain education information on a sample of the workforce via other administrative data links to the long form of the decennial census. Since education can change for workers aged 18-24, we subset the data to only include workers over age 25. We then follow Angrist and Krueger (1991) in using detailed place of birth, month of birth, year of birth, race, and gender to impute education for the balance of the workforce.

The information in the UI wage records is also quite limited with regard to characteristics of the employer. We link the UI data to the Standard Statistical Establishment List (SSEL), which is the Census Bureau's business register. All SSEL information about individual businesses is confidential under Title 13, United States Code. The SSEL is the source of basic employment and payroll measures summarized by industry and geographic area in the Annual County Business Patterns series, and the SSEL also serves as a resource for research into topics such as longitudinal business

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14 The state based UI system provides a virtual census (98 percent) of employees on nonfarm payrolls. The major exclusions from private sector UI coverage are agricultural employees, self-employed workers, private household workers, unpaid family workers, and employees in small nonprofit organizations.
15 The long form is only sent to 1/6 of households.
16 This imputation seems reasonable as the R-squared is 0.11.
demographics. Walker (1997) provides an excellent description of the SSEL. We use the natural log of payroll per worker as our measure of earnings in the empirical work below, and we use the natural log of sales per worker as our measure of productivity.

While the preferred productivity measure would be value-added per hour or perhaps even better multifactor productivity, we believe our measure is a reliable measure of productivity and we also make some further adjustments to increase its reliability. For one, we note that the standard BLS measure of labor productivity at the detailed industry level is output per hour. As such, there is a close correspondence both conceptually and in terms of measurement between our measure of gross output at the establishment level and the industry-level measures published by BLS. In addition, studies using micro data have shown that the relationship between labor productivity (measured as gross output per worker) and multifactor productivity is strong. Foster, Haltiwanger and Krizan (2001) show that for manufacturing establishments the within-industry correlation between these two measures is roughly 0.8 in levels and 0.5 in growth rates. Unfortunately, establishment-level measures of multifactor productivity are largely confined to the manufacturing sector and to Economic Census years but such results provide reassurance that the variation we are capturing has content.

Nevertheless, because of lingering concerns about price variation, variation in hours per worker, or variation in capital usage that vary across years and industries, virtually all of the empirical work below uses data measured as deviations from year and four-digit industry means. Note that in all of the analysis, the year and four-digit means are fully interacted so that results should be interpreted as reflecting within-year, within industry variation.

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17 It is worth noting that for most sectors there are not highly reliable measures of value added per hour even at the industry level that differ from the measures of gross output per hour. The reason is that materials usage data is poor in most sectors other than manufacturing. As Triplett and Bosworth (2001) note, for most service sector industries the correlation between gross output per hour measures from BLS and value-added per hour measures from BEA is extremely high for many service sector industries because the measurement of materials usage is poor.
The analytical dataset that we construct from these merged files has the employer as the unit of analysis. We aggregate the individual worker data into summary measures for each firm. For example, we construct firm level proportions of workers under age 30, between 30 and 55, and over 55. We construct the proportion of the firm's workforce that is female and the proportion that is foreign born. We also construct firm level proportions of workers with low, medium, and high amounts of education (where these categories roughly correspond to less than high school, high school graduates and those with some college, and college graduates). The resulting dataset has annual observations on essentially every firm in the State of Maryland between 1985 and 1997.

We impose a series of restrictions before turning to the analysis. We restrict the data to those firms in the UI with a valid match to the SSEL, and we keep single establishment firms with nonmissing sales data in the SSEL.\textsuperscript{18} While restricting attention to single establishment firms has limitations for some purposes, it is not a major concern in the current context where we want to focus on the dynamics in the first few years after entry. As Spletzer (2000) has shown, almost 90 percent of entering establishments are single unit firms and thus we have the set of firms that dominate entry dynamics. Because of concerns about partial year data, we delete observations from 1985 and 1997 and we delete observations in the year of birth and the year of death. We further restrict our data to firms not in the agriculture and public administration industries, and we delete observations in the top and bottom 1% of the productivity and earnings distributions.

Since the focus of the paper is on the evolution and selection of newly born firms, we create several analytical datasets. The first dataset consists of a balanced panel of firms that exist every year 1985-1997. There are 22,420 of these firms, with full information available in 116,461 employer-year

\textsuperscript{18} Each of these restrictions is somewhat severe in terms of losing observations. The Maryland UI data identifies firms with a state-specific identifier, whereas the SSEL identifies firms with a federal identifier. We have the crosswalk between these two identifiers for 1988 Q1 and 1992 Q1. This implies that all births after 1992 Q1 and all deaths before 1988 Q1 will not be in the merged dataset. Because the sales data in the SSEL is reported at the EIN level rather than the establishment level, and because most births are single establishment births, we have chosen to delete multi-establishment companies from our analysis.
observations (sales data are missing in the SSEL in 1988, 1989, 1990 and 1993; sales data are, on average, missing for 32 percent of single establishments in the other years) The average firm in the balanced panel has 11.9 employees. This balanced panel is the sample of mature firms from which we estimate the $\beta$ coefficients (the long run profile). The data in Figure 1 are from this balanced panel. The second dataset consists of firms born within the 1985-1990 period; we restrict on births in these years so we can observe their growth and survival during their initial six years of life. There are 20,338 such births, contributing 48,664 employer-year observations. Of these births, 14,722 survive for at least six years, and these successful births contribute 39,981 employer-year observations.

7. Basic Patterns in the Relationship between Productivity, Earnings, and Worker Mix

Table 2 presents very basic regressions relating productivity, earnings, and worker mix. The regressions in table 2 use the simple specification described in section 5 to relate firm-level outcomes to the characteristics of the workers employed by the firm. Our focus is on the long run productivity-skill profile since we need estimates of this profile (what we have called $\beta$) in order to conduct the tests of the predictions of the model. Thus, the key column in Table 2 is the third column of the productivity regressions. However, as useful background results, we also report the productivity-skill profiles for entering cohorts and we also report the earnings-skill profiles in a like manner.

We find that firms in our data have higher measures of labor productivity and earnings if they have workforces with a higher fraction of foreign born workers, a lower fraction of female workers, a higher fraction of prime age workers, and a higher fraction of more educated workers. Many of

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19 Not surprisingly, given the sample size, a simple Chow test rejects the null hypothesis that these parameter estimates are stable over the entire period. However, when we estimate the regressions for specific years, the signs and the orders of magnitude of the coefficients are very similar.

20 Haltiwanger, Lane, and Spletzer (1999) note that the female coefficient in these regressions requires special interpretation. Because we are using employment rather than hours in the denominator of the productivity and the earnings variables, these coefficients might be biased downward if the propensity to work part-time is greater for females. More generally of course, there may be many factors that influence
these coefficients are statistically significant. There are undoubtedly many different dimensions to skill and we capture only part of these dimensions here with our measures. Nevertheless, it is apparent from Table 2 that for mature businesses both the productivity/skill and earnings/skill profiles are “upward sloping” in that workers with higher measured skill have both higher productivity and higher earnings. While the estimates vary somewhat across the age of businesses (which our theoretical arguments suggest should happen), the slopes of the productivity and wage profiles with respect to worker characteristics appear to be qualitatively similar across businesses of different ages.

It is tempting of course to compare the magnitudes of the coefficients in the productivity and earnings regressions and draw inferences regarding the extent to which different workers are being paid their marginal products. For example, it appears that increasing the percentage of highly educated workers raises earnings per worker more than output per worker. Our discussion of the simple theoretical model in section 4 cautions against interpreting such interesting findings as implying that, in this case, highly educated workers are being paid more than their marginal products. Our theory and evidence presented above suggests that, amongst other things, there are inherently unobserved factors “k” that may influence productivity and wages differentially. These factors are likely to be correlated with our measures of worker characteristics and as such, it is important to interpret the coefficients in Table 2 as reflecting the empirical covariances between productivity, earnings, and worker characteristics. Along related lines, the resolution of uncertainty may have

\footnote{For example, Hellerstein, Neumark and Troske (1999) present analysis that compares slopes of similarly specified earnings and productivity profiles in order to examine questions of discrimination. As they carefully show there are important issues of functional forms that can influence tests of the productivity versus earnings differentials. Since such tests are not the focus of our analysis we do not attempt to investigate the sensitivity to functional form issues in the same manner.}
differential impacts on wages and productivity so that the slopes of the estimated profiles for young businesses have additional sources of possible differences between the profiles.

While some caution is called for, it is interesting to compare the coefficients – especially since we are interested in using the patterns in these coefficients in empirical exercises that follow. The last columns on the right of Table 2 report differences in the coefficients for each of the respective worker characteristic variables and a test of statistical significance. For the balanced panel, we find that the coefficient in the productivity equation is less than that in the wage equation for foreign born, older, and more educated workers. Again, for the balanced panel, we find that the coefficient in the productivity equation is greater than that in the wage equation for female, younger, and less educated workers. All of these differences are statistically significant. For the younger businesses, the pattern of the difference in coefficients is roughly similar but somewhat more erratic and less statistically significant. An interesting aspect of these findings is that whatever the factors that are driving the differences in the productivity and earnings coefficients, they are apparently more important for well-established businesses. Since uncertainty would presumably be less important for mature businesses, this suggests that the wedge between productivity and wages for mature businesses must be driven by other factors.

In what follows, we focus on the long run productivity-skill profiles. Specifically, we use the coefficients reported in the 3rd column of the productivity regressions as a key input in constructing the measures of the errors that firms make upon entry. In addition, in order to investigate the predictions regarding changes in the skill mix, we use these long run profile coefficients to create a skill index for each firm. We now turn to these empirical exercises.


8A. Learning: Changes in Worker Mix
The theory predicts that firms with positive surprises in initial productivity are more likely to have underestimated k and will exhibit increases in skill, and firms with negative surprises in initial productivity are more likely to have overestimated k and will exhibit decreases in skill. The dependent variable we use to measure changes in skill is a change in a skill index from the second year to the sixth year for a successful entrant (measured formally as \((X_6 - X_2) \bar{\beta}\), where \(X_t\) is the vector of workforce composition variables in the \(t^{th}\) year after birth, and \(\bar{\beta}\) is the vector of regression coefficients estimated from the balanced panel from the productivity regression on worker characteristics). We measure the change in skill between years 2 and 6 to avoid problems with measures of initial year productivity as explanatory variables in the regression.

In column 1 of table 3, we regress the change in the productivity skill index on the firm’s initial productivity error. We find that those firms with positive errors (such as firm 1 in figure 5 that underestimated its k) tend to increase their skill mix, and those firms with negative errors (such as firm 3 in figure 5 that overestimated its k) tend to decrease their skill mix. To see whether this result might be driven by regression to the mean effects, we control for the initial worker skill mix by including the initial predicted productivity in column 2. The coefficient on the initial error is reduced somewhat but remains positive and statistically significant. We interpret these results as saying that the initial error in choosing skill level has important empirical content. This is consistent with the theoretical prediction that new firms systematically experiment with their mix of workers as they learn about their type.

8B. Learning: Changes in Productivity and Earnings

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22 We have also replicated the analysis in Table 4 using the earnings specification. We find qualitatively similar results although they are somewhat less strong and estimated less precisely. Part of the reason for this is that the implications for responses to “errors” may not carry over to earnings. In the absence of rent sharing, there is no sense in which the gap between actual and predicted earnings reflects an error.

23 Of course, learning is a potential source of regression to the mean effects but there may be other factors generating regression to the mean effects in the worker mix. By controlling for initial worker mix, we abstract from such factors and focus on the impact of the “error” made in the choice of worker mix.
We now investigate the evidence on the evolution of changes in dispersion of productivity and earnings as an entering cohort ages. Using our sample of successful births, the productivity and earnings dynamics are given in table 4. Table 4 demonstrates that successful births exhibit systematic changes in the variance of productivity and earnings during their first six years: as the firm ages, the standard deviation of both productivity and earnings falls. Recall however that while this fall in dispersion in productivity and earnings is consistent with learning, the specific prediction is that deviations from the long run profile should diminish over time. Specifically, the dispersion in the errors should fall over time. Table 5 shows that 92% of the declining productivity dispersion is due to declining dispersion of the “errors” (measured as deviations from the long run profiles). We also repeated the analysis using earnings per worker and found that 22% of the declining earnings dispersion is due to declining dispersion of “errors” (deviations from the long run earnings profile).

These findings (especially those on productivity dispersion) are consistent with the predictions of the learning model. It is interesting that changes in the errors account for a greater fraction of the changes in dispersion of productivity than in earnings. This finding is consistent with the prediction that deviations from the long run profile are less likely to be important in accounting for changes in earnings dispersion. Recall that the prediction about falling dispersion in productivity from “errors” (deviations from the long run profile) may not carry over to earnings. In the absence of rent sharing, there is no clear prediction of a reduction in the variance of earnings and in particular a reduction in the variance of the “error” from the long run earnings-skill relationship. Thus, it is interesting that the earnings results roughly mimic the productivity results.

8C. Selection

As discussed earlier, our theory has specific predictions about both selection and learning. With regard to selection, we present simple OLS death regressions in Table 6. For each cohort of entering businesses, we define an indicator variable that is equal to one if the business does not survive within the first six years and zero otherwise. In the first column, we regress this indicator of death within the
first six years on the firm's actual productivity in its first year. We find that the firms with initially low productivity are more likely to exit. This is in keeping with the theoretical predictions, where we expect that firms with lower levels of initial productivity are more likely to be close to the marginal firm (i.e., close to the fixed cost threshold at which exit is optimal).24

In keeping with the theoretical analysis, and with the visual depiction in Figures 4 and 5, we decompose actual productivity into two parts: the component that is on the long run productivity/skills locus, and the residual. The former is where the firm expects to be given its chosen skill mix, and the latter is what we term the firm's error in identifying its type. In addition to the predicted component signaling the firm's belief about its type k, we expect firms that make pessimistic errors about k will exhibit positive productivity errors, which leads to firms learning that they are higher k and therefore a lower likelihood of exit. These hypotheses are empirically valid: the coefficients in column 2 are negative and statistically significant. Interestingly, the coefficient on the predicted component of productivity is substantially larger in magnitude than the coefficient on the error component. One interpretation for this result is that the observed worker mix is a good proxy for type and thus a good predictor for productivity, whereas the error is a noisy predictor of type (as it should be) but nevertheless has predictive power in terms of predicting survival.

9. Concluding Remarks

We began this study by exploiting a rich new employer-employee dataset to find substantial and persistent differences in earnings per worker, output per worker, and worker mix across businesses

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24 This result is mirrored in a death regression that uses earnings instead of productivity: we find that firms with low initial earnings are likely to exit. At first glance, this result might seem counter-intuitive: one would expect that all else equal, firms with lower earnings would have higher expected profits and thus be more likely to survive. One explanation for this finding is that low earnings reflect low skill, and skill is chosen based upon the firm's expectation of type. Indeed, in the model, wages w(s) are equal to \( (1-\delta)\alpha(s)+\delta[\theta(k,s)-F] \), and in the presence of rent sharing (\( \delta > 0 \)), wages are a function of k and thus become an alternative measure of productivity. When we estimate a death regression with actual productivity and actual earnings as explanatory variables, both
within narrowly defined industries. We found that these remained even after controlling for other observable characteristics. We argued that these were all manifestations of the same underlying dynamic: the type of firm that generated these differences. We sketched a model in which businesses deliberately choose different worker mixes because of differences in their types and productivity interactions (e.g., k-skill complementarity) between the type of business and the mix of workers. Following the industrial organization literature, we posited that businesses learn about their types over time so there is churning and evolution of the worker mix at businesses and this is related to the observed earnings and productivity dynamics. In order to understand the dynamics underlying the choice of workforce composition, our empirical analysis focused on the productivity and earnings dynamics of young businesses.

We found that, at entry, new businesses exhibit substantially greater heterogeneity in productivity than do mature businesses, but that two factors contribute to the lower productivity dispersion of mature businesses. First, new firms learn to adjust their workforce composition as they age. Indeed, we found that businesses adjust their workforce composition in the direction consistent with a learning model. Second, new firms with low initial productivity, or new firms that make initial mistakes in that they are overly optimistic about their type, are more likely to exit. We also found that many of these same findings carry over to earnings per worker indicating that idiosyncratic differences in productivity across firms often carry over to idiosyncratic differences in earnings per worker.

In sum, this paper extends a very basic result from the empirical industrial organization literature – namely that learning and selection effects matter for firm dynamics – to the labor economics literature in showing that this experimentation process involves the choice of worker mix in both the selection and the learning process. Put differently, new firms struggle to find their way in deciding how to undertake production and run a business – some do not succeed and fail while others learn and come in with statistically significant negative coefficients. We interpret this to mean that both earnings and productivity are noisy measures of underlying firm type.
prosper. In this sense, our results, although derived from a new dataset, are very consistent with both the rich empirical literature documenting marked differences in firm behavior within industries, and the explicit theoretical understanding of the impact of different initial endowments – like managerial skill, physical and organizational capital – on firm outcomes.

There are clearly aspects of the results that require further research. A particularly interesting area of future research is investigating the contribution of rent sharing and internal labor market considerations to the dynamics of earnings and productivity as firms age. In addition, it would be useful to investigate the interaction between different types of k and different sets of worker characteristics on earnings and productivity. A question that we do not directly address but which is equally interesting is the impact of these firm dynamics on workers. In particular, we know that the types of firms that are more likely to exit are those that are low productivity, with a low level of workforce skill. We also know from the recent literature that this entry and exit plays an important role in productivity growth, yet that the effects of involuntary job loss can be large and persistent, at least for long tenure mature workers. Quantifying and understanding the potential economy wide gains in productivity from this process of creative destruction and adjustment via the costs borne by workers should be an important area for future research.
References


Figure 1: Heterogeneity & Persistence
Firms Alive in 1986 and 1996 with >10 Employees Each Year

Proportion Female: 1986 vs. 1996, by firm

Proportion Highly Educated: 1986 vs. 1996, by firm

Productivity: 1986 vs. 1996, by firm

Actual Earnings: 1986 vs. 1996, by firm
Figure 2: Productivity, Earnings and Worker-Mix in Restaurant Industry

All Restaurants

Table Service Restaurants
Figure 3: Productivity, Earnings and Worker-Mix in Plumbing Industry

All Plumbing Businesses

Capital-Intensive Plumbing Businesses
Figure 4: No uncertainty, No rent sharing, Linear Wages
Three different values of $k$
Figure 5: The link between k, skill, and productivity
Uncertainty: 3 different values of K, one value of k
### Table 1: Descriptive Statistics

<table>
<thead>
<tr>
<th>Mean (Std. Dev.)</th>
<th>6-year Successful Births: 1 year after birth</th>
<th>6-year Successful Births: 6 years after birth</th>
<th>Balanced Panel</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Productivity</strong></td>
<td>4.32 (.851)</td>
<td>4.26 (.827)</td>
<td>4.32 (.792)</td>
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<tr>
<td><strong>Earnings</strong></td>
<td>8.20 (.708)</td>
<td>8.25 (.699)</td>
<td>8.39 (.675)</td>
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<tr>
<td>% Foreign Born</td>
<td>.096 (.230)</td>
<td>.101 (.231)</td>
<td>.075 (.173)</td>
</tr>
<tr>
<td>% Female</td>
<td>.436 (.382)</td>
<td>.449 (.372)</td>
<td>.463 (.346)</td>
</tr>
<tr>
<td>% Age &lt;30</td>
<td>.348 (.332)</td>
<td>.245 (.271)</td>
<td>.249 (.245)</td>
</tr>
<tr>
<td>% Age &gt;55</td>
<td>.067 (.173)</td>
<td>.102 (.214)</td>
<td>.140 (.211)</td>
</tr>
<tr>
<td>% Low Educated</td>
<td>.216 (.276)</td>
<td>.284 (.286)</td>
<td>.257 (.239)</td>
</tr>
<tr>
<td>% High Educated</td>
<td>.054 (.158)</td>
<td>.048 (.141)</td>
<td>.038 (.106)</td>
</tr>
<tr>
<td><strong>Sample Size</strong></td>
<td>4,168</td>
<td>9,389</td>
<td>116,461</td>
</tr>
</tbody>
</table>

Descriptive Statistics are presented before removing Year & 4-Digit SIC means.

Productivity = \( \ln\left\{ \frac{\text{Annual Sales ($1000)}}{\text{GDP Deflator}} / \text{March 12th Employment} \right\} \)

Earnings = \( \ln\left\{ \frac{\text{1st Quarter Payroll}}{\text{GDP Deflator}} / \text{March 12th Employment} \right\} \).
<table>
<thead>
<tr>
<th></th>
<th>Productivity Regressions</th>
<th>Earnings Regressions</th>
<th>Differences in Coefficients between Productivity and Earnings Regressions</th>
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<tr>
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<td>6-year Successful Births: 6-year Successful Births: Balanced Panel</td>
<td>6-year Successful Births: 6-year Successful Births: Balanced Panel</td>
<td>6-year Successful Births: 6-year Successful Births: Balanced Panel</td>
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<tr>
<td>% Foreign Born</td>
<td>.085 (.053)</td>
<td>.031 (.043)</td>
<td>.053 (.055)</td>
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<tr>
<td></td>
<td>* .080 (.032)</td>
<td>.042 (.027)</td>
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<tr>
<td></td>
<td>.068 (.011)</td>
<td>.097 (.010)</td>
<td>-.030* (.011)</td>
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<tr>
<td>% Female</td>
<td>-.181 (.041)</td>
<td>-.398 (.033)</td>
<td>.217* (.042)</td>
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<td>* -.134 (.027)</td>
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<td></td>
<td>-.181 (.008)</td>
<td>-.562 (.007)</td>
<td>.382* (.008)</td>
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<tr>
<td>% Age &lt;30</td>
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<td></td>
<td>.046 (.042)</td>
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<td>% Age &gt;55</td>
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<td></td>
<td>* -.230 (.036)</td>
<td>-.217 (.030)</td>
<td>-.013* (.035)</td>
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<tr>
<td></td>
<td>-.206 (.010)</td>
<td>-.160 (.009)</td>
<td>-.046* (.010)</td>
</tr>
<tr>
<td>% Low Educated</td>
<td>-.150 (.049)</td>
<td>-.280 (.040)</td>
<td>.130* (.051)</td>
</tr>
<tr>
<td></td>
<td>* -.215 (.039)</td>
<td>-.188 (.033)</td>
<td>-.027 (.038)</td>
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<td></td>
<td>-.181 (.010)</td>
<td>-.249 (.008)</td>
<td>.069* (.010)</td>
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<tr>
<td>% High Educated</td>
<td>.142 (.049)</td>
<td>.093 (.061)</td>
<td>.109* (.078)</td>
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<td></td>
<td>.070 (.052)</td>
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<td></td>
<td>.128 (.018)</td>
<td>.209 (.016)</td>
<td>-.082* (.018)</td>
</tr>
<tr>
<td>R-Squared</td>
<td>.017 .016 .017</td>
<td>.078 .069 .081</td>
<td>.078 .051 .081</td>
</tr>
</tbody>
</table>

All regressions include an intercept and an indicator for whether initial employment exceeds 100. The successful birth regressions include cohort dummies. The balanced panel regressions include controls for age. All data (except intercept and cohort dummies) have Year & 4-Digit SIC (interacted) means removed. Productivity and earnings per worker are in logs.
Table 3:  Skill Index Change Regressions, 1990 Successful Births

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
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<tbody>
<tr>
<td>X* $\overline{\beta}$: Predicted Productivity</td>
<td>-.244 *</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.024)</td>
</tr>
<tr>
<td>Error: Actual -</td>
<td>.010 *</td>
<td>.008 *</td>
</tr>
<tr>
<td>Predicted</td>
<td>(.003)</td>
<td>(.003)</td>
</tr>
<tr>
<td>R-Squared</td>
<td>.008</td>
<td>.097</td>
</tr>
</tbody>
</table>

All regressions include an intercept. Sample size=1051.
Dependent Variable is [X(year 6 after birth) - X(year 2 after birth)]* $\overline{\beta}$ (Productivity); mean=-.0030.
All explanatory variables are measured as of the first year after birth. $\overline{\beta}$ is estimated from the balanced panel.
All data (except intercept) have Year & 4-Digit SIC (interacted) means removed.

Table 4:  Productivity and Earnings Dynamics, 6-year Successful Births

<table>
<thead>
<tr>
<th>Productivity</th>
<th>Standard Deviation</th>
<th>Earnings</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Year After Birth</td>
<td>.737</td>
<td>1 Year After Birth</td>
<td>.619</td>
</tr>
<tr>
<td>2 Years After Birth</td>
<td>.704</td>
<td>2 Years After Birth</td>
<td>.616</td>
</tr>
<tr>
<td>3 Years After Birth</td>
<td>.700</td>
<td>3 Years After Birth</td>
<td>.627</td>
</tr>
<tr>
<td>4 Years After Birth</td>
<td>.704</td>
<td>4 Years After Birth</td>
<td>.609</td>
</tr>
<tr>
<td>5 Years After Birth</td>
<td>.696</td>
<td>5 Years After Birth</td>
<td>.594</td>
</tr>
<tr>
<td>6 Years After Birth</td>
<td>.686</td>
<td>6 Years After Birth</td>
<td>.591</td>
</tr>
</tbody>
</table>

All data have Year & 4-Digit SIC (interacted) means removed.
Table 5: Dispersion in “Errors” for Productivity & Earnings, 6-year Successful Births

<table>
<thead>
<tr>
<th></th>
<th>90-10 from “Errors”</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Productivity</td>
</tr>
<tr>
<td>1 Year After Birth</td>
<td>1.830</td>
</tr>
<tr>
<td>6 Years After Birth</td>
<td>1.699</td>
</tr>
<tr>
<td>Difference</td>
<td>-.131</td>
</tr>
<tr>
<td>(92%)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>90-10 from “Errors”</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Earnings</td>
</tr>
<tr>
<td>1 Year After Birth</td>
<td>1.555</td>
</tr>
<tr>
<td>6 Years After Birth</td>
<td>1.479</td>
</tr>
<tr>
<td>Difference</td>
<td>-.076</td>
</tr>
<tr>
<td>(22%)</td>
<td></td>
</tr>
</tbody>
</table>

Table 6: Probability of Death Regressions, 1986 & 1990 Births

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Productivity</td>
<td>-.039 *</td>
<td>-.035 *</td>
</tr>
<tr>
<td></td>
<td>(.007)</td>
<td>(.007)</td>
</tr>
<tr>
<td>X* ( \hat{β} ) : Predicted Productivity</td>
<td>-.271 *</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.057)</td>
<td></td>
</tr>
<tr>
<td>Error: Actual - Predicted</td>
<td></td>
<td>-.035 *</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.007)</td>
</tr>
<tr>
<td>R-Squared</td>
<td>.031</td>
<td>.033</td>
</tr>
</tbody>
</table>

All regressions include an intercept and cohort dummies. Sample size=6631.
Dependent Variable (before removing (interacted) year and 4-digit SIC means) = 1 if establishment does not survive 6 years, 0 otherwise; mean (before removing year and 4-digit SIC means) = .3714.
All explanatory variables are measured as of the first year after birth. \( \hat{β} \) is estimated from the balanced panel. All data (except intercept and cohort dummies) have (interacted) Year & 4-Digit SIC means removed.