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Augmenting the Human Capital Earnings Equation With Measures of Where People Work / Erling Barth, James Creece Davis, Richard Freeman

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Augmenting the Human Capital Earnings Equation with Measures of Where People Work

Abstract

We augment standard log earnings equations for workers with variables reflecting measured and unmeasured attributes of their employer. Using panel employee-establishment data for US manufacturing we find that the number of workers and education of co-workers at an establishment, the capital equipment per worker, and the R&D intensity of the firm that owns the employing establishment impact earnings substantially. In addition, unobserved characteristics of employers captured by fixed effects also contribute to the variance of log earnings, though less than unobserved characteristics of individuals, also captured by fixed effects. The observed and unobserved measures of employers mediate the estimated effects of individual characteristics on earnings and increase earnings inequality through sorting of workers among establishments.

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Introduction

Standard earnings equations relate log earnings of individuals to their measured human capital or demographic attributes.¹ These equations account for a sizable proportion of the variation in individual earnings but still leave a sufficiently large residual among workers with the same measured characteristics to challenge “the law of one price” in the US labor market. Exemplifying the dispersion of earnings for workers with similar skills, Devroye and Freeman (2001) found that variance of log earnings among US workers within narrow bands of adult literacy test scores exceeded the variance of earnings among all workers in the United Kingdom, the Netherlands, and Sweden. Much of the increased earnings inequality in the US from the 1970s to the 2000s, moreover, has taken the form of increased inequality among workers with the same measured human capital or demographic attributes.

What underlies the level and change in the residual variance from log earnings equations? One identifiable factor is the firm or establishment that employs the worker. The simplest market clearing models postulate either a single wage or a narrow band of wages associated with costs of information and mobility among jobs for workers with comparable skills but the evidence often shows that employers pay sizable differences for workers with the same measured attributes.² Commensurately, the same worker often earns substantially more or less working for different employers in closely aligned periods of time.

Analysis of Variance of Establishment Earnings

To see the extent to which earnings of individuals depends on where they work in the US in recent years, we analyzed the log earnings of individual workers in the Longitudinal Employer-Household Dynamics (LEHD) Employment History Files for the nine states with LEHD data from 1992 through 2007³. We decomposed the total variance of log earnings into a part attributable to differences in earnings among establishments and a part due to differences in earnings of workers within establishments. To keep as many observations as possible on each individual for panel data analysis, we included all workers-jobs observed in the 2nd quarter of each year in the LEHD. We estimated establishment effects by regressing the log earnings of individuals on establishment dummies separately for each year and then used the variance of the estimated coefficients on establishment dummies to measure the variance of log earnings due to the between-establishments effect. The remaining variance reflects earnings differences within establishments and interactions between individuals and establishments. Since the ANOVA does not adjust earnings for the measured attributes of individuals within establishments or for establishment differences in average worker attributes or observable establishment attributes, the calculations are a descriptive representation of the raw earnings data.

¹ We use “attributes” and “characteristics” interchangeably in this paper.

² Earlier studies include Davis and Haltiwanger (1991), Groshen (1991), Abowd, Kramarz and Margolis (1999), Lane, Salmon, and Spletzer (2007), Gruetter and LaLive (2009), Nordström Skans, Edin, and Holmlund (2009), Card, Devicienti and Maida (2010), Barth, Bryson, Davis and Freeman (2016), Song et al. (2015) and the contributions in Lazear and Shaw (2009).

³The LEHD provides annualized quarterly earnings from the unemployment insurance benefit programs, linked to the Quarterly Census of Employment and Wages. We use only observations with positive earnings in the 2nd quarter of the year. Abowd et al. (2002) describe the construction of the LEHD data. The nine states (California, Colorado, Idaho, Illinois, Maryland, North Carolina, Oregon, Washington, and Wisconsin) cover approximately half of US employment. The nine state sample seems reasonably representative of the country (Barth et al. 2016).

Table 1 displays the results of the ANOVA for 1992-2007 for the whole US economy and for eight large one-digit sectors. The columns give the total variance of individual earnings in 1992 and 2007, the share of the variance attributable to variance among establishments, the change in variance over time, and the share of the change attributable to increased variance of earnings among establishments. The first line shows that in the economy as a whole 48 percent of the variance of log earnings among workers comes from variation among establishments and that 66 percent of the 0.091 increased variance of earnings is due to the increase in variance among establishments.⁴

The remaining lines of Table 1 show differences in the level and change in the variance of log earnings among sectors. Variance is highest in business services, finance, insurance, and real estate, and lowest in manufacturing, mining, utilities, and transportation, and in private services. The share of the total variance associated with establishments is largest in business services and private services and lowest for health, education, and social services. Manufacturing, on which this paper focuses, has lower variance of earnings than the economy as a whole; is close to the economy-wide share of variance associated with earnings differences among establishments; and has a lower establishment share of the 1992=2007 increase in variance.

What employer attributes determine whether an employer pays above or below average market wages? How much do the individual attributes in standard log earnings equations and unobserved individual attributes associated with earnings affect the contribution of the employer effects on the Table 1 variances? What economic forces compress earnings across employers? What forces increase divergence? Do earnings differentials associated with worker characteristics differ by employer enough to contribute to the overall dispersion of earnings?

We examine these questions for manufacturing. We focus on manufacturing because of the quality of data on that sector: the Annual Survey of Manufacturers provides information on manufacturing establishments annually that is unavailable for other sectors and detailed evidence on investment in capital and other inputs that are likely to affect labor productivity across establishments, potentially leading to heterogeneity of pay through some kind of rent sharing mechanism⁵. For our analysis, we combined individual earnings from the LEHD with data on worker attributes from the Decennial Census and the Current Population Survey (CPS) and data on establishment attributes from the Census of Manufacturing and data on firm attributes from the Longitudinal Business Database (LBD) and the Survey of Industrial Research and Development (SIRD)⁶.

Methodology

The traditional human capital earnings equation (Mincer 1974) relates earnings w_{it} of individual i in period t to observable measures/indicators of personal skill and other individual

⁴ These estimates are nearly identical to those in Barth, Bryson, Davis, and Freeman (2016) based on analysis of full year main jobs, which found that 49 percent of variance of log earnings was associated with variance of earnings in 2007 and that 67 percent of the increase in labor earnings inequality from 1992 to 2007 was due to the increased variance of earnings among establishments.

⁵ The literature on rent sharing relates individual earnings to establishment/firm productivity or profitability, see eg. Hellerstein, Neumark and Troske (1999), Margolis and Salvanes (2001), Dunne, Foster, Haltiwanger and Troske (2004), Faggio, Salvanes and van Reenen (2007), Dobbelaere and Mairesse (2010), Mortensen, Christensen, and Bagger (2010), and Card, Heining, and Kline (2013).

⁶ These data measure: firm employment, establishment employment, capital per worker, the percentage of output exported overseas, and R&D per employee and to estimate the average characteristics of the establishment work force: years of schooling, age, gender and race.

characteristics that ideally reflect productivity but that may also reflect employer attitudes or perceptions resulting from prejudicial or statistical discrimination:

$$(1) \log w_{it} = \beta_0 + \gamma_t + x_{it} \beta + u_{it}$$

where γ_t is a period effect, x_{it} is a vector that includes years of schooling and individual attributes such as age, gender and race. The equation does not include attributes of the establishment or firm, though they can be added to the equation to reflect compensating differential or other factors related to the full compensation of workers that are not captured by the earnings measure.

Our augmented earnings equation adds the measured and unmeasured characteristics of an individual's establishment/firm to equation (1):

$$(2) \ln w_{ijt} = \beta_0 + \gamma_t + x_{it} \beta + z_{j(it)t} d + \psi_{ij(it)} + e_{ijt}$$

where $j(it)$ is an index of the workplace which employs individual i at time t , and where $\psi_{ij(it)}$ is a unique job fixed effect for every individual and workplace pair. For clarity of exposition, we omit the (it) index and write only the index j to indicate the workplace which employs individual i at time t in the following. The t subscript on z_{jt} allows observed employer characteristics to vary over time at a workplace, which could potentially affect the earnings of workers. Our analysis assumes that an employer characteristic affects the earnings of all workers similarly. With a panel of workers and employers, the d coefficients for the establishment characteristics are estimable using within job variation in employer characteristics – for example, if z relates to employment (“larger establishments pay more”), the effect of employment on earnings can be estimated for workers in the same job when the establishment changes employment.

Having multiple observations on a person along with employer identifiers in longitudinal data allows us to decompose the job effect into an individual fixed effect via a dummy variable for each worker, an establishment fixed effect via a dummy variable for each employer, and a match component orthogonal to the individual and establishment fixed effects per the “AKM decomposition” (Abowd, et al. 1999): $\psi_{ij} = \alpha_i + \phi_j + \zeta_{ij}$. Defining $\alpha_i = X_i B + a_i$, and $\phi_j = Z_j D + \varphi_j$ where X and Z are covariates for each individual and establishment, we identify the B and D parameter vectors by assuming that the residual of the individual fixed effect is orthogonal to individual fixed characteristics and that the residual of the establishment fixed effect is orthogonal to establishment fixed characteristics. However, the components of both fixed effects can correlate with time varying characteristics and each other. Our final augmented equation is:

$$(3) \ln w_{ijt} = \beta_0 + \gamma_t + x_{it} \beta + X_i B + a_i + z_{jt} d + Z_j D + \varphi_j + \zeta_{ij} + e_{ijt} = \beta_0 + \gamma_t + \omega_{it} + \Omega_{jt} + \zeta_{ij} + e_{ijt}$$

where ω_{it} is the individual component of the earning, and Ω_{jt} is the establishment component, both of which contain observable and unobservable parts.

Comparing equations 1 and 3, if personal skills and attributes are the sole factors included in the estimation, the coefficients of equation (1) estimate the gross return to those skills/attributes *inclusive of possible gains from access to different employers* whereas the coefficients of equation (3) measure the net return exclusive of the earnings characteristics of employers. Alternatively, to the extent that the covariates in equation (1) are correlated with the equation (2) variables, the estimated coefficients of (1) can be viewed as biased estimates of the net effects of skills/ attributes in equation (2).

Matched LEHD, Establishment & Firm Data

As noted, our dependent variable is the earnings of individual workers in the LEHD Employment History Files for the nine states with LEHD data from 1992 through 2007.⁷ We link the LEHD to the quinquennial Census of Manufacturers (CoM) for the economic census years 1992, 1997, 2002 and 2007, and to the Annual Survey of Manufacturers (ASM) in intermediate years, using the LEHD Business Register Bridge that links data at the firm level. LEHD establishments are linked by firm, detailed industry and county to CoM/ASM establishments. For the vast majority of observations, single-unit firms and plants of a firm located in a different county than other plants of the firm in the same industry, the mapping from LEHD to CoM/ASM establishments is unique within detailed industry and county. But for plants of a firm in the same industry and county, the link is not one-to-one. For these establishments, we aggregate plant characteristics to the firm-industry-county level and link these measures to their workers.

The COM/ASM data provide production-related data on manufacturing establishments, which we add to the files on employees: number of workers at establishments, and establishment capital equipment and building stock as constructed by Foster, Grim, and Haltiwanger (2016) with perpetual inventory methods. We measure firm employment from the LBD, and whether a firm reports R&D expenditures and the amount from the Survey of Industrial R&D (SIRD). Appendix Table A gives summary statistics for our key variables

We obtain measures of the years of schooling, occupation, age, race and gender of workers in the LEHD by linking workers to their characteristics in the 1990 and 2000 Decennial Census long form and March CPS files for 1986-1997. The Census Center for Administrative Records staff matched these data using the Protected Identification Key (PIK) identifier, which is the person identifier in the Census, CPS and LEHD. Beginning with 2000 decennial files have very high PIK match rates of 90-93% (Mulrow et al. 2011, Rastogi and O'Hara 2012). However, the 1990 PIK is more limited due to the vintage of address files.⁸ Matching Census/CPS data to the LEHD Employee History Files (EHF) provides us with data on years of schooling and other worker attributes for 20.5% of employees in the LEHD data.⁹ In the matched sample we require that a person is observed at least 4 times.

Appendix Table A1 shows that the matching process produces a sample that is higher in earnings and worker attributes that are positively associated with earnings such as age and being white and a sample that is also higher in firm and establishment attributes that are positively associated with earnings such as number of employees and capital per employee.

Variance Decomposition in Manufacturing

⁷The LEHD data provides annualized quarterly earnings from the unemployment insurance (UI) benefit programs, linked to the Quarterly Census of Employment and Wages Program. We use only observations that include positive earnings in the second quarter of the year. Abowd et al. (2002) describe the construction of the LEHD data. The nine states are: California, Colorado, Idaho, Illinois, Maryland, North Carolina, Oregon, Washington, and Wisconsin. They cover approximately half of US employment. Comparisons with data for states that cover different time periods show that the nine state sample are reasonably representative (Barth et al. 2016).

⁸ Individual name and address files are highly sensitive and not generally distributed in the Census Bureau with the data files. Our versions of 1990 decennial files did not have original name and address data, and had to be reconstructed with other data sets. As a result, the PIK matches favor less mobile adult heads of household.

⁹ We first matched to the 2000 Census, then matched missing cases to the 1990 Census, and finally matched missing cases to the CPS data.

Table 2 gives a variance decomposition for the subset of manufacturing workers for whom we match observations in the LEHD and Census of Manufacturers to Decennial Census or CPS files. This is the sample on which the rest of our analysis focuses. The increase in variance in the subsample falls short of the increase in the full LEHD – a variance of 0.272 compared to the table 1 figure of 0.398 in 1992 and a variance of 0.330 compared to 0.490 in 2007, producing a smaller increase in variance over time. A major reason is that the matched sample loses many small establishments where earnings are relatively low. The proportion of the variance in log earnings attributable to between establishment differences is as a result lower as well. The 43% contribution of increased earnings between establishments in the matched sample is smaller than the 57% in the full LEHD. The matched sample *understates* the contribution of establishments to the variation in earnings.

As establishments belong to firms that include other establishments, all of which may be covered by firm-wide human resource and compensation policies, we decomposed the between-establishments contribution to the variance of earnings into an effect associated with firms and an effect associated with establishments within firms. We did this in two stages: first by regressing log of earnings on dummy variables for establishments and then regressing the estimated establishment fixed effects on dummy variables for firms. The proportion of the variance attributed to firms reflects the overall pay practices of firms while the remaining proportion reflects pay differences among establishments in the same firm.

The table 2 calculations show that consistent with the emphasis of Song et al. (2015) on the importance of the *firm* in accounting for the increased dispersion in worker earnings over time, the firm component dominates the variation in log earnings among establishments. In our manufacturing data 90.4% ($= 0.113/0.125$) of the variance in earnings between establishments in 1992 is assigned to firm fixed effects and 93.3%, ($=0.140/0.150$) of the establishment variance in 2007 is similarly assigned to firm fixed effects. Over time, moreover, the variance in establishment earnings for establishments within firms fell, so that 110% ($= 0.47/0.43$) of the increased earnings dispersion associated with establishment was due to increased earnings variance among firms.¹⁰

Cross Section Earnings Equations

Column (1) of Table 3 records estimated coefficients and standard errors for OLS regressions of the benchmark cross section log earnings equation with years of schooling, age, gender, and some interactions to allow for differences in effects among those attributes. In addition, the regression includes 171 geographic area dummies and 16 year dummies so that the coefficients are estimated within year and area. The estimated coefficients are similar to those typically found in the human capital earnings literature: an estimated average returns to years of schooling of about 9.4 percent per year and a concave age profile captured by the negative squared term and gender and race earnings gaps at 30% and 17%, respectively. The R^2 of the equation of 0.45 is larger than the R^2 in earnings functions fit on CPS data,¹¹ presumably because variation in earnings in the entire economy exceeds that in manufacturing and/or because the

¹⁰ Because many small firms have only a single establishment, the calculation that assigns virtually all of the variance of single establishment firms to the firm could overstate the dominance of firms in establishment effects. To see how much of the table 2 result is due to single-unit firms we eliminated them from the data set and decomposed the variances of earnings among multi-unit establishments. Appendix table B shows that among multi-establishment firms 83% ($= 0.094/0.113$) of the variation in establishment fixed effects is associated with the firm fixed effect, which supports the conclusion in the text.

administrative LEHD earnings has less measurement error than self-reported earnings in the CPS.

Column 2 adds a set of workplace variables to reflect place of employment: 4-digit NAICS industry dummies, the log number of employees of the *firm* and the log number of employees in the establishment and establishment age and its square¹². The estimates show significant firm- and establishment effects, and a concave earning-establishment age profile. Adding the firm and establishment characteristics raises the R^2 to 0.505 and thus explains 10% of the residual variance of earnings for demographically similar persons. The firm and establishment variables shrink the positive coefficients on years of schooling and age and the negative coefficients on gender and nonwhite, indicating that some of the impact of those factors comes through sorting of workers among establishments and industries within manufacturing.

Column 3 adds variables relating to the attributes of the establishment's work force: mean years of schooling, mean age, share female and share non-white; capital structures per worker and capital equipment per worker; the export share of establishment revenues; and the R&D investment of the firm to which the establishment belongs. The most striking result is the high estimated coefficient on the years of schooling of all workers. The estimated 0.069 coefficient on the mean years of schooling in the workers' establishment compared to the 0.074 coefficient on the workers' own education suggests that it is almost as good to work in an establishment with more educated workers as it is to have more education. The estimates also show that workers earn more in establishments with older workers and less in establishments with a larger proportion of female or nonwhite workers. More capital equipment per worker raises earnings more than more capital structures per worker (a coefficient difference of 0.046 vs 0.007) and earnings are higher in establishments with a high export share. Finally, earnings rise with R&D intensity of a firm: workers in firms with one standard deviation higher R&D intensity average 2% more earnings.

Column 4 gives the regression results with dummy variables for firms added to the equation while Column 5 gives results with dummy variables for establishments replacing those for firms. With establishment fixed effects in the model, it is no longer possible to identify the linear effect of establishment age and the time dummies, so we have removed the linear term for establishment age. Since the effect of linear age is now absorbed by the time dummies, none of the remaining estimators are affected. Addition of the firm fixed effects substantially reduces the estimated impact of the number of employees at the firm, indicating that short run changes in firm employment have little effect on earnings, but only reduce the coefficient on number of employees at the establishment modestly. The Column 5 estimates with dummy variables for establishment also markedly reduce the coefficient for firm employment but leave a substantial effect of establishment employment on earnings. With establishment fixed effects in the equation, the positive effect of establishment employment suggests that an establishment operates along a rising supply curve of labor for short term increases in employment, which suggests some monopsony power in the labor market (Manning, 2005).

Addition of the firm and establishment dummies naturally shrinks the estimated effect of firm and establishment variables on earnings. The Column 4 firm fixed effects regression eliminates the negative relationship between the share of non-white employees. Working in an

¹¹ Estimating a similar regression with CPS data for the whole work force gave an R^2 of 0.35.

¹² Dickens and Katz (1986) examine industry wage differentials. Brown and Medoff (1989) study employer size-wage effect.

establishment with a large non-white share is associated with low earnings, but short run changes in the non-white share do not affect establishment earnings much. The Column 4 fixed effects regression also greatly weakens the relationship between R&D and earnings, reducing the estimated coefficient by over 80 percent. While R&D firms pay more than firms that do less R&D, changes in R&D activity within a firm has little impact on earnings.

The Column 5 regressions which include establishment fixed effects further shrink the coefficients of most of the establishment workforce characteristics compared to those in column 3. The column 3 estimated 0.0690 effect of the mean years of schooling on earnings drops to 0.0249 in column 5 while the estimated -0.3176 for being female in column 3 drops to -0.1084 in column 5. While measurement error usually accounts for some of the lower coefficient on variables in longitudinal analysis compared to cross section analysis (Freeman 1984), the pooling of observations to create average characteristics is likely to diminish measurement error so that huge drops in the effects of these characteristics are likely to reflect at least in part economic behavior as firms adjust earnings to changing characteristics gradually over time.

Panel Earnings Equations

The longitudinal structure of the LEHD allows us to estimate the effects of employer characteristics on earnings for the *same* individual in two ways: 1) by comparing workers who remain in the same job while management changes characteristics of the establishment or accepts changes due to such factors as workers retiring or quitting for another job without replacing the leaver with someone similar; or 2) by comparing workers who quit an employer with one set of characteristics to join an employer with other characteristics. Outside of recession years, the bulk of the labor mobility comes from worker decisions to move to a new employer willing to hire them. In recessions, mobility depends more on the layoff decisions of firms, with the number of layoffs increasing to approach or exceed the number of quits¹³. While our data lack information on whether a worker left a job by quitting or by layoff, recession years are less frequent than non-recession years in our data, which suggests that the bulk of the worker changes reflect quits rather than layoffs.¹⁴

Table 4 presents estimates of the effect of employer attributes on the earnings of the same worker when those attributes change. The first column shows the results of adding individual fixed effects to the basic log earnings regression from column 3 in table 3 for all workers in the matched sample. The coefficients on some employer variables decline with the addition of the worker fixed effects: the estimated coefficient for average years of schooling of workers in an establishment falls by 59% (from 0.0737 to 0.0299), suggesting that much of the large co-worker schooling impact is due to positive sorting of workers by unmeasured individual characteristics into establishments with more educated workers. The coefficient on the equipment stock of capital per employee drops more massively by 70% (from 0.0462 to 0.0140), suggesting positive sorting of unmeasured individual characteristics into establishments with more equipment capital. And the coefficient on R&D drops by 83% (from 0.762 to 0.1290), suggesting that most of the cross section R&D effect is due to a positive matching between R&D firms and unmeasured individual characteristics.

¹³ For non-recession years the number of quits divided by the number of layoffs exceeds 1.0 by 30%-50%. In recession years, the number of layoffs exceeds quits. http://www.bls.gov/jlt/jlt_labstatgraphs_oct2015.pdf, chart 7.

¹⁴ We did not probe possible differences between job changes from establishments having large drops in employment, where layoffs are potentially important, and job changes from establishments with stable or growing employment, where the locus would likely be voluntary shifts to better outside opportunities.

The next two columns unpack the fixed effects model into its two parts. Column 2 estimates the effect of employer characteristics on the earnings of workers who stay in the same establishment. This specification controls for what we call *job-individual fixed effects* – the unique combination of an individual and the establishment, which encompass both the establishment fixed effects and the individual fixed effect from the AKM decomposition, in addition to a potential match-specific fixed effects. As in Table 3, the linear effect of establishment age is no longer separately identified from the time effects and is thus omitted from the model. Column 3 estimates the impact of employer factors on the earnings of workers who changed employers, which identifies the effects of establishment characteristics through changes in the employer, and thus does not control for establishment fixed effects or match-specific effects.¹⁵

For most establishment characteristics, the column 3 estimated effects of worker initiated changes have a *much greater* impact on earnings than the column 2 estimated effects of employer-initiated changes. Moving to a firm which has greater employment gives an earnings increase of 0.0162 while working in a firm that increases employment changes gives a 0.0056 boost to earnings -- about one-third as large. Moving from an establishment with more years of schooling increases earnings by 0.0322 compared to an increase of 0.0048 in earnings when a workers' current establishment increases its years of schooling. Moving to an establishment with older workers raises the earning of the mover while staying in an establishment with a rising age of the work force reduces the workers' earning. The effect of R&D on earnings is more than twice as large for movers than for stayers (0.2075 vs 0.0860). But not all characteristics have a larger effect for movers than stayers. An increase in establishment employment has a modestly larger effect for persons who stay with an establishment than for those who move, and similarly for the share of non-whites.

Mechanically, the differences between the column 2 stayers-based estimates and the column 3 movers-based estimates reflect the fact that the stayers analysis controls for unobserved establishment fixed effects and thus removes correlations between those effects and the earnings while the movers model does not do this. But the differences also reflect economic behavior. A worker who chooses to change employers will likely require a larger increase in pay to cover the costs of mobility than one who stays at a job. An establishment that changes characteristics will likely adjust operations slowly and alter pay less in the short run compared to employers whose characteristics differ over longer periods and whose pay structures reflect long term differences in the mode of operating.¹⁶

Earnings equations with individual fixed effects cannot identify the relation between stable individual characteristics and earnings: those effects are absorbed in the individual dummy variables. But it is possible to learn something about how years of schooling and demographic factors such as gender, race, or age affect the individual fixed effects by regressing the estimated fixed effect for individuals on those characteristics. Say we have ten workers with two defining characteristics, years of schooling and gender. The fixed effects earnings equation would produce estimated coefficients for each of the ten workers that could be regressed on the

¹⁵ For this analysis we examine every job-to-job move in the data, retaining only the observations before and after the move, and include individual fixed effects in the regression.

¹⁶ Measurement error will also bias downward the estimates based on changes, for the basic reason that a given error will have proportionately larger impact on the small variation in year to year changes at the same workplace than on the larger differences between the employer the worker joins and the employer the worker leaves.

workers' schooling and gender to capture their relation to the fixed effects. Columns 1-3 of table 5 give the results of such an analysis in three regression models. Model 1 uses estimated individual fixed effects from a regression without employer characteristics.¹⁷ Model 2 uses estimated individual fixed effects from a regression with observable employer characteristics. Model 3 uses estimated individual fixed effects from a stayers' regression that includes establishment and match-specific fixed effects (eq. 3). The estimated relations between the individual effects that are positively related to the characteristics of employers decline across the columns, as we add increasing information on where the employee works. The returns to years of schooling drops from 0.1076 to 0.0841 from the model 1 specification that has no controls for employee characteristics to the model 3 specification that controls for observed and unobserved establishment effects. The coefficient on female falls by more than 10% and the coefficient on age falls by 18%.

The bottom line in Table 5 labeled "variance of the estimated unobserved individual fixed effect" shows how the addition of establishment characteristics reduces the contribution of the fixed effects for individuals to the variation of earnings among workers. In model 1, the individual fixed effect variance is 0.149, or 51% of the total variance. In model 2, which includes measured establishment characteristics, the individual fixed effect variance falls to 0.127 or 43% of the total variance. In model 3 with observed and unobserved establishment characteristics, the variance of the individual effect is 0.112, or about 38% of the total variance in earnings. Put differently, establishment factors account for 25% $((0.149 - 0.112)/0.149)$ of the variance of estimated individual effects.

A Full Decomposition

Table 6 summarizes our findings with a full decomposition of log earnings in the augmented earnings equation. The standard individual characteristics of years of schooling, age, gender, and race account for 26% of the total variation in earnings; unobserved individual effects account for 37% of the variation; observed establishment characteristics account for 8% of the variance; unobserved establishment effects account for 7% of the variance, and the match component accounts for 3%. The covariance between the individual and establishment components of the earnings equation adds 13% of the variance. The remaining variation arises from the transitory within-match residual comprising 7% of the total variation, and to small negative covariance terms between the observed and unobserved parts of the individual and establishment components respectively.¹⁸ The most important factors relate to individuals but employer factors and their relation to individual factors are significant and substantive.

The Sorting of Workers Between Establishments

The interaction between individual characteristics and establishment characteristics suggests that sorting of workers with given characteristics among workplaces with different characteristics affects inequality at large. Positive assortative matching of workers high in

¹⁷The difference is that in the fixed effects specification, the unobserved individual fixed effects are allowed to be correlated with all the included time-varying covariates.

¹⁸ Our model assumes that the fixed individual and establishment/firm effects remain constant throughout the sample period. Experiments with estimation on sub-periods show that in fact the variance of both the individual and establishment fixed effects appear to rise during the sample period. The period over which to treat individual and establishment/firm fixed effects as fixed raises statistical and modeling issues merits further analysis.

measured or unmeasured skills/wages to high-wage establishments raises inequality of earnings. By contrast, assortative matching of workers with workers of similar measured skill does not create “extra inequality” but points to complementarity of skills of similar workers in the production process and allocation of labor.

Assortative matching also affects the interpretation of estimated coefficients on particular variables. When workers positively sort by education into higher paying establishments, the traditional log earnings equation that excludes establishment factors captures two effects in its estimated coefficient on years of schooling: the return of higher skills to earnings within an establishment and the differential access that schooling gives workers to obtaining jobs in higher paying establishments. Addition of dummy variables for establishments limits the effect of years of schooling to its effect within an establishment. Given that sorting of workers between establishments affects the dispersion of pay and the returns to individual characteristics, we analyze next the ways in which workers and firms match up.

Table 7 gives the correlation coefficients for sorting by key earnings determinants. The largest correlations show considerable sorting of workers with workers like themselves: correlations of educated workers with educated workers (0.477), of older workers with older workers (0.333), of females with females (0.349) and of non-whites with non-whites (0.471). But other characteristics of employers are sufficiently correlated with worker characteristics to suggest sorting of workers among establishments beyond homophily. Educated workers work in large firms and in R&D intensive firms, in establishments with high capital per worker and high export shares. These patterns make it likely that some of the education earnings premium comes through the greater likelihood that educated workers find jobs in employers with other earning enhancing characteristics. Older workers are also associated with establishments with high earning characteristics, though the correlations are much smaller. By contrast, women work in establishments with lower capital intensity and non-white workers are largely employed in establishments with low earning characteristics.

The bottom two lines of the table shows the correlation between a composite measure of the establishment contribution to earnings through observed variables plus industry and region, weighted by their estimated effect on earnings, and through establishment fixed effects. Both the establishment observables and fixed effects are highly correlated with years of schooling, making schooling potentially the most important dimension of worker sorting among establishments.

Figure 1 summarizes the relations between the characteristics of workers and those of the establishments where they work via the correlations between indices of the observed characteristics as a group, weighted by their respective coefficients in the earnings equation, and the fixed effects associated for workers as well as for establishments. The largest correlation is between the individual observables weighted by their contribution to earnings and establishment observables weighted by their contribution to earnings (0.253), followed by the correlation between the individual observables and the establishment unobserved fixed effect. By contrast, the fixed effect of individuals is weakly positively correlated with the establishment observables while the individual unobservables and unobserved establishment fixed effects are negatively correlated – a result consistent with Abowd et al. (2014). As Andrews et al. (2008) note, a negative correlation between two unobserved components of earnings could result from sampling and measurement errors,¹⁹ so the safest conclusion from these correlations is that sorting of workers occurs largely on observable characteristics.

¹⁹ Lise, Meghir and Robin (2013) give further discussion of these issues.

Mobility Across Employers

The impact of employer characteristics on the earnings of workers with similar measured characteristics and fixed effects and the table 7 and figure 1 correlations direct attention at the potential role of worker mobility among employers in determining pay. To what extent does mobility from job to job raise pay? How often do workers who start their careers in establishments with low earning characteristics move to firms with better observable and unobservable characteristics over time; and conversely, how much downward firm mobility is there among workers who begin their careers at firms with high earning characteristics?

To examine the transitions of workers among establishments with different establishment components of earnings, we formed a transition matrix for workers in our data both in 1992 and 2007. We attached to every worker the total establishment contribution to earnings, defined as the sum of the contribution to earnings of the time varying establishment characteristics, such as firm size and R&D spending, the fixed observables, such as industry and region, and the unobserved establishment effects. With an establishment contribution for each worker in 1992 and 2007, the natural measure of each workers' mobility is the change in the establishment component of earnings of their employer in those years.

Table 8 summarizes the transition pattern by quintiles of the distributions, ordered from low-paying firms in quintile 1 to high-paying firms in quintile 5. The rows in the table show the distribution of workers by the 1992 quintile distribution of their employer into the 2007 quintile distribution of their employer. While the largest probabilities are for workers to remain in the same quintile over time, there is evidence of upward movement among establishments. Workers in the low quintiles have larger shares going up in the distribution than workers in the top quintiles have shares falling in the distribution. Among workers in the 3rd quintile 38 percent move to a higher quintile, whereas only 21 percent move down while 40 percent remain in the same quintile. New workers come into the distribution of firms at the lower end and change jobs over time to produce a lifetime move up the distribution. Measured by productivity of establishments rather than earnings, Haltiwanger, Hyatt, and McEntarfer (2017) find a similar pattern in productivity, with younger workers in particular moving from less productive to more productive firms over time.

Finally, we characterize the sorting of *workers with workers* between establishments by Kremer and Maskin's (1996) index of segregation, $\rho = cov(\omega, \underline{\omega})/V(\omega)$, where $\underline{\omega}$ is the average individual component of the establishment and $V(\omega)$ is the variance of the individual components of the standard earnings equation. If workers segregate completely between establishments according to their individual earnings components, $\rho = 1$, whereas if they randomly allocate between establishments $\rho = 0$. The index of segregation for observable characteristics in our data is 0.24, while the index for unobservable characteristics is 0.17. This supports the implication of the correlations that sorting of workers according to observed individual characteristics such as years of schooling, age, gender, and race is considerably stronger than segregation according to unobserved attributes.

We characterize the sorting of *workers with establishments* by the equivalent Kremer-Maskin (1996) index $\rho_{\Omega} = cov(\omega, \Omega)/V(\omega)$, where Ω is the earnings components of establishment and divide the decomposition into its within (V^w) establishment and between (V^b) establishment parts by the identities:

$$(4a) V^w(\log w) = V(\omega)(1-\rho) + V(\xi) + V(e)$$

$$(4b) V^b(\log w) = V(\omega)(\rho + 2*\rho_\Omega) + V(\Omega)$$

In our data, $\rho=0.247$ and $\rho_\Omega=0.100$. The within establishment component is 59% of the variance in earnings, of which 82% arises from the observed and unobserved individual component, 6% from the match component, and 12% from the residual. The between component contributes 41% of the variance in earnings, of which 36% is due to worker-worker sorting, 30% to worker-establishment sorting, and 34% to variance of the establishment effect. That most of the within establishment variation in earnings is associated with variables related to individuals and most of the between-establishments variation in earnings is associated with variables related to establishments and sorting of workers among establishments suggests that the simple within and between decomposition offers powerful insight into the role of supply and demand factors in earnings determination.

Conclusion

Augmenting the earnings equation with measured characteristics of employers and unobserved earnings-related fixed effects for establishment or firm adds substantially to the variance in log earnings explicable by an earnings equation. The regressions identify observable employer side factors – capital equipment per worker; R&D investments; export performance, the level of schooling of an establishment's work force, the number of employees and up to a point the age of the establishment – associated with higher workers earnings. While the sizable cross section effects of measured employer characteristics diminish in longitudinal data with the inclusion of firm and establishment fixed effects, those fixed effects are another manifestation of the importance of where a person works on what they earn.

The evidence that addition of establishment or firm related variables reduces estimated coefficient on the key human capital variable, years of schooling, by about one-fifth directs attention at the role of schooling in giving workers access to higher paying workplaces. The near comparability of the estimated effect of average establishment schooling and of the individual's years of schooling (absent firm or establishment fixed effects) further suggests that some of the gains from human capital investments spill over to other workers²⁰, while the drop in the estimated coefficient on average years of schooling with addition of establishment fixed effects reflects the strong positive relation between average years of schooling and establishment fixed effects.

The evidence that the estimated coefficients on gender, race, and age diminish when we introduce individual, and establishment fixed effects provides further support for the notion that the sorting of workers among employers is important in earnings differentials. Youth, females, and non-whites are more likely to be found in low paying establishments, and the coefficients for the establishment specific average of the demographic characteristics change signs or turns insignificant once we control for job fixed effects. While the dynamics of worker mobility has workers moving to enterprises with higher observable and fixed effects earnings components

²⁰ The relation between the average years of schooling at an establishment and individual pay is mindful of the observed positive relation between the average level of education at a regional or city level, and earnings, which Glaeser, and Moretti, among others, interpret as a human capital externality.

over time, assortative matching tends to magnify the effect on inequality beyond what is would be the direct impact of earnings differences across establishments.

Taken together, the dual findings that where a person works affects their earnings and that sorting of workers among employers accounts for some of the differentials in earnings associated with years of schooling and demographic characteristics raises new questions for analysis: Why does having more educated co-workers affect individual earnings so much? To what extent do costs of mobility account for the greater impact of employee instituted than employer instituted changes in the payoff from working with other inputs? How important are explicit human resource and compensation policies in positioning employers in the distribution of earnings? And do their decisions equilibrate the marginal payoffs to paying above or below market average levels of pay? Finally, given manufacturing's modest and declining share of employment, our analysis suggests the value of estimating augmented earnings functions in other industries to see whether the role of employers and sorting of workers found here generalizes to the labor market writ large.

Table 1 Variance Decomposition of Log earnings, All Sectors 1992 and 2007

	Variance Log (earnings)		Share of variance Between establishments 2007	Change in variance 1992- 2007	Share of growth Between establishments 1992-2007
	1992	2007			
ALL	0.510	0.601	0.48	0.091	0.66
Mining, Utilities, Transport	0.434	0.457	0.40	0.022	0.39
Business Services	0.612	0.713	0.56	0.101	0.86
Communication	0.502	0.634	0.40	0.132	0.53
Retail, Wholesale, Restaurants	0.508	0.551	0.48	0.044	0.80
Finance, Insurance, Real Estate	0.531	0.660	0.39	0.129	0.65
Private Services	0.427	0.482	0.49	0.054	0.90
Health, Education, Social Services	0.495	0.508	0.27	0.013	-0.15
Manufacturing	0.398	0.490	0.45	0.092	0.57

Note: Numbers calculated from yearly regressions of log annualized sum of quarterly earnings for all jobs in the second quarter of the year on establishment dummies. Data from LEHD. Establishment is the sein unit.

Table 2 Variance Decomposition of Log Earnings in Matched LEHD Manufacturing Panel, 1992 and 2007

	Variance 1992	Share	Variance 2007		Change 92-07	Share of change
Log earnings	0.272	1	0.330	1	0.058	1.00
Between establishments	0.125	0.46	0.150	0.45	0.025	0.43
Between firms	0.113	0.42	0.140	0.42	0.027	0.47
Between estab. within firm	0.012	0.04	0.011	0.03	-0.001	-0.02
Within establishments	0.146	0.54	0.180	0.55	0.033	0.59

Note: Numbers calculated from a regression of log earnings on time dummies and establishment dummies. The matched sample include LEHD data matched to the Census of Manufacturers with valid observations of capital (from the ASM/CoM tfp-files, see Foster et al. 2016), to the education data from the Decennial Censuses and CPS, and that each individual is observed at least four times (see data description for details). All jobs included are observed in the second quarter of the year. Slight differences between the between-establishments numbers and the sum of between firms and between-establishments within firms due to rounding errors.

Table 3 Estimated Regression Coefficients and Standard Errors for Augmented Earnings Equations Including Firm and Establishment Characteristics for Manufacturing 1992-2007

	Model 1: No estab. char.	Model 2: Estab.char. I	Model 3: Estab.char II	Model 4: + Firm fixed effects	Model 5: +Estab. fixed effects
Years of schooling	0.0943*** (0.0001)	0.0820*** (0.0001)	0.0737*** (0.0001)	0.0739*** (0.0001)	0.0739*** (0.0001)
Age	0.0132*** (0.0000)	0.0118*** (0.0000)	0.0116*** (0.0000)	0.0116*** (0.0000)	0.0115*** (0.0000)
Age square	-0.0005*** (0.0000)	-0.0005*** (0.0000)	-0.0005*** (0.0000)	-0.0005*** (0.0000)	-0.0005*** (0.0000)
Female	-0.3022*** (0.0006)	-0.2897*** (0.0006)	-0.2691*** (0.0005)	-0.2671*** (0.0005)	0.2669*** (0.0005)
Non-white	-0.1707*** (0.0005)	-0.1539*** (0.0005)	-0.1405*** (0.0005)	-0.1397*** (0.0005)	-0.1400*** (0.0005)
Female x Age	-0.0050*** (0.0000)	-0.0045*** (0.0000)	-0.0045*** (0.0000)	-0.0045*** (0.0000)	-0.0044*** (0.0000)
Female x Age ²	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)
Female x Non-white	0.0309*** (0.0009)	0.0318*** (0.0009)	0.0384*** (0.0008)	0.0371*** (0.0008)	0.0373*** (0.0000)
Establishment and firm characteristics					
Log firm employment		0.0295*** (0.0001)	0.0173*** (0.0001)	0.0071*** (0.0005)	0.0012*** (0.0003)
Log establishment employment		0.0266*** (0.0002)	0.0270*** (0.0002)	0.0258*** (0.0003)	0.0232*** (0.0006)
Establishment age		0.0032*** (0.0001)	0.0045*** (0.0001)	0.0032*** (0.0001)	-
Establishment age squared		-0.0001*** (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)	-0.0000*** (0.0000)
Mean years of schooling			0.0690*** (0.0003)	0.0483*** (0.0004)	0.0249*** (0.0007)
Mean age			0.0027*** (0.0001)	0.0017*** (0.0001)	-0.0034*** (0.0001)
Share female			-0.3176*** (0.0016)	-0.2548*** (0.0029)	-0.1084*** (0.0056)
Share non-white			-0.0185*** (0.0017)	0.0029 (0.0028)	0.0256*** (0.0046)
Export share			0.0115*** (0.0004)	0.0062*** (0.0005)	0.0068*** (0.0006)
Log capital structures/employee			0.0074*** (0.0002)	0.0033*** (0.0003)	0.0018*** (0.0004)
Log capital equipment/employee			0.0462*** (0.0003)	0.0211*** (0.0004)	0.0075*** (0.0005)
Firm R&D/employee			0.7260*** (-0.0104)	0.1228*** (0.0131)	0.1627*** (0.0129)
Industry effects	-	Y	Y	Y	-
Firm effects	-	-	-	Y	-
Establishment effects	-	-	-	-	Y
Region (171) effects	Y	Y	Y	-	-
Year (16) effects	Y	Y	Y	Y	Y
r ² _adjusted	0.452	0.505	0.526	0.566	0.577
N	5.13E+06	5.13E+06	5.13E+06	5.13E+06	5.13E+06

Table 4: Estimated Regression Coefficients and Standard Errors for Firm and Establishment Characteristics: Individual Fixed Effects and Job Fixed Effects Models

	Model 1: Individual FE All Workers	Model 2: Individual-Job FE Stayers	Model 3: Individual FE Movers
Log firm employment	0.0161*** (0.0001)	0.0056*** (0.0002)	0.0162*** -0.0003
Log establishment employment	0.0305*** (0.0002)	0.0214*** (0.0003)	0.0180*** -0.0005
Establishment age	0.0037*** (0.0001)		-0.0008*** (0.0002)
Establishment age square	-0.0001*** (0.0000)	-0.0000*** (0.0000)	0.0000 (0.0000)
Mean years of schooling	0.0299*** (0.0003)	0.0048*** (0.0004)	0.0322*** -0.0008
Mean age	0.0023*** (0.0002)	-0.0129*** (0.0001)	0.0023*** -0.0002
Share female	-0.1573*** (0.0020)	-0.0036 (0.0033)	-0.1765*** -0.0044
Share non-white	0.0250*** (0.0019)	0.1025*** (0.0029)	0.0230*** -0.0042
Export share	0.0000 (0.0003)	-0.0021*** (0.0003)	0.0020* -0.0009
Log capital structures/employee	0.0059*** (0.0002)	0.0002 (0.0003)	0.0031*** -0.0004
Log capital equipment/employee	0.0140*** (0.0002)	0.0027*** (0.0003)	0.0189*** -0.0006
Firm R&D expenses/employee	0.1290*** (0.0060)	0.0860*** (0.0057)	0.2075*** -0.0188
r2_adjusted	0.873	0.913	0.827
N	5.13E+06	5.13E+06	7.31E+05

Note: All models include year dummies, age square, the interaction between gender and age, age square. The first and last models include individual fixed effects, and the second model includes job (i.e. match: the unique combination of individual and establishment) fixed effects. Individual specific variables that do not vary over time, such as years of education, are absorbed by the individual fixed effects.

Table 5:Regression of Estimated Individual Fixed Effects on Years of Schooling and Demographic Individual Characteristics, from Three Models of Log (Earnings)

	Model 1: Fixed Effects from model with only individual characteristics	Model 2: Fixed Effects from model with individual & establishment characteristics	Model 3: Fixed Effects from model with individual & establishment characteristics and & establishment fixed effects
Years of schooling	0.1076*** (0.0001)	0.0917*** (0.0001)	0.0841*** (0.0001)
Dummy variable for female	-0.3553*** (0.0004)	-0.3326*** (0.0004)	-0.3129*** (0.0004)
Dummy variable for non-white	-0.1001*** (0.0005)	-0.0882*** (0.0005)	-0.1119*** (0.0004)
Age	0.0136*** (0.0000)	0.0128*** (0.0000)	0.0112*** (0.0000)
Interaction gender non-white	0.0504*** (0.0009)	0.0500*** (0.0008)	0.0429*** (0.0007)
r2_adjusted	0.441	0.422	0.416
Variance of the estimated unobserved individual effects	0.149	0.127	0.112

Note: The dependent variable is the individual fixed effects from models including time varying covariates. Number of observations 5.13E+06 in all columns.

Table 6: Variance Decomposition of the Full Augmented Earnings Equation Model

Determinants of earnings	Variance decomposition	
Log earnings	0.299	
Individual components	0.188	
Observed individual		0.078
Unobserved individual.		0.112
2*Cov (Obs. indiv., Unobs.indiv.)		-0.002
Within match residual	0.020	
Establishment components	0.043	
Observed estab.		0.024
Unobserved estab.		0.020
Unobserved firm		0.016
Unobs. estab. within firm		0.005
2*Cov (Obs. estab, Unobs.estab)		-0.001
2*Cov(Indiv. comp., Estab.comp)	0.038	
2*Cov (Obs.ind., Obs.est.)		0.022
2*Cov (Obs.ind., Unobs.est.)		0.012
2*Cov (Unobs.ind., Obs.est.)		0.008
2*Cov (Unobs.ind, Unobs.est)		-0.006
Match component	0.010	

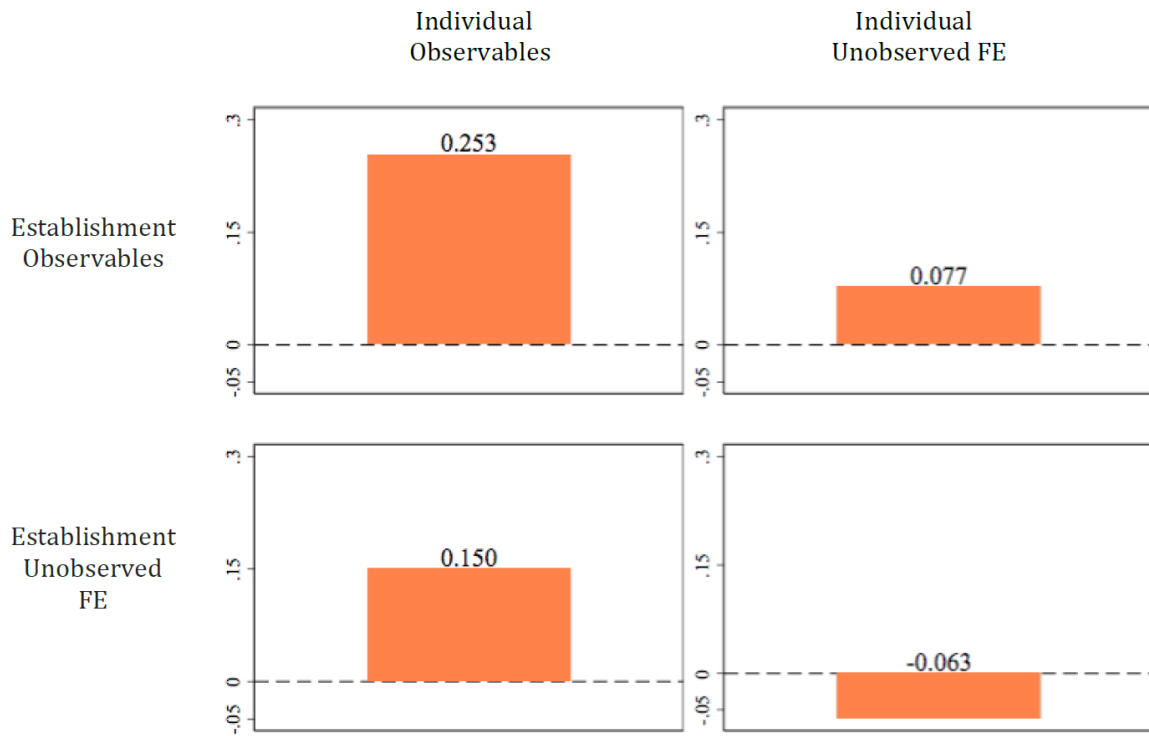
Note: Calculations using equation (3) to structure decomposition. Number of observations is 5.13E+06. Data for manufacturing matched sample, as described in text. Year dummies are not included in the calculations. Some numbers do not add up due to rounding errors.

Table 7: Correlation Coefficients between Individual and Establishment/Firm Characteristics

	Years of Schooling	Age	Female	Nonwhite
Log firm employment	0.200	0.060	-0.002	-0.059
Log establishment employment	-0.028	0.149	-0.014	-0.028
Establishment age	0.214	0.034	0.015	-0.042
Export share	0.103	0.044	0.005	-0.054
Log structures capital/employee	0.185	0.069	-0.059	-0.087
Log equipment capital/employee	0.117	0.071	-0.100	-0.075
Firm R&D/employee	0.216	0.015	0.000	0.000
Mean years of schooling	0.477	0.031	-0.030	-0.128
Mean age	0.110	0.333	-0.060	-0.036
Share female	-0.033	-0.041	0.349	0.105
Share non-white	-0.146	0.005	0.080	0.471
Establishment observables as a group, weighted by effect on earnings	0.258	-0.022	-0.084	0.030
Establishment fixed effect	0.112	0.069	-0.061	-0.066

Source: Tabulated from matched data file for manufacturing workers as described in text.

Figure 1: Correlation Coefficients between Individual Observables and Unobservable with Establishment Observables and Unobservables



Source: Calculated from matched data file for manufacturing workers as described in text.

Table 8: Transitions of Workers Among Establishments Ordered by Establishment Contribution to Earnings (Observable Characteristics Weighted by Their Earnings Coefficients Plus Fixed Effect, by Quintile of the Distribution 1992-2007

1992	2007						Change in Share	
	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5	All	Up	Down
Quintile 1	0.564	0.258	0.097	0.056	0.024	1.000	0.436	
Quintile 2	0.172	0.401	0.287	0.108	0.032	1.000	0.427	0.172
Quintile 3	0.078	0.136	0.403	0.329	0.054	1.000	0.383	0.214
Quintile 4	0.042	0.062	0.113	0.451	0.331	1.000	0.331	0.217
Quintile 5	0.017	0.024	0.033	0.136	0.790	1.000		0.210

Note: Calculated on the balanced panel only. Quintiles of the distribution of the establishment effect include both unobserved and observed components of the establishment contribution.

Appendix Table A: Summary Statistics. Mean and Standard Deviation of Variables for the Full Sample of Persons in the LEHD Manufacturing Data Set and in the Matched Sample that Includes Measures of Years of Schooling

	Full Sample		Matched Sample	
	Mean	Std. dev	Mean	Std. dev.
Age			12.72	2.311
Female	42.58	10.183	43.41	9.978
Non-white	0.300	0.458	0.294	0.456
Log firm employment	0.302	0.459	0.237	0.425
Log establishment employment	8.234	2.403	8.288	2.268
Log capital structures/employee	6.300	1.572	6.317	1.512
Log capital equipment/employee	3.250	1.333	3.297	1.296
Export share of establishment	3.918	1.049	3.953	1.035
Firm R&D/employee	0.626	0.484	0.638	0.481
Log earnings	0.009	0.021	0.009	0.020
	6.649	0.554	6.682	0.543
Observations	23.4		5.1	
	million		million	

Note: Full sample tabulated for all workers in LEHD; matched sample for workers reporting years of schooling in match with Census or CPS as described in the text. Years of schooling measured as years after high school.

Appendix Table B: Variance Decomposition of Earnings Among Workers, in All Firms and in Multi-Establishment Firms, Matched Panel, 1992-2007

	All	Share	MU's	Share
Log earnings	0.293	1	0.279	1
Between establishments	0.119	0.41	0.113	0.41
Between firms	0.106	0.36	0.094	0.34
Between establishments		0.04		0.06
Within firm	0.013		0.018	
Within establishments	0.174	0.59	0.166	0.59

Note: Firms in the “All” establishment sample include the establishment effects for single-unit firms whereas the “MU’s” sample only include multi establishment firms (defined as multi-unit firms within manufacturing only). Numbers calculated from a regression of log earnings on time dummies and establishment dummies. The total variance is calculated after subtracting variance due to the time dummies. Firm effects estimated from regression of establishment fixed effects on firm dummies. Multi-unit firms are defined as multi-unit firms within manufacturing only.

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²¹ <http://www.norc.org/PDFs/May%202011%20Personal%20Validation%20and%20Entity%20Resolution%20Conference/PVS%20Assessment%20Report%20FINAL%20JULY%202011.pdf>

²² https://www.census.gov/2010census/pdf/2010_Census_Match_Study_Report.pdf