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Is it Who You Are, Where You Work, or With Whom You Work? Reassessing the Relationship Between Skill Segregation and Wage Inequality

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Is it Who You Are, Where You Work, or *With Whom You Work*? Reassessing the Relationship Between Skill Segregation and Wage Inequality*

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Abstract

In a recent paper, Kremer & Maskin (QJE, forthcoming) develop an assignment model in which increases in the dispersion and mean of the skill distribution can lead simultaneously to increases in wage inequality and skill segregation. They then present evidence that, concurrent with rising wage inequality, wage segregation increased for production workers in the United States between 1975 and 1986. My paper argues that relying on wages as a proxy for skill may be problematic. Using a newly developed longitudinal dataset linking virtually the entire universe of workers in the state of Illinois to their employers, I decompose wages into components due, not only to person and firm heterogeneity, but also to the characteristics of their co-workers. Such "co-worker effects" capture the impact of a weighted sum of the characteristics of all workers in a firm on each individual employee's wage. While rising wage segregation can result from greater skill segregation, it may also be due to changes in the variance of co-worker effects in the economy, or to changes in the covariance between the person, firm, and co-worker components of wages.

Due to the limited availability of demographic information on workers, I rely on the person specific component of wages to proxy for co-worker "skills." Because these person effects are unknown ex ante, I implement an iterative estimation approach where they are first obtained from a preliminary regression that excludes any role for co-workers. Because virtually all person and firm effects are identified, the approach yields consistent estimates of the co-worker parameters. My estimates imply that a one standard deviation increase in both a firm's average person effect and experience level is associated, on average, with wage increases of 3% to 5%. Firms that increase the wage premia they pay workers appear to do so in conjunction with upgrading worker quality. Interestingly, the average effect masks considerable variation in the relative importance of co-workers across industries. After allowing the co-worker parameters to vary across 2 digit industries, I find that industry average co-worker effects explain 26% of observed inter-industry wage differentials. Finally, I decompose the overall distribution of wages into components due to persons, firms, and co-workers. While co-worker effects do indeed serve to exacerbate wage inequality, the tendency for high and low skilled workers to sort non-randomly into firms plays a considerably more prominent role.

Keywords: wage inequality, skill segregation, employer-employee data, panel data
JEL Codes: J31, J24, C23, C81

1 Introduction

An emerging strand of research in labor economics focuses on the extent to which rising wage inequality and increased segregation by skill are related. In a widely cited paper, Kremer and Maskin (forthcoming, hereafter KM) build an assignment model in which increases in the dispersion and mean of the skill distribution can simultaneously increase wage inequality and reduce the tendency for high and low skill workers to work together in firms. While increased wage inequality has been well documented in many industrialized nations, few studies exist which quantify the level of skill segregation in the economy, let alone its trend. Data linking employees and their firms would appear to be a prerequisite, but such data are rare and have only recently been developed and studied by economists. Lacking linked employer-employee data for the United States, KM develop a segregation index which depends only on the overall variance of skill in the economy and on the variance of mean skill between firms and can thus be computed using separate data sources. Using wages as a proxy for skill, they find that, concurrent with rising wage inequality, wage segregation rose for production workers in the U.S. manufacturing sector between 1975 and 1987.

However, using wages as proxy for skill may be problematic. A central focus of recent research using linked employer-employee data has been documenting the often complex connections between worker and firm heterogeneity. Haltiwanger, Lane, and Spletzer (1999, 2000), for instance, find that even within narrowly defined industries, firms choose very different skill mixes. This choice appears highly persistent and is positively correlated with firm outcomes like productivity and survival. With respect to worker outcomes, Abowd, Kramarz and Margolis (1999, hereafter AKM) develop a regression framework for decomposing wages into person and firm specific components, and find that the sorting of heterogenous workers into heterogenous firms plays an important role in explaining individual wage outcomes, inter-industry wage differentials, and firm-size wage premia.[1] Thus, to the extent that firm specific factors exert an influence on wages, rising wage segregation may not be indicative of increased skill segregation. In the KM model, because firms are simply teams of workers, there is no scope for firm heterogeneity as distinct from, but possibly related to, worker heterogeneity.

In this paper, I build on the recent econometric advances of AKM with the goal of revisiting the issue of skill segregation and wage inequality. In what follows, I develop and test a new procedure for decomposing wages into components due, not only to person and firm heterogeneity ("who you are" versus "where you work"), but also to the characteristics of co-workers ("with whom you work"). Such co-worker effects capture the impact of a weighted sum of the characteristics of all workers in a firm on each individual employee's wage. As a consequence, observationally equivalent individuals working in observationally

[1] See Abowd & Kramarz (1999a) for a detailed review of available employer-employee datasets. Goux and Marin (1999), Entorf et al. (1999), and Belzil (2000) are among a growing list of papers that estimate wage equations which attempt to control simultaneously for person and firm fixed effects.

equivalent firms, may still earn different amounts if the skill mix of their co-workers differs. My empirical work makes use of a new large scale, linked employer-employee dataset currently under development by U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) Program. While the analysis that follows will be based on data from a single U.S. state (Illinois), the LEHD Program plans to dramatically expand its coverage in the near future. The advantage of such data is clear: by linking virtually the entire universe of workers to their employers in the state over a period of nine years, one can directly measure how workers are grouped together inside firms and study whether this grouping has evolved over time.

While KM describe one mechanism whereby co-worker characteristics might influence wages–an approach I use to anchor the discussion throughout the paper–a wide array of topics in labor economics concern themselves with the interaction of workers within firms. These include, but are certainly not limited to: studies of wage differentials across demographic groups, skill substitution and demand elasticities, immigration's impact on native wages and migration, bargaining and rent sharing models, and tournament models of compensation. For all of these topics, while the mix of inputs chosen by firms is of critical importance, only recently data have been available to consider such choices directly.[2] Even recent work using linked employer-employee data has focused on distinguishing between persons and firm specific factors, rather studying the interaction of workers within firms. Thus, I view my work as an initial attempt to go one step further and "look inside the black box." My focus here is on establishing whether co-worker characteristics contribute meaningfully to individual, industry, and economy wide wage outcomes. Attempts to distinguish between various competing theories as to why co-worker effects might matter are deferred until a later date.

More specifically, I use my wage accounting framework to focus on three questions. First, to what extent do wages at the individual level depends on the characteristics of co-workers? Second, do inter-industry wage differentials reflect differences in skill segregation across industries? Third, does skill segregation alter the overall distribution of wages? To the extent that co-worker characteristics positively affect wages, any trend towards increased skill segregation within firms will further exacerbate wage differentials between high and low skilled individuals. In addition to this direct effect, a rising tendency for high wage workers to sort into high wage firms, can also contribute to rising skill segregation and wage inequality. Finally, changes in the economy-wide distributions of either worker characteristics through entry into and exit out of the labor force or firm characteristics through births and deaths could potentially set off a reallocation process whereby skill segregation and inequality are affected. In a way, the question of whether co-worker characteristics influence wages parallels questions studied in the literature on peer effects, which focuses on the influence of class-

[2] Also of critical importance is information on worker productivity and capital structures, neither of which are available for this study. Hellerstein et al. (1999) and Haltiwanger et a.l (2001) represent two recent efforts to incorporate such information into employer-employee data.

mates on school performance and other social behaviors.[3] While my estimation approach is quite different from those employed in that literature, we will see that the problem of omitted variables is almost as important here as it is there when it comes to interpreting results.

The paper proceeds as follows. In Section II, I briefly summarize skill segregation trends in Illinois and discuss the importance of simultaneously controlling for both person and firm characteristics when studying the impact of co-worker characteristics on wages. Section III introduces the model in its most general form, before discussing issues of identification, interpretation, and detailing my estimation strategy. Section IV presents the data, describes the construction of my analysis sample, and presents some summary statistics. These results are then compared to similar statistics generated using the Current Population Survey. Section V presents the co-worker estimates from my baseline model and shows how they change when alternative specifications are implemented. My estimates imply that a one standard deviation increase in both a firm's average person effect and experience level is associated, on average, with wage increases of 3-5%. This average effect masks considerable variation across industries. After allowing for co-worker parameters to vary across 2 digit industries, I find that skill segregation explains 26% of raw inter-industry wage differentials, where skill segregation is defined as the industry average co-worker effect. Returning to KM debate, I then decompose the overall distribution of wages into components due to persons, firms, and co-workers. While co-worker effects do appear to exacerbate inequality, the tendency for high and low skilled workers to sort non-randomly into firms plays a considerably more prominent role. Section VI concludes.

2 The Relationship Between Skill Segregation, Person Heterogeneity, and Firm Heterogeneity

While a detailed discussion is deferred until Section IV, the data used in this paper permit the direct computation of the segregation index developed by KM. This index can be computed for the economy as a whole or broken out along various industry lines. Table 1 presents estimates of the KM segregation index for all workers employed in single establishment firms in the state of Illinois between 1990 and 1998.[4] The index is computed not only for wages but also for several demographic characteristics (age, race, sex, education) as well as the individual specific components of predicted wages (purged of firm heterogeneity). A

[3] See Evans et al. (1992) for a review of the peer effects literature.

[4] Like KM, I avoid computing the index for firms with multiple establishments. Skill segregation trends for single establishment firms, should be more economically meaningful, because while skill mix may vary considerably across establishment of a multi-unit firm, the data do not permit this distinction. In the words of KM, "it is not clear that anything of economic importance changes if a holding company acquires both Microsoft and McDonalds."

value of zero would indicate that all firms have the same skill mix of workers, while a value of one would indicate complete segregation by skill. Between 1990 and 1998, wage segregation increased slightly from 0.372 to 0.393. While small, this 5% increase matches the increase in wage segregation, calculated by KM for production workers in the manufacturing sector between 1975-1986. Race and age based segregation also increased slightly. Interestingly, however, segregation for individual specific components of wages actually declined. Segregation of predicted experience, the time-invariant person effect, and the wage residual fell by 2%, 11%, and 25% respectively. Thus, firms may actually be less homogenous with respect to skill mix of their workers today than they were in 1990. Such a finding is inconsistent with the KM story and suggestive of a class of models in which the mix of firm heterogeneity in the economy and the productive trade-offs faced by firms when choosing different worker skill mixes feature more prominently.

Table 2 shows that overall segregation trends mask substantial variation both within and across major industry divisions. For instance, while wage segregation rose in industries like construction, retail trade, and services, it remained stable in manufacturing and actually declined in transportation, communications and public utilities (TCPU). There is also sizeable variation (see the values for σ_{km}) in the amount segregation that exists for the three digit industries which comprise each SIC division. Nevertheless, the puzzling trend documented in Table 1 remains. For most industries, wage segregation moved in the opposite directions of segregation for the individual specific components of wages during the 1990s. This difference can only be explained by changes in distribution of person and firm heterogeneity in the economy as well as the matching process between workers and firms. Haltiwanger et al. (2001) consider this issue in greater detail and find that the economy wide distribution of skill appears to have shifted to the right in Illinois during the 1990s.

In order to better understand the overall relationship between skill segregation, person heterogeneity, and firm heterogeneity, Figures 1 and 2 plot the relationship between skill segregation (the KM index for person fixed effects) at the 3 digit SIC level and the standard deviation of person and firm fixed effects for each of these industries. Recall that KM posit a relationship between the economy-wide distribution of skill and its implications for how various kinds of workers are grouped together in firms. Figure 1 shows this relationship exists, at least at the industry level. Industries with a high degree of skill dispersion are more skill segregated. In other words, firms in these industries appear less willing to employ workers with different skill levels than firms in other industries where the distribution of skill is more compressed.

Interestingly, a positive and slightly stronger relationship also exists between the dispersion of firm effects in an industry and the level of skill segregation (see Figure 2). Industries with more varied compensation structures appear more likely to structure production so that there is less interaction between high and low skilled workers within firms. Industry average person and firm heterogeneity also appear to positively co-vary (see Figure 3), meaning that individuals with high external wages (portable across employers) are more likely to sort into industries with firms that pay above average internal wages (wage premia shared by all employees).

The main point to emphasize is that any attempt to measure the impact of co-worker characteristics on individual wage outcomes needs to worry about the complex relationship between skill segregation, person heterogeneity, and firm heterogeneity. Put another way, in order to learn whether "with whom you work" matters, one needs to also control for "who you are" and "where you work." KM modelled the first two effects but ignored the third, AKM, Groshen (1991), and others worried about the latter two effects but not the first. This paper exploits the rich structure of the LEHD data in order to simultaneously control for all three.

Unfortunately, a major disadvantage of the LEHD data is that only limited demographic information is available for the approximately 9 million workers in my analysis sample. As a result I rely on the person specific component of wages to proxy for co-worker "skills." The problem with such an approach is these person effects are ex ante unknown, and hence cannot initially be included on the right hand side of a wage regression. I therefore use an iterative estimation approach in which person effects are first obtained from a preliminary regression that excludes any role for co-workers. After this step, a weighted sum of co-worker person effects from the previous iteration appears on the right hand side. New person and firm effect estimates are generated, along with those for the co-worker effects, and the procedure is repeated. I argue below that because virtually all person and firm effects are identified in my co-worker model, this iterative approach should yield consistent estimates of co-worker effects, even though the preliminary person effect estimates contain a combination of the true person effects, and an employment-duration weighted average of the co-worker effects. Simulation results suggest this appears to be the case.

3 Statistical Model

3.1 Specification of the General Model

My point of departure is the wage accounting framework recently developed by AKM. They define

$$y_{it} = x_{it}\beta + \theta_i + \psi_{\mathbf{J}(i,t)} + \varepsilon_{it} \tag{1}$$

where

y_{it} is the log of the real wage for worker i at time t, less its grand mean
x_{it} is a 1xK vector of time varying characteristics, less their grand means
θ_i is the time invariant, individual component of wages
$\mathbf{J}(i,t)$ is a function revealing the employer for worker i at time t
$\psi_{\mathbf{J}(i,t)}$ represents the firm effect for worker i in firm j at time t
ε_{it} is the statistical residual

and: $i = 1, ..., N$; $j = 1, ..., J$; $t = 1, ..., T$

Viewed in this light, a worker's wage is the sum of the market valuation of her personal characteristics (the external wage)–some of which evolve over time (for instance, experience) and others like education, race, gender, and unobserved "ability" remain constant –and the compensation policy (the internal wage) chosen by her employer. Stochastic changes to these so called "person effects" and "firm effects" are ignored and are thus essentially smoothed out over the sample period. AKM assume:

$$\mathbf{E}[\varepsilon_{it} \mid i, t, \mathbf{J}(i,t), x_{it}] = 0 \tag{2}$$

and:

$$cov[\varepsilon_{it}, \varepsilon_{ns} \mid i, t, n, s, \mathbf{J}(i,t), \mathbf{J}(n,s), x_{it}, x_{ns}] = \left\{ \frac{\sigma_\varepsilon^2 \text{ for } i = n \text{ and } \ t = s}{0 \text{ otherwise}} \right\} \tag{3}$$

For ease of subsequent exposition denote:

N_{jt} as the number of employees in firm j at time t
$\overline{\theta}_{jt}$ as the firm average person effect in firm j at time t
$\overline{\psi}_i$ as the average firm effect for person i

One can re-write the AKM wage equation in matrix notation as

$$y = X\beta + D\theta + F\psi + \varepsilon \tag{4}$$

where X is the N^*xK matrix of observable, time-varying characteristics, D is the N^*xN matrix of indicators for individual i, F is the N^*xJ matrix of indicators for the firm effects, y is the N^*x1 vector of wage data , and ε is the N^*x1 vector of residuals. For ease of exposition, assume a balanced panel of workers and firms and define $N^* = NT$. The parameters are β, the $Kx1$ vector of coefficients on the time-varying personal characteristics, θ, the $Nx1$ vector of individual effects, ψ, the $Jx1$ vector of firm effects, and the error variance, σ_ε^2.

Conceptually, one way to introduce a role for co-worker characteristics is to make an analogy to the well known Ashenfelter & Krueger (1994) twins study. In their model, an unobservable "family" effect existed which was common to each set of twins and correlated with their observable characteristics, thereby representing a potential source of omitted variables bias. By specifying a linear relationship between the family effect and the observable characteristics of the twins and substituting it into each twin's wage equation, what resulted was a wage model in which Twin A's wage depended not only on her own characteristics but also on those of Twin B. The family effect of Ashenfelter & Krueger (1994) is essentially the firm effect of AKM, while the effect of twin B's characteristics on the wage of Twin A would be a "co-worker" effect, if all firms were limited to two employees. Unfortunately, this analogy is less useful when it comes to estimation strategies. While Ashenfelter & Krueger (1994) do not specify a role for unobserved, individual heterogeneity in conjunction with the family effect, distinguishing person heterogeneity from firm heterogeneity has become a central theme in the emerging literature using linked employer-employee data. Given a suitably rich dataset and subject to the validity of the identifying assumptions (see below), one can calculate the unobserved person and firm heterogeneity, and thereby reduce substantially traditional concerns over omitted variables.

I augment equation (1) as follows:

$$\begin{aligned} y_{it} &= X_{it}\beta + W^1_{i\cdot jt}X_{jt}\lambda_1 + \theta_i + W^2_{i\cdot jt}\theta_{jt}\lambda_2 + \psi_j + u_{it} & (5)\\ u_{it} &= W^3_{i\cdot jt}u_{jt}\lambda_3 + \varepsilon_{ijt} & (6)\end{aligned}$$

where:

$W^k_{i\cdot jt}$ is a $1xN_{jt}$ row vector, belonging to, W^k_{jt}, $k = 1, 2, 3$
W^k_{jt} is the $N_{jt}xN_{jt}$ weighting matrix for firm j at time t
X_{jt} is the $N_{jt}xK$ matrix of worker characteristics in firm j at time t
θ_{jt} is the $N_{jt}x1$ vector of person effects for workers in in firm j at time t

"Co-worker effects," are denoted by $W^1_{i\cdot jt}X_{jt}\lambda_1$,$W^2_{i\cdot jt}\theta_{jt}\lambda_2$,and $W^3_{i\cdot jt}u_{jt}\lambda_3$. They capture the effect of a weighted sum of the characteristics of all N_{jt} workers on the wage of individual i. In AKM, these effects were subsumed into both the person and the firm effects. While the λ coefficients are common to all workers, the overall co-worker effects are person specific and time varying. They depend not only on the skill mix of co-workers in firm j at time t but also on the structure of the relevant weighting matrix. To see this further, let $\omega^k_{iljt} = \omega^k(d_{iljt})$ be the i, l^{th} element of $W^k_{i\cdot jt}$, i.e. the "weight" given to the effect of person l's characteristics on person i's wage. The term d_{iljt} is a distance measure between worker i and worker l, whose parameterization will be discussed in greater detail below. For estimation purposes, I impose

$W_{i\cdot t}^1 = W_{i\cdot t}^2 = W_{i\cdot t}$. and define $\omega_{iljt}^k = 0$ whenever $i = l$. Individuals do not contribute to their own weighted sum of co-worker characteristics. As is common in most spatial econometric specifications, I also assume that, $\sum_{l=1}^{N_{jt}} \omega_{iljt}^k = 1$. In other words, the weighting matrix is said to be "row normalized."

A number of tests for spatial correlation of the residuals exist (see for instance, Anselin 1988) which can be implemented without undue difficulty. One test, based on the so-called Moran I* Statistic, assumes a single weighting matrix for all observations over all time periods. While thus far I have discussed the weighting matrices as firm and time specific, one can easily view them as belonging to an overall weighting scheme, in which for any given worker-firm-time combination, zero weight is given to workers in other firms and time periods. To see this, rewrite equation (1) in matrix notation:

$$
\begin{aligned}
y &= X\beta + GW^1\widetilde{X}\lambda_1 + D\theta + GW^2\widetilde{\theta}\lambda_2 + F\psi + u && (7)\\
u &= GW^3\widetilde{u}\lambda_3 + \varepsilon && (8)
\end{aligned}
$$

where X, D, θ, F, ψ, and ε are defined as above, u is an N^*x1 vector of residuals. W^1, W^2, and W^3 are the "overall" weighting matrices of dimension $\sum_{j=1}^J \sum_{t=1}^T N_{jt}\ x\ \sum_{j=1}^J \sum_{t=1}^T N_{jt} = N^*xN^*$, $\widetilde{X}$ is N^*xK, and $\widetilde{\theta}$ and $\widetilde{u}$ are N^*x1. G is the N^*xN^* matrix of indicators that selects the appropriate weight for each individual i in firm j at time t.

To be more precise, observe that W_{jt}^2, the $N_{jt}xN_{jt}$ weighting matrix for firm j at time t, and θ_{jt} the $N_{jt}x1$ vector of person effects for the individuals employed in firm j at time t, can be aggregated across all the time periods firm j appears in the data, and restated as the $\sum_{t=1}^T N_{jt}\ x\ \sum_{t=1}^T N_{jt}$ matrix, W_j^2, and the $\sum_{t=1}^T N_{jt}\ x\ 1$ vector, θ_j :

$$
\begin{aligned}
W_j^2 &= \begin{bmatrix} W_{j1}^2 & 0 & ... & 0 \\ 0 & W_{j2}^2 & ... & 0 \\ ... & ... & ... & ... \\ 0 & ... & 0 & W_{jT}^2 \end{bmatrix} && (9)\\
\theta_j &= \begin{bmatrix} \theta_{j1} \\ ... \\ \theta_{jT} \end{bmatrix}.
\end{aligned}
$$

Each element of the $\sum_{t=1}^T N_{jt}\ x\ 1$ matrix product, $W_j^2\theta_j$, therefore provides a weighted sum of person effects for every co-worker of each individual employed in firm j at time t. Aggregating W_j^2 and θ_j over all J employers yields the "overall" weighting matrix, W^2, as well as $\widetilde{\theta}$, which appear in equation (7):

$$W^2 = \begin{bmatrix} W_1^2 & 0 & ... & 0 \\ 0 & W_{j2}^2 & ... & 0 \\ ... & ... & ... & ... \\ 0 & ... & 0 & W_J^2 \end{bmatrix}$$

$$\widetilde{\theta} = \begin{bmatrix} \theta_1 \\ ... \\ \theta_J \end{bmatrix}$$

As stated above, G is a matrix of indicators that selects the appropriate weighted sum of person effects for each of the N^* observations in the dataset when post-multiplied with $W^2\widetilde{\theta}$. $W^2, W^3, \widetilde{X}$, and $\widetilde{\theta}$ are constructed in an identical fashion. The Moran I* Statistic is defined as:

$$I^* = \frac{N^*}{s}\frac{\widehat{u}'W^3\widehat{u}}{\widehat{u}'\widehat{u}}, \text{ where } s = \sum_{i=1}^{N}\sum_{l=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\omega_{iljt}^3 \tag{10}$$

Based on the null hypothesis, $H_0 = u \sim N(0, \sigma^2 I)$, and estimates for $E(I^*)$ and $\sigma_{I^*}^2$(see Anselin, 1988), it can be shown that $\frac{I^*-E(I^*)}{\sigma_{I^*}^2} \xrightarrow{D} N(0,1)$, thereby providing the basis of the test for spatial correlation among wage residuals.[5]

Following AKM, when the estimated version of equation (7) excludes co-worker effects, the estimated person effects, $\widehat{\theta}$, are the sum of the true person effects, θ, and the employment-duration weighted average of the co-worker effects for the firms in which the worker was employed, conditional on the individual time-varying characteristics, X, and the firm effects, ψ:

$$\widehat{\theta} = \theta + (D'M_{[X\ F]}\ D)^{-1}D'M_{[X\ |F]}G\tau \tag{11}$$

where $\tau \equiv W^2\widetilde{\theta}\lambda_2$, $\lambda_1 = \lambda_3 = 0$ for simplicity, and the notation $M_A \equiv I - A(A'A)^{-1}A'$ for any arbitrary matrix, A. If X and F were orthogonal to D and G, meaning that $D'M_{[X\ |F]}$ $D = D'D$ and $D'M_{[X\ |F]}G = D'G$, then the difference between $\widehat{\theta}$ and θ, would be an $Nx1$ vector consisting, for each individual i, of the employment-duration weighted average of the co-worker effects τ_{ijt} for all $j \in \{\mathbf{J}(i,1), ..., \mathbf{J}(i,T)\}$:

$$\widehat{\theta}_i - \theta_i = \sum_{t=1}^{T}\frac{\tau_{ijt}}{T} \tag{12}$$

Using a similar logic, the estimated firm effects, $\widehat{\psi}$, for when equation (7) is calculated ignoring co-worker effects, can be interpreted as the sum of the true firm effects, ψ, and the

[5]Implementation of the Moran I* Statistic test will be deferred to a subsequent draft.

employment duration weighted average of the co-worker effects for each firms' employees in the sample, conditional on the individual time-varying characteristics, X, and the person effects, θ:

$$\widehat{\psi} = \psi + (F' M_{[X\ |D]}\ F)^{-1} F' M_{[X\ D]} G\tau \tag{13}$$

Hence, if X and D were orthogonal to F and G, meaning that $F' M_{[X\ |D]}\ F = F'F$ and $F' M_{[X\ |D]} G = F'G$, then the difference between $\widehat{\psi}$ and ψ, would be a $Jx1$ vector consisting, for each firm j, of the employment-duration weighted average of the co-worker effects τ_{ijt} for all $i \in \{\mathbf{J}(i,1), ..., \mathbf{J}(i,T)\}$:

$$\widehat{\psi}_j - \psi_j = \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{\tau_{ijt} 1(\mathbf{J}(i,t) = j)}{N_j} \tag{14}$$

where $N_j = \sum_{t=1}^{T} N_{jt}$ and the function $1(A)$ takes the value 1 when A is true and 0 otherwise. A similar derivation can be easily obtained for the estimated coefficients for the time-varying characteristics.

3.2 Identification of Person & Firm Effects

Because y_{it} in equation (5) depends not only on θ_i and ψ_j but also on a weighted sum of all the person effects in firm j at time t, it is not obvious that the same number of person and firm effects can be identified in my co-worker model as in the AKM framework. At first glance, the presence of multiple person effects in each wage observation certainly appears to complicate identification and I originally believed that identification restrictions above and beyond those required by AKM would be necessary. Interestingly, however, the reverse turns out to be the case. The co-worker framework actually adds an additional degree of freedom to the task of simultaneously identifying θ and ψ. Indeed, within a connected group of workers and firms (defined below) all person and firm effects appear to be identified. This contrasts with the AKM model in which either one person effect or one firm effect must be excluded from each group.

Of course, in both frameworks, mobility of workers across firms is necessary for the separate identification of person and firm effects. These effects are simultaneously identified whenever an individual that appears in the sample works for a firm that employs at least one individual who moves to another firm in the sample. In both cases, the cross product matrix associated with the full design matrix is of such high dimension, that the standard technique of eliminating singular row-column combinations will not work when attempting to solve the normal equations by directly inverting the cross product matrix. Abowd & Kramarz (1999b) present a useful framework for establishing conditions under which equation (4) can be solved for some subset of person and firm effects. They divide workers and firms into G disjoint groups, each containing all workers who ever worked for any of the firms with the group as well as all firms that ever hired any of the workers. Within each group, all person effects are identified as well as all firm effects, up to a constraint that a weighted sum of all the firm effects must equal zero. In practice, one firm effect in each group is set to zero and hence the values for all remaining firm effects are calculated relative to it.[6] By removing the column associated with each excluded firm from the original normal equations, the resulting equations are now of full rank, meaning the solution for the parameter vector should be unique. Thus, exactly $N + J - G$ total person and firm effects are identified in the AKM framework. Table 3 presents the results from applying this grouping procedure to unemployment insurance wage data from the state of Illinois over the period 1990-1998. While a detailed discussion of the data follows in Section IV, it is nevertheless worthwhile to point out that the largest group contains virtually all persons and firms ever to appear in the sample.

In the co-worker effects model, however, it is not necessary to exclude firm effects from any group, so long as the group is comprised of more than one firm. Unlike the AKM model, the cross product matrix associated with each group is initially of full rank for a given value of λ_2. The basic intuition is as follows. For simplicity, suppress the effects of the observable, time varying characteristics X. In the AKM model, this implies that $E[y_{it}]$ remains constant over time for job stayers, and that repeat observations for such workers do not contribute towards disentangling person heterogeneity from firm heterogeneity. In contrast, in the co-worker effects model, as long at least one other person either arrives at the firm or leaves it, $E[y_{it}]$ will time vary even for job stayers. Thus, repeat observations on job stayers now contribute to the identification of the person effects of workers that recently entered or exited the firm.[7]

One implication of this result is that because it is no longer necessary to exclude any firm effects, their values should be fully comparable across groups. Thus, one must be careful when comparing firm effects from the AKM model to those from the co-worker effects models I estimate below. Such comparisons will only make sense if one deliberately excludes the same firms from the co-worker model prior to estimation. Finally, given the co-worker model permits the identification of virtually all person and firm effects, it is straightforward to

[6] The choice of which firm effect to exclude is completely arbirtrary. It should be noted that the same procedure could be followed in which every firm effect in a group is identified and one person effect is excluded. However, because the iterative estimation approach for the co-worker model described in the next section uses estimates of θ from the AKM model as starting values, it is easier to exclude firm effects.

[7] Consider the following simple example of a connected group, g, with three workers, two firms, and two time periods. Worker 1 works in firm A for both periods, Worker 2 switches from Firm A to Firm B, and Worker 3 remains at Firm B both periods. Once again, suppress the effects of the observable time varying characteristics, X and let $E[y_{it}] = \theta_i + \psi_j + \overline{\theta}_{ijt}\lambda_2$.In the AKM model, $\lambda_2 = 0$, and so while there are 6 observations and 5 unknowns, only 4 observations contribute meaningfully towards the identification of person and firm effects, necessitating a single identification restriction. This is because $E[y_{it}]$ remains constant for the two job stayers. In the co-worker model, this is not the case, because for a given value of λ_2, repeat observations for job stayers directly identify the person effect for the Worker 2: $E[y_{11}] - E[y_{12}] = \theta_2\lambda_2$ and $E[y_{31}] - E[y_{32}] = -\theta_2\lambda_2$.

show that a linear search algorithms will yield reliable estimates for λ_2. I return to this issue below.

3.3 Estimation Methods

If θ were known ex ante, estimation of equation (7) would be relatively straightforward. However, because one does not initially observe θ and thus cannot form $W^2\widetilde{\theta}$, estimation is complicated by the fact that θ and λ_2 enter the equation non-linearly. As such, I implement the following approach, which closely resembles the method of iterated linearization frequently used in NLLS:[8]

1. Obtain initial estimates of θ from a model in which $\lambda_1 = \lambda_2 = 0$. Unlike AKM, who implement a series of conditional estimation methods, I solve the least squares normal equations directly, using a conjugate gradient algorithm (CG) developed by Robert Creecy of the U.S. Census Bureau based upon techniques detailed in Dongarra (1991).[9]. As formalized in equation (12), these initial estimates are a combination of the true person effects, θ, and the employment-duration weighted averages of the co-worker effects

2. Form $W^2\widetilde{\theta}$ using the latest estimates for θ and then estimate equation (7) using the CG algorithm.

3. Repeat Step 2 M times (currently $M = 5$) or until sensible convergence criteria are attained.

Given that virtually all person and firm effects are identified, this approach should yield consistent estimates for both $\lambda_1$and λ_2. Table 3 presents results from a preliminary simulation in which wages are determined by the simplified expression $E[y_{it}] = \theta_i + W^2_{i\cdot jt}\theta_{jt}\lambda_2 + \psi_j$, where $\lambda_2 = 0.10.$, $\theta \tilde{} N(0, 0.36)$, and $\psi \tilde{} N(0, 0.12)$. Matching of workers to firms is non-random. I set the overall $cov(\theta, \psi) = 0.4$, meaning that high (low) skill workers are more likely to work in high (low) wage firms. After the first period, workers switch employers with an exogenous probability of 0.25. I ignore entry and exit of workers and firms. Table 3 shows that even though my preliminary estimates of θ and ψ include weighted averages of co-worker effects, my iterative approach alleviates this bias and converges to the "true" value for λ_2 after only a few iterations. This result is robust to different matching schemes, sample sizes, and mobility assumptions.

[8] The procedure described below ignores the possibility of spatial correlation among the wage residuals ($\lambda_3 = 0$). See Amemiya (1985) or Davidson and MacKinnon (1993) for detailed discussions of iterated linearized regression as well as other non-linear regression techniques.

[9] This approach has been used recently by Haltiwanger, Lane, & Sandusky (2001), Abowd, Lengermann, and McKinney (2001), and Abowd & Kramarz (1999). Algorithm details are available upon request.

In the results that follow, I structure $W^1_{i\cdot jt}X_{jt}$ and $W^2_{i\cdot jt}\theta_{jt}$ to yield $\overline{X}_{ijt}$ and $\overline{\theta}_{ijt}$ respectively. This identifies the "average" worker characteristics at firm j less individual i's contribution. Subsequent work will explore the influence of other weighting specifications. For instance, one could use various measures of "spread" (standard deviation, inter-quartile range), the actual skill shares of employment, or various measures of skill inequality within firms. Furthermore, distance measures could be used to assign greater weight to the characteristics of individuals more similar to the reference individual. Hierarchy models of wage determination in which an individual's wage is influenced only by her superiors or by very high skilled "stars" (for instance, Lazear & Rosen 1981) could also be tested using this framework.

3.4 Interpreting Co-Worker Effects

The theme I am attempting to tap into is that it may not just be who you are and where you work (i.e. AKM, Groshen 1991) that influence what you earn but also with whom you work. In other words, observationally equivalent individuals (same $X\beta, \theta$) working in observationally equivalent firms (same ψ), may nonetheless earn different amounts if the skill mix of their co-workers differs. Viewed in this light, equation (7) represents an extension of the long debate over inter-industry wage differentials. However, it also provides a direct connection to the recent models developed by KM and Acemoglu (1999) which link changes in wage inequality to changes in skill segregation. As discussed in Section 1, if who you work with affects your wage, then changes in skill segregation can lead directly to changes in wage inequality. It is important to stress that this kind of analysis is intended to complement, more traditional explanations for rising wage inequality. Co-worker effects as well and the non-random matching of workers to firms ($cov(D, F) \neq 0$) may both be avenues by which the usual suspects–skill-biased technological change, changes in the supply of and demand for skill, and institutional factors—all work to affect wage inequality.

More practically, what will the estimates for $\lambda_1$and λ_2 really tell us? An important issue that has been raised is whether what I have labelled "co-worker effects" truly result from the characteristics of co-workers rather than simply proxying for stochastic (unobserved) changes in firm effects. Suppose firm effects are time varying: $\psi_{\mathbf{J}(i,t),t} = \phi_j + q_{jt}\rho$. In such a world, if $cov(\tau_{ijt}, q_{jt}\rho) \neq 0$, $\widehat{\lambda}_1$and $\widehat{\lambda}_2$ will at least partially reflect changes in the compensation strategies chosen by firms. It seems entirely plausible that such changes could be associated with a simultaneous restructuring of the workforce. For instance, if firms simultaneously upgrade the quality of their workforce and replace older workers with newer ones when increasing the premium paid to workers, then $\widehat{\lambda}_1$will be downward biased while $\widehat{\lambda}_2$ will be upward biased. At this stage, I want to emphasize that even in the absence of a direct connection between workers' wages and co-worker characteristics, a finding that skill homogenous firms tend to pay more (or less) even after controlling for time invariant person and firm heterogeneity would still be important for explaining wage outcomes over time, both within and across industries. As it stands, I believe I get closer to establishing a plausible causal link than, for instance, most peer effects studies concerned with the extent to which classmates characteristics influence school performance and other social behaviors (Evans et al. 1992). The data used for such studies are rarely rich enough to simultaneously identify how classmate characteristics evolve within and across schools and to follow the progress of students who switch schools.

Nevertheless, in order to focus on the interpretation question more closely, I estimate three variants of equation 7: the baseline model, a limited time varying firm effects model, and a time varying firm effects model. Each approach has a number of advantages and disadvantages, which I detail briefly below.

3.4.1 Model 1: Time Invariant Firm Effects

This is the baseline model introduced formally above. Time invariant firm effects mean that co-worker effects can never be completely disentangled from unobserved, stochastic changes in the wage premia paid by firms to all of their employees, so long as such changes are correlated with changes in the skill mix of firms. In this model, estimation of $\lambda_1$and λ_2 is based off of within firm variation in $\overline{\theta}_{ijt}$ and $\overline{X}_{ijt}$[10] both in a given time period and over time. Any differences in firm average person and experience effects that remain constant across firms will be absorbed into the firm effect. To see this more clearly, if $\overline{\theta}_{ijt} \approx \overline{\theta}_{jt}$and $\overline{\theta}_{jt} \approx \overline{\theta}_{j}$, the effect of firm average person effects on workers' wages will be indistinguishable from the time invariant compensation policies of the firm, ψ_j.The former case will typically hold for large firms, and the latter for firms whose skill mix remains essentially unchanged during their time in the sample. Thus, the variation necessary to identify co-worker effects in the baseline model comes primarily from small firms and firms, regardless of size, that alter the skill composition of their work force.

3.4.2 Model 2: Limited Time Varying Firm Effect*s*

In this model, long lived firms are assigned two firm effects, one for the first five years they appear in the data, another for all remaining years. Practically, this is accomplished by assigning firms new identifiers after they are observed for five years. Thus, while for estimation purposes, the original firms and their spin off "pseudo firms" are treated as distinct entities, they are subsequently reconnected for all post-estimation analyses. It should be noted that this procedure does not affect the identification of the firm effects, since the grouping assignments do not change. The employees of firm $j\_period1$ remain in the same group as those of firm $j\_period2$ so long as either a single worker appears in both $j\_period1$ and $j\_period2$ or a single worker who once worked in firm $j\_period1$ ever works with

[10] Recall these variables reflect the average person effect and experience in firm j and time t *less* the contribution of person i.

someone who was once a co-worker of someone employed in $j\_period2$.[11] To the extent that firm effects evolve gradually over time, this approach should aid in clarifying interpretation for the estimated co-worker effects. Furthermore, as in Model 1, estimation of λ_1 and λ_2 continues to be based off of within firm variation in $\overline{\theta}_{ijt}$ and $\overline{X}_{ijt}$ across workers in a given time period as well as over time.

3.4.3 Model 3: Time Varying Firm Effects

This model uses the same framework as Model 2, except that now I compute separate firm effects for each year a firm appears in the data (ψ_{jt} instead of ψ_j) Once again, the grouping assignments are virtually identical to those of the baseline model, meaning that firm effects are directly comparable across models. The advantage of this approach is that the initial concern over omitted variables–a likely covariance between firm average person and experience effects and time varying firm effects–is essentially eliminated. Co-worker effects can only be explained as resulting from factors other than co-worker characteristics to the extent these factors are not shared by all workers in the firm in any given time period (or, as always, if they are not absorbed by $X_{it}\beta$ and θ_i). The disadvantage of this approach, however, is that by allowing firm effects to fully time vary, estimation of $\lambda_1$and λ_2 is based solely off of the variation in $\overline{\theta}_{ijt}$ and $\overline{X}_{ijt}$ that occurs across workers within the same firm in a given year. In other words, since in large firms $\overline{\theta}_{ijt} \approx \overline{\theta}_{jt}$, only small firms contribute towards the estimation of co-worker effects estimated in Model 3. This poses a problem only to the extent that the role played by co-workers in small firms is more important than in large firms. To the extent this is true, generalizing the results of Model 3 to the economy at large will be problematic.

4 Construction of the Data

This paper is based on data assembled as a part of the U.S. Census Bureau's new Longitudinal Employer-Household Dynamics (LEHD) Program. I use the LEHD Program's Employment Dynamics Estimates database, which is described briefly below. See Abowd et al. (2000) for a much more in depth discussion. When a variable was created with an exact link to another database, I use the actual value from that data source. When a variable was created with a statistical link to another database, I impute the value of the variable 10 times using the same statistical linking model, thereby providing information on the precision of the statistical links.[12]

[11] By restricting my analysis to firms with five or more employees (see the Data section), this condition holds for 99.9% of observations. The remaining 0.1% are dropped prior to estimation.

[12] This approach is detailed at length in Rubin (1987). This draft contains no statistics using the additional imputations.

4.1 Individual Data

The individual data were derived from the universe of unemployment insurance (UI) quarterly wage records for the State of Illinois for the period 1990 to 1998.[13] Individuals are uniquely identified and followed for all quarters in which their employer had an Illinois reporting requirement in the UI system. Using Census Bureau and other LEHD data bases sex, race, date of birth, and education were added to the individual information.[14] At each individual's first appearance in the sample, labor force experience is calculated as potential labor force experience (age - education - 6). In subsequent periods, experience is measured as the sum of observed experience and initial (potential) experience.

4.2 Employment History & Wage Data

Each individual is associated with every employer from whom the individual received wages during a given calendar quarter for the period 1990:I to 1998:IV. The employment history record is identified by the same personal identifier that is used in the individual data. Employers are identified by the state unemployment insurance account number (SEIN). Thus, while all workers can be matched to their employer, it is not possible to match workers employed in firms with multiple establishments to specific places of work. This problem is not overly pervasive, as approximately 72% of employment in Illinois occurs in firms with only a single establishment. For each individual, I define a "dominant" employer in every year so as to ultimately approximate the individual's full-time, full-year annual wage rate. The dominant employer in a given year is the one for whom the sum of quarterly earnings over all four quarters is the greatest. I estimate full-year earnings from the dominant employer using the following steps. Full quarter employment in quarter t is defined as having an employment history with positive earnings for quarters $t-1$, t , and $t+1$. Continuous employment during quarter t means having an employment history with positive earnings for either $t-1$ and t or t and $t+1$. Employment spells that are neither full quarter nor continuous are designated discontinuous.

- If the individual was full quarter employed for at least one quarter at the dominant employer, then full year earnings are computed as 4 times average full quarter earnings at that employer (total full quarter earnings divided by the number of full quarters worked). [79% of the individuals]

[13] Other participating states are California, Florida, Maryland, Minnesota, and Texas. Future work will incorporate these states into the analysis.According to the BLS Handbook of Methods (1997), wages include "gross wages and salaries, bonuses, stock options, tips, and other gratuities, and the value of meals and lodging, where supplied." They do not include OASDI, health insuranance, workers compensation, unemployment insurance, and private pension and welfare funds.

[14] Sex, race, and date of birth are based on an exact match to adminstrative data. Education is based on a statistical match.

- Otherwise, if the individual was continuously employed for at least one quarter at the dominant employer, then full year earnings are the average earnings in all continuous quarters of employment at the dominant employer multiplied by 8 (i.e., 4 quarters divided by an expected employment duration during the continuous quarters of 0.5). [13% of the individuals]

- Otherwise, full year earnings are average earnings in each quarter multiplied by 12 (i.e., 4 quarters divided by the expected employment duration during discontinuous quarters of 0.33). [8% of individuals]

I use full-time, full-year earnings in order to best approximate workers' annual wage rates in all subsequent analyses. Full time status is assigned using a statistical link to the Current Population Survey.

4.3 Analysis Sample & Summary Statistics

The data are further restricted to exclude workers employed in agriculture or government. Workers employed in firms with fewer than five employees and all observations with "extreme" wage values ($1,000 > full-time, full-year earnings > $1,000,000) are also excluded. Table 5 presents sample means for a number of earnings, demographic, industry, and labor force attachment variables calculated over the entire nine year period under consideration. The final analysis sample contains 41 million observations for 9 million individuals and 191,129 firms. In comparison to the base LEHD file, the analysis sample contains considerably fewer firms, has somewhat higher average wages and earnings, and is slightly more educated, male, white, and experienced. Over fifty percent of observations are from individuals who worked four full quarters during the year. A mean annualized wage of $36,661 reflects the average value of what individuals *would* have earned at their dominant had they worked full-time for the entire year.

For purposes of comparison, Table 6 presents summary statistics from the Census internal March Current Population Survey (CPS)[15] for the same time period. I subset the CPS to only include respondents residing in Illinois. CPS sample weights were utilized for all calculations. While respondents that reside in Illinois are not necessarily employed there, the CPS does not gather location information on employers. One also cannot decompose annual earnings across jobs, meaning that mean values are not fully comparable to those in Table 5 which are based on earnings at the dominant employer. Thus, as one might expect, mean annual earnings for the IL-CPS file exceed mean raw annual earnings in the LEHD file. However, by restricting the IL-CPS file to closely resemble my analysis sample (a firm size restriction could not be made), mean annualized wages are quite comparable, as is the weighted sample size, and most demographic characteristics.[16] While CPS sample weights

[15] Unlike the public use version, the internal CPS does not top-code earnings values.

[16] In the IL-CPS, annualized wages were computed as average weekly earnings multiplied by 50.

are not representative across *both* state and industry, the industry affiliation of respondents in the IL-CPS closely parallels those in the LEHD sample.

Finally, Figures 4A and 4B plot mean annualized wages for each year of the sample period broken out along gender lines. Annualized wages in the LEHD file are also distinguished for individuals working 4 full quarters and for those working less than 4 full quarters. For men, until 1994 the CPS and LEHD annualized wages track each other quite closely. After this time, however, male wages rise somewhat more rapidly in the CPS. This seems to be the result of a sizeable decline in wages for those working less than 4 full quarters in the LEHD file. Wages for males working 4 full quarters increased slightly over the same time period. This pattern is even more pronounced for women. CPS and LEHD-4 full quarter wages increased steadily, but again fell for women working less than 4 full quarters. Perhaps this result can be attributed to the kind of skill composition bias story described by Solon et al. (1994) in their study of wage cyclicality using the PSID. Because the labor force attachment of lower skilled workers is more cyclical, as economic conditions improve low skilled workers that were previously either unemployed or out of the labor force return to work, at least in a limited capacity, while low skilled workers that were already employed increase their labor supply. To the extent this is true, the skill mix of those working less than four full quarters may have declined during the 1990s, causing average wages for the group to fall. Regardless, these divergent patterns suggest that the annualized wage measure is not entirely free from influence of unobserved labor supply factors. Because of this, all subsequent regressions contain numerous controls for labor force attachment status. Dummy variables for discontinuous employment and the number of full quarters worked (0-3) are created, and all year dummies are interacted with 4 full quarter and less than 4 full quarter status.

5 Estimation Results

This section presents results from my estimation of the three co-worker effects models using the iterative approach described above. In all models, the dependent variable is the log of the real annualized wage. In the time invariant and limited time varying firm effects models, the matrix of time varying personal characteristics, X, includes a quadratic in experience, year dummies for persons working four full quarters, year dummies for persons working less than four full quarters, and dummies for discontinuous employment, and 0-3 full quarters worked. All of these variables are interacted with gender thereby providing separate estimates for men and women. Year effects were not included in the time varying firm effects model as doing so would prevent identification of ψ_{jt}. Experience is the only variable used in the computation of firm average observable characteristics, $\overline{X}_{ijt}$.

Table 7 presents a summary of the estimates for β, the coefficients on the time-varying individual characteristics for the baseline model (Model1) and contrasts them with ordinary least squares as well as models that alternately exclude either person effects or firm effects but not both. Appendix 1 contains β coefficients from additional specifications (Models 2 and 3 and models which distinguish industry specific co-worker effects). Both models that control for person heterogeneity appear to explain a larger fraction of the variance of the log of real annualized wages (between 83-85%) than the model which controls for firm effects only (46%). For both males and females, the return to experience varies noticeably across estimation models. The OLS estimates are more in line (although generally smaller) with those for Model 1 than those from models that only exclude person heterogeneity or firm heterogeneity. The large scale of the data being analyzed ensures that virtually all parameters are estimated with a high degree of precision.

5.1 Results from the Baseline Model

Table 8 summarizes the evolution of person effects, time invariant firm effects, and co-worker parameters from a preliminary iteration in which co-worker effects are ignored to five subsequent iterations in which $\overline{\widehat{\theta}}_{ijt}$ and $\overline{X}_{ijt}$ appear on the right hand side. In all cases, the firm average person effects are based off of estimates for θ generated in the previous iteration. The mean absolute difference between the person and firm effects of the preliminary iteration and first iteration is small but not inconsequential, especially for firm effects. As equations (12) and (13) suggest, this should be due in part to the fact that in the absence of controls for co-worker effects, these effects are lumped in with the estimated person and firm effects. However, after the first iteration the mean absolute deviations fall dramatically. Subsequent iterations yield smaller and smaller changes to $\widehat{\theta}$ and $\widehat{\psi}$. Recall a similar result was observed in the convergence simulation in Table 4. Interestingly, while the coefficient on the firm average person effect is fairly large ($\widehat{\lambda}_2 = 0.098$), the coefficient on firm average experience is small and negative. All else constant, in the time invariant firm effects model, firms with high average experience appear to pay less. To better understand the importance of these coefficients, note that $\overline{X}_{ijt}$ and $\overline{\widehat{\theta}}_{ijt}$ have standard deviations of five years and 0.27 respectively. Hence, while a one standard deviation increase in the average person effect of one's co-workers increases wages by approximately 3%, changes in the average experience of one's co-workers does not appear exert a meaningful influence on wages, ceteribus paribus. The estimate for $\widehat{\lambda}_2$ provides some evidence that skill segregation may indeed play a role in explaining wage differences across firms and industries as well as (possibly) the economy-wide distribution of wages.

Table 9 shows the inter-correlations of the various components of annualized wages after five iterations of the time invariant firm effects model. $X\beta$ is decomposed into a *time* effect that also includes the labor force attachment variables and an experience effect, $X_2\beta_2$. Personal heterogeneity and firm heterogeneity are both highly correlated with log real annualized wages, with values of 0.59 and 0.52 respectively. Experience ($X_2\beta_2$) and firm average person effects are also positively correlated with wages but appear to be somewhat less important. Because $\widehat{\lambda}_1 < 0$, firm average experience effects are negatively correlated with wages As in

AKM, the overall correlation between person and firm heterogeneity is positive but essentially indistinguishable from zero. Firm average person effects are not mildly correlated with most of the other wage components, the two exceptions being firm average experience effects and (not surprisingly) person effects. While there is essentially no relationship between firm effects and firm average person effects, firm effects and firm average experience effects are negatively correlated at approximately -0.3.

While focusing on the implied 1 standard deviation effect is one way of summarizing the contribution of co-workers to individual wage outcomes, because skill segregation varies across industries, this approach says nothing about how much actual differences in wage outcomes across firms are due to differences in the skill mix of firms. For instance, what would be the effect of taking an individual from a firm with a particular skill mix and placing her into a firm with a very different mix of workers? The extent to which her wages change even after controlling for differences in the compensation structures of the two firms reveals the relative importance of co-worker characteristics to wages. Table 10 presents results for selected 3 digit industries sorted by the average person effect ($\overline{\theta}_{jt}$) of a "typical" firm in the industry in 1998. Not surprisingly, the highest skill industries are predominately members of the financial sector, while the lowest skill industries are an amalgam of industries one might *a' priori* suspect to be low wage. Note that the highest skill industries also appear to have above average firm effects. In other words, as illustrated earlier in Figure 3, high skill workers tend to sort into firms that pay a sizeable wage premium (a high internal wage) to all workers irrespective of their skill. High skill industries tend to employ workers with experience levels that are slightly below average (recall variables are expressed as deviations from their grand means), while low skill industries tend to employ individuals with above average experience.

It is important to keep in mind that not all workers in a high (low) wage industry are high (low) skilled. My wage accounting framework implies that an individual employed in foreign banking enjoys a 7.7% wage premium simply because she is surrounded by high skill individuals, irrespective of her own skill and the fact that firms in this industry tend to pay all workers a sizeable wage premium ($\overline{\psi}_{jt} = 0.29$). In contrast, an observationally equivalent individual employed in fabric mills, earns 4.3% less because of the low average skill in her firm, despite the fact that fabric mills also have high average firm effects. Thus, the implied effect of moving from foreign banking to fabric mills would be 12% decline in wages due simply to the fact that the skill mix of workers has changed. At least when comparing high and low skill industries, co-worker effects appear to exert a sizeable impact on wages, above and beyond the contribution of person and firm heterogeneity.

5.2 Comparing the 3 Models

Table 11 summarizes the estimates for λ_1 and λ_2 that result after 5 iterations for each of the three co-worker effect models. Looking first at the coefficients for firm average person effects, the hypothesized concern over an omitted variables bias certainly appears to have been substantiated. $\widehat{\lambda}_2$ declines from 0.098 in the time invariant firm effects model, to 0.087 in the limited time varying firm effects model, to 0.056 in the time varying firm effects. It would appear that firms that choose to increase the wage premia they pay their workers do so in conjunction with up-skilling their workforce. Depending on the model, these estimates imply that a one standard deviation increase in a firm's average person effect (net of your own contribution) is associated with wage increases of approximately 1.5% to 3%.

The opposite pattern is observed for firm average experience effects as moving from time invariant firm effects to time varying firm effects causes $\widehat{\lambda}_1$ to change dramatically, so much so that it actually changes signs. The implied one standard deviation effect of -0.002 in the baseline model becomes 0.044 in the time varying firm effects model. As discussed above, this pattern can also be potentially explained by an omitted variables bias. If time varying firm effects co-vary negatively with firm average experience then by controlling for the former, $\widehat{\lambda}_1$ could rise. It seems plausible that when firms overhaul their compensation policies that they may simultaneously attempt to replace older, less skilled workers with younger, more skilled ones. Of course, this result could also be due to the presumably low amount of within firm, within year variation in $\overline{X}_{ijt}$ present in the data. Recall that the cost of moving to time varying firm effects framework is that estimation of co-worker effects is now based solely off of small firms. Thus an alternative explanation for the observed pattern for $\widehat{\lambda}_1$ could be that co-worker experience is simply much more important in small firms than in large firms.

5.3 Skill Segregation and Inter-Industry Wage Differentials

So far, I have assumed that the co-worker parameters $\lambda_1$and λ_2 remain constant across industries. Clearly, however, one might expect that because production technologies and work systems vary systematically across industries, co-worker parameters might vary as well. To the extent this is true, interpretation of the "overall" co-worker effects presented less meaningful. Table 12 presents results in which separate co-worker parameters have been estimated for each 2 digit industry.[17] As expected, there appears to be considerable variation in impact of co-worker characteristics on wages. The standard deviations for the firm average experience and person effect parameters are very large relative to the overall effect estimated previously.

The firm average person effect parameter is particularly large in industries like construction, air transportation, depository institutions, and motion pictures, while it is small in

[17] Estimating industry specific co-worker effects at the 2 digit level, tripled the run time for the conjugate gradient (CG) algorithm used throughout the paper. Because each regression already requires approximately 24 hours of CPU time, estimates at the 3 and 4 digit level have been deferred until a future date. Appendix 1 presents the time varying individual characteristics. Appendices 2A & 2B present industry specific co-worker effects for the limited time varying firm effects and time varying firm effects models. In the latter model, the implausibly large size of many of several co-worker parameters suggests that the CG algorithm failed to converge.

industries like food products, water transportation, apparel stores, and legal services. The parameter also varies noticeably across manufacturing sectors. For instance, while co-worker skills would appear to be an important determination of wages in textile mills (SIC 22), they do not appear to matter in primary metal industries (SIC 33). Interestingly, while the coefficient on firm average experience is negative for most industries just as it was for the overall coefficient, it is actually positive for most industries in the financial sector (see, for instance, SICs 60-64). In these industries, working in a firm with many high experience individuals actually raises wages, ceteribus paribus. For security and commodity brokers (SIC 62), the overall 1 standard deviation effect of 4.5% is explained almost entirely by the high average experience of co-workers.

Clearly, there are many reasons why such differences might exist. While the primary focus of this paper has been ascertaining whether or not co-worker effects exist at all, studying the determinants of co-worker parameters would appear to be a fruitful area for future research. Sakellaris (2000) uses detailed industry level data to characterize the production systems and technologies in the manufacturing industry, while Haltiwanger *et al.* (2001). study the influence of technology investment on the evolving distribution of human capital across industries. It would be interesting to measure the extent to which such factors are related to co-worker effects.

Because skill segregation varies across industries, one might also imagine that co-worker effects contribute, at least partially, to inter-industry wage differentials. While the cause of persistent inter-industry wage differentials has long been a source of debate in economics (see for instance, Krueger and Summers, 1988; Murphy and Topel, 1987; and Gibbons and Katz, 1991), previous explanations have focused either on industry level differences in worker characteristics or on differences in firm compensation policies across industries. My wage accounting framework, permits an additional mechanism for explaining inter-industry wage differentials: differences in the within firm skill mix of workers across industries. AKM develop a statistical framework for decomposing inter-industry wage differentials into components due to individuals characteristics (measured and unmeasured) and firm heterogeneity. It is straightforward to show that this decomposition can augmented to allow for co-worker effects. Following AKM, an industry effect is defined as a characteristics of the firm. Thus, industry wage effects are simply aggregations of the firm effects in each industry. Following this logic, I incorporate industry effects into equation (5) as follows:

$$y_{it} = X_{it}\beta + \overline{X}_{ijt}\lambda_1 + \theta_i + \overline{\theta}_{ijt}\lambda_2 + \kappa_{K(J(i,t))} + (\psi_j - \kappa_{K(J(i,t))}) + \varepsilon_{it} \tag{15}$$

where what remains of the firm effect is its deviation from the industry effect. The function $K(j)$ delivers the industry of firm j, and hence $\kappa_{K(J(i,t))}$ denotes the true industry effect, which again is simply an aggregation of firm effects. Using notation from Section III, equation (15) can be re-stated in matrix notation as follows:[18]

[18] To reduce notational complexity in equations (15) and (16) I set $\lambda_3 = 0$ (meaning $u_{it} = \epsilon_{it}$), define

$$y = X\beta + G[\overline{X}\ \overline{\theta}]\lambda + D\theta + FA\kappa + (F\psi - FA\kappa) + \epsilon \tag{16}$$

where A is a matrix which maps firms into industries and κ is a vector of true industry effects. In contrast, define κ^{raw} as the vector of "raw" inter-industry wage differentials that results from ignoring unobserved person and firm heterogeneity. κ^{raw}can be decomposed into the following three components:

$$\kappa^{raw} = (A'FM_XFA)^{-1}A'F'M_XD\theta + (A'FM_XFA)^{-1}A'F'M_XF\psi + (A'FM_XFA)^{-1}A'F'M_XG\lambda \tag{17}$$

In other words, raw inter-industry wage differentials can be expressed as the weighted sum of person effects, firm effects, and co-worker effects. The weights return the industry average person, firm, and co-worker effects less the contribution of time varying person characteristics, X.

Table 13 implements equation (17) for firms classified according to their SIC Division. The raw industry effect measures how much more (or less) the average worker in each industry earns relative to the average worker in the entire sample, after controlling for time varying, observable person characteristics. For example, manufacturing workers enjoy a 9.9% wage premium, which can be fully decomposed as the sum of industry average person effects (-0.043), firm effects (0.182), and co-worker effects (-0.04). The final two rows of Table 13 show there is considerable variation in raw industry differentials as well as average firm effects across SIC divisions. Industry variation in average person effects and co-worker effects, while smaller, is nevertheless non-trivial. Interestingly, at the SIC Division level, co-worker effects only contribute meaningfully to raw industry wage differentials for workers employed in Finance, Insurance, and Real Estate (FIRE). Such workers enjoy a 22.6% wage premium, which appears to be split evenly between person effects and co-worker effects.

Moving to a more disaggregated classification of industries yields a more consistent relationship between skill segregation and raw inter-industry wage differentials. Figure 5 graphically depicts the relationship between raw industry wage differentials at the 2 digit level and industry average person, firm, and co-worker effects. Industry average co-worker effects are further decomposed into the person effect ($\overline{\theta}_{ijt}\lambda_2$) and experience ($\overline{X}_{ijt}\lambda_1$) components described earlier. While industry variation in person and firm effects perform best in terms of predicting industry wage differentials, co-worker effects, in particular the component due to firm average person heterogeneity, also appear to play a meaningful role. Approximately, 26% of raw inter-industry wage differentials can be explained solely by variation across industries in the component of overall co-worker effects due to firm average person heterogeneity. Co-worker effects in experience do not help explain raw inter-industry wage differentials. To summarize, workers in high wage industries earn more not only because on average they are

$\lambda = [\lambda_1\ \lambda_2]'$, and structure $GW\widetilde{X} = G\overline{X}$,and $GW\widetilde{\theta} = G\overline{\theta}$.

more skilled or because firms in high wage industries typically pay high internal wages but also because there is an additional boost to wages that results from being grouped in firms with other high skilled.

5.4 Skill Segregation and Wage Inequality

In this section I return to the proposition put forward by KM that skill segregation and wage inequality are related. While their model is geared towards explaining changes in the distribution of wages, because there were only minimal changes in wage inequality in Illinois during the 1990s, I focus instead on decomposing the level of inequality.[19] This approach should still allow for useful inferences to be made as to the relative importance of skill segregation ("with whom you work"), person heterogeneity ("who you are") and firm heterogeneity ("where you work") to the overall distribution of wages. More specifically, I study the impact of incrementally adding together wage components on the shape of the resulting distribution. To the extent that persons and firms match non-randomly, combining wage components should not have a neutral effect. Of course, while combining all three components yields the actual distribution of observed wages (less a statistical residual), the order in which this occurs is completely arbitrary. For instance, one could implement a persons first ordering in which one starts with the distribution of persons effects, adds in co-worker effects, and then finally adds in firms effects. Alternatively, one could start with the distribution of firm effects, add in co-worker effects, and then add person heterogeneity .

Table 14 presents the results of implementing this decomposition using both a persons first and firms first ordering. For each combination, it details the implied log wage differentials for selected percentiles of the distribution as well as the standard deviation in 1990, 1994, and 1998. In all years, the distribution of persons plus firms plus co-workers is the same as that of firms plus persons and co-workers and equal to the observed distribution of wages in Illinois (again less a statistical residual). Looking across years, one can see that wage inequality fell slightly between 1990 and 1994 before returning to close to its original level in 1998. The 90-10 log wage differential was 1.96 in 1990, 1.92 in 1994, and 1.95 in 1998.

Focusing on 1990, if workers were compensated solely according to their individual characteristics, the log wage differential between workers at the 90th percentile of the skill distribution and those at the 10th percentile would be 1.59. If, instead, both persons and co-workers contributed to individual compensation, this differential would rise by approximately 4 log points[20], an increase of approximately 2.5% that appears robust across time periods. To put this into perspective, Katz and Autor (1999) find that the same differential

[19] Throughout this section, the "person" component of wages refers to the sum of unobserved individual heterogeneity (θ) and time varying observed individual characteristics, less less year effects and labor force attachment dummies ($X_2\beta_2$) Recall, $X\beta = time + X_2\beta_2$. All calculations are based off of the time invariant firm effects model that allows for industry specific co-worker parameters.

[20] The convention used here is to refer to log changes multiplied by 100 as changes in "log points."

increased by approximately 7% for real wages between 1985 and 1995 as measured in the CPS.

Viewed in this light, skill segregation would appear to exert a mild but not altogether unimportant effect on inequality.[21] However, this effect is many times smaller than the effect of adding firm heterogeneity to the distribution of person and co-worker effects. Doing so increases the 90-10 differential by 33 log points in 1990. Such an increase is roughly comparable to the *entire* change in the 90-10 log wage differential reported by Katz and Autor (1999) to have taken place over the 25 year period from 1963-1995. Clearly, the process whereby high skill workers sort disproportionately into high wage firms, while low wage workers sort disproportionately into low wage firms matters a great deal with respect to overall distribution of wages. In other words, the level of inequality that would result simply because of differences in individual characteristics is further exacerbated because high skill workers are more likely to work in firms with high internal wages. Both Acemoglu (1999) and Haltiwanger *et al.* (2000) model such an outcome as resulting from capital-skill complementarities. In the absence of data on capital structures that can be integrated with the UI data used in this paper, such a conjecture cannot be verified, and so remains a topic for future research.

Another point to note is that from the vantage point of the persons first decomposition, the influence of co-worker effects and firm heterogeneity on the overall distribution of wages appears much more pronounced for workers at the left tail of the skill distribution. For instance, the 90-75 differentials do not change when co-worker effects and firm person effects are added sequentially to person effects. Other differentials such as the 50-25, 75-25, and 50-10, increase by 1-2 log points when co-worker effects are added to person heterogeneity, and by 14-20 log points after subsequently adding in firm heterogeneity. Thus, sorting also appears to exacerbate wage differentials between middle and low skilled workers, albeit not as dramatically as between high and low skilled workers.

The results from the persons first decomposition of wages are summarized graphically in Figure 6A, which plots the cumulative distribution of different combinations of wage components for Illinois in 1990. Starting with the distribution of person heterogeneity, adding in co-worker effects causes a very small change in the shape of the distribution, which is only apparent at the left and right tails. Adding firm heterogeneity subsequently causes a much more pronounced shift in the distribution. The actual distribution of wages that results from combining all three wage components has considerably more mass at the left and right tails than would have existed in the absence of firm effects. One can show that while worker sorting makes the modal worker better off, some low wage workers are actually made worse off–absolutely and relatively–because of the combined effects of being grouped

[21] Here, and throughout the remainder of the paper, the term "skill segregation" refers to the wage premium (penalty) received by workers grouped in firms with above (below) average skill levels. While this is a different concept than the skill segregation index developed by KM, it is generally in line with their theoretical model in which wages are a function of *both* individual and co-worker characteristics.

with other low skill workers and being employed in low wage firms

Finally, switching to the firms first decomposition shows the distribution of firm heterogeneity to be considerably more compressed than the one for person heterogeneity (see Table 6B). If worker compensation depended solely on the internal wage paid by firms, the 90-10 log wage differential would be 0.86 in 1990, 0.82 in 1994, and 0.81 in 1998. Adding, co-worker effects to firm effects increases inequality only slightly, raising the 90-10, 90-75, 90-50, and 75-25 differentials by 1 to 2 log points in 1999 and 1994 (in 1990 they either fell or remained unchanged). However, subsequently adding person heterogeneity has very large effects, more than doubling log differentials at all points along the distribution. Thus, both the persons first and firms first ordering suggest that the sorting of heterogenous workers into heterogenous firms has a much greater impact than co-worker effects on the actual distribution of wages.

6 Conclusion

The primary goal of this paper was to explore the extent to which wage outcomes–at the individual, industry, and economy wide level–might depend on the characteristics of co-workers. While a wide array of fields within labor economics focus on the interaction of workers within firms, only recently have data been available to consider this issue directly. Although the data used here are extremely useful because they connect virtually the entire universe of workers to their employers in the state of Illinois, they unfortunately contain only limited information on worker characteristics. As a result, it was necessary to implement an iterative estimation approach which relied on the person specific component of wages to proxy for co-worker "skills."

Throughout the paper, I have used the recent work by KM to anchor my discussion of the relationship between co-worker characteristics and wages. KM posit that increases in the dispersion and mean of the skill distribution can simultaneously increase wage inequality and reduce the tendency for high and low skill workers to be grouped together in firms. Applying their skill segregation index yielded an initially puzzling result. While wage segregation increased slightly during the 1990s, segregation of the individual specific components of wages actually declined. This difference can only be explained by changes in distributions of person and firm heterogeneity as well as the matching process between workers and firms. Thus, any attempt to measure the impact of co-worker characteristics on individual wage outcomes needs to worry about the complex relationship between skill segregation, person heterogeneity, and firm heterogeneity. This paper represents the first attempt to distinguish all three simultaneously.

At the individual level, my results suggest that there is a small yet economically meaningful role for co-worker characteristics in the wage determination process. While some of what I label "co-worker effects" appears to at least partially reflect changes in the general compensation strategies chosen by firms, my estimates imply that a one standard deviation increase in both a firm's average person effect and experience level is associated with an average wage increase of 3% to 5%. Because skill segregation varies considerably across different industries, co-worker effects are particularly pronounced for individuals employed in high and low skilled industries.

Because because production technologies, capital structures, and work systems undoubtedly vary across industries, I also estimated industry specific co-worker parameters. Doing so revealed considerable variation in the impact of co-worker characteristics on wages. The standard deviations for the firm average experience and person effect parameters are very large relative to the overall effects, and a more detailed consideration of the causes of this variation will likely be a topic of future research. Using the industry specific co-worker parameters, I re-expressed raw inter-industry wage differentials as the weighted sum of industry average person, firm, and co-worker effects. Approximately 26% of raw inter-industry wage differentials at the two digit level can be explained solely by variation across industries in the component of overall co-worker effects due to firm average person effects. Workers in high wage industries appear to earn more not only because they tend to be more skilled or because firms in high wage industries typically pay all workers high wages but also because of the wage gains that result from being grouped with high skilled workers.

As a final application, I used my wage accounting framework to decompose the actual distribution of wages into components due to persons, firms, and co-workers. Because workers match to firms non-randomly, these components are not independent. Hence combining them cannot be expected to exert a neutral effect on the resulting distribution. While the order of this decomposition is arbitrary, two results are clear. First, as suggested by KM, co-worker effects appear to mildly exacerbate wage differentials between high and low skilled workers. However, this effect is considerably smaller than the effect of combining person and firm heterogeneity. Thus, in terms of the overall distribution of wages, "who you are" and "where you work matters" appears to matter much more than "with whom you work."

In future work, I plan to expand this approach to studying inequality. I am also in the process of incorporating data from additional states. It should be interesting to learn how skill segregation trends and co-worker parameter estimates in other states compare to those in Illinois. Initial processing of data from California suggests that wage segregation increased more dramatically during the 1990s. The econometric model in Section III was also specified quite generally in order to permit future modifications. While the results in this paper were for the average co-worker in firms, other weighting schemes, for instance ones which assign greater weight to the characteristics of individuals more "similar" to the reference individual, may better approximate an individual's true co-workers, especially in large firms. It would also be interesting to contrast my results with those from a weighting structure in which only high wage "stars" are given positive weight. Finally there is a long and established literature that attempts to explain the lower average wages received by women and minorities. A straightforward application of my model would be to estimate the extent to which these differentials are explained by the fact that certain firms and industries are highly segregated along gender and racial lines.

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Table 1: Kremer & Maskin Skill Segregation Index, Single Establishment Firms, Illinois 1990-1998

Year	Wage	White	Male	Age	Education	Predicted Experience Effect ($x\beta$)	Person Fixed Effect (θ)	Wage Residual (ε)
1990	0.372	0.294	0.262	0.167	0.149	0.184	0.172	0.077
1991	0.373	0.295	0.265	0.167	0.134	0.186	0.176	0.086
1992	0.378	0.298	0.264	0.171	0.124	0.186	0.174	0.095
1993	0.379	0.302	0.263	0.173	0.117	0.186	0.173	0.065
1994	0.384	0.302	0.260	0.171	0.110	0.183	0.170	0.059
1995	0.386	0.300	0.260	0.169	0.102	0.181	0.168	0.057
1996	0.393	0.299	0.260	0.168	0.097	0.181	0.162	0.055
1997	0.396	0.304	0.259	0.171	0.092	0.183	0.157	0.054
1998	0.393	0.304	0.260	0.171	0.088	0.180	0.153	0.058
% Change:	5.4%	3.5%	-0.6%	2.3%	-41.3%	-2.1%	-11.2%	-25.4%

Notes: The Kremer & Maskin (2001) index is the ratio of the between firm variance to the within firm variance of each variable, and ranges from zero (all firms have the same skill mix of workers) to one (complete segregation by skill). Data are Illinois unemployment insurance (UI) wage and ES-202 records which have been combined with Census administrative databases in order to obtain demographic detail. Education is imputed for all workers using a statistical link to the 1990 Decennial Census (see Section 3). The final three columns are come from a regression of log real annualized wages on year dummies, labor force attachment variables, and experience (up to a quartic, $X\beta$), all fully interacted with sex. Following Abowd *et al.* (1999), the regression simultaneously controls for person (θ) and firm (ψ) heterogeneity. Person and firm effects are estimated directly using a conjugate gradient (CG) algorithm (see Dongarra, 1991).

Table 2: Kremer & Maskin Skill Segregation Index by SIC Division, Single Establishment Firms, Illinois 1990-1998

SIC Division	Year	Wage	White	Male	Age	Education	Predicted Experience Effect ($x\beta$)	Person Fixed Effect (θ)	Wage Residual (ε)
Construction	1990	0.278	0.226	0.108	0.158	0.068	0.162	0.158	0.084
	1994	0.303	0.240	0.106	0.171	0.073	0.181	0.167	0.084
	1998	0.311	0.264	0.110	0.151	0.064	0.163	0.152	0.072
	% Change:	11.8%	17.1%	1.5%	-4.4%	-5.6%	0.5%	-4.1%	-14.2%
	σ_{km} (3 digit):	0.038	0.104	0.040	--	0.016	0.035	0.059	0.014
Manufacturing	1990	0.293	0.258	0.168	0.117	0.042	0.119	0.128	0.073
	1994	0.302	0.276	0.158	0.116	0.041	0.122	0.121	0.057
	1998	0.292	0.278	0.152	0.107	0.036	0.110	0.106	0.057
	% Change:	-0.5%	7.6%	-9.6%	-8.8%	-14.7%	-6.9%	-17.3%	-22.2%
	σ_{km} (3 digit):	0.110	0.121	0.060	--	0.017	0.067	0.049	0.035
TCPU	1990	0.402	0.312	0.208	0.181	0.067	0.212	0.223	0.126
	1994	0.341	0.314	0.201	0.165	0.058	0.172	0.214	0.065
	1998	0.327	0.300	0.217	0.166	0.047	0.170	0.180	0.055
	% Change:	-18.7%	-3.8%	4.3%	-7.9%	-29.8%	-19.9%	-19.0%	-56.6%
	σ_{km} (3 digit):	0.120	0.147	0.080	--	0.024	0.064	0.072	0.027
Wholesale Trade	1990	0.326	0.265	0.149	0.142	0.080	0.145	0.171	0.084
	1994	0.324	0.269	0.156	0.144	0.079	0.144	0.175	0.069
	1998	0.341	0.275	0.164	0.141	0.068	0.138	0.160	0.072
	% Change:	4.4%	3.7%	10.1%	-0.6%	-15.2%	-4.9%	-6.9%	-14.7%
	σ_{km} (3 digit):	0.063	0.058	0.036	--	0.012	0.036	0.030	0.011
Retail Trade	1990	0.349	0.328	0.202	0.201	0.067	0.203	0.145	0.060
	1994	0.374	0.342	0.196	0.211	0.071	0.221	0.148	0.058
	1998	0.371	0.341	0.193	0.207	0.066	0.218	0.137	0.059
	% Change:	6.4%	4.3%	-4.3%	2.9%	-0.8%	7.2%	-5.8%	-1.6%
	σ_{km} (3 digit):	0.086	0.127	0.021	--	0.024	0.075	0.050	0.024
FIRE	1990	0.296	0.204	0.137	0.109	0.074	0.111	0.167	0.090
	1994	0.285	0.205	0.148	0.129	0.071	0.115	0.187	0.065
	1998	0.323	0.229	0.159	0.135	0.067	0.119	0.184	0.065
	% Change:	8.9%	12.3%	16.2%	24.0%	-9.0%	7.6%	10.1%	-28.0%
	σ_{km} (3 digit):	0.104	0.110	0.059	--	0.029	0.057	0.085	0.027
Services	1990	0.334	0.317	0.213	0.166	0.070	0.159	0.164	0.070
	1994	0.360	0.315	0.218	0.169	0.078	0.153	0.164	0.050
	1998	0.380	0.313	0.219	0.175	0.069	0.154	0.150	0.048
	% Change:	13.7%	-1.3%	3.0%	5.1%	-1.6%	-2.9%	-8.3%	-31.3%
	σ_{km} (3 digit):	0.109	0.126	0.064	--	0.009	0.074	0.065	0.036

Notes: The Kremer & Maskin (2001) index is the ratio of the between firm variance to the within firm variance for each variable in each SIC Division, and ranges from 0 (all firms have the same skill mix of workers) to one (complete segregation by skill). Data are Illinois unemployment insurance (UI) wage and ES-202 records which have been linked to Census administrative databases in order to obtain demographic detail. Education is imputed for all workers using a statistical link to the 1990 Decennial Census (see Section 3). The final three columns are based upon a regression of log real annualized wages on year dummies, labor force attachment variables, and experience (up to a quartic, $x\beta$), all fully interacted with sex. Following Abowd *et al.* (1999), the regression simultaneously controls for person (θ) and firm (ψ) heterogeneity. Person and firm effects are estimated directly using a conjugate gradient (CG) algorithm (see Dongarra, 1991). σ_{km} (3 digit) refers to the 1998 standard deviation of the Kremer & Maskin segregation index for 3 digit industries within each SIC division.

Figure 1: Skill Segregation & Worker Heterogeneity, Illinois 1998 (3 Digit SIC)

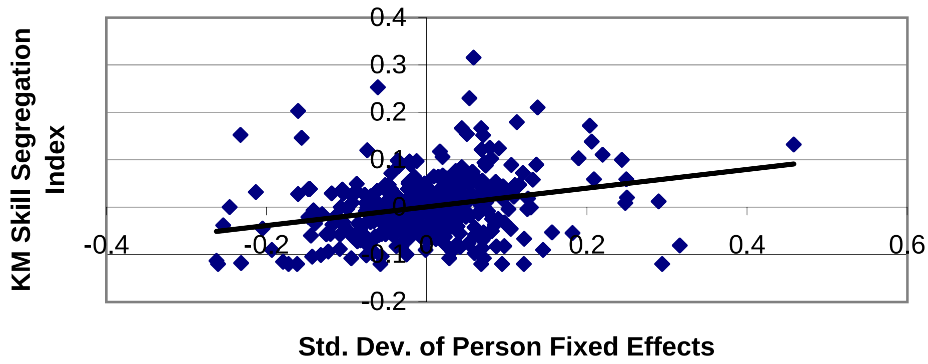


Figure 2: Skill Segregation & Firm Heterogeneity, Illinois 1998 (3 Digit SIC)

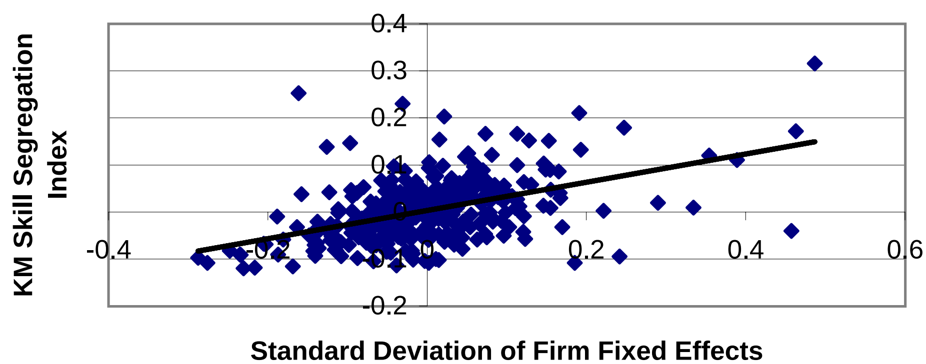


Figure 3: The Relationship Between Person & Firm Heterogeneity, Illinois 1998 (3 Digit SIC)

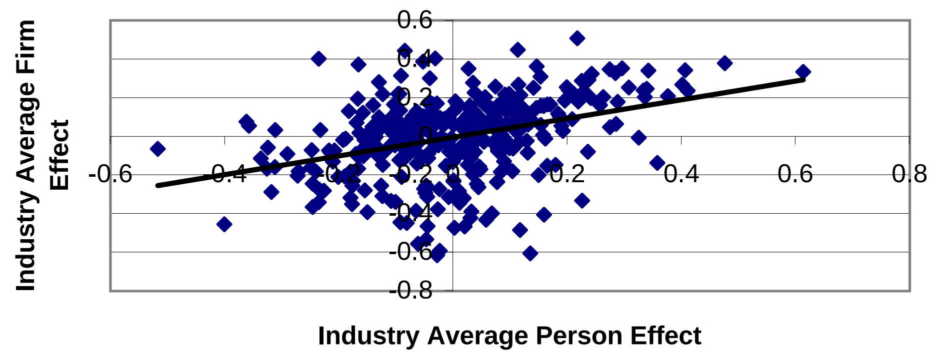


Table 3: Results of Applying the Grouping Algorithm, Illinois UI records 1990-1998

	Largest Group	Second Largest Group	Average of all Others	Total of All Groups	AKM Identified Effects
Observations	41,211,269	136	12.4	41,226,758	--
Persons	9,055,134	64	64	9,063,502	9,063,502
Firms	189,855	2	2	191,129	189,879

Table 4: Convergence Simulation, Time Invariant Firm Effects Model

Iteration	Mean Person Effect Bias	Mean Firm Effect Bias	Co-Worker Parameter
0	0.0042233	0.0173235	--
1	0.000110081	0.000346187	0.0987214
2	0.000011066	2.00E-06	0.100011
3	1.09E-06	4.74E-08	0.0999998
4	1.09E-07	1.23E-09	0.1
5	1.09E-08	3.41E-11	0.1

Notes: N=10,000, J=500, λ=0.10, T=9. θ and ψ are drawn from normal distributions with θ~N(0, 0.36) and ψ~N(0, 0.12). After T=1, workers switch employers with probability 0.25. Matching is non-random. *Cov* (θ,ψ) = 0.4 is enforced, meaning high (low) θ workers are somewhat more likely to match with high (low) ψ firms. Wages are defined as *log* $(w_{it})=\theta_I+\psi_j+\theta_{ij\tau}\lambda_2$, the the sum of person, firm, and a parameter, λ_2, multiplied by firm average person effects (less individual *i*'s contribution).

Table 5: Sample Construction & Mean Values, Illinois 1990-1998

	(1)	(2)	(3)
	Base Sample	Full Time Sample	Analysis Sample
	all obs	full time workers in (1)	(2) plus: firmsize, industry restictions
N	57,101,720	46,562,383	41,226,758
Persons	11,207,030	9,831,217	9,063,502
Firms	462,577	450,006	191,129
Earnings & Demographics:			
Annualized Wage ($1998)	33,445	38,604	36,661
Raw Earnings ($1998)	25,107	29,471	29,263
Education	12.78	12.92	12.91
Male	52.3%	55.5%	55.0%
Age	37.29	38.10	37.88
White	74.0%	74.8%	74.4%
Experience	19.09	19.72	19.52
Industry Affiliation:			
Agriculture	1.1%	1.0%	0.0%
Mining	0.3%	0.3%	0.3%
Construction	4.2%	4.7%	5.1%
Manufacturing	17.7%	20.2%	22.1%
TCU	6.3%	6.8%	7.2%
Wholesale Trade	9.6%	8.1%	8.3%
Retail Trade	13.6%	14.5%	15.1%
FIRE	9.2%	7.8%	7.8%
Services	34.1%	32.6%	34.0%
Public Administration	4.7%	4.9%	0.0%
Labor Force Attachment:			
Fulltime	81.5%	100.0%	100.0%
Discontinuously Employed	8.3%	5.3%	4.7%
0 Full Quarters Worked	21.1%	15.8%	15.0%
1 Full Quarter Worked	12.8%	12.0%	12.0%
2 Full Quarters Worked	11.9%	11.9%	12.1%
3 Full Quarters Worked	9.6%	10.1%	10.4%
4 Full Quarters Worked	44.7%	50.1%	50.6%

Notes: Earnings and labor force attachment data are from unemployment insurance quarterly wage records for the State of Illinois. Demographic characteristics and industry affiliation were added through use of other Census Bureau and LEHD data bases. Raw earnings and annualized wages are for each individual's dominant employer (see text for definitions). A tiny number of observations (104,910) in the base sample possessed invalid industry codes and were excluded from the analysis sample. The analysis sample also excludes workers in firms with less than five employees and all workers employed in agriculture or the public sector. Observations with extreme annual earnings (< $1,000 or > $1,000,000) have also been deleted.

Table 6: Current Population Survey, Mean Values, Illinois 1990-1998

	(1)	(2)	(3)
	Base Sample	Full Time Sample	Analysis Sample
	all obs	full time workers in (1)	(2) plus: industry restictions
N	27,435	21,529	20,219
Weighted N	54,554,989	42,609,928	39,931,617
Earnings & Demographics:			
Annualized Wage ($1998)	27,435	34,659	34,735
Annual Earnings ($1998)	28,265	33,945	34,008
Education	13.20	13.35	13.34
Male	52.4%	57.8%	57.4%
Age	38.09	38.91	38.86
White	84.6%	84.3%	84.5%
Potential Experience	18.89	19.57	19.51
Industry Affiliation:			
Agriculture	1.3%	1.3%	0.0%
Mining	0.3%	0.4%	0.4%
Construction	5.2%	5.9%	6.3%
Manufacturing	18.6%	22.5%	24.0%
TCU	7.5%	8.6%	9.2%
Wholesale Trade	3.8%	4.3%	4.5%
Retail Trade	17.9%	12.7%	13.5%
FIRE	7.8%	8.7%	9.3%
Services	33.3%	30.7%	32.6%
Public Administration	4.2%	4.7%	0.0%
Labor Force Attachment:			
Fulltime	78.1%	100.0%	100.0%
Weeks Worked	45.04	47.71	47.73
Hours Per Week	38.26	43.24	43.27

Notes: All data are from the Census internal March Current Population Survey (CPS), subset to include respondents residing in the state of Illinois between 1990 and 1998. CPS sample weights are utilized for the above calculations. While a non-trivial fraction of these respondents likely work outside of Illinois, such information is not contained within the CPS. Annual earnings are the sum of earnings for all jobs held during the year, as the CPS does not permit designation of a "dominant employer." The annualized wages is computed by dividing annual earnings by weeks worked, and then multiplying by 50. I use Jaeger's (1997) "assigned" method to linearize the categorical education variables contained in the 1992 CPS.

Figure 4A: Male Wage Trends, Analysis Samples: CPS vs UI

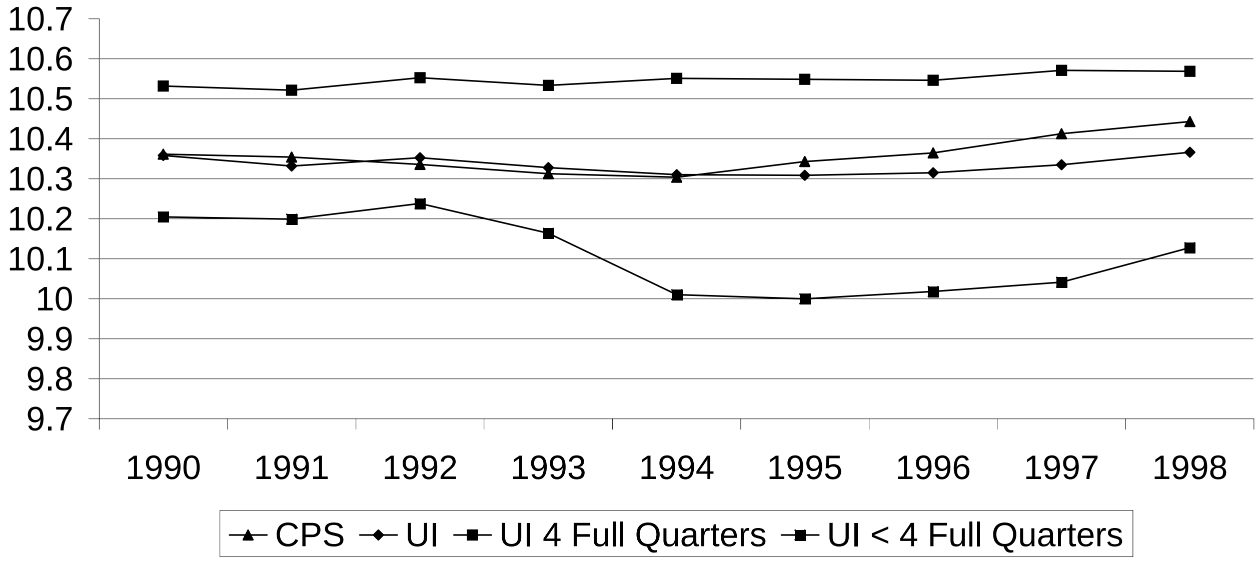


Figure 4B: Female Wage Trends, Analysis Samples: CPS vs. UI

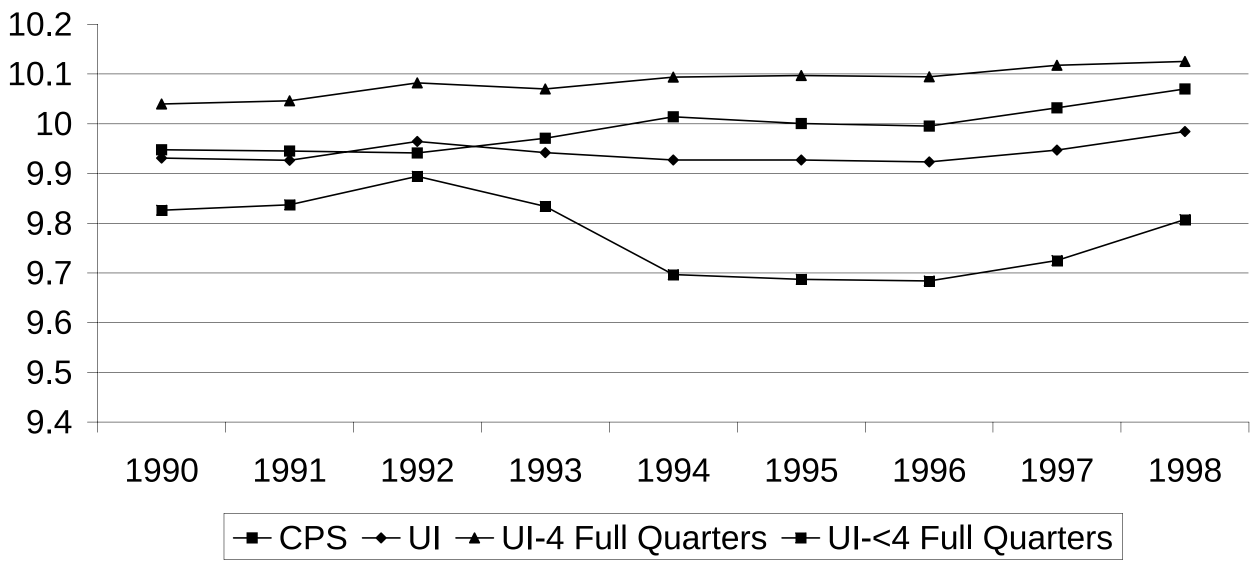


Table 7: Least Squares Estimates of the Effect of Labor Force Experience, Year, and Labor Force Attachment Status on the Log of Real Annualized Wages, Illinois 1990-1998

Variable	*No Person Effects, No Firm Effects* Parameter Estimate	t-statistic	*Within Persons, No Firm Effects* Parameter Estimate	t-statistic	*Within Firms, No Person* Parameter Estimate	t-statistic	*Person, Firm, & Co-Worker Effects* Parameter Estimate	t-statistic
Males:								
Total Labor Force Experience	0.1468	933.2	0.2240	689.0	0.0973	729.1	0.1616	2376.0
(Labor Force Experience)^2/100	-0.5787	-501.2	-0.9004	-536.4	-0.3447	-353.8	-0.6180	-1239.9
(Labor Force Experience)^3/1000	0.1012	321.8	0.1778	370.3	0.0544	205.7	0.1187	874.0
(Labor Force Experience)^4/10,000	-0.0071	-251.6	-0.0137	-300.6	-0.0036	-151.5	-0.0092	-758.0
4 Full Quarters Worked x Year 1991	0.0294	30.3	-0.0518	-87.2	0.0309	38.1	-0.0405	-96.8
4 Full Quarters Worked x Year 1992	0.0470	46.4	-0.0655	-92.5	0.0388	45.8	-0.0454	-104.1
4 Full Quarters Worked x Year 1993	0.0254	26.8	-0.0970	-118.4	0.0311	39.1	-0.0676	-165.1
4 Full Quarters Worked x Year 1994	0.0383	43.3	-0.1051	-109.2	0.0341	45.9	-0.0694	-181.6
4 Full Quarters Worked x Year 1995	0.0342	38.8	-0.1197	-104.5	0.0325	44.0	-0.0777	-204.5
4 Full Quarters Worked x Year 1996	0.0280	31.9	-0.1351	-101.1	0.0277	37.5	-0.0868	-228.9
4 Full Quarters Worked x Year 1997	0.0478	54.5	-0.1293	-84.3	0.0427	57.7	-0.0753	-198.7
4 Full Quarters Worked x Year 1998	0.0490	55.6	-0.1264	-73.0	0.0423	56.6	-0.0689	-180.8
< 4 Full Quarters Worked x Year 1991	-0.0266	-29.4	-0.0660	-117.7	-0.0140	-18.2	-0.0476	-121.7
< 4 Full Quarters Worked x Year 1992	-0.0088	-9.8	-0.0763	-121.7	0.0187	24.5	-0.0446	-115.7
< 4 Full Quarters Worked x Year 1993	-0.0578	-63.0	-0.1146	-153.0	-0.0216	-27.5	-0.0728	-183.8
< 4 Full Quarters Worked x Year 1994	-0.1641	-170.6	-0.1536	-169.7	-0.0980	-118.4	-0.1088	-262.1
< 4 Full Quarters Worked x Year 1995	-0.1796	-186.5	-0.1808	-171.7	-0.1181	-142.0	-0.1331	-320.0
< 4 Full Quarters Worked x Year 1996	-0.1684	-175.2	-0.1876	-155.2	-0.1127	-135.2	-0.1332	-320.9
< 4 Full Quarters Worked x Year 1997	-0.1442	-151.4	-0.1724	-125.9	-0.0948	-114.1	-0.1188	-289.0
< 4 Full Quarters Worked x Year 1998	-0.0799	-84.6	-0.1431	-93.1	-0.0518	-62.3	-0.0998	-244.8
Discontinuous Employment	-0.0362	-42.9	0.0645	101.5	0.0177	24.9	0.0750	205.9
0 Full Quarters Worked	-0.2370	-240.9	0.1499	221.8	-0.1310	-155.6	0.1571	369.5
1 Full Quarter Worked	-0.1863	-191.4	-0.0070	-10.9	-0.1579	-190.0	-0.0124	-29.4
2 Full Quarters Worked	-0.0848	-86.8	0.0015	2.4	-0.0807	-96.9	-0.0059	-14.1
3 Full Quarters Worked	-0.0071	-7.0	-0.0056	-8.6	-0.0269	-31.5	-0.0110	-25.3

Table 7 (Continued): Least Squares Estimates of the Effect of Labor Force Experience, Year, and Labor Force Attachment Status on the Log of Real Annualized Wages

	No Person Effects, No Firm Effects		*Within Persons No Firm Effects*		*Within Firms No Person*		*Person, Firm, & Co-Worker Effects*	
Variable	Parameter Estimate	t-statistic	Parameter Estimate	t-statistic	Parameter Estimate	t-statistic	Parameter Estimate	t-statistic
Females:								
Total Labor Force Experience	0.1187	773.1	0.1936	546.9	0.0650	499.1	0.1339	2014.4
(Labor Force Experience)^2/100	-0.5181	-481.5	-0.7893	-472.6	-0.2354	-259.4	-0.5287	-1137.3
(Labor Force Experience)^3/1000	0.0887	321.1	0.1651	354.6	0.0329	141.8	0.1100	922.1
(Labor Force Experience)^4/10,000	-0.0054	-235.5	-0.0128	-299.9	-0.0016	-84.6	-0.0088	-880.2
4 Full Quarters Worked x Year 1991	-0.0696	-66.3	-0.0291	-44.1	-0.0413	-47.2	-0.0154	-34.0
4 Full Quarters Worked x Year 1992	-0.0418	-38.0	-0.0399	-50.1	-0.0190	-20.6	-0.0150	-31.6
4 Full Quarters Worked x Year 1993	-0.0582	-56.7	-0.0717	-77.1	-0.0251	-29.2	-0.0359	-81.0
4 Full Quarters Worked x Year 1994	-0.0386	-40.4	-0.0857	-77.9	-0.0162	-20.3	-0.0413	-100.2
4 Full Quarters Worked x Year 1995	-0.0367	-38.7	-0.0997	-75.9	-0.0103	-13.0	-0.0466	-113.9
4 Full Quarters Worked x Year 1996	-0.0404	-42.9	-0.1143	-74.3	-0.0110	-13.9	-0.0523	-128.5
4 Full Quarters Worked x Year 1997	-0.0192	-20.4	-0.1101	-62.3	0.0071	8.9	-0.0405	-99.5
4 Full Quarters Worked x Year 1998	-0.0092	-9.7	-0.1031	-51.6	0.0180	22.6	-0.0280	-68.7
< 4 Full Quarters Worked x Year 1991	-0.0067	-6.5	-0.0363	-55.9	0.0034	3.9	-0.0208	-46.9
< 4 Full Quarters Worked x Year 1992	0.0302	30.0	-0.0331	-45.5	0.0456	53.3	-0.0051	-11.7
< 4 Full Quarters Worked x Year 1993	-0.0116	-11.1	-0.0756	-86.5	0.0138	15.6	-0.0360	-80.2
< 4 Full Quarters Worked x Year 1994	-0.1140	-103.5	-0.1215	-114.0	-0.0505	-53.9	-0.0742	-156.1
< 4 Full Quarters Worked x Year 1995	-0.1256	-114.3	-0.1354	-109.0	-0.0625	-66.6	-0.0833	-175.6
< 4 Full Quarters Worked x Year 1996	-0.1308	-120.2	-0.1480	-103.9	-0.0662	-71.1	-0.0880	-187.4
< 4 Full Quarters Worked x Year 1997	-0.0924	-86.4	-0.1225	-75.8	-0.0395	-42.8	-0.0649	-140.7
< 4 Full Quarters Worked x Year 1998	-0.0231	-21.7	-0.0791	-43.5	0.0084	9.1	-0.0313	-68.2
Discontinuous Employment	0.2078	203.8	0.1683	210.5	0.2153	252.2	0.1667	378.7
0 Full Quarters Worked	-0.2664	-243.7	0.1756	229.2	-0.0995	-107.1	0.1985	420.1
1 Full Quarter Worked	-0.2703	-250.8	-0.0126	-17.4	-0.1881	-205.9	-0.0086	-18.5
2 Full Quarters Worked	-0.1622	-150.6	-0.0107	-14.9	-0.1227	-134.4	-0.0106	-22.8
3 Full Quarters Worked	-0.1061	-95.6	-0.0183	-25.0	-0.0936	-99.7	-0.0169	-35.3
Pooled:								
Sample Size	41,226,758		41,226,758		41,226,758		41,226,758	
Coefficient Degrees of Freedom (β)	50		50		50		52	
Individual Degrees of Freedom (θ)			9,063,502				9,063,502	
Firm Degrees of Freedom (ψ)					191,129		191,129	
Error Degrees of Freedom (ε)	41,226,708		32,163,206		41,035,579		31,972,075	
R^2	0.22		0.83		0.47		0.86	

Table 8: Time Invariant Firm Effects Model, Iterative Changes in Person & Firm Effects, Illinois 1990-1998

		Person Effects: (θ)			*Firm Effects:* (ψ)		*Co-Worker Effects:*	
Iteration	Person Obs	mean abs. difference	std_dev abs difference	Firm Obs	mean abs. difference	std_dev abs difference	Firm Avg. Experience Effects (λ_1)	Firm Avg. Person Effect (λ_2)
preliminary	9,063,502	--	--	191,129	--	--		
1		0.0056	0.0074		0.0301	0.0272	-0.00128	0.09632
2		0.0002	0.0002		0.0007	0.0007	-0.00131	0.09823
3		6.87E-05	4.88E-05		1.25E-05	2.86E-05	-0.00131	0.09821
4		1.13E-04	8.32E-05		1.94E-05	3.74E-05	-0.00131	0.09822
5		7.19E-05	5.23E-05		9.40E-06	2.53E-05	-0.00131	0.09822

Table 9: Simple Correlations Among Wage Components, Time Invariant Firm Effects Model, Illinois 1990-1998

	y	$x_2\beta_2$	$\overline{\theta}_{ijt}\lambda_2$	$\overline{X}_{ijt}\lambda_1$	θ	ψ	ε
y, log real annualized wage	1.000	0.359	0.213	-0.222	0.587	0.520	0.383
$x_2\beta_2$, Predicted Effect of Experience Variables	0.359	1.000	-0.122	-0.346	-0.348	0.199	0.000
$\overline{\theta}_{ijt}\lambda_2$, Co-Worker Effect (Firm Average Person Effect)	0.213	-0.122	1.000	0.392	0.335	-0.008	0.000
$\overline{X}_{ijt}\lambda_1$, Co-Worker Effect (Firm Average Experience)	-0.222	-0.346	0.392	1.000	0.098	-0.312	0.000
θ, Individual Effect	0.587	-0.348	0.335	0.098	1.000	0.029	0.000
ψ, Firm Effect	0.520	0.199	-0.008	-0.312	0.029	1.000	0.000
ε, Residual Wage Component	0.383	0.000	0.000	0.000	0.000	0.000	1.000

Notes: Here, $x\beta$ in the text is decomposed as $x\beta$ = *time* + $x_2\beta_2$, where *time* captures all year dummies and labor foce attachment controls. Hence, $x_2\beta_2$ properly captures the predicted effect of experience (interacted with sex) on the log of real annualized wages.

Table 10: Co-Worker Effects in Selected 3 Digit Industries, Illinois 1998

Industry	Average Person Effect	Average Experience	Average Firm Effect	Firm Avg. Person Effect	Firm Avg. Experience Effect	Overall Co-Worker Effect
Top Five:						
Foreign Banking & Branches	0.74	-3.51	0.287	0.073	0.004	0.077
Holding Offices	0.55	2.36	0.164	0.054	-0.003	0.052
Advertising	0.50	-4.08	0.182	0.049	0.005	0.054
Security Brokers	0.49	-1.46	0.183	0.048	0.002	0.049
Surety Insurance	0.42	-1.62	0.231	0.041	0.002	0.043
Middle Five:						
Misc. Health & Allied Services	0.01	0.11	0.039	0.001	0.000	0.001
General Building Contractors	0.01	1.70	0.227	0.001	-0.002	-0.001
Concrete Products	0.01	1.45	0.077	0.001	-0.002	0.000
Metal Working Machinery& Equip.	0.01	3.09	0.141	0.001	-0.004	-0.002
Trusts	0.01	0.12	-0.069	0.001	0.000	0.001
Lowest Five:						
Fabric Mills	-0.35	7.27	0.302	-0.034	-0.009	-0.043
Womens' Outerwear	-0.35	9.12	-0.355	-0.035	-0.011	-0.046
Intercity & Rural Bus Transport	-0.36	5.40	0.161	-0.035	-0.007	-0.042
Private Households	-0.36	3.10	-0.178	-0.036	-0.004	-0.039
Camps & RV Parks	-0.37	-9.34	-0.387	-0.037	0.011	-0.025

Table 10: Summary of Implied Co-Worker Effects After 5 Iterations, Illinois 1990-1998

Model	Variable	Standard Deviation	Parameter Estimate	t-statistic	Implied 1 Std.dev. Effect
Time Invariant Firm Effects	firm avg. person effect	0.264	0.098	481.1	0.026
	firm avg. experience	5.015	-0.001	-115.8	-0.007
Limited Time Varying Firm Effects	firm avg. person effect	0.278	0.087	433.2	0.024
(limited)	firm avg. experience	5.015	-0.001	-105.4	-0.006
Time Varying Firm Effects	firm avg. person effect	0.262	0.056	283.2	0.015
	firm avg. experience	5.015	0.009	795.5	0.044

Table 12: Industry Specific Co-Worker Parameters & Implied Effects, Time Invariant Firm Effects Model, Illinois 1990-1998

Level of Aggregation	Firm Average Experience Parameter	Firm Average Experience t-statistic	Firm Average Person Effect Parameter	Firm Average Person Effect t-statistic	1 Std Dev. Experience Effect	1 Std. Dev. Firm Avg. Person Effect	Total Co-Worker Effect
All Industries:	-0.001	-115.8	0.098	481.1	-0.005	0.026	0.021
Standard Deviation (2-Digit SIC):	0.003	--	0.078	--	0.013	0.020	0.023
2-digit SIC:							
15 General building contractors	-0.003	-123.4	0.137	73.9	-0.016	0.034	0.018
16 Heavy construction contractors	-0.004	-118.2	0.260	87.9	-0.018	0.065	0.048
17 Special trade contractors	-0.003	-153.2	0.158	141.0	-0.014	0.040	0.026
20 Food and kindred products	-0.004	-187.9	0.018	11.4	-0.020	0.005	-0.015
22 Textile mill products	-0.005	-41.5	0.199	22.3	-0.025	0.050	0.025
23 Apparel and other textile products	-0.006	-88.5	0.047	10.8	-0.030	0.012	-0.018
24 Lumber and wood products	-0.003	-63.3	0.099	26.1	-0.016	0.025	0.009
25 Furniture and fixtures	-0.004	-80.8	0.122	27.0	-0.020	0.031	0.011
26 Paper and allied products	-0.005	-178.7	0.090	24.4	-0.027	0.023	-0.004
27 Printing and publishing	-0.003	-153.2	0.119	74.3	-0.015	0.030	0.015
28 Chemicals and allied products	-0.004	-162.3	0.164	78.5	-0.020	0.041	0.021
29 Petroleum and coal products	-0.005	-83.3	0.157	18.5	-0.027	0.039	0.012
30 Rubber and miscellaneous plastics products	-0.003	-122.2	0.157	63.9	-0.016	0.039	0.023
31 Leather and leather products	-0.009	-61.0	0.002	0.3	-0.045	0.001	-0.044
32 Stone, clay, glass, and concrete products	-0.005	-151.8	0.082	24.4	-0.026	0.021	-0.006
33 Primary metal industries	-0.004	-134.7	0.028	8.4	-0.019	0.007	-0.012
34 Fabricated metal products	-0.004	-186.1	0.103	52.6	-0.018	0.026	0.008
35 Industrial machinery and equipment	-0.004	-269.2	0.051	33.4	-0.021	0.013	-0.009
36 Electrical and electronic equipment	-0.003	-180.8	0.117	82.4	-0.018	0.029	0.012
37 Transportation equipment	-0.003	-123.6	0.077	28.2	-0.017	0.019	0.003
38 Instruments and related products	-0.003	-118.0	0.172	56.6	-0.016	0.043	0.027
39 Miscellaneous manufacturing industries	-0.005	-119.3	0.075	23.0	-0.023	0.019	-0.005
40 Railroads	-0.005	-8.1	0.093	2.5	-0.027	0.023	-0.003
41 Local and interurban passenger transit	0.002	56.3	0.193	60.6	0.011	0.048	0.060
42 Motor freight transportation and warehousing	-0.002	-83.5	0.179	118.9	-0.009	0.045	0.036
44 Water transportation	-0.003	-36.4	0.040	4.9	-0.016	0.010	-0.006
45 Transportation by air	-0.001	-35.2	0.355	120.8	-0.007	0.089	0.082
46 Pipelines, except natural gas	-0.004	-24.4	0.159	11.0	-0.019	0.040	0.021
47 Transportation services	-0.003	-84.7	0.072	23.3	-0.016	0.018	0.002
48 Communications	-0.003	-140.5	0.138	73.8	-0.016	0.035	0.018

Table 12 (Continued): Industry Specific Co-Worker Parameters & Implied Effects, Time Invariant Firm Effects Model, Illinois 1990-1998

Level of Aggregation	Firm Average Experience Parameter	Firm Average Experience t-statistic	Firm Average Person Effect Parameter	Firm Average Person Effect t-statistic	1 Std Dev. Experience Effect	1 Std. Dev. Firm Avg. Person Effect	Total Co-Worker Effect
49 Electric, gas, and sanitary services	-0.002	-91.8	0.105	31.3	-0.012	0.026	0.014
50 Wholesale trade--durable goods	-0.002	-150.2	0.116	129.3	-0.012	0.029	0.017
51 Wholesale trade--nondurable goods	-0.003	-158.8	0.115	99.8	-0.015	0.029	0.014
52 Building materials, hardware, garden supply, + mo	-0.002	-45.9	0.092	30.1	-0.008	0.023	0.015
53 General merchandise stores	-0.001	-30.6	0.275	107.8	-0.004	0.069	0.065
54 Food stores	-0.005	-188.6	0.105	54.1	-0.023	0.026	0.003
55 Automotive dealers and gasoline service stations	-0.002	-76.2	0.088	51.8	-0.009	0.022	0.013
56 Apparel and accessory stores	-0.003	-79.0	0.007	2.5	-0.015	0.002	-0.014
57 Furniture, home furnishings and equipment stores	-0.002	-56.7	0.065	24.3	-0.010	0.016	0.006
58 Eating and drinking places	-0.001	-35.0	0.141	120.3	-0.004	0.035	0.031
59 Miscellaneous retail	-0.002	-86.7	0.054	34.3	-0.011	0.014	0.003
60 Depository institutions	0.003	117.3	0.225	133.2	0.013	0.056	0.069
61 Nondepository credit institutions	0.002	44.0	0.084	28.1	0.012	0.021	0.033
62 Security, commodity brokers, and services	0.009	144.2	0.005	2.4	0.044	0.001	0.045
63 Insurance carriers	0.000	14.5	0.170	85.6	0.002	0.043	0.044
64 Insurance agents, brokers, and service	0.000	8.3	0.060	25.7	0.001	0.015	0.017
65 Real estate	-0.001	-37.9	0.096	61.4	-0.005	0.024	0.019
67 Holding and other investment offices	0.001	14.5	0.023	7.1	0.006	0.006	0.012
70 Hotels, rooming houses, camps, and other lodging	-0.002	-33.8	0.190	67.0	-0.008	0.048	0.040
72 Personal services	-0.003	-72.2	0.032	15.8	-0.013	0.008	-0.005
73 Business services	-0.001	-73.0	0.264	448.1	-0.007	0.066	0.060
75 Automotive repair, services, and parking	-0.002	-55.7	0.104	47.5	-0.010	0.026	0.016
76 Miscellaneous repair services	-0.002	-48.0	0.131	37.4	-0.012	0.033	0.021
78 Motion pictures	-0.003	-47.9	0.276	72.5	-0.017	0.069	0.052
79 Amusement and recreational services	-0.004	-119.1	0.077	42.8	-0.018	0.019	0.001
80 Health services	-0.004	-262.9	0.097	130.4	-0.020	0.024	0.005
81 Legal services	-0.002	-47.0	0.011	5.4	-0.011	0.003	-0.008
82 Educational services	0.000	-31.4	-0.039	-41.6	-0.002	-0.010	-0.012
83 Social services	-0.001	-26.4	0.185	108.5	-0.004	0.047	0.042
84 Museums, art galleries, botanical + zoological gard	0.001	12.7	-0.070	-6.9	0.006	-0.018	-0.012
86 Membership organizations	-0.001	-48.8	0.085	45.6	-0.007	0.021	0.015
87 Engineering and management services	-0.002	-76.2	0.098	99.7	-0.009	0.025	0.016
88 Private households	-0.001	-3.4	0.142	16.1	-0.004	0.036	0.032
89 Miscellaneous services	0.000	-0.6	0.136	25.8	0.000	0.034	0.034

Table 13: Co-Worker Effects & Inter-Industry Wage Differentials, Illinois 1990-1998

SIC Division	Raw Industry Effect	Person Effect (θ)	Firm Effect (ψ)	*Industry Average:* Co-Worker Effect (Experience) $(\overline{X}_{ijt}\hat{\lambda}_1)$	Co-Worker Effect (Persons) $(\overline{\theta}_{ijt}\hat{\lambda}_2)$	Co-Worker Effect (Overall)
Construction	0.200	0.047	0.159	-0.016	0.011	-0.005
Manufacturing	0.099	-0.043	0.182	-0.039	-0.001	-0.040
TCPU	0.182	0.019	0.142	0.008	0.013	0.021
Wholesale Trade	0.129	0.026	0.101	-0.007	0.009	0.002
Retail Trade	-0.340	-0.034	-0.313	0.013	-0.005	0.007
FIRE	0.226	0.101	0.034	0.078	0.013	0.091
Services	-0.068	0.005	-0.076	0.009	-0.006	0.003
Standard Deviation:	0.202	0.049	0.176	0.036	0.009	0.040
Standard Deviation (2-Digit SIC):	0.249	0.104	0.199	0.050	0.018	0.053

Notes: The above averages are industry effects estimated by least squares controlling for labor force experience (through a quartic), year, labor force attachment (full quarter status dummies), education (imputed), and sex (fully-interacted). The raw industry effect is fully decomposed by the industry average person, firm, and co-worker effects.

Figure 5: Actual & Predicted Industry Effects Using Industry Average Wage Components

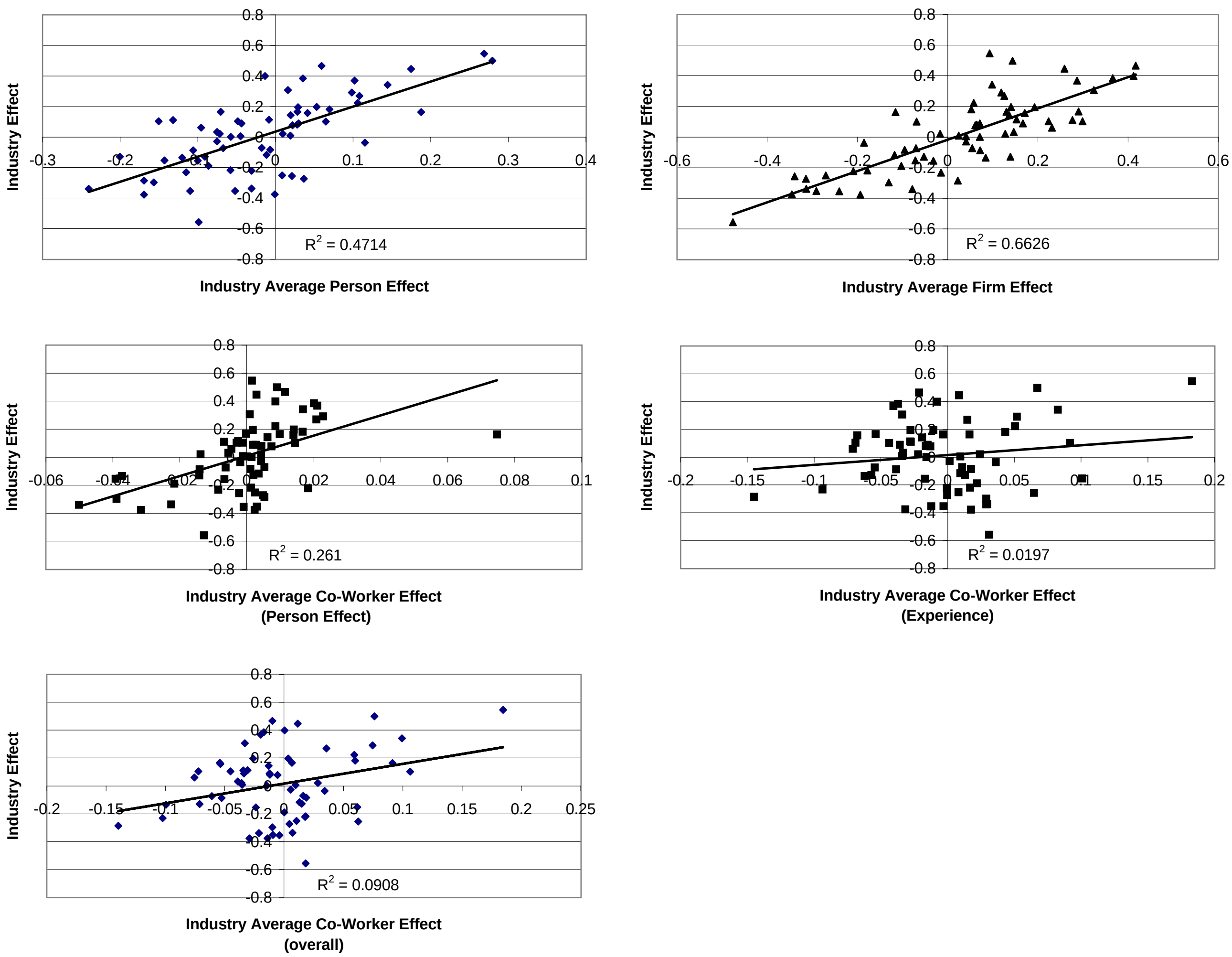


Table 14: The Contribution of Person, Firm, & Co-Worker Effects to the Observed Distribution of Wages in Illinois

		Percentiles of Log Wage Distribution:					
Wage Component(s)	Standard Deviation	90-10	90-75	90-50	50-25	50-10	75-25
A. 1990							
Persons	0.63	1.59	0.41	0.83	0.39	0.76	0.81
Persons & Firm Avg. Person Effect	0.63	1.62	0.42	0.84	0.40	0.78	0.83
Persons & Firm Avg. Experience Effect	0.63	1.59	0.42	0.84	0.39	0.76	0.81
Persons & Co-Workers	0.64	1.63	0.42	0.85	0.40	0.77	0.83
Persons & Firms	0.73	1.95	0.41	0.90	0.53	1.06	1.02
Persons, Firms, & Firm Avg. Person Effect	0.74	1.99	0.41	0.91	0.54	1.08	1.03
Persons, Firms, & Firm Avg. Experience Effect	0.72	1.93	0.40	0.88	0.52	1.05	1.01
Persons, Firms, & Co-Workers	0.73	1.96	0.41	0.89	0.54	1.07	1.02
Firms	0.35	0.86	0.16	0.35	0.26	0.51	0.44
Firms & Firm Avg. Person Effect	0.35	0.87	0.17	0.35	0.27	0.52	0.46
Firms & Firm Avg. Experience Effect	0.33	0.83	0.16	0.34	0.23	0.49	0.42
Firms & Co-Workers	0.33	0.85	0.15	0.34	0.25	0.51	0.44
Firms & Persons	0.73	1.95	0.41	0.90	0.53	1.06	1.02
Firms, Persons, & Firm Avg. Person Effect	0.74	1.99	0.41	0.91	0.54	1.08	1.03
Firms, Persons, & Firm Avg. Experience Effect	0.72	1.93	0.40	0.88	0.52	1.05	1.01
Firms, Persons, & Co-Workers	0.73	1.96	0.41	0.89	0.54	1.07	1.02
B. 1994							
Persons	0.61	1.52	0.39	0.79	0.37	0.73	0.77
Persons & Firm Avg. Person Effect	0.62	1.56	0.40	0.81	0.38	0.75	0.79
Persons & Firm Avg. Experience Effect	0.61	1.53	0.40	0.80	0.37	0.73	0.77
Persons & Co-Workers	0.62	1.56	0.40	0.81	0.38	0.75	0.79
Persons & Firms	0.72	1.90	0.39	0.86	0.52	1.04	0.99
Persons, Firms, & Firm Avg. Person Effect	0.73	1.94	0.40	0.88	0.53	1.07	1.01
Persons, Firms, & Firm Avg. Experience Effect	0.71	1.88	0.39	0.85	0.51	1.03	0.98
Persons, Firms, & Co-Workers	0.72	1.92	0.39	0.87	0.53	1.05	1.00
Firms	0.33	0.82	0.15	0.33	0.24	0.49	0.42
Firms & Firm Avg. Person Effect	0.34	0.85	0.15	0.35	0.26	0.50	0.45
Firms & Firm Avg. Experience Effect	0.32	0.79	0.14	0.32	0.23	0.47	0.41
Firms & Co-Workers	0.33	0.83	0.15	0.34	0.25	0.49	0.44
Firms & Persons	0.72	1.90	0.39	0.86	0.52	1.04	0.99
Firms, Persons, & Firm Avg. Person Effect	0.73	1.94	0.40	0.88	0.53	1.07	1.01
Firms, Persons, & Firm Avg. Experience Effect	0.71	1.88	0.39	0.85	0.51	1.03	0.98
Firms, Persons, & Co-Workers	0.72	1.92	0.39	0.87	0.53	1.05	1.00
C. 1998							
Persons	0.62	1.56	0.38	0.78	0.37	0.78	0.77
Persons & Firm Avg. Person Effect	0.63	1.59	0.39	0.79	0.39	0.80	0.79
Persons & Firm Avg. Experience Effect	0.62	1.55	0.39	0.78	0.37	0.77	0.77
Persons & Co-Workers	0.63	1.59	0.39	0.80	0.38	0.79	0.79
Persons & Firms	0.72	1.94	0.40	0.87	0.53	1.07	1.00
Persons, Firms, & Firm Avg. Person Effect	0.73	1.98	0.40	0.89	0.54	1.09	1.02
Persons, Firms, & Firm Avg. Experience Effect	0.72	1.92	0.39	0.86	0.52	1.05	0.99
Persons, Firms, & Co-Workers	0.73	1.95	0.40	0.88	0.53	1.08	1.01
Firms	0.33	0.81	0.15	0.33	0.24	0.48	0.43
Firms & Firm Avg. Person Effect	0.34	0.85	0.16	0.36	0.25	0.49	0.45
Firms & Firm Avg. Experience Effect	0.32	0.80	0.15	0.33	0.23	0.46	0.41
Firms & Co-Workers	0.33	0.83	0.16	0.35	0.24	0.48	0.44
Firms & Persons	0.72	1.94	0.40	0.87	0.53	1.07	1.00
Firms, Persons, & Firm Avg. Person Effect	0.73	1.98	0.40	0.89	0.54	1.09	1.02
Firms, Persons, & Firm Avg. Experience Effect	0.72	1.92	0.39	0.86	0.52	1.05	0.99
Firms, Persons, & Co-Workers	0.73	1.95	0.40	0.88	0.53	1.08	1.01

Figure 6A: Cumulative Distribution of Selected Wage Components, Person Ordering, Illinois 1990

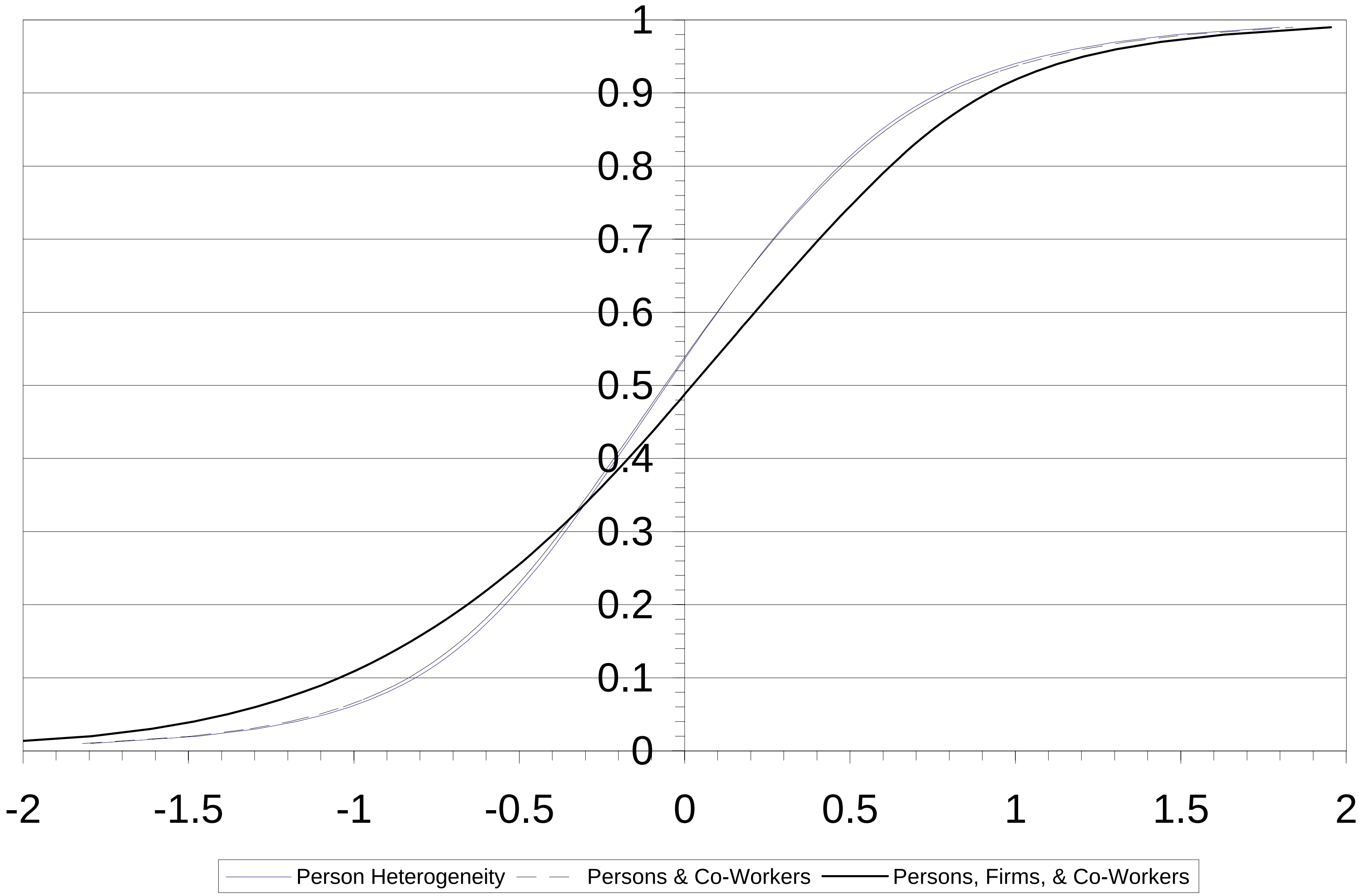
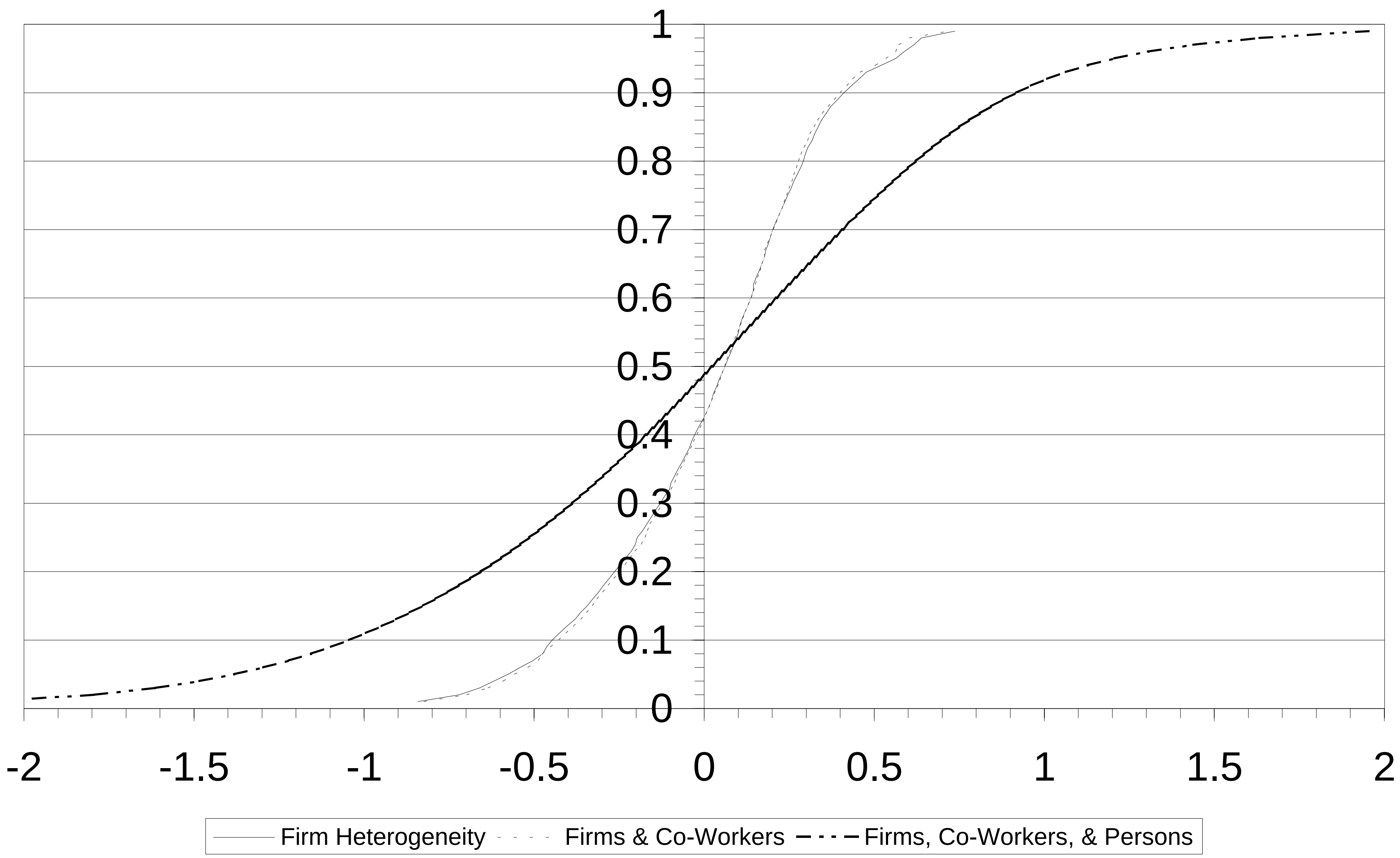


Figure 6B: Cumulative Distribution of Selected Wage Components, Firm Ordering, Illinois 1990



Appendix 1: Least Squares Estimates of the Effect of Labor Force Experience, Year, & Labor Force Attachment Status on the Log of Real Annualized Wages: Alternate Models

	Limited Time Varying Firm Effects, Constant Co-Worker Effect		*Time Varying Firm Effects, Constant Co-Worker Effect*		*Time Invariant Firm Effects, Industry Co-Worker Effects*		*Limited Time Varying Firm Effects, Industry Co-Worker Effects*		*Time Varying Firm Effects Industry Co-Worker Effects*	
Variable	Parameter Estimate	t-statistic	Parameter Estimate	t-statistic	Parameter Estimate	t-statistic	Parameter Estimate	t-statistic	Parameter Estimate	t-statistic
Males:										
Total Labor Force Experience	0.1622	2421.7	0.1537	2567.0	0.1504	2294.9	0.1476	2266.1	0.1547	2426.6
(Labor Force Experience)^2/100	-0.6141	-1244.1	-0.5882	-1294.2	-0.6090	-1253.2	-0.5973	-1237.0	-0.5755	-1218.0
(Labor Force Experience)^3/1000	0.1196	887.1	0.1138	902.0	0.1167	875.9	0.1152	869.7	0.1106	853.2
(Labor Force Experience)^4/10,000	-0.0094	-775.9	-0.0089	-778.8	-0.0091	-757.1	-0.0090	-756.2	-0.0087	-740.6
Year 1991	-0.0994	-342.2	--	--	--	--	--	--	--	--
Year 1992	-0.1002	-345.3	--	--	--	--	--	--	--	--
Year 1993	-0.1309	-446.9	--	--	--	--	--	--	--	--
Year 1994	-0.1532	-525.3	--	--	--	--	--	--	--	--
Year 1995	-0.0075	-25.7	--	--	--	--	--	--	--	--
Year 1996	-0.0161	-55.4	--	--	--	--	--	--	--	--
Year 1997	-0.0064	-22.0	--	--	--	--	--	--	--	--
Year 1998	0.0290	103.8	--	--	--	--	--	--	--	--
4 Full Quarters Worked x Year 1992	--	--	--	--	-0.0120	-29.9	-0.0108	-27.0	-0.0467	-119.8
4 Full Quarters Worked x Year 1993	--	--	--	--	-0.0244	-65.7	-0.0243	-65.8	-0.0845	-234.0
4 Full Quarters Worked x Year 1994	--	--	--	--	-0.0163	-47.8	-0.0176	-52.1	-0.0873	-263.4
4 Full Quarters Worked x Year 1995	--	--	--	--	-0.0145	-43.0	0.1009	300.0	-0.1008	-306.1
4 Full Quarters Worked x Year 1996	--	--	--	--	-0.0135	-40.1	0.1011	301.6	-0.1241	-377.5
4 Full Quarters Worked x Year 1997	--	--	--	--	0.0081	24.1	0.1222	364.8	-0.1259	-383.3
4 Full Quarters Worked x Year 1998	--	--	--	--	0.0243	71.5	0.1377	408.2	-0.1121	-338.8
< 4 Full Quarters Worked x Year 1992	--	--	--	--	-0.0055	-16.8	-0.0046	-14.1	-0.0401	-126.3
< 4 Full Quarters Worked x Year 1993	--	--	--	--	-0.0254	-74.7	-0.0244	-72.2	-0.0611	-184.9
< 4 Full Quarters Worked x Year 1994	--	--	--	--	-0.0525	-145.2	-0.0534	-148.5	-0.0941	-267.5
< 4 Full Quarters Worked x Year 1995	--	--	--	--	-0.0680	-187.5	0.0458	127.1	-0.1248	-354.0
< 4 Full Quarters Worked x Year 1996	--	--	--	--	-0.0592	-163.6	0.0559	155.5	-0.1344	-382.1
< 4 Full Quarters Worked x Year 1997	--	--	--	--	-0.0360	-100.7	0.0795	224.1	-0.1348	-387.6
< 4 Full Quarters Worked x Year 1998	--	--	--	--	-0.0086	-24.2	0.1069	304.5	-0.1013	-294.3
Discontinuous Employment	0.0740	211.7	0.0669	195.9	0.0745	204.5	0.0723	199.6	0.0607	171.4
0 Full Quarters Worked	0.1505	637.6	0.0900	398.6	0.1510	450.5	0.1449	435.2	0.0760	233.2
1 Full Quarter Worked	-0.0549	-242.2	-0.0875	-402.4	-0.0177	-54.1	-0.0223	-68.7	-0.0727	-229.2
2 Full Quarters Worked	-0.0424	-186.5	-0.0589	-270.3	-0.0101	-30.6	-0.0137	-41.8	-0.0507	-158.2
3 Full Quarters Worked	-0.0517	-241.7	-0.0552	-308.4	-0.0148	-43.6	-0.0176	-52.0	-0.0449	-135.7

Females:										
Total Labor Force Experience	0.1335	2043.2	0.1306	2232.3	0.1292	2017.1	0.1262	1982.1	0.1297	2081.2
(Labor Force Experience)^2/100	-0.5269	-1145.2	-0.5057	-1192.0	-0.5250	-1157.7	-0.5108	-1133.6	-0.4851	-1099.9
(Labor Force Experience)^3/1000	0.1099	928.6	0.1050	946.3	0.1092	931.7	0.1063	912.9	0.1005	882.4
(Labor Force Experience)^4/10,000	-0.0088	-885.3	-0.0083	-890.3	-0.0087	-885.7	-0.0085	-869.4	-0.0080	-839.6
Year 1991	-0.0676	-211.1	--	--	--	--	--	--	--	--
Year 1992	-0.0570	-177.8	--	--	--	--	--	--	--	--
Year 1993	-0.0862	-267.0	--	--	--	--	--	--	--	--
Year 1994	-0.1078	-334.6	--	--	--	--	--	--	--	--
Year 1995	0.0387	120.6	--	--	--	--	--	--	--	--
Year 1996	0.0330	103.6	--	--	--	--	--	--	--	--
Year 1997	0.0486	154.0	--	--	--	--	--	--	--	--
Year 1998	0.0900	293.9	--	--	--	--	--	--	--	--
4 Full Quarters Worked x Year 1992	--	--	--	--	-0.0012	-2.6	0.0015	3.5	-0.0402	-94.4
4 Full Quarters Worked x Year 1993	--	--	--	--	-0.0178	-44.0	-0.0159	-39.8	-0.0807	-205.8
4 Full Quarters Worked x Year 1994	--	--	--	--	-0.0187	-50.7	-0.0184	-50.2	-0.0841	-234.0
4 Full Quarters Worked x Year 1995	--	--	--	--	-0.0194	-53.1	0.0904	248.4	-0.1025	-287.9
4 Full Quarters Worked x Year 1996	--	--	--	--	-0.0207	-56.8	0.0892	246.9	-0.1245	-352.0
4 Full Quarters Worked x Year 1997	--	--	--	--	-0.0045	-12.3	0.1053	291.0	-0.1297	-366.1
4 Full Quarters Worked x Year 1998	--	--	--	--	0.0123	33.6	0.1222	336.3	-0.1197	-336.2
< 4 Full Quarters Worked x Year 1992	--	--	--	--	0.0125	34.0	0.0131	35.9	-0.0350	-98.2
< 4 Full Quarters Worked x Year 1993	--	--	--	--	-0.0146	-38.0	-0.0137	-36.0	-0.0557	-149.5
< 4 Full Quarters Worked x Year 1994	--	--	--	--	-0.0486	-117.5	-0.0479	-116.6	-0.0862	-214.5
< 4 Full Quarters Worked x Year 1995	--	--	--	--	-0.0537	-130.2	0.0537	131.0	-0.1080	-269.3
< 4 Full Quarters Worked x Year 1996	--	--	--	--	-0.0542	-133.3	0.0555	137.4	-0.1247	-315.0
< 4 Full Quarters Worked x Year 1997	--	--	--	--	-0.0269	-67.7	0.0848	214.6	-0.1206	-311.9
< 4 Full Quarters Worked x Year 1998	--	--	--	--	0.0103	26.1	0.1223	312.0	-0.0825	-215.0
Discontinuous Employment	0.1630	388.0	0.1450	353.2	0.1666	378.7	0.1630	372.8	0.1389	324.6
0 Full Quarters Worked	0.2029	759.1	0.1327	518.5	0.1942	520.2	0.1871	504.6	0.1083	298.5
1 Full Quarter Worked	-0.0427	-170.2	-0.0766	-317.7	-0.0124	-34.5	-0.0169	-47.1	-0.0669	-191.0
2 Full Quarters Worked	-0.0366	-146.8	-0.0532	-222.4	-0.0139	-38.4	-0.0174	-48.4	-0.0519	-147.5
3 Full Quarters Worked	-0.0470	-201.5	-0.0550	-282.8	-0.0203	-54.2	-0.0234	-62.9	-0.0485	-133.5
Pooled:										
Sample Size	41,226,758		41,226,758		41,226,758		41,226,758		41,226,758	
Coefficient Degrees of Freedom (β)	36		20		184		184		184	
Individual Degrees of Freedom (θ)	9,063,502		9,063,502				9,063,502		9,063,502	
Firm Degrees of Freedom (ψ)	287,030		880,081		191,129		287,030		880,081	
Error Degrees of Freedom (ε)	31,876,190		31,283,155		41,035,445		31,876,042		31,282,991	
R^2	0.86		0.86		0.86		0.86		0.87	

Appendix 2A: Industry Specific Co-Worker Parameters & Implied Effects, Limited Time Varying Firm Effects Model

Level of Aggregation	Firm Average Experience Parameter	Firm Average Experience t-statistic	Firm Average Person Effect Parameter	Firm Average Person Effect t-statistic	1 Std Dev. Experience Effect	1 Std. Dev. Firm Avg. Person Effect	1 Std. Dev. Total Co-Worker Effect
All Industries:	-0.0012	-105.4	0.0874	433.2	-0.0060	0.0231	0.0171
Standard Deviation (2-Digit SIC):	0.0026	--	0.0869	--	0.0129	0.0218	0.0263
2-digit SIC:							
15 General building contractors	-0.0035	-135.1	0.1222	66.47	-0.0176	0.0307	0.0130
16 Heavy construction contractors	-0.0036	-120.2	0.2661	89.89	-0.0179	0.0668	0.0489
17 Special trade contractors	-0.0021	-115.5	0.1346	121.00	-0.0104	0.0338	0.0234
20 Food and kindred products	-0.0036	-174.6	-0.0304	-18.82	-0.0180	-0.0076	-0.0256
22 Textile mill products	-0.0045	-37.5	0.1380	15.37	-0.0225	0.0346	0.0121
23 Apparel and other textile products	-0.0054	-81.6	0.0356	8.20	-0.0270	0.0089	-0.0181
24 Lumber and wood products	-0.0029	-57.6	0.0551	14.47	-0.0148	0.0138	-0.0009
25 Furniture and fixtures	-0.0044	-89.1	0.0885	19.58	-0.0219	0.0222	0.0003
26 Paper and allied products	-0.0041	-136.2	0.0594	16.00	-0.0205	0.0149	-0.0055
27 Printing and publishing	-0.0025	-128.0	0.1100	68.92	-0.0124	0.0276	0.0152
28 Chemicals and allied products	-0.0045	-183.4	0.1586	76.38	-0.0225	0.0398	0.0173
29 Petroleum and coal products	-0.0060	-94.1	0.2308	27.71	-0.0302	0.0579	0.0278
30 Rubber and miscellaneous plastics products	-0.0033	-122.1	0.1575	63.67	-0.0163	0.0395	0.0232
31 Leather and leather products	-0.0098	-66.8	-0.0421	-5.03	-0.0489	-0.0106	-0.0595
32 Stone, clay, glass, and concrete products	-0.0046	-133.1	0.0757	22.41	-0.0230	0.0190	-0.0040
33 Primary metal industries	-0.0043	-148.8	0.0222	6.67	-0.0215	0.0056	-0.0159
34 Fabricated metal products	-0.0036	-188.2	0.0903	46.26	-0.0181	0.0227	0.0045
35 Industrial machinery and equipment	-0.0050	-320.2	0.0565	37.85	-0.0253	0.0142	-0.0111
36 Electrical and electronic equipment	-0.0040	-208.2	0.1274	89.97	-0.0201	0.0320	0.0119
37 Transportation equipment	-0.0041	-152.8	0.0190	6.99	-0.0204	0.0048	-0.0156
38 Instruments and related products	-0.0034	-123.9	0.1614	53.12	-0.0171	0.0405	0.0234
39 Miscellaneous manufacturing industries	-0.0040	-103.4	0.0986	30.41	-0.0201	0.0247	0.0046
40 Railroads	-0.0022	-3.3	0.4886	13.05	-0.0109	0.1226	0.1117
41 Local and interurban passenger transit	0.0026	64.1	0.1904	59.51	0.0131	0.0478	0.0609
42 Motor freight transportation and warehousing	-0.0007	-33.3	0.1853	123.38	-0.0034	0.0465	0.0431
44 Water transportation	-0.0038	-43.9	0.0018	0.22	-0.0188	0.0004	-0.0184
45 Transportation by air	-0.0002	-5.0	0.2114	71.27	-0.0011	0.0531	0.0520
46 Pipelines, except natural gas	-0.0031	-20.2	0.2387	16.69	-0.0156	0.0599	0.0443
47 Transportation services	-0.0021	-54.7	0.0670	22.07	-0.0104	0.0168	0.0064

Appendix 2A (Continued): Industry Specific Co-Worker Parameters & Implied Effects, Limited Time Varying Firm Effects Model

Level of Aggregation	Firm Average Experience Parameter	Firm Average Experience t-statistic	Firm Average Person Effect Parameter	Firm Average Person Effect t-statistic	1 Std Dev. Experience Effect	1 Std. Dev. Firm Avg. Person Effect	Total Co-Worker Effect
48 Communications	-0.0064	-280.1	0.1253	68.85	-0.0320	0.0315	-0.0005
49 Electric, gas, and sanitary services	-0.0015	-54.9	0.0929	28.05	-0.0073	0.0233	0.0160
50 Wholesale trade--durable goods	-0.0027	-171.5	0.1178	133.2	-0.0136	0.0296	0.0160
51 Wholesale trade--nondurable goods	-0.0028	-157.5	0.1030	90.2	-0.0143	0.0259	0.0116
52 Building materials, hardware, garden, & mobile	-0.0008	-24.9	0.0826	27.2	-0.0042	0.0207	0.0166
53 General merchandise stores	-0.0017	-64.8	0.2771	109.2	-0.0084	0.0695	0.0611
54 Food stores	-0.0038	-156.5	0.0767	39.9	-0.0191	0.0193	0.0002
55 Automotive dealers and gasoline stations	-0.0018	-73.5	0.0729	42.9	-0.0090	0.0183	0.0093
56 Apparel and accessory stores	-0.0029	-74.4	0.0397	14.5	-0.0145	0.0100	-0.0045
57 Furniture, home furnishings and equip. stores	-0.0021	-57.0	0.0546	20.5	-0.0103	0.0137	0.0034
58 Eating and drinking places	-0.0006	-23.5	0.1278	110.5	-0.0029	0.0321	0.0291
59 Miscellaneous retail	-0.0026	-106.2	0.0332	21.3	-0.0128	0.0083	-0.0045
60 Depository institutions	0.0015	70.4	0.2122	125.5	0.0076	0.0533	0.0609
61 Nondepository credit institutions	0.0026	48.5	0.0851	29.1	0.0128	0.0214	0.0342
62 Security, commodity brokers, and services	0.0084	138.0	-0.0038	-2.0	0.0422	-0.0010	0.0412
63 Insurance carriers	-0.0001	-5.9	0.1265	64.9	-0.0007	0.0318	0.0310
64 Insurance agents, brokers, and service	0.0003	8.1	0.0497	21.5	0.0000	0.0125	0.0125
65 Real estate	-0.0008	-27.5	0.0917	59.5	0.0015	0.0230	0.0245
67 Holding and other investment offices	0.0019	24.9	0.0425	13.0	-0.0038	0.0107	0.0069
70 Hotels, rooming houses, camps, & other lodging	-0.0020	-42.6	0.1773	62.5	0.0097	0.0445	0.0542
72 Personal services	-0.0016	-42.3	0.0354	17.7	-0.0100	0.0089	-0.0011
73 Business services	-0.0013	-75.4	0.2261	387.2	-0.0078	0.0568	0.0490
75 Automotive repair, services, and parking	-0.0012	-35.0	0.0863	39.5	-0.0068	0.0217	0.0149
76 Miscellaneous repair services	-0.0019	-38.8	0.1260	36.2	-0.0061	0.0316	0.0256
78 Motion pictures	-0.0027	-38.5	0.2161	56.8	-0.0095	0.0542	0.0448
79 Amusement and recreational services	-0.0018	-59.4	0.0911	51.6	-0.0136	0.0229	0.0092
80 Health services	-0.0020	-134.5	0.0895	121.0	-0.0091	0.0225	0.0134
81 Legal services	-0.0011	-23.5	0.0250	12.1	-0.0100	0.0063	-0.0037
82 Educational services	0.0005	37.6	0.0518	55.6	-0.0054	0.0130	0.0076
83 Social services	0.0002	5.7	0.1853	107.3	0.0025	0.0465	0.0490
84 Museums, art galleries, botanical & zoos	-0.0012	-13.6	-0.0304	-3.1	0.0009	-0.0076	-0.0068
86 Membership organizations	-0.0008	-30.4	0.0776	41.8	-0.0060	0.0195	0.0135
87 Engineering and management services	-0.0012	-52.7	0.1026	106.1	-0.0041	0.0258	0.0216
88 Private households	0.0012	6.0	0.1784	20.6	-0.0060	0.0448	0.0388
89 Miscellaneous services	-0.0007	-6.5	0.1255	23.9	0.0063	0.0315	0.0377

Appendix 2B: Industry Specific Co-Worker Parameters & Implied Effects, Time Varying Firm Effects Model

Level of Aggregation	Firm Average Experience Parameter	Firm Average Experience t-statistic	Firm Average Person Effect Parameter	Firm Average Person Effect t-statistic	1 Std Dev. Experience Effect	1 Std. Dev. Firm Avg. Person Effect	1 Std. Dev. Total Co-Worker Effect
All Industries:	0.0087	795.5	0.0556	283.2	0.0437	0.0147	0.0584
Standard Deviation (2-Digit SIC):	0.0281	--	0.4791	--	0.1409	0.1203	0.2388
2-digit SIC:							
15 General building contractors	0.0161	623.8	0.3542	205.4	0.0806	0.0889	0.1695
16 Heavy construction contractors	0.0221	710.3	0.1362	48.7	0.1108	0.0342	0.1450
17 Special trade contractors	0.0197	1116.1	0.2915	275.4	0.0987	0.0732	0.1719
20 Food and kindred products	-0.0087	-411.0	0.1313	83.6	-0.0436	0.0329	-0.0106
22 Textile mill products	0.0013	10.1	0.7527	86.3	0.0064	0.1889	0.1953
23 Apparel and other textile products	0.0023	34.0	0.1272	30.4	0.0117	0.0319	0.0436
24 Lumber and wood products	0.0197	383.1	0.4798	128.4	0.0989	0.1204	0.2194
25 Furniture and fixtures	0.0189	363.9	0.4854	114.1	0.0946	0.1218	0.2165
26 Paper and allied products	0.0198	622.2	0.8423	236.1	0.0992	0.2114	0.3107
27 Printing and publishing	0.0210	1090.4	0.2625	175.4	0.1051	0.0659	0.1710
28 Chemicals and allied products	0.0106	465.9	0.8460	435.4	0.0534	0.2124	0.2658
29 Petroleum and coal products	0.0025	44.3	0.3015	40.6	0.0128	0.0757	0.0884
30 Rubber and miscellaneous plastics products	0.0083	297.5	0.3383	136.7	0.0418	0.0849	0.1267
31 Leather and leather products	-0.0326	-213.3	-0.7501	-87.4	-0.1633	-0.1883	-0.3516
32 Stone, clay, glass, and concrete products	0.0115	308.3	0.2290	70.4	0.0578	0.0575	0.1153
33 Primary metal industries	0.0149	444.8	1.1103	374.2	0.0746	0.2787	0.3533
34 Fabricated metal products	0.0160	767.8	0.6338	340.2	0.0801	0.1591	0.2392
35 Industrial machinery and equipment	0.0201	1189.9	0.4031	294.4	0.1007	0.1012	0.2019
36 Electrical and electronic equipment	0.0074	380.5	0.4045	312.6	0.0372	0.1015	0.1387
37 Transportation equipment	0.0143	495.6	0.2864	111.3	0.0719	0.0719	0.1438
38 Instruments and related products	0.0191	689.7	0.4479	159.9	0.0957	0.1124	0.2081
39 Miscellaneous manufacturing industries	0.0181	446.6	0.6323	195.8	0.0908	0.1587	0.2495
40 Railroads	-0.0492	-71.9	-0.9026	-23.9	-0.2467	-0.2265	-0.4732
41 Local and interurban passenger transit	0.0778	1689.7	1.3076	430.2	0.3901	0.3282	0.7184
42 Motor freight transportation and warehousing	0.0481	2287.9	1.0921	779.8	0.2413	0.2741	0.5154
44 Water transportation	0.0366	431.3	0.5559	71.0	0.1837	0.1395	0.3232
45 Transportation by air	0.0405	973.4	1.6370	548.8	0.2032	0.4109	0.6141
46 Pipelines, except natural gas	-0.1021	-746.6	-0.3028	-22.8	-0.5122	-0.0760	-0.5881
47 Transportation services	0.0586	1571.1	1.3035	473.6	0.2937	0.3272	0.6209
48 Communications	0.0340	1530.3	0.8162	498.7	0.1705	0.2049	0.3753
49 Electric, gas, and sanitary services	0.0255	1050.8	0.5562	185.9	0.1278	0.1396	0.2674

Appendix 2B (Continued): Industry Specific Co-Worker Parameters & Implied Effects, Time Varying Firm Effects Model

Level of Aggregation	Firm Average Experience Parameter	Firm Average Experience t-statistic	Firm Average Person Effect Parameter	Firm Average Person Effect t-statistic	1 Std Dev. Experience Effect	1 Std. Dev. Firm Avg. Person Effect	1 Std. Dev. Total Co-Worker Effect
50 Wholesale trade--durable goods	0.0336	2135.2	0.8928	1099.1	0.1683	0.2241	0.3924
51 Wholesale trade--nondurable goods	0.0249	1387.0	0.6788	630.6	0.1249	0.1704	0.2953
52 Building materials, hardware, garden supply	0.0430	1298.6	1.0126	361.2	0.2155	0.2542	0.4696
53 General merchandise stores	-0.0042	-170.0	0.8426	315.8	-0.0211	0.2115	0.1903
54 Food stores	-0.0037	-154.0	0.7943	436.1	-0.0187	0.1994	0.1807
55 Automotive dealers & gasoline service stations	0.0379	1577.6	0.9232	564.7	0.1903	0.2317	0.4220
56 Apparel and accessory stores	-0.0171	-451.7	0.0798	34.5	-0.0855	0.0200	-0.0655
57 Furniture, home furnishings and equip. stores	0.0425	1192.8	1.0762	456.5	0.2129	0.2701	0.4830
58 Eating and drinking places	-0.0091	-375.6	0.5996	559.3	-0.0454	0.1505	0.1051
59 Miscellaneous retail	0.0141	592.4	0.7299	508.2	0.0707	0.1832	0.2539
60 Depository institutions	0.0058	269.4	1.0849	702.6	0.0291	0.2723	0.3014
61 Nondepository credit institutions	0.0615	1131.7	0.8036	294.5	0.3087	0.2017	0.5104
62 Security, commodity brokers, and services	0.0395	651.6	0.8622	472.0	0.1981	0.2164	0.4145
63 Insurance carriers	0.0427	1726.4	1.1469	632.8	0.2143	0.2879	0.5021
64 Insurance agents, brokers, and service	0.0137	392.3	0.6942	325.5	0.0686	0.1742	0.2428
65 Real estate	0.0184	679.7	0.7728	542.5	0.0922	0.1940	0.2862
67 Holding and other investment offices	0.0316	430.4	0.8845	286.4	0.1584	0.2220	0.3804
70 Hotels, rooming houses, camps, & other lodging pl	0.0294	694.1	0.8162	309.8	0.1473	0.2049	0.3522
72 Personal services	0.0431	1210.8	0.7322	395.4	0.2162	0.1838	0.4000
73 Business services	0.0511	2850.7	0.9214	1635.0	0.2565	0.2313	0.4878
75 Automotive repair, services, and parking	0.0470	1378.7	0.9044	452.8	0.2358	0.2270	0.4628
76 Miscellaneous repair services	0.0456	955.3	1.0115	312.1	0.2288	0.2539	0.4827
78 Motion pictures	0.0051	71.0	0.8505	241.0	0.0254	0.2135	0.2388
79 Amusement and recreational services	0.0273	910.3	0.5339	327.2	0.1368	0.1340	0.2709
80 Health services	0.0029	191.4	-0.1708	-237.4	0.0143	-0.0429	-0.0285
81 Legal services	0.0120	261.5	0.8447	443.5	0.0603	0.2120	0.2723
82 Educational services	0.0458	3508.3	-0.4459	-489.7	0.2297	-0.1119	0.1178
83 Social services	0.0692	2364.3	1.6645	1015.8	0.3469	0.4178	0.7647
84 Museums, art galleries, botanical & zoos	0.0700	799.7	0.8434	93.7	0.3510	0.2117	0.5627
86 Membership organizations	-0.0004	-14.4	0.4295	245.9	-0.0019	0.1078	0.1059
87 Engineering and management services	0.0437	1982.4	0.9157	1050.4	0.2191	0.2298	0.4490
88 Private households	0.0250	118.0	0.8816	103.3	0.1256	0.2213	0.3469
89 Miscellaneous services	0.0376	359.9	0.5698	115.6	0.1884	0.1430	0.3314