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EVIDENCE FROM WASHINGTON ADMINISTRATIVE DATA

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ABSTRACT

We study the time-series properties of firm effects in the two-way fixed effects models popularized by Abowd, Kramarz, and Margolis (1999) (AKM) using two approaches. The first—the rolling AKM approach (R-AKM)—estimates AKM models separately for successive two-year intervals. The second—the time-varying AKM approach (TV-AKM)—is an extension of the original AKM model that allows for unrestricted interactions of year and firm indicators. We apply to both approaches the leave-one-out methodology of Kline, Saggio and Sølvsten (2019) to correct for biases in the resulting variance components. Using administrative wage records from Washington State, we find, first, that firm effects for hourly wage rates and earnings are highly persistent. Specifically, the autocorrelation coefficient between firm effects in 2002 and 2014 is 0.74 for wages and 0.82 for earnings. Second, the R-AKM approach uncovers cyclicality in firm effects and worker-firm sorting. During the Great Recession the variability in firm effects increased, while the degree of worker-firm sorting decreased. Third, we document an increase in wage dispersion between 2002–2003 and 2013–2014. This increase in wage dispersion is driven by increases in the variance of worker effects and sorting, with an accompanying decrease in the variance of firm wage effects. Auxiliary analyses suggest that the misspecification of standard AKM models resulting from restricting firm effects to be fixed over time is a second-order concern.

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1 Introduction

The variance decomposition method proposed by Abowd, Kramarz, and Margolis (AKM, 1999) has been the workhorse of a large and growing literature examining earnings differentials and structural change in labor markets. By decomposing earnings variability into components attributable to workers, firms, and the sorting of workers to firms, it has produced a wealth of insights regarding labor market inequality (Card, Heining and Kline, 2013; Song, Price, Guvenen, Bloom and von Wachter, 2019), gender wage differences (Card, Cardoso and Kline, 2015), compensating differentials for firm characteristics (Sorkin, 2018), the influence of outsourcing on earnings (Goldschmidt and Schmieder, 2017), and the sources of displaced workers' earnings losses (Schmieder, von Wachter and Heining, 2018; Lachowska, Mas and Woodbury, 2019).

The standard AKM model imposes the assumption that firm effects—the contribution of a given firm's pay policies to workers' earnings—are time invariant. This assumption allows researchers to pool multiple years of data to estimate the model parameters. Pooling is helpful because it is known that the simple "plug-in" estimator commonly used to obtain the AKM variance components is biased and inconsistent due to sampling error in the estimated worker and firm effects, as originally noted by Krueger and Summers (1988) and Abowd et al. (2004). This bias is particularly severe in datasets with few worker transitions—Andrews, Gill, Schank and Upward (2008) refer to this as limited mobility bias. The assumption of time-invariant firm effects justifies pooling multiple years of data to increase the number of observed worker transitions, reducing sampling error and alleviating the bias in estimating variance components.

However, the literature on rent sharing provides evidence that firm pay policies may change over time. For example, Van Reenen (1996) and Kline et al. (2019) document that pay is related to time-varying patent activity, and a growing literature has estimated the co-movement of firm performance and compensation (Guiso, Pistaferri and Schivardi, 2005; Card, Devicienti and Maida, 2014; Card, Cardoso, Heining and Kline, 2018). By assuming that firm pay policies are time invariant and pooling many time periods, we risk understating the true variability of firm pay policies.

In this paper, our primary goal is to examine the stability of firm effects and the role of time-varying firm effects in decompositions of the variance of earnings and wages. We consider two approaches. The first—the rolling AKM approach (R-AKM)—was popularized by Card, Heining and Kline (2013) and estimates AKM models separately for successive two-year time intervals. The second—the time-varying AKM approach (TV-AKM)—is based on an extension of the original AKM model where we allow for unrestricted interactions of year and firm indicators. We apply both methods to Washington State administrative wage records, which are particularly attractive because they allow us to observe hourly wage rates as well as quarterly earnings and are available over the most recent business cycle—from 2002 through 2014.

A second goal of the paper is to appraise the importance of the limited mobility bias using the "leave-one-out" bias correction proposed by Kline, Saggio and Sølvsten (2019) (KSS). We apply this correction to the variance components estimated in both the R-AKM and TV-AKM models, and compare these estimates to the uncorrected ones based on a simple plug-in approach, commonly used in the literature.

The main findings are as follows. First, we find that firm wage and earnings effects show a remarkable degree of stability. Specifically, in a balanced panel of firms observed in every year during 2002–2014, the autocorrelation coefficient between firm effects in 2002 and 2014 is 0.74 for wages and 0.82 for earnings. We find that firm effects for both earnings and wages are well approximated by a persistent AR(1) process. The stability of firm effects provides evidence that, by and large, firm effects represent permanent differences in firm compensation policies.

Second, we find that variance components estimates are similar when comparing two-way models based on time-invariant or time-varying firm effects. Specifically, we find the KSS bias-corrected variance of time-varying firm effects explain 13% of the variance of wages and 21% of the variance of earnings. These estimated variance components are very similar to those obtained in an AKM model with time-invariant firm effects (12% for wages and 20% for earnings). Interestingly, we find that bias-corrected variance components estimates are very close to those obtained via a simple plug-in approach when pooling multiple years of data. This suggests a small incidence of limited mobility biases when working with relatively longer time-series.

Third, we find that, for the 2002–2014 balanced panel of firms, the dispersion of firm effects changed over time. Specifically, the variances of firm effects for both wage rates and earnings fell in the years leading up to the Great Recession (2002–2007), increased during the Great Recession, then decreased dramatically in the post-recession years. This counter-cyclical pattern in the dispersion of firm effects appears to be a novel finding.

Finally, we examine how firm effects, worker effects, and worker-firm sorting each contribute to the observed increases in inequality of earnings and wages in Washington during 2002–2014. The variance decompositions obtained from both the AKM plug-in method and the KSS bias-correction estimator suggest those increases are attributable almost entirely to increases in the variation of worker-specific effects and increased sorting of "good" workers to "good" firms. Changes in firm-specific wage and earnings policies account for less than 10 percent of the increase in inequality over the years we observe. For worker-firm sorting, we observe an interesting pattern. Before the Great Recession, the degree of sorting, as measured by the KSS adjusted correlation in worker and firm fixed effects, increased, then fell during the recession, and finally reached a new high after the recession.

We conclude the analysis with two simple applications that provide evidence about the degree of misspecification stemming from restricting firm effects to be fixed over time. We first show that regressing TV-AKM firm wage effects on time-invariant AKM firm wage effects results in a projection slope close to unity, and the associated scatter plot is tightly concentrated around the 45-degree line. Second, we find that regressing separation rates on time-invariant AKM firm wage effects results in virtually the same estimated relationship as regressing separation rates on TV-AKM firm wage effects. These results lead us to conclude that the degree of misspecification derived from imposing time invariance of firm effects is likely to be a second order concern.

The paper is organized as follows. Section 2 describes the econometric framework, reviewing both the KSS bias-correction estimator and the methods of estimating time-varying firm effects. Section 3 discusses the data and describes differences between the largest connected set used to obtain the AKM estimates and the leave-one-out connected set generated for the KSS bias-correction. Section 4 describes the empirical findings. We compare the simple AKM plug-in and KSS bias-corrected variance decompositions for two intervals (2002–2003 and 2013–2014), examine the implications of these decompositions for the growth of wage and earnings inequality, and discuss the autocovariance structure of firm fixed effects. Section 5 discusses the findings and offers some concluding remarks. To keep the discussion as direct as possible, we relegate a more detailed description of the data to a data appendix.

2 Econometric Framework

Our baseline econometric specification is the two-way fixed effects model popularized by AKM. In this model, the log earnings or log hourly wage of worker g at time t, y_{gt}, is decomposed into the sum of a worker component, α_g, a firm component, ψ_j, and an error component ε_{gt}:

$$y_{gt} = \alpha_g + \psi_{j(g,t)} + \varepsilon_{gt}. \tag{1}$$

The function $j(\cdot,\cdot) : \{1,\ldots,N\} \times \{1,\ldots,\max_g T_g\} \rightarrow \{0,\ldots,J\}$ allocates each of $n = \sum_{g=1}^{N} T_g$ worker-year observations to one of $J+1$ firms, where T_g denotes the total number of years in which we observe worker g. In equation (1), α_g is a worker effect that captures a combination of time-invariant skills and other factors of a given worker that are rewarded equally across different firms. The term ψ_j represents a firm-specific relative pay premium that is paid equally by firm j to all its employees. Finally, ε_{gt} represents an unobserved time-varying error that captures random match effects, shocks to human capital, and other unobserved factors.

The AKM model is a useful tool to assess the influence of firms in setting wages. According to equation (1), the variance of, say, log wages can be decomposed as

$$\text{var}(y_{gt}) = \text{var}(\alpha_g) + \text{var}(\psi_{j(g,t)}) + 2\text{cov}(\psi_{j(g,t)}, \alpha_g) + \text{var}(\varepsilon_{gt}). \tag{2}$$

This decomposition highlights that, if firms have significant latitude in setting wages, wage inequality will be affected through two terms: $\text{var}(\psi_{j(g,t)})$ and $\text{cov}(\psi_{j(g,t)}, \alpha_g)$, where the latter captures the extent to which workers with a higher fixed wage component tend to be sorted into firms paying a higher wage premium. The growing availability of large administrative datasets and improvements in computational methods has allowed economists to provide new evidence on the contribution of firms and worker-firm sorting to wage inequality—e.g., Card, Heining and Kline (2013) for Germany; Song, Price, Guvenen, Bloom and von Wachter (2019) for the US.

Two challenges arise when interpreting the results from these recent studies. First, current evidence on the importance of firms and worker-firm assortativity in setting wages is based on a simple "plug-in" approach, where each variance component in (2) is calculated as the variance of OLS estimates of (α, ψ) from equation (1). However, as initially pointed out by Krueger and Summers (1988) and Abowd et al. (2004), sampling error in the estimates of (α, ψ) will impart bias in the estimated variance components, a phenomenon often referred to as "limited mobility bias." These biases can be particularly severe when the number of workers transitioning between different employers is relatively low compared to the overall dimensionality of the model (Andrews, Gill, Schank and Upward, 2008; Kline, Saggio and Sølvsten, 2019).

Second, the original AKM model assumes the firm-specific effects $\psi_{j(g,t)}$ to be time invariant. This assumption might be problematic if, in an attempt to minimize limited mobility bias, researchers estimate the original AKM model by pooling a long panel (10 or more years) (Goldschmidt and Schmieder, 2017; Bana, Bedard and Rossin-Slater, 2018; Lachowska, Mas and Woodbury, 2019). However, it is unclear why firm wage or earnings policies should remain fixed over such long horizons. In fact, recent evidence suggests firm wage policies are sensitive to within-firm idiosyncratic shocks (Kline, Petkova, Williams and Zidar, 2019; Garin, Silvério et al., 2019). A more realistic representation of the wage-setting process is therefore one where firm effects are allowed to vary over time. However, this in turn can magnify issues due to limited mobility bias.

The rest of this section is organized as follows. Section 2.1 describes a method for correcting the biases in estimated variance components of the AKM model. Section 2.2 then discusses two approaches to allowing for time-varying firm heterogeneity. The first is the rolling AKM model

(R-AKM), which estimates separate AKM models for successive two-year intervals. The second is the time-varying AKM model (TV-AKM), a simple extension of the AKM model in which firm effects are allowed to vary over time and are estimated in a dataset that pools all available time intervals.

2.1 Correcting for Bias: The Leave-One-Out-Correction

It is useful to rewrite model (1) as follows

$$y_i = d_i'\alpha + f_i'\psi + \varepsilon_i = x_i'\beta + \varepsilon_i \tag{3}$$

where i indexes a particular worker-year observation (g,t); d_i and f_i denote worker and firm identifiers respectively and we have $x_i = (d_i', f_i')'$, $\beta = (\alpha', \psi')'$ with $\alpha = (\alpha_1, \ldots, \alpha_N)$ and $\psi = (0, \ldots, \psi_J)$.[1]

Each variance decomposition parameter in (2) can be written as a simple quadratic form in β. For instance, the variance of firm effects is given by

$$\text{var}(\psi_{j(g,t)}) = \beta' A \beta \tag{4}$$

where A is a known matrix equal to $A = \begin{pmatrix} 0 & 0 \\ 0 & A_{ff} \end{pmatrix}$, with $A_{ff} = \frac{1}{n}\sum_{i=1}^{n}(f_i - \bar{f})(f_i - \bar{f})'$ and $\bar{f} = \frac{1}{n}\sum_{i=1}^{n} f_i$.

Most available estimates of $\text{var}(\psi_{j(g,t)})$ are based on a plug-in approach, that is

$$\widehat{\text{var}(\psi_{j(g,t)})} = \hat{\beta}' A \hat{\beta} \tag{5}$$

where $\hat{\beta}$ is the usual OLS estimate of β: $\hat{\beta} = S_{xx}^{-1}\sum_{i=1}^{n} x_i' y_i$, where $S_{xx} = \sum_{i=1}^{n} x_i x_i'$.

Kline, Saggio and Sølvsten (2019) showed formally that variance decompositions based on the plug-in approach are finite sample biased and inconsistent. To show this simple but important

[1] As noted by AKM, estimation of equation (3) requires one normalization of the vector ψ within a particular connected set of firms and workers. We therefore normalize the firm effect of the first firm to be zero and assume for simplicity that all firms present in the data are connected so that only one normalization is required.

result, we start by assuming that the unobserved error terms $\{\varepsilon_i\}$ are mutually independent with heteroskedatic variances σ_i^2. Then, the expectation of the plug-in estimator of the variance of firm effects is given by

$$\mathrm{E}[\widehat{\mathrm{var}(\psi_{j(g,t)})}] = \mathrm{var}(\psi_{j(g,t)}) + \sum_{i=1}^{n} B_{ii}\sigma_i^2 \tag{6}$$

where $B_{ii} = x_i' S_{xx}^{-1} A S_{xx}^{-1} x_i$. The plug-in bias, $\sum_{i=1}^{n} B_{ii}\sigma_i^2$, can be particularly severe in situations where the number of firms is large compared to the total number of workers transitioning between different firms, see the discussion in KSS.

Andrews, Gill, Schank and Upward (2008) propose to correct for limited mobility bias by assuming a homoskedastic error structure: $\sigma_i^2 = \sigma^2, \forall i$. Bonhomme, Lamadon and Manresa (2019) provide a framework that delivers consistent estimates of variance components by restricting the support of the unobserved firm heterogeneity to a finite number of group types and by relying on an asymptotic framework where firm sizes diverge in the limit. Kline, Saggio and Sølvsten (2019) propose a solution based on a "leave-one-out" correction that delivers unbiased and consistent estimates of variance components under an asymptotic framework that allows the number of firms to grow in the limit while allowing unrestricted patterns of heteroskedasticity in ε_i.

The methodology of Kline, Saggio and Sølvsten (2019) (KSS) is based on introducing "cross-fit" estimates of σ_i^2, that is

$$\hat{\sigma}_i^2 = \sum_{i=1}^{n} y_i(y_i - x_i'\hat{\beta}_{-i}) \tag{7}$$

where $\hat{\beta}_{-i}$ is the OLS estimator of β in (5) after leaving observation i out. It is easy to verify that $\mathrm{E}[\hat{\sigma}_i^2] = \sigma_i^2$. One can then bias-correct the original plug-in estimator to deliver unbiased estimation of any quadratic form in β. For instance, going back to the variance of firm effects, the leave-one-out bias corrected estimate of this quantity is

$$\widetilde{\mathrm{var}(\psi_{j(g,t)})} = \widehat{\mathrm{var}(\psi_{j(g,t)})} - \sum_{i=1}^{n} B_{ii}\hat{\sigma}_i^2 \tag{8}$$

Remark 1: Leave-One-Out Connectedness. A key requirement of the KSS estimator is that $\hat{\beta}_{-i}$

exists, which is satisfied whenever $P_{ii} = x_i' S_{xx}^{-1} x_i < 1$. This requirement on the statistical leverage of the AKM model effectively requires dropping any firm associated with only one mover.[2] For estimation, KSS therefore rely on the so-called "leave-one-out connected set," which corresponds to a bipartite network of workers and firms such that removing any one worker from the graph does not break its connectivity.

Remark 2: Two Time Periods When fitting the model with two time periods [$\max(T_g) = 2$], KSS show that one can construct an unbiased estimator of both $\text{var}(\psi_{j(g,t)})$ and $\text{cov}(\psi_{j(g,t)})$ not only under unrestricted heteroskedasticity, but also when ε_{g2} and ε_{g1} are arbitrarily serially correlated.

Remark 3: Clustering. When $\max(T_g) > 2$, it may be important to allow for dependence in the error terms in $\{\varepsilon_g\}$. One can easily extend the framework presented above from leaving out a single observation to leaving out a particular cluster—see Remark 2 in KSS. In the empirical exercise below, we will verify the importance of allowing for arbitrary dependence of the error term within a worker-firm match when working with a stacked dataset that spans the time frame 2002–2014.[3]

Remark 4: Computation. The KSS methodology relies on computation of both $\{B_{ii}, P_{ii}\}$. Finding, say, P_{ii} requires solving a system of n equation in $k = N + J$ unknowns—i.e., solving for Z in $\underset{k\times k}{S_{xx}} \underset{k\times n}{Z} = \underset{k\times n}{X'}$, where X stacks the different x_i in (3). This is computationally infeasible with the Washington data, which involves millions of worker effects and hundreds of thousands of firm effects. We therefore rely on a variation of the Johnson-Lindestrauss approximation developed by KSS. In particular, we consider solutions of p systems of k linear equations, $\underset{k\times n}{Z_{JLA}} = \underset{k\times p}{R_P X'}$, where R_P is a $n \times p$ matrix composed by mutually independent Rademacher random variables. KSS show that the Johnson-Lindestrauss approximation allows recovery of extremely accurate variance decompositions while cutting computation time by a factor of roughly 100.

[2] We define a mover as a worker who moved between different firms at least once during the observed sample period.

[3] Note that when leaving out a worker-firm match, the worker effects of workers who are observed with only one firm are not identified.

2.2 Time-Varying Firm Heterogeneity

An important assumption of the AKM model is that unobserved firm heterogeneity, as captured by $\{\psi_j\}$ in (1), is time-invariant. It is natural to question the validity of this assumption, especially in light of two facts. First, economists are gaining access to ever longer panels of administrative data. Fitting AKM models to these longer panels is sometimes viewed as a way to reduce limited mobility bias (Goldschmidt and Schmieder, 2017; Bana, Bedard and Rossin-Slater, 2018). But the longer is T, the harder it becomes to justify the assumption that firm effects are fixed over time.

Second, recent work has suggested that the firm effects $\{\psi_j\}$ in (1) capture primarily heterogeneity across firms in available surplus per worker (Card, Cardoso and Kline, 2015; Card, Cardoso, Heining and Kline, 2018). Clearly, surplus per worker can vary within a firm over time for several firm-specific reasons. Kline, Petkova, Williams and Zidar (2019) use plausibly exogenous variation in firms' patent allowances to gauge how firm-level idiosyncratic shocks affect the wages of both incumbent workers and new hires within the firm. Lamadon, Mogstad and Setzler (2019) develop a model where standard AKM firm effects vary over time whenever pass-through rent sharing elasticities differ from zero and a given firm experiences an idiosyncratic change to its value added.

How can one capture this firm-by-year heterogeneity when modeling the wage process? A straightforward approach used by Card, Heining and Kline (2013) is to estimate the AKM separately for different time-intervals. Using this "rolling"AKM approach (R-AKM), we fit AKM models to successive two-year ($T = 2$) intervals (2002–2003, 2003–2004, ..., 2013–2014) and correct the associated variance decompositions for each time interval using the KSS approach. These estimates can be used to gauge how the magnitude and relative importance of the AKM variance components changed over the 2002–2014 period and in particular during the Great Recession.

The key advantage of the R-AKM approach is its simplicity and transparency. The main drawback is that, by taking advantage of mobility patterns only within two-year intervals, the number of identified firm effects can be significantly reduced due to a smaller mobility network.

Accordingly, in the next subsection we introduce the time-varying AKM model (TV-AKM), a simple extension of the AKM model in which firm effects are allowed to vary across time. This model is estimated by pooling all the available time periods, which greatly increases the number of identified firm-by-year effects.

2.2.1 The Time-Varying AKM Model

A natural extension of the original AKM model that allows one to control flexibly for firm-by-year unobserved heterogeneity is the following

$$y_{gt} = \alpha_g + \psi_{j(g,t),t} + \varepsilon_{gt}. \tag{9}$$

where $\{\psi_{j,t}\}$ represents a vector of firm-by-year indicators. Our interest focusses on the variance decomposition parameters $\text{var}(\psi_{j(g,t),t})$ and $\text{cov}(\psi_{j(g,t),t}, \alpha_g)$ and on their contrast with the estimates one would obtain from the time-invariant model of equation (1). Relatedly, we are interested in the extent of the "drift" in $\{\psi_{j(g,t),t}\}$ for a given firm over time.

By the logic described in the previous section, the naive plug-in approach is biased for $\text{var}(\psi_{j(g,t),t})$, $\text{cov}(\psi_{j(g,t),t}, \alpha_g)$, and in addition for the autocovariance function $\{\psi_{j(g,t),t}\}$. Fortunately, the KSS framework extends to *any* quadratic form constructed from the coefficients of a linear regression model. We therefore rely on the KSS leave-one-out approach to correct the variance decomposition and autocovariance estimates resulting from the TV-AKM model of equation (9).

Remark 5: Connected Set. Identification of the firm-by-year fixed effects poses a challenge similar to the one originally faced by AKM. A useful starting point is to consider the bipartite network formed by workers and firm-by-year identifiers, as opposed to firm-only identifiers as in the original AKM formulation. By treating each firm-year combination as a single vertex in this graph, it follows that identification of $\{\alpha_g, \psi_{j(g,t),t}\}$ requires (i) the associated bipartite network to be connected and (ii) normalizing one firm-by-year combination within this connected set to ensure that S_{xx} is full rank.

Remark 6: Never-movers. By treating each firm-year combination as a single vertex in the corresponding bipartite network of firms and workers, it follows that "never-movers"—workers who remain with the same employer during the entire sample period—play an active role in identification of $\{\psi_{j,t}\}$. This is in contrast with the standard AKM model where firm effects are solely identified via workers moving between employers. To see the importance of never-movers in driving identification of $\psi_{j,t}$, consider the following moment condition based on the TV-AKM model:

$$\mathrm{E}[y_{it}|i \text{ is a firm} j \text{ never-mover}] - \mathrm{E}[y_{it-1}|i \text{ is a firm} j \text{ never-mover}] = \psi_{j,t} - \psi_{j,t-1}. \qquad (10)$$

The expectations above condition on the worker being employed only by firm j, and y denotes the wage rate. This implies that the average wage change of never-movers within firm j is a key source of identification of $\{\psi_{j,t}\}$. Relatedly, the same source of variation is typically used to identify rent sharing elasticities—see for instance equation (15) in Card, Cardoso and Kline (2015) and the discussion in Card et al. (2018). That never-movers contribute to identification of $\{\psi_{j,t}\}$ is important when contrasting the TV-AKM and the R-AKM approaches described previously. In R-AKM, identification of firm effects within a given time interval relies solely on inter-firm transitions made by workers in that particular interval. This restricts the set of identified firm effects within and across intervals to a significant degree. On the other hand, the TV-AKM model draws on a pooled mobility network that exploits observations associated with never-movers. As a consequence, we should expect the TV-AKM model to have significantly higher number of identified firm-by-year effects than the R-AKM approach.

Remark 6: Leave-One-Out Connected Set in the TV-AKM Model. As discussed in Remark 1, the KSS approach requires the associated connected bipartite network to remain connected after removing a single worker. Allowing for time-varying firm heterogeneity implies some additional refinements in the leave-one-out connected set introduced in Remark 1 for the standard AKM model. Figure 2 illustrates this latter point using a simplified example. It shows a bipartite graph that satisfies the definition of leave-one-out connectedness when estimating a model with time-invariant firm heterogeneity. However, if we were to estimate the full set of firm-by-year effects in this example, the associated definition of leave-one-out connectedness would no longer be satisfied.

3 Estimation Sample and Descriptive Statistics

The estimation sample is based on quarterly earnings records from all employers covered by unemployment insurance (UI) in Washington from 2002:I through 2014:IV. A more detailed description of the data is in the data appendix.

We construct a linked employer-employee panel using a procedure similar to that developed by Sorkin (2018). We first identify each worker's primary employer in a quarter as the employer from which the worker had the largest share of earnings in that quarter. We then define an employment spell as at least five consecutive quarters during which a worker had earnings from the same primary employer. For each spell, we drop the first quarter (to avoid making inferences about earnings based on partial quarters of employment) and the last two quarters (to avoid making inferences based on earnings in the quarter before and the quarter of a separation). We then annualize the remaining quarterly data on earnings and hours within each calendar year, conditional on the calendar year including at least two consecutive quarters of earnings from the same primary employer. Finally, we adjust earnings by the CPI-U (indexed to 2005) and calculate the real hourly wage rate by dividing adjusted annualized earnings from the primary employer by annualized hours worked with that employer.

Figure 3 illustrates the procedure and gives some examples, described in the figure notes. The unit of observation is the worker-year, with a focus on the primary employer in a year.

3.1 Descriptive Statistics

Figure 1, Panel (a) displays the trends we analyze for our variance decomposition exercise—the variances of real log hourly wages and log earnings in Washington from 2002 to 2014. Wage and earnings inequality both increased between 2002 and 2014 with a similar trend: the variance of log wages increased by roughly 19%, and the variance of log earnings increased by about 16%. This suggests that increased inequality of wages and earnings was particularly pronounced in Washington during this period. For example, using tax data, Song, Price, Guvenen, Bloom and von Wachter (2019) find the variance of log annual earnings increased by about 4% in the United States overall during 2001–2013.[4]

Panels (b) and (c) of Figure 1 show the time series evolution of different percentiles of the log wage and log earnings distributions underlying the trends shown in Panel (a). Over the 2002–2014 period, the gap between the 90th and 10th percentiles expanded by about 15 log points for wages, and by about 20 log points for earnings; however, this expansion occurred in three phases. Between 2002 and 2007, the increased inequality seen in Panel (a) was driven mainly by increases in the top quartile, but from 2007 to 2010 inequality accelerated, driven by a fanning out of the percentiles. After 2010, wages and earnings continued to grow for the highest quartile, and the lowest percentiles regained some of their lost ground. This was especially true for the 10th and 25th percentiles for earnings and the 5th and 10th percentiles for wages, although only the 5th wage percentile returned to its 2002 level. The relative improvement of the lower percentiles post-2010 is consistent with the relatively modest growth of inequality from 2010 to 2014 shown in Panel (a).

Table 1 displays summary statistics that are useful in assessing the econometric strategies described in Section 2. Panel (a) focuses on three intervals: 2002–2003, 2013–2014, and the full 2002–2014 period. For each interval, we report descriptive statistics concerning the largest connected set and the leave-one-out connected set. The former represents the largest connected set formed by worker-employer links and is the sample typically used to fit AKM wage decompositions—see for instance Card, Heining and Kline (2013). The leave-one-out connected set is the sample used for the bias correction approach of KSS discussed in Remark 1 of Section 2.1.

The largest connected set for the 2002–2003 interval includes about 3.4 million worker-year observations, with approximately 142,000 workers who move between employers leading to 41,000 identified firm effects. This implies that the average number of movers is approximately 3.4 movers

[4]Because the data underlying our estimates and those of Song, Price, Guvenen, Bloom and von Wachter (2019) differ, this comparison could overstate differences between Washington and the United States as a whole; however, it stands to reason that earnings inequality would increase more in Washington than in the United States generally because the Washington economy includes the Seattle metropolitan area, which is one of a handful of innovation hubs where wage growth has been unusually high (Moretti, 2012). Appendix A in Lachowska, Mas and Woodbury (2019) compares labor market conditions in Washington to those in the United States as a whole during 2002–2014 and concludes that the level and dynamics of the Washington unemployment rate was very similar to the national average. See also the discussion in Abowd, McKinney and Zhao (2018) regarding differences between samples based on UI wage records and nationally representative samples.

per firm, and that a potentially large fraction of firms is associated with only one mover. The largest connected set for the 2013–2014 interval is somewhat larger than for 2002–2003—about 4 million worker-year observations, 170,000 movers, and 50,000 firms, implying on average about 3.5 movers per firm. For the full 2002–2014 period (Column 5), the largest connected set includes more than 27 million worker-year observations, nearly 2 million movers, and 218,000 firms. The longer time horizon associated with these data implies a larger mobility network and therefore a larger ratio of movers to firms, roughly 9.1.

The KSS bias correction requires each firm to remain connected to all others in the data after removing any particular worker, and the leave-one-out sample ensures that this requirement is satisfied. The two-year interval samples (2002–2003 and 2013–2014) retain about half of the firms from the original largest connected set (Columns 2 and 4). Despite this, the leave-one-out samples still include about 80% of the original worker-year observations and 85% of the movers. This suggests that firms associated with only one mover tend to be rather small in size. Consistent with this observation and the evidence on premia paid by large firms (Oi and Idson, 1999), average log wages and average log earnings in the leave-one-out sample are higher than those in the original largest connected set by 6% and 9%. Also, in the leave-one-out samples the variances of log wages are smaller by 2% to 5% (depending on the time interval) and the variances of log earnings are smaller by about 10%.[5]

Although the levels of the first and second moments of log wages and log earnings are different in the leave-one-out samples than in the largest connected sets, their trends are well-preserved in the leave-one-out samples. Also, the leave-one-out connected set for the full 2002–2014 period retains 96% of the worker-year observations, 97% of the movers, and 76% of the employers. Compared with the two-year intervals, the full observation window substantially reduces the amount of pruning needed to ensure leave-one-out connectivity.

Table 1, Panel (b) reports descriptive statistics for the sample used to fit the TV-AKM model, which allows firm effects to vary over time. As discussed in Remark 5 of Section 2.2.1, when the

[5]Note also that, while average log wages increased by 3% between 2002–2003 and 2013–2014, the variance of log wages increased by more than 17%, consistent with the raw evidence presented in Figure 1.

underlying model incorporates firm-by-year effects, the relevant bipartite network is one where vertices are formed by worker and firm-by-year identifiers, as opposed to firm-only identifiers. This implies a potential change in the definitions of the largest connected sets and the leave-one-out connected sets shown in Columns 1–4. Ultimately, though, this change appears trivial: a comparison of Columns 5 and 7 shows the two samples closely overlap, and a similar conclusion can be drawn for the associated leave-one-out samples (Columns 6 and 8). Finally, each firm is observed on average for about 5.7 years in the largest connected set, and for about 6.4 years in the leave-one-out connected set, suggesting a fair degree of attrition at the firm level.

4 Results

This section presents the main results of the analysis. In Sections 4.1 and 4.2, we fit AKM models to successive two-year intervals and construct the associated variance decomposition within each interval. This R-AKM approach reveals the extent to which the rising inequality documented in Figure 1 can be attributed to worker-specific effects, firm-specific wage-setting policies, and worker-firm sorting. Within the R-AKM framework, we focus on two contrasts. The first is between variance decompositions based on the standard plug-in approach and the KSS leave-one-out approach. The second is between variance decompositions of log hourly wages (a unique feature of the Washington data) and variance decompositions of log earnings—the outcome usually examined in AKM models for the US (Song, Price, Guvenen, Bloom and von Wachter, 2019).

Sections 4.3 and 4.4 present results from the TV-AKM approach where we pool all available data and fit an AKM model with firm-by-year indicators. We then contrast variance decompositions based on the TV-AKM with those based on standard AKM models. Relatedly, we investigate the extent to which firm effects "drift" over time. Finally, we provide informal evidence that can be used to gauge the degree of misspecification that may occur when fitting models that restrict firm effects to be time invariant.

4.1 Rolling Specification: Log Wages

Table 2 displays the variance decompositions obtained by fitting the AKM model from equation (1) for log wages in the first (2002–2003) and last (2013–2014) of the two-year intervals we observe. Focusing first on 2002–2003, the plug-in method suggests that variation in worker-specific factors explains by far the largest share (86%) of the overall variance in log wages in 2002–2003, whereas firm effects explain only about 14%. The plug-in estimate of the covariance between worker and firm effects is negative, raising the question whether there is in fact negative sorting in the Washington labor market, or if this negative estimated covariance results from the limited mobility bias discussed in Section 2.1.

The KSS leave-one-out bias correction yields a positive estimated covariance between worker and firm effects for 2002–2003, which suggests the negative correlation estimated by the plug-in approach is indeed due to sampling error in the estimated worker and firm effects. As expected, the KSS correction also shrinks the estimated variances of worker and firm effects: for 2002–2003, the explained variation in wages attributable to firm effects falls from about 14% with the plug-in estimator to about 9% with the leave-one-out bias correction.

The plug-in and KSS-corrected decompositions for the 2013–2014 interval are similar to 2002–2003, except that firm effects are even less important, and the covariance between worker and firm effects is positive even when estimated by the plug-in method. The covariance term explains a larger share of wage variation in the 2013–2014 interval than in 2002–2003: the KSS-corrected estimates suggest the covariance between worker and firm effects explains 12% of overall wage variation.

The rightmost two columns in Table 2 show changes in the estimated variance components between 2002–2003 and 2013–2014. Estimates based on the plug-in method suggest the variance of worker effects increased by 14% (= 0.0444/0.3109), the variance of firm effects *decreased* by nearly 20% (= –0.0095/0.0488), and the covariance of worker and firm effects increased by 386% (= 0.0324/0.0085). Qualitatively, the estimates using the KSS correction show similar patterns: Wage inequality increased between 2002–2003 and 2013–2014 because of increases in the variance of worker effects and the covariance between worker and firm effects. But quantitatively, the KSS correction yields somewhat different implications than the plug-in estimator: under the KSS approach, the increased variance of worker effects from 2002–2003 to 2013–2014 explains nearly 72% of the overall increase in wage inequality from 2002–2003 to 2013–2014 (rather than 67% under the plug-in approach), and the covariance of worker and firm effects explains only 41% (rather than nearly 49% under the plug-in approach). Also, the variance of firm effects decreased between 2002–2003 and 2013–2014 under both the plug-in and KSS estimators, but the decrease was somewhat less under the KSS approach (about 10% rather than 14%).

To summarize, Table 2 shows that between 2002–2003 and 2013–2014, wage inequality in Washington increased substantially. This increase was due to increases in the variation of worker-specific factors and the degree of worker-firm sorting, rather than an increase in the variation of fixed employer wage policies. This pattern is broadly consistent with the one in Song et al. (2019) who fit AKM models to log earnings for seven-year time intervals using 1980–2013 US administrative tax data.

But how did the components of wage inequality evolve year-by-year over 2002–2014, a period covering the second most severe recession in US history? To address this question we move from the static comparison of Table 2 to the dynamic representation in Figure 4. This figure reports the variance decomposition represented by equation (2) for each two-year time interval. We consider variance decompositions under both the plug-in method (Panels a and c) and the KSS method (Panels b and d).

The KSS-corrected estimates displayed in Panels (b) and (d), suggest that worker effects varied little during 2002–2006, but with the onset of the Great Recession the variability of worker effects started to increase, then plateaued around 2010. This pattern appears to track relatively well the overall trend in the variance of log wages shown in Panel (a) of Figure 1, reflecting the dominant role of worker effects in explaining the growth of wage inequality between 2002–2003 and 2013–2014.

The variability of firm effects followed a clear counter-cyclical pattern, declining by almost

20% between 2002–2003 and 2007–2008, increasing by about 40% during the Great Recession, then decreasing by 47% in the post-recession years (2010–2014). In contrast, the covariance between worker and firm effects was pro-cyclical, growing by about 50% in the years leading up to the Great Recession, decreasing during the recession, then increasing by 95% in the post-recession years. The variability of firm effects and the importance of worker-firm sorting, then, had opposite cyclical patterns in Washington between 2002 and 2014.

Figure 4 highlights two important differences between the KSS-corrected estimates and those obtained by the plug-in method. First, the levels of all three variance components are shifted by the KSS correction: the variances of the firm and worker effects both shrink, while the covariance between worker and firm effects increases. Second, although the plug-in method reproduces the qualitative dynamics of each component (for example, the pro-cyclicality of worker-firm sorting), Figure 4 shows that changes over time in each component are clearly highly contaminated by sampling error when using the plug-in method. This is true particularly for the covariance of worker and firm effects.

4.2 Rolling Specification: Log Earnings

The ability to observe hourly wage rates in the Washington data allows us to evaluate whether the conclusions from a variance decomposition based on log hourly wages differ from those based on log earnings, the outcome usually examined in the literature.

Table 3 shows plug-in variance decompositions for log earnings for the 2002–2003 and 2013–2014 intervals. In 2002–2003, variation in worker effects accounted for roughly 77% of the variance of log earnings, variation in firm effects accounted for about 16%, and the covariance between worker and firm effects accounted for about 5%. The KSS correction shrinks the shares of earnings variation explained by worker effects (to 70%) and firm effects (to 11%), but more than doubles the share explained by the covariance between worker and firm effects (to 13%). A similar pattern can be seen for the 2013–2014 interval: compared with the plug-in method, the KSS-corrected estimates suggest that variation in worker and firm effects were less important in explaining the variance of log earnings, but variation in the covariance of worker and firm effects was more important (explaining 18%, compared with 12% under the plug-in approach).

How did these components change between 2002–2003 and 2013–2014? Earnings inequality, as estimated by the variance of log earnings, increased by around 17% during 2002–2014 (from 0.49 to 0.57). The KSS estimates show that most of this increase was due to increases in the covariance of worker and firm effects (which accounts for almost 47% of the overall increase in the variance of log earnings) and in the variance of worker effects (which accounts for about 45% of the overall increase). In contrast to the findings in Table 2, which showed a decrease in the variability of firm wage rate effects during 2002–2014, the variability of firm earnings effects increased, although this increase is relatively small and accounts for only about 9% of the overall increase in earnings inequality.

The year-by-year evolution of variance decompositions for log earnings is shown in Figure 5. Most of the patterns found in Figure 4 for log wages can also be seen for earnings. The variance of worker effects for earnings increased during the Great Recession and remained high in the recession's aftermath. The variability of firm effects for earnings was again countercyclical but, unlike the variability of firm effects for wages, remained above its initial (2002–2003) pre-recession level. The covariance between worker and firm effects for earnings was again countercyclical, although its relationship to the business cycle appears somewhat less pronounced than the covariance between worker and firm effects for wages.

Figure 4 again highlights two differences between the plug-in estimates and the KSS-corrected estimates. First, the levels of all three variance components of the earnings decomposition are shifted by the KSS correction—downward for the worker and firm components, upward for the covariance of worker and firm effects. Second, although the plug-in method and the leave-one-out approach highlight similar qualitative trends, the plug-in estimates appear to be contaminated by limited mobility bias. For example, the plug-in estimates suggest a large pre-recession drop in the covariance of worker and firm effects for earnings, but the KSS-corrected estimates suggests this drop reflects mainly different degrees of limited mobility bias across years.

Figure 6 brings together the findings on the correlations of worker and firm effects for wages and earnings, showing the correlations over time for the two alternative estimation methods. The figures highlight the substantial increase in positive sorting between workers and firms that occurred during 2002–2014 in the Washington economy, interrupted only by the Great Recession. The KSS-corrected estimates suggest the correlation between worker and firm effects for wages grew from 0.12 to about 0.28, and for earnings from 0.24 to 0.33. The figure highlights the countercyclical pattern of worker-firm sorting.

4.3 Time-Varying Firm Heterogeneity

We now turn to the results obtained from fitting the TV-AKM model on the pooled 2002–2014 data. Table 4 shows the resulting variance decompositions for log wages and earnings after estimating equation (9) using the leave-one-out connected set described in Table 1, Panel (b). In this pooled dataset, the KSS-corrected estimates with fixed firm effects suggest that firm effects explain 11.6% of the total variance of log wages. When firm effects are allowed to vary over time using the TV-AKM estimator, they explain 13.5% of the total variance of wages, an increase of about 16%. The TV-AKM model also reduces the contribution of assortativity from 16.9% to 14.8% (a 12% decrease) but has no discernible effect on the variance of worker effects.

The patterns for earnings are somewhat different. Allowing firm effects to vary over time increases the contribution of firm effects somewhat (from 19.7% to 20.8%, or about 5%), increases the contribution of worker effects very slightly (from 52.8% to 54.8%, or about 2%), and reduces the importance of the covariance between worker and firm effects from 16.2% to 14.5% (just under 10%). The small differences between the AKM and TV-AKM estimates in the variance of firm effects for log earnings are consistent with the findings of Lamadon, Mogstad and Setzler (2019), who decompose the variance of log earnings after removing variation induced by time-varying firm-level changes in value added per worker (rescaled by an estimated pass-through coefficient).[6]

[6] Lamadon, Mogstad and Setzler (2019) find that the AKM variance decomposition of their adjusted measure of log earnings gives estimates that are virtually identical to those based on log earnings that are not pre-adjusted, after restricting the support of unobserved heterogeneity for both workers and firms using the approach developed by Bonhomme, Lamadon and Manresa (2019).

We conclude that allowing firm effects to vary over time increases the shares of wage and earnings variation that can be attributed to firm effects (particularly for wages); however, these increases do not appear large enough to alter the basic conclusions about the relative importance of the variance components that one would draw from the standard AKM model with time-invariant firm effects.

The analysis in Table 4 offers two additional points. First, the KSS correction leads to relatively modest changes in the variance decompositions produced by both the AKM and TV-AKM models. This suggests that mobility in the Washington pooled data is substantial and sufficient to make limited mobility bias a second-order concern. Still, as pointed out by KSS and in Remark 3, it is important to allow for serial correlation in the error term when working with a panel with more than two time periods. To address this, Table A1 in the Appendix displays the variance of firm effects and the covariance of worker and firm effects for both the AKM and the TV-AKM models under two different leave-one-out strategies: one where we leave out a single worker-year observation as in Table 4, and another where we leave out an entire worker-firm match. These alternative leave-one-out strategies produce few changes for either model, particularly when looking at the overall variance of firm effects. All in all, this suggests again that mobility in the pooled data is adequate to make limited mobility bias a minor concern, even after allowing firm effects to drift over time and the error term to be serially correlated within a match.

Second, when pooling the data over 2002–2014, firm effects explain a significantly higher share of the variance of wages and earnings than in the rolling analysis. For example, firm effects explain about 6–9% of the variation in wages for the 2002–2003 and 2013–2014 intervals shown in Table 2, whereas they explain about 11.6% in the comparable pooled analysis in Table 4. This pattern suggests differences in the composition of firms over time. In particular, the wage and earnings policies of firms that exist in 2002 appear to differ from those in 2014; see also the discussion in the data appendix regarding new firms. The important role played by new firms in driving heterogeneity in firm-specific wage policies was also highlighted by Card, Heining and Kline (2013) in Germany and represents an interesting avenue for future research.

4.4 Autocorrelation of Firm Effects

We now analyze the time-series properties of the estimated firm effects. Computing the covariance between the "fixed" effects of firm j in years t and s requires a bias correction of the associated plug-in quadratic form. We therefore extend the KSS-framework to bias-correct all the autocovariance and autocorrelation functions of the associated firm effects. These parameters are estimated on a balanced subsample of firms for which we can identify firm effects in each year from 2002 to 2014. Each autocovariance is then weighted by average firm employment across 2002–2014.

Table 5 reports autocovariance and autocorrelation matrices of firm effects for log wages in this balanced subsample of firms. The table confirms a pattern that was already emerging from Table 4: firm effects for log wages exhibit some degree of "drift", but they remain highly correlated even 13 years apart (the correlation between firm effects for 2002 and 2014 is 0.74, see Table 5B). Moreover, the diagonal of Table 5A suggests that $\psi_{j,t}$ does not represent a stationary process: the variance of firm effects in the balanced subsample of firms increases over time, which indicates the presence of a non-stationary component in $\psi_{j,t}$. Specifically, during 2002–2014, the variance of firm effects for wages increased from 0.0446 to 0.0582 (more than 30%). This suggests intertemporal variation in firm-specific wage effects, and moreover this variation increases over a firm's life cycle (Babina, Ma, Moser, Ouimet and Zarutskie, 2019).

Table 6 suggests that the time-series properties of the firm effects for log earnings are broadly similar to those for wages. Again, firm effects are highly correlated even 13 years apart (the correlation between firm effects for 2002 and 2014 is 0.82, see Table 6B), and again the variance of the corresponding firm effects does not appear to be stable over time. In particular, consistent with the evidence in Figure 5, this variance actually decreased by about one log point in the years preceding the Great Recession (2002–2007). During 2009–2014, the trend reversed, and variability of firm effects for earnings increased by about 2.5 log points.

Figures 7 and 8 depict the autocorrelation plots of firm effects for log wages and log earnings, respectively. In each figure we overlay the autocorrelation function of the AR(1) process that best fits the empirical autocorrelations. For log wages the best-fitting autoregressive parameter is 0.9765, and for log earnings it is 0.9832.[7] Hence, the empirical autocorrelations suggest a persistent AR(1) process for firm effects. Figure 7 shows that, for log wages, the empirical autocorrelations are somewhat higher than would be predicted by an AR(1) process at lower lags (in particular, lag 1) but closely track the predicted values at higher lags. Figure 8 shows that, for log earnings, the empirical autocorrelations are slightly lower than the predicted values at lower lags (for example, lags 1 through 5), but are essentially the same for higher lags.

4.5 Does Allowing for Time-Varying Firm Heterogeneity Matter?

In the previous subsections, we documented that firm effects are highly autocorrelated and that the variance decompositions resulting from the standard AKM model and the TV-AKM model are quite similar. Nevertheless, by restricting firm effects to be fixed over time, the standard AKM model may still be misspecified. A formal specification test is challenging due to the high-dimensionality of the AKM and TV-AKM models. Still, it may be possible to provide suggestive evidence to inform applied researchers about the degree of misspecification stemming from restricting firm effects to be fixed over time.

We offer two types of such evidence. The first is to project the firm effects for log wages estimated by the TV-AKM model on the firm effects estimated by the AKM model. Assuming the AKM model represents the true data generating process, we would expect the slope of this projection to be unity, and the associated scatter plot to be highly concentrated around the 45-degree line. Panel (a) of Figure 9 shows such a projection, where the observations are worker-year weighted averages of the KSS-corrected TV-AKM and AKM firm effects within each centile bin of the AKM firm effects. The resulting slope is 0.99, and the centile bins are tightly concentrated around the associated 45-degree line, consistent with the AKM model being correctly specified.

Second, several researchers have examined the relationships between firm effects and other out-

[7] Given an AR(1) process $y_t = \delta + \nu y_{t-1} + u_t$, the autocorrelation between y_t and y_{t-k} is $\rho(k) = \nu^k$. The estimate of the autoregressive parameter ν can be obtained by fitting the model $\ln(\rho(k)) = \beta \cdot k + \varepsilon(k)$, where k is the lag order, $\rho(k)$ is the kth-order autocorrelation, and ε is the regression error term. The estimate of β can be interpreted as an estimate of $\ln(\nu)$. To fit this model, the analysis uses autocorrelations reported in Tables 5 (for wages) and 6 (for earnings). We interpret the antilog of $\hat{\beta}$ as an estimate of ν.

comes. For example, Bana, Bedard and Rossin-Slater (2018) use California administrative records from 2000 to 2014 to estimate an AKM model for log earnings. They then use the estimated firm fixed effects for log earnings to gauge the importance of firm-specific earnings premia in predicting the propensity of individuals to use public leave-taking benefits. Goldschmidt and Schmieder (2017) take a similar approach in estimating the relationship between firm effects and the wage penalty associated with outsourcing. The question is whether these estimated relationships are similar whether the firm effects are estimated conventionally or by TV-AKM.

We address this question by estimating the relationship between separation rates and firm effects, as in Card, Heining and Kline (2012). In particular, we consider a worker-year weighted OLS regression of the following type

$$\text{Separation}_{it} = a + b\hat{\psi}_{j(i,t),t} + e \tag{11}$$

where Separation_{it} equals one if the worker is employed in year t with a primary employer j and is employed with a different primary employer in year $t+1$; $\hat{\psi}_{j(i,t),t}$ is a firm effect estimated using the TV-AKM model; and e is a regression error term.

Figure 9, Panel (b) shows the results of estimating equation (11) where we compute the worker-year weighted average of the separation rates, TV-AKM firm effects, and AKM firm effects within each centile bin of the AKM firm effects. The figure suggests a minimal degree of misspecification in the AKM model, as the overall relationship between separation rates and firm effects are similar for both fixed and time-varying firm effects. The sign of the estimate of b is negative, consistent with the evidence provided by Card, Heining and Kline (2012) for Germany and by Bassier, Dube and Naidu (2019) for the state of Oregon.

5 Discussion and Conclusion

We have addressed two main questions. First, do firm effects "drift" over time? Surprisingly perhaps, our analysis suggests that by and large, firm effects are quite stable. This conclusion is based on three pieces of evidence from Washington State administrative wage records: First, when estimated over 13 years, fixed and time-varying firm effects explain similar shares of variance decompositions. This implies a high degree of correlation between fixed and time-varying firm effects—see section 4.3. Second, the autocorrelation function of firm effects for wages and earnings appears to be generated by a process resembling a highly persistent AR(1) (specifically, with an autoregressive parameter equal to about 0.98)—see section 4.4. The implication is that, even 13 years apart, firm effects for both wages and earnings remain highly autocorrelated. Third, when using estimated firm effects as explanatory variables, as in several recent papers, fixed and time-varying firm effects generate nearly identical predictions—see section 4.5.

Knowing that firm effects exhibit little drift is a useful finding for applied researchers because estimating time-varying AKM firm effects is clearly computationally more burdensome than estimating an AKM model with fixed firm-effects. Hence, finding that firm effects are relatively stable provides a justification for pooling multiple years of data to estimate AKM firm effects. The observed stability of firm effects also has broader implications: The time-invariance of firm pay policies suggests that firm effects for pay reflect permanent differences in compensation policies. Whether these differences arise from inter-firm differences in value-added per worker and associated rent sharing, from differences in worker preferences for the nonwage characteristics of employers, or other reasons remains an open question.

The second main finding is that correcting for limited mobility bias is important when estimating the AKM model over short time intervals. Specifically, without the KSS bias correction, AKM variance decompositions calculated over two-year intervals attribute too much importance to worker and firm effects and too little to worker-firm sorting. Conversely, AKM variance decompositions calculated over relatively long time intervals (10 years or more) are similar with and without the KSS bias correction. This similarity holds whether or not firm effects are fixed or allowed to vary over time.

Our results suggest avenues for future work. One is to reconcile economic models that give rise to firm wage and earnings premia with the stochastic process of the time-varying firm effects reported here. For example, one could extend the static model in Card et al. (2018) to allow for richer dynamics. A second avenue could be to examine the generality of the pattern of firm effects over the business cycle in Washington State, and to better understand the mechanism behind this pattern within existing or new macroeconomic models.

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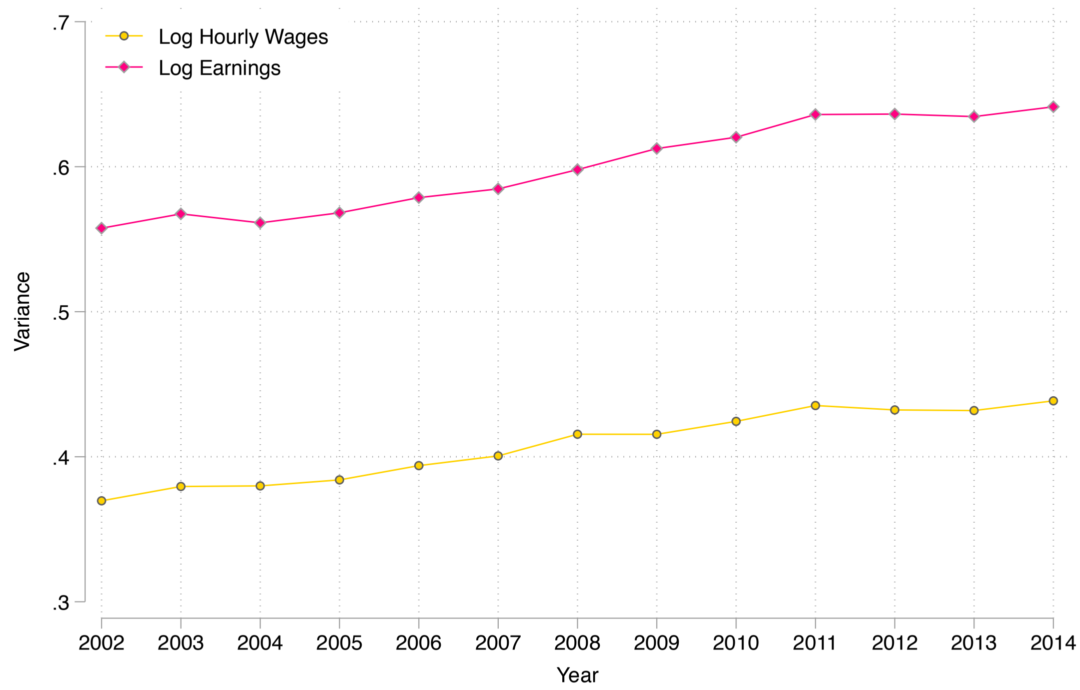
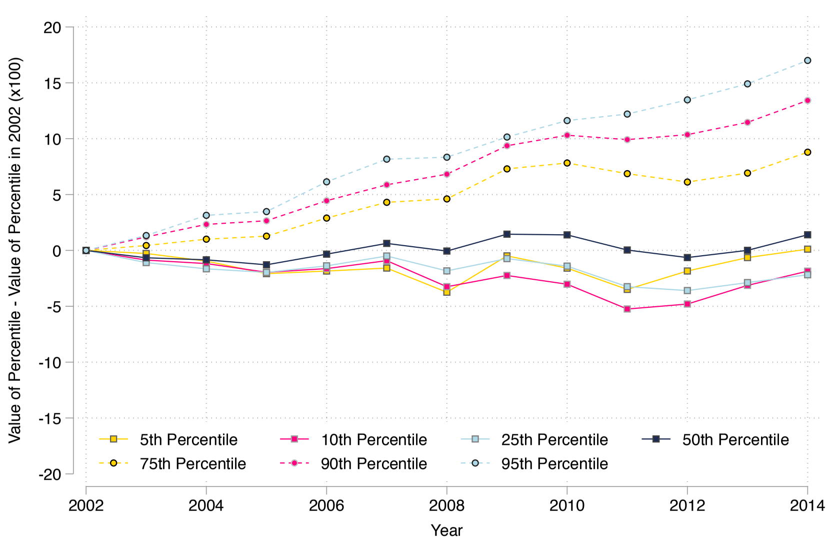
6 Figures and Tables

Figure 1: Trends in Wage and Earnings Inequality

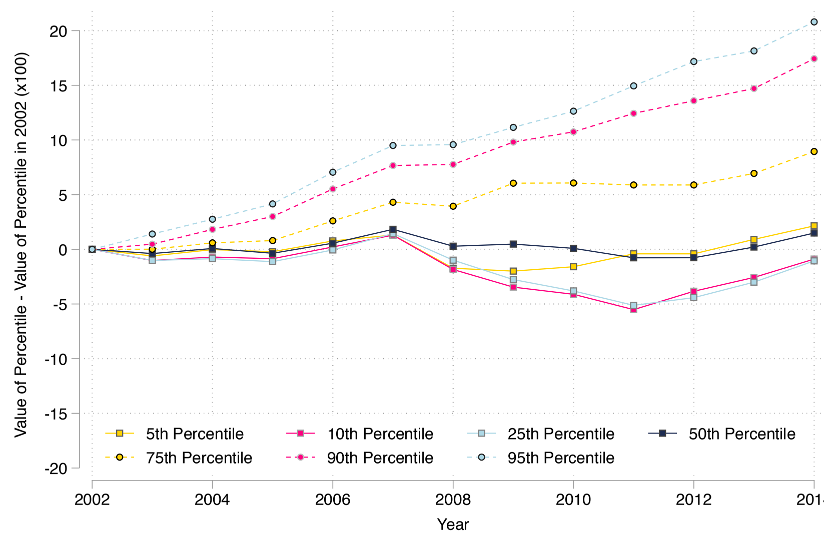
(a) Variance of Log Wages, Earnings



(b) Trends in Percentiles – Log Wages



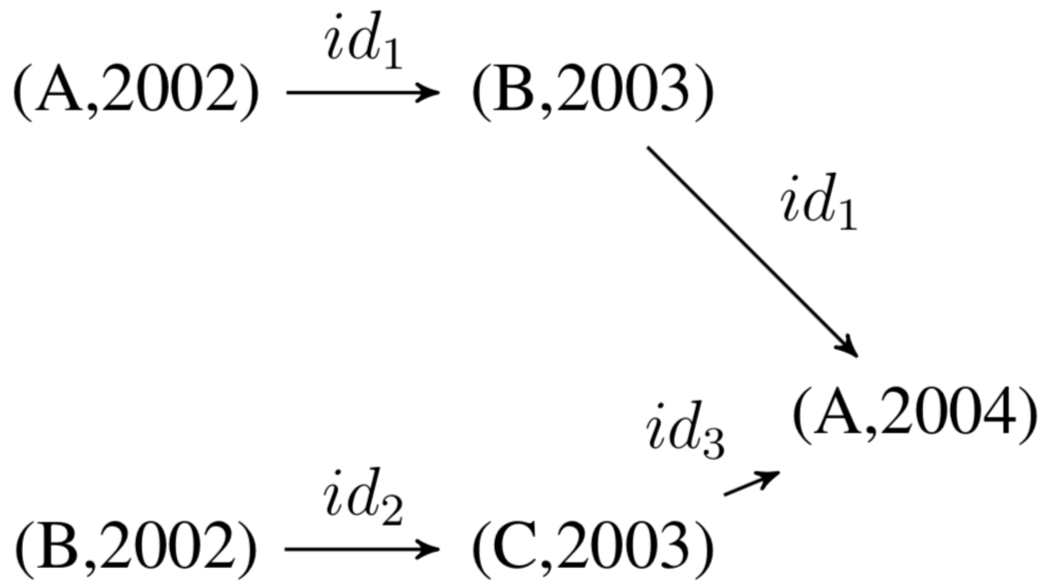
(c) Trends in Percentiles – Log Earnings



Note:

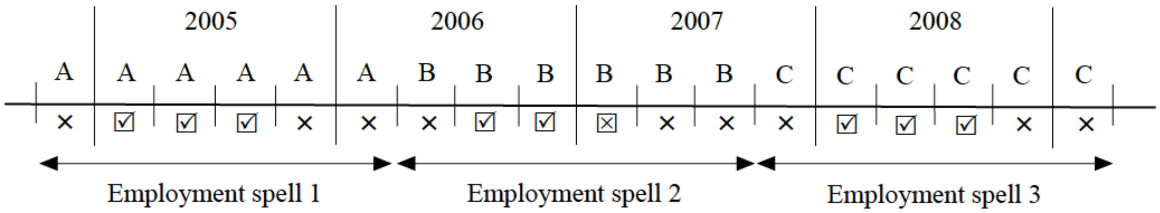
Panel (a) plots the unconditional variance of log earnings and log wages in the Washington administrative data. Panel (b) and Panel (c) plots the evolution of the log wages and log earnings percentiles, where each percentile has been deviated from the value of the same percentile in 2002.

Figure 2: Leave-One-Out Connected Set with Time-Varying Firm Heterogeneity



Note: The figure depicts a connected bipartite graph where vertices are given by firm-by-year combinations—e.g. firm A in year 2003—and edges are formed whenever a given worker (id_1, id_2, id_3) transition from one vertex to another. The above graph does not satisfy the condition of leave-one-out connected set as dropping one worker disconnects the graph. If one defines vertices as a single firm instead of a firm-by-year combination, the resulting graph would satisfy the condition of a leave-one-out connected set.

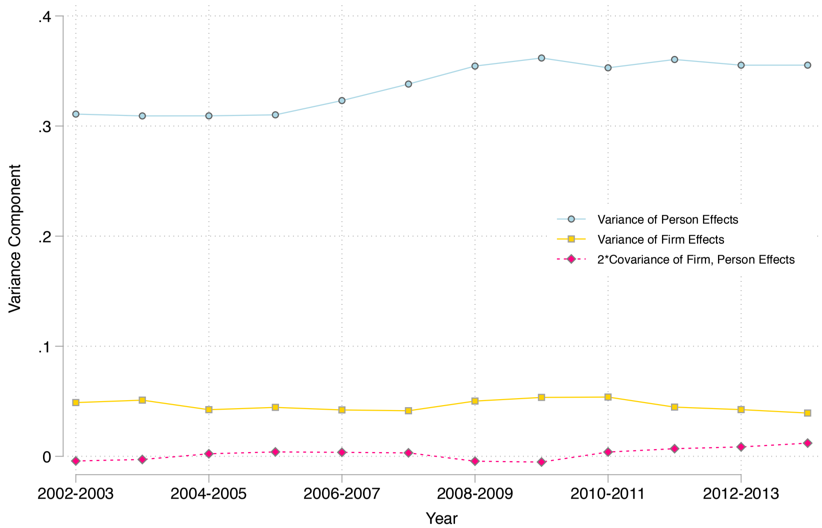
Figure 3: Construction of the Analysis Sample



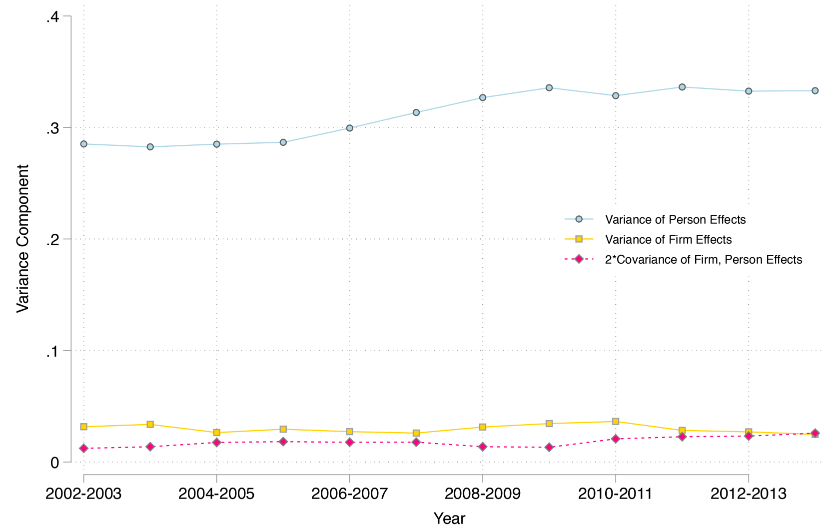
Notes: The figure shows three hypothetical employment spells with three different employers (A, B, and C), each of which has the minimum five quarters required to be included in the analysis sample. The first quarter and last two quarters of each employment spell (denoted by ×) are dropped from the analysis, and outcomes from the remaining quarters are then annualized for each calendar year, conditional on the calendar year including at least two consecutive quarters of earnings from the same primary employer. For example, outcomes for 2005 (Employment spell 1) and 2008 (Employment spell 3) are obtained by averaging the outcomes for the first, second, and third quarters of 2005 (or 2008) and multiplying by four. (The quarters used in the calculations are denoted by ☑.) Outcomes for 2007 (part of Employment spell 2) are excluded because 2007 does not include two consecutive quarters that can be used under the selection criteria (that is, after excluding the first quarter and last two quarters of each employment spell). As a result, the data from 2007:Q1 (denoted by ☒) are not used.

Figure 4: Rolling Variance Decomposition: Log Wages

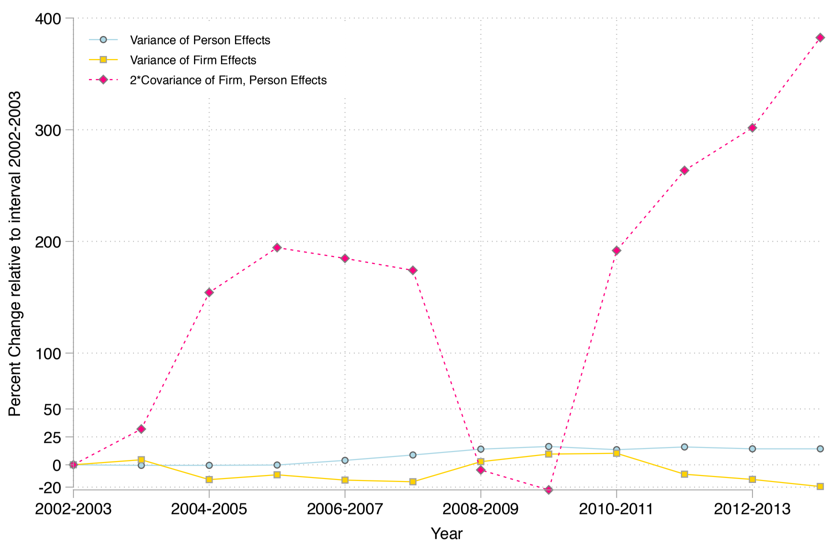
(a) Levels – Plug-In



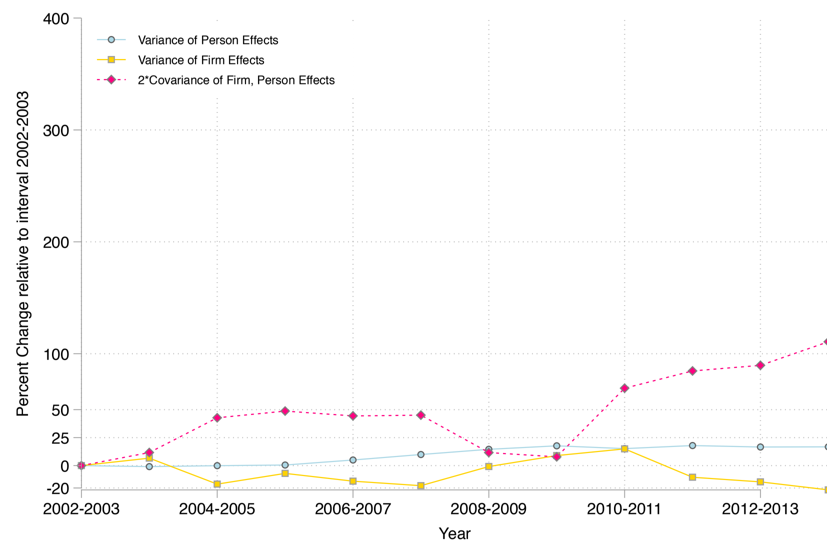
(b) Levels – KSS



(c) Changes – Plug-In



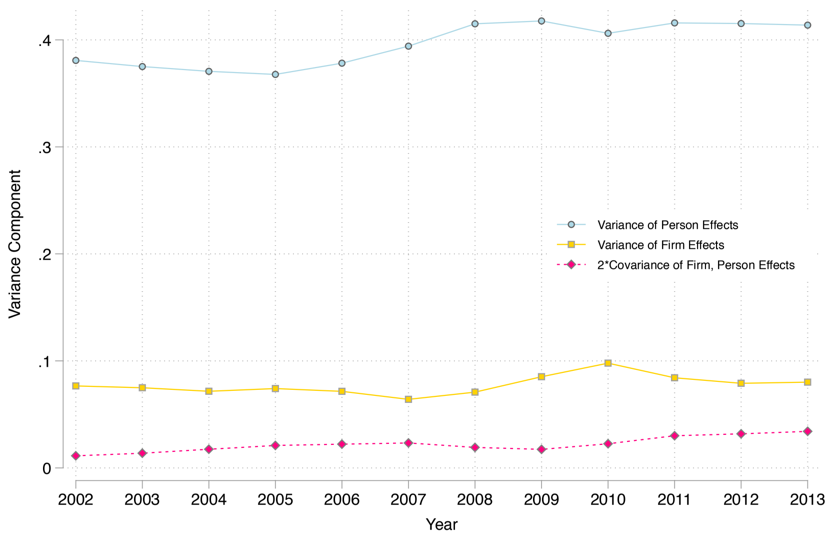
(d) Changes – KSS



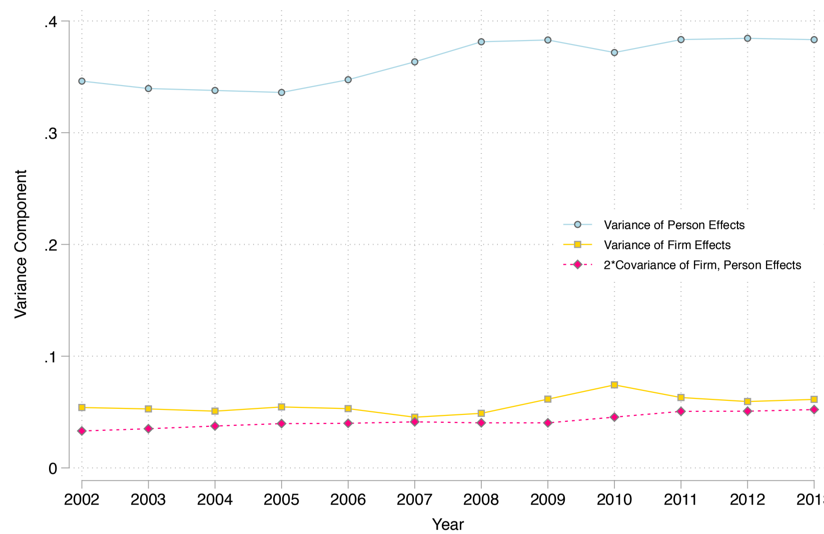
Note: Panel (a)-(b) reports the results obtained from a "rolling" variance decomposition of an AKM model. In particular, we fit AKM models separately for each $T = 2$ adjacent interval $(2002-2003, 2003-2004, \ldots, 2013-2014)$. Panel (a) reports variance decomposition estimates based on the plug-in approach, while Panel (c) reports estimates based on the leave-one-out approach of Kline, Saggio and Sølvsten (2019). Panel (b) and Panel (d) report the changes over time for a given variance component relative to its corresponding initial value estimated in the first interval, 2002-2003.

Figure 5: Rolling Variance Decomposition: Log Earnings

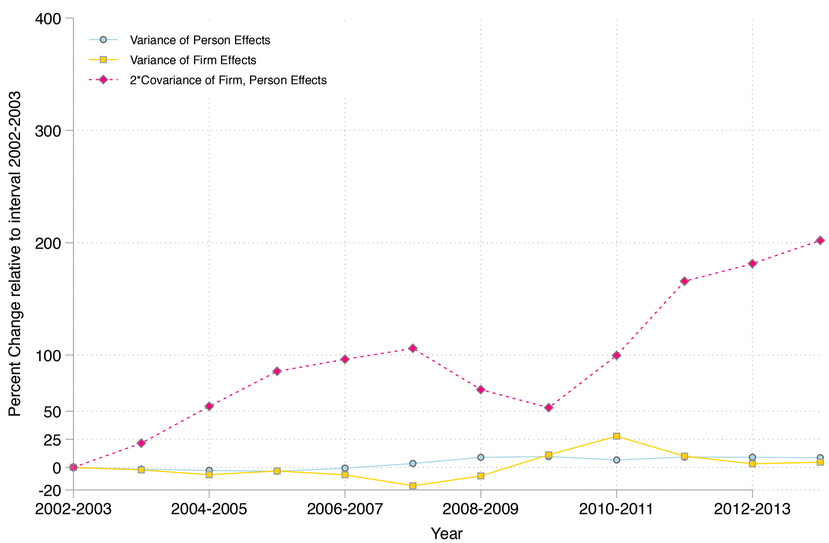
(a) Levels – Plug-In



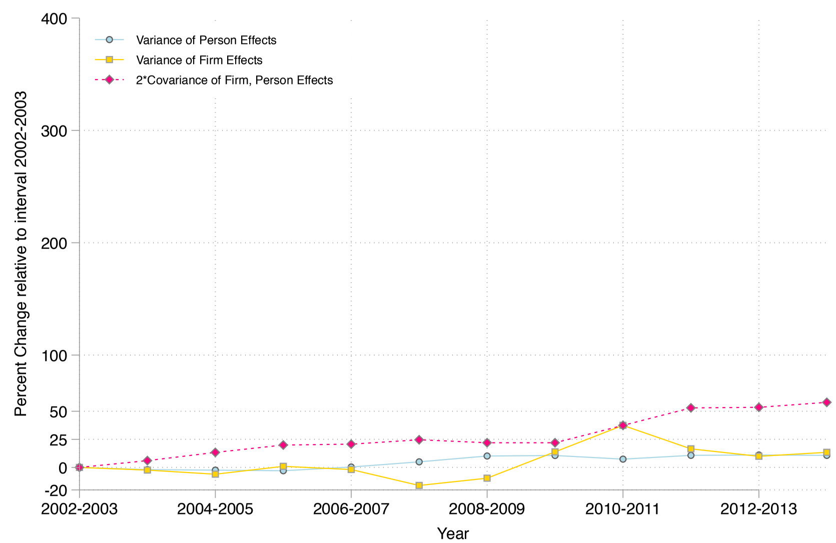
(b) Levels – KSS



(c) Changes – Plug-In



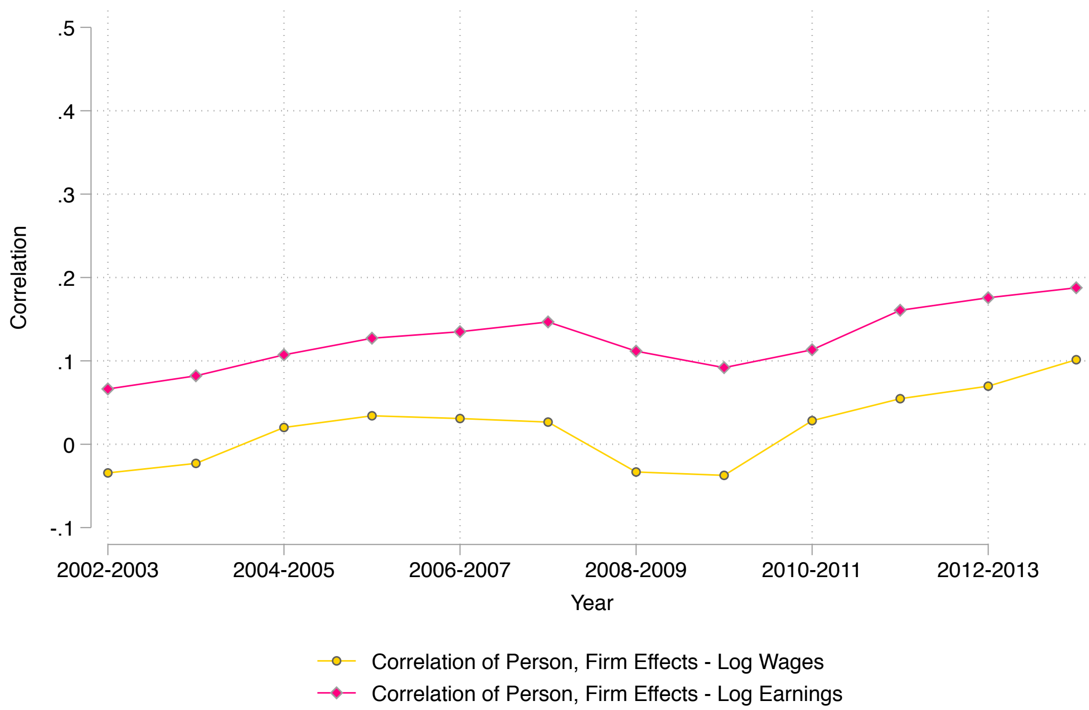
(d) Changes – KSS



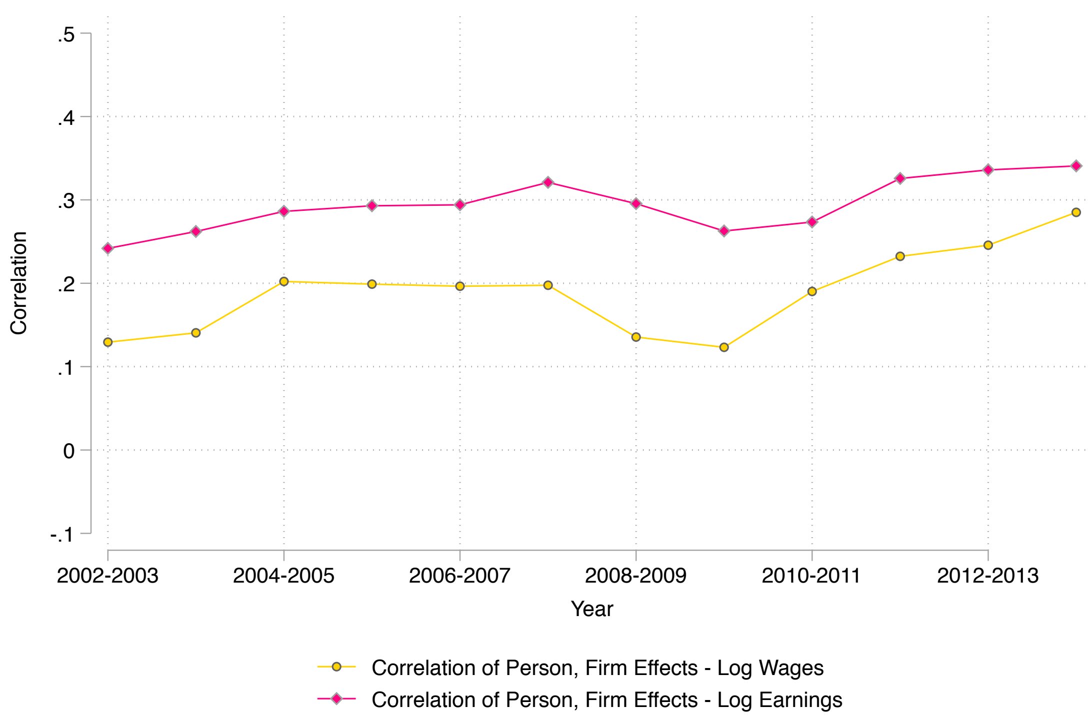
Note: Panel (a)-(b) reports the results obtained from a "rolling" variance decomposition of an AKM model. In particular, we fit AKM models separately for each $T = 2$ adjacent interval $(2002-2003, 2003-2004, \ldots, 2013-2014)$. Panel (a) reports variance decomposition estimates based on the plug-in approach, while Panel (c) reports estimates based on the leave-one-out approach of Kline, Saggio and Sølvsten (2019). Panel (b) and Panel (d) report the changes over time for a given variance component relative to its corresponding initial value estimated in the first interval, 2002-2003.

Figure 6: Sorting over Time

(a) AKM

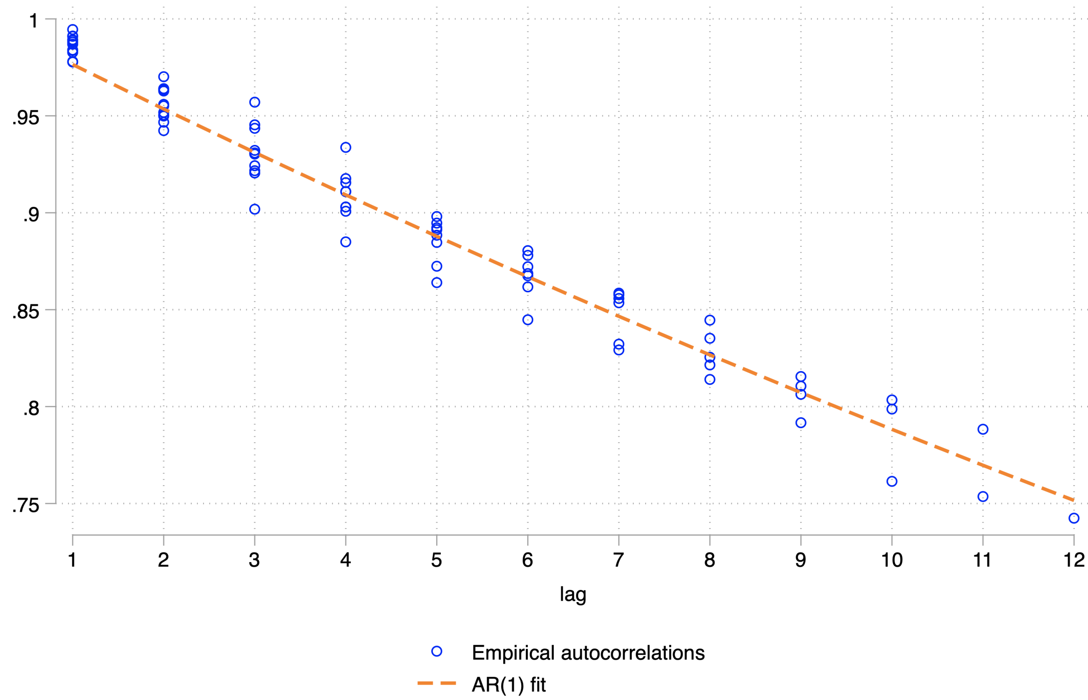


(b) KSS



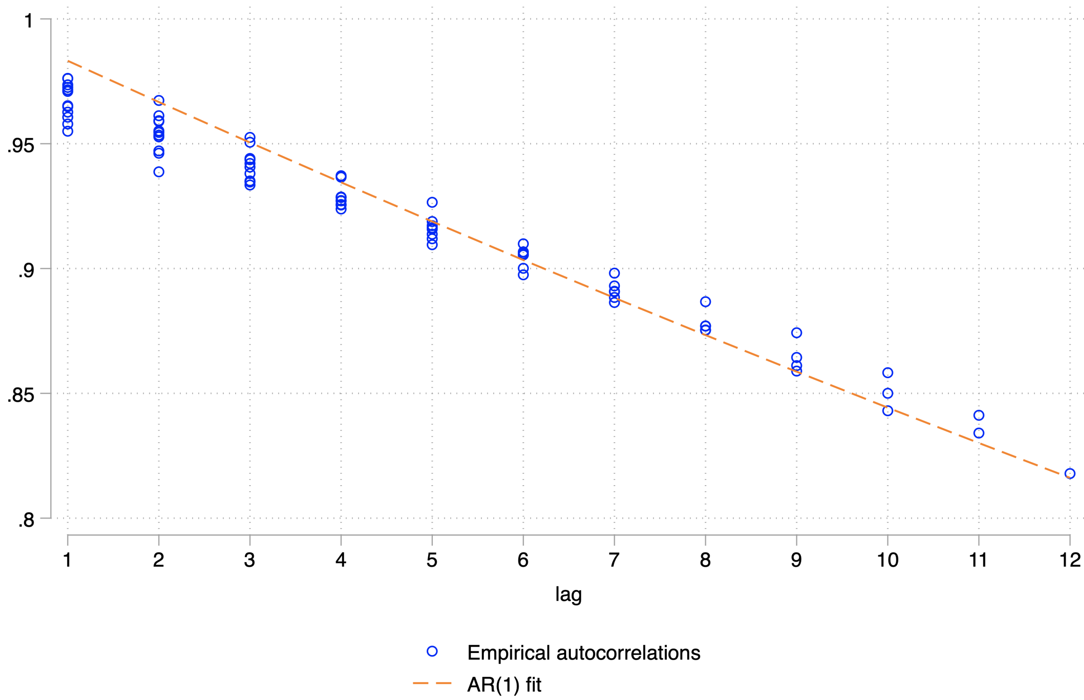
Note: Both panels display the estimated correlation between worker and firm effects. This correlation is obtained by fitting AKM models separately for each $T = 2$ adjacent interval $(2002-2003, 2003-2004, \ldots, 2013-2014)$. Panel (a) reports the estimated correlation obtained via the plug-in approach. Panel (b) reports the estimated correlation based on the leave-one-out approach of Kline, Saggio and Sølvsten (2019).

Figure 7: Autocorrelation of Firm Effects for Wages



Note: The figure plots the estimated autocorrelations in Table 5B (blue dots) and the autocorrelation function of the AR(1) process $\psi_{j,t} = 0.9765\psi_{j,t-1} + \zeta_{jt}$.

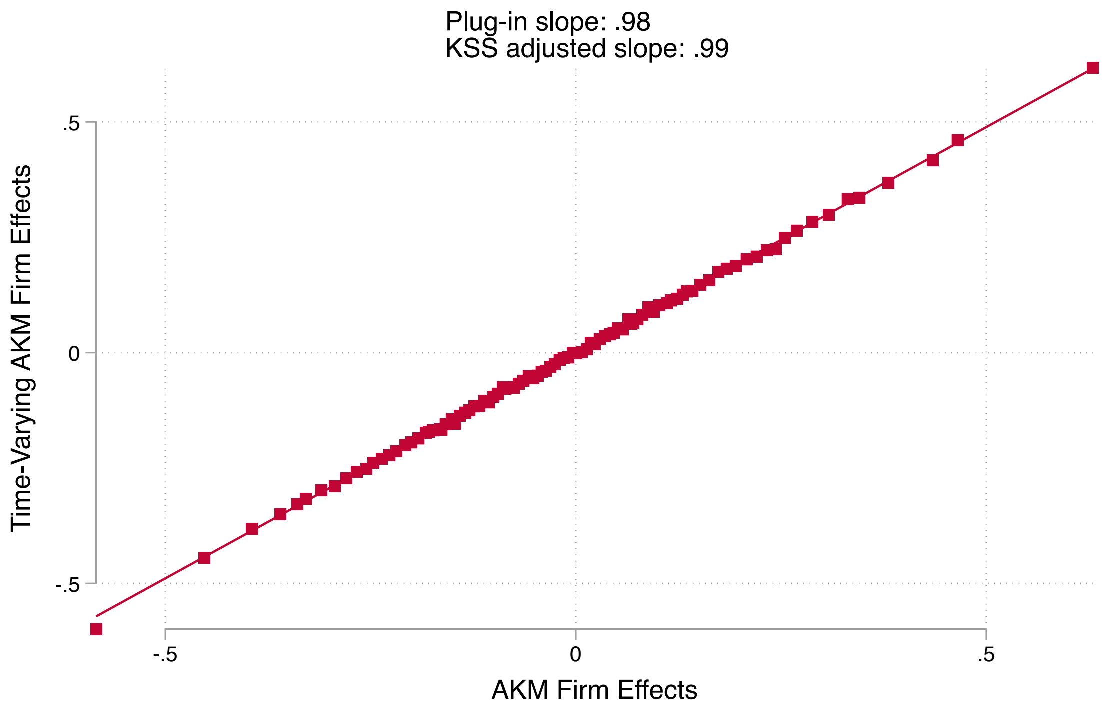
Figure 8: Autocorrelation of Firm Effects for Earnings



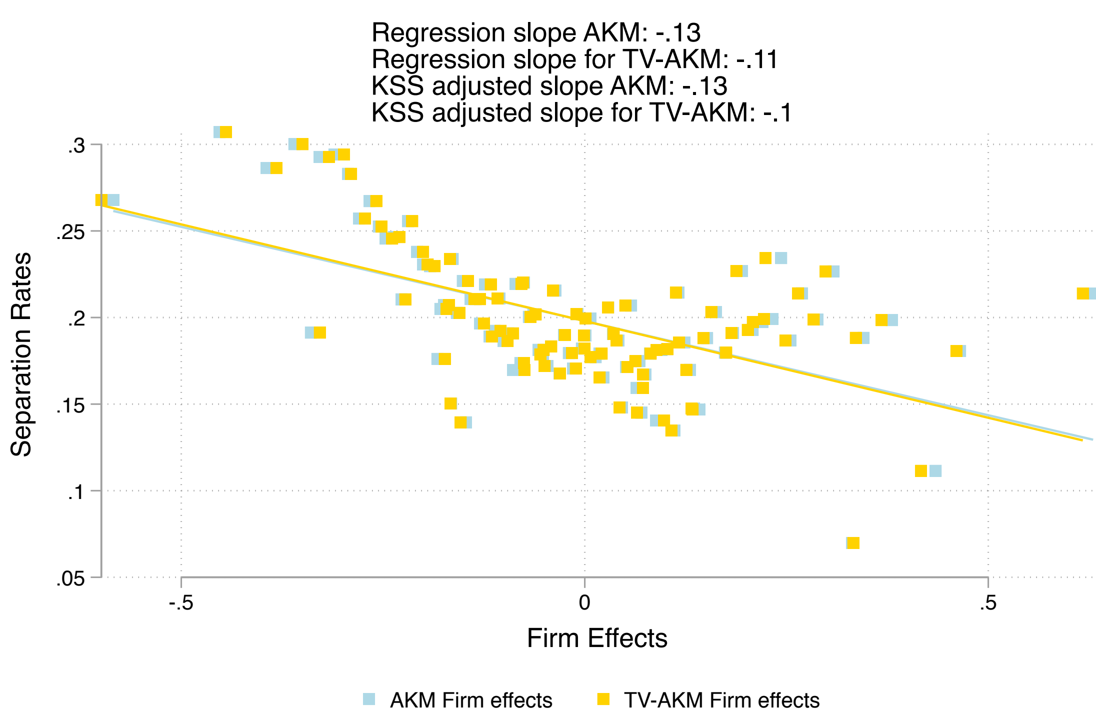
Note: The figure plots the estimated autocorrelations in Table 6B (blue dots) and the autocorrelation function of the AR(1) process $\psi_{j,t} = 0.9832\psi_{j,t-1} + \zeta_{jt}$.

Figure 9: Does Allowing for Time-Varying Firm Heterogeneity Actually Matter?

(a) TV-AKM vs. AKM



(b) KSS



Note: Panel (a) reports the worker-year averages of the AKM firm effects and the TV-AKM firm effects within each centile bin of the AKM effects, see the text for further details. Both set of effects are estimated in a pooled dataset which stacks together all available years from 2002 to 2014. In Panel (b) we report worker-year averages of separation rates within each centile bin of the AKM and TV-AKM effects.

Table 1: Summary Statistics

	Panel (a): AKM Model						*Panel (b): TV-AKM Model*	
	Interval: 2002-2003		*Interval: 2013-2014*		*Interval: 2002-2014*		*Interval: 2002-2014*	
	Largest Connected Set [1]	Leave-One-Out Connected Set [2]	Largest Connected Set [3]	Leave-One-Out Connected Set [4]	Largest Connected Set [5]	Leave-One-Out Connected Set [6]	Largest Connected Set [7]	Leave-One-Out Connected Set [8]
# of Worker-Year Obs	3,435,285	2,667,196	4,071,696	3,224,108	27,484,072	26,308,782	27,452,303	25,000,763
# of Movers	142,085	119,890	172,740	148,239	1,945,791	1,893,651	1,944,954	1,745,732
# of Firms	41,483	20,795	49,107	25,986	219,006	165,979	218,310	123,081
# of Firms by year							1,247,620	788,548
Mean Log Wages	3.03	3.09	3.06	3.12	3.02	3.03	3.02	3.04
Variance of Log Wages	0.38	0.36	0.44	0.43	0.41	0.41	0.41	0.41
Mean Log Earnings	10.50	10.59	10.54	10.63	10.48	10.50	10.48	10.52
Variance of Log Earnings	0.55	0.49	0.63	0.57	0.60	0.59	0.60	0.58

Note: This table reports the descriptive statistics on the different samples used in the analysis. Panel (a) summarizes the samples used when fitting standard AKM models where firm effects are not allowed to vary over time. Panel (b) describes samples used to fit an AKM model where firm effects are allowed to vary over time. The largest connected set in Panel (a) is defined as the largest sample where all the firms are connected to each other via workers' moves. The largest connected set in Panel (b) is defined as the largest sample where all the firm-by-year combinations are connected to each other by workers' moves. The leave-one-out connected set is largest sample where all firms (or all firms-by-year combinations, for Panel b) remain connected to each other even after one has dropped any one worker from the sample. A mover is defined in both Panel (a) and Panel (b) as an individual that switched employers within a given period. All statistics on wages and earnings are worker-year weighted. See the text for details.

Table 2: Variance Decomposition - Log Wages

	Interval 2002-2003		*Interval 2013-2014*		*Change from 2002-2003 to 2013-2014*	
	Variance Component	Share of Total (%)	Variance Component	Share of Total (%)	Variance Component	Share of Total (%)
Variance of Log Wages	0.3598	100.00%	0.4264	100.00%	0.0666	100.00%
Variance Decomposition: Plug-In						
Variance of Worker Effects	0.3109	86.40%	0.3553	83.33%	0.0444	66.73%
Variance of Firm Effects	0.0488	13.57%	0.0393	9.22%	-0.0095	-14.27%
2*Cov of Worker, Firm Effects	-0.0085	-2.36%	0.0240	5.62%	0.0324	48.69%
Variance Decomposition: KSS						
Variance of Worker Effects	0.2852	79.28%	0.3330	78.10%	0.0478	71.73%
Variance of Firm Effects	0.0316	*8.79%*	0.0248	*5.81%*	-0.0069	*-10.32%*
2*Cov of Worker, Firm Effects	0.0246	6.83%	0.0518	12.14%	0.0272	40.84%

Note: All variance decomposition parameters are calculated in the corresponding leave-one-out connected set described in Table 1, Panel (a) and are worker-year weighted. Plug-in reports the variance components without adjusting for sampling error in the estimated worker and firm effects. KSS adjusts each variance component using the leave-one-out approach detailed by Kline, Saggio, and Sølvsten (2019). The residual share of total variance is not reported. The last two columns report the change in a corresponding row over time. That change is then scaled by the change in the variance of log wages reported in first row. Source: WA administrative records.

Table 3: Variance Decomposition - Log Earnings

	Interval 2002-2003		*Interval 2013-2014*		*Change from 2002-2003 to 2013-2014*	
	Variance Component	Share of Total (%)	Variance Component	Share of Total (%)	Variance Component	Share of Total (%)
Variance of Log Earnings	0.4921	100.00%	0.5738	100.00%	0.0817	100.00%
Variance Decomposition: Plug-In						
Variance of Worker Effects	0.3808	77.38%	0.4138	72.11%	0.0330	40.36%
Variance of Firm Effects	0.0766	15.56%	0.0801	13.96%	0.0035	4.33%
2*Cov of Worker, Firm Effects	0.0226	4.59%	0.0684	11.92%	0.0458	56.03%
Variance Decomposition: KSS						
Variance of Worker Effects	0.3462	70.35%	0.3833	66.79%	0.0371	45.40%
Variance of Firm Effects	0.0541	*10.98%*	0.0613	*10.69%*	0.0073	*8.89%*
2*Cov of Worker, Firm Effects	0.0662	13.45%	0.1045	18.20%	0.0383	46.81%

Note: All variance decomposition parameters are calculated in the corresponding leave-one-out connected set described in Table 1, Panel (a) and are worker-year weighted. Plug-in reports the variance components without adjusting for sampling error in the estimated worker and firm effects. KSS adjusts each variance component using the leave-one-out approach detailed by Kline, Saggio, and Sølvsten (2019). The residual share of total variance is not reported. The last two columns report the change in a corresponding row over time. That change is then scaled by the change in the variance of log earnings reported in first row. Source: WA administrative records.

Table 4: Variance Decomposition - Pooled Data 2002-2014

	Log Wages				***Log Earnings***			
	AKM		*TV-AKM*		*AKM*		*TV-AKM*	
	Variance Component	Share of Total (%)	Variance Component	Share of Total (%)	Variance Component	Share of Total (%)	Variance Component	Share of Total (%)
Variance of Log Wages	0.4074	100.00%	0.4074	100.00%	0.5821	100.00%	0.5821	100.00%
Variance Decomposition: Plug-In								
Variance of Worker Effects	0.2567	63.01%	0.2596	63.72%	0.3136	53.86%	0.3190	54.80%
Variance of Firm Effects	0.0480	11.77%	0.0570	13.99%	0.1111	19.09%	0.1190	20.44%
2*Cov of Worker, Firm Effects	0.0679	16.67%	0.0591	14.51%	0.1014	17.42%	0.0920	15.81%
Variance Decomposition: KSS								
Variance of Worker Effects	0.2502	61.40%	0.2534	62.20%	0.3071	52.75%	0.3131	53.79%
Variance of Firm Effects	0.0473	11.60%	0.0549	13.47%	0.1147	19.70%	0.1209	20.76%
2*Cov of Worker, Firm Effects	0.0687	16.87%	0.0604	14.81%	0.0944	16.21%	0.0845	14.52%

Note: All variance decomposition parameters are calculated in the corresponding leave-one-out connected set described in Table 1, Panel (b) and are worker-year weighted. TV-AKM corresponds to an AKM model where firm effects are allowed to vary over time. The AKM model includes a set of year fixed effects. Plug-in reports the variance components without adjusting for sampling error in the estimated worker and firm effects. The residual share of total variance is not reported. KSS adjusts each variance component using the leave-one-out approach detailed by Kline, Saggio, and Sølvsten (2019) by leaving a worker-year observation out. Source: WA administrative records.

Table 5A: Autocovariance of Firm Effects - Log Wages

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
2002	0.0446	0.0427	0.0399	0.0377	0.0380	0.0369	0.0370	0.0361	0.0363	0.0367	0.0365	0.0364	0.0378
2003		0.0428	0.0412	0.0388	0.0389	0.0378	0.0380	0.0372	0.0374	0.0380	0.0379	0.0378	0.0394
2004			0.0403	0.0393	0.0390	0.0378	0.0380	0.0369	0.0372	0.0379	0.0376	0.0374	0.0389
2005				0.0393	0.0401	0.0386	0.0388	0.0375	0.0374	0.0378	0.0375	0.0372	0.0387
2006					0.0414	0.0407	0.0407	0.0391	0.0394	0.0400	0.0398	0.0397	0.0414
2007						0.0409	0.0415	0.0396	0.0394	0.0401	0.0401	0.0401	0.0418
2008							0.0431	0.0421	0.0417	0.0425	0.0425	0.0422	0.0441
2009								0.0426	0.0426	0.0432	0.0431	0.0430	0.0447
2010									0.0447	0.0459	0.0458	0.0457	0.0476
2011										0.0483	0.0491	0.0488	0.0507
2012											0.0516	0.0511	0.0528
2013												0.0523	0.0547
2014													0.0582

Table 5B: Autocorrelation of Firm Effects - Log Wages

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
2002	1.00	0.98	0.94	0.90	0.88	0.86	0.84	0.83	0.81	0.79	0.76	0.75	0.74
2003		1.00	0.99	0.95	0.92	0.90	0.88	0.87	0.86	0.84	0.81	0.80	0.79
2004			1.00	0.99	0.96	0.93	0.91	0.89	0.88	0.86	0.83	0.82	0.80
2005				1.00	0.99	0.96	0.94	0.92	0.89	0.87	0.83	0.82	0.81
2006					1.00	0.99	0.96	0.93	0.92	0.89	0.86	0.85	0.84
2007						1.00	0.99	0.95	0.92	0.90	0.87	0.87	0.86
2008							1.00	0.98	0.95	0.93	0.90	0.89	0.88
2009								1.00	0.98	0.95	0.92	0.91	0.90
2010									1.00	0.99	0.96	0.95	0.93
2011										1.00	0.98	0.97	0.96
2012											1.00	0.98	0.96
2013												1.00	0.99
2014													1.00

Note: This table computes the autocovariance and autocorrelation function of the firm effects for log wages, correcting using the leave-one-out approach of Kline, Saggio, and Sølvsten (2019). All autocovariance and autocorrelation parameters reported are computed for the sample of firms that are present in each year from 2002–2014 and are weighted using the average number of workers associated with a given firm from 2002 to 2014.

Table 6A: Autocovariance of Firm Effects - Log Earnings

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
2002	0.1101	0.1031	0.0972	0.0971	0.0979	0.0963	0.0953	0.0949	0.0945	0.0973	0.0965	0.0949	0.0958
2003		0.1059	0.0975	0.0973	0.0979	0.0964	0.0955	0.0953	0.0951	0.0979	0.0973	0.0957	0.0966
2004			0.0973	0.0950	0.0955	0.0938	0.0926	0.0920	0.0919	0.0945	0.0935	0.0921	0.0928
2005				0.0980	0.0974	0.0958	0.0945	0.0935	0.0933	0.0962	0.0953	0.0939	0.0949
2006					0.1016	0.0985	0.0969	0.0959	0.0962	0.0994	0.0987	0.0973	0.0987
2007						0.1001	0.0976	0.0964	0.0961	0.0994	0.0989	0.0976	0.0990
2008							0.1004	0.0982	0.0976	0.1009	0.1004	0.0991	0.1004
2009								0.1036	0.1010	0.1041	0.1035	0.1019	0.1034
2010									0.1059	0.1073	0.1067	0.1051	0.1067
2011										0.1152	0.1127	0.1110	0.1131
2012											0.1169	0.1131	0.1151
2013												0.1175	0.1159
2014													0.1247

Table 6B: Autocorrelation of Firm Effects - Log Earnings

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
2002	1.00	0.96	0.94	0.93	0.93	0.92	0.91	0.89	0.88	0.86	0.85	0.83	0.82
2003		1.00	0.96	0.96	0.94	0.94	0.93	0.91	0.90	0.89	0.87	0.86	0.84
2004			1.00	0.97	0.96	0.95	0.94	0.92	0.91	0.89	0.88	0.86	0.84
2005				1.00	0.98	0.97	0.95	0.93	0.92	0.91	0.89	0.88	0.86
2006					1.00	0.98	0.96	0.94	0.93	0.92	0.91	0.89	0.88
2007						1.00	0.97	0.95	0.93	0.93	0.91	0.90	0.89
2008							1.00	0.96	0.95	0.94	0.93	0.91	0.90
2009								1.00	0.96	0.95	0.94	0.92	0.91
2010									1.00	0.97	0.96	0.94	0.93
2011										1.00	0.97	0.95	0.94
2012											1.00	0.97	0.95
2013												1.00	0.96
2014													1.00

Note: This table computes the autocovariance and autocorrelation function of the firm effects for log wages, correcting using the leave out approach of Kline, Saggio, and Sølvsten (2019). All autocovariance and autocorrelation parameters reported are computed for the sample of firms that are present in each year from 2002-2014 and are weighted using the average number of workers associated with a given firm from 2002 to 2014.

Table A1: Comparing Leave Out Strategies

	Log Wages				***Log Earnings***			
	AKM		*TV-AKM*		*AKM*		*TV-AKM*	
	Variance Component	Share of Total (%)	Variance Component	Share of Total (%)	Variance Component	Share of Total (%)	Variance Component	Share of Total (%)
Variance of Log Wages	0.3850	100.00%	0.3850	100.00%	0.5520	100.00%	0.5520	100.00%
KSS-Leave Person-Year out								
Variance of Firm Effects	0.0468	12.16%	0.0548	14.23%	0.1101	19.95%	0.1183	21.43%
2*Cov of Worker, Firm Effects	0.0680	17.67%	0.0599	15.56%	0.0974	17.65%	0.0885	16.04%
KSS-Leave Match out								
Variance of Firm Effects	0.0445	11.55%	0.0578	15.02%	0.1067	19.33%	0.1177	21.33%
2*Cov of Worker, Firm Effects	0.0697	18.11%	0.0589	15.31%	0.0983	17.81%	0.1267	22.96%

Note: All variance components are calculated for the sample of movers belonging to the leave-one-out connected set of the TV-AKM model and are worker-year weighted.TV-AKM corresponds to an AKM model where firm effects are allowed to vary over time. The AKM model includes a set of year fixed effects. Plug-in reports the variance components without adjusting for sampling error in the estimated worker and firm effects. The residual share of total variance is not reported. KSS adjusts each variance component using the leave-one-out approach detailed by Kline, Saggio, and Sølvsten (2019) by leaving a worker-year observation out. Source: WA administrative records.

A Data Appendix

This appendix first describes the data used in the estimation of firm effects for earnings and hourly wages used in the main text. It then describes the sample restrictions imposed on the estimation sample. Finally, we highlight some considerations specific to working with single-state administrative wage records.

A.1 Further Description of the Data

The data used in this paper are based on quarterly administrative wage records maintained by the Employment Security Department of Washington State to administer the state's unemployment insurance (UI) system. The available quarterly data provide information on earnings and work hours of all workers employed by UI-covered employers in the state between 2002–2014. Workers who drop out of the labor force, become self-employed, work in the underground economy, or move out of state will not appear in the records. This is because self-employed workers are not covered by UI, underground earnings are not reported, and out-of-state earnings will be picked up in the earnings records of another state; see also the discussion below.

UI-covered employers in Washington are required to report each worker's quarterly earnings and work hours, which allows us to construct an hourly wage rate in each quarter for most workers in Washington's formal labor market. Lachowska, Mas and Woodbury (2018) examine the reliability of the Washington hours data and conclude they are of high quality. Each worker's quarterly record also includes an employer identifier and the employer's four-digit North American Industry Classification System (NAICS) code, making it possible to construct employment at both the employer and industry level; see also Lachowska, Mas and Woodbury (2019) for further discussion of Washington administrative wage records.

A.2 Sample Restrictions

As in Lachowska, Mas and Woodbury (2019), we impose several restrictions on the estimation sample, dropping the following:

- Workers with more than 9 employers in a year
- Workers with annual earnings less than \$2,850 (in 2005 dollars) and workers with calculated hourly wage rates $\leq$\$2.00/hour (in 2005 dollars) (following Card, Heining and Kline 2013; Sorkin 2018)
- Workers who worked fewer than 400 hours in the year
- Employer-year observations with fewer than 5 employees in the year (following Song, Price, Guvenen, Bloom and von Wachter, 2015)

A.3 Additional Considerations

First, although we use the terms "employer" and "firm" interchangeably, they are not always the same. The employer is the entity from which UI payroll taxes are collected and is the unit of observation in the wage records. For firms with a single establishment, and for firms with multiple establishments all located in Washington, the employer is also the firm. (In some cases, a multi-establishment firm may be divided into more than one employer.) For firms with multiple establishments some of which are located outside Washington, the employer covers only the firms' establishments located in Washington.

Second, an employer identification (ID) number may disappear if the employer becomes inactive or reorganizes in some way—through merger, acquisition, spinoff, breakout, or other reason. The available data do not include an employer "successor file," so we cannot distinguish among these cases with certainty,[8] but like Card, Heining and Kline (2013), we take the view that a new employer ID likely implies reorganization and new employment policies, so it makes sense to treat an employer ID change as the creation of a new entity and to estimate a separate (new) employer fixed effect. As Card, Heining, and Kline (2013) point out, treating assignment of a new ID to an existing employer leads to a loss of efficiency but no bias.

[8]Using information on worker flows, Benedetto et al. (2007) develop probabilistic approach to identifying employers that have undergone an employer identification number change due to merger, acquisition, spin off, or breakout.

Third, we cannot follow workers who move out of Washington. To examine how such attrition might influence the estimated AKM employer fixed effects, Lachowska, Mas and Woodbury (2019) reestimate the AKM model after dropping random subsamples of 30 percent and 50 percent of employers from the full AKM sample described above. The resulting firm effects are highly correlated with those obtained in the full AKM analysis, suggesting that interstate migration is not a substantial source of bias in estimating the AKM fixed effects.