Do firm effects drift? Evidence from Washington Administrative Data

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Abstract

We investigate the time-series properties of firm effects in the AKM models popularized by Abowd et al. (1999). We consider two approaches. The first approach — labelled as the rolling approach — estimates AKM models separately in each \( T = 2 \) adjacent time interval. The second approach is based on an extension of the original AKM — labelled as the Time Varying AKM Model (TV-AKM) — in which we allow for unrestricted interactions of year and firm dummies. We correct for biases in the resulting variance decompositions using the leave out correction of Kline et al. (2019). These approaches allow us to examine how firm effects evolve stochastically, their relation to the business cycle, and their contribution to changes in the wage structure at a higher frequency than previously possible. Using data from Washington State, we find that firm effects in earnings and hourly wages are highly persistent. The autocorrelation coefficient between firm effects for wage rates in 2002 and 2014 is 0.74, and between firm effects for earnings in 2002 and 2014 is 0.82. The rolling approach uncovers a significant degree of cyclical in firm effects. Variability in firm premiums tended to increase during the great recession while the degree of worker and firm assortativity decreased. Time-varying firm effects explains 13% of the variance of log wages and 21% of the variance of log earnings in the Washington state over 2002–2014. Between 2002-2003 and 2013-2014 the variance of firm wage premia decreased by 10%, but this decline was offset by increases in the variance in individual premia and increases in assortative matching that resulted in an overall increase in the variance of wages. Auxiliary evidence suggests that misspecification in AKM models due to the drifting of firm effects is a second-order concern.

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1 Introduction

The variance decomposition method pioneered 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 and firms, it has produced an abundance of insights on labor market inequality (Card, Heining, and Kline, 2013; Song, Price, Guvenen, Bloom, and Von Wachter, 2018), 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 (Lachowska, Mas, and Woodbury, 2019; Schmieder, von Wachter, and Bender, 2018).

The standard application of the AKM model imposes the assumption that firm effects — the contribution of a given employer or firm to workers’ earnings —are time-invariant. This assumption allows analysts to pool multiple years of data to estimate the model parameters. Pooling is helpful since 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 fixed effects, as originally noted by Krueger and Summers (1988) and Abowd et al. (2004). This bias can be particularly pronounced when there are fewer worker transitions (Andrews, Gill, Schank, and Upward, 2008). This is why researchers try to alleviate these concerns by pooling multiple years of data as this mechanically increases the number of observed workers’ moves.

This assumption of time invariance may not be benign, however, if employer pay policies change over time. The literature on rent sharing gives reason to believe that firm premia are changing over time. For example, Van Reenen (1996) and Kline et al. (2019) document that worker compensation is related to time-varying patent activity, and a large 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). Moreover, a time ho-
mogeneity assumption on the firm premia may ultimately understate the true variability of these effects when pooling different time intervals.

In this paper we examine the stability of firm effects and the role of time-varying effects in decompositions of changes in the variance of wages. We circumvent the sampling error problem by using the “leave-one-out” correction proposed by Kline et al. (2019) — KSS henceforth — to estimate firm effects. We consider two approaches. The first approach — labelled as the rolling approach — estimates AKM models separately in each $T = 2$ adjacent time interval. The second approach is based on an extension the original AKM — labelled as the Time Varying AKM Model (TV-AKM) — in which we allow for unrestricted interactions of year and firm dummies. We apply these estimators to data from Washington State during 2002–2014. Washington is a good choice for this exercise both because Washington administrative wage records are available over a full business cycle, and because those data make it possible to observe hourly wage rates as well as quarterly earnings, which is unusual in administrative data.

Our examination of the stability of firm effects suggests that, although employer wage and earnings policies exhibit some degree of “drift” over time, both show a degree of stability that is perhaps surprising. For example, in a balanced panel of firms observed in every year during 2002–2014, the autocorrelation coefficient between firm effects for wage rates in 2002 and 2014 is 0.74, and between firm effects for earnings in 2002 and 2014 is 0.82. Firm effects for both earnings and hourly wages are well-approximated by a highly persistent AR(1) models that are close to unit root. The stability of firm effects is evidence that a component of firm premia represent permanent compensation policies, as could arise from rent sharing or efficiency wages, in addition to those arising from idiosyncratic demand or productivity shocks. Overall, we find that KSS adjusted time-varying firm effects explains 13% of the variance of log wages and 21% of the variance of log earnings in the Washington state over 2002–2014. These estimated variance components are really similar to the ones that one would obtain via a standard AKM model that imposes a time-homogeneity assumption (12% for log wages and 20% for log earnings).
We also find that the variance of firm effects in the balanced subsample of firms is nonstationary, with the variances of firm effects for both wage rates and earnings falling in the years leading up to the Great Recession (2002–2007), then increasing rather dramatically after 2009. This counter-cyclical pattern of the dispersion of firm premia has not been documented before, to our knowledge. Over this period assortative matching of workers and firms increased before the Great Recession, fell during the recession, then reached new highs in the post-recession period. Although we would not suggest these patterns extend to other states and other business cycles, they may offer a reference point for future work.

We also examine how the dispersion of firm and individual effects and assortative matching contributed to the trend of rising inequality over the 2002-2014 period. Overall, we find that the variances of real log hourly wages and log earnings in Washington significantly increase from 2002 to 2014. The variance decompositions obtained from both the AKM plug-in method and the KSS bias-corrected estimator suggest that the increases in wage and earnings inequality just described are attributable almost entirely to increases in the variation of worker-specific effects and to increased sorting of workers and firms. Less than 10% of the increases can be attributed to firm-specific wage and earnings policies.

Finally, we provide auxiliary evidence on the degree of misspecification that one may incur when forcing firm wage effects to be time-invariant. We start by project TV-AKM firm wage effects onto firm wage effects obtained from the traditional AKM model. The slope obtained out of this projection is equal to 1 and the associated scatter plot is highly concentrated around the 45 degree line. A person-year regression of separation rates onto AKM wage effects returns virtually the same slope and overall non-parametric relationship that one would obtain when regressing quit rates onto TV-AKM firm wage effects. We conclude that the degree of misspecification derived from imposing the assumption of time invariance of firm effects is likely to be a second order concern in most applications.

The paper is organized as follows. Section 2 describes the econometric framework, reviewing
both the KSS estimator and the method of estimating variation over time in firm fixed 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 approach. Section 4 describes the empirical findings. We compare the AKM and KSS variance decompositions for 2002–2003 and 2013–2014, examine the implications of these decompositions for the growth of wage and earnings inequality that occurred between 2002–2003 and 2013–2014, and discuss the auto-covariance structure of firm fixed effects. Section 5 summarizes the findings and offers some concluding observations.

2 Econometric Framework

Our baseline econometric specification is the two-way fixed effects model popularized by AKM. Under this model, the log earnings or log hourly wage of individual $g$ at time $t$, $\log y_{gt}$, is decomposed into the sum of a worker component, $\alpha_g$, a firm component, $\psi_j$, and an error component $\varepsilon_{gt}$:

$$y_{gt} = \alpha_g + \psi_j(g,t) + \varepsilon_{gt}. \quad (1)$$

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), $\alpha_g$ 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 $\psi_j$ represents a firm-specific relative pay premium that is paid equally by firm $j$ to all its employees. Finally, $\varepsilon_{gt}$ represents an unobserved, time-varying, error term 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 the AKM model in equation (1), the variance of, say, log wages can be decomposed as

$$\text{var}(y_{gt}) = \text{var}(\alpha_g) + \text{var}(\psi_j(g,t)) + 2\text{cov}(\psi_j(g,t), \alpha_g) + \text{var}(\varepsilon_{gt}). \quad (2)$$
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 to what extent individuals 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 on computation methods has allowed economists to provide new evidence on the contribution of firms and worker-firm assortativity to wage inequality—e.g., Card, Heining, and Kline (2013) for Germany; Song, Price, Guvenen, Bloom, and Von Wachter (2018) 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 estimated using OLS estimates of \((\alpha, \psi)\) from equation (1). However, as initially pointed out by Krueger and Summers (1988) and Abowd et al. (2004), sampling error in \((\hat{\alpha}, \hat{\psi})\) will impart bias the estimated variance components, a phenomenon often referred to as the “limited mobility bias.” Specifically, biases in the resulting estimated variance components can be particularly severe when the number of individuals transitioning between different employers is relatively low compared to the overall dimensionality of the model (Andrews, Gill, Schank, and Upward, 2008; Kline, Saggio, and Solvsten, 2019).

Second, the original AKM model assumes the firm-specific effect \(\psi_{j(g,t)}\) to be time-invariant. This assumption might be problematic in contexts where, to try alleviate concerns induced by the limited mobility bias, researchers estimate the original AKM model on a very long time horizon of 10 or more years (Goldschmidt and Schmieder, 2017; Bana, Bedard, Rossin-Slater, and Stearns, 2018). It is unclear why firm wage or earnings policies should remain fixed over such longer 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. This, in turn, can potentially magnify issues due to the limited mobility bias.

Based on the above, the rest of this section is organized as follows. We first describe a method
for correcting the biases in the estimated variance components of the AKM model. Next, we dis-
cuss how to allow for time-varying firm heterogeneity. We discuss advantages and disadvantages
of estimating AKM models separately within each $T = 2$ interval. Next, we introduce a simple
extension of the AKM model: the Time Varying AKM Model (TV-AKM). In the TV-AKM model
firm effects are allowed to vary across time and can be estimated in a dataset that pools across all
available time intervals.

2.1 Correcting for Bias: The Leave-Out-Correction

It is useful to rewrite model (1) as follows

$$y_i = d_i'\alpha + f_i'\psi + \varepsilon_i = x_i'\beta + \varepsilon_i$$  \hspace{1cm} (3)

where $i$ indexes a particular person 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 $\beta$.
For instance, the variance of firm effects is given by

$$\text{var}(\psi_j(g,t)) = \beta' A \beta$$  \hspace{1cm} (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

$$\underline{\text{var}}(\psi_j(g,t)) = \hat{\beta}' A \hat{\beta}$$  \hspace{1cm} (5)

where $\hat{\beta}$ is the usual OLS estimate of $\beta$:

$$\hat{\beta} = S_{xx}^{-1} \sum_{i=1}^{n} x_i' y_i,$$

where $S_{xx} = \sum_{i=1}^{n} x_i x_i'$.

\(^1\)As noted by AKM, estimation of equation (3) requires one normalization of the vector $\psi$ 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.
Kline, Saggio, and Solvsten (2019) showed formally that variance decompositions based on the plug-in approach are finite sample biased and inconsistent. To show this simple but important result, we start by assuming that the unobserved error terms \( \{ \varepsilon_i \} \) are mutually independent with heteroskedastic variances \( \sigma_i^2 \). Then, the expectation of the plug-in estimator of the variance of firm effects is given by

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

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 individuals 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 Solvsten (2019) propose a solution based on a leave-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 with unrestricted patterns of heteroskedasticity.

The methodology of Kline, Saggio, and Solvsten (2019) (KSS-henceforth) is based on introducing “cross-fit” estimates of \( \sigma_i^2 \), that is

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

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

$$\widetilde{\text{var}}(\widetilde{\psi}_j(g,t)) = \text{var}(\widetilde{\psi}_j(g,t)) - \sum_{i=1}^{n} B_{ii} \hat{\sigma}_i^2$$

(8)

**Remark 1: Leave-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 — $\max(T_g) = 2$— Kline, Saggio, and Solvsten (2019) 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 $\varepsilon_{g2}$ and $\varepsilon_{g1}$ 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 Kline, Saggio, and Solvsten (2019). 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 $S_{xx}^{-1} Z = X'$, where $X$ stacks the different $x_i$ in (3). This is computationally infeasible with the Washington data, which involves millions of worker plus firm effects. We therefore rely on

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\(^2\)We define a mover as a worker who moved between different firms at least once during the observed sample period.

\(^3\)Notice that when leaving a match out the person effects of “stayers”, i.e. individuals that stayed always with the same firm, will not be identified.
a variation of the Johnson-Lindestrauss approximation developed by KSS. In particular, we consider solutions of $p$ systems of $k$ linear equations, $Z_{JLA}^{k \times n} = R_{p \times p} X'$, where $R_{p \times p}$ 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.

2.2 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 longer and longer panels of administrative data. Fitting AKM models to these longer panels is sometimes viewed as a way to minimize concerns induced by the limited mobility bias (Goldschmidt and Schmieder, 2017; Bana, Bedard, Rossin-Slater, and Stearns, 2018). However, it is clear that the longer $T$ is, the harder it becomes to justify why firm effects should remain fixed over time.

This concern becomes even more pressing in light of theoretical work suggesting that the firm premiums $\{\psi_j\}$ 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 this firm-level idiosyncratic shock affects 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 simple approach, which we label as the "Rolling Approach" is to simply estimate the AKM separately across different time-intervals, an approach pioneered by Card et al. (2013). In what follows, we
are going to fit AKM models to successive $T = 2$ intervals (2002 − 2003; 2003 − 2004 . . . 2013 − 2014) in the Washington data. We will use the KSS correction to bias correct the associated variance decompositions for each time-interval. These estimates can then 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 rolling approach is represented by its simplicity and transparency. The main drawback is that, by leveraging only on within-interval mobility patterns, the overall number of identified firm effects can be significantly lower compared to what one would obtain when pooling across different time intervals and therefore mobility networks.

In the next subsection we therefore introduce a simple extension of the AKM model: the Time-Varying AKM (TV-AKM) model where firm effects are allowed to vary across time and the model can be estimated jointly by stacking all the available time periods which, as we detail below, is going to greatly increase 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 to control flexibly for firm-by-year unobserved heterogeneity is the following

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

where $\{\psi_{j,t}\}$ represents a vector of firm by year fixed effects. 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 also would like to assess the intertemporal “drift” in $\{\psi_{j(g,t),t}\}$ for a given firm.

Estimation of $\text{var}(\psi_{j(g,t),t})$, $\text{cov}(\psi_{j(g,t),t}, \alpha_g)$ as well as the autocovariance function $\{\psi_{j(g,t),t}\}$ via a naive plug-in approach will bias the resulting estimates by the same logic described in the previous section. Fortunately, the framework of Kline, Saggio, and Solvsten (2019) extends to any
quadratic form constructed from the coefficients of a linear regression model. We will therefore rely on the leave-out approach of Kline, Saggio, and Solvsten (2019) 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: Stayers. By treating each firm-year combination as a single vertex in the corresponding bipartite network of firms and workers, it follows that stayers — individuals that 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 individuals switching between different employers. To see the importance of stayers in driving identification of \( \psi_{j,t} \), consider the following moment condition based on the TV-AKM model:

\[
E[y_{it} | i \text{ is a stayer for firm } j] - E[y_{it-1} | i \text{ is a stayer for firm } j] = \psi_{j,t} - \psi_{j,t-1}.
\] (10)

where the expectation above conditions of the employees that always remained with firm \( j \) during this sample period. This implies that a key source of identification of \( \{\psi_{j,t}\} \) is represented by the average wage change of incumbent, stayers, workers within firm \( j \). Relatedly, the same source of variation is typically used to identify rent sharing elasticities, see for instance equation (15) in Card et al. (2015) and the discussion in Card et al. (2018). The fact that stayers contribute to identification of \( \{\psi_{j,t}\} \) is important when contrasting the TV-AKM with the rolling approach described previously. In the latter, identification of firm effects within a given interval relies solely on transitions made by individuals in that particular interval. This is going to restrict the set of
identified firm effects within and across intervals to a significant degree. On the other hand, the TV-AKM model leverages from a pooled mobility network that exploits also observations associated with stayers. As a consequence, we should expect the TV-AKM model to have a significantly higher number of identified firm by year effects compared to a simple rolling 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 is going to impose some additional refinements on 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 Data and Descriptive Statistics

The estimation sample is based on records maintained by the Employment Security Department of Washington State to administer the state’s unemployment insurance (UI) system: quarterly earnings records from all UI-covered employers in Washington from 2002:I through 2014:IV.⁴ 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.⁵ Each worker’s quarterly record also includes an employer

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⁴Although we used the terms “employer” and “firm” interchangeably throughout the paper, 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 UI 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.

⁵Lachowska, Mas, and Woodbury (2018) examine the reliability of the Washington hours data and conclude they are of high quality.
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.

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. Ultimately, the unit of observation is the worker-year, with a focus on the primary employer in a year. We impose several restrictions on the 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 \( \leq \$2.00 \text{/hour} \) (in 2005 dollars) (Sorkin, 2018; Card, Heining, and Kline, 2013).
- Workers who worked fewer than 400 hours in the year.
- Employer-year observations with fewer than 5 employees in the year (Song, Price, Guvenen, Bloom, and Von Wachter, 2018)
3.1 Descriptive Statistics

Figure 1, Panel (a) displays the basic trends we analyze for our variance decomposition exercise—the variances of real log hourly wages and log earnings in Washington from 2002 to 2014. (The sample on which these series are based is described in Section 3.) 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 (2018) find the variance of log annual earnings increased by about 4% in the United States overall during 2001–2013.

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 2007 and 2010, 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 on the Washington data that are useful in assessing the different econometric strategies described in Section 2. Panel (a) focuses on three intervals: 2002–

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6Because the data underlying our estimates and those of Song, Price, Guvenen, Bloom, and Von Wachter (2018) 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).
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 et al. (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 the average number of movers is approximately 3.4 movers per employer, and that a potentially large fraction of employers 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 employers, implying on average about 3.5 movers per employer. 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 employers. The longer time horizon associated with these data implies a larger mobility network and therefore a larger ratio of movers to employers, now equal to roughly 9.1.

The KSS bias correction requires each employer to remain connected to all others in the data after removing any particular worker, and the leave-one-out sampling ensures that this requirement is satisfied. The two-year interval samples (2002–2003 and 2013–2014) retain about half of the employers 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 employers associated with only one mover tend to be smaller in size. Consistent with this observation and the evidence on premiums paid by large firms (Oi and Idson, 1999), the restrictions implied by the leave-one-out sample result in increases in average log wages and average log earnings of 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%.\footnote{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}

Although the levels of the first and second moments of log wages and log earnings are smaller in the leave-one-out samples than in the largest connected sets, their trends over time 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, then, the extended time period substantially reduces the amount of pruning needed to ensure leave-one-out connectivity.

Panel (b) of Table 1 reports descriptive statistics on the sample used to fit an AKM model in which firm effects are allowed to vary over time. As discussed in Remark 5 of Section 2.2.1, when the underlying model incorporates firm-by-year fixed effects, the relevant bipartite network is one where vertices are formed by worker and employer-by-year identifiers, as opposed to employer-only identifiers. This implies a potential change in the definitions of the largest connected set and the leave-one-out connected set 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 employer 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

We now present the main results from our 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 rolling approach will reveal to what extent the rise in inequality documented in Figure 1 can be attributed to worker-specific effects, firm-specific wage-setting policies, and assortative
worker-firm matching. Within this rolling framework, we zoom into two types of contrasts. The first is between variance decompositions based on the plug-in approach—the standard tool used to investigate the evolution of different components of wage inequality—and the bias-corrected decompositions based on the leave-one-out approach of KSS. The second is between variance decompositions of log hourly wages (which represent a unique feature of the Washington data) and variance decompositions of log earnings, which is the typical outcome used to fit AKM models in the US (Song, Price, Guvenen, Bloom, and Von Wachter, 2018).

Sections 4.3 and 4.4 present results from a complementary approach where we pooled data from all the available time intervals and fit an AKM model with (firm × year) dummies which we label as the TV-AKM model. We contrast variance decompositions based on the TV-AKM as opposed to traditional AKM models. Relatedly, we investigate to what extent firm effects “drift” over-time for a given firm. Finally, we provide informal evidence that can be used to gauge the degree of misspecification that one can occur when fitting models that restricts firm effects to be homogenous over-time.

4.1 Rolling Specification: Log Wages

Table 2 displays the variance decompositions obtained from fitting the AKM model 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 explain by far the largest share (86%) of the overall variance in log wages in 2002–2003. Firm effects are less important, explaining only about 14%. The plug-in estimate of the covariance between worker and firm effects is negative, raising the question of whether negative assortativity really exists in the Washington labor market, or if alternatively the negative estimated covariance is a manifestation of the limited mobility bias discussed in Section 2.1.

The KSS leave-one-out correction yields a positive estimated covariance between worker and firm effects for 2002–2003, which suggests the negative correlation estimated by the plug-in ap-
approach is due to sampling error in the estimated worker and firm effects. As expected, the KSS adjustment 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 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 leave-one-out estimates suggest the covariance between worker and firm effects explains 12% of overall wage variation.

Turning to the changes in estimated variance components between 2002–2003 and 2013–2014 (the rightmost two columns in Table 2), the plug-in method suggests that 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). The qualitative patterns under the KSS bias correction are similar—that is, wage inequality increase 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 approach has 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 by a substantial margin. This increase was not due to an increase in the variation of fixed employer wage policies, but rather to increases in the variation of worker-specific
factors and the degree of worker-firm wage assortativity. This pattern is broadly consistent with
the one highlighted by Song et al. (2018) when fitting AKM models to log earnings for different
time intervals of length $T = 7$ using US administrative tax data from 1980-2013.

But how did the components of wage inequality evolve over 2002–2014, a period covering the
second most dramatic recession in US history? To address this question we move from the static
representation of Table 2 to the dynamic representation in Figure 4. This figure reports the results
from 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
leave-one-out method (Panels b and d).

The KSS 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 be-
tween 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

Figure 4 makes clear two important differences between the KSS-corrected estimates and those
obtained by the plug-in method commonly used in the literature. 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 procyclicality of assortative matching). Figure 4 shows that changes over time in each component are 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 differs from one based on log earnings, which is the decomposition usually seen 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 adjustment 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).

What about the evolution of these components? Earnings inequality, as measured by the variance of log earnings, increased by around 17% during 2002–2014. The KSS estimates show that most of this increase was due to increases in assortative matching (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.

Dynamic variance decompositions for log earnings are 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 makes clear 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 correlation 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 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 and for the two alternative methods of estimation. The figure highlights the substantial increase in assortative matching between workers and firms that occurred during 2002–2014 in the Washington economy, interrupted only by the Great Recession. 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 when fitting the the TV-AKM model on the pooled Washington data panning 2002–2014. Table 4 shows the resulting variance decompositions for log wages and earnings after estimating equation (9) to the leave-one-out connected set described in Table 1, Panel (b). In this pooled data, the bias-corrected, time-homogenous, AKM estimates 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).

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 traditional AKM model. Section 4.5 will provide some additional auxiliary evidence useful to assess the degree of misspecification that one can occur when assuming firm effects to be constant over-time.

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8Lamadon, 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 (see Bonhomme, Lamadon, and Manresa (2019)).
The analysis in Table 4 suggests two additional points. First, the KSS bias 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 under two different leave-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 two alternative leave-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 alleviate concerns about limited mobility bias, 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 12% in the comparable pooled analysis in Table 4. This pattern suggests the presence of cohort firm effects. In particular, the wage and earnings policies of firms that exist, say, in 2002 appear relatively different to those of firms operating in 2014. 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 objects such as 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 auto-covariance 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 2002–2014. Each auto-covariance is then weighted by average firm employment across

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” over time, but they remain highly
correlated even 13 years apart (correlation= 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 signals the presence of a non-stationary
component in $\psi_{j,t}$. During 2002–2014, the variance of firm effects for wages increased from
0.0446 to 0.0582 (more than 30%). This suggests that there may be intertemporal variation in
firm-specific wage policies, and also that this variability increases over the life-cycle of a firm
(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 (correlation= 0.82, in Table 6B), and the variability 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 0.9764


and for log earnings it is 0.9833. As is visually evident, the empirical autocorrelations closely track those of these highly persistent AR(1) models. For log earnings the empirical correlations are slightly lower than would be predicted by an AR(1) for lower lags, but are essentially the same for higher lags. For log wages the empirical correlations are somewhat higher than the predicted values at lower lags but closely track the predicted values at higher lags.

4.5 Does allowing for time-varying firm heterogeneity actually matters?

The evidence on the auto-correlation functions of the firm effects show that firm effects for both wages and earnings remain highly correlated even 13 years apart. This is reflected in the variance decomposition shown in Table 4 where we see that a model that allows firm effects to vary over-time reaches the same broad conclusions of the canonical AKM model.

A similar variance decomposition between the AKM and the TV-AKM model, however, does not necessarily imply that one cannot incur in a significant degree of misspecification when restricting the firm effects to be homogenous across time periods. A formal specification test between the AKM and TV-AKM model is challenging due to the high-dimensionality of both models. Yet, it remains possible to provide some useful evidence that can inform applied researchers about the degree of misspecification stemming from restricting the firm effects in an AKM model to be fixed over-time.

Such evidence is presented in Figure 9. In Panel (a) we consider the projection of the firm effects estimated in the TV-AKM model onto the firm effects estimated in the AKM model for log wages. Under the null hypothesis that the AKM model represents the true data generating process, we would expect the slope from this projection to be 1 and the associated scatter plot to be highly concentrated around the 45 degree line. This is exactly what we see in Panel (a) where we compute the person-year weighted average of the TV-AKM and AKM firm effect within each centile bin of

\[ \ln(k) = \beta \cdot k + \varepsilon(k), \]

where \( k \) is the lag, and \( \rho(k) \) is the \( k \)th order autocorrelation. Because the autocorrelation function of an AR(1) is \( \rho(k) = \nu^k \), where \( \nu \) is the autoregressive parameter, the estimate of \( \beta \) is interpretable as an estimate of \( \ln(\nu) \). For this analysis we use all of the autocorrelations reported in Tables 5 and 6.

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9To estimate the autoregressive parameters we estimate \( \ln(\rho(k)) = \beta \cdot k + \varepsilon(k), \) where \( k \) is the lag, and \( \rho(k) \) is the \( k \)th order autocorrelation. Because the autocorrelation function of an AR(1) is \( \rho(k) = \nu^k \), where \( \nu \) is the autoregressive parameter, the estimate of \( \beta \) is interpretable as an estimate of \( \ln(\nu) \). For this analysis we use all of the autocorrelations reported in Tables 5 and 6.
the AKM firm effects. Adjusting the resulting projection slope via the KSS approach, we find a slope equal to 0.99 with all centile bins tightly concentrated around the associated 45 degree line.

Other evidence can be constructed by considering two-step regression approaches where AKM firm effects estimated in a first step are then used as predictors in a second step regression. For instance, Bana et al. (2018) estimate in a first step an AKM model using social security data from California pooling all years from 2000 to 2014. The estimated firm effects are then used to gauge the importance of employer-specific factors in the propensity of individuals to use public leave-taking benefits. Practically, this involves running a firm by year level regression where average public leave-take up rates in a given firm by year cell is regressed onto AKM effects and other firms’ observables. Similar two-step approaches are taken by Card, Heining and Kline (2013), Goldschmidt and Schmieder (2017), and Schmieder, von Wachter and Heining (2018). How different would the resulting estimates be if the firm effects were allowed to vary over-time in the first step?

We evaluate this question in the context of estimating the relationship between separation rates and firm effects, an economically interesting parameter previously estimated by Card, Heining and Kline (2013). In particular, we consider a person-year weighted regression of the following type

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

where \(\text{Separation}_{it} = 1\{j(i,t) \neq j(i,t + 1)\} \) and \(\hat{\psi}_{j(i,t),t}\) is a time-varying firm effect estimated according to the TV-AKM model. Figure 9, Panel (b) provides a visual representation of the relationship underlying equation (11) where we compute the person-year weighted average of the quit rates, TV-AKM and AKM firm effect within each centile bin of the AKM firm effects. Figure 9, Panel (b) again suggests a minimal degree of misspecification, as both the slope and overall distribution of quit rates and firm effect remains stable regardless of whether we consider time-varying or time homogenous firm effects. As expected, the sign of \(b\) is negative, consistent with the evidence provided for instance by Card et al. (2013) in Germany.
5 Conclusions

In this paper we show that with existing methods, and in particular the leave one out bias correction of KSS, it is possible to estimate AKM firm effects at a high frequency and provide unbiased estimates of variance decomposition parameters and autocovariance functions. We use this approach to document that firm effects are persistent, that they exhibit cyclicality, and that in the case of Washington State they did not contribute to increases in the overall variance of wages and earnings in a relatively short time span. These findings are helpful because they provide a justification for pooling multiple years of data to estimate AKM firm effects, but also because they highlight the advantages of considering higher-frequency variation in firm premia. Our results suggest several avenues of future work. One is to formally reconcile economic models that give rise to firm wage and earnings premia with the stochastic process of the firm premia documented here. A second is to determine whether the cyclical patterns of firm effects we document are more general, and to better understand the mechanism behind this pattern within existing or new macroeconomic models.
References


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

Panel (a) plots the unconditional variance of log earnings and log wages in the Washington administrative data. Panel (b) and Panel (c) plot 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.
Note: This figure depicts a connected bipartite graph where vertices are given by firms 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 out connected set as dropping one individual 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 out connected set.
Figure 3: Construction of the Data

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, . . . , 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 Solvsten (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, . . . , 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 Salvsten (2019).
Figure 7: Autocorrelation of firm effects in wages

Note: This figure plots the estimated autocorrelations in Table 5B (blue dots) and the autocorrelation function of the AR(1) process fitted by minimum distance estimation on the empirical autocorrelations: $\psi_{j,t} = 0.9765\psi_{j,t-1} + \zeta_{jt}$. 
Figure 8: Autocorrelation of firm effects in earnings

Note: This figure plots the estimated autocorrelations in Table 6B (blue dots) and the autocorrelation function of the AR(1) process fitted by minimum distance estimation on the empirical autocorrelations: $\psi_{j,t} = 0.9832\psi_{j,t-1} + \zeta_{jt}$. 
Figure 9: Does allowing for time-varying firm heterogeneity actually matters?

(a) TV-AKM vs. AKM

Plug-in slope: .98
KSS adjusted slope: .99

(b) KSS

Regression slope AKM: -.13
Regression slope for TV-AKM: -.11
KSS adjusted slope AKM: -.13
KSS adjusted slope for TV-AKM: -.1

Note: In Panel (a) we report the person-year averages of the AKM firm effects and the TV-AKM firm effects within each centile bin of the AKM effects, see 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 person-year averages of separation rates within each centile bin of the AKM and TV-AKM effects.
Table 1: Summary Statistics

<table>
<thead>
<tr>
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<th>Panel (a): AKM Model</th>
<th>Panel (b): TV-AKM Model</th>
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<tr>
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<td>Leave One Out</td>
<td>Largest Connected Set</td>
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<td>0.36</td>
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<td>Mean Log Earnings</td>
<td>10.50</td>
<td>10.59</td>
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<tr>
<td>Variance of Log Earnings</td>
<td>0.55</td>
<td>0.49</td>
</tr>
</tbody>
</table>

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 employer within a given time-frame. All statistics on wages and earnings are person-year weighted. See text for details.
### Table 2: Variance Decomposition - Log Wages

<table>
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</thead>
<tbody>
<tr>
<td></td>
<td>Variance Component</td>
<td>Share of Total (%)</td>
<td>Variance Component</td>
<td>Share of Total (%)</td>
<td>Variance Component</td>
<td>Share of Total (%)</td>
<td></td>
</tr>
<tr>
<td>Variance of Log Wages</td>
<td>0.3598</td>
<td>100.00%</td>
<td>0.4264</td>
<td>100.00%</td>
<td>0.0666</td>
<td>100.00%</td>
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</tr>
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</tr>
<tr>
<td>Variance of Person Effects</td>
<td>0.3109</td>
<td>86.40%</td>
<td>0.3553</td>
<td>83.33%</td>
<td>0.0444</td>
<td>66.73%</td>
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<tr>
<td>Variance of Firm Effects</td>
<td>0.0488</td>
<td>13.57%</td>
<td>0.0393</td>
<td>9.22%</td>
<td>-0.0095</td>
<td>-14.27%</td>
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<tr>
<td>2*Cov of Person, Firm Effects</td>
<td>-0.0085</td>
<td>-2.36%</td>
<td>0.0240</td>
<td>5.62%</td>
<td>0.0324</td>
<td>48.69%</td>
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<td><strong>Variance Decomposition: KSS</strong></td>
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<tr>
<td>Variance of Person Effects</td>
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<td>79.28%</td>
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<tr>
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<td>0.0248</td>
<td>5.81%</td>
<td>-0.0069</td>
<td>-10.32%</td>
<td></td>
</tr>
<tr>
<td>2*Cov of Person, Firm Effects</td>
<td>0.0246</td>
<td>6.83%</td>
<td>0.0518</td>
<td>12.14%</td>
<td>0.0272</td>
<td>40.84%</td>
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</tr>
</tbody>
</table>

**Note:** All variance decomposition parameters are calculated in the corresponding leave one out connected set described in Table 1, Panel (a) and are person-year weighted. Plug-in reports the variance components without adjusting for sampling error in the estimated person and firm effects. KSS adjusts each variance component using the leave out approach detailed by Kline, Saggio and Sølvsten (2019). 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

<table>
<thead>
<tr>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Variance Component</td>
<td>Share of Total (%)</td>
<td>Variance Component</td>
<td>Share of Total (%)</td>
<td>Variance Component</td>
</tr>
<tr>
<td>Variance of Log Earnings</td>
<td>0.4921</td>
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<td>0.5738</td>
<td>100.00%</td>
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<td></td>
</tr>
<tr>
<td>Variance of Person Effects</td>
<td>0.3808</td>
<td>77.38%</td>
<td>0.4138</td>
<td>72.11%</td>
<td>0.0330</td>
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<tr>
<td>Variance of Firm Effects</td>
<td>0.0766</td>
<td>15.56%</td>
<td>0.0801</td>
<td>13.96%</td>
<td>0.0035</td>
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<td>2*Cov of Person, Firm Effects</td>
<td>0.0226</td>
<td>4.59%</td>
<td>0.0684</td>
<td>11.92%</td>
<td>0.0458</td>
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<tr>
<td><strong>Variance Decomposition: KSS</strong></td>
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<td></td>
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<tr>
<td>Variance of Person Effects</td>
<td>0.3462</td>
<td>70.35%</td>
<td>0.3833</td>
<td>66.79%</td>
<td>0.0371</td>
</tr>
<tr>
<td>Variance of Firm Effects</td>
<td>0.0541</td>
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<td>0.0613</td>
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<td>0.0073</td>
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<td>2*Cov of Person, Firm Effects</td>
<td>0.0662</td>
<td>13.45%</td>
<td>0.1045</td>
<td>18.20%</td>
<td>0.0383</td>
</tr>
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</table>

Note: All variance decomposition parameters are calculated in the corresponding leave one out connected set described in Table 1, Panel (a) and are person-year weighted. Plug-in reports the variance components without adjusting for sampling error in the estimated person and firm effects. KSS adjusts each variance component using the leave out approach detailed by Kline, Saggio and Sølvsten (2019). 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

<table>
<thead>
<tr>
<th></th>
<th>Log Wages</th>
<th>Log Earnings</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>AKM</td>
<td>TV-AKM</td>
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<tr>
<td>Variance of Log Wages</td>
<td>0.4074</td>
<td>0.4074</td>
</tr>
<tr>
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<td>100.00%</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

**Variance Decomposition: Plug-In**

<table>
<thead>
<tr>
<th></th>
<th>Log Wages</th>
<th>Log Earnings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance of Person Effects</td>
<td>0.2567</td>
<td>0.2596</td>
</tr>
<tr>
<td></td>
<td>63.01%</td>
<td>63.72%</td>
</tr>
<tr>
<td>Variance of Firm Effects</td>
<td>0.0480</td>
<td>0.0570</td>
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<tr>
<td></td>
<td>11.77%</td>
<td>13.99%</td>
</tr>
<tr>
<td>2*Cov of Person, Firm Effects</td>
<td>0.0679</td>
<td>0.0591</td>
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<td></td>
<td>16.67%</td>
<td>14.51%</td>
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</tbody>
</table>

**Variance Decomposition: KSS**

<table>
<thead>
<tr>
<th></th>
<th>Log Wages</th>
<th>Log Earnings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance of Person Effects</td>
<td>0.2502</td>
<td>0.2534</td>
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<td></td>
<td>61.40%</td>
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<tr>
<td>Variance of Firm Effects</td>
<td>0.0473</td>
<td>0.0549</td>
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<tr>
<td></td>
<td>11.60%</td>
<td>13.47%</td>
</tr>
<tr>
<td>2*Cov of Person, Firm Effects</td>
<td>0.0687</td>
<td>0.0604</td>
</tr>
<tr>
<td></td>
<td>16.87%</td>
<td>14.81%</td>
</tr>
</tbody>
</table>

**Note:** All variance decomposition parameters are calculated in the corresponding leave one out connected set described in Table 1, Panel (b) and are person-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 person and firm effects. KSS adjusts each variance component using the leave out approach detailed by Kline, Saggio and Solvsten (2019) by leaving a person year observation out. Source: WA administrative records.
### Table 5A: Autocovariance of Firm Effects - Log Wages

<table>
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<tbody>
<tr>
<td>2002</td>
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<td>0.0399</td>
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### Table 5B: Autocorrelation of Firm Effects - Log Wages

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<tr>
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</tbody>
</table>

**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 Salvsten (2019). All auto-covariance and autocorrelation parameters reported in the table above are computed for the sample of firms that are alive 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

<table>
<thead>
<tr>
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</tr>
</thead>
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### Table 6B: Autocorrelation of Firm Effects - Log Earnings

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**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 Salvsten (2019). All auto-covariance and autocorrelation parameters reported in the table above are computed for the sample of firms that are alive 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

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**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 person-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 person and firm effects. KSS adjusts each variance component using the leave out approach detailed by Kline, Saggio and Sølvsten (2019) by leaving a person year observation out. Source: WA administrative records.

**KSS-Leave Person-Year out**

**KSS-Leave Match out**