Conference Version

Rising Between Firm Inequality and Declining Labor Market Fluidity: Evidence of a Changing Job Ladder

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I. Introduction

A large literature has documented the growth of real earnings dispersion in the U.S. economy since the late 1970s, often referred to as increasing earnings inequality. During this same time, labor market fluidity in the U.S. has declined as evidenced by a decline in the overall pace of hires and separations (see, Davis, Faberman and Haltiwanger (2012), Hyatt and Spletzer (2013), Davis and Haltiwanger (2014) and Malloy et. al. (2016)). The decline in the hiring rate includes both a decline in the pace of employer-to-employer flows as well as hires from non-employment. In this paper, we explore potential connections between the rise in earnings inequality and declining labor market fluidity.

Our analysis of these issues uses matched employer-employee data from the LEHD program at Census to conduct a series of empirical exercises that help understand the connections from the findings from the distinct literatures on inequality and labor market fluidity. We use this data infrastructure to show increasing inequality in the upper tail of the earnings distribution during the last two decades (1998 – 2018). Using the same data infrastructure, we illustrate key components of the observed declining fluidity focusing on the decomposition of workers into four hires types: stayers, job switchers within the same industry, job switchers across industries, and hires from non-employment. We find that the share of stayers has been increasing as a fraction of employment while the share of hires have declined, with especially large declines of hires from non-employment.

Our empirical analysis also builds on the recent literature that shows substantial firm and industry dimensions to increasing inequality. Recent findings emphasize that much of rise in earnings inequality in the U.S. over the last few decades is accounted for by rising between firm inequality (see, Song et. al. (2019) and Barth et. al. (2016)) Our recent work (Haltiwanger and

Spletzer (2020)) shows that this rising between firm inequality is dominated by rising industry inequality. For our sample and definition of firms, we replicate that finding in our analysis.

The dominant role of rising between firm and between industry inequality provides a potential connection to the changing patterns of fluidity via a changing job ladder. There is much evidence that individuals tend to start their careers at lower earnings (lower rungs of the job ladder) and move up over the course of their careers. Topel and Ward (1992) found that a large fraction of earnings increases for young workers is accounted for by job switches rather than within firm increases in earnings. A core prediction of job ladder models (see, e.g., Burdett and Mortensen (1998) and Moscarini and Postel-Vinay (2013)) is that high wage firms should have more of their hires via job switchers while low wage firms should have more of their hires via non-employment. Recent evidence provides empirical support for this prediction. Haltiwanger, Hyatt, Kahn and McEntarfer (2018) show that high wage firms have a large share of hires from other firms while low wage firms have large share of hires from non-employment. These patterns hold for job switches both within and between industries.[1]

Our findings in this paper along with those in the recent literature support the hypothesis that there has been a change in the job ladder. Rising between firm inequality suggests that the rungs of the job ladder have become further apart. Declining fluidity suggests that it has become more difficult to get on the ladder and the pace of climbing the ladder has slowed. The current paper explores this hypothesis of a changing job ladder on a number of dimensions. In turn, we assess the contribution of the changing job ladder for understanding the increase in earnings inequality.

[1] Haltiwanger, Hyatt, Kahn and McEntarfer (2018) include both within and between industry job switchers in their analysis. Haltiwanger, Hyatt and McEntarfer (2016) provide evidence that there is a between industry job ladder.

We exploit the dominant role of industry effects to investigate the connection between changing inter-industry earnings differentials and changes in the job ladder. Using detailed industry level data, we find that industries with a high share of hires from job switchers and especially from job switchers between industries have significantly higher earnings. Relatedly we find that industries with a high share of hires from non-employment have significantly lower earnings. These patterns hold for earnings of stayers, job switchers, and hires from non-employment. These patterns also hold whether or not we control for the demographic composition of workers (e.g., worker age, education, and gender) and firms (i.e., firm size and firm age) in the industry. These results are consistent with the empirical job ladder evidence above and are also consistent with the theoretical predictions of job ladder models cited above.

Not only do industries with a larger share of hires from job switchers have especially high wages but the earnings differential for such industries has been rising during the past two decades. The differentials for both hires from the same industry and hires from other industries have been increasing. Likewise, the industries with a larger share of hires from non-employment have increasingly lower earnings differentials over the past two decades. Using simple accounting decompositions, we find that changing differentials by hires types in combination with the changing distribution of hires types accounts for about 30 percent of rising inter-industry earnings differentials. This finding is without any controls. Using only firm and worker demographic controls, we can account for about 60 percent of the rising inter-industry earnings differentials. In specifications including both hires types and firm and worker controls, we can account for about 80 percent of rising inter-industry earnings differentials. The latter differs from the implied 90 percent (adding the separate 30 + 60 contributions) given covariance effects in the accounting decompositions.

We also investigate the role of composition effects resulting from declining fluidity. We find that using either individual level or detailed industry-level data, there is rising inequality within each of the hires types: stayers, job switchers within industries, job switchers between industries, and hires from non-employment. This finding highlights that composition changes in hires types from declining fluidity does not help account for rising inequality. If anything, this composition effect works in the wrong direction since the variance of earnings of stayers is the lowest and the variance of earnings for hires from non-employment is the highest among the four groups.

The paper proceeds as follows. Section II describes the data infrastructure. Section III shows that rising overall earnings inequality is dominated by rising between firm inequality and in turn by rising between industry inequality. Section IV explores the patterns of declining fluidity through the lens of the four hires types we use in our subsequent analysis: stayers, job switchers within industries, job switchers between industries, and hires from non-employment. Section V analyzes the variance of earnings for each of the four hires types. Section VI investigates the connection between rising inter-industry earnings differentials and earnings differentials by hires types along with controlling for and exploring the contribution of changing firm and worker demographic effects. Section VII provides concluding remarks. We view our results as exploratory bringing together two distinct literatures. We focus on a range of open questions in our concluding remarks.

II. Data Infrastructure

All of our analysis is based on data from the Longitudinal Employer Household Dynamics (LEHD). The LEHD is a longitudinally linked employer-employee dataset created by the U.S. Census Bureau as part of the Local Employment Dynamics federal-state partnership. The data are derived from state-submitted Unemployment Insurance (UI) wage records and the Quarterly Census of Employment and Wages (QCEW) data. Every quarter, employers who are subject to state UI laws -- approximately 98% of all private sector employers, plus state and local governments -- are required to submit to the states information on their workers (the wage records, which lists the quarterly earnings of every individual in the firm) and their workplaces (the QCEW, which provides information on the industry and location of each establishment). The wage records and the QCEW data submitted by the states to the U.S. Census Bureau are enhanced with census and survey microdata in order to incorporate information about worker demographics (age, gender, and education) and the firm (firm age and firm size). Abowd et al. (2009) provide a thorough description of the source data and the methodology underlying the construction of the LEHD data.

A job in the LEHD is defined as the presence of an individual-employer match, and earnings is defined as the amount earned from that job during the quarter. We use full-quarter jobs in our analysis, where a full-quarter job is defined as a contemporaneous employer-employee match that also exists in the previous quarter and in the following quarter. The underlying assumption is that individuals in full-quarter jobs are working all 13 weeks of the quarter, which avoids the issue of not knowing the number the weeks worked during the quarter for individuals who start a job or end a job during that quarter. Restricting to full-quarter jobs is similar in spirit to the full-time or full-year restriction used when analyzing inequality with household survey data.

We impose two recodes on the LEHD earnings data. First, to minimize the effect of outliers and smooth the first two moments of the earnings time series, we topcode earnings at the

99.5th percentile of the state-year-quarter distribution. Second, all of our analysis uses the natural log of real quarterly earnings, where nominal values are converted to real using the 2018:Q1 CPI-U-RS deflator.

Because states have joined the LEHD program at different times and have provided various amounts of historical data upon joining the LEHD program, the length of the time series of LEHD data varies by state. We use data from the 20 states that have data available from 1996:Q4 through 2018:Q2, which gives us full quarter data from 1997:Q1 to 2018:Q1.[2] We restrict the LEHD data to the private sector. In order to focus on long-run trends and avoid issues of seasonality, we use data from the first quarter of the year.[3]

Key statistics from our annual data are given in Figure 1. The top left panel shows the number of full-quarter jobs in our 20 state data from 1998 to 2018, and the top right panel shows the number of firms in our data. The primary definition of firms we use in our analysis is business units defined by the State UI number, referred to by users of the LEHD data as the SEIN. This definition of firms is narrower than the enterprise definition used in Haltiwanger and Spletzer (2020) and the EIN based definition as used by Song et. al. (2019). We explore the sensitivity of analysis to using the SEIN vs. EIN vs. Census enterprise firm (Census firm IDs) below. The SEIN has the advantage that is includes more geographic variation which is relevant

[2] These 20 states are: CA, CO, CT, HI, ID, IL, KS, LA, MD, MN, MO, MT, NC, NJ, NM, OR, RI, TX, WA, and WY. These 20 states account for roughly 46 percent of national employment. The time series of employment from these 20 states closely tracks the national time series of total private sector employment published by the QCEW program at the Bureau of Labor Statistics (BLS).

[3] The key findings from our variance decomposition are not sensitive to whether we use full-quarter earnings from the first, second, third, or fourth quarter of the year, nor are they sensitive to whether we sum the LEHD quarterly earnings into an annual measure of earnings with a minimum earnings threshold. Annual earnings are used by Song et.al (2018) using SSA data, as well as by Abowd et.al (2018) using LEHD data. The key findings do change dramatically when no minimum earnings threshold is applied to annual earnings data, most likely due to a decline in short-duration jobs and thus a compositional change in the lower part of the earnings distribution -- see Hyatt and Spletzer (2017) for further elaboration on this point.

for declining labor market fluidity since part of the latter is declining geographic mobility (see, e.g., Malloy et al. (2016)).

In 2018:Q1, there are over 50 million full-quarter jobs and approximately 3.2 million SEIN firms in our 20 state LEHD data. The graph in the bottom left panel of Figure 1 shows average real earnings of full-quarter jobs in the LEHD. Real earnings are cyclical with no obvious trend between 1998 and the mid-2000s; there is some evidence of increasing real earnings during the last several years of our data. The graph in the bottom right panel of Figure 1 shows a rising variance of full-quarter LEHD earnings – this rising variance, often referred to as "increasing earnings inequality," is the focus of our analysis in this paper.

III. Rising Earnings Inequality: The Dominant Role of Between Firm and Between Industry Effects

IIIa. Percentiles of Earnings Distribution in the LEHD and CPS data

We begin by characterizing the percentiles of the LEHD full quarter earnings distribution. This enables us to analyze whether changes in the upper tail or lower tail, or both tails, of the earnings distribution are driving the increasing variance. These percentiles also allow for a comparison of the LEHD earnings distribution to published data from the Current Population Survey (CPS).

The top left panel of Figure 2 shows the level of real LEHD full-quarter earnings associated with the first percentile, the fifth percentile, the tenth percentile, the median, the 90^{th} percentile, the 95^{th} percentile, and the 99^{th} percentile.[4] With the scale of the vertical axis, it is

[4] To be exact, in each year we estimated the percentiles from the log real earnings data and then converted these point estimates into levels of real earnings. Following standard Census Bureau disclosure avoidance methodology, the X^{th} percentile is computed as the mean LN earnings for all individuals who have LN earnings between the $(X-½)^{th}$ and the $(X+½)^{th}$ percentiles.

difficult to distinguish the levels of the lower percentiles. Full-quarter real earnings are approximately \$250 per quarter at the 1st percentile, \$1100 per quarter at the 5th percentile, and \$2100 per quarter at the 10th percentile. Median real full quarter earnings average approximately \$9100 per quarter; median real full quarter earnings are procyclical with a noticeable upward trend from \$8500 in the first quarter of 2010 to \$9500 in the first quarter of 2018.

The graph in the top right panel of Figure 2 shows the LEHD full-quarter earnings percentiles indexed to 100 in 1998. The first percentile of earnings has fallen by roughly six percent between 1998 and 2018, whereas the 5th, 10th, and 50th percentiles have risen by four to 10 percent. During the 1998 to 2018 time period, the 90th percentile has risen by 28 percent, the 95th percentile has risen by 35 percent, and the 99th percentile has risen by 46 percent. The LEHD full quarter earnings data is consistent with findings in the literature that much of the recent increase in earnings dispersion during the past several decades is at the upper end of the earnings distribution.

The LEHD full quarter earnings distribution is quite similar to the published statistics from the CPS. The BLS publishes the 10th, 50th, and 90th percentiles of usual weekly earnings of full time wage and salary workers.[5] Multiplying these data by 13 to create quarterly statistics, and converting to real, the CPS and the LEHD percentiles are given in the graph in the bottom left panel of Figure 3. The LEHD full-quarter earnings distribution is wider than the CPS full time wage and salary earnings distribution (the LEHD 10th is less than the CPS 10th and the LEHD 90th is greater than the CPS 90th), but otherwise the two distributions are reasonably close. Of special note is the increasing 90th percentile in both distributions.

[5] These percentiles are available at http://www.bls.gov/webapps/legacy/cpswktab5.htm. The median is available for 1979 to the present. The 10th and 90th percentiles are available for years 2000 to the present, with earlier years available by request.

This similarity between the LEHD full-quarter earnings distribution and the CPS full time wage and salary earnings distribution is also apparent in the bottom right panel of Figure 2, which indexes all the series at 100 in 1998. Between 1998 and 2018, the 10th percentiles of the LEHD and the CPS earnings distribution rose by seven to eleven percent, the medians rose by nine to twelve percent, and the 90th percentiles exhibited the largest increases (23 to 28 percent).

IIIb. Variance Decompositions into Within Firm, Between Firm, and Between Industry Effects

Proceeding further, we focus on the variance as the measure of the dispersion of LEHD full-quarter earnings. This focus facilitates the decomposition of the variance of individual earnings into within firm and between firm components:

(1a) $$Var(W_{if}) = Var(W_{if} - W_f) + Var(W_f)$$

where "i" refers to the individual and "f" refers to the firm. The first term on the right side of the equation is the variance within firms, and the second term is the variance between firms. Furthermore, letting "k" refer to industries, we can further write this variance decomposition as:

(1b) $$Var(W_{ifk}) = Var(W_{ifk} - W_{fk}) + Var(W_{fk} - W_k) + Var(W_k)$$

The middle term on the right side of the equation is the between firm within industry variance, and the third term is the variance between industries. Calculating this variance decomposition in each year, and letting Δ denote changes across time, we have

(1c) $$\Delta Var(W_{ifk}) = \Delta Var(W_{ifk} - W_{fk}) + \Delta Var(W_{fk} - W_k) + \Delta Var(W_k).$$

The increase in the variance of individual level wages can be decomposed into a change within firms (the first term on the right-hand side of equation 1c), the change between firms within industries (the second term), and the change between industries (the third term).

The variance decompositions with the LEHD full-quarter earnings data are presented in Figure 3. The top black line is the variance of individual earnings, which was presented earlier in Figure 1. This variance increases from 1.109 in 1998 to 1.291 in 2018. The within firm variance is the red line in Figure 3, and is roughly constant across time (rising slightly from .566 in 1998 to .575 in 2018). The between firm variance, from equation (1a), is the solid blue line in Figure 3, rising from .543 in 1998 to .716 in 2018. These statistics tell us that 95.1 percent of total variance growth from 1998 to 2018 is between firms, with only 4.9 percent of the variance growth within firms. This finding that most variance growth is between firms rather than within firms is consistent with much of the recent literature – Barth et. al. (2016), Handwerker and Spletzer (2016), Song et. al. (2019), Haltiwanger and Spletzer (2020), as well as a much earlier literature – Davis and Haltiwanger (1991) and Dunne, Foster, Haltiwanger, and Troske (2004).

The rising between firm variance can further be decomposed into within industry and between industry components. Using 4-digit North American Industrial Classification System (NAICS) industries, the between-firm within-industry variance rises from .272 in 1998 to .337 in 2018, and the between-industry variance rises from .271 in 1998 to .379 in 2018. These statistics show that 62.4 percent of the large increase in between-firm variance is between industries, and 37.6 percent is within industries using 4-digit industries. This finding that a substantial amount of variance growth is between industries is the focus of recent work by Haltiwanger and Spletzer (2020), and it plays an important role in the methodology we use later in this paper. As we emphasize in that companion paper, this finding of a dominant role for industry effects challenges conventional wisdom from the recent literature. We argue that this reflects limitations in industry codes in the prior literature that we overcome with high quality industry codes on business level data at BLS and Census. Our approach and methodology builds on the finding of a dominant role for industry effects in rising between firm inequality in the companion paper. We contribute to that finding here by extending this result for a longer sample period and using the SEIN as the definition of the firm.

We conclude this section with two sensitivity analyses. Table 1 presents the basic variance decomposition (from the equations above) using different levels of NAICS industry detail. To read this table, begin with the column titled "4-digit naics." The first panel presents the 2018 decomposition of earnings discussed above, and the second panel presents the 1998 to 2018 decomposition of variance growth. The key panel is the fourth panel, where we present the decomposition of variance growth in percentage terms. Staying with the 4-digit naics column, we see that 59.3 percent of total variance growth is between industries, which translates into 62.4 percent of the between firm variance growth being between industries.

How does this 62.4 percent statistic vary with the level of industry detail? There are 23 two-digit industries, and 30.6 percent of between firm variance growth is between these 23 industries.[6] The amount of between firm variance growth between industries rises with the level of industry detail, to 53.8% of variance growth between the 91 three-digit industries and 62.4% between the 304 four-digit industries. Additional industry detail shows that 65.3 percent of between firm variance growth is between the 682 five-digit industries, and 66.5 percent is between the 1034 six-digit industries.

Our second sensitivity analysis is to examine how changing the definition of the firm affects our results. In almost all of this paper, we use the SEIN as the definition of the firm. The SEIN is the UI number that represents the firm within the State. We have two other firm identifiers in the LEHD data – the Federal Employer Identification Number (EIN) and the

[6] Our reference to two-digit industries refers to the first two digits of the six-digit NAICS code. This is slightly different from NAICS sectors, in which 31-33 are aggregated into Manufacturing, 44-45 are aggregated into Retail Trade, and 48-49 are aggregated into Transportation and Warehousing.

enterprise level firm ID. The latter encompasses all activity under common operational control. Both the EIN and the enterprise firm ID are national whereas the SEIN is state specific.

Table 2 presents the variance decomposition when using the SEIN, the EIN, and the enterprise definition of the firm. The first column replicates the basic variance decomposition from Figure 3 and Table 1, and the second and third columns present the decomposition for different years (1998-2016 rather than 1998-2018) and for a sample with nonmissing enterprise firm ID codes (the enterprise firm ID is missing in our 2017 and 2018 extracts of the LEHD data given that integration of the Longitudinal Business Database (LBD) and LEHD data are not yet accomplished for those years, and is missing for a small percentage of observations in all other years). In the latter three columns that use a consistent sample, the percentage of total variance growth that is between 4-digit NAICS industries is 59.6 percent when using the SEIN, is 58.3 percent when using the EIN, and is 55.0 percent when using the enterprise firm ID.[7] These results show that our finding that more than half of variance growth is between 4-digit NAICS industries is unaffected by the definition of the firm.

Not surprisingly, changing the definition of the firm affects the amount of variance growth that is within firms versus between firms. In the latter three columns of Table 2, we document that 94.0 percent of total variance growth is between firms when using the SEIN, 90.1 percent is between firms when using the EIN, and 74.8 percent is between firms when using the enterprise firm ID as the definition of the firm. We believe that these statistics help to reconcile the various statistics in the literature that estimate the amount of variance growth that is within firms versus between firms. Studies that use establishment-level data tend to find a large amount

[7] We have redefined industries at each level of firm aggregation, using maximum employment to define industries at higher levels of aggregation. For example, if an EIN contains two SEINs with different SEIN-level industries, the EIN-level industry is the industry of the SEIN with the higher employment.

of variance growth between establishments, whereas studies that use enterprise-level data find a large yet somewhat smaller amount of variance growth between firms.

IV. Declining Labor Market Fluidity

Many studies have found a decline in indicators of labor market fluidity -- see, for example, Davis et. al. (2007), Davis, Faberman and Haltiwanger (2012), Hyatt and Spletzer (2013), Davis and Haltiwanger (2015), and Molloy et. al. (2016). Such indicators include a decline in the pace of worker reallocation (hires + separations), job reallocation (job creation + destruction), and employer-to-employer flows. These findings on declining labor market fluidity are drawn from studies that use administrative data such as the LEHD and the LBD, business survey data such as the Job Openings and Labor Turnover Survey (JOLTS), and individual survey data such as the CPS. The LEHD data are the most comprehensive, in that the decline in fluidity can be analyzed by characteristics of the firms as well as characteristics of the workers. In addition, the LEHD data permit decomposing hires (and separations) into employer-to-employer flows and hires from non-employment.

In this paper, we are interested in the potential connection between rising earnings variance and declining labor market fluidity. We start with the simple observation that persons employed today were either in the same firm last year (stayers) or not in the firm last year (hires):

(2a) Total Employment = Stayers + Hires.

Hires can be either a person working in a different firm last year (employer-to-employer hire) or a person who was not employed last year (hire from non-employment):

(2b) Total Employment = Stayers + Employer-to-Employer Hires + Hires NonEmp.

Persons hired from a different firm could be persons hired from a firm in the same industry (E2E Same Ind) or persons hired from a different industry (E2E Diff Ind):

(2b) Total Employment = Stayers + E2E Same Ind + E2E Diff Ind + Hires NonEmp.

Equation (2b) identifies the four "hires type" groups we use in our subsequent analysis. Some details are required to implement this decomposition in practice. Our measurement approach is designed to yield a decomposition of FQ jobs in Q1 of each year given our focus on earnings of FQ jobs in Q1 of each year. Stayers are thus jobs where the individual holds a FQ job at the same firm in Q1 of adjacent years. Job Switchers are those that switch firms while holding FQ jobs in Q1 of adjacent years. "Hires from Nonemp" are a residual reflecting hires from non-full-quarter employment in the prior year to a FQ Q1 job in the current year. These definitions are distinct from related measures in the literature as we discuss in more detail below. It is also worth noting that our dataset is jobs rather than persons, so accounting for multiple jobholding is a slight complication.[8]

Figure 4 presents our measures of hires types as percentages of total full-quarter employment. The top left panel of Figure 4 shows that the percentage of full-quarter jobs that are stayers increased from 63.0 percent in 1998 to 68.5 percent in 2018. Expressed in terms of hires rather than stayers, our data shows evidence of declining labor market fluidity – the percentage of full-quarter jobs that are hires fell from 37.0 percent in 1998 to 31.5 percent in 2018.

[8] Persons holding one full-quarter job last year and more than one full-quarter job this year (1:N) are coded as follows: if last-year's job is also held this year, then that job is a stayer and the other "N-1" jobs this year are classified as hires from nonemployment. Persons holding more than one full-quarter job last year but only one full-quarter job this year (N:1) are classified based on whether this year's job could be found last year (stayers) or if the current year's job is new (E2E Same Ind or E2E Diff Ind). Persons holding two full-quarter jobs this year and two full-quarter jobs last year are classified by looking for the same job across years (stayers) or whether the current year's jobs are new (E2E same ind or E2E diff ind). A very small number of persons with N1 full-quarter jobs last year and N2 full quarters jobs this year, where N1$\geq$2, N2$\geq$2, and N1>2 and/or N2>2, are deleted from the data.

The top right panel of Figure 4 shows the decomposition of total hires into employer-to-employer flows and hires from nonemployment. Employer-to-employer hires only slightly declined from 10.0 percent in 1998 to 9.1 percent in 2018, whereas hires from nonemployment fell from 27.0 percent to 22.4 percent. The bottom left panel of Figure 4 shows the decomposition of employer-to-employer hires based upon whether the hire was from the same 4-digit NAICS industry or a different 4-digit NAICS industry. Hires from the same industry are relatively small without much movement over time, whereas hires from a different industry are cyclical with a slight downward trend during our time period.

Our measures of labor market fluidity are, as noted, based upon the status of employment for workers in the first quarter across years. These measures are related to but distinct from the published quarterly measures from the LEHD Quarterly Workforce Indicator (QWI) and Job-to-Job (J2J) programs (see, https://lehd.ces.census.gov/data/). Figure 5 provides comparisons of our measures with the published QWI and J2J series from LEHD.[9] For the published quarterly series we report only the Q1 series. Panel A shows alternative quarterly hires series from the QWI and J2J. The range of published series corresponds to a broad based hires measure (e.g, hires for QWI all matches that are new in the current quarter) to narrower definitions (e.g., hires for QWI that are transitions to a FQ position in the current quarter). Not surprisingly the levels of these alternatives differ and are substantially lower than the annual hires series into FQ positions that we use. In addition, definitional differences as well as the presence of job turnover implies that the annual measures are not simply interpreted as aggregates of the quarterly measures. However, the pairwise correlations between all of the alternatives in panel A including our annual series are all above 0.9. Relatedly, the long run decline in the alternative series is quite

[9] We intentionally use the term employer-to-employer flows in this paper (and shorthand E2E) to avoid confusion with the published job-to-job flows (J2J) series from LEHD.

similar in terms of percent changes from 2001 to 2018. QWI all hires and FQ hires decline by 25% and 17% respectively. The annual hires series we construct declines by 16% from 2001 to 2018.

Panel B of Figure 5 turns to decompositions of hires into hires from nonemployment and transitions between employers. The published J2J Job-to-Job Flow series reflects job-to-job transitions from one main job to another in the current quarter. The published J2J hires from nonemployment series reflects hires into new main jobs in the current quarter following at least a brief spell of nonemployment. Again the magnitudes of these quarterly series (for Q1) are lower than those of our annual series but the correlation between our annual series and the quarterly published series are very high (about 0.9 for J2J job-to-job flow series vs. the annual employer-to-employer series and also for the J2J hires from nonemployment vs. the annual hires from nonemployment series). The percent declines in the alternative series are similar. Published J2J quarterly (Q1) job-to-job flows decline by 12% from 2001-18 while the annual employer-to-employer series we construct declines by 13% over this same period. Published quarterly (Q1) hires from non-employment decline by 21% from 2001-18 and the annual hires from nonemployment series declines by 18% over that same period.

Our takeaway from Figure 5 is that our annual measures are capturing the well-known findings of a declining pace of hires with an especially large decline in hires from non-employment. In addition, we primarily exploit the between-industry variation in these measures in the analysis below. Our measures of the share of employment accounted for by employer-to-employer transitions are conservative in that we require that the transitions are from one FQ job to another. Relatedly our measures of stayers are conservative based on requiring being at the same employer one year to the next in a FQ capacity. As will become clear, these measures not only are highly correlated with related published measures of fluidity but also are closely connected to inter-industry earnings differentials both in the cross section and over time.

V. Earnings dispersion by Hires Types

Figure 6 presents mean earnings for the various types of stayers and hires (hires from nonemployment, E2E hires from the same industry, and E2E hires from a different industry). The black line in Figure 6 is mean earnings of all full-quarter jobs, identical to what is shown in the lower left panel of Figure 1. The data in Figure 6 are broadly consistent with a job ladder. Mean earnings of stayers are the highest, and mean earnings of hires from nonemployment are the lowest. Mean earnings of persons hired from a different firm in the same industry are somewhat higher than mean earnings of persons hired from a different firm in a different industry.

The variance of earnings for each of the classifications of hires and stayers are presented in Figure 7. The top left panel of Figure 7 shows the total variance, the top right panel shows the between industry variance, and the bottom right panel shows the within industry variance. In all panels of Figure 7, the black line is the variance of all full-quarter jobs.

There are two striking results in Figure 7. First, the variance of earnings is increasing over time for stayers and for each type of hire. This pattern of within hires type increase in earnings dispersion holds at the individual level overall, between industry, and within industry. Second, the variance of earnings of hires from nonemployment is greater than the variance of stayers. This is consistent with the predictions of the Burdett and Mortensen (1998) model of a job ladder since transitions from non-employment include all rungs of the job ladder while employer-to-employer flows include only rungs of the ladder above the current position of the ladder for workers. This pattern may also reflect the role of ex ante heterogeneity of workers. For example, heterogeneous individuals transit from non-employment to substantially different starting earnings (e.g., high school vs college graduates transiting from non-employment to employment).

These findings from Figure 7 imply that compositional changes in hires types cannot account for rising earnings inequality. First, the rise in earnings inequality is pervasive within each hires type. Second, declining fluidity implies that, over time, there is a larger share of stayers (low variance) and a smaller share of hires from nonemployment (high variance), and the resulting composition effects act to dampen the overall increase in variance. Put differently, there is even more rising inequality to account for after considering such composition effects.

VI. The Contribution of Earnings Differentials by Hires Types

VIa. Accounting Decomposition Methodology

Since the rising inter-industry earnings differentials is within hires types groups, in this section we explore the potential connection between rising inter-industry earnings differentials and the job ladder within groups. We use simple accounting decompositions for this purpose and focus our attention on rising between industry earnings inequality. The focus on rising between industry dispersion is motivated by our findings above that the vast majority of rising overall inequality is due to between firm effects and in turn most of the latter is due to between industry. Using the rising inter-industry earnings differentials has numerous advantages since it permits a transparent mapping between the characteristics of the industry in terms of its position on the job ladder while also permitting controlling for firm and worker demographics of the industry. The simple regression and associated accounting decompositions we use in this section are intended to be exploratory and descriptive. Such regressions and decompositions don't identify causal channels for rising inter-industry differentials but help provide guidance about the nature of the connection between rising inequality and the changing job ladder.

We start by exploring the relationship between full-quarter industry earnings W_{kt}^{j} for hires type j and industry level measures of the share of workers in the four hires types (H_{kt}) as well as industry-level measures of firm and worker demographics (D_{kt}).[10] We estimate the following two specifications:

(3a) $$W_{kt}^{j} = H_{kt}'\bar{\delta}^{j} + D_{kt}'\bar{\gamma}^{j} + \tilde{\varepsilon}_{kt}^{j}$$

(3b) $$W_{kt}^{j} = H_{kt}'\delta_t^{j} + D_{kt}'\gamma_t^{j} + \varepsilon_{kt}^{j}\ .$$

Specification (3a) is a pooled specification with time invariant coefficients, and specification (3b) permits the coefficients to vary over time. Observe that we permit the shares of all hires types to impact the earnings of each hires type (more generally, the right hand side variables are the same for each type j but the coefficients vary by j). Specification (3b) can be rewritten as:

(3c) $$W_{kt}^{j} = H_{kt}'\bar{\delta}^{j} + D_{kt}'\bar{\gamma}^{j} + H_{kt}'\left(\delta_t^{j} - \bar{\delta}^{j}\right) + D_{kt}'(\gamma_t^{j} - \bar{\gamma}^{j}) + \varepsilon_{kt}^{j}$$

Following Juhn, Murphy and Pierce (1992) (hereafter JMP), Davis and Haltiwanger (1991), and Dunne et. al. (2004), the changes in dispersion (either the variance or other moments) can be decomposed into quantity *(H_{kt} and D_{kt})* effects for average prices ($\bar{\delta}^{j}, \bar{\gamma}^{j}$), price effects (δ_t^{j} and γ_t^{j}) and the residual. We don't pursue the full distribution accounting insights from this

[10] By design the right hand side variables are the same for each of the specifications by hires type. For example, each regression in Table 3 includes the percentage of females in the industry as an explanatory variable, and each regression includes the share of hires from non-employment in the industry as an explanatory variable. The right hand side variables represent characteristics of the industry.

approach but focus on the decomposition of variance.[11] The estimation and decomposition is on an employment-weighted basis to be consistent with the variance trends reported in Figure 7.

VIb. Regressions and Decompositions

We present estimates of regression equation for (3a) for each of the hires type groups and for overall earnings in the industry. The explanatory variables include the hires types shares (with stayers as the omitted group) and the firm and worker demographic variables. Worker characteristics (age, gender, and education) are meant to capture differences in the mix of workers across industries, and firm characteristics (firm age and firm size) capture differences in firm observables across industries.[12,13] The industry-level employment weights in each regression reflect the share of the hires type of the dependent variable for that industry relative to the economy-wide total. This implies that the mean of the dependent variable is the earnings for that hires type in the overall economy, and the variances of the dependent variable replicate the between-industry variances in the top right panel of Figure 7.

Table 3 presents estimates from these specifications. We report the time invariant pooled estimated coefficients from equation (3a). In the bottom of Table 3, we report the variance decompositions that are based on equation (3c). All of the specifications include controls for

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[11] There are some limitations of the JMP decomposition methodology as highlighted by DiNardo et. al. (1996) and Fortin et. al. (2010). These limitations primarily apply to the full distribution accounting (e.g., decomposing the 90-50 vs. the 50-10) which we do not pursue.

[12] To be precise, we create industry-year means of worker age, gender, education, firm age, and firm size, and then take the natural log of the industry-year means for worker age, education, firm age, and firm size. Worker and firm demographics are deviations from pooled means.

[13] We acknowledge that the education variable in the LEHD is mostly imputed -- Vilhuber (2018) reports that 92% of PIKs have an education impute. Earnings is one of the variables used to impute education, which limits the value added of this variable in accounting for rising variance of earnings. Formally, this implies we are controlling for the covariance between education and earnings in our analysis. We include this variable in the main specification since our focus is on the hires type variables and we seek to understand the impact of those variables even after controlling for a rich set of firm and worker controls. In unreported results, we find that many of the basic patterns reported in this section are robust to the exclusion of this variable, and if anything, the relative effect of the changing job ladder contribution (i.e., the hires types) is even larger without including education.

firm and worker demographics in an industry. These demographic variables have the expected effects (for all hires types): industries with older workers have higher earnings, industries with more females have lower earnings, and industries with higher educated workers have higher earnings. On the firm side, industries with larger firms and younger firms have higher earnings.[14]

We find broadly similar patterns for the relationship between the shares of hires types in the industry and earnings for each hires type. Industries with a higher share of employer-to-employer flows (especially from job switchers between industries) have higher earnings for stayers, job switchers within industries, job switchers from other industries, and hires from non-employment (these represent the pooled time invariant $\delta's$ in equation (3a)).[15] We also find that industries with a higher share of hires from nonemployment have lower earnings for stayers, job switchers from the same industry, job switchers from different industries, and hires from nonemployment. While there are some quantitative differences across hires types, our conclusion is that the hires shares in an industry have basically similar effects on the earnings of each hires type.

The finding that that the factors influencing earnings of each hires type at the industry level are quite similar is interesting in its own right. These patterns are consistent with our interpretation of a job ladder with earnings for all hires types being higher in industries with a high share of hires from employer-to-employer flows and lower in industries with a high share of hires from non-employment. It is striking, for example, that earnings for stayers are higher in

[14] The finding that earnings are higher at younger firms might seem surprising but in Table 3 this is the marginal effect of firm age controlling for a rich set of other factors. In Table 4, we find that without the hires types controls that the marginal effect of firm age is positive. The relationship between earnings and firm age is not our focus but it is interesting that this effect flips sign once we control for hires types.

[15] Given that we include an exhaustive set of hires types with the omitted group being stayers, the estimated effect of an increase in hires of a specific type can be interpreted as an increase in the share of hires from that type (since this estimated effect holds the hires of other types constant).

industries with a larger share of hires from employer-to-employer flows, and similarly, earnings for stayers are lower in industries with a larger share of hires from non-employment. This is consistent with top of the job ladder industries paying higher wages for all workers. But it may also reflect the type of competitive pressures discussed in Faberman and Justiniano (2015), wherein a higher pace of employer-to-employer flows puts upward pressure on wage growth within an industry.

Given that the patterns are so similar for each of the hires type groups considered separately, it is not surprising that the first column of Table 3 shows that overall earnings for an industry is higher with a larger share of employer-to-employer flows and lower for an industry with a higher share of hires from non-employment. We exploit that finding below to dig into the findings in more detail.

The lower panel of Table 3 shows the results of JMP style decompositions. The results of these accounting decompositions are quite similar for each of the hires type groups and overall industry earnings. We find that taking into account both the changing distribution of characteristics including hires types and firm and worker demographics (the X's) and the changing earnings differentials from these characteristics (the $\beta's$) accounts for about 80 percent of the rising variance in inter-industry earnings differentials.[16] Overwhelming the positive contribution derives from the changing β's while the changing distribution of characteristics is a drag on rising inter-industry earnings differentials.

[16] We use changing β's as a label for the combined contribution of changes in δ's and Υ's and changing X's as a label for the combined contribution of changing H_{kt}'s and D_{kt}'s. In Table 4 below, we provide guidance of the marginal contribution of the hires type variables in terms of both changing differentials and changing characteristics. Even there we use the same type of placeholder labeling.

To dig into the patterns in Table 3 in more detail, we focus on the results of the first column of Table 3 using overall industry earnings (mean ln real earnings) as the dependent variable.[17] Table 4 and Figure 8 presents additional results for this specification. Summary statistics in Table 4 provide more information about the changing distribution of characteristics. Declining fluidity is evident in the second column with declining means of hires shares of employer-to-employer flows and from non-employment. For the firm and worker demographics there is an increase over time in the age of workers and age of businesses as well as an increase in the average firm size. Of greater relevance for changing inequality is the fourth column showing changing dispersion in the characteristics. There is compression of dispersion in hires rates across industries accounted for mostly by compression of dispersion in hires from non-employment and job switchers across industries. Thus, not only is there a decline in the average pace of fluidity but there is also declining less dispersion across industries. There is also a large decline in dispersion in education and firm size across industries. These patterns help explain the findings in Table 3 about the negative contribution of the changing distribution of characteristics in the decompositions.

Specifications (1a), (1b), and (1c) in Table 4 present estimates of equation (3a) with time invariant coefficients and only the hires types as explanatory variables. The specification in column (1a) shows that industries with more hires have lower earnings, but as seen in column (1b), industries with more employer-to-employer hires have higher earnings and industries with more hires from non-employment have lower earnings. Column (1c) shows that industries with more job switchers from other industries have especially high earnings. Industries with a larger share of hires from non-employment have lower earnings.

[17] In unreported results we have found the patterns we discuss from Table 4 and Figure 8 are broadly similar for all hires types.

Specification (2) of Table 4 shows the results from only using the firm and worker demographic controls. Specification (3) repeats the results from Table 3 for overall earnings. We also consider a specification in (4) which includes year effects and 2-digit industry dummies (we could not estimate the year-specific regressions if we include four-digit industry dummies). The basic patterns are robust to the inclusion of these additional controls.

Figure 8 presents the estimated year-specific coefficients from specification (3) of Table 4 – these are the coefficient estimates δ_t^j and γ_t^j from equation (3b). The top panel shows the coefficients of the hires type variables. The coefficients on both of the employer-to-employer hires variables, hires from the same industry and hires from a different industry, are positive and increasing over time. On the other hand, the year-specific coefficients for hires from non-employment are negative declining over time, from -3.7 in 1998 to -5.0 in 2018.

The bottom panel of Figure 8 presents the estimated year-specific coefficients for the worker and firm demographic variables. The education coefficient is on the right axis, and all other coefficients are measured on the left axis. The education coefficients are increasing over time, from 3.8 in 1998 to 7.9 in 2018. The other worker and firm demographic coefficients are not changing much over time. The coefficients on worker age increase from 1.004 in 1998 to 1.172 in 2018 (the coefficient on worker age spikes in 2011 for reasons we don't fully understand), and the coefficients on female gradually decline from -.887 in 1998 to -1.220 in 2018. The coefficients on firm age and firm size are essentially invariant over time.

The lower half of Table 4 presents the results from the JMP variance decompositions. We are particularly interested in quantifying the marginal contribution of the hires type variables. We find that without firm and worker demographic controls (specification 1c), the combined contribution of changing distribution of hires types along with the changing pattern of earnings differentials by hires types accounts for 30 percent of the rising dispersion in inter-industry earnings differentials. The analogous contribution of combined characteristics and changing prices for firm and worker demographics (specification 2) accounts for as much as 60 percent of rising dispersion in inter-industry earnings differentials. Together hires types and firm and worker demographics account for about 80 percent of rising inter-industry earnings differentials. The latter differs from the "implied" 90 percent from adding up the separate contributions and reflects covariance effects in the accounting decompositions. Overall, then, we find that the marginal contribution of the hires type variables in accounting for rising between industry inequality is about 20 percent (with firm and worker demographic controls) to 30 percent (without firm and worker demographic controls). As noted above, this positive contribution is overwhelming coming through the changing "prices" – the δ_t's of equation (3b).

IVc. A Changing Job Ladder

We interpret the regression results and variance decompositions through the lens of a changing job ladder over time. To facilitate this interpretation, Figure 9 illustrates the relationship between earnings changes for selected industries ranked by the share of hires from job switchers from different industries. Panel A of Figure 9 shows selected industries in the bottom quintile of industries ranked in this fashion while Panel B shows selected industries in the top quintile. The share of hires from job switchers from different industries is twice as large (on average from 1998 and 2018) in the bottom panel compared to the top panel. Earnings are about 140 log points larger in the bottom panel on average in the top panel compared to the top panel. Moreover, the increase in earnings in the bottom panel from 1998 to 2018 is more than 25 log points greater than in the top panel.

Figure 9 is consistent with a job ladder with the rungs of the ladder becoming further apart over time. Appropriate caution is required given we show only selected industries and without any controls. It is naïve to interpret Figure 9 as suggesting that individuals get on the job ladder at the bottom in industries like restaurants and drinking places early in their career and climb the ladder to find themselves at software publishers later in their career. Still Figure 9 highlights that the top industries in terms of shares of hires of job switchers from other industries are very high earnings industries and the earnings gap for such industries is growing. Moreover, Figure 9 mimics the patterns in Tables 3 and 4 and Figure 8. The latter show much higher earnings in industries with a higher share of job switchers and that this earnings gap is rising over time. Tables 3 and 4 also shows that this pattern is robust to inclusion of firm and worker demographic controls. Not depicted but consistent with Figure 9 is that the bottom panel industries have a high share of hires from nonemployment. Consistently Tables 3 and 4 and Figure 8 show that industries with a share of hires from nonemployment are low earnings industries. In addition, the negative earnings differential associated with this bottom of the ladder industries is growing in magnitude over time.

VII. Concluding Remarks

Rising earnings inequality in the last few decades is dominated by rising between firm inequality. In turn rising between firm inequality is dominated by rising inter-industry earnings differentials. Over this same period, there has been declining labor market fluidity. The pace of hires and separations has slowed. Viewed from the perspective of hires, there has been an especially large decline in the pace of hires from non-employment.

We present evidence that these patterns are connected through the lens of a changing job ladder. Stated simply, our results suggest it has become more difficult to get on the job ladder, as evidenced by the declining hires from nonemployment. Moreover, the rungs of the job ladder have become further apart as evidenced by the year-specific coefficients on both of the employer-to-employer hires variables which are increasing over time, as well as by the year-specific coefficients for hires from non-employment which are declining over time. The widening of the rungs of the ladder is also evident in the rising between firm and between industry differentials. In combination, our results suggest there has been an increase in inequality accompanied by a decline in an important form of economic mobility – that is, it has become more difficult to get on and climb the job ladder.

We view our results as exploratory with many open questions. We have focused on rising inter-industry earnings differentials since rising between industry dispersion accounts for much of the rising between firm dispersion in earnings. The finding of rising inter-industry earnings differentials is important since it implies that the structural change underlying rising earnings inequality is working through mechanisms that change the structure of industries. This points towards looking more intensively at changes in technology, globalization, and market structure that vary across industries. Identifying these industry-specific driving forces should be a high priority for future research. There is also rising between firm dispersion within industries that deserves further attention. In principle, the approach we have taken here can be used at the firm-level for exploring within industry rising between firm dispersion.

In companion research (Haltiwanger and Spletzer (2020)), we have found that the rising inter-industry earnings differentials are almost completely accounted for by occupation effects. The latter reflect differences across industries in the changing mix of occupations as well as changing differentials for occupations that vary widely across industries. These findings are consistent with the findings of Acemoglu and Autor (2011) and related literature highlighting the increasingly important role of changing tasks and changing returns for tasks. Our contribution in this companion research is to show that that the changing role of occupations is working primarily through rising inter-industry earnings differentials.

An open question is how to relate this occupation/task-based perspective with the findings in this paper. The job ladder is changing over time and we find this is closely connected to rising inter-industry earnings differentials. Getting on the job ladder has become more difficult and the earnings differential for starting at the bottom of the ladder has declined. Presumably our findings on the changing job ladder can be related to the changing relative demand for occupations and tasks. Understanding this connection should be an important area for future research.

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Figure 1: Descriptive Statistics

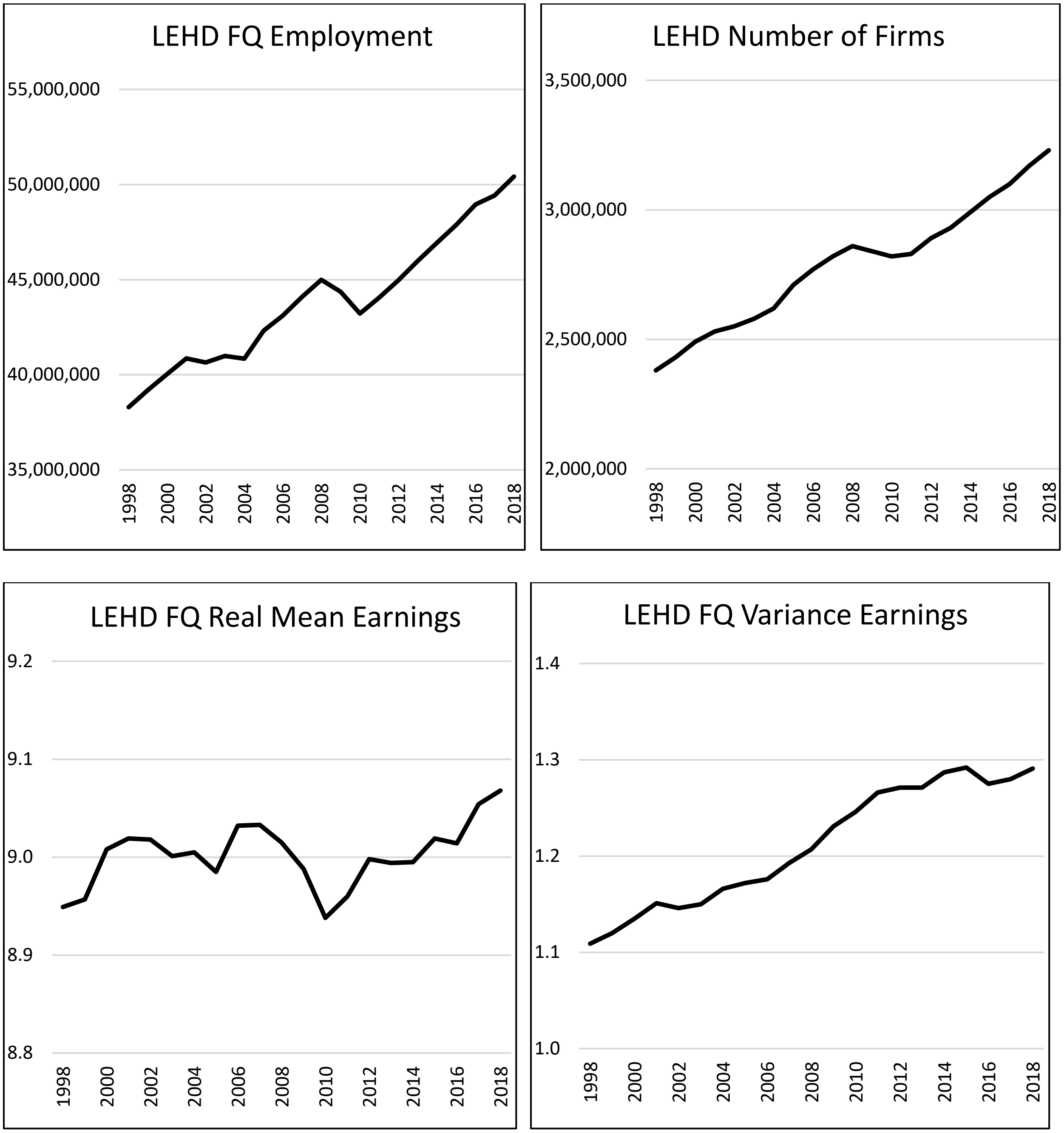


Figure 2: Percentiles from the LEHD and CPS Earnings Distribution

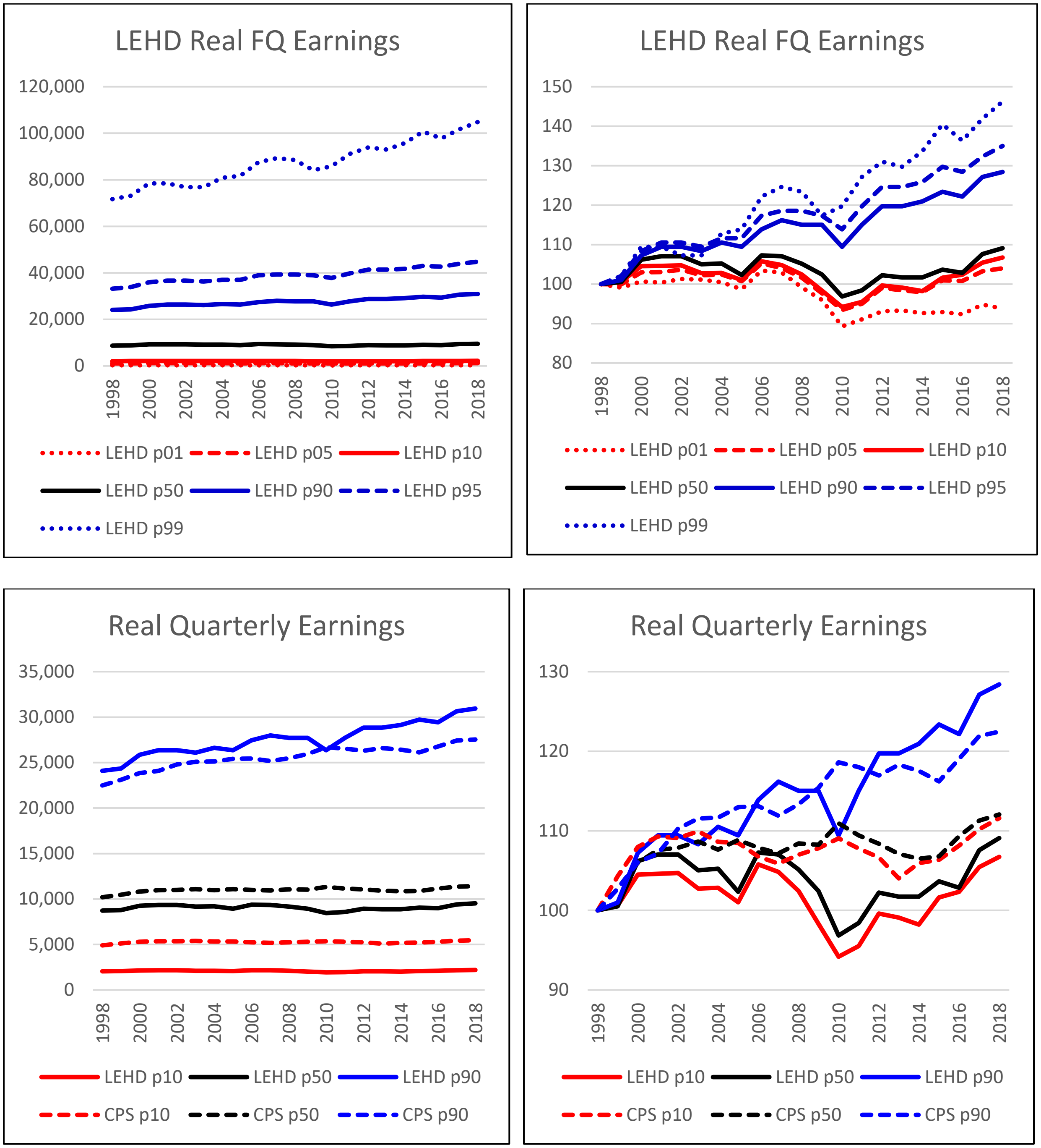


Figure 3: Variance Decomposition

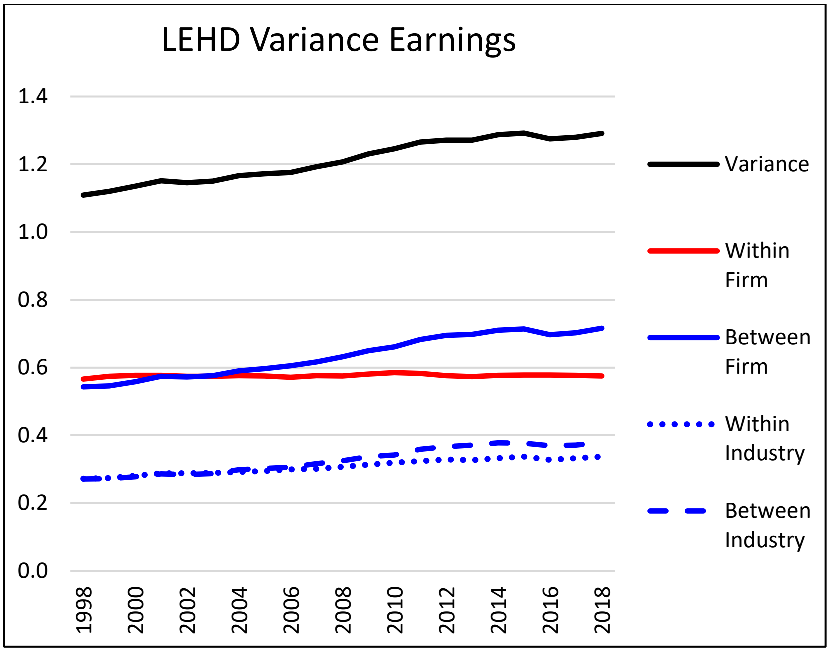


Figure 4: Labor Market Fluidity

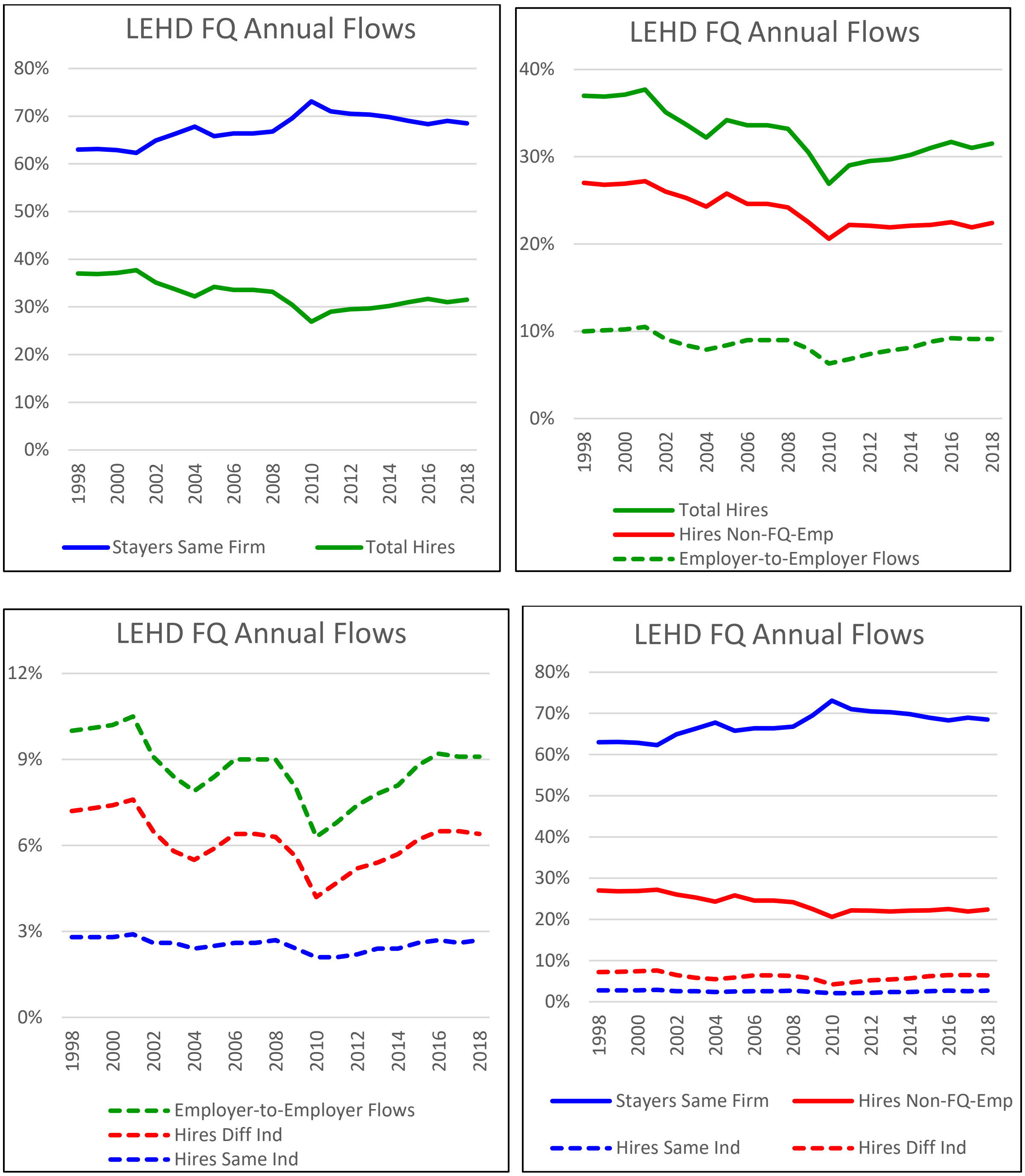
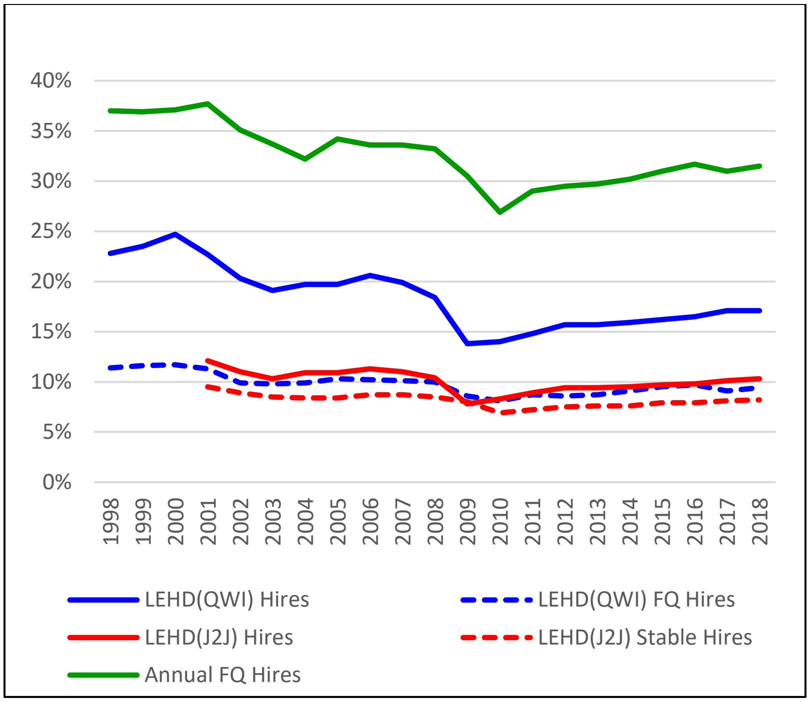


Figure 5. Comparisons of Annual Fluidity Measures to Published QWI and J2J Quarterly Flows.

A. Annual FQ Hires vs. Published QWI and J2J Hires



B. Annual FQ Hires from Nonemployment and E2E vs. Published Quarterly J2J

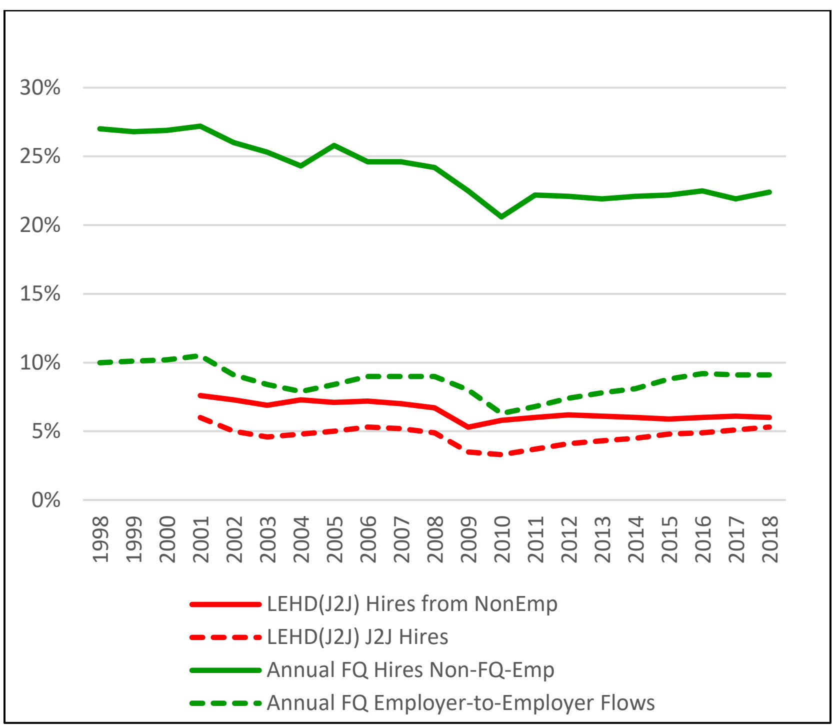


Figure 6: Mean Full-Quarter Earnings by Type of Annual Flow

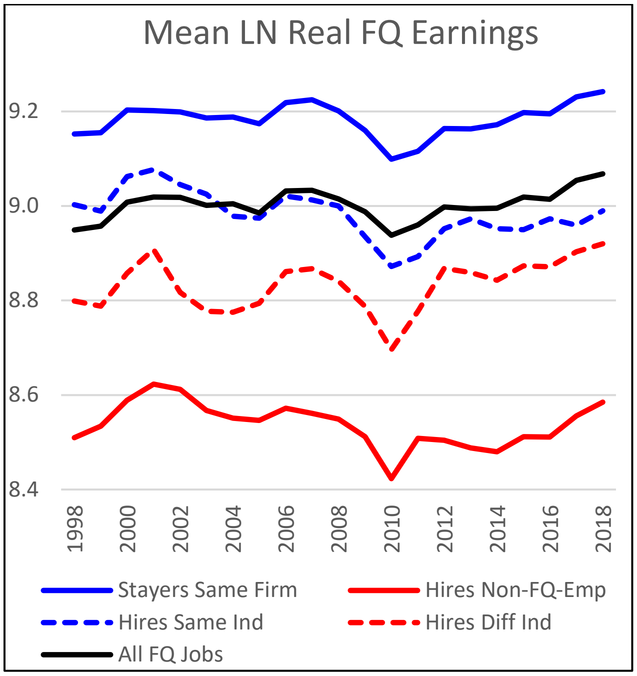


Figure 7: Variance of Full-Quarter Earnings by Type of Annual Flow

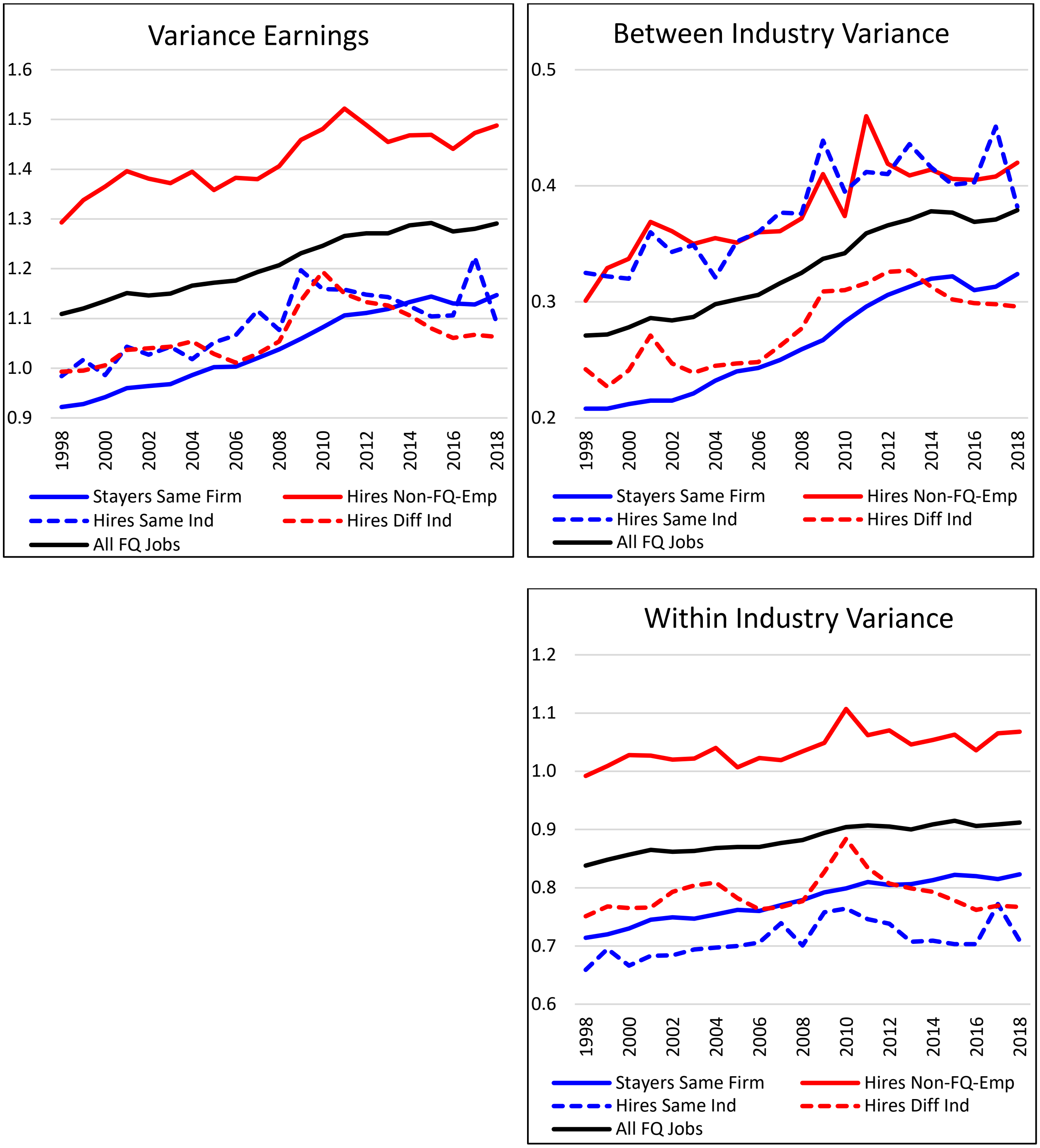
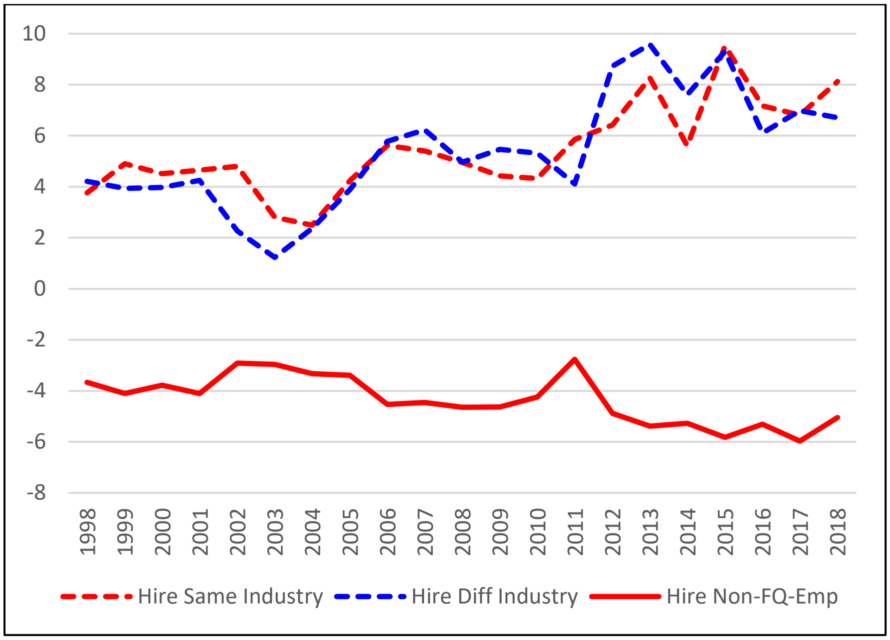


Figure 8: Year-Specific Coefficient Estimates from Earnings Regressions (Equation (3a))



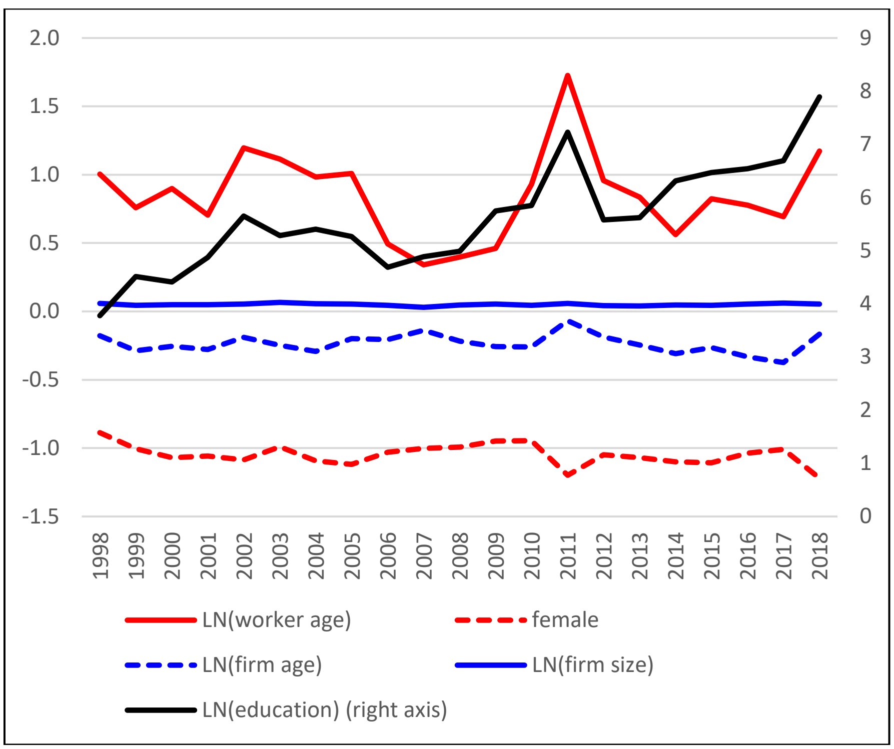
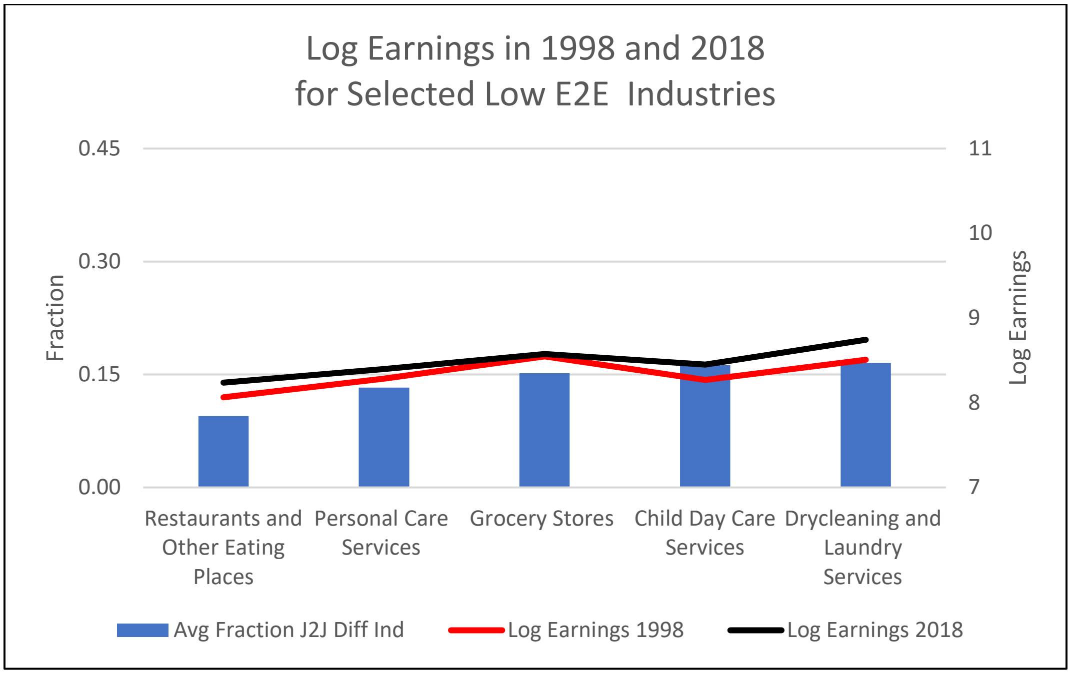


Figure 9: Employer-to-employer Flows and Earnings for Selected Industries

A. Low E2E from Different Industries



B. High E2E from Different Industries

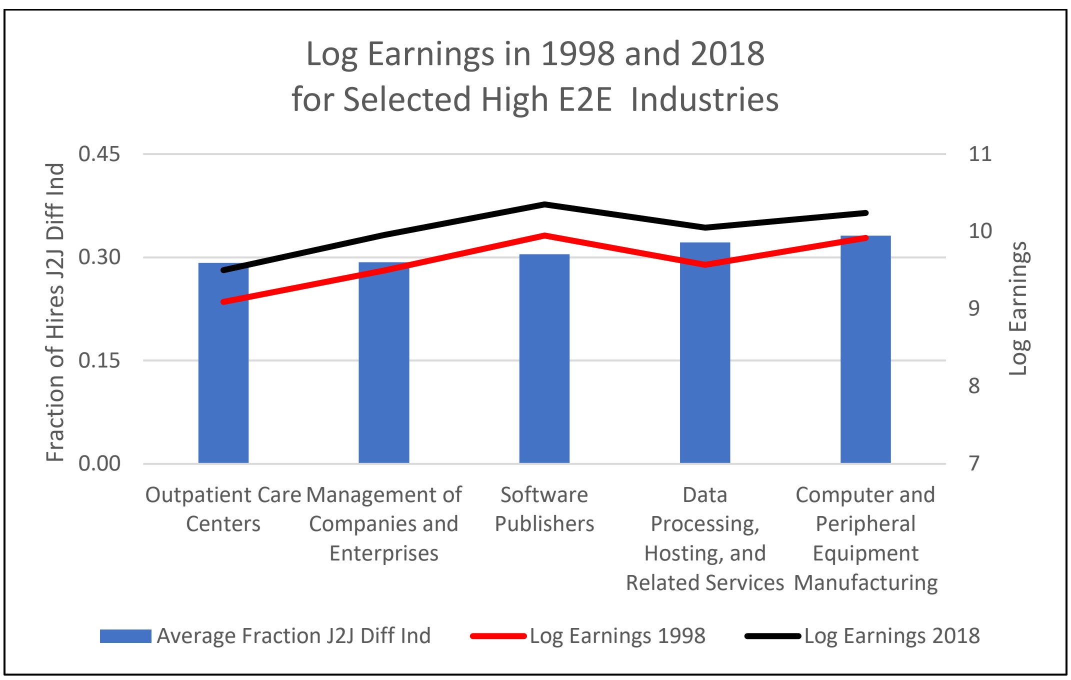


Table 1: Variance Decomposition

	2-digit naics	3-digit naics	4-digit naics	5-digit naics	6-digit naics
2018 Levels					
Variance LN($)	1.291	1.291	1.291	1.291	1.291
Within Firms	0.575	0.575	0.575	0.575	0.575
Between Firms	0.716	0.716	0.716	0.716	0.716
Within Industry	0.474	0.387	0.337	0.316	0.306
Between Industry	0.242	0.329	0.379	0.400	0.410
1998-2018 Growth					
Variance LN($)	0.182	0.182	0.182	0.182	0.182
Within Firms	0.009	0.009	0.009	0.009	0.009
Between Firms	0.173	0.173	0.173	0.173	0.173
Within Industry	0.120	0.080	0.065	0.060	0.058
Between Industry	0.053	0.093	0.108	0.113	0.115
2018 Levels					
Variance LN($)	100.0%	100.0%	100.0%	100.0%	100.0%
Within Firms	44.5%	44.5%	44.5%	44.5%	44.5%
Between Firms	55.5%	55.5%	55.5%	55.5%	55.5%
Within Industry	36.7%	30.0%	26.1%	24.5%	23.7%
Between Industry	18.7%	25.5%	29.4%	31.0%	31.8%
Between Firms	100.0%	100.0%	100.0%	100.0%	100.0%
Within Industry	66.2%	54.1%	47.1%	44.1%	42.7%
Between Industry	33.8%	45.9%	52.9%	55.9%	57.3%
1998-2018 Growth					
Variance LN($)	100.0%	100.0%	100.0%	100.0%	100.0%
Within Firms	4.9%	4.9%	4.9%	4.9%	4.9%
Between Firms	95.1%	95.1%	95.1%	95.1%	95.1%
Within Industry	65.9%	44.0%	35.7%	33.0%	31.9%
Between Industry	29.1%	51.1%	59.3%	62.1%	63.2%
Between Firms	100.0%	100.0%	100.0%	100.0%	100.0%
Within Industry	69.4%	46.2%	37.6%	34.7%	33.5%
Between Industry	30.6%	53.8%	62.4%	65.3%	66.5%
Number of Industries	23	91	304	682	1034

Table 2: Variance Decomposition

Firm Definition:	SEIN	SEIN	SEIN	EIN	Enterprise
Years:	1998-2018	1998-2016	1998-2016	1998-2016	1998-2016
Sample:	Full Sample	Full Sample	Nonmiss Firm ID	Nonmiss Firm ID	Nonmiss Firm ID
Levels (Final Year)					
Variance LN($)	1.291	1.275	1.259	1.259	1.259
Within Firms	0.575	0.578	0.579	0.599	0.648
Between Firms	0.716	0.697	0.680	0.660	0.611
Within Industry	0.337	0.328	0.321	0.301	0.266
Between Industry	0.379	0.369	0.359	0.359	0.345
1998-Final Year Growth					
Variance LN($)	0.182	0.166	0.151	0.151	0.151
Within Firms	0.009	0.012	0.009	0.015	0.038
Between Firms	0.173	0.154	0.142	0.136	0.113
Within Industry	0.065	0.056	0.052	0.048	0.030
Between Industry	0.108	0.098	0.090	0.088	0.083
Levels (Final Year)					
Variance LN($)	100.0%	100.0%	100.0%	100.0%	100.0%
Within Firms	44.5%	45.3%	46.0%	47.6%	51.5%
Between Firms	55.5%	54.7%	54.0%	52.4%	48.5%
Within Industry	26.1%	25.7%	25.5%	23.9%	21.1%
Between Industry	29.4%	28.9%	28.5%	28.5%	27.4%
Between Firms	100.0%	100.0%	100.0%	100.0%	100.0%
Within Industry	47.1%	47.1%	47.2%	45.6%	43.5%
Between Industry	52.9%	52.9%	52.8%	54.4%	56.5%
1998-Final Year Growth					
Variance LN($)	100.0%	100.0%	100.0%	100.0%	100.0%
Within Firms	4.9%	7.2%	6.0%	9.9%	25.2%
Between Firms	95.1%	92.8%	94.0%	90.1%	74.8%
Within Industry	35.7%	33.7%	34.4%	31.8%	19.9%
Between Industry	59.3%	59.0%	59.6%	58.3%	55.0%
Between Firms	100.0%	100.0%	100.0%	100.0%	100.0%
Within Industry	37.6%	36.4%	36.6%	35.3%	26.5%
Between Industry	62.4%	63.6%	63.4%	64.7%	73.5%

Table 3: Regressions and Decompositions Using Industry-by-Year Earnings by Hires Type

	Earnings All Jobs	Earnings Same Firm Stayers	Earnings Hires Same Ind	Earnings Hires Diff Ind	Earnings Hires Non-Emp
Intercept	9.566	9.624	9.806	9.044	9.028
Hire Same Industry	4.861	4.070	2.281	5.066	7.360
Hire Diff Industry	5.030	4.959	7.004	6.783	5.570
Hire Non-FQ-Emp	-4.165	-3.679	-5.046	-3.167	-3.943
LN(worker age)	0.913	0.628	-0.110	1.428	1.441
female	-1.068	-1.038	-0.990	-1.048	-1.176
LN(education)	5.583	5.681	5.121	5.431	5.371
LN(firm age)	-0.263	-0.197	-0.248	-0.205	-0.449
LN(firm size)	0.054	0.045	0.027	0.038	0.082
R-Squared	0.839	0.835	0.819	0.830	0.750
Variance Growth					
Predicted X(t) *β	-0.122	-0.097	-0.120	-0.105	-0.133
Predicted X(t)*β(t)	0.085	0.092	0.043	0.043	0.092
Residual	0.023	0.024	0.014	0.011	0.027
Total	0.108	0.116	0.057	0.054	0.119
% Contribution					
Changing X	-113.0	-83.6	-210.5	-194.4	-111.8
Changing β's	191.7	162.9	286.0	274.1	189.1
Residual	21.3	20.7	24.6	20.4	22.7

Dependent variable is LN real full-quarter earnings of the hires type listed at the top of the row.
N=6384 industry year observations.
Weighted regressions, where weight is number of industry-year full-quarter jobs for the hire type.
Worker and firm demographic variables are deviations from pooled means.
All regression coefficients have an estimated t statistic greater than 2.

Table 4: Regressions and Decompositions Using Industry-by-Year Earnings

	Mean	ΔMean	Std. Dev.	ΔStd. Dev.	(1a)	(1b)	(1c)	(2)	(3)	(4)
Intercept					10.18	9.869	9.824	9.004	9.566	9.459
Hires	0.325	-0.055	0.102	-0.009	-3.632					
Hires E2E	0.087	-0.009	0.027	-0.002		8.951				
Hire Same Industry	0.026	-0.001	0.017	0.002			5.134		4.861	1.761
Hire Diff Industry	0.061	-0.008	0.022	-0.004			10.80		5.030	3.653
Hire Non-FQ-Emp	0.238	-0.046	0.083	-0.011		-6.875	-6.751		-4.165	-3.398
LN(worker age)	0.000	0.079	0.093	0.009				2.172	0.913	0.510
female	0.000	0.018	0.207	-0.004				-1.272	-1.068	-0.851
LN(education)	0.000	-0.006	0.045	-0.014				7.658	5.583	6.555
LN(firm age)	0.000	0.515	0.290	0.049				0.039	-0.263	-0.244
LN(firm size)	0.000	0.394	1.590	-0.054				0.046	0.054	0.062
Year Dummies					No	No	No	No	No	Yes
2-Digit Industry					No	No	No	No	No	Yes
R-Squared					0.418	0.615	0.633	0.746	0.839	0.903
Variance Growth										
Predicted X(t) * β					-0.023	-0.101	-0.080	-0.047	-0.122	-0.104
Predicted X(t) * β(t)					0.045	0.034	0.033	0.064	0.085	0.092
Residual					0.063	0.074	0.075	0.044	0.023	0.016
Total					0.108	0.108	0.108	0.108	0.108	0.108
% Contribution										
Changing X					-21.3	-93.5	-74.1	-43.5	-113.0	-96.3
Changing β					63.0	125.0	104.6	102.8	191.7	181.5
Residual					58.3	68.5	69.4	40.7	21.3	14.8

Dependent variable is LN real full-quarter earnings. Mean of the dependent variable is 9.004 (standard deviation = 0.576).
N=6384 industry year observations. Weighted regressions, where weight is number of industry-year full-quarter jobs.
Worker and firm demographic variables are deviations from pooled means.
All regression coefficients have an estimated t statistic greater than 2.