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

John Haltiwanger and James R. Spletzer

2.1 Introduction

A large literature has documented the growth of real earnings dispersion in the US economy since the late 1970s, often referred to as increasing earnings inequality. During this same time, labor market fluidity in the US has declined as evidenced by a decline in the overall pace of hires and separations (see Davis, Faberman and Haltiwanger 2012; Davis and Haltiwanger 2014; Hyatt and Spletzer 2013; and Molloy 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 nonemployment. In this chapter, 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

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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 nonemployment. We find that the share of stayers has been increasing as a fraction of employment while the share of hires has declined, with especially large declines of hires from nonemployment.

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 the rise in earnings inequality in the US over the last few decades is accounted for by rising between-firm inequality (see Barth et al. 2016; Song et al. 2019). 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; 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 nonemployment. Recent evidence provides empirical support for this prediction. Haltiwanger et al. (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 nonemployment. These patterns hold for job switches both within and between industries.[1]

Our findings in this chapter 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 work 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.

We exploit the dominant role of industry effects to investigate the con-

1. Haltiwanger et al. (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.

nection between changing interindustry 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 nonemployment have significantly lower earnings. These patterns also hold for earnings of different hires types: stayers, job switchers, and hires from nonemployment. 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 nonemployment 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 interindustry 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 interindustry earnings differentials. In specifications including both hires types and firm and worker controls, we can account for about 80 percent of rising interindustry 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 nonemployment. 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 nonemployment is the highest among the four groups.

The chapter proceeds as follows. Section 2.2 describes the data infrastructure. Section 2.3 shows that rising overall earnings inequality is dominated by rising between-firm inequality and in turn by rising between-industry inequality. Section 2.4 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 nonemployment. Section 2.5 analyzes the variance of earnings for each of the four hires types. Section 2.6 investigates the connection between rising interindustry earnings differentials and earnings differentials by hires types along with controlling for and exploring the contribution of changing firm and worker demographic effects. Section 2.7 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.

2.2 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 US 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 percent 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 US 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).

A job in the LEHD is defined as the presence of an individual-employer match, and earnings are defined as the amount earned from that job during the quarter. We use full-quarter (FQ) jobs in our analysis, where an FQ 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 FQ 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 FQ 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 2018Q1 Consumer Price Index for Urban Consumers Research Series (CPI-U-RS) deflator.

Because states have joined the LEHD program at different times and have provided various amounts of historical data on 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 1996Q4 through 2018Q2, which gives us full-quarter data from 1997Q1 to 2018Q1.[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]

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 state employer identification number (SEIN). This definition of firms is narrower than the enterprise definition used in Haltiwanger and Spletzer (2020) and the definition based on the federal Employer Identification Number (EIN), 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 for declining labor market fluidity since part of the latter is declining geographic mobility (see, e.g., Molloy et al. 2016).

Key statistics from our annual data are given in figure A.1 of the online appendix (http://www.nber.org/data-appendix/c14447/appendix.pdf). To summarize, in 2018Q1, there are over 50 million FQ jobs and approximately 3.2 million SEIN firms in our 20-state LEHD data. The variance of FQ LEHD earnings is increasing between 1998 and 2108. This rising variance, often referred to as "increasing earnings inequality," is the focus of our analysis in this chapter. In figure A.2 of the online appendix, we present percentiles of the LEHD full-quarter earnings distribution from 1996 to 2018, as well as published percentiles of full-time wage and salary earnings from the Current Population Survey (CPS). The time series of the LEHD and CPS percentiles, indexed to 100 in 1996, are similar.

2.3 Rising Earnings Inequality: The Dominant Role of Between-Firm and Between-Industry Effects

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:

$$\mathrm{Var}(W_{if}) = \mathrm{Var}(W_{if} - W_f) + \mathrm{Var}(W_f), \tag{2.1a}$$

2. These 20 states are: California, Colorado, Connecticut, Hawaii, Idaho, Illinois, Kansas, Louisiana, Maryland, Minnesota, Missouri, Montana, North Carolina, New Jersey, New Mexico, Oregon, Rhode Island, Texas, Washington, and Wyoming. 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. (2019) using SSA data, as well as by Abowd, McKinney, and Zhao (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.

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

$$\text{(2.1b)} \qquad \mathrm{Var}(W_{ifk}) = \mathrm{Var}(W_{ifk} - W_{fk}) + \mathrm{Var}(W_{fk} - W_k) + \mathrm{Var}(W_k).$$

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

$$\text{(2.1c)} \qquad \Delta\mathrm{Var}(W_{ifk}) = \Delta\mathrm{Var}(W_{ifk} - W_{fk}) + \Delta\mathrm{Var}(W_{fk} - W_k) + \Delta\mathrm{Var}(W_k).$$

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 (2.1c)), 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 2.1. The top line is the variance of individual earnings, which is the same as in online appendix figure A.1. This variance increases from 1.109 in 1998 to 1.291 in 2018. The within-firm variance in figure 2.1 is roughly constant across time (rising slightly from 0.566 in 1998 to 0.575 in 2018). The between-firm variance in figure 2.1, from equation (2.1a), rises from 0.543 in 1998 to 0.716 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; Haltiwanger and Spletzer 2020; Handwerker and Spletzer 2016; Song et al. 2019), as well as a much earlier literature (Davis and Haltiwanger 1991; Dunne et al. 2004).

The rising between-firm variance can further be decomposed into within-industry and between-industry components. Using four-digit North American Industrial Classification System (NAICS) industries, the between-firm within-industry variance rises from 0.272 in 1998 to 0.337 in 2018, and the between-industry variance rises from 0.271 in 1998 to 0.379 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. 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 chapter. 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 build on the finding in the

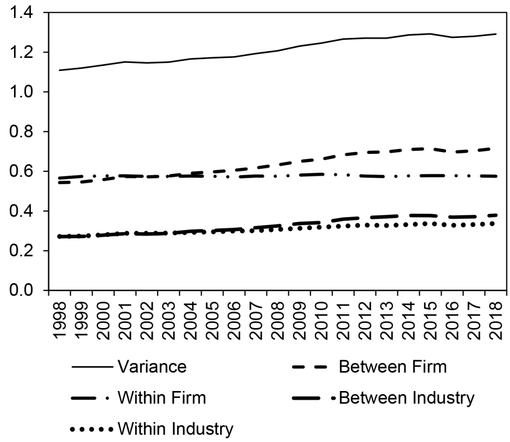

Fig. 2.1 Variance decomposition

companion paper of a dominant role for industry effects in rising between-firm inequality. 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 2.1 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 1998–2018 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.[4] The amount of between firm variance growth between industries rises with the level of industry detail, to 53.8 percent of variance growth between the 91 three-digit industries and 62.4 percent 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 1,034 six-digit industries.

Our second sensitivity analysis is to examine how changing the definition

4. 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.

Table 2.1 **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

of the firm affects our results. In almost all of this chapter, 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 EIN and the 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. We present results in the online appendix (http://www.nber.org/data-appendix/c14447/appendix.pdf, see table A.1); they show that our finding that more than half of variance growth is between four-digit NAICS industries is unaffected by the definition of the firm.

2.4 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; Davis and Haltiwanger 2014; Hyatt and Spletzer 2013; 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 nonemployment.

In this chapter, 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):

$$\text{(2.2a)} \qquad \text{Total Employment} = \text{Stayers} + \text{Hires.}$$

A hire 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 nonemployment):

$$\text{(2.2b)} \qquad \text{Total Employment} = \text{Stayers} + \text{Employer-to-Employer Hires} + \text{Hires NonEmp.}$$

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):

$$\text{(2.2c)} \qquad \text{Total Employment} = \text{Stayers} + \text{E2E Same Ind} + \text{E2E Diff Ind} + \text{Hires NonEmp.}$$

Equation (2.2b) 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 residual reflecting hires from non-FQ employment in the year before a FQ Q1 job in the current year. These definitions are distinct from related

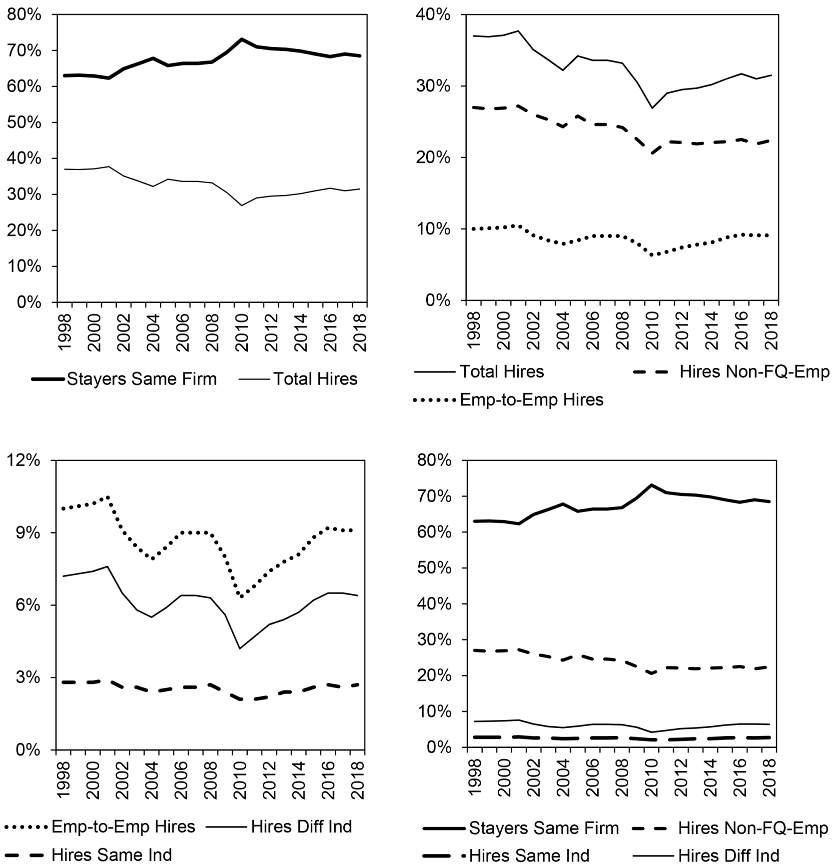

Fig. 2.2 Labor market fluidity

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.[5]

Figure 2.2 presents our measures of hires types as percentages of total full-quarter employment. Figure 2.2a shows that the percentage of full-quarter jobs that are stayers increased from 63.0 percent in 1998 to 68.5 per-

5. Persons holding one FQ job last year and more than one FQ 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 FQ job last year but only one FQ 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 FQ jobs this year and two FQ 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 FQ jobs last year and N2 full quarters jobs this year, where N1 > 2, N2 > 2, and N1 > 2 and/or N2 > 2, are deleted from the data.

cent 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.

Figure 2.2b 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. Figure 2.2c shows the decomposition of employer-to-employer hires based on whether the hire was from the same four-digit NAICS industry or a different four-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. Figure 2.2d shows the four key labor market flows that we will use in the following analysis.

Our measures of labor market fluidity are, as noted, based on 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/). In figure A.3 of the online appendix (http://www.nber.org/data-appendix/c14447/appendix.pdf) we provide comparisons of our measures with the published QWI and J2J series from LEHD.[6] As described in the appendix, our takeaway 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 nonemployment. As will become clear, these measures not only are highly correlated with related published measures of fluidity but also are closely connected to interindustry earnings differentials both in the cross section and over time.

2.5 Earnings Dispersion by Hires Types

Figure 2.3 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 dotted black line in figure 2.3 is mean earnings of all FQ jobs, which is the same as in online appendix figure A.1. The data in figure 2.3 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 2.4. Figure 2.4a shows the total variance, figure 2.4b

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

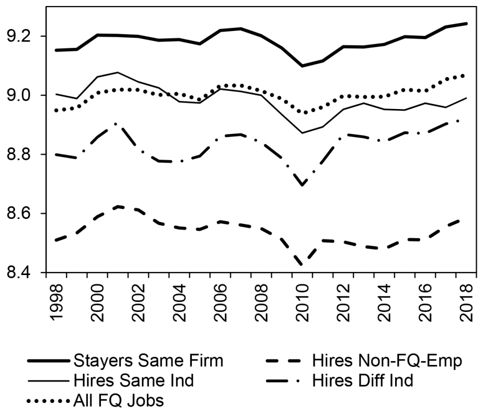

Fig. 2.3 Mean full-quarter earnings by type of annual flow

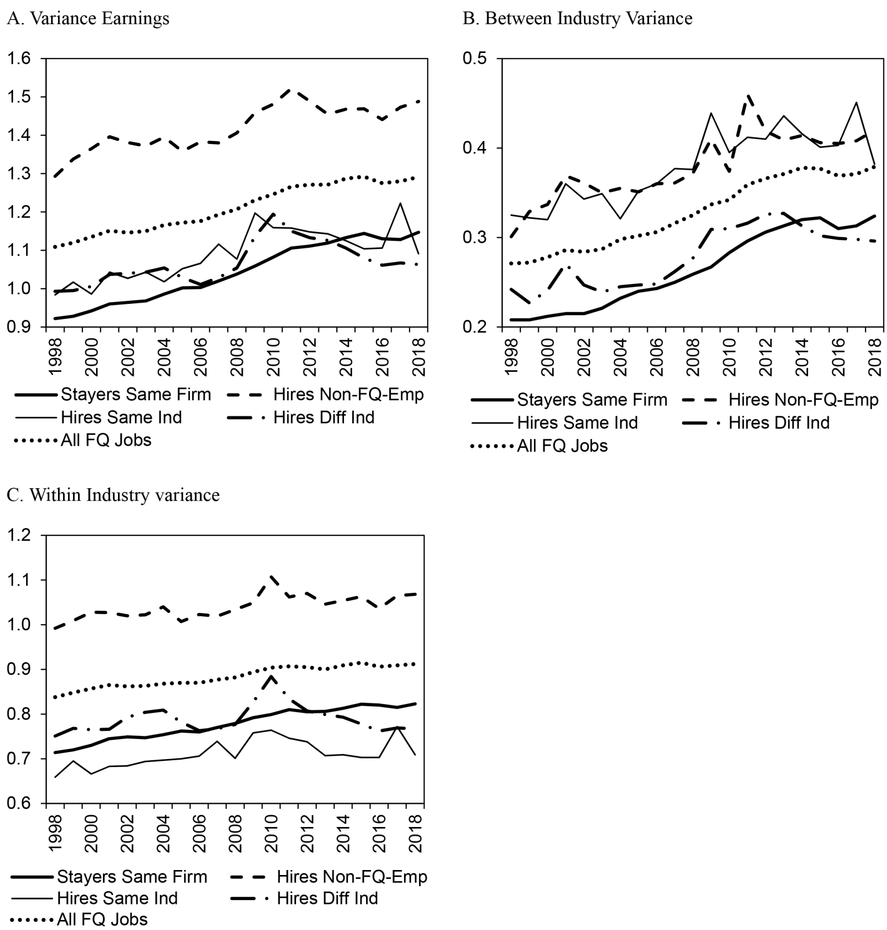

Fig. 2.4 Variance of full-quarter earnings by type of annual flow

shows the between-industry variance, and figure 2.4c shows the within-industry variance. In all panels of figure 2.4, the dotted black line is the variance of all FQ jobs.

There are two striking results in figure 2.4. 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 nonemployment 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 nonemployment to substantially different starting earnings (e.g., high school versus college graduates transiting from nonemployment to employment).

These findings from figure 2.4 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.

2.6 The Contribution of Earnings Differentials by Hires Types

2.6.1 Accounting Decomposition Methodology

Since the rising interindustry earnings differentials are within hires types groups, in this section we explore the potential connection between rising interindustry 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 effects. Using the rising interindustry 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 interindustry 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 FQ 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}).[7] We estimate the following two specifications:

$$W_{kt}^{j} = H_{kt}'\bar{\delta}^{j} + D_{kt}'\bar{\gamma}^{j} + \tilde{\varepsilon}_{kt}^{j} \tag{2.3a}$$

$$W_{kt}^{j} = H_{kt}'\delta_{t}^{j} + D_{kt}'\gamma_{t}^{j} + \varepsilon_{kt}^{j}. \tag{2.3b}$$

Specification (2.3a) is a pooled specification with time invariant coefficients, and specification (2.3b) 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

$$W_{kt}^{j} = H_{kt}'\bar{\delta}^{j} + D_{kt}'\bar{\gamma}^{j} + H_{kt}'(\delta_{t}^{j} - \bar{\delta}^{j}) + D_{kt}'(\gamma_{t}^{j} - \bar{\gamma}^{j}) + \varepsilon_{kt}^{j}. \tag{2.3c}$$

Following Juhn, Murphy, and Pierce (1993) (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 do not pursue the full distribution accounting insights from this approach but focus on the decomposition of variance.[8] The estimation and decomposition is on an employment-weighted basis to be consistent with the variance trends reported in figure 2.4.

2.6.2 Regressions and Decompositions

We present estimates of regression equation for (2.3a) 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.[9] The industry-level employ-

7. By design the right-hand side variables are the same for each of the specifications by hire type. For example, each regression in table 2.3 includes the percentage of females in the industry as an explanatory variable, and each regression includes the share of hires from nonemployment in the industry as an explanatory variable. The right-hand side variables represent characteristics of the industry.

8. There are some limitations of the JMP decomposition methodology as highlighted by DiNardo, Fortin, and Lemieux (1996) and Fortin, Lemieux, and Firpo (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.

9. 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.

Table 2.2 **Regressions and decompositions using industry-by-year earnings by hires type**

	Earnings all jobs	Earnings same firm stayers	Earnings hires same industry	Earnings hires different industry	Earnings hires nonemployment
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 $X(t) * \beta$	−0.122	−0.097	−0.120	−0.105	−0.133
Predicted $X(t) * \beta(t)$	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	191.7	162.9	286.0	274.1	189.1
Residual	21.3	20.7	24.6	20.4	22.7

Notes: 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.

ment weights in each regression reflect the share of the hires type of the dependent variable for that industry relative to the economywide 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 2.4.

Table 2.2 presents estimates from these specifications. We report the time invariant pooled estimated coefficients from equation (2.3a). In the bot-

We acknowledge that the education variable in the LEHD is mostly imputed—Vilhuber (2018) reports that 92 percent of Protected Identification Keys (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.

tom of table 2.2, we report the variance decompositions that are based on equation (3c). All of the specifications include controls for 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.[10]

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 nonemployment (these represent the pooled time invariant $\delta's$ in equation (2.3a)).[11] 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 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 nonemployment. It is striking, for example, that earnings for stayers are higher in 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 nonemployment. 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 2.2 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

10. The finding that earnings are higher at younger firms might seem surprising but in table 2.3 this is the marginal effect of firm age controlling for a rich set of other factors. 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.

11. 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).

of hires from nonemployment. We exploit that finding below to dig into the findings in more detail.

The lower panel of table 2.2 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 Xs) and the changing earnings differentials from these characteristics (the βs accounts for about 80 percent of the rising variance in interindustry earnings differentials.[12] Overwhelming the positive contribution derives from the changing βs while the changing distribution of characteristics is a drag on rising interindustry earnings differentials.

To dig into the patterns in table 2.2 in more detail, we focus on the results of the first column, using overall industry earnings (mean ln real earnings) as the dependent variable.[13] Table 2.3 and figure 2.5 present additional results for this specification. Summary statistics in table 2.3 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 nonemployment. 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 nonemployment 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 2.2 about the negative contribution of the changing distribution of characteristics in the decompositions.

Specifications 1a, 1b, and 1c in table 2.3 present estimates of equation (2.3a) 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 nonemployment have lower earnings. Column 1c shows that industries with more job switchers from other industries have especially

12. We use changing βs as a label for the combined contribution of changes in δs and χs and changing Xs as a label for the combined contribution of changing H_{kt}s and D_{kt}s. In table 2.3, 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.

13. In unreported results we have found the patterns we discuss from table 2.3 and figure 2.5 are broadly similar for all hires types.

Table 2.3 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 different industry	0.061	−0.008	0.022	−0.004			10.80		5.030	3.653
Hire non-FQ employment	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 $X(t) * \beta$					−0.023	−0.101	−0.080	−0.047	−0.122	−0.104
Predicted $X(t) * \beta(t)$					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

Notes: 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.

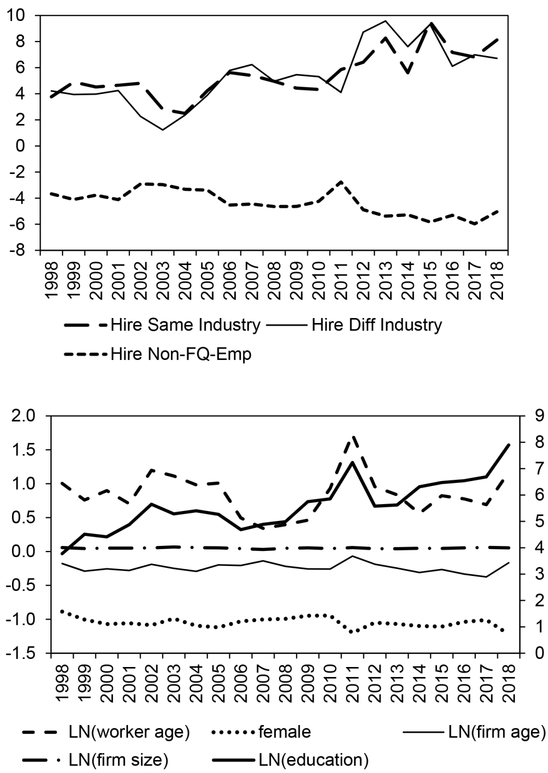

Fig. 2.5 Year-specific coefficient estimates from earnings regressions

high earnings. Industries with a larger share of hires from nonemployment have lower earnings.

Specification 2 of table 2.3 shows the results from only using the firm and worker demographic controls. Specification 3 repeats the results from table 2.2 for overall earnings. We also consider a specification in 4 which includes year effects and two-digit industry dummies (we could not estimate the year-specific regressions if we included four-digit industry dummies). The basic patterns are robust to the inclusion of these additional controls.

Figure 2.5 presents the estimated year-specific coefficients from specification 3 of table 2.3—these are the coefficient estimates δ_t^j and γ_t^j from equation (2.3b). Figure 2.5a 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 nonemployment are negative declining over time, from −3.7 in 1998 to −5.0 in 2018.

Figure 2.5b 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 do not fully understand), and the coefficients on female gradually decline from −0.887 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 2.3 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 interindustry 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 interindustry earnings differentials. Together, hires types and firm and worker demographics account for about 80 percent of rising interindustry 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 overwhelmingly coming through the changing "prices"—the δ_ts of equation (2.3b).

We interpret the regression results and variance decompositions through the lens of a changing job ladder over time. Consistently tables 2.2 and 2.3 and figure 2.5 show that industries with a larger share of hires from nonemployment are low-earnings industries. In addition, figure 2.5 shows that the negative earnings differential associated with these bottom-of-the-ladder industries is growing in magnitude over time. In contrast, figure 2.5 shows that the top-of-the-ladder industries have a growing positive differential.[14]

2.7 Concluding Remarks

Rising earnings inequality in the last few decades is dominated by rising between-firm inequality. In turn, rising between-firm inequality is domi-

14. The online appendix (http://www.nber.org/data-appendix/c14447/appendix.pdf) section D includes supplementary analysis of selected industries. We show that industries such as software publishers are at the top of the ladder in terms of average and growing earnings differentials. In contrast, industries such as grocery stores are at the bottom of the ladder in terms of average and decreasing relative earnings differentials.

nated by rising interindustry 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 nonemployment.

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 moved 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 nonemployment, 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 interindustry earnings differentials since rising between-industry dispersion accounts for much of the rising between-firm dispersion in earnings. The finding of rising interindustry 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 toward 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 interindustry 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 interindustry earnings differentials.

An open question is how to relate this occupation/task-based perspective with the findings in this chapter. The job ladder is changing over time and we find this is closely connected to rising interindustry 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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