Within-Job Wage Inequality: Performance Pay and Skill Match *

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Abstract

Over recent decades, we find about 80% of widening residual wage inequality to be within jobs (industry-occupation pairs). To explore the underlying drivers, we incorporate into a sorting equilibrium framework two extensive margin channels - across-job sorting and within-job selection of a performance-pay position - and an intensive margin channel via skill match quality in addition to general job productivity. We show that equilibrium sorting is positive assortative both within jobs and across jobs. In such a sorting equilibrium, these channels interact with each other, leading to rich comparative static results on within-job wage dispersion. By calibrating the model to the U.S. in 1990 and 2000, we find our model to fit almost perfectly the within-job wage inequality data in all the 25 broadly defined jobs, where improved match quality and rising performance-pay incidence amplify each other, jointly accounting for almost 90% of the widening within-job wage inequality. Match quality and performance-pay are particularly important in jobs with rising average wages and expansionary employment. Once performance-pay and match quality channels are incorporated, job sorting becomes less important and general job productivity is inconsequential throughout for explaining the rising within-job wage inequality.

Keywords: Within-job wage inequality, performance pay, match quality, positive assortative job sorting
JEL Code: E24, I24, J31

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1 Introduction

It has been extensively documented in the literature that the residual wage inequality accounts for a major proportion of the overall wage inequality and tends to increase faster over time among individuals with higher education. In this paper, we show particularly that four-fifths of the residual wage inequality is driven by wage dispersion within jobs, defined by industry–occupation pairs. Understanding the causes of the within-job inequality is thus crucial for explaining the main sources of the overall inequality. The main purpose of our paper is to explore theoretically some potentially important channels, both the intensive and the extensive margins, and then to quantify their contributions based on a calibrated sorting equilibrium model.

We classify individuals into high and low education groups according to their years of schooling, with the former including workers having some college or above. We then compute the residual wage inequality for both groups during 1983-2013 using data from a variety of sources. The results suggest that inequality in the high education group is not only higher but also increases faster than that in the low education group; moreover, the pattern becomes more prominent in the 1990s and 2000s. In the high education group, even if we control for more job characteristics including industry, occupation, firm size, location, and citizenship, about 90% of the residual wage inequality remains. This suggests that the wage inequality is primarily driven by the within-industry/occupation inequality. To further confirm this finding, we decompose the residual wage inequality into the between-job and within-job components overall industry–occupation pairs. The decomposition result shows that the within-job wage inequality accounts for about 80% of the residual wage inequality between 1990 and 2000. To the best of our knowledge, this pattern has not thus far been fully explored in the literature.[1]

To explain the aforementioned facts, we adopt a sorting equilibrium model that allows workers to optimally self-select into different jobs and pay positions. In addition to different job productivity levels, we consider two extensive margin channels (job sorting and the within-job selection in the performance-pay and fixed-pay positions) and an intensive channel (the quality of skill match). While the sorting margin needs to be backed out upon calibrating the model, the performance-pay incidence and match quality margins have direct data measurements. Workers in the performance-pay position are paid according to how much they contribute, and such payments usually include

[1]There are a few exisiting works with similar findings, and we will compare the differences in the section of literature review.

bonuses, commission, piece-rates, and tips. The counterpart to this is the payment of a fixed hourly wage. While the literature has identified a positive wage effect of performance-pay, as shown, for example, by Lemieux et al. (2009), we further examine the relation between the within-job wage inequality and the performance-pay incidence and find a significant positive relationship: jobs with a higher performance-pay incidence usually have higher wage inequality. This hints at the potential role of the rising performance-pay incidence for widening wage dispersion. We measure job match quality based on the inverse relationship with skill mismatch. We compute the skill mismatch index for each job using workers' occupation-relevant skill and ability measures from the 1979 National Longitudinal Survey of Youth (NLSY79) and occupation skill requirements from O*Net. Literature shows that skill mismatch has a negative wage effect and thus better job match quality is associated with higher compensation (Guvenen et al., 2020). We find a negative relationship between the skill mismatch index and within-job wage inequality: jobs with lower quality matches are paid more equally. Hence, improved match quality could also explain the within-job wage inequality.

The correlation results are refined by regression of the change of inequality on the change of performance pay incidence and mismatch index. In particular, the result is significant that increase in performance pay incidence or match quality will increase wage inequality. The empirical analysis presumes a linear relationship between the wage inequality of each job and the job characteristics of interests in a partial equilibrium. The result might be different in general equilibrium and when we consider about interactions between different channels. In addition, the regression results are silent on the counterfactual scenario, which thus limits the availability of rich policy analysis. This thereby requires a deep structure to discipline the interactions among them.

In our sorting equilibrium framework, workers are heterogeneous in their innate abilities. Each job is associated with different productivity and two payment schemes: performance-pay and fixed-pay. In a fixed-pay position, a worker earns a pooled wage independent of the worker and job characteristics. In the performance-pay position, a worker's pay positively depends on his or her contribution to production. A worker in a better matched job is captured by drawing a higher productivity premium from matching, which leads to a higher wage payment. Higher expected match quality thus plays an important role in position selection and job sorting.

Job-specific disutilities are incurred for workers in a performance-pay position to capture the monitoring cost. Quality matching and the resulting productivity premium also vary by job. In a sorting equilibrium, workers optimally choose their jobs and positions. Under proper assumptions, we show that equilibrium sorting is positive assortative, with the least talented workers choosing the fixed-pay position and the more talented workers selecting the performance-pay position in different jobs based on job productivity and the expected returns induced by the matching premium.

The within-job wage inequality can then be decomposed into that within the performance-pay position and the differences in the average wage between the performance-pay and the fixed-pay positions. In principle performance-pay income is more dispersed than fixed-pay income. Analytically, we can establish a positive relationship between the performance-pay incidence and within-job wage inequality when fewer than half of the educated workers are in the performance-pay position. In this case with a given sorting outcome, a better technology or higher match quality amplifies the effect of the performance-pay incidence on the within-job and the within-performance-pay inequality, but dampens its effect on the within-job and between-position inequality, resulting in an ambiguous net impact overall. The relative magnitudes of these effects depend crucially on the degree of complementarity between workers in different positions and their relative employment size. With endogenous sorting across jobs, the resulting cutoff abilities further interact with the performance pay and the match quality in a complex manner. As a consequence, how various channels affect the within-job wage inequality becomes a quantitative question.

To quantify the importance of the performance-pay incidence, match quality, job productivity, and job sorting for rising wage inequality, we calibrate the model by matching several of the key job-specific features of wage inequality and employment in the US economy in 2000. The overall fit of the calibrated model is good, with an almost perfect fit in all the 25 broadly categorized jobs. To conduct a counterfactual–based decomposition exercise, we restore the value of each job-specific factor in 2000 to the corresponding value in 1990 by perturbing the distribution of each variation, while maintaining all the other parameters at their benchmark values. The model can capture most of the changes in within-job wage inequality from 1990 to 2000 (with an essentially zero residual component). Our decomposition analysis indicates that changes in performance pay and match quality alone account for around 90% of widening within-job wage inequality. Moreover, we find an amplifying interactive effects compared with the situation if we either let the performance-pay incidence or match quality take their values in 1990. While sorting makes a modest contribution to the widening inequality, the role of general job productivity is inconsequential. Since performance pay and match quality are the main drivers, pro-active policy intervention aiming to reduce inequality may be at the expense of less prevalent of performance pay or skill mismatch.

Intuitively, once match quality is assured and workers are offered with correct incentives by performance pay with better ones sorted into performance pay positions, the role played by positive assortative sorting across jobs diminishes much. Ex ante one cannot tell which types of sorting is strong and the existing literature is slient about this. In this paper, we provide a thorough quantitative contrast between them. Moreover, job-specific productivity alone does not convert to higher output—it must be combined with workers' ability and the quality of match. Thus, to some degree, it resembles the Solow residual in neoclassical aggregate production—departing from the neoclassical canonical framework, however, within- and cross-job sorting is in play in our paper. Our results indicate that upon incorporating match quality and performance pay, this residual productivity adds little explanatory power to underlying drivers in the model.

We further conduct decomposition analysis at the industry and occupation level, respectively. Match quality contributes more than performance-pay incidence in almost all the industries except for the Trade industry, which accounts for about 20% of the changes in the overall within-job inequality. In Transport and FIRE industries, which jointly account for another 20% of the changes in the overall within-job inequality, match quality plays a dominant role. In the Business industry, the contribution of performance-pay incidence is higher than the average level among all the industries. At the occupation level, performance-pay incidence is more important than match quality only in the Clerical occupation, which accounts for about 22% of the changes in the overall within-job inequality. In Manager, Sales and Production Labor occupation, which together account for more than 60% of the changes in the overall within-job inequality, the contribution of match quality is higher than the average level.

We have also performed similar decomposition exercises based upon changes in rankings of average wage and employment share from 1990 to 2000, respectively. The major contribution (more than 85%) to widening within-job inequality comes from jobs whose average earnings rankings change moderately (by 1 or 2) or remain unchanged, where both performance-pay and match quality play comparably important roles. For jobs whose employment share rankings remain unchanged, which make up more than half of the changes in the overall within-job inequality, match quality are found to play greater role than performance-pay incidence.

The main takeaway of our paper is that while the within-job wage inequality accounts for about 80% of the residual wage inequality between 1990 and 2000, approximately 90% of such rising dispersion is a consequence of higher performance-pay incidence and improved matching quality. Once the extensive margin via performance-pay and intensive margin via match quality are incorporated, job sorting becomes much less important and general job productivity is inconsequential throughout for the within-job wage inequality. Policymakers' focus should thus be on the primary sources of wage dispersions within jobs.

Related Literature

A large number of studies have documented the trend in the rising wage inequality since the 1970s (e.g., Katz and Autor (1999), Piketty and Saez (2003), Acemoglu and Autor (2011)). One convincing theory claims that skill–biased technology change can account for the rising skill premium (e.g., Juhn et al. (1993), Krusell et al. (2000), Acemoglu (2003)). Altonji et al. (2016) argues that earnings differences among college students across majors can be larger than the skill premium between college and high school.

Recent studies focus on the within-industry or the within-firm wage inequality. Barth et al. (2011) emphasize the role of plant differences within industry and argue that this could explain two-thirds of wage inequality in the United States. Card et al. (2013) show that plant heterogeneity and assortativeness between plants and workers explain a large part of the increase in wage inequality in West Germany. Mueller et al. (2017) study the skill premium within firms and find that firm growth has increased wage inequality. Papageorgiou (2010) highlights the labor markets within firms and concludes that the within-firm part might explain one-eighth to one-third of the rise in wage inequality. Song et al. (2018), however, argue that the between-firm component is more important.

A growing number of studies also focus on the within-occupation wage inequality. While Kambourov and Manovskii (2009) argue that the variability of productivity shocks on occupations coupled with endogenous occupational mobility could account for most of the increase in within-group wage inequality between the 1970s and mid-1990s, Scotese (2012) shows that changes in wage dispersion within occupations are quantitatively as important as wage changes between occupations for explaining wage inequality between 1980 and 2000.

Performance pay The literature on performance pay either studies incentives and productivity(e.g., Jensen and Murphy (1990), Lazear (2000)) or explain the white-black wage gap through the different performance-pay rates by race(Heywood and Parent (2012)). Makridis (2019) finds a positive relationship between the performance-pay incidence and wage premium. In addition, he shows that longer working hours lead to more on-the-job human capital investment. While his study focuses on the dynamic effects of performance pay on human capital accumulation, our study emphasizes the interactions among performance pay, match quality and sorting within and between jobs. The most relevant study to ours is Lemieux et al. (2009). They suggest performance pay as a channel through which the underlying changes in returns to skills are translated into higher wage inequality. They compare performance-pay jobs with non-performance-pay jobs, concluding that wages in performance-pay jobs are more sensitive to abilities and that inequality in performance-pay is much higher. However, the within-job selection in their work is partial equilibrium outcome, while our general equilibrium framework has the following two features: (i) the wages in the non-performance-pay position affect selections in all the jobs. (ii) sorting across jobs affects within-job sorting. In addition, while they emphasize the monitoring cost on selection, we highlight match quality as another factor affecting sorting within and between jobs.

Skill mismatch The general idea of skill mismatch is that workers that share the same characteristics might have different productivity from the job or machine in or on which they are working. Violante (2002) provides a channel through vintage capital to decompose the residual wage inequality into a worker's ability dispersion, a machine's productivity dispersion, and the correlation between them. The author argues that this channel could explain most transitory wage inequality and 30% of residual wage inequality. Jovanovic (2014) builds a learning–by–doing model to emphasize the role of matching between employees and employers. Under this framework, he discusses the roles of improving signal quality and assignment efficiency. Previous studies suggest two measurement approaches. The first is to measure the distance between skill requirement and acquirement based on the scores of skills from NLSY79 and O*NET (e.g., Sanders (2014), Guvenen et al. (2020), Lise and Postel-Vinay (2020)). The second approach is to measure job relatedness between the field of study in the highest degree and current occupation (e.g., Robst (2007), Arcidiacono (2004), Ritter and West (2014), Kirkeboen et al. (2016)). Since the second measurement relies on subjective responses, which might be biased, we thus use the first approach to construct a skill mismatch index following Guvenen et al. (2020).

2 Stylized Facts

In this section, we document several stylized facts on wage inequality, the performance-pay incidence, and skill mismatch. We first present how the performance-pay incidence and skill mismatch index are estimated. We then compute the wage inequality using different measurements and decompose it into the between-job and within-job components. Finally, we examine the relationships among the performance-pay incidence, skill mismatch, and within-job wage inequality.

The data in this study are collected from several sources including the March Current Population Survey (March CPS),[2] Panel Study of Income Dynamics (PSID), 1979 National Longitudinal Survey NLSY79, and O*NET. The March CPS includes the most extended high-frequency data series enumerating labor force participation and earnings in the US economy. The PSID contains detailed information on earnings, including commission, bonuses, piece-rates, and tips. In NLSY79, respondents were given an occupational placement test—the Armed Services Vocational Aptitude Battery (ASVAB)—that provides detailed measures of occupation-relevant skills and abilities. In addition, respondents also reported various measures of noncognitive skills, which can reflect a worker's ability for socially interactive work. O*NET provides the skill requirements of each occupation.

2.1 Estimation of the Performance-pay Incidence and Skill Mismatch Index

Industry/occupation classification The Center for Economic Policy Research (CEPR) provides two-digit and three-digit occupation and industry codes, but the classification is inconsistent during 1983-2013. To address this issue, we build a consistent one-digit industry and occupation code as same as in Lemieux et al. (2009). A consistent three-digit code is also built following Dorn (2009). The same method is used to group a consistent two-digit code.[3] To circumvent the mis-classification problem over different years due to changes in the content of either occupation or industry and the problem of empty cells, we use the one-digit industry code and occupation code throughout this paper, while checking the inclusion of the two-digit occupation code when there is a potential concern.

Performance-pay incidence Performance-pay includes bonuses, commission, piece-rates, and overtime payments. A significant challenge is to identify workers in a performance-pay position. The PSID dataset has been intensively discussed in the literature. It reports the format of the payment that a worker has received in a given year, such as bonuses, commissions, or piece rates. However, for workers without those payments, we cannot distinguish whether they work in a fixed-pay position or do not merit, say, a bonus in that given period. Fortunately, the longitudinal nature of the PSID data enables us to track the payment history to examine whether a worker has ever received any form of performance pay in his or her current job, which provides a much more accurate measure

[2] These data are collected by the Center for Economic and Policy Research(CEPR).

[3] The original two-digit code is consistent in 1983–2002 and 2003–2013.

(see Lemieux et al. (2009)). Following Lemieux et al. (2009), the performance-pay incidence over time is estimated using a linear probability model in which the calendar years and how many times a job-match is observed are controlled for. We estimate the performance-pay incidence for the highly educated for 80 jobs separately for year 1990 and 2000.[4] Tables A.16 and A.17 present the results for 1990 and 2000, respectively. To have a consistent code with skill mismatch, we also group them into 25 jobs. Table A.18 and A.19 present the results for 1990 and 2000 respectively.

Skill mismatch index We compute the skill mismatch index using NLSY79 and O*NET. NLSY79 tracks a nationally representative sample of individuals aged between 14 and 22 years on January 1, 1979. It contains detailed information on the industry and occupation in which each individual worked. All the respondents took the ASVAB test at the start of the survey. The respondents were also given a behavioral test to elicit their social attitudes (e.g., self-esteem, willingness to engage with others). The version of the ASVAB taken by NLSY79 respondents had 10 component tests. We focus on the following four components on verbal and math abilities, which can be linked to skill counterparts: Word Knowledge, Paragraph Comprehension, Arithmetic Reasoning, and Mathematics Knowledge. Because age differences can affect the score, we normalize the mean and variance of each test score by the respondents' age-specific values following Guvenen et al. (2020).

O*NET includes information on 974 occupations, which can be mapped to the 292 occupation categories included in NLSY79. For each of these occupations, analysts at O*NET score the importance of the 277 descriptors. We use the 26 descriptors that are most related to the ASVAB component tests—a choice dictated by our measures that relate the ASVAB to O*NET —and another six descriptors related to social skills. Following Guvenen et al. (2020), we first compute the individual-level mismatch index and then the weighted-average of the mismatch index for each industry–occupation pair for 25 jobs in 1990 and 2000 (See Table A.20 and Table A.21). A higher mismatch index implies a lower quality match.

2.2 Measuring Wage Inequality

We compute the wage inequality using the March CPS dataset. Only full-time and full-year workers, defined as those working for least 40 weeks in a year and 35 hours in a week, aged between 16 and 65 years are kept in our sample. Wages are defined as real hourly earnings. We drop earnings

[4] In each year, the PSID dataset has 10 industries and 8 occupations(i.e., 80 jobs in total).

below half the minimum wage in 1982 dollars or higher than USD 1000. The top-coding wage is low in some existing literature; for example, it is 100 (in 1979 dollars) in Lemieux et al. (2009) and around 180 in Acemoglu and Autor (2011). However, since we only focus on highly educated individuals, we retain a larger share of the sample.

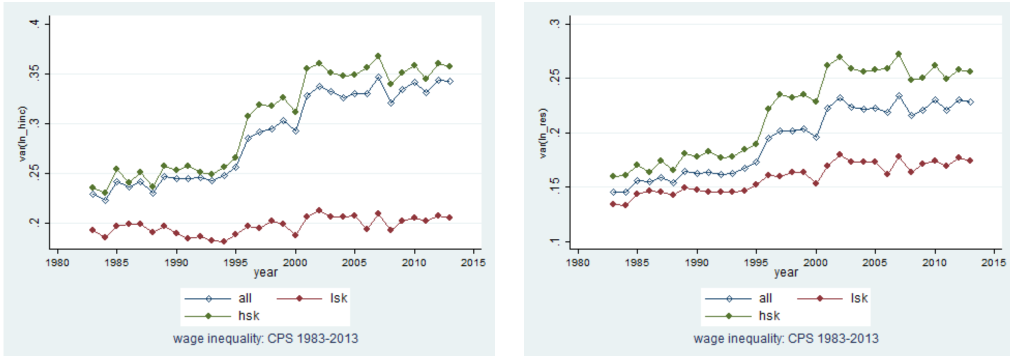
In the March CPS, education level is grouped into six categories: primary, high school dropout, high school graduate, some college, college graduate, and post-college. The implied years of schooling are 6, 9, 12, 14, 16, and 18, respectively. Potential experience is then computed as the difference between the year after graduation and age.[5] The highly educated group includes workers who have some college and above; the proportion of this group increased from 45% in 1983 to 66% in 2013.

We measure wage inequality as the variance of log wage. The left panel of Figure 1 presents the evolution of the wage inequality by the education group from 1983 to 2013. In general, wage inequality has been increasing since the 1980s among all the groups. However, the patterns also vary across education groups. Compared with the low education group, the highly educated group has a higher level of wage inequality increasing at a faster speed, especially since the late 1990s.

Following the convention in the literature (e.g., Kambourov and Manovskii, 2009), we obtain residual wages after controlling for sex, race, experience, and education. The residual wage inequality is then measured as the variance in the residual wages. As shown in the right panel of Figure 1, the residual wage inequality accounts for a large proportion of the overall wage inequality. The two series also evolve in a similar pattern over time. As a robustness check, we calculate the Gini coefficient and 90-10 ratio as well. Figure A.11 shows that the Gini coefficient exhibits a similar pattern. For the 90-10 ratio, the pattern in the high education group remains. To sum up, both facts confirm the substantial level of within-group inequality. In addition, the residual wage inequality within the highly educated group is above the overall average and it increases faster, especially between 1990 and 2000.

We now examine the inequality within the highly educated group. The left panel of Figure 2 presents the evolution of both the overall wage inequality and the residual wage inequality, showing that the residual wage inequality accounts for around 70% of the overall wage inequality among the highly educated. This proportion is higher than that commonly documented in the literature (e.g., Lemieux (2006)) for the whole sample, in which individuals of different education levels are

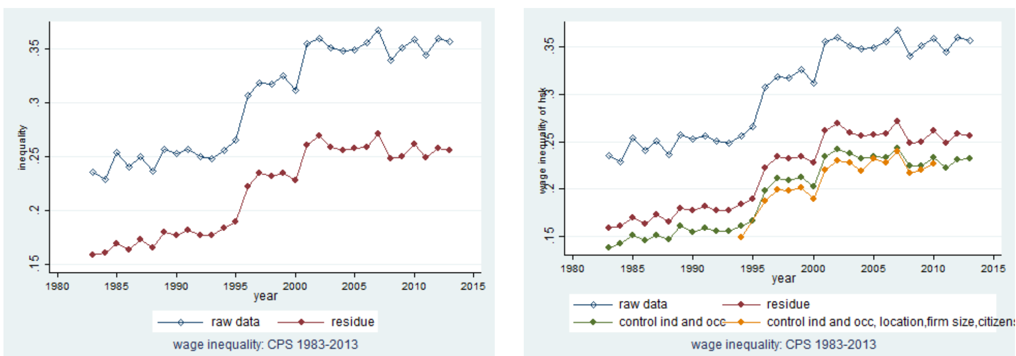
[5] Specifically, the formula to compute the years of experience is $\max(\text{age} - \text{year of schooling} - 6, 0)$.



(a) Overall Wage Inequality (b) Residual Wage Inequality

Figure 1: Wage inequality by education group

Notes: In the left (right) panel, the inequality is measured as the variance in the log value of hourly wages (residual wages). In both panels, the blue line represents the inequality for the whole sample and the green line only includes those highly educated. The red line is for the low education group. Data source: March CPS from the CEPR (1983-2013).



(a) Overall and Residual Wage Inequality (b) Overall, Residual and Within-job Wage Inequality

Figure 2: Residual wage inequality of the highly educated

Notes: In both panels, the inequality is measured among the highly educated. The blue line represents the raw wage inequality. The red line is the residual wage inequality after controlling for only demographic characteristics. The green line is the residual wage inequality after further controlling for occupation and industry. The yellow line is the residual wage inequality after further controlling for location, firm size, and citizenship. Data source: March CPS from the CEPR (1983–2013).

pooled together. The right panel shows the trend of the residual wage inequality when controlling for more job characteristics, including industry, occupation, location, firm size, and citizenship. It shows that controlling for industry and occupation can only explain 10% more and the result changes little when more variables such as location and firm size are controlled for. These facts suggest that the wage inequality within the industry and occupation significantly contribute to the overall wage inequality. To consolidate this finding, we decompose the residual wage inequality in the next subsection.

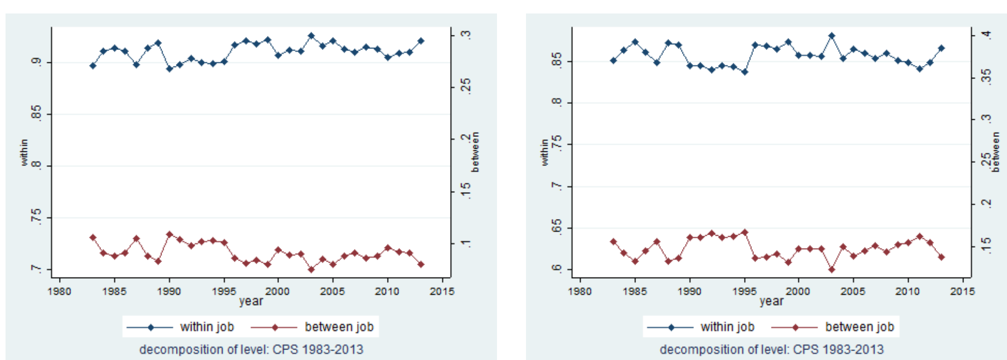
2.3 Decomposition of the Wage Inequality

In this subsection, we decompose both the level and the change in residual wage inequality into within-job and between-job wage inequality. A job is defined as an industry-occupation pair. Examples of jobs include sales in the FIRE industry, managers in business, clerical workers in retail/wholesale trade, and production workers in durable/nondurable goods, among others.

Decomposition of the level Suppose there are J jobs indexed as $j = 1, ...J$. In job j, we denote P_j as the employment share, V_j as the within-job wage inequality, and E_j as the average earnings. Then $\sum_j P_j V_j$ is the average within-job wage inequality weighted by the employment share, and $\sum_j P_j (\ln E_j - \sum_{j'} P_{j'} \ln E_{j'})^2$ is the weighted average of between-job wage inequality, where $\sum_{j'} P_{j'} \ln E_{j'}$ is the weighted average of log earnings in the economy. Finally, the overall wage inequality $var(\ln E)$ can be decomposed into the between-job and within-job components as follows:

$$var(\ln E) = \sum_j P_j V_j + \sum_j P_j (\ln E_j - \sum_{j'} P_{j'} \ln E_{j'})^2. \tag{1}$$

The contribution of the within-job wage inequality to the overall wage inequality is then the ratio of $\sum_j P_j V_j$ to $var(\ln E)$.



(a) One-digit Industry and One-digit Occupation Codes

(b) One-digit Industry and Two-digit Occupation Codes

Figure 3: Decomposition of residual wage inequality

Notes: Both panels show the proportion of within-job wage inequality to total residual wage inequality (blue) and the proportion of the between-job to total residual wage inequality (red). The left panel is for the one-digit industry and occupation code and the right panel is for the one-digit industry and two-digit occupation code. Data source: March CPS from the CEPR (1983-2013).

Figure 3 shows that the contribution of the within-job wage inequality is persistently substantial. Specifically, it is around 90% under the one-digit industry and one-digit occupation codes, as shown in the left panel. There may be a concern that the significant contribution of the within-job wage inequality is a result of the broad occupation categorization. We thus perform a robustness check using the one-digit industry and two-digit occupation codes. As shown in the right panel, the contribution of the within-job wage inequality remains sizable, at about 80%. More importantly, the contribution of the within-job component has been rising, especially since the late 1990s.

We also perform several other robustness checks. Figure A.12 decomposes the raw wage inequality, showing that the contribution of the within-job wage inequality is still above 75%. Figure A.13 presents the decomposition result using the CPSORG dataset. Tables A.13 and A.14 present the decomposition results using Census data under the one-digit and three-digit codes, respectively. The results show that the contribution of the within-job component is above 80% and 70%, respectively.

Decomposition of the change We also decompose the changes in the residual wage inequality over time into the various components of interest. In job j in year t, let $V_{j,t}$ be the wage inequality, $\ln E_{j,t}$ be the average log earnings, $P_{j,t}$ be the employment share, and $\ln E_t$ be the average log earnings among all the jobs. Then, the change in the within-job wage inequality from t to $t+1$ is $V_{j,t+1} - V_{j,t}$, change in the between-job wage inequality is $(\ln E_{t+1} - \ln E_{j,t+1})^2 - (\ln E_t - \ln E_{j,t})^2$, and change in the employment share is $P_{j,t+1} - P_{j,t}$. Therefore, the change in the wage inequality between years $t+1$ and t, $V_{t+1} - V_t$, can be decomposed into four components: the weighted average change in the within-job wage inequality $\sum_{j=1}^{J} P_{j,t}[V_{j,t+1} - V_{j,t}]$, the weighted average change in the between-job wage inequality $\sum_{j=1}^{J} P_{j,t}[(\ln E_{t+1} - \ln E_{j,t+1})^2 - (\ln E_t - \ln E_{j,t})^2]$, the weighted average change in the employment share $\sum_{j=1}^{J}(P_{j,t+1} - P_{j,t})[V_{j,t} + (\ln E_t - \ln E_{j,t})^2]$, and an interaction term that is the product of the changes in the employment share and in the sum of within and between-job wage inequality (simply referred to as the "interaction" in the decomposition exercise):

$$\sum_{j=1}^{J}(P_{j,t+1} - P_{j,t})\{(V_{j,t+1} - V_{j,t}) + [(\ln E_{t+1} - \ln E_{j,t+1})^2 - (\ln E_t - \ln E_{j,t})^2]\}.$$

Formally, we decompose the change in wage inequality as follows:

$$
\begin{aligned}
V_{t+1} - V_t \quad = \quad & \sum_{j=1}^{J} P_{j,t}[V_{j,t+1} - V_{j,t}] \\
+ \quad & \sum_{j=1}^{J} P_{j,t}[(\ln E_{t+1} - \ln E_{j,t+1})^2 - (\ln E_t - \ln E_{j,t})^2] \\
+ \quad & \sum_{j=1}^{J} (P_{j,t+1} - P_{j,t})[V_{j,t} + (\ln E_t - \ln E_{j,t})^2] \\
+ \quad & \sum_{j=1}^{J} (P_{j,t+1} - P_{j,t})\{(V_{j,t+1} - V_{j,t}) + [(\ln E_{t+1} - \ln E_{j,t+1})^2 - (\ln E_t - \ln E_{j,t})^2]\}.
\end{aligned}
\tag{2}
$$

Similarly, each component's contribution is defined as the ratio of its change to the total change in the residual wage inequality. Table 1 presents the results between 1990 and 2000. Under the benchmark definition of jobs using the one-digit industry and occupation code, the within-job component plays a dominant role, accounting for about 83% of the change in the residual wage inequality. Again, we also check the result with the one-digit industry and two-digit occupation codes. The within-job component is also found to be important, accounting for about 80% of the change in residual wage inequality.

As further robustness checks, Table A.12 presents the results for the one-digit industries and occupations using the CPSORG dataset, showing that the within-job component accounts fir 110%. In addition, Table A.15 presents the decomposition results using Census data under the one-digit and three-digit industry and occupation codes, respectively. The results show that the contributions of the within-job component to the change in the residual wage inequality between 1990 and 2000 are both above 84%.

Table 1: Decomposition of the changes in residual wage inequality: 1990-2000

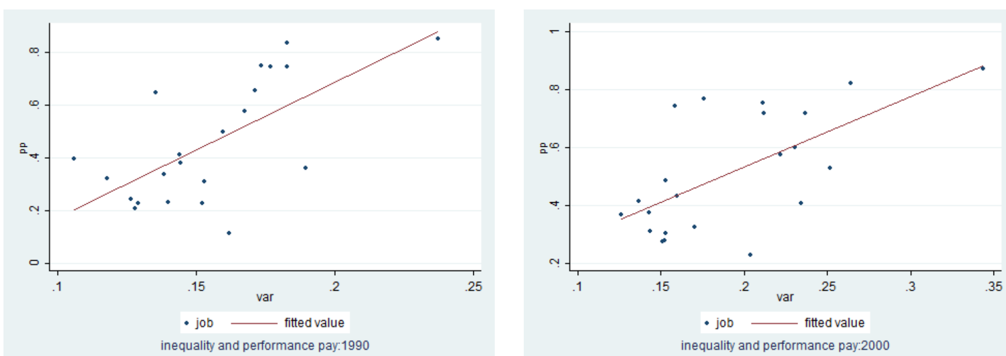
	Within-job	Between-job	Employment	Interaction
1-d code	**82.6%**	9.2%	2.7%	3.5%
1-d ind, 2-d occ	**79.5%**	8.1%	8.5%	0.3%

Notes: This table computes the contribution of within-job, between-job wage inequality, the employment share interactions to the changes in the residual inequality from 1990 to 2000. The row "1-d code" indicates the one-digit industry and occupation code, "1-d ind, 2-d occ" indicates the one-digit industry and two-digit occupation codes. Data source: March CPS from the CEPR.

2.4 Performance-pay Incidence, Skill Mismatch and Wage Inequality

In the following, we first explore the causality between performance-pay incidence, skill mismatch and within-job wage inequality. We then empirically examine how changes in the performance-pay incidence and skill mismatch over time may contribute to the increasing wage inequality. As the datasets are from various sources, throughout the remainder of the paper, we classify industries and occupations each into 5 categories consistent with the classification in the PSID and NLSY79. [6]

Figure 4 plots the performance-pay incidence against the within-job wage inequality for each of the 25 jobs in 1990 and 2000, respectively. It shows a significant positive relationship. That is, jobs with a higher performance-pay incidence usually have higher within-job wage inequality. In Section A, we also show that the relation is robust to using the same job classification as in Lemieux et al. (2009), containing 52 jobs (Figure A.14). In another robustness check, we plot the performance-pay incidence using the PSID data against wage inequality from the CPSORG dataset in Figure A.15 and Figure A.16 for 25 jobs and 52 jobs, respectively. The positive correlation always remains.



(a) 1990 (b) 2000

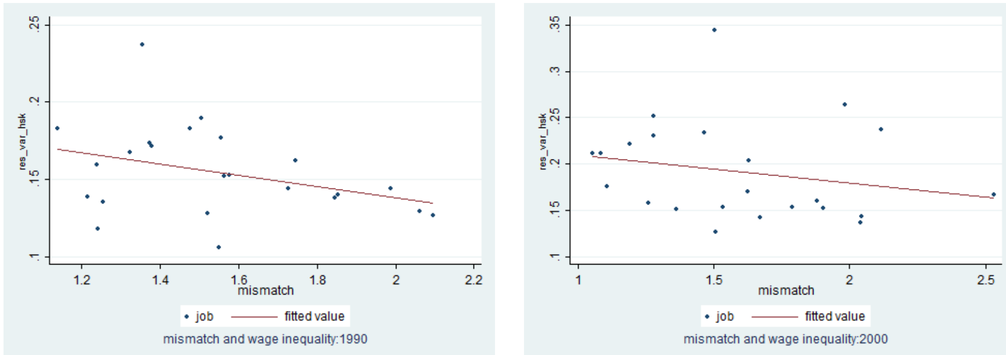
Figure 4: The Performance-pay incidence and wage inequality

Notes: In both panels, each dot represents a job(25 jobs in total). The x-axis is the performance-pay incidence. The y-axis is the within-job wage inequality. The left panel is based on 1990 data and right panel is based on 2000 data. Data source: PSID and March CPS.

On the contrary, we find a negative relationship between the wage inequality and the skill mismatch index as delineated in Figure 5. This indicates that jobs with better matching quality

[6] In total, there are 25 jobs. The five industries are (1) Goods (containing durables/non-durables, construction, and mining), (2) Transport (transportation and utility), (3) FIRE, (4) Business (business and professional service), and (5) Trade (whole/retail trade and personal services). The five occupations are: (1) Professional, (2) Manager, (3) Sales, (4) Production/Operative Labor (including craftsmen), and (5) Clerical (including other services).

tend to experience higher wage inequality.



(a) 1990 (b) 2000

Figure 5: Wage inequality and the skill mismatch index

Notes: In both panels, each dot represents a job(25 jobs in total). The y-axis is the wage inequality. The x-axis is the mismatch index. The left panel is based on 1990 data, and the right panel is based on 2000 data. Data source: NLSY79 and March CPS.

To further explore how performance pay incidence and match quality drive up the rising wage inequality, we first compute the changes in the level of wage inequality, performance pay incidence and mismatch index between the current and the previous year. We then regress the changes in the wage inequality against the changes in performance pay incidence and skill mismatch index while controlling for industry and occupation fixed effects:[7]

$$\triangle var_{ij} = \beta_1 \Delta_{pp,ij} + \beta_2 \Delta_{mm,ij} + \beta_3 i + \beta_4 j + \epsilon_{ij}.$$

Table 2 presents the results. The positive coefficient on the change of performance pay incidence (Δ_{pp}) implies that rising performance pay incidence tends to increase the wage inequality. Specifically, if the performance pay incidence rises by 10 percentage points, the wage inequality tends to rise by 0.4 percentage points. Similarly, the negative coefficient on the change of skill mismatch index (Δ_{mm}) implies that improving matching quality(lowering mismatch index) tends to push up the wage inequality. The results are robust and significant if we let either or both variables be the regressor.

The empirical analysis presumes a linear relationship between the wage inequality of each job and the job characteristics of interests. The practical situation can be more complicated than that.

[7]We excute the analysis as a pooled panel regression by ignoring the time dimension since our sample periods are not continuous and relatively short.

Table 2: The Impacts of Performance pay and Skill mismatch on Wage Inequality

	(1)	(2)	(3)
	Δvar_{ij}	Δvar_{ij}	Δvar_{ij}
Δ_{pp}	0.04***	0.05***	
	(0.00)	(0.00)	
Δ_{mm}	-0.02**		-0.03***
	(0.01)		(0.01)
Constant	0.00*	0.00*	0.00**
	(0.00)	(0.00)	(0.00)
Observations	389	389	389
R-squared	0.203	0.195	0.032
Industry FE	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Δvar_{ij} denotes the changes in residual wage inequality between two consecutive years. Δ_{pp} and Δ_{mm} is the change in performance pay incidence and mismatch index between two consecutive years.

In addition, the regression coefficients are only meaningful with a small deviation from their data counterparts. This thus limits the availability of rich policy analysis. This thereby requires a deep structure to discipline the interactions among performance pay incidence, match quality and wage inequality, to which we now turn.

3 The Model

Environment There are J jobs available in the economy, defined as industry–occupation pairs and indexed by $j = 1, 2, ...J$. In each job, two types of positions are offered: a fixed-pay (FP) position and a performance-pay (PP) position. Workers are heterogeneous in innate ability a and choose jobs, positions, and efforts to maximize their utilities. Job characteristics and workers' abilities are both public information.

Performance-pay position A worker's efficient labor supply in the performance-pay position depends on his or her ability a, the job-specific productivity A, an idiosyncratic matching premium η, and his or her effort level e. Specifically, the efficient labor supply is given by

$$h = Aa\eta e. \tag{3}$$

Ability a follows a Pareto distribution $a \sim G(a) = 1 - (\frac{1}{a})^{\theta_a},\ a \geq 1, \theta_a > 2$, with the minimum ability normalized to one. The assumption of $\theta_a > 2$ is to guarantee finite variance, which is essential for studying wage inequality measured by the variance in log wages. To capture the idea of the quality of skill match, we assume each worker draws an idiosyncratic matching premium from a job-specific Pareto distribution $\eta \sim F(\eta) = 1 - (\frac{\underline{\eta_j}}{\eta})^{\theta_{sj}}$ defined over $[\underline{\eta_j}, \infty)$, where $\theta_{sj} > 2$ is the inverse of the tail parameter that captures the dispersion of the matching premium in job j.

We assume abilities and the matching premium are distributed independently. The total efficient labor supply in the performance-pay position of job j is thus

$$H_{jp} = \int_{a \in D_{jp}} \int_{\eta} h_{jp}(a, \eta) dF_j(\eta) dG(a), \tag{4}$$

where D_{jP} is the ability domain for workers and $h_{jp}(a, \eta)$ is the efficient labor supply from a worker of ability a and matching premium η.

Fixed-pay position A worker's efficient labor supply in the fixed-pay position depends neither on the innate ability nor on the effort level. It is assumed to be only linear in the job-specific productivity. Precisely, in job j, the efficient labor supply from a worker in the fixed-pay position is A_j. The total efficient labor supply in the fixed-pay position of job j is thus $H_{jF} = A_j N_{jF}$, where N_{jF} is the employment level in the fixed-pay position of job j.

Production and payment The production function in job j is a CES aggregator of the efficient labor supply from the performance-pay position and fixed-pay position. Specifically, the output of job j is given by

$$Y_j = \left[\alpha_j H_{jF}^{\gamma} + (1 - \alpha_j) H_{jp}^{\gamma}\right]^{\frac{1}{\gamma}},\ \gamma < 1, \tag{5}$$

where $\frac{1}{1-\gamma}$ is the elasticity of substitution between the labor supply from the two positions — they are substitute (complementary) if $\gamma > 0$ ($\gamma < 0$); α_j is job specific to reflect the intensity of the fixed-pay position in each job.

We denote w as the wages that each worker in the fixed-pay position can earn. In each job j, given wages w, the representative firm decides the employment level in the fixed-pay position to maximize the revenue net of the payment to workers in the fixed-pay position. That is,

$$\max_{N_{jF}} Y_j - w N_{jF}. \tag{6}$$

It is straightforward to show that N_{jF} satisfies $N_{jF} = \frac{\chi_j H_{jP}}{A_j}$, where $\chi_j \equiv \left[\frac{(\frac{w}{\alpha_j A_j})^{\frac{\gamma}{1-\gamma}} - \alpha_j}{1-\alpha_j}\right]^{-\frac{1}{\gamma}}$. We show in Appendix D that the total payment to workers at the fixed-pay position, E_{jF}, is equivalent to $E_{jF} = \tilde{\alpha}_j \tilde{A}_j H_{jP}$, where $\tilde{A}_j = \left[\alpha_j \chi_j^\gamma + (1-\alpha_j)\right]^{\frac{1}{\gamma}}$, and $\tilde{\alpha}_j = \frac{\alpha_j \chi_j^\gamma}{\alpha_j \chi_j^\gamma + (1-\alpha_j)}$. We also show in Appendix D that the total output can be expressed as $Y_j = \tilde{A}_j H_{jP}$. Therefore, the residual profit is $E_{jP} = (1-\tilde{\alpha}_j)\tilde{A}_j H_{jP}$.

Firms and workers in the performance-pay position share the residual profit. We assume workers' bargaining power is μ. Therefore, the total payment to workers in the performance-pay position is $E_{jP} = \mu(1-\tilde{\alpha}_j)\tilde{A}_j H_{jP}$, and the payment to a worker of ability a and the matching premium η in the performance-pay position is thus $\mu(1-\tilde{\alpha}_j)\tilde{A}_j A_j a \eta e_j(a,\eta)$.

Workers A worker's utility is assumed to positively depend on his or her consumption c and negatively depend on his or her effort level e. In addition, workers in the performance-pay position also suffer from the job-specific disutility of being monitored.[8] We further assume that a worker's utility function is linear in consumption and quadratic in effort level. Specifically, a worker's utility function from working in the performance-pay position of job j takes the following form:

$$U_j^P = \max_e \quad \mu(1-\tilde{\alpha}_j)\tilde{A}_j A_j a \eta e - \frac{1}{2} b e^2 - M_j, \tag{7}$$

where b measures the degree of disutility on effort. M_j is the disutility incurred from working in job j.

Workers make decisions on jobs, positions, and efforts. Figure 6 summarizes the timeline of the worker's decision. Workers choose the job and position before the realization of the matching premium. By contrast, the optimal effort level is chosen after workers observe the outcome of the matching premium.

The ex-ante expected utility from working in the performance-pay position of job j for a worker of ability a is thus $EU_j^P(a) = E_\eta[U_j^P(a,\eta)]$.

Workers in the fixed-pay position always exert the minimum effort since their pay is independent

[8] Monitoring aims to prevent workers in the performance-pay position from shirking. To simplify the analysis, we make the following two assumptions. First, when there is shirking, the worker's effort decreases to $(1-\delta)$ of the optimal effort level. Second, we assume the following condition, which assures incentive compatibility for any job j: $1 > \delta^2 > \frac{2\mu b M_j}{[\mu(1-\tilde{\alpha}_j)\tilde{A}_j A_j]^2}$. The condition is met in our quantitative analysis.

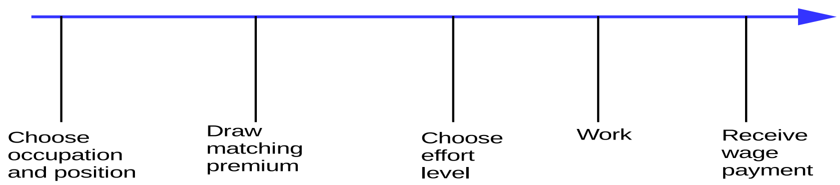


Figure 6: Timeline

of their effort level. A worker's payoff from the fixed-pay position can thus be expressed as

$$U^F = w - \frac{b}{2}\underline{e}^2. \tag{8}$$

Finally, a worker chooses the job and position that delivers the highest expected utility

$$EV(a) = \max_j \{U^F, EU_j^P(a)\}. \tag{9}$$

Thus, the fixed-pay position is chosen by a worker of ability a if $U^F > \max_j \{EU_j^P(a)\}$. Otherwise, a worker of ability a chooses the performance-pay position in a job given by $j^*(a) = \arg\max_j \{EU_j^P(a)\}$.

4 Theoretical Analysis

4.1 Equilibrium

Given the job-specific characteristics $\{A_j, \alpha_j, M_j, \theta_{sj}, \underline{\eta_j}\}$, a *sorting equilibrium* is described by the wages that each worker in the fixed-pay position earns and the labor allocation across jobs and positions $\{D_{jF}, D_{jp}\}$ such that:

1. Given the wages that each worker in the fixed-pay position earns, workers optimally choose jobs and positions $\{D_{jF}, D_{jp}\}$ as in equation (9).

2. Given the wages that each worker in the fixed-pay position earns and the efficient labor supply from the performance-pay position H_{jP}, firms decide employment in the fixed-pay position N_{jF} to maximize their profits.

3. The labor market clears $\sum_j \int_{a \in \{D_{jF} \cup D_{jP}\}} dG(a) = 1$, where the total labor force is normalized to one.

4.2 Analytical Results

In the following, we solve the worker's decision in a backward fashion:

- (Stage 2) We first solve the effort exerted by a worker of ability a given that the performance-pay position has been chosen and the matching premium draw has been realized.
- (Stage 1) We then move backward to determine whether this worker would select a performance-pay position and, if so, which job he or she would take.

Specifically, in Stage 2, a worker of ability a in the performance-pay position of job j after realizing the productivity premium η chooses effort to maximize his or her utility shown in equation (7). Consumption c_j equals the wage income: $c_j = \mu(1-\tilde{\alpha}_j)\tilde{A}_j A_j a\eta e$, and thus the resulting effort level is $e_j(a,\eta) = \mu(1-\tilde{\alpha}_j)\tilde{A}_j A_j a\eta/b$.

Substituting in the effort level above, a worker's efficient labor supply is thus

$$h_{jp}(a,\eta) = \frac{\mu[(1-\tilde{\alpha}_j)\tilde{A}_j A_j a\eta]^2}{b}$$

and the ex-post utility from working in job j can be derived as

$$U_j^P(a;\eta) = \frac{1}{2b}((1-\tilde{\alpha}_j)\tilde{A}_j A_j \eta\mu a)^2 - M_j.$$

In Stage 1, before the realization of the matching premium draw, the decision to select the performance-pay position depends on the expected utility:

$$EU_j^P(a) \equiv E_\eta[U_j^P(a,\eta)] = \tilde{C}_j a^2 - M_j, \tag{10}$$

where $\tilde{C}_j = \frac{1}{2b}((1-\tilde{\alpha}_j)\tilde{A}_j A_j \mu)^2 E_j(\eta^2)$ and

$$E_j(\eta^2) = \frac{\theta_{sj}}{\theta_{sj}-2}(\underline{\eta_j})^2. \tag{11}$$

Because this second moment $E_j(\eta^2)$ term enters the expected utility from the performance-pay position, we can conveniently use this to measure match quality in job j. Our result shows that match quality depends positively on both the job-specific minimum matching premium $\underline{\eta_j}$ and its dispersion measured by the tail parameter $1/\theta_{sj}$. Recall that $j^*(a)$ denotes the job in which a worker of ability a gains the highest expected utility from the performance-pay position. Thus, the performance-pay position in job $j^*(a)$ is selected by a worker of ability a if and only if $EU^P_{j^*(a)}(a) > U^F$.

In summary, the two extensive margins — selection into a performance-pay position and job sorting captured by $j^*(a)$ — are interconnected, depending crucially on the worker's ability a and an intensive margin of the match quality measure $E_j(\eta^2)$. In the sorting equilibrium, all the margins, in addition to general job productivity, in turn affect the wage dispersion within each job, which we will now investigate further.

4.3 Illustration of the One-job Case

Consider only one job of the two available positions: fixed-pay and performance-pay. The income earned from each position positively depends on the individual's ability a. We denote $y(a)$ and $z(a)$ as the income of an agent of ability a in the performance-pay and fixed-pay positions, respectively. As long as $y''(a) > z''(a)$ and $y(\underline{a}) < z(\underline{a})$, workers of higher ability work in the performance-pay position. Let a^* be the cutoff. The income inequality expressed as the variance in income can be obtained as

$$VI = \int_{a^*}^{\bar{a}} y(a)^2 dG(a) + \int_{\underline{a}}^{a^*} z(a)^2 dG(a) - \left[\int_{a^*}^{\bar{a}} y(a) dG(a) + \int_{\underline{a}}^{a^*} z(a) dG(a)\right]^2 \tag{12}$$

Denote $n_p = \int_{a^*}^{\bar{a}} dG(a)$; then, $1 - n_p = \int_{\underline{a}}^{a^*} dG(a)$. We show in Appendix C that

$$\frac{d(VI)}{dn_p} = Var(y(a)) - Var(z(a)) + (1 - 2n_p)\big[E[y(a)] - E[z(a)]\big]^2. \tag{13}$$

Thus, under normal circumstances, where performance-pay incomes is more dispersed than fixed-pay income ($Var(y(a)) > Var(z(a))$), we have the following proposition.

Proposition 1 *(Performance-pay Incidence and Wage Inequality) Under $Var(y(a)) > Var(z(a))$, the overall inequality in the job increases with n_p if $n_p < 1/2$.*

Since wage inequality increases with the performance-pay incidence, next we focus on how n_p is determined within a job. For illustrative purposes, we further assume that the production function takes a Cobb–Douglas form. The firm's profit maximization problem then becomes

$$\max \quad (AN_F)^{\alpha} H_p^{1-\alpha} - wN_F.$$

The relationship between wages and employment in the fixed-pay position is $N_F = \left[\frac{w}{\alpha A}\right]^{\frac{1}{\alpha-1}} \frac{H_p}{A}$.

Defining $\chi(w) \equiv \left[\frac{w}{\alpha A}\right]^{\frac{1}{\alpha-1}}$, the total payment to the fixed-pay position can be summarized as $\chi(w)^{\alpha} \alpha H_p$. Following the same notation as in the full-fledged model, we let $\widetilde{A} = \chi(w)^{\alpha}$ and $\widetilde{\alpha} = \alpha$.

The expected utility from working in the performance-pay position is $\frac{1}{2b}\left[(1-\widetilde{\alpha})\widetilde{A}A\mu\right]^2 E\left[\eta^2\right] a^2$. The expected utility from working in the fixed-pay position is w if we normalize the minimum effort level to zero. Thus, a worker chooses the performance-pay position if and only if $\frac{1}{2b}\left[(1-\widetilde{\alpha})\widetilde{A}A\mu\right]^2 E\left[\eta^2\right] a^2 > w$.

In this simple illustration, we also drop the monitoring cost because it is only useful for sorting workers across jobs. Moreover, since $(1-\widetilde{\alpha})\widetilde{A}A = (1-\alpha)\left[\frac{w}{\alpha A}\right]^{\frac{\alpha}{\alpha-1}} A$, the cutoff ability a can thus be pinned down from

$$\frac{\mu^2}{2b}\left[(1-\alpha)\left[\frac{w}{\alpha A}\right]^{\frac{\alpha}{\alpha-1}} A\right]^2 E\left[\eta^2\right] a^2 = w.$$

In addition, the labor market–clearing condition can be expressed as

$$\left[\frac{w}{\alpha A}\right]^{\frac{1}{\alpha-1}} \frac{H_p}{A} = 1 - a^{-\theta_a},$$

where $H_p = \frac{\mu}{b}(1-\alpha)^2\left[\frac{w}{\alpha A}\right]^{\frac{2\alpha}{\alpha-1}} A^2 E\left[\eta^2\right] \frac{\theta_a}{\theta_a-2} a^{2-\theta_a}$.

We can now prove the existence and uniqueness of the solution (a, w) and characterize the impacts of A and $E[\eta^2]$ on the equilibrium outcome. To do this, we substitute the cutoff condition into the labor market equilibrium condition to eliminate $E[\eta^2]$ and manipulate it to arrive at

$$\frac{\mu}{2}\frac{\theta_a - 2}{\theta_a}\left(a^{\theta_a} - 1\right)\left[\frac{w}{A}\right]^{\frac{\alpha}{1-\alpha}} = \alpha^{\frac{1}{1-\alpha}}, \tag{14}$$

which is referred to as the Labor-market Equilibrium (LE) locus. Manipulating the cutoff condition, we obtain

$$\frac{\mu^2}{2b}(1-\alpha)^2\left[\frac{1}{\alpha}\right]^{\frac{2\alpha}{1-\alpha}} AE\left[\eta^2\right] a^2 \left[\frac{w}{A}\right]^{\frac{1+\alpha}{\alpha-1}} = 1, \tag{15}$$

which is referred to as the Cutoff Ability (CA) locus.

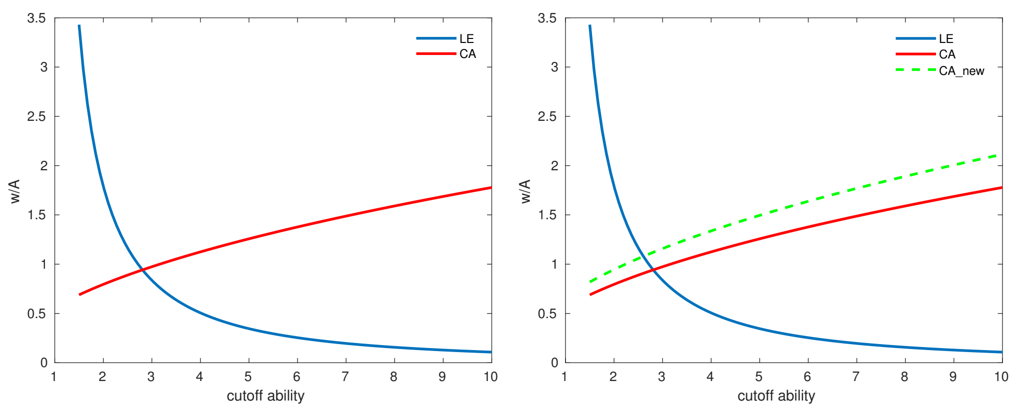
We can see that LE is increasing in $\frac{w}{A}$ and a but independent of A and $E[\eta^2]$. Moreover, CA is decreasing in w/A but increasing in a and A. Thus, the LE locus is downward sloping in the $(a, \frac{w}{A})$ space whereas the CA locus is upward sloping, as shown in Figure 7. Intuitively, a higher cutoff ability means more workers in the fixed-pay position, thereby leading to lower fixed-pay wages under the labor market equilibrium. On the contrary, for the marginal worker to be indifferent, higher fixed-pay wages raise one's outside options, thus requiring a higher cutoff ability to maintain indifference.

We first study the boundary properties. Recall that $a \geq 1$ and $\theta_a > 2$. Consider the LE locus: as $a \to 1$, $\frac{w}{A} \to \infty$; as $a \to \infty$, $\frac{w}{A} \to 0$. Consider the CA locus: as $a \to 1$, $\frac{w}{A} \to \left[\frac{w}{A}\right]_{\min} \equiv \left\{\frac{\mu^2}{2b}(1-\alpha)^2\left[\frac{1}{\alpha}\right]^{\frac{2\alpha}{1-\alpha}} AE\left[\eta^2\right]\right\}^{\frac{1-\alpha}{1+\alpha}}$; as $a \to \infty$, $\frac{w}{A} \to \infty$. These together with the slope properties of the two loci ensure the following proposition.

Proposition 2 *(Existence and Uniqueness) For any job, the position cutoff ability and the fixed pay wages are uniquely determined.*

Moreover, in the $(a, \frac{w}{A})$ space, an increase in either A or $E[\eta^2]$ shifts only the CA locus up, without affecting the LE locus. This thereby leads to a lower a, a higher $\frac{w}{A}$, and hence a higher w.

Proposition 3 *(Comparative Statics: Wage and Position Selection) For any job, an increase in technology or match quality reduces the position cutoff ability and increases the fixed pay wages.*



(a) LE v.s. CA Locus (b) Double Productivity or Match Quality

Figure 7: Comparative statics in the one-job case

Notes: The blue curve denotes equation (14) and the red curve denotes equation (15). The left panel shows the existence and uniqueness of the equilibrium outcome in the simple one-job setting. In the right panel, we either double productivity A or match quality summarized by $E[\eta^2]$ to evaluate the changes in w/A.

Figure 7 illustrates the comparative statics from doubling either productivity or match quality (summarized as $E(\eta^2)$). Intuitively, when the technology improves, the overall productivity is higher. While this raises the fixed-pay wages, the cutoff ability is lower, as the performance-pay position becomes even more rewarding. As a result, the labor supply to the fixed-pay position is lower, thus leading to a more-than-proportional increase in the fixed-pay wages. On the contrary, an increase in match quality raises the reward in the performance-pay position. By complementarity, this also raises the productivity of the fixed-pay workers and hence the fixed-pay wages.

We now return to the characterization of the within-job wage inequality in equation (13). A natural inquiry arises: how do technology and match quality influence the impacts of performance-pay incidence on the overall wage inequality within the job? As shown in Proposition 3, either shift reduces the cutoff ability and raises the fixed-pay wages. While the latter tends to reduce $\big[E[y(a)]-E[z(a)]\big]^2$, the former expands the range of workers in the performance-pay position but suppresses that in the fixed-pay position, which together lead to higher $Var(y(a))$, lower $Var(z(a))$, and hence larger $Var(y(a)) - Var(z(a))$. The presence of these channels of endogenous cross-position spillovers is novel. One may thus conclude that rising fixed-pay technology amplifies the effect of the performance-pay incidence in the overall within-job wage inequality if $1 - 2n_p$ is sufficiently small. Regarding higher match quality, an additional direct effect widens the performance-pay dispersion $Var(y(a))$ resulting from heterogeneous premium draws. Thus, while its net impact on the effect of the performance-pay incidence on the overall within-job wage inequality is generally ambiguous, the likelihood of amplifying the effect of the performance-pay incidence on the overall within-job wage inequality is greater than the technology effect. To sum up, we have the following proposition.

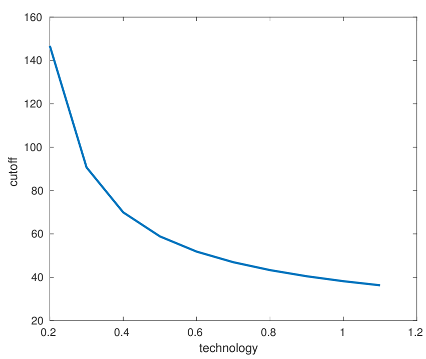
Proposition 4 *(Comparative Statics: Inequality) Under $Var(y(a)) > Var(z(a))$ and $n_p < 1/2$, a better technology or higher match quality amplifies the effect of the performance-pay incidence n_p on the within-job and within-performance-pay inequality ($Var(y(a))$), but dampens the effect of the performance-pay incidence n_p on the within-job and between-position wage inequality ($\big[E[y(a)] - E[z(a)]\big]^2$), leading to an overall ambiguous net impact.*

We summarize the rich mechanisms underlying the comparative static results presented in Propositions 3 and 4. First, as in standard neoclassical theory, contributions from fixed-pay and performance-pay workers to production are Pareto complements. Thus, the fixed-pay technology raises not only the productivity of fixed-pay workers but also that of performance-pay workers; likewise, match quality enhances the productivity of workers in both positions. Here, the direct effect on its own position should dominate the indirect effect on the other position. Their impacts on the within-job and between-position wage inequality are thus unambiguous. Second, there is a labor composition effect via changes in the cutoff ability, as in occupational choice models. When the cutoff is lower, there are more workers in the performance-pay position but fewer in the fixed-pay position. This labor composition effect feeds back to affect income in each job via the labor-market equilibrium and subsequently change the between-position inequality. Third, as a result of changes in the cutoff ability, the range of ability changes, thereby affecting the dispersion of income in both positions. When the cutoff is lower, inequality in the fixed-pay position narrows, whereas that in the performance-pay position widens. Fourth, changes in the cutoff ability also affect the selection of performance-pay workers. When the cutoff is lower, the performance-pay position is less selective, thus reducing the average productivity of performance-pay workers as a whole. In summary, even under this simplified setup, there are four interactive mechanisms via *complementarity*, *labor composition*, *relative ability dispersion* and *performance-pay selectivity.*

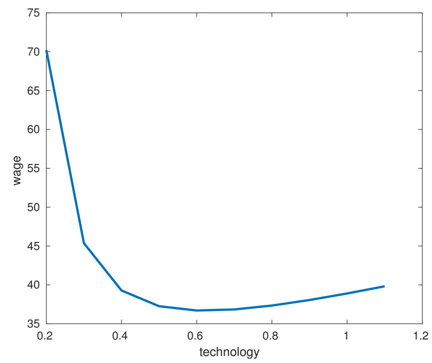
To this end, if we consider a CES production or sorting mechanism across jobs, the comparative static properties regarding the effect of the performance-pay incidence on the overall within-job wage inequality would become even more complicated. While we examine sorting in the next subsection more in depth, note that CES production enriches the complementarity mechanism, whereas sorting affects the labor composition, relative ability dispersion, and performance-pay selectivity mechanisms. As shown in Figure 8, when the performance-pay and fixed-pay positions become more complementary ($\gamma = -2$), and hence the elasticity of substitution is $1/(1-\gamma) = 1/3$. The value of the fixed-pay position tends to decrease with both productivity and match quality, as opposed to increasing in the case of the Cobb–Douglas production function. This is because that stronger complementarity dampens the negative labor composition effect in the performance-pay positions. This thereby strengthens positive interactions between match quality and performance-pay incidence as indicated by the negative relationship between match quality and cutoff ability. Due to all such rich interactions, understanding such impacts thus becomes a quantitative question, which we investigate in Section 5.

4.4 An Equilibrium with Positive Assortative Sorting

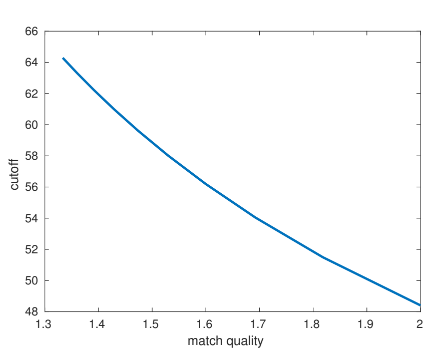
We return to the full-fledged model in this section. To circumvent the potential issues associated with multiple equilibria in a general setting, we restrict our attention to the case of a monotone



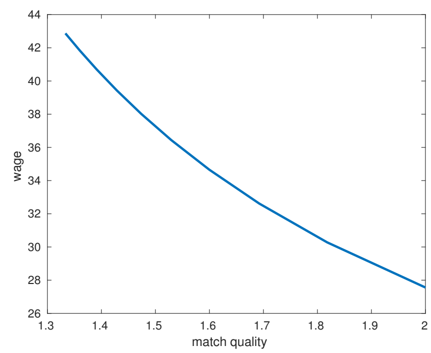
(a) CES: Productivity and Cutoff-Ability



(b) CES: Productivity and the Value of the Fixed-pay Position



(c) CES: Match Quality and Cutoff-Ability



(d) CES: Match Quality and the Value of the Fixed-pay Position

Figure 8: Simulation of the one-job case with the CES production function

Notes: When the performance-pay and fixed-pay positions become more complementary ($\gamma = -2$) as opposed to in the benchmark Cobb–Douglas production function, we re-evaluate how productivity and match quality affect cutoff abilities and wages.

job ranking under which we order n such that $\{M_n\}$ and $\{\tilde{C}_n\}$ are increasing sequences of n.[9] In this case, we can characterize the sorting equilibrium.

We start with the following lemma to show that in the performance-pay position, higher ability workers choose the job of a larger index.

Lemma 5 *If a worker of ability a chooses to work in the performance-pay position of job k , then workers of ability $a' > a$ prefer the performance-pay position in any job $n \geq k$ than in job k.*

We further impose the following assumption to ensure the existence of a sorting equilibrium.

***Assumption 1*:** $\frac{M_n - M_{n-1}}{\tilde{C}_n - \tilde{C}_{n-1}}$ is increasing in n for all $n > 1$.

[9] Recall that $\{\tilde{C}_n\}$ are defined in equation (10). In the remainder of this section, we relabel job index as $n = 1, 2..J$ to denote the ranking of jobs in the sorting equilibrium.

When the assumption above holds, we can further characterize workers' preferences over jobs within the performance-pay position in the following lemmas.

Lemma 6 *Under Assumption 1, workers of ability* $a \in \left(\sqrt{\frac{M_n - M_{n-1}}{\tilde{C}_n - \tilde{C}_{n-1}}}, \sqrt{\frac{M_{n+1} - M_n}{\tilde{C}_{n+1} - \tilde{C}_n}}\right)$ *prefer the performance-pay position at job* n *to that at* $n-1$ *and* $n+1$.

Lemma 7 *Under Assumption 1, if a worker of ability* a *prefers the performance-pay position in job* n *to* $n-1$*, then he or she also prefers the performance-pay position in job* n *to any job* $k < n-1$.

Lemma 8 *Under Assumption 1, if a worker of ability* a *prefers the performance-pay position in job* n *to* $n+1$*, then he or she also prefers the performance-pay position in job* n *to any job* $k > n+1$.

The proof of the above three lemmas can be found in Appendix C. These lemmas together imply that conditional on the performance-pay position, workers of ability $a \in \left(\sqrt{\frac{M_n - M_{n-1}}{\tilde{C}_n - \tilde{C}_{n-1}}}, \sqrt{\frac{M_{n+1} - M_n}{\tilde{C}_{n+1} - \tilde{C}_n}}\right)$ find it optimal to work in job n. Denote $a_n^* := \sqrt{\frac{M_n - M_{n-1}}{\tilde{C}_n - \tilde{C}_{n-1}}}$ as the cutoff ability. We can thus conclude that workers of ability $a \in [a_n^*, a_{n+1}^*)$ prefer the performance-pay position in job n than in any other jobs.

The previous analysis is restricted to workers in the performance-pay position. In the following, we explore how workers choose between the performance-pay and fixed-pay positions, for which we need to impose the following additional assumption.

Assumption 2: $\exists \underline{a} < a_2^*$ s.t. $\tilde{C}_1 \underline{a}^2 - M_1 < \underline{U} < \tilde{C}_1 \left(a_2^*\right)^2 - M_1$ holds.

Lemma 9 *Under Assumption 2, workers of ability* $a \in \left[\underline{a}, \left(\frac{\underline{U}+M_1}{\tilde{C}_1}\right)^{1/2}\right)$ *choose to work in the fixed-pay position and workers of ability* $a \in \left[\left(\frac{\underline{U}+M_1}{\tilde{C}_1}\right)^{1/2}, a_2^*\right)$ *choose to work in the performance-pay position of job 1.*

Combining all the lemmas above yields the following proposition.

Proposition 10 *Under Assumptions 1 and 2, a sorting equilibrium is positive assortative both within and across jobs.*

- **(i)** *Sorting across jobs: Workers of ability* $a \in \left(\sqrt{\frac{M_n - M_{n-1}}{\tilde{C}_n - \tilde{C}_{n-1}}}, \sqrt{\frac{M_{n+1} - M_n}{\tilde{C}_{n+1} - \tilde{C}_n}}\right)$ *find it optimal to work in the performance-pay position of job* $n > 2$*, whereas workers of ability* $a \in \left[\left(\frac{\underline{U}+M_1}{\tilde{C}_1}\right)^{1/2}, a_2^*\right)$ *chooses to work in the performance-pay position of job 1.*

- **(ii)** Sorting within jobs: Workers of ability $a \in \left[\underline{a}, \left(\frac{\underline{U}+M_1}{\tilde{C}_1}\right)^{1/2}\right)$ choose to work in the fixed-pay position of any job.

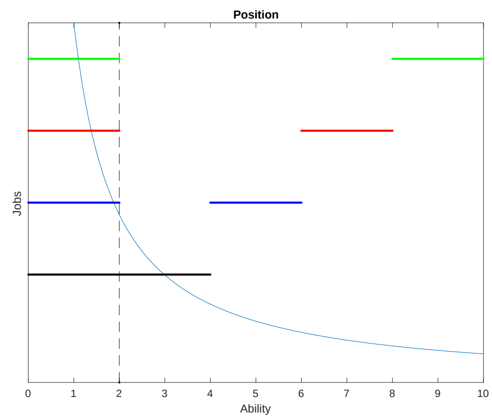


Figure 9: Job and position choice

An illustration of job and position choices To illustrate the sorting equilibrium defined above, Figure 9 provides a simple example. There are four jobs: job one (green), job two (red), job three (blue), and job four (black). Hence, there are four cutoff abilities which, shown in the figure, as $a_{min} = a_1^* = 2$, $a_2^* = 4$, $a_3^* = 6$, and $a_4^* = 8$. Workers work in the fixed-pay position if $a < a_1^*$ and choose the performance-pay position of job n if $a_n^* \leq a < a_{n+1}^*, n = 1, 2, 3$. Finally, workers work in the performance-pay position of job 4 if $a \geq a_4^*$. Therefore, in each job, there are some workers in the performance-pay position and others in the fixed-pay position.

5 Quantitative Analysis

5.1 Calibration

We calibrate the benchmark model to the US economy in 2000. Similar to in Section 2.4, we focus on a selection of 25 jobs, as observed in the March CPS, PSID, and NLSY79 datasets. In our model, there are four common parameters $\{\mu, \theta_a, \gamma, b\}$ and six job-specific parameter series $\{A_j, M_j, \theta_{sj}, \underline{\eta_j}, \alpha_j\}_{j=1}^J$. Two parameters can be preset based on the literature or simple targets. One is μ, which governs workers' bargaining power in the performance-pay position. This is set to 0.54 by Hall and Milgrom (2008) and 0.72 by Shimer (2005), with others choosing lower values such as 0.4 and 0.5. Because we consider only highly educated workers whose bargaining strength is above average, we set $\mu = 0.6$. Another is θ_a, the shape parameter of the Pareto distribution for workers' innate abilities. We set $\theta_a = 8.0$ so that the 90-10 earning ratio in our calibrated economy is about 5.

All the other parameters are jointly calibrated based on the model, but each is more closely connected to a primary target. For the crucial parameter of the elasticity of substitution between the efficient labor supply in the production function γ, as discussed in Section 4.3, we target it to match the overall between-job wage inequality. The calibrated elasticity indicates workers at different job positions are complementary and the value of the fixed-pay position and the cutoff ability are decreasing in the match quality. Thus, the higher the match quality is, the stronger are sorting incentives for the the performance-pay position and job sorting. For the disutility parameter from exerting effort b, we set it such that the least talented individual in performance-pay position chooses to exert the same effort level as those workers in the fixed-pay position(i.e., the minimum effort: $e_{\min}$). With regard to job-specific monitoring costs $\{M_j\}$, we normalize M_1 to zero and calibrate the remaining M_j to match the number of workers in the performance-pay position in each job. As $\{\theta_{sj}\}$ captures the skewness of the matching premium of each job, they are calibrated to minimize the distance between the model-predicted within-job standard deviation of log-earnings and their data counterparts. Concerning $\underline{\eta_j}$ that governs the minimum scale of the Pareto distribution of the matching premium, we first establish the following one-to-one mapping between the mismatch index (m_j) measured in Section 2.1 and match quality(η_j) in job j:

$$m_j = m_{j0} + \frac{1}{\eta_j}.$$

If η_j follows a Pareto distribution defined over $[\underline{\eta}_j, \infty)$ with the shape parameter θ_{sj}, the distribution function of m_j is then

$$\tilde{F}(m_j) = [\underline{\eta}_j \cdot (m_j - m_{j0})]^{\theta_{sj}}.$$

We thus jointly calibrate the job-specific $\{\underline{\eta_j}, m_{j0}\}$ to minimize the distance between the model-predicted mean and standard deviation of the job-specific mismatch index and their data counterparts.[10] This enables us to obtain a match quality series using equation (11). Recall that α_j is the coefficient on the labor supply from the fixed-pay position in the production function. It is thus calibrated to match the performance-pay incidence in each job, which is equivalent to the employment share

[10] We may not exactly match both moments since the estimation is subject to the constraint $\theta_{sj} > 2$.

of workers in the performance-pay position in any job. Finally, turning to job-specific productivity $\{A_j\}$, we calibrate A_1 to match the number of workers in the fixed-pay position and then compute $\{A_j\}_{j=2}^N$ according to the ratio of average pay in job j to that in job 1. Because these parameters are interconnected in the model, they are jointly calibrated to meet the targets by minimizing distance.

Table 3 summarizes the parameter values and their targets. Table 4 reports the model-predicted within-job, between-job, and overall wage inequality as opposed to the data counterpart in 2000. The model matches the untargeted between-job wage inequality and overall wage inequality reasonably well.

Table 3: Benchmark parameterizations

Description	**Para.**	**Value.**	**Source/Targets**
		External Parameters	
Number of jobs	N	25	Section 2.4
Bargaining power	μ	0.6	Shimer (2005) and Hall and Milgrom (2008)
Shape of the ability distribution	θ_a	8.0	90-10 earning ratio
		Jointly Determined Parameters	
Elas. of subs. between two pos	$\frac{1}{1-\gamma}$	0.357	between-job wage inequality
Coefficient on disutility from working	b	212.3	minimum effort is 1
Lowest job-specific productivity	A_1	0.86	fraction of workers at fixed-pay
Job-specific productivity	$\{A_j\}_{j=2}^N$	Figure B.18	relative wages of each job
Coefficient on fixed-pay in production	$\{\alpha_j\}$	Figure B.18	Performance-pay incidence
Monitoring cost	$\{M_j\}_{j=2}^N$	Figure B.18	dist. of workers at performance-pay
Shape of the matching premium distribution	$\{\theta_{sj}\}$	Figure B.18	Within-job wage inequality
Scale of the matching premium distribution	$\{\underline{\eta}_j\}$	Figure B.18	mean of the mismatch index

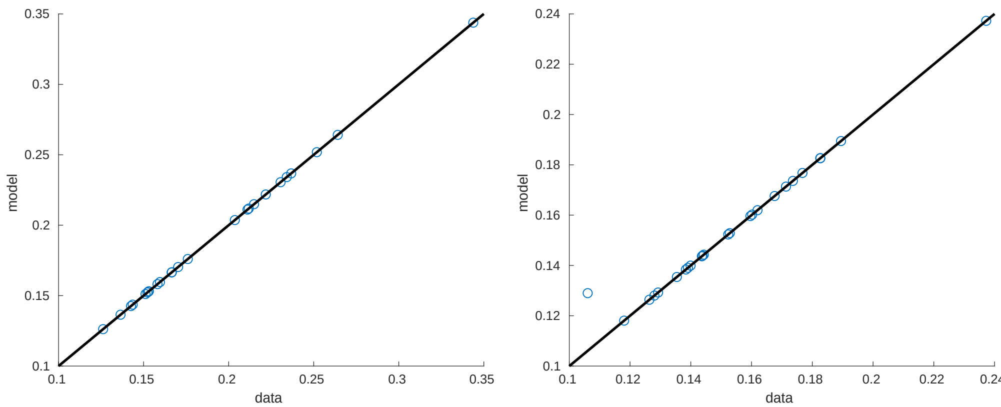
Table 4: Benchmark inequality: Model versus data

	1990		2000	
	Data	Model	Data	Model
Within Job	0.150	0.151	0.183	0.183
Between Job	0.019	0.018	0.021	0.014
Overall	0.177	0.169	0.228	0.197

Note: The data on each type of wage inequality are computed from the March CPS dataset. Model-implied wage inequality is based on the calibrated parameters summarized in Table 3.

Owning to the strict parameter restriction,[11] it is not guaranteed that we can exactly match

[11] For example, $\{\alpha_j\}$ need to be between 0 and 1 and γ needs to be smaller than 1. In addition, $\{M_j\}$ are required to be sorted ascending.



(a) 2000

(b) 1990

Figure 10: Model fitness in 2000 and 1990

Note: The x-axis represents job-specific within-job wage inequality computed from the data and the y-axis is the wage inequality within each job computed from the model. Each dot represents a job.

the data counterparts of each job. Nonetheless, the model can still perfect match the within-job inequality of each job in 2000 as shown in Figure 10. The model over-predicts the inequality in only one job in 1990, and perfect matches the inequality in all other jobs.

5.2 Decompose the changes in within-job inequality

To further disentangle how the performance-pay incidence, match quality, sorting, and job-specific productivity affect the pattern of within-job wage inequality, we conduct a decomposition analysis that changes the values of each job-specific series in 2000 into their respective values in 1990, while maintaining all the other parameters at their benchmark values.

To obtain those job-specific series in 1990, we also recalibrate the model to 1990 following an identical strategy to the exercise in 2000. Table 4 compares the aggregate results between the data and model. The model slightly overpredicts both within- and between- job wage inequality. Figure 10 plots the within-job wage inequality between the data and model in 1990, showing that out of the 25 job pairs, the model only overpredicts the within-job wage inequality for the (Goods, professional) pair by about 30%.[12]

To evaluate the contribution of factor k to the changes in inequality from 1990 to 2000 in job

[12]Table B.26 provides more details.

j, denoted as π_k^j, we apply the following formula:

$$\pi_k^j = \frac{(model_{2000}^j - counter_k^j)}{\sum_{k'}(model_{2000}^j - counter_{k'}^j)}(\frac{model_{2000}^j - model_{1990}^j}{data_{2000}^j - data_{1990}^j}),$$

where $model_{1990}^j$ and $model_{2000}^j$ denote model-predicted inequality in 1990 and 2000 in job j, respectively. $data_{1990}^j$ and $data_{2000}^j$ in turn denote the inequality in the data in these two years. $counter_k^j$ is the inequality obtained from the counterfactual economy, in which we restore the job-specific factor k from their values in 2000 to those in 1990.

Overall, we evaluate four contributing factors from the model: the performance-pay incidence, match quality, job-specific productivity, and sorting-induced changes in abilities and employment shares. The fraction that cannot be accounted for the model is due to "residuals" arising from missing factors, which is small in the benchmark economy.

Finally, the overall contribution of factor k, denoted as $\bar{\pi}_k$, is an average of its contribution in each job weighted by the employment share of each job

$$\bar{\pi}_k = \frac{\sum_j \pi_k^j N_j}{\sum_{k'} \sum_j \pi_{k'}^j N_j}, \tag{16}$$

where N_j is the employment share in job j.

Table 5: Contribution of each channel

Channel	Performance(%)	Match Quality(%)	Productivity(%)	Sorting(%)	Residual(%)	Total(%)
Contribution	37.6	51.9	-0.8	9.2	2.1	100.00

Note: The contribution of factor k in any job is summarized in equation 16. The overall contribution of factor k across all the jobs is computed as the average of its contribution in each job weighted by the employment share.

Table 5 reports the overall contribution of each channel, showing that the contributions of the performance-pay incidence, match quality, job-specific productivity, and sorting are 37.6%, 51.9%, −0.8%, and 9.2%, respectively. Overall, the model mimics the data counterpart fairly well with a nearly zero residual component. The changes in the performance-pay incidence and match quality can capture almost 90% the changes in within-job wage inequality from 1990 to 2000. Finally, the role of general job productivity is inconsequential.

One may inquire why job sorting or job-specific productivity does not widen within-job inequality by much. On the one hand, once match quality is assured and workers are offered with correct incentives by performance pay with better ones sorted into performance pay positions, the role

Table 6: Contribution of each channel

Channel	Performance(%)	Match Quality(%)	Performance+Match Quality(%)
Contribution	37.6	51.9	96.2

Note: We either set both channels or one channel to their values in 1990 and compute the contribution to changes in the wage inequality in each case.

played by positive assortative sorting across jobs diminishes much. One the other hand, job-specific productivity resembles Solow residuals in neoclassical aggregate production. Our results indicate that upon incorporating match quality and performance pay, this residual productivity adds little explanatory power to underlying drivers in the model.

Interactions between performance-pay incidence and match quality One may wonder when both the channel of performace-pay incidence and match quality are incorporated, whether they tend to reinforce or offset each other. In the following we address this question by either setting both the performance-pay incidence and the match quality, or set one of them to their levels in 1990. As shown in Table 6, when both are set to their levels in 1990, the joint contribution to changes in the overall wage inequality is 77.5 percent. This implies a positive amplication effect between the two channels by $96.2 - (37.6 + 51.9) \approx 6.7$ percent, which also enchos our findings in Proposition 4.

In summary, once the extensive margin via performance-pay and intensive margin via match quality are incorporated, the contribution of the remaining extensive margin via job sorting becomes modest, accounting for a bit less than 10 percent of the rising within-job wage inequality from 1990 to 2000. Moreover, general job productivity that has been emphasized in most of previous studies is inconsequential throughout when performance-pay and match quality are taken into account. Thus, while widening wage inequality may be a concern, it is less warranted if improved matching quality and better incentivized performance-pay contracts are the underlying drivers. It is particularly so because the modest role played by job sorting suggests that typical labor market search frictions are less likely to be the main source of the widening within-job wage inequality. Our results also offer, on a more micro-structured basis, insights toward better understanding of the main findings in Jovanovic (2014) that, in an incomplete information world, improved signaling quality about workers' true abilities may widen the within-the-group inequality. While improved match quality may be thought of as due partly to more informed signaling, performance-pay contracts may induce better incentives for worker that would in turn mitigate informational frictions.

5.2.1 Contribution by industry and occupation

To futher examine the role of each channel, we have conducted similar decomposition exercises at the industry/occupation level. The contribution of each channel in a given group is computed as the employment-weighted average of the job-level contributions:

$$\bar{\pi}_k^g = \frac{\sum_{j \in g} \pi_k^j N_j}{\sum_{j \in g} N_j}$$

where j denotes the job index that belongs to the group g. For brevity, we focus on those with significant deviations in group outcomes from the overall aggregate outcomes. To evaluate the relative importance of each industry/occupation in driving the widening wage inequality, we have also computed the contribution of each industry/occupation to the increase in the overall within-job inequality. The brief algorithm is to first compute the changes in the wage inequality of each job from 1990 to 2000. The changes of wage inequality in the industry (occupation) level is then an employment-weighted average of job-level changes. The contribution of each industry (occupation) is then the fraction of the changes in each industry or occupation for the changes in the overall within-job inequality. The results are reported in Table B.22 and B.23.

Table 7 presents the results of grouping by industry. We find that match quality is more important than the performance-pay incidence in almost all the industries except for the Trade industry, which accounts for about 21% of the increase in the overall within-job inequality as shown in Table B.22. The role of match quality is dominant and higher than the average contributions among all industries in the Transport and FIRE industry, which jointly account for another 20% of the increase in the overall within-job inequality. On the contrary, performance-pay incidence in Trade and Business industries contributes more than the average level among all the industries, accounting for about 45% of the changes in the overall within-job inequality – that is, incentive provision is more crucial for explaining the widening inequality in Trade and Business industries. The contribution of sorting is relatively larger in Goods and Transport industries, exceeding 10%.

At the occupation-level, in the Clerical occupation, which accounts for 22% changes in the overall within-job inequality as shown in Table B.23, performance pay is more important than match quality in driving up the wage inequality, while in all the remaining occupations the contribution of match quality is the largest among different channels. In Manager, Sales and Production Labor occupations, which together can explain more than 60% of the changes in the overall within-job inequality, the contribution of match quality is higher than the average level. In only

Table 7: Decomposition by industry

Industry	Performance(%)	Match quality(%)	Productivity(%)	Sorting(%)	Residual(%)	Total(%)
Goods	30.6	52.5	0.5	10.5	6.0	100.0
Transport	24.4	65.0	0.3	10.3	0.0	100.0
FIRE	30.3	64.4	-2.3	7.7	0.0	100.0
Business	40.8	52.0	-1.4	8.6	-0.0	100.0
Trade	52.9	40.7	-1.8	8.2	0.0	100.0
Aggregate	37.6	51.9	-0.8	9.2	2.1	100.0

Notes: The five industries are (1) Goods (containing durables/non-durables, construction and mining), (2) Transport (transportation and utility), (3) FIRE, (4) Business (business and professional services), and (5) Trade (whole/retail trade and personal services). The contribution of each factor in an industry is the average of its contribution in each job belonging to that industry weighted by the employment share.

two occupations, Production Labor and Clerical, the contribution of job sorting exceeds 10%.

Table 8: Decomposition by occupation

Occupation	Performance (%)	Match quality (%)	Productivity (%)	Sorting (%)	Residual (%)	Total (%)
Professional	32.8	46.3	-0.8	9.2	12.5	100.0
Manager	32.6	61.1	-1.8	8.2	0.0	100.0
Sales	40.6	62.5	-6.6	3.4	0.0	100.0
Production Labor	35.5	52.7	0.9	10.9	-0.0	100.0
Clerical	46.3	42.4	0.6	10.6	0.0	100.0
Aggregate	37.6	51.9	-0.8	9.2	2.1	100.0

Notes: The five occupations are (1) Professional, (2) Manager, (3) Sales, (4) Production/Operative Labor (including craftsmen), and (5) Clerical (including other services). The contribution of each factor in an occupation is the average of its contribution in each job belonging to that occupation weighted by the employment share.

Among all industries and occupations, the Professional occupation is the only category where the model cannot capture a noticeable portion (12.5%) of the widening inequality. In the Goods industry, the residual accounts for a mild 6%, while in all other categories, the residual shares are all negligible.

5.2.2 Contribution by wage, employment or inequality rankings

In the benchmark economy, jobs are sorted by average wages. The ranking of jobs may change from 1990 to 2000. In our exercise, ranking at the first slot implies that the job has the lowest average wage among all the jobs. In the following analysis, we group jobs with similar changes in ranking to examine how the role of each channel varies by category. If the job's job bin rises, then this job stands at a higher ranking in 2000 than in 1990; in other words, there are more jobs with a lower average wage than in 1990. Table 9 presents the decomposition results grouped by job bin changes.[13] For jobs whose average earnings rankings rise/drop moderately (by 1 or 2) or remain

[13] To facilitate the comparison, we have also computed the contribution of each catergory to the changes in the overall within-job inequality following similar ways as we did in Section 5.2.1. The results are reported in Table B.24

unchanged, which accounts for more than 85% changes in the overall within-job inequality, match quality and performance pay jointly contribute to widening wage inequality. For jobs whose average earnings rankings rise/drop sharply (by 3 or more), which contribute to slightly more than 10% of changes in the within-job inequality, match quality plays a more dominant role with contributions high than the overall average whereas sorting or general productivity tend to be more important than in other catergories.

Similarly, we can group by the ranking of each job's employment share, which also changes from 1990 to 2000 with a first-place ranking representing the lowest employment share. We again group jobs with similar changes in ranking. If the job's employment bin rises, then there are more jobs with a lower employment share than the specific job in 2000 than in 1990. Table 10 presents the results grouped by employment bin changes.[14] For jobs whose employment share rankings rise, which accounts for about 15% changes in the overall within-job inequality, match quality plays a dominant role. For jobs whose employment share rankings remain unchanged, which make up more than 50% of contributions to changes in the overall within-job inequality, the dominant role of match quality diminishes – its role continues to decline for jobs whose employment share rankings fall, where sorting contributes more than 10% of changes in the within-job inequality.

Table 9: Decomposition by average wage bin change

	Performance(%)	Match quality(%)	Productivity(%)	Sorting(%)	Residual(%)	Total(%)
Rise by 3 or more	19.1	91.0	-10.1	-0.1	0.0	100.0
Rise by 1 or 2	43.0	51.5	-2.3	7.7	0.0	100.0
Stay	40.5	48.8	0.4	10.4	0.0	100.0
Drop by 1 or 2	25.0	49.1	-0.3	9.7	16.5	100.0
Drop by 3 or more	28.0	59.8	1.1	11.1	0.0	100.0
Aggregate	37.6	51.9	-0.8	9.2	2.1	100.0

Notes: We group jobs with similar changes in ranking. If the jobs average wage bin rises, then there are more jobs with a lower average wage than this job in 2000 than in 1990. The contribution of each factor in a category is again the weighted average of its contribution in each job within that category.

5.2.3 Contribution in selected jobs

We conclude the decomposition analysis by investigating six selected jobs based on their large earnings and employment shares. Table 11 shows that for Sales in the Business industry, match quality plays a dominant role (almost 90%) in explaining changes in the wage inequality between 1990 and 2000. For Manager in the FIRE industry, match quality is the sole driver of the rising

and Table B.25.

[14]The contribution of each catergory to the changes in the overall within-job inequality can be found in Table B.25.

Table 10: Decomposition by employment bin change

	Performance(%)	Match quality(%)	Productivity(%)	Sorting(%)	Residual(%)	Total(%)
Rise	34.1	61.0	-2.6	7.4	0.0	100.0
Stay	37.7	54.1	-0.9	9.1	0.0	100.0
Drop	39.1	43.3	0.4	10.4	6.8	100.0
Aggregate	37.6	51.9	-0.8	9.2	2.1	100.0

Notes: We group jobs with similar changes in ranking of the employment share. If the jobs job bin rises, then there are more jobs with a lower employment share than this job in 2000 than in 1990. The contribution of each factor in a category is again the weighted average of its contribution in each job within that category.

within-job inequality, but for Manager and Professional in the Business industry, match quality and performance pay are the joint forces underlying the rising wage inequality. Clerical in the Trade industry and Sales in the Goods industry are the only two jobs with declining wage inequality from 1990 to 2000. Our findings suggest: such a decline for Clerical in the Trade industry is largely driven (about 70%) by the fall in performance-pay incidence, whereas that Sales in the Goods industry is a result of lower match quality and less performance pay. Sorting plays a more significant role for Clerical in the Trade industry than in other jobs. While changes in the general productivity are mostly inconsequential, its decline mitigates the widening wage inequality by more than 10% for Sales in the Business industry.

Table 11: Decomposition by selected jobs

Job pair (i,j)	Performance(%)	Match quality(%)	Productivity(%)	Sorting(%)	Residual(%)	Total(%)
(Trade, Clerical)	70.4	16.9	1.3	11.3	0.0	100.0
(Business, Sales)	22.9	88.8	-10.8	-0.8	0.0	100.0
(FIRE, Manager)	27.7	66.4	-2.1	7.9	0.0	100.0
(Business, Manager)	39.3	55.2	-2.3	7.7	0.0	100.0
(Goods, Sales)	28.1	66.3	-2.2	7.8	0.0	100.0
(Business, Professional)	42.6	50.3	-1.4	8.6	0.0	100.0

Notes: We select six jobs based on their earnings and employment shares. The contribution of each factor in a job is computed using equation (16).

6 Conclusion

In this paper, we have documented that within-job wage inequality greatly contributes to residual wage inequality. To explain this fact, we have developed a sorting equilibrium model in which within-job wage inequality is influenced by, in addition to general job productivity, two extensive margins — the performance-pay incidence and job sorting — as well as an intensive margin — match quality. Workers with higher abilities are sorted into higher paid jobs and performance-pay positions across all jobs. While better match quality encourages job sorting and selection into performance pay jobs, the overall impact of the performance-pay incidence on within-job wage inequality depends crucially on the complementarity, labor composition, relative ability dispersion, and performance-pay selectivity effects as well as the interplays between match quality, job sorting, and the performance-pay incidence. By calibrating the model to fit the U.S. data in 1990 and 2000, we have identified match quality and positive assortative sorting across all jobs as the two most important forces for widening within-job wage inequality. The paper thus shed light on the primary source of residual wage inequality within jobs. While widening wage inequality may be a concern, it is less warranted if improved matching and more prevalent performance pay are the underlying drivers.

Some interesting future research directions arise from these findings. The model could be extended to discuss the underlying reasons for skill matching. In particular, a worker may be employed in a mismatched job because of search frictions or the trade-off between personal interests and earnings. Incorporating these underlying reasons, the model could generate richer policy implications. The model could also be extended to include multiple dimension skills to study the effects of multi-tasking on wage inequality. With rising demand for multi-tasking, the dimension of skill requirements expands and that of job specialization declines. While a worker who fits the job or a special task well may have a higher wage, such a highly specialized skill may turn him or her into a loser both in multi-tasking requirements and in re-sorting. Within-job wage inequality may thus change as the requirements for multi-tasking change in different types of jobs.

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Appendix

(Not Intended for Publication)

A Stylized Facts

(a) Gini Coefficient

(b) 90-10 Percentile Ratio

Figure A.11: Wage inequality: Gini and 90-10 ratio

Notes: In the left (right) panel, the inequality is measured as Gini coefficient (90-10 ratio). In both panels, the blue line represents the inequality for the whole sample, and the green line only includes those highly educated. The red line is for the low education group. Data source: March CPS from CEPR (1983-2013).

Figure A.12: Decomposition of the raw wage inequality

Notes: The figure shows the proportion of the within-job inequality in the total raw inequality (blue) and the proportion of the between-job to the total raw inequality (red) under 1-digit industry and occupation code. Data source: March CPS from CEPR (1983-2013).

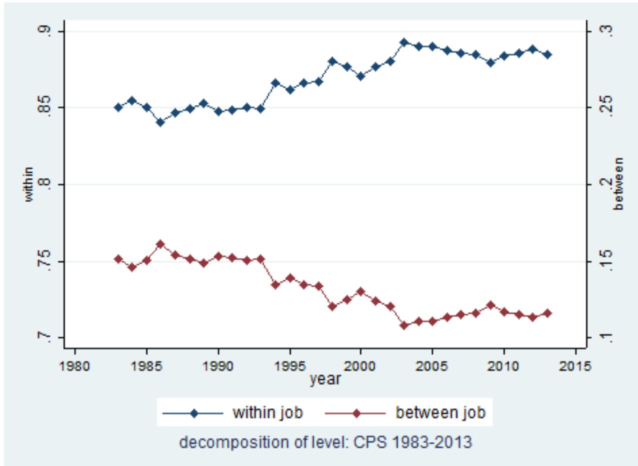


Figure A.13: Decomposition of the residue wage inequality

Notes: The figure shows the proportion of the within-job inequality to the total residue inequality (blue) and the proportion of the between-job inequality to the total residue inequality (red) under 1-digit industry and occupation code. Data source: CPSORG from CEPR (1983-2013).

Table A.12: Decomposition of the changes in the residual wage inequality: 1990-2000

	Within-job	Between-job	Employment	Interaction
1-d code	**110%**	-31.8%	17.7%	4.6%

Notes: This table computes the contribution of within-job, between-job inequality, employment share and interactions to the changes in residual inequality from 1990 to 2000. The row "1-d code" indicates 1-digit industry and occupation code. Data source: CPSORG from CEPR.

Table A.13: Decomposition with CENSUS: 1-d

year	inequality			contribution	
	overall	within	between	within	between
1990	.406	.330	.077	**81%**	19%
2000	.429	.351	.078	**82%**	18%

Source: CENSUS from CEPR.

Table A.14: Decomposition with CENSUS: 3-d

year	inequality			contribution	
	overall	within	between	within	between
1990	.408	.298	.112	**73%**	27%
2000	.431	.314	.117	**73%**	27%

Source: CENSUS from CEPR.

Table A.15: Decomposition of the changes in the residual wage inequality: 1990-2000

	Within-job	Between-job	Employment	Interaction
1-d code	**84.4%**	2.1%	6.9%	6.4%
3-d code	**101%**	-12.2%	11.1%	0

Notes: This table computes the contribution of the within-job, between-job inequality, employment share and interactions to the changes in the residual inequality from 1990 to 2000. The row "1-d code" indicates 1-digit industry and occupation code, "3-d code" indicates 3-digit industry and occupation code. Data source: CENSUS from CEPR.

Table A.16: Incidence of Performance-pay: 1990

	Professionals	Managers	Sales	Clerical	Craftsmen	Operatives	Laborers	Services
Min durables	0.35	0.57	0.75	0.21	0.16	0.20	0.24	0.15
Nondurables	0.47	0.59	0.74	0.34	0.24	0.35	0.25	0.02
Transport Utils	0.11	0.31	0.74	0.20	0.14	0.33	0.31	0.26
Fin. insur. real est.	0.65	0.65	0.85	0.34	0.18	0.01	0.07	0.28
Bus. prof. serv.	0.36	0.50	0.84	0.30	0.41	0.34	0.14	0.20
Personal serv.	0.28	0.63	0.15	0.24	0.49	0.28	0.78	0.41
Whol-tr oth serv.	0.76	0.61	0.79	0.50	0.33	0.43	0.21	0.01
Retail trade	0.34	0.56	0.73	0.30	0.43	0.25	0.18	0.48
Construction	0.69	0.43	0.73	0.21	0.29	0.21	0.24	0.14
Agri. fishing	0.58	0.90	0.22	0.90	0.17	0.62	0.41	0.77

Note: This table presents the estimated performance-pay incidence for the highly educated in different jobs for year 1990, following the approach in Lemieux et al. (2009). Data source: PSID.

Table A.17: Incidence of Performance-pay: 2000

	Professionals	Managers	Sales	Clerical	Craftsmen	Operatives	Laborers	Services
Min durables	0.46	0.60	0.73	0.35	0.21	0.26	0.26	0.19
Nondurables	0.51	0.61	0.79	0.38	0.26	0.42	0.25	0.06
Transport Utils	0.23	0.53	0.82	0.27	0.27	0.37	0.43	0.37
Fin. insur. real est.	0.74	0.72	0.87	0.38	0.29	0.05	0.21	0.33
Bus. prof. serv.	0.41	0.57	0.72	0.39	0.47	0.40	0.19	0.25
Personal serv.	0.42	0.63	0.61	0.24	0.33	0.20	0.29	0.49
Whol-tr oth serv.	0.64	0.67	0.82	0.46	0.30	0.46	0.30	0.04
Retail trade	0.26	0.57	0.72	0.33	0.48	0.32	0.22	0.46
Construction	0.72	0.47	0.81	0.21	0.33	0.30	0.30	0.17
Agri. fishing	0.73	0.76	0.88	0.24	0.16	0.42	0.45	0.77

Note: This table presents the estimated performance pay incidence for the highly educated in different jobs for year 2000, following the way in Lemieux et al. (2009). Data source: PSID.

Table A.18: Incidence of Performance-pay: 1990

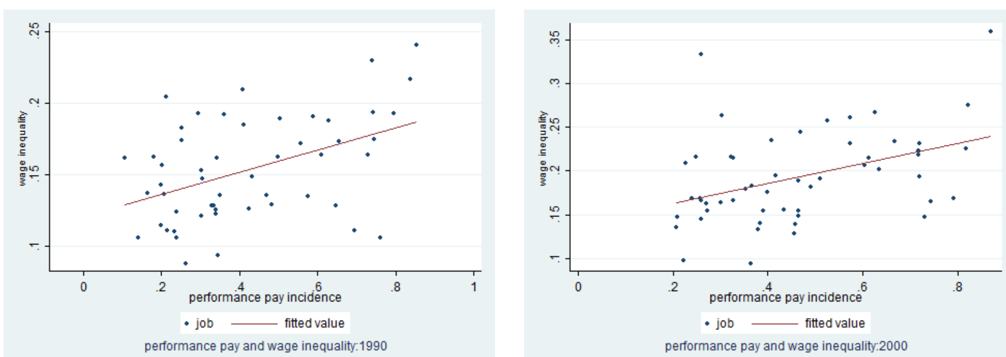
	Professional	Manager	Sales	Production	Clerical
Goods	0.40	0.55	0.75	0.23	0.23
Transport	0.11	0.31	0.75	0.23	0.21
FIRE	0.65	0.66	0.85	0.13	0.32
Business	0.36	0.50	0.84	0.38	0.25
Trade	0.41	0.58	0.75	0.34	0.41

Note: This table presents the estimated performance-pay incidence for the highly educated in different jobs for year 1990, following the approach in Lemieux et al. (2009). Data source: PSID.

Table A.19: Incidence of Performance-pay: 2000

	Professional	Manager	Sales	Production	Clerical
Goods	0.49	0.58	0.77	0.28	0.31
Transport	0.23	0.53	0.82	0.32	0.27
FIRE	0.74	0.72	0.87	0.24	0.37
Business	0.41	0.57	0.72	0.43	0.30
Trade	0.41	0.60	0.75	0.38	0.41

Note: This table presents the estimated performance pay incidence for the highly educated in different jobs for year 2000, following the way in Lemieux et al. (2009). Data source: PSID.

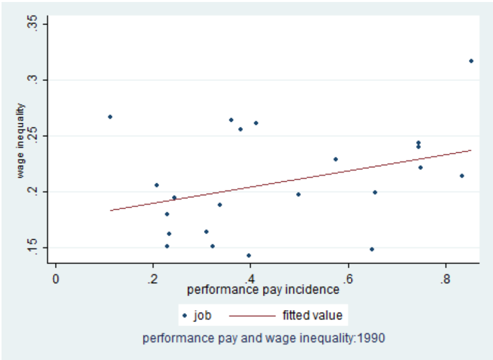


(a) 1990

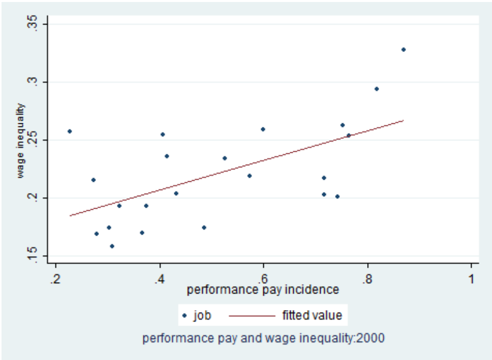
(b) 2000

Figure A.14: The performance-pay incidence and wage inequality

Notes: In both panels, each dot represents a job. x-axis is the performance-pay incidence. y-axis is the within-job wage inequality. Left panel is based on 1990 data, and right panel is based on 2000 data. Data source: PSID and March CPS.



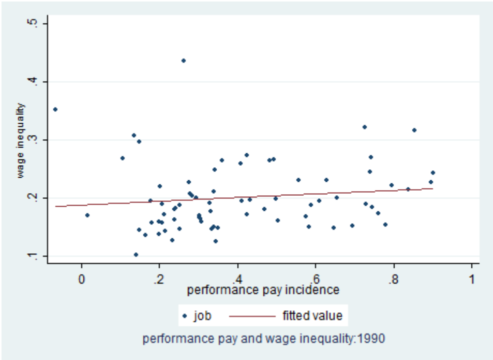
(a) 1990



(b) 2000

Figure A.15: The Performance-pay incidence and wage inequality

Notes: In both panels, each dot represents a job. In total we have 25 jobs. x-axis is the performance-pay incidence. y-axis is the within-job wage inequality. Left panel is based on 1990 data, and right panel is based on 2000 data. Data source: PSID and CPSORG.



(a) 1990

(b) 2000

Figure A.16: The performance-pay incidence and wage inequality

Notes: In both panels, each dot represents a job. In total we have 52 jobs. x-axis is the performance-pay incidence. y-axis is within-job wage inequality. Left panel is based on 1990 data, and right panel is based on 2000 data. Data source: PSID and CPSORG.

Table A.20: Skill Mismatch Index in 1990

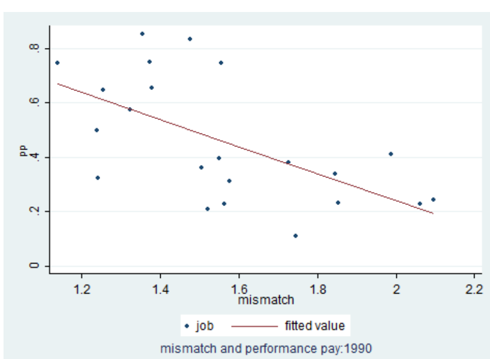
	Professional	Manager	Sales	Production	Clerical	mm_ind
Goods	1.549	0.918	1.557	1.853	2.062	1.570
Transport	1.747	1.576	1.139	1.564	1.522	1.557
FIRE	1.255	1.380	1.355	1.215	1.242	1.329
Business	1.504	1.240	1.475	1.727	2.095	1.523
Trade	0.807	1.324	1.373	1.847	1.987	1.532
mm_occ	1.504	1.244	1.414	1.782	1.875	

Sources: NLSY79 and ONET, and authors' calculation. Each column reports the average skill mismatch in each industry, and each row reports the average skill mismatch in each occupation. The 5 industries are: (1) Goods (containing durables/non-durables, construction and mining), (2) Transport (transportation and utility), (3) FIRE, (4) Business (business and professional service), and (5) Trade (whole/retail trade and personal service). The 5 occupations are: (1) Professional, (2) Manager, (3) Sales, (4) Production/Operative Labor (including craftsmen), and (5) Clerical (including other service).

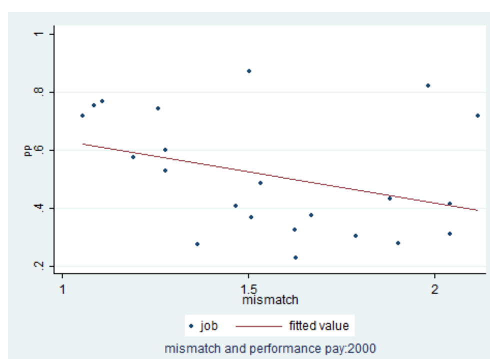
Table A.21: Skill Mismatch Index in 2000

	Professional	Manager	Sales	Production	Clerical	mm_ind
Goods	1.532	1.079	1.107	1.902	2.043	1.511
Transport	1.629	1.277	1.984	1.626	1.363	1.516
FIRE	1.258	1.055	1.504	2.533	1.508	1.280
Business	1.466	1.191	2.118	1.882	1.790	1.431
Trade	1.565	1.278	1.085	1.671	2.041	1.408
mm_occ	1.499	1.173	1.268	1.812	1.807	

Sources: NLSY79 and O*NET, and authors' calculation. Each column reports the average skill mismatch in each industry, and each row reports the average skill mismatch in each occupation. The 5 industries are: (1) Goods (containing durables/non-durables, construction and mining), (2) Transport (transportation and utility), (3) FIRE, (4) Business (business and professional service), and (5) Trade (whole/retail trade and personal service). The 5 occupations are: (1) Professional, (2) Manager, (3) Sales, (4) Production/Operative Labor (including craftsmen), and (5) Clerical (including other service).



(a) 1990



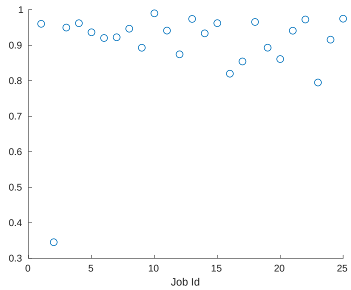
(b) 2000

Figure A.17: The performance-pay incidence and skill mismatch index

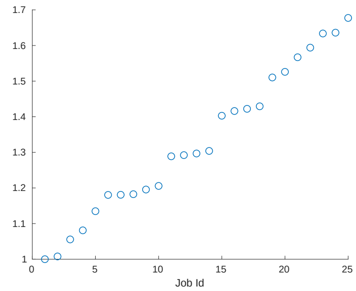
Notes: In both panels, each dot represents a job(25 jobs in total). The y-axis is the performance-pay incidence. The x-axis is the mismatch index. The left panel is based on 1990 data, and the right panel is based on 2000 data. Data source: NLSY79 and PSID.

B Quantitative Results

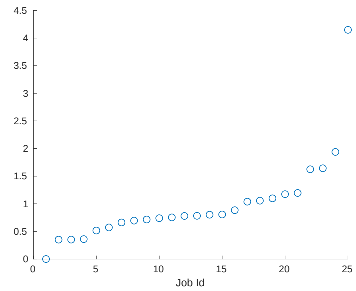
B.1 Calibration Outcome



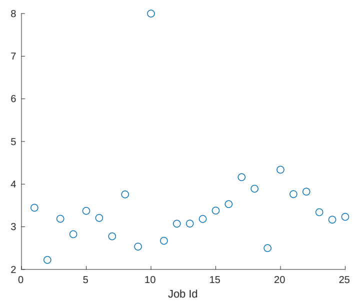
(a) Coefficients on fixed-pay



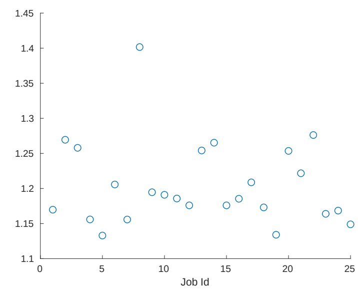
(b) Relative Productivities to Job 1



(c) Monitoring Costs



(d) Shape of the matching premium distribution



(e) Minimum matching premium

Figure B.18: Calibration Outcome

Notes: Panel (a) plots the job-specific coefficients on fixed-pay α_j, which are calibrated to match the performance-pay incidence of each job. Panel (b) plots the relative productivities of each job to job 1 A_j/A_1, which are calibrated to match relative wages of each job. Panel (c) plots the job-specific monitoring costs M_j, which are calibrated to match the distribution of workers at the performance-pay task. Panel (d) plots the job-specific shape parameter of the matching quality distribution θ_{sj}, which are calibrated to match the wage inequality of each job. Panel (e) plots the minimum matching premium $\underline{\eta}_j$, which are calibrated to match the estimated mean of the mismatch index.

B.2 Decompose the changes in inequality from 1990 to 2000

Table B.22: Contribution to the changes in the overall within-job inequality by industry

Industry	Contribution(%)
Goods	36.1
Transport	9.2
FIRE	10.1
Business	23.7
Trade	21.0

Table B.23: Contribution to the changes in the overall within-job inequality by occupation

Occupation	Contribution(%)
Professional	17.0
Manager	18.3
Sales	12.4
Production Labor	30.5
Clerical	21.8

Table B.24: Contribution to the changes in the overall within-job inequality by average wage bin change

Occupation	Contribution(%)
Rise by 3 or more	3.4
Rise by 1 or 2	31.3
Stay	41.6
Drop by 1 or 2	15.0
Drop by 3 or more	8.6

Table B.25: Contribution to the changes in the overall within-job inequality by employment bin change

Occupation	Contribution(%)
Rise	15.3
Stay	53.5
Drop	31.2

Table B.26: Decomposition

Job pair(i,j)	Data 00	Data 90	Benchmark	Benchmark 90	Performance pay	match quality	Productivity	Sorting
(Trade,Clerical)	0.136	0.144	0.136	0.144	0.286	0.193	0.139	0.139
(FIRE,Production)	0.167	0.139	0.167	0.139	0.235	0.348	0.192	0.192
(Trade,Production)	0.143	0.138	0.143	0.138	0.334	0.382	0.146	0.146
(Business,Clerical)	0.153	0.126	0.153	0.126	0.309	0.383	0.153	0.153
(FIRE,Clerical)	0.126	0.118	0.126	0.118	0.306	0.385	0.129	0.129
(Business,Production)	0.160	0.144	0.160	0.144	0.366	0.439	0.155	0.155
(Goods,Clerical)	0.144	0.129	0.144	0.129	0.282	0.423	0.146	0.146
(Trade,Sales)	0.211	0.174	0.211	0.174	0.408	0.452	0.188	0.188
(Transport,Clerical)	0.151	0.128	0.151	0.128	0.283	0.419	0.159	0.159
(Goods,Production)	0.152	0.140	0.152	0.140	0.302	0.433	0.157	0.157
(Transport,Production)	0.170	0.152	0.170	0.152	0.308	0.493	0.175	0.175
(Trade,Professional)	0.166	0.144	0.166	0.144	0.384	0.496	0.172	0.172
(Business,Professional)	0.234	0.189	0.234	0.189	0.452	0.543	0.227	0.227
(Trade,Manager)	0.231	0.168	0.231	0.168	0.473	0.559	0.219	0.219
(Business,Manager)	0.222	0.160	0.222	0.160	0.460	0.617	0.208	0.208
(Business,Sales)	0.237	0.183	0.237	0.183	0.356	0.754	0.180	0.180
(Goods,Sales)	0.176	0.177	0.176	0.177	0.360	0.677	0.161	0.161
(Goods,Professional)	0.153	0.106	0.153	0.129	0.355	0.583	0.153	0.153
(Transport,Professional)	0.204	0.162	0.204	0.162	0.229	0.560	0.202	0.202
(FIRE,Professional)	0.158	0.135	0.158	0.135	0.378	0.702	0.162	0.162
(FIRE,Manager)	0.212	0.171	0.212	0.171	0.432	0.819	0.195	0.195
(Goods,Manager)	0.215	0.160	0.215	0.160	0.444	0.854	0.205	0.205
(Transport,Sales)	0.264	0.183	0.264	0.183	0.463	1.056	0.196	0.196
(FIRE,Sales)	0.344	0.237	0.344	0.237	0.482	1.179	0.262	0.262
(Transport,Manager)	0.252	0.153	0.252	0.153	0.388	1.309	0.238	0.238
overall within	0.183	0.150	0.183	0.151	0.359	0.515	0.177	0.177
between job	0.021	0.019	0.014	0.018	0.042	0.016	0.014	0.014

Notes: Colume 2-5 present wage inequality of each job in the data and predicted by the model in year 1990 and 2000, respectively. Column "Performance pay" set the performance-pay incidence of each job to theri value in 1990, while all the other parameters are kept at their benchmark levels. Similarly, column "match quality" set the match quality summarized as $E[\eta^2]$ to their values in 1990. Column "productivity" set the productivity of each job to their levels in 1990. Finally, column "sorting" set the employment level of each job at the performance-pay task to their levels in 1990. We report the wage inequality for each job, as well as the overall within-job and between-job inequality.

C Proofs

C.1 Proposition 1

Proof: Equation (12) can be re-written as follows:

$$
\begin{aligned}
VI = & \int_{a^*}^{\bar{a}} dG(a) \frac{\int_{a^*}^{\bar{a}} y(a)^2 dG(a)}{\int_{a^*}^{\bar{a}} dG(a)} + \frac{\int_{\underline{a}}^{a^*} z(a)^2 dG(a)}{\int_{\underline{a}}^{a^*} dG(a)} \int_{\underline{a}}^{a^*} dG(a) \\
& - \left[\frac{\int_{a^*}^{\bar{a}} y(a) dG(a)}{\int_{a^*}^{\bar{a}} dG(a)} \int_{a^*}^{\bar{a}} dG(a) + \frac{\int_{\underline{a}}^{a^*} z(a) dG(a)}{\int_{\underline{a}}^{a^*} dG(a)} \int_{\underline{a}}^{a^*} dG(a) \right]^2, \\
& = n_p E[y(a)^2] + (1-n_p) E[z(a)^2] - \Big[E[y(a)] n_p + E[z(a)](1-n_p) \Big]^2, \\
& = n_p Var(y(a)) + (1-n_p) Var(z(a)) + n_p(1-n_p) \big[E[y(a)] - E[z(a)] \big]^2.
\end{aligned}
$$

Differentiating the last equation above with respect to n_p gives:

$$
\frac{\partial VI}{\partial n_p} = Var(y(a)) - Var(z(a)) + (1-2n_p) \big[E[y(a)] - E[z(a)] \big]^2.
$$

Therefore, when $Var(y(a)) > Var(z(a))$, the overall within-job inequality increases with n_p if $n_p < 1/2$. This completes the proof. ∎

C.2 Lemma 5

Proof: worker of ability a chooses to work in job k if $\tilde{C}_k a^2 - M_k \geq \tilde{C}_n a^2 - M_n, n \neq k$. That is,

$$
\left(\tilde{C}_k - \tilde{C}_n \right) a^2 \geq M_k - M_n, \ \forall n \neq k.
$$

For job $n < k$, we have $\tilde{C}_k - \tilde{C}_n > 0$. It is then straightforward to have the following hold:

$$
\left(\tilde{C}_k - \tilde{C}_n \right) a'^2 > \left(\tilde{C}_k - \tilde{C}_n \right) a^2 \geq M_k - M_n, \ \forall n < k.
$$

This implies for workers of ability $a' > a$, the utility from working at job k is always higher than working at any job $n < k$. Therefore, workers with ability higher than a will choose to work in job $j \geq k$. ∎

C.3 Lemma 6

Proof: Worker prefers job n to $n-1$ if

$$\tilde{C}_n a^2 - M_n > \tilde{C}_{n-1} a^2 - M_{n-1}.$$

Similarly, worker prefers job n to $n+1$ if

$$\tilde{C}_n a^2 - M_n > \tilde{C}_{n+1} a^2 - M_{n+1}.$$

Therefore, workers at job n whose abilities must satisfy:

$$\frac{M_{n+1} - M_n}{\tilde{C}_{n+1} - \tilde{C}_n} > a^2 > \frac{M_n - M_{n-1}}{\tilde{C}_n - \tilde{C}_{n-1}}.$$

$\blacksquare$

C.4 Lemma 7

Proof: If worker of ability a prefers job n to $n-1$, then

$$\tilde{C}_n a^2 - M_n > \tilde{C}_{n-1} a^2 - M_{n-1}.$$

The above is equivalent to: $a^2 > \frac{M_n - M_{n-1}}{\tilde{C}_n - \tilde{C}_{n-1}}$. When assumption 1 holds, we also have $a^2 > \frac{M_{n-1} - M_{n-2}}{\tilde{C}_{n-1} - \tilde{C}_{n-2}}$, which is equivalent to:

$$\tilde{C}_{n-1} a^2 - M_{n-1} > \tilde{C}_{n-2} a^2 - M_{n-2}.$$

Therefore, $\tilde{C}_n a^2 - M_n > \tilde{C}_{n-2} a^2 - M_{n-2}$ also holds, and worker thus prefers job n to $n-2$.

By similar induction, it is straightforward to show worker prefers job n to any job $k < n-1$.

$\blacksquare$

C.5 Lemma 8

Proof: If worker of ability a prefers job n to $n+1$, then

$$\tilde{C}_n a^2 - M_n > \tilde{C}_{n+1} a^2 - M_{n+1}.$$

The above is equivalent to: $a^2 < \frac{M_{n+1}-M_n}{\tilde{C}_{n+1}-\tilde{C}_n}$. When assumption 1 holds, we also have $a^2 < \frac{M_{n+2}-M_{n+1}}{\tilde{C}_{n+2}-\tilde{C}_{n+1}}$, which is equivalent to:

$$\tilde{C}_{n+1}a^2 - M_{n+1} > \tilde{C}_{n+2}a^2 - M_{n+2}.$$

Therefore, $\tilde{C}_n a^2 - M_n > \tilde{C}_{n+2}a^2 - M_{n+2}$ also holds, and worker thus prefers job n to $n+2$.

By similar induction, it is straightforward to show worker prefers job n to any job $k > n+1$.

$\blacksquare$.

C.6 Lemma 9

Proof: The previous arguments imply that workers of ability $a^2 < \frac{M_2-M_1}{\tilde{C}_2-\tilde{C}_1}$ gains more utilities from performance-pay position at job 1 than job 2. Therefore, the two remaining options for the worker is either fixed-pay position or performance-pay position at job 1.

When $\tilde{C}_1\underline{a}^2 - M_1 < \underline{U}$, the employment level at the fixed-pay position is positive since those least-talented ones gain higher utility from the fixed-pay position. In addition, when

$$C_1\left(a_2^*\right)^2 - M_1 > \underline{U},$$

the performance-pay position at job 1 is also non-empty. $\blacksquare$

C.7 Proposition 10

Proof: It is a direct consequence of Lemma 5-9. $\blacksquare$

D Math details on solving model

Given the definition of χ_j:

$$\chi_j = \left[\frac{\left(\frac{w}{\alpha_j A_j}\right)^{\frac{\gamma}{1-\gamma}} - \alpha_j}{1-\alpha_j}\right]^{-\frac{1}{\gamma}},$$

we can then solve $\frac{w}{A_j}$ as

$$\frac{w}{A_j} = \alpha_j^{\frac{1}{\gamma}}\left[\frac{\alpha_j\chi_j^{\gamma} + (1-\alpha_j)}{\alpha_j\chi_j^{\gamma}}\right]^{\frac{1-\gamma}{\gamma}}.$$

Hence, the total wage payment to fixed-pay position $\frac{w\chi_j H_{jP}}{A_j}$ can be written as:

$$
\begin{aligned}
\tilde{E}_{jF} &= \alpha_j^{\frac{1}{\gamma}} [\frac{\alpha_j \chi_j^\gamma + (1-\alpha_j)}{\alpha_j \chi_j^\gamma}]^{\frac{1-\gamma}{\gamma}} \chi_j H_{jP} \\
&= [\alpha_j \chi_j^\gamma + (1-\alpha_j)]^{\frac{1}{\gamma}} [\frac{\alpha_j \chi_j^\gamma}{\alpha_j \chi_j^\gamma + (1-\alpha_j)}] H_{jP} \\
&= \tilde{A}_j \tilde{\alpha}_j H_{jP},
\end{aligned}
$$

where $\tilde{\alpha}_j = \frac{\alpha_j \chi_j^\gamma}{\alpha_j \chi_j^\gamma + (1-\alpha_j)}$. The total payment to performance-pay position is thus $\tilde{E}_{jP} = \mu(1 - \tilde{\alpha}_j)\tilde{A}_j H_{jP}$.

The representative firm decides the employment level at fixed-pay position to maximize the revenue net of payment to workers at fixed-pay position. That is,

$$
\max_{N_{jF}} \quad \left[\alpha_j A_j H_{jF}^\gamma + (1-\alpha_j) H_{jp}^\gamma\right]^{\frac{1}{\gamma}} - wN_{jF}.
$$

Solving the maximization problem above, the following relation can be established: $H_{jF} = \chi_j H_{jP}$. Substituting it into the production function, we have:

$$
Y_j = \left[\alpha_j (\chi_j H_{jP})^\gamma + (1-\alpha_j) H_{jp}^\gamma\right]^{\frac{1}{\gamma}} = \tilde{A}_j H_{jP},
$$

where $\tilde{A}_j = [\alpha_j \chi_j^\gamma + (1-\alpha_j)]^{\frac{1}{\gamma}}$.