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. To quantify the role played by these factors, we calibrate the model to the US economy in 1990 and 2000. Our model almost perfectly fits the within-job wage inequality data on 23 of 25 broadly defined jobs, in which match quality and equilibrium job sorting account for more than 90% of the overall rising within-job wage dispersion from 1990 to 2000. We find that match quality and job sorting are particularly important in jobs with rising average wages and expansionary employment. While the performance-pay incidence makes a modest contribution to the aggregate outcome, its role in the Trade industry and in the Clerical occupation is more noticeable, whereas general job productivity is inconsequential throughout.

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 explanining 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.

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 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, MacLeod and Parent (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. We show that skill mismatch has a negative wage effect and thus better job match quality is associated with higher compensation. Moreover, 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.

Empirical analyses have only established the simple correlation between the performance-pay incidence/skill match and the within-job inequality. However, in reality, skill mismatch may affect the performance-pay incidence, and the within-job inequality may also influence the extent of the skill mismatch and the performance-pay incidence. 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 of preventing workers from shirking. 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. Under normal circumstances, 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 23 of 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. Based on the results from the 23 perfectly fitting jobs, 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 the changes in match quality and job sorting alone account for more than 90% of widening within-job wage inequality. This is partially due to the amplified interaction between the match quality and job sorting. While the performance pay makes a modest contribution (less than 10 %), its role is more noticeable in the Trade industry categorization and in the Clerical occupation. By contrast, general job productivity is inconsequential throughout.

We further conduct decomposition analysis in various groups of jobs and individuals jobs. More than half of the widening in within-job inequality is from the Business and Trade industries, whereas more than half of rising wage inequality is in the Professional and Sales occupations. Hence, match quality and sorting matter more in these industries and occupations, which is why they play stronger roles in the aggregate outcome. Rising wage inequality in jobs whose average earnings rankings rise moderately accounts for more than half of the overall variation, mainly driven by match quality and sorting. For jobs whose employment share rankings rise or remain the same, which account for over 80% of the overall variation, match quality and job sorting are again the joint drivers contributing to widening wage inequality. Thus, improved match quality and positive assortative job sorting drive up wage dispersion in jobs with rising average wages and expansionary employment.

Our main contribution is to show that while the within-job wage inequality accounts for about 80% of the residual wage inequality between 1990 and 2000, more than 90% of such rising dispersion is a consequence of improved match quality and positive assortative job sorting, where the more able are sorted into higher paid jobs on average. Once the broad extensive margin via job sorting and intensive margin via match quality are incorporated, the performance-pay incidence 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. Since match quality improvement and positive assortative job sorting are the main drivers, pro-active policy intervention aiming to reduce inequality may be at the expense of skill mismatch or inefficient sorting across 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, Murphy and Pierce (1993), Krusell et al. (2000), Acemoglu (2003)). Altonji, Kahn and Speer (2016) argues that earnings differences across college 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, Heining and Kline (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, Ouimet and Simintzi (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, MacLeod and Parent (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 (2015)). 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, Leuven and Mogstad (2016)). Since the second measurement relies on subjective responses, which might be biased, we thus use the first approach by constructing 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),[1] 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.

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

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

Industry/occupation classification The Center for Economic and Policy 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 following the approach of Lemieux, MacLeod and Parent (2009). A consistent three-digit code is also built following Dorn (2009). The same method is used to group a consistent two-digit code.[2] 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 (see Lemieux, MacLeod and Parent (2009)). Following Lemieux, MacLeod and Parent (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 among the highly educated for 80 jobs separately for year 1990 and 2000.[3] Tables A.15 and A.16 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.

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

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

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 in 1990 and 2000(See Table A.17). 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 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, MacLeod and Parent (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.[4] 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

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

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.

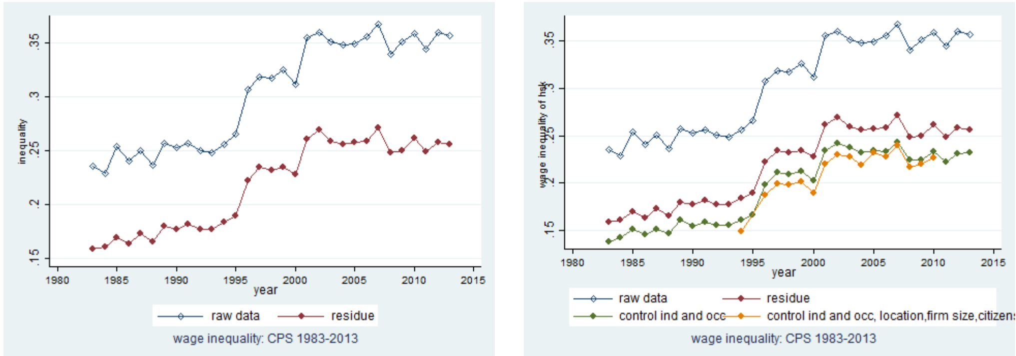
(a) Overall Wage Inequality

(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).

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 pooled



(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).

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

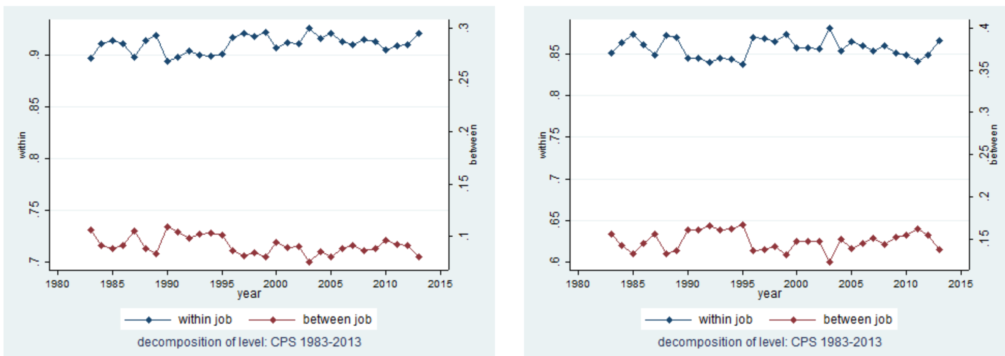
In this subsection, we decompose both the level and the change in residual wage inequality into within-job and between-job wage inequality. A job is defined as an industry-occupation pair. Examples of jobs include sales in the FIRE industry, managers in business, clerical workers in retail/wholesale 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 upper panel is for the one-digit industry and occupation code and the lower 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.12 and A.13 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:

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

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.11 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.14 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%

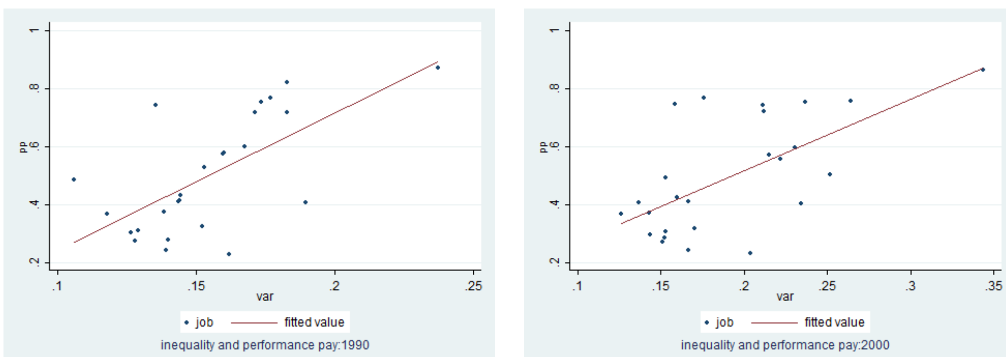
Notes: This table computes the contribution of within-job, between-job wage inequality, the employment share interactions to the changes in the residual inequality from 1990 to 2000. The row "1-d code" indicates the one-digit industry and occupation code, "1-d ind, 2-d occ" indicates the one-digit industry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

2.4 Performance-pay Incidence, Skill Mismatch and Wage Inequality

Since 1990, the number of performance-pay positions has grown. As noted by Lazear (2000), both the performance-pay and the fixed-pay positions may coexist within the same job and the performance-pay wages may be guaranteed to be no lower than the fixed-pay wages. As such, it has wages in the performance-pay position are generally higher than those in the fixed-pay positions (e.g., Lemieux, MacLeod and Parent (2009)). We further show the relationship between the performance-pay incidence and the within-job wage inequality. The within-job wage inequality is again measured using the March CPS dataset. Throughout the remainder of the paper, we classify industries and occupations each into five categories consistent with the classification in the PSID and NLSY79. 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).

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 between the performance-pay incidence and the within-job wage inequality. 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, MacLeod and Parent (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

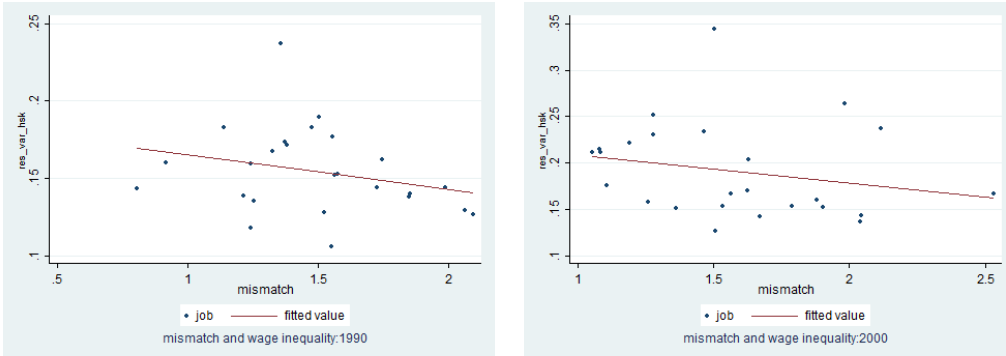
(b) 2000

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.

Figure A.17 plots the performance-pay incidence against the skill mismatch index for each of the 25 jobs in 1990 and 2000, respectively. It shows that jobs with a lower mismatch index usually have a higher performance-pay incidence. Moreover, we find a negative relationship between the wage inequality and the skill mismatch index, as delineated in Figure 5.

This evidence enables us to examine how the performance-pay incidence and the skill mismatch may affect the within-job wage inequality. By comparing data from 1990 with those from 2000, we see that only two of the 25 jobs have lowered within-job wage inequality: (Trade, Clerical) and (Goods,



(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.

Sales).[5] From Figure 4 and Figure 5, we may thus conjecture that a rising performance-pay incidence and decreasing skill mismatch (improving match quality) help explain widening within-job wage inequality. Yet, empirical analyses have only established a simple correlation between the performance-pay incidence/skill mismatch and the within-job wage inequality. In reality, skill mismatch may in turn affect the performance-pay incidence and the within-job wage inequality may also influence the magnitude of the skill mismatch and the performance-pay incidence. This thereby requires a deep structure to discipline the interactions among them, 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,

[5] Table B.18 provides more details.

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

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

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 substitutable (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,

$$\max_{N_{jF}} Y_j - wN_{jF}.$$

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.[6] 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:

$$U_j^P = \max_e \quad \mu(1-\tilde{\alpha}_j)\tilde{A}_j A_j a\eta e - \frac{1}{2}be^2 - \mu M_j, \tag{6}$$

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 3 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.

[6] 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: $1 > \delta^2 > \frac{2\mu b M_j}{[\mu(1-\tilde{\alpha}_j)\tilde{A}_j A_j]^2}$.

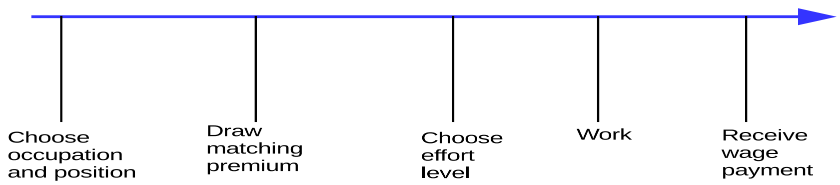


Figure 6: Timeline

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

$$U^F = w - \frac{b}{2}\underline{e}^2. \tag{7}$$

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

$$EV(a) = \max_j \{U^F, EU_j^P(a)\}. \tag{8}$$

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 (8).

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 6. 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:

$$EU_j^P(a) \equiv E_\eta[U_j^P(a,\eta)] = \tilde{C}_j a^2 - M_j, \tag{9}$$

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

$$E_j(\eta^2) = \frac{\theta_{sj}}{\theta_{sj}-2}(\underline{\eta_j})^2. \tag{10}$$

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 iff $EU^P_{j^*(a)}(a) > U^F$.

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

$$VI = \int_{a^*}^{\bar{a}} y(a)^2 dG(a) + \int_{\underline{a}}^{a^*} z(a)^2 dG(a) - \left[\int_{a^*}^{\bar{a}} y(a) dG(a) + \int_{\underline{a}}^{a^*} z(a) dG(a)\right]^2 \tag{11}$$

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

$$\frac{d(VI)}{dn_p} = Var(y(a)) - Var(z(a)) + (1-2n_p)\big[E[y(a)] - E[z(a)]\big]^2. \tag{12}$$

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

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

$$\frac{\mu}{2}\frac{\theta_a - 2}{\theta_a}\left(a^{\theta_a} - 1\right)\left[\frac{w}{A}\right]^{\frac{\alpha}{1-\alpha}} = \alpha^{\frac{1}{1-\alpha}}, \tag{13}$$

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

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

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.

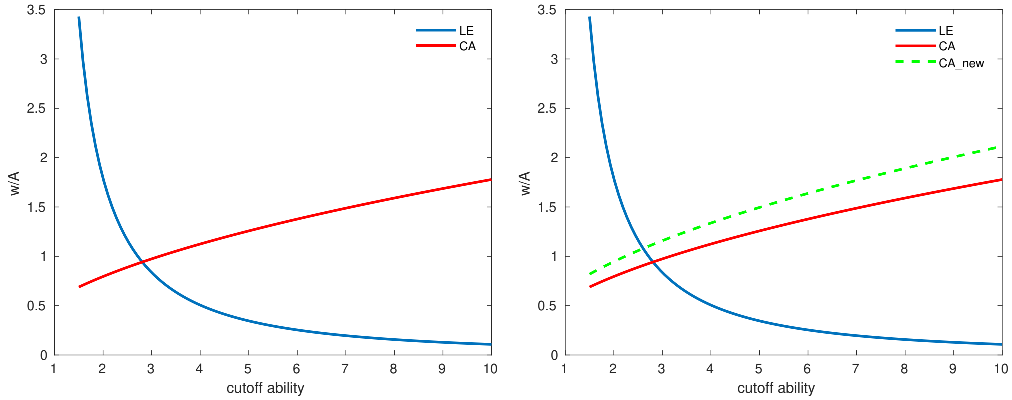
Proposition 2 *(Existence and Uniqueness) For any job, the position cutoff ability and the fixed pay wages are uniquely determined.*

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.*

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 (12). A natural inquiry arises: how do technology and match quality influence how the performance-pay incidence



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

Figure 7: Comparative statics in the one-job case

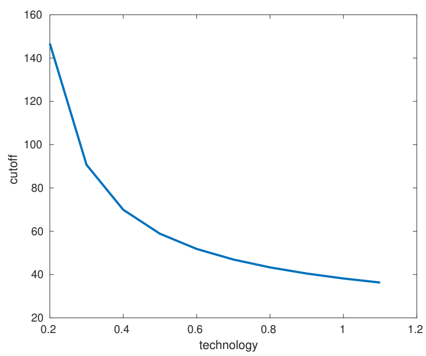
Notes: The blue curve denotes equation 13 and the red curve denotes equation 14. The left panel shows the existence and uniqueness of the equilibrium outcome in the simple one-job setting. In the right panel, we either double productivity A or match quality summarized by $E[\eta^2]$ to evaluate the changes in w/A.

affects 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.

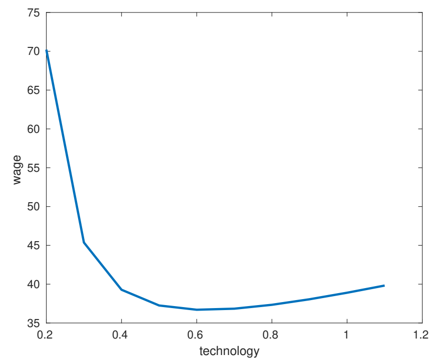
Proposition 4 *(Comparative Statics: Inequality) Under $Var(y(a)) > Var(z(a))$ and $n_p < 1/2$, a better technology or higher match quality amplifies the effect of the performance-pay incidence n_p on the within-job and within-performance-pay inequality ($Var(y(a))$), but dampens the effect of the performance-pay 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*.

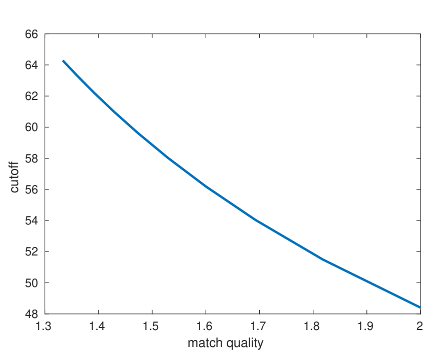
To this end, if we consider a CES production or sorting mechanism across jobs, the comparative static properties regarding the effect of the performance-pay incidence on the overall within-job wage inequality would become even more complicated. While we examine sorting in the next subsection more in 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 strenghtens 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.



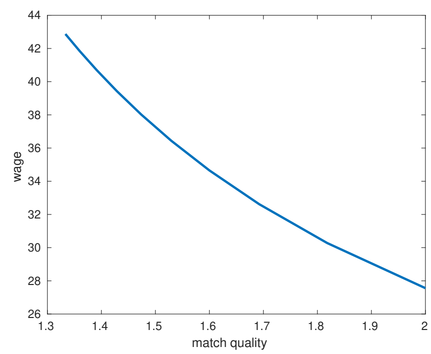
(a) CES: Productivity and Cutoff-Ability



(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.

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 job ranking under which we order n such that $\{M_n\}$ and $\{\tilde{C}_n\}$ are increasing sequences of n.[7] 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

[7] Recall that $\{\tilde{C}_n\}$ are defined in equation 9. 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.

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 $n > 1$.

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.

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.

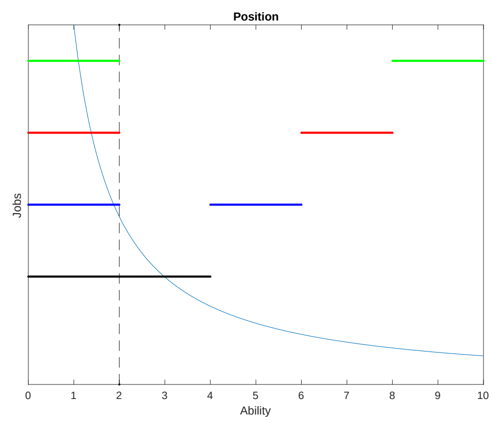


Figure 9: Job and position choice

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

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 vallue 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.[8] This enables us to obtain a match quality series using equation (10). 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 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 2 summarizes the parameter values and their targets. Table 3 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 reasonablly well.

Table 2: 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

Owning to the strict parameter restriction,[9] it is impossible to exactly match the data counterparts. Nonetheless, the model can still match the key features of inequality patterns. To see this, Figure 10 plots within-job wage inequality in the data versus the model. Our model fitness is good. As noted earlier, in 23 of the 25 jobs, our model fits almost perfectly. For the (Transport, Professional) job pair, the model underpredicts within-job wage inequality by a wide margin; for the (Goods,

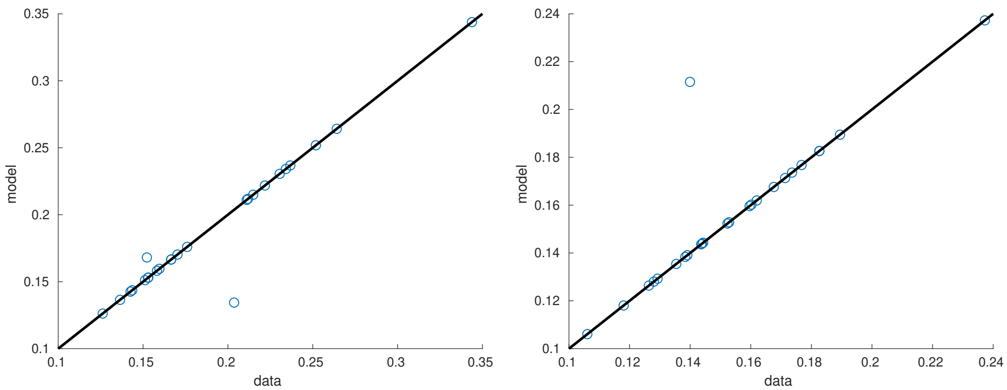
[8] We may not exactly match both moments since the estimation is subject to the constraint $\theta_{sj} > 2$.

[9] 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.

Table 3: Benchmark inequality: Model versus data

	1990		2000	
	Data	Model	Data	Model
Within Job	0.158	0.166	0.207	0.185
Between Job	0.019	0.024	0.021	0.030
Overall	0.177	0.189	0.228	0.215

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 2.



(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.

Production/Operative Labor) pair, the model overpredicts moderately.

5.1 Counterfactual Exercises

To understand what drives the within-job wage inequality, we next explore changes in the first and second moments of job-specific productivity, match quality, the performance-pay incidence, and sorting measured by the employment share in the performance-pay position of each job.

5.1.1 Productivity

To examine how the variation in job productivity affects the wage inequality, we perturb the productivity distribution while preserving the mean $\bar{A}$

$$\tilde{A}_j = \lambda \cdot \bar{A} + (1 - \lambda) \cdot A_j, \tag{15}$$

where higher λ indicates a reduced dispersion. To identify the contribution of the productivity distribution, given $\tilde{A}_j$, we re-calibrate $\{\alpha_j, M_j\}$ to match the performance-pay incidence and employment level in the performance-pay position of each job, while all the other parameters including the distribution of the matching premium are kept at their benchmark levels. Figure B.19 shows that a reduction in productivity variation captured by a less dispersed productivity distribution via higher λ lowers both within-job and between-job inequality. The payoff from working in the fixed-pay position, on the contrary, decreases with the dispersion of the productivity distribution.

To explore how the first moment of job-specific productivity affects the inequality pattern, we also uniformly scale up or down the productivity distribution by varying the productivity of each job from 0.5 to 1.5 times their benchmark value. The results in Figure B.20 show that the overall improvement in productivity lowers the between-job inequality and increases the value from working in the fixed-pay position. However, the impacts on the within-job wage inequality are almost negligible.

In each job, Figure B.21 suggests that for those jobs whose productivity is lower than their benchmark levels, which corresponds to those jobs whose productivity is above the mean level in the benchmark economy, the within-job wage inequality lowers. On the contrary, for those jobs whose productivity is below the mean in the benchmark economy, the within-job wage inequality remains roughly similar at the benchmark level. The uniform expansion of productivity among all the jobs exerts little impact on the within-job wage inequality.

5.1.2 Match Quality

Match quality when individuals decide on their job and position can be summarized as $E(\eta_j^2)$, which depends on the job-specific sequence of $\left\{\theta_{sj}, \underline{\eta_j}\right\}$. We again perturb the variation in $E(\eta_j^2)$:

$$\tilde{E}(\eta_j^2) = \lambda \cdot \bar{E}(\eta_j^2) + (1-\lambda) \cdot E(\eta_j^2), \tag{16}$$

where higher λ implies less dispersion in match quality. To capture such a change by only the shape rather than the location parameter, we fix $\underline{\eta}_j$ at their benchmark values. Thus, given $\tilde{E}(\eta_j^2)$, we only re-compute θ_{sj} to match it. To isolate the role of skill mismatch, given $\tilde{E}(\eta_j^2)$, we re-calibrate $\{\alpha_j, M_j\}$ to match the performance-pay incidence and cutoff abilities a_j^*, with all the other parameters kept at their benchmark levels.

The results in Figure B.22 indicate that less dispersed distribution of the matching premium across jobs leads to higher within-job and lower between-job wage inequality. The payoff from working in the fixed-pay position increases when the distribution of the matching premium becomes more even. As before, we uniformly scale up or down the distribution of the matching premium by varying its simple mean from 0.5 to 1.5 times its benchmark value. The results in Figure B.23 show that the overall improvement in match quality, similar to the role of productivity, lowers both between-job and within-job wage inequality and increases the value from working in the fixed-pay position. Further, the impacts on the within-job wage inequality appear to be larger than adjusting productivity by the same scale.

In each job, Figure B.24 suggests that for those jobs whose match quality rises higher than the benchmark levels, which corresponds to those jobs whose match quality are below the mean level in the benchmark economy, the within-job wage inequality increases. On the contrary, for those jobs whose match quality is above the mean in the benchmark economy, the within-job wage inequality remains roughly at the benchmark levels. In addition, the uniform expansion of match quality among all the jobs seems to exert little impact on the within-job wage inequality. The impacts is larger for those jobs with lower match quality in the benchmark economy.

5.1.3 Performance-pay incidence

To understand how the variation in the performance-pay incidence affects the pattern of inequality, we perturb its distribution:

$$P\tilde{P}I_j = \lambda \cdot P\bar{P}I + (1 - \lambda) \cdot PPI_j, \tag{17}$$

where higher λ is again associated with less dispersion in the performance-pay incidence. Note that $P\tilde{P}I_j$ may not be consistent with the benchmark cutoff abilities a_j^* or employment level in each performance-pay position. In other words, it is possible to have $\sum_{j=1}^{N}(1-P\tilde{P}I_j)\frac{F(a_{j+1}^*)-F(a_j^*)}{P\tilde{P}I_j} \neq F(a_1^*)$. Therefore, given $P\tilde{P}I_j$, we adjust $\{a_j^*\}_{j=1}^{N}$ such that the previous equality holds, while the share of workers in each job's performance-pay position among all the workers in the performance-pay position, $\frac{F(a_{j+1}^*)-F(a_j^*)}{1-F(a_1^*)}$, also remains the same as in the benchmark economy.

The results in Figure B.25 suggest that a reduction in the performance-pay incidence variation captured by a less dispersed distribution of the performance-pay incidence leads to higher within-job wage inequality and lower between-job wage inequality as well as a lower payoff from working in the fixed-pay position. The uniform expansion of the performance-pay incidence exerts a negligible impact on the within-job wage inequality. However, it can lower the between-job wage inequality and increase the payoff from working in the fixed-pay position.

At the job-level, as shown in Figure B.27, more than half of the jobs have a higher performance-pay incidence than the benchmark levels, which corresponds to those jobs whose performance-pay incidence are below the mean level in the benchmark economy, for which the within-job wage inequality is amplified. Whereas for jobs whose performance-pay incidence are above the mean in the benchmark economy, the changes in the within-job wage inequality are ambiguous. The uniform expansion of the performance-pay incidence, as shown in Figure B.26, similar to the impact from the uniform expansion of productivity, leads to little impact on the within-job wage inequality.

5.1.4 Ability sorting

We first denote the employment level in job j's performance-pay position as $NP_j = F(a^*_{j+1}) - F(a^*_j)$. To examine how the variation in ability sorting affects the inequality pattern, we also let $\{NP_j\}$ be less dispersed by moving toward their mean: $\tilde{NP}_j = \lambda \cdot \bar{NP} + (1-\lambda) \cdot NP_j$.

As before, the following may not hold given $\tilde{NP}_j$ and benchmark cutoff $\{a^*_j\}$: $\sum_{j=1}^{N} NP_j = 1 - F(a^*_1)$.

Therefore, we similarly adjust the sequence of $\{a^*_1\}$ such that the above holds, while $\frac{NP_j}{\sum_{j=1}^{N} NP_j}$ also remains the same as in the benchmark economy.

The results in Figure B.28 suggest that a reduction in the ability sorting variation captured by less dispersion of NP_j lowers both within-job and between-job wage inequality and increases the payoff from the fixed-pay position. The uniform adjustment over $\{NP_j\}$ does not affect within-job or between-job wage inequality, as shown in Figure B.29. At the job-level, Figure B.30 suggests that for those jobs whose employment in the performance-pay position is higher than the mean level in the benchmark economy, the within-job wage inequality decreases.

Table 4 summarizes the findings from our previous counterfactual exercises.

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

Table 4: Summary of Findings in Counterfactual Exercises

	Overall		**Individual-job**	
	Between-job	**Within-job**	**Aboven bench mean**	**Below bench mean**
less variation in productivity	lower	lower	lower	lower
improvement in productiivty	lower	little	little	little
less variation in match quality	lower	higher	little	higher
improvement in match quality	lower	lower	little	little
less variation in PPI	lower	higher	ambiguous	higher
improvement in PPI	lower	little	little	little
less variation in ability sorting	lower	lower	lower	higher
improvement in ability sorting	small	small	small	small

Note: The table summaries the comparison in the overall within-job and between-job wage inequality, as well as the wage inequality within each job between the benchmark economy and each counterfactual exercise. "Lower(higher)" means the value of the corresponding item is lower(higher) than its benchmark level. "Little" means the value of the corresponding item does not change much from its benchmark level. "Ambiguous" denotes the changes in sign are not uniform. Refer to the main text for more details.

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 3 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, Production/Operative Labor) pair, although by a wide margin.[10]

Combining the 1990 and 2000 predictions and the 2000 shows that in both the (Transport, Professional) and the (Goods, Production/Operative Labor) job pairs, the within-job wage inequality rises in the data but falls in the model predictions. Because the residuals would turn out to be over 100% in the decomposition analysis and the outcomes would be misleading. We remove these two jobs from our analysis. For the remaining 23 jobs, our predicted changes in the within-job wage inequality are not only correct but precise. To evaluate the contribution of factor k to the changes in inequality from 1990 to 2000 in job j, denoted as π_k^j, we apply the following formula:

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

[10]Table B.18 provides more details.

where $model^j_{1990}$ and $model^j_{2000}$ denote model-predicted inequality in 1990 and 2000 in job j, respectively. $data^j_{1990}$ and $data^j_{2000}$ in turn denote the inequality in the data in these two years. $counter^j_k$ 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 with 23 jobs.

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

$$\bar{\pi}_k = \frac{\sum_j \pi^j_k N_j}{\sum_{k'} \sum_j \pi^j_{k'} N_j}, \tag{18}$$

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	6.0	59.4	-2.0	36.7	0.0	100.00

Note: The contribution of factor s in any job is summarized in equation 18. The overall contribution of factor s across all the jobs is computed as the average of its contribution in each job weighted by the employment share.

5.2.1 Overall contribution

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 6.0%, 59.4%, −2.0%, and 36.7%, respectively. Thus, the model can capture most of the changes in within-job wage inequality from 1990 to 2000, with an essentially zero residual component. Moreover, the changes in match quality and job sorting alone account for more than 90% of the widening wage dispersion in each job. This is partially driven by the amplified interaction between the match quality and job sorting. Finally, while performance pay makes a modest contribution(less than 10%), general job productivity is inconsequential.

Next, we conduct additional decomposition analyses by different groupings, by industry and occupation, and by changes in the ranking of job earnings or employment shares from 1990 to 2000 to gain further insights. To examine the contribution of each factor in a group g, we aggregate its contribution at the job level; this group level is then adjusted by the employment share

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

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.

5.2.2 Contribution by industry and occupation

Table 6 presents the results of grouping by industry. We find that in the Trade industry, match quality is the main contributor to widening within-job wage inequality, followed by performance-pay. Match quality and sorting are the main drivers of wage inequality in the Goods and Business industries, accounting for more than half of rising wage inequality, with match quality more dominant in the Goods industry and sorting more important in the Business industry. In the FIRE industry, match quality is the sole force widening wage inequality. In the Transport industry, sorting widens wage inequality, whereas match quality narrows it. Overall, match quality in the FIRE, Trade, and Goods industries exhibits higher than aggregate contributions, accounting for more than two-thirds of the widening within-job wage inequality. On the contrary, sorting in the Transport and Business industries contributes more than the aggregate level, accounting for over half of the changes in wage dispersion in each job. Only in the Trade industry does performance pay makes a significant contribution, accounting about one-seventh of the variation. The fact that more than half of the widening within-job wage inequality is from the Business and Trade industries shows that, match quality and sorting play relatively strong roles in the aggregate outcome.

Table 6: Decomposition by industry

Industry	Performance(%)	Match quality(%)	Productivity(%)	Sorting(%)	Residual(%)	Total(%)
Goods	7.5	68.0	-1.8	26.3	0.0	100.0
Transport	-3.0	-31.9	-0.9	135.8	0.0	100.0
FIRE	1.2	107.6	-1.2	-7.6	0.0	100.0
Business	2.3	39.6	-3.7	61.7	0.0	100.0
Trade	14.2	87.8	-1.0	-0.9	0.0	100.0
Aggregate	6.0	59.4	-2.0	36.7	0.0	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.

Similarly, we can compute each factor's contribution at the occupation level. As shown in Table 7, in the Clerical occupation, match quality and performance pay drive the within-job wage inequality, accounting for most of its variation. In the Professional and Manager occupations, match quality and sorting are the key drivers of wage inequality, with match quality more dominant in the latter and sorting in the former. In the Sales occupation, match quality is the most dominant force widening wage inequality, accounting for almost 90%. In the Production/Operative Labor occupation, sorting widens wage inequality, whereas match quality narrows it. More than half of rising wage inequality is in Professional/Sales, where match quality and sorting matter more.

Table 7: Decomposition by occupation

Occupation	Performance (%)	Match quality (%)	Productivity (%)	Sorting (%)	Residual (%)	Total (%)
Professional	1.6	46.1	-3.6	55.9	0.0	100.0
Manager	3.1	77.8	-3.2	22.3	0.0	100.0
Sales	8.1	88.3	-1.4	5.0	0.0	100.0
Production Labor	0.8	-22.1	-0.4	121.7	-0.0	100.0
Clerical	12.6	80.2	-1.2	8.4	0.0	100.0
Aggregate	6.0	59.4	-2.0	36.7	0.0	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.

5.2.3 Contribution by wage, employment or inquality 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 this job in 2000 than in 1990. Table 8 presents the decomposition results grouped by job bin changes. For jobs whose average earnings rankings rise sharply (by 3 or more), we find that match quality is the dominant driver of wage inequality, accounting for almost 90% of inequality variation with each job. That is, match quality plays a key role in driving up both the level and the dispersion of wages. For jobs whose average earnings rankings rise or fall moderately (by 1 or 2), match quality and sorting jointly contribute to widening wage inequality. For jobs whose average earnings rankings remain unchanged, performance pay and match quality are the main drivers. For jobs whose average earnings rankings fall sharply (by 3 or more), sorting is the main force, more precisely a mechanism of downward sorting where the less performed are optimally sorted into less pay jobs with less dispersion. Rising wage inequality in jobs whose average earnings rankings rise moderately accounts for more than half of the overall variation, mainly driven by match quality and sorting.

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 9 presents the results grouped by employment bin changes. For jobs whose employment share rankings rise or remain the same, which account for over 80% of the overall variation, match quality and sorting are the joint drivers contributing to the widening wage inequality. For jobs whose employment share rankings fall, performance pay and match quality are the forces underlying the more modestly rising wage inequality.

Table 8: Decomposition by average wage bin change

	Performance(%)	Match quality(%)	Productivity(%)	Sorting(%)	Residual(%)	Total(%)
Rise by 3 or more	8.9	89.7	0.7	0.6	0.0	100.0
Rise by 1 or 2	2.6	52.7	-2.9	47.6	0.0	100.0
Stay	13.9	86.2	-1.8	1.6	0.0	100.0
Drop by 1 or 2	6.0	67.4	-1.9	28.4	0.0	100.0
Drop by 3 or more	-5.1	-16.3	-0.5	121.8	0.0	100.0
Aggregate	6.0	59.4	-2.0	36.7	0.0	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.

Table 9: Decomposition by employment bin change

	Performance(%)	Match quality(%)	Productivity(%)	Sorting(%)	Residual(%)	Total(%)
Rise	-0.0	28.9	-1.8	72.9	0.0	100.0
Stay	2.7	54.8	-3.1	45.6	0.0	100.0
Drop	12.5	79.8	-1.0	8.7	0.0	100.0
Aggregate	6.0	59.4	-2.0	36.7	0.0	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.

5.2.4 Contribution in selected jobs

We conclude the decomposition analysis by investigating six selected jobs based on their earnings and employment shares. Table 10 shows that for Sales in the Business industry and Clerical in the Trade industry, performance pay and match quality are the dominant forces, driving up the rising wage inequality in the latter but inducing the falling wage inequality in the former. For Manager in the FIRE industry, match quality is the sole driver of the rising within-job inequality. For Manager in the Business industry and Professional in the Goods industry, match quality and sorting are the joint forces underlying the rising wage inequality. For Professional in the Business industry, sorting is the dominant driver for the rise in wage inequality. In two jobs contributing more significantly to rising wage inequality, Professional and Manager in the Business industry, match quality and sorting are the dominant drivers for the rise in wage inequality. Hence, for all 23 jobs, performance pay plays a larger role in the two jobs with falling within-job wage inequality (Clerical in Trade and Sales in Goods) and in the three other jobs with rising wage inequality (Sales in Business, Clerical in Goods, Manager in FIRE), each contributing at least 20% of wage inequality despite their modest contributions at the aggregate level.

Table 10: Decomposition by selected jobs

Job pair (i,j)	Performance(%)	Match quality(%)	Productivity(%)	Sorting(%)	Residual(%)	Total(%)
(Trade, Clerical)	30.6	65.1	-0.1	4.4	0.0	100.0
(Business, Sales)	20.0	80.4	-0.2	-0.3	0.0	100.0
(FIRE, Manager)	0.8	106.9	-3.1	-4.6	-0.0	100.0
(Business, Manager)	5.1	71.7	-4.8	28.0	0.0	100.0
(Goods, Professional)	-0.1	69.6	-2.0	32.4	0.0	100.0
(Business, Professional)	2.2	19.7	-4.9	83.0	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 18.

6 Conclusion

In this paper, we documented that within-job wage inequality greatly contributes to residual wage inequality. To explain this fact, we 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 — and 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. Calibrating to fit data on 1990 and 2000, we 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 efficient sorting 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 resorting. Within-job wage inequality may thus change as the requirements for multi-tasking change in different types of jobs.

References

Acemoglu, Daron. 2003. "Patterns of skill premia." *The Review of Economic Studies* 70(2):199–230.

Acemoglu, Daron and David Autor. 2011. "Skills, tasks and technologies: Implications for employment and earnings." *Handbook of Labor Economics* 4:1043–1171.

Altonji, Joseph G, Lisa B Kahn and Jamin D Speer. 2016. "Cashier or consultant? Entry labor market conditions, field of study, and career success." *Journal of Labor Economics* 34(S1):S361–S401.

Arcidiacono, Peter. 2004. "Ability sorting and the returns to college major." *Journal of Econometrics* 121(1):343–375.

Barth, Erling, Alex Bryson, James C Davis and Richard Freeman. 2011. The contribution of dispersion across plants to the increase in US earnings dispersion. Working paper.

Card, David, Jörg Heining and Patrick Kline. 2013. "Workplace Heterogeneity and the Rise of West German Wage Inequality." *The Quarterly Journal of Economics* 128(3):967–1015.

Dorn, David. 2009. Essays on inequality, spatial interaction, and the demand for skills PhD thesis Verlag nicht ermittelbar.

Guvenen, Fatih, Burhan Kuruscu, Satoshi Tanaka and David Wiczer. 2020. "Multidimensional Skill Mismatch." *American Economic Journal: Macroeconomics* 12(1):210–44.

Hall, Robert E. and Paul R. Milgrom. 2008. "The Limited Influence of Unemployment on the Wage Bargain." *American Economic Review* 98(4):1653–74.

Heywood, John S and Daniel Parent. 2012. "Performance pay and the white-black wage gap." *Journal of Labor Economics* 30(2):249–290.

Jensen, Michael C and Kevin J Murphy. 1990. "Performance pay and top-management incentives." *Journal of Political Economy* 98(2):225–264.

Jovanovic, Boyan. 2014. "Misallocation and Growth." *The American Economic Review* 104(4):1149–1171.

Juhn, Chinhui, Kevin M Murphy and Brooks Pierce. 1993. "Wage inequality and the rise in returns to skill." *Journal of Political Economy* 101(3):410–442.

Kambourov, Gueorgui and Iourii Manovskii. 2009. "Occupational mobility and wage inequality." *The Review of Economic Studies* 76(2):731–759.

Katz, Lawrence F and David H. Autor. 1999. "Changes in the wage structure and earnings inequality." *Handbook of Labor Economics* 3:1463–1555.

Kirkeboen, Lars J, Edwin Leuven and Magne Mogstad. 2016. "Field of study, earnings, and self-selection." *The Quarterly Journal of Economics* 131(3):1057–1111.

Krusell, Per, Lee E Ohanian, José-Víctor Ríos-Rull and Giovanni L Violante. 2000. "Capital-skill complementarity and inequality: A macroeconomic analysis." *Econometrica* 68(5):1029–1053.

Lazear, Edward P. 2000. "Performance Pay and Productivity." *The American Economic Review* 90(5):1346–1361.

Lemieux, Thomas. 2006. "Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill?" *The American Economic Review* 96(3):461–498.

Lemieux, Thomas, W Bentley MacLeod and Daniel Parent. 2009. "Performance Pay and Wage Inequality." *The Quarterly Journal of Economics* 124(1):1–49.

Lise, Jeremy and Fabien Postel-Vinay. 2015. Multidimensional Skills, Sorting, and Human Capital Accumulation. Working paper.

Makridis, Christos. 2019. "Work and Grow Rich : The Dynamic Effects of Performance Pay Contracts." Working Paper.

Mueller, Holger M, Paige P Ouimet and Elena Simintzi. 2017. "Wage inequality and firm growth." *American Economic Review* 107(5):379–83.

Papageorgiou, Theodore. 2010. "Large Firms and Internal Labor Markets." Working paper.

Piketty, Thomas and Emmanuel Saez. 2003. "Income Inequality in the United States, 1913-1998." *The Quarterly Journal of Economics* 118(1):1–39.

Ritter, Joseph A. and Kristine L. West. 2014. "Field of Study and Earnings Inequality among the Highly Educated: 1993-2010." Working paper.

Robst, John. 2007. "Education and job match: The relatedness of college major and work." *Economics of Education Review* 26(4):397–407.

Sanders, Carl. 2014. "Skill Uncertainty, Skill Accumulation, and Occupational Choice." Working Paper.

Scotese, Carol A. 2012. "Wage inequality, tasks and occupations." Working Paper.

Shimer, Robert. 2005. "The Cyclical Behavior of Equilibrium Unemployment and Vacancies." *American Economic Review* 95(1):25–49.

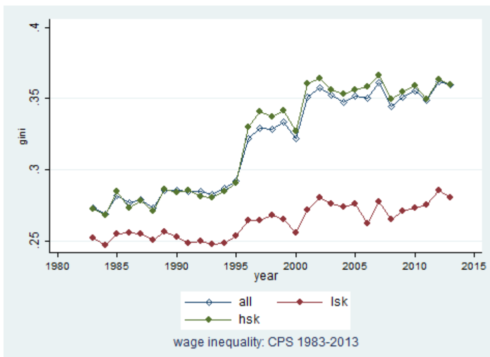
Song, Jae, David J Price, Fatih Guvenen, Nicholas Bloom and Till Von Wachter. 2018. "Firming up inequality." *The Quarterly Journal of Economics* 134(1):1–50.

Violante, Giovanni L. 2002. "Technological acceleration, skill transferability, and the rise in residual inequality." *The Quarterly Journal of Economics* 117(1):297–338.

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).

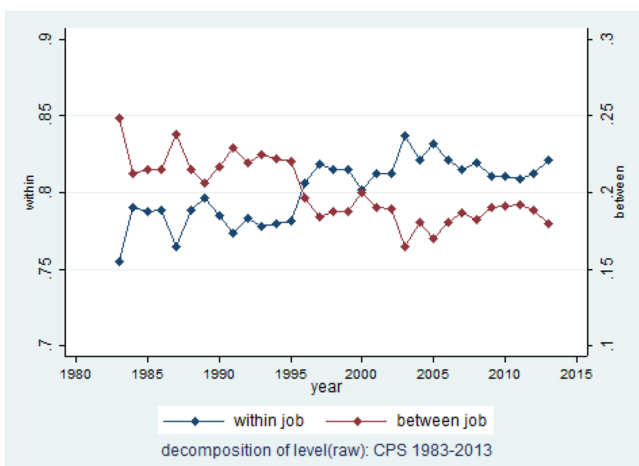


Figure A.12: Decomposition of the raw wage inequality

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).

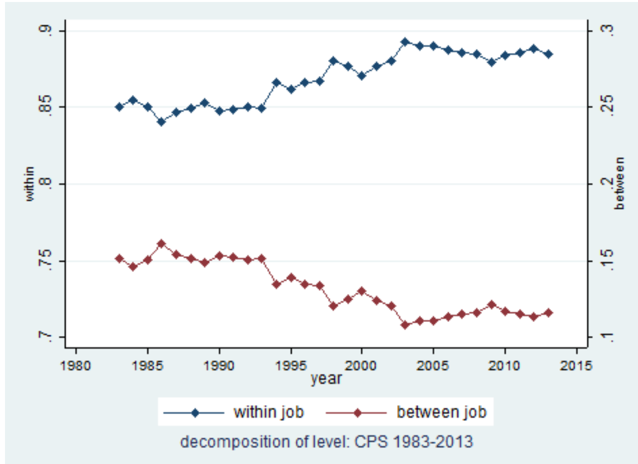


Figure A.13: Decomposition of the residue wage inequality

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.11: 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.12: 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.13: 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.14: 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.15: Incidence of Performance-pay: 1990

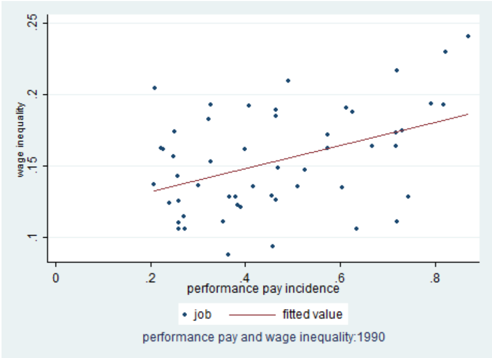
	Professionals	Managers	Sales	Clerical	Craftsmen	Operatives	Laborers	Services
Min durables	0.46	0.60	0.73	0.35	0.21	0.26	0.26	0.19
Nondurables	0.51	0.61	0.79	0.38	0.26	0.42	0.25	0.06
Transport utils	0.23	0.53	0.82	0.27	0.27	0.37	0.43	0.37
Fin. insur real est.	0.74	0.72	0.87	0.38	0.29	0.05	0.21	0.33
Bus. 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 among the highly educated in different jobs for year 1990, following the approach in Lemieux, MacLeod and Parent (2009). Data source: PSID.

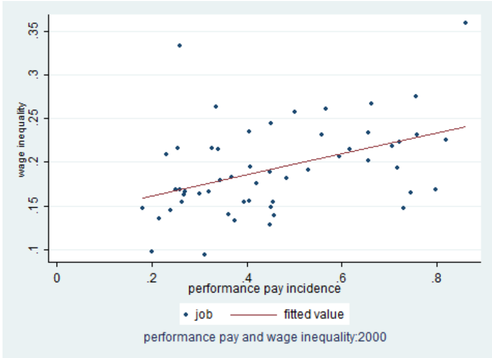
Table A.16: Incidence of Performance-pay: 2000

	Professionals	Managers	Sales	Clerical	Craftsmen	Operatives	Laborers	Services
Min durables	0.46	0.59	0.73	0.34	0.21	0.26	0.26	0.21
Nondurables	0.53	0.62	0.80	0.36	0.24	0.41	0.26	0.08
Transport utils	0.23	0.50	0.76	0.27	0.26	0.37	0.40	0.31
Fin. insur real est.	0.75	0.72	0.86	0.37	0.29	0.04	0.21	0.35
Bus. prof. serv.	0.41	0.56	0.76	0.39	0.45	0.42	0.22	0.25
Personal serv.	0.38	0.66	0.51	0.25	0.32	0.21	0.26	0.48
Whol-tr oth serv.	0.66	0.66	0.82	0.45	0.29	0.46	0.28	0.14
Retail trade	0.27	0.57	0.71	0.32	0.48	0.33	0.20	0.45
Construction	0.72	0.45	0.81	0.18	0.34	0.30	0.34	0.24
Agri. fishing	0.43	0.78	0.88	0.24	0.17	0.45	0.43	0.78

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



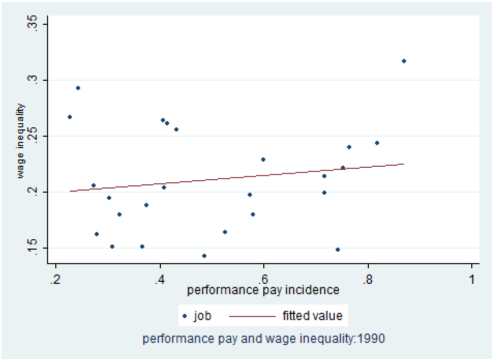
(a) 1990



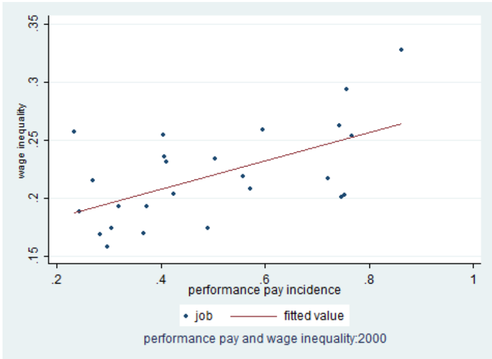
(b) 2000

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

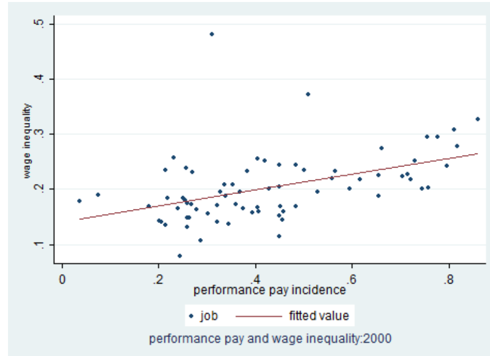


(b) 2000

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.

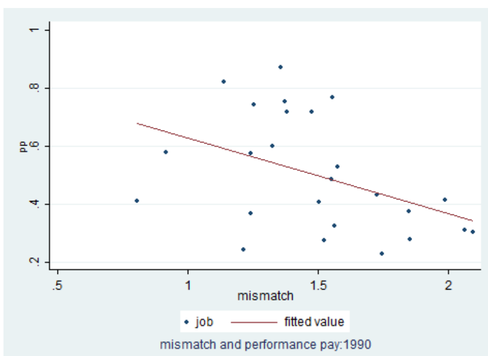
(a) 1990



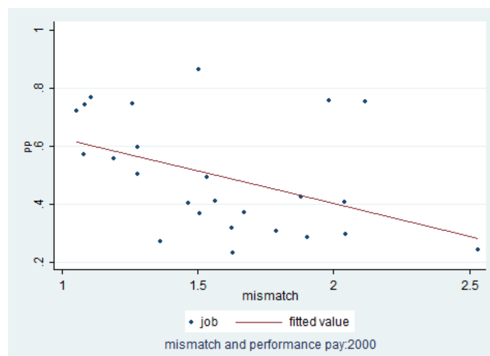
(b) 2000

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.



(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.

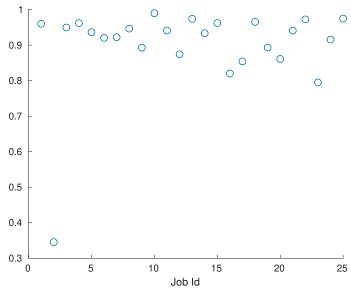
Table A.17: Skill Mismatch Index

1990						2000					
ind	occ	(ind,occ)	ind	occ	year	ind	occ	(ind,occ)	ind	occ	year
1	1	1.549	1.570	1.504	1.523	1	1	1.532	1.511	1.499	1.444
1	2	0.918	1.570	1.244	1.523	1	2	1.079	1.511	1.173	1.444
1	3	1.557	1.570	1.414	1.523	1	3	1.107	1.511	1.268	1.444
1	4	1.853	1.570	1.782	1.523	1	4	1.902	1.511	1.812	1.444
1	5	2.062	1.570	1.875	1.523	1	5	2.043	1.511	1.807	1.444
2	1	1.747	1.557	1.504	1.523	2	1	1.629	1.516	1.499	1.444
2	2	1.576	1.557	1.244	1.523	2	2	1.277	1.516	1.173	1.444
2	3	1.139	1.557	1.414	1.523	2	3	1.984	1.516	1.268	1.444
2	4	1.564	1.557	1.782	1.523	2	4	1.626	1.516	1.812	1.444
2	5	1.522	1.557	1.875	1.523	2	5	1.363	1.516	1.807	1.444
3	1	1.255	1.329	1.504	1.523	3	1	1.258	1.280	1.499	1.444
3	2	1.380	1.329	1.244	1.523	3	2	1.055	1.280	1.173	1.444
3	3	1.355	1.329	1.414	1.523	3	3	1.504	1.280	1.268	1.444
3	4	1.215	1.329	1.782	1.523	3	4	2.533	1.280	1.812	1.444
3	5	1.242	1.329	1.875	1.523	3	5	1.508	1.280	1.807	1.444
4	1	1.504	1.523	1.504	1.523	4	1	1.466	1.431	1.499	1.444
4	2	1.240	1.523	1.244	1.523	4	2	1.191	1.431	1.173	1.444
4	3	1.475	1.523	1.414	1.523	4	3	2.118	1.431	1.268	1.444
4	4	1.727	1.523	1.782	1.523	4	4	1.882	1.431	1.812	1.444
4	5	2.095	1.523	1.875	1.523	4	5	1.790	1.431	1.807	1.444
5	1	0.807	1.532	1.504	1.523	5	1	1.565	1.408	1.499	1.444
5	2	1.324	1.532	1.244	1.523	5	2	1.278	1.408	1.173	1.444
5	3	1.373	1.532	1.414	1.523	5	3	1.085	1.408	1.268	1.444
5	4	1.847	1.532	1.782	1.523	5	4	1.671	1.408	1.812	1.444
5	5	1.987	1.532	1.875	1.523	5	5	2.041	1.408	1.807	1.444

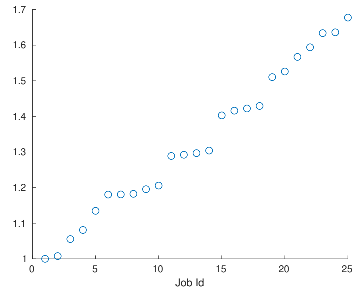
Notes: The column "(ind,occ)" reports the mismatch index for each industry-occupation pair. The column "ind" reports the mismatch index for each industry. The column "occ" is the mismatch index for each occupation. The column "year" is the mismatch index at a given year. Sources: NLSY79 and O*NET, and authors' calculation. 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).

B Quantitative Results

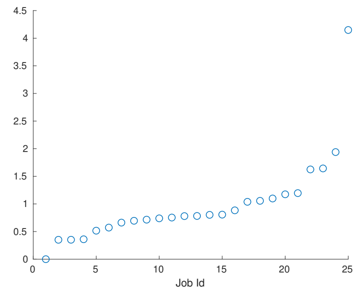
B.1 Calibration Outcome



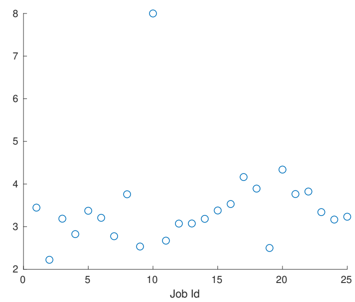
(a) Coefficients on fixed-pay



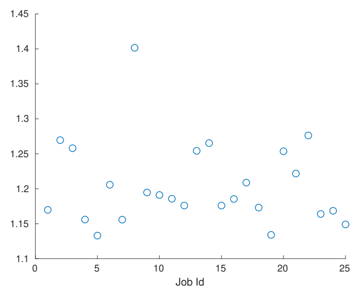
(b) Relative Productivities to Job 1



(c) Monitoring Costs



(d) Shape of the matching premium distribution

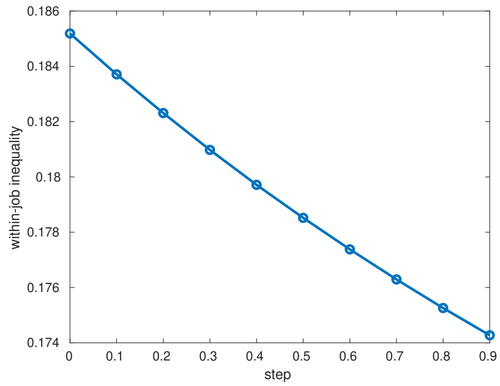


(e) Minimum matching premium

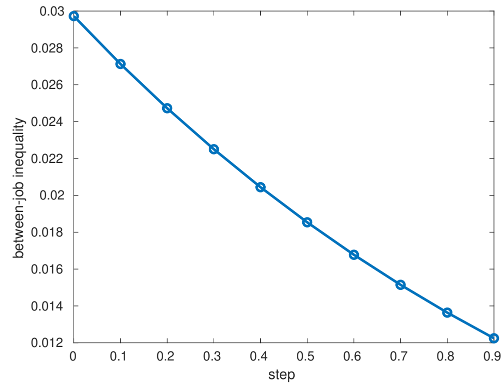
Figure B.18: Calibration Outcome

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.

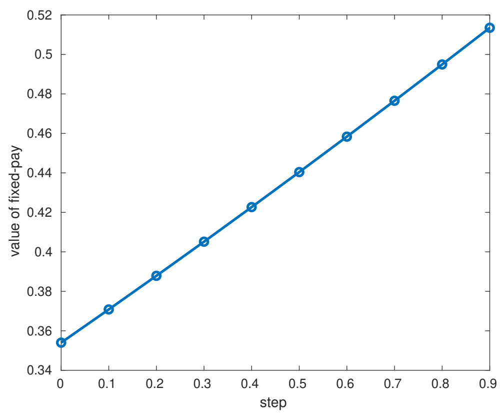
B.2 Counter-factual Exercises



(a) Withi-job Inequality



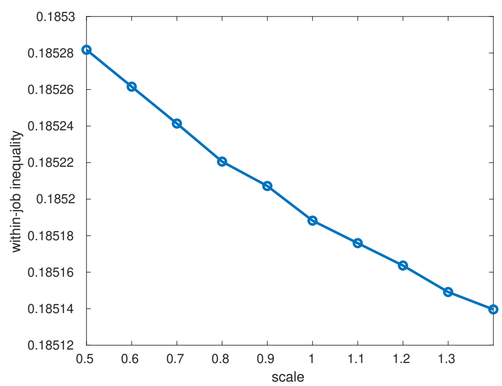
(b) Between-job Inequality



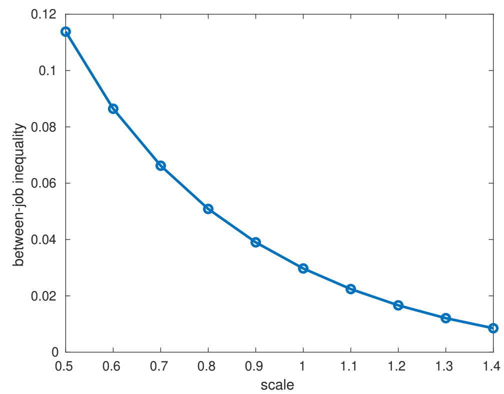
(c) Value of fixed-pay

Figure B.19: The role of productivity: mean preserve spread of productivity distribution

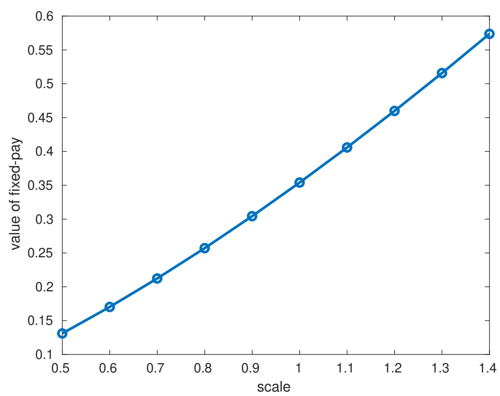
Notes: We adjust the productivities of each job according to equation 15. The x-axis denotes the value of λ. Higher λ imples a less dispersed distribution of productivities.



(a) Withi-job Inequality



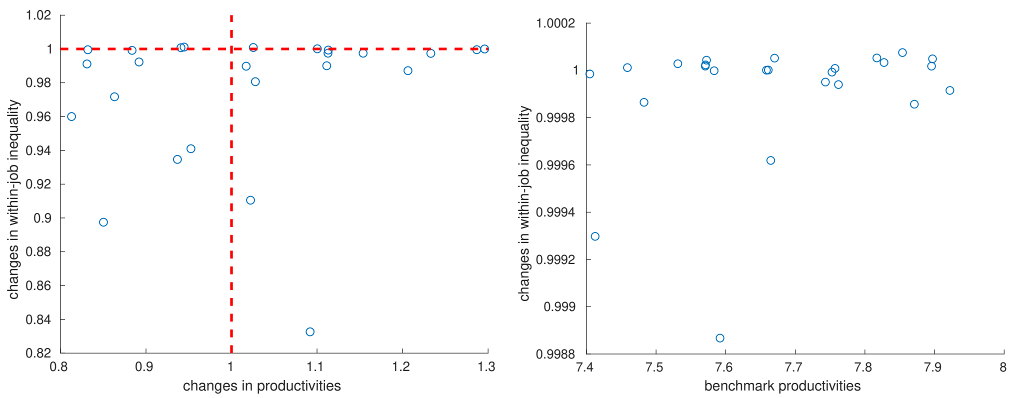
(b) Between-job Inequality



(c) Value of fixed-pay

Figure B.20: The role of productity: uniform scale of productivities

Notes: We uniformly scale down/up the value of productivities at each job. The x-axis denotes the value of the scaler. A value smaller than 1 implies a uniform reduction in productivities.

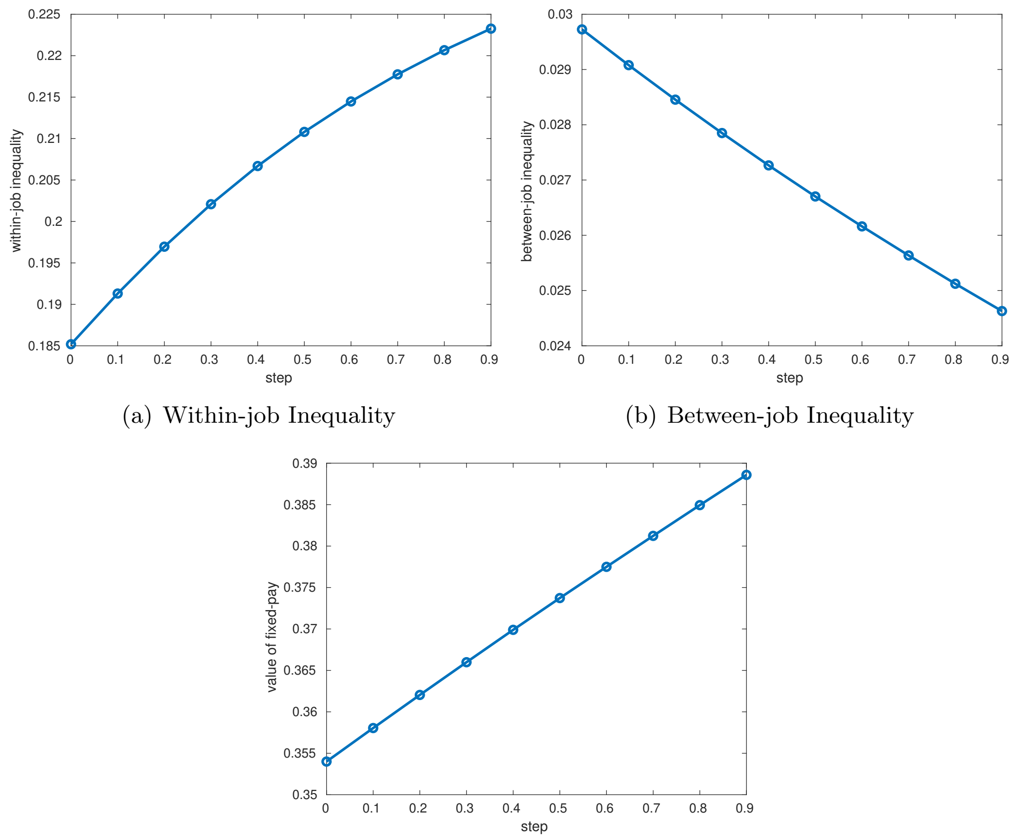


(a) Mean-preserve

(b) Uniform expansion

Figure B.21: The role of productity: job level

Notes: In both panels, we plot the ratio of wage inequality at each job in the counter-factual economy to that in the benchmark economy. In panel (a), the counter-factual economy is one from a mean-preserve spread of productivity distribution with $\lambda = 0.9$. In panel (b), the counter-factual economy is one with a uniform sacler of productivities, and the value of the scaler equals to 1.4.



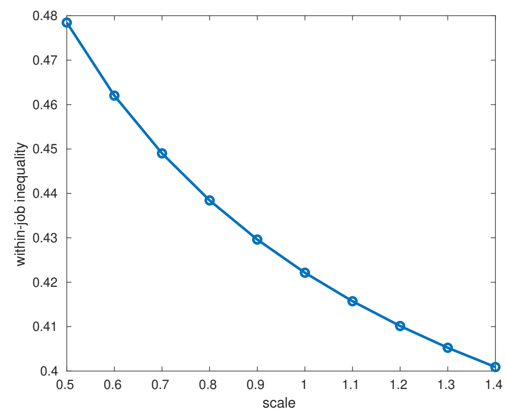
(a) Within-job Inequality

(b) Between-job Inequality

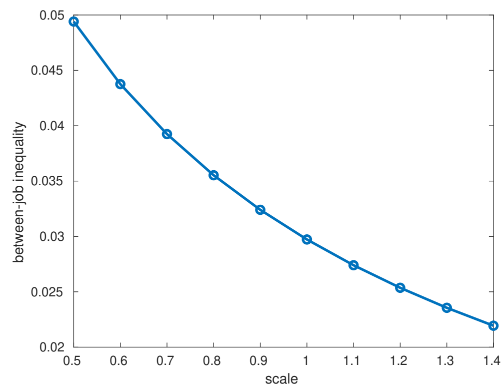
(c) Value of fixed-pay

Figure B.22: The role of match quality: mean preserve spread of matching premium distribution

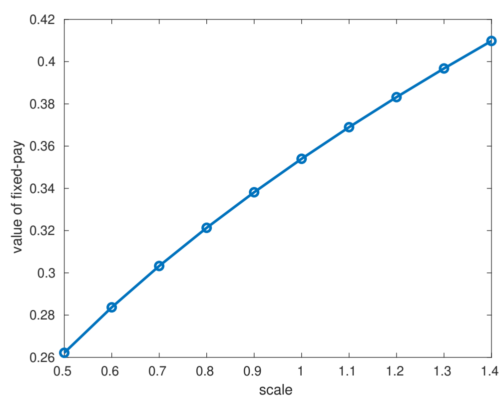
Notes: We adjust the value of matching quality summarized as $E[\eta^2]$ of each job according to equation 16. The x-axis denotes the value of λ. Higher λ imples a less dispersed distribution of matching qualities.



(a) Withi-job Inequality



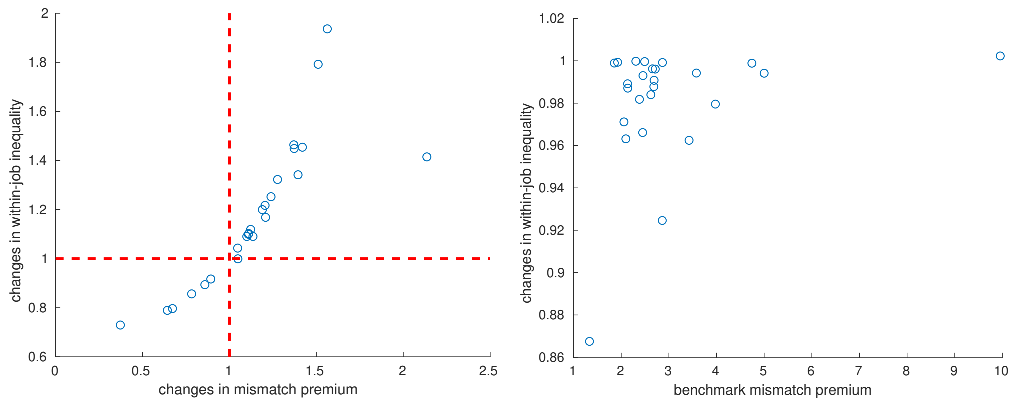
(b) Between-job Inequality



(c) Value of fixed-pay

Figure B.23: The role of match quality: uniform scale of matching premium

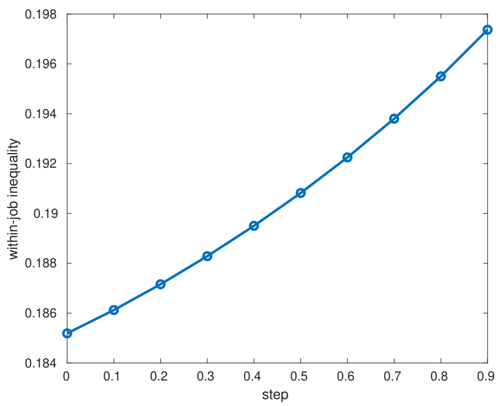
Notes: We uniformly scale down/up the value of matching premium summarized as $E[\eta^2]$ at each job. The x-axis denotes the value of the scaler. A value smaller than 1 implies a uniform reduction in the matching premium.



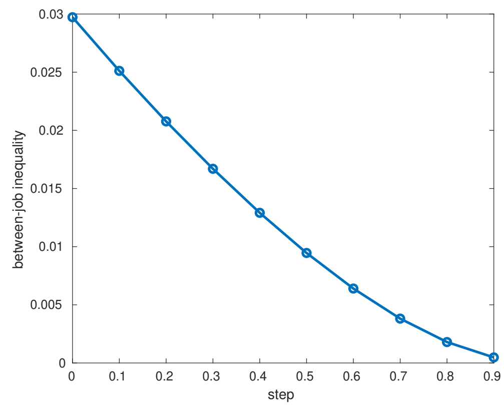
(a) Mean-preserve (b) Uniform expansion

Figure B.24: The role of match quality: job level

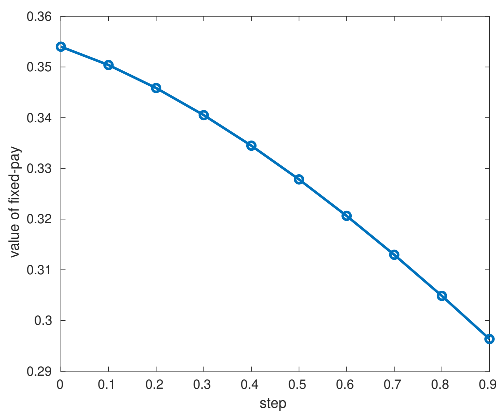
Notes: In both panels, we plot the ratio of wage inequality at each job in the counter-factual economy to that in the benchmark economy. In panel (a), the counter-factual economy is one from a mean-preserve spread of the matching premium distribution with $\lambda = 0.9$. In panel (b), the counter-factual economy is one with a uniform sacler of matching premium, and the value of the scaler equals to 1.4.



(a) Within-job Inequality



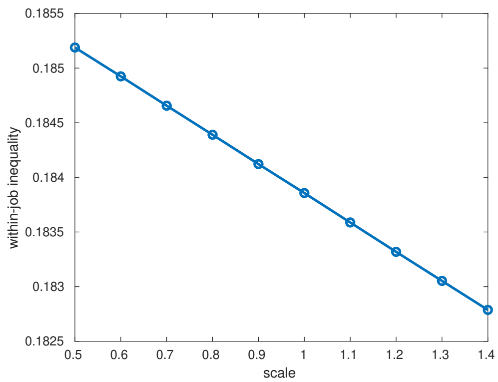
(b) Between-job Inequality



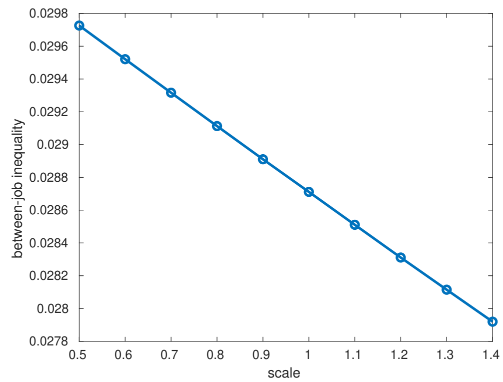
(c) Value of fixed-pay

Figure B.25: The role of performance-pay: mean preserve spread of PPI distribution

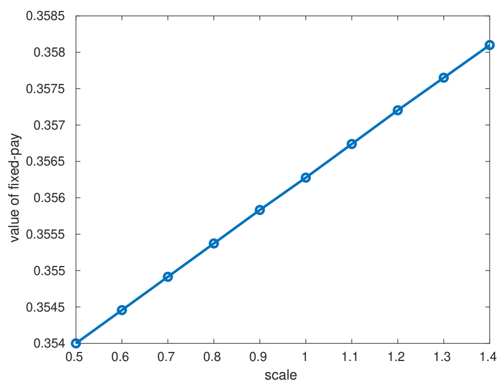
Notes: We adjust the value of the performance-pay incidence of each job according to equation 17. The x-axis denotes the value of λ. Higher λ imples a less dispersed distribution of performance-pay incidence.



(a) Within-job Inequality



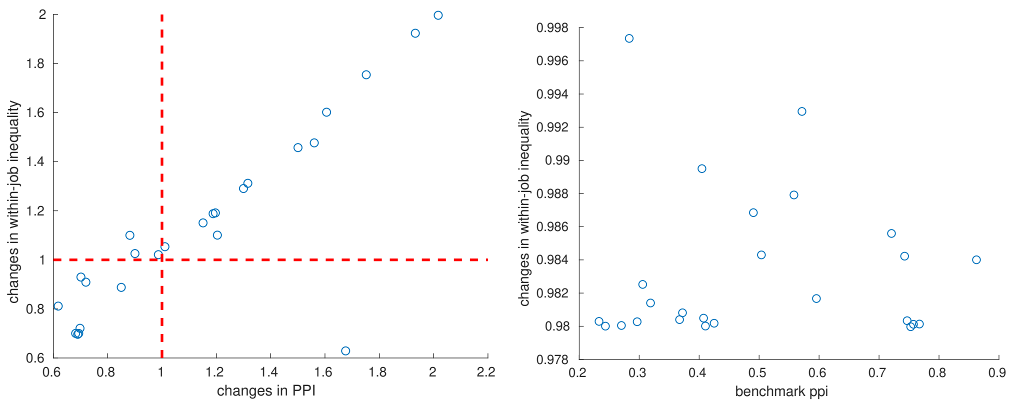
(b) Between-job Inequality



(c) Value of fixed-pay

Figure B.26: The role of performance-pay: uniformly adjusted PPI

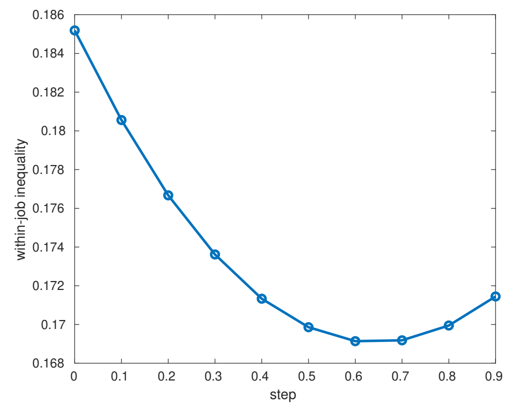
Notes: We uniformly scale down/up the value of performance-pay incidence at each job. The x-axis denotes the value of the scaler. A value smaller than 1 implies a uniform reduction in the performance-pay incidence.



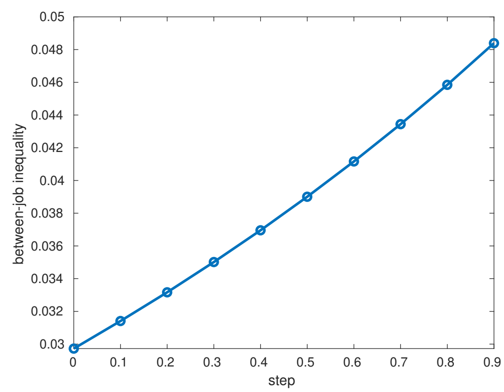
(a) Mean-preserve (b) Uniform expansion

Figure B.27: The role of performance-pay: job level

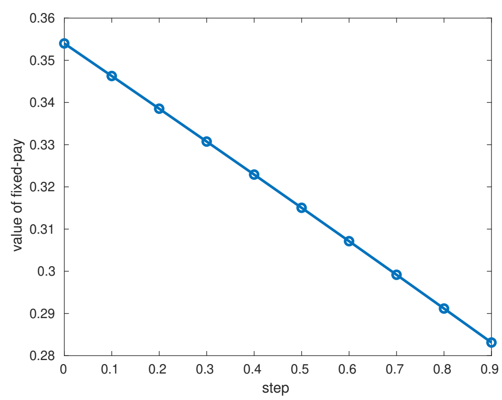
Notes: In both panels, we plot the ratio of wage inequality at each job in the counter-factual economy to that in the benchmark economy. In panel (a), the counter-factual economy is one from a mean-preserve spread of the performance-pay incidence distribution with $\lambda = 0.9$. In panel (b), the counter-factual economy is one with a uniform sacler of the performance-pay incidence, and the value of the scaler equals to 1.4.



(a) Withi-job Inequality



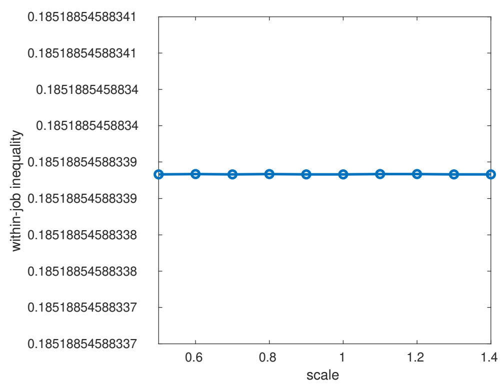
(b) Between-job Inequality



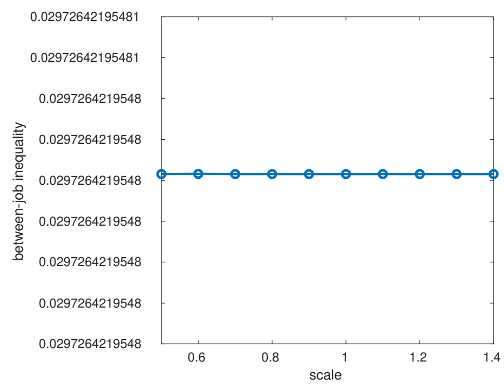
(c) Value of fixed-pay

Figure B.28: The role of ability sorting: mean preserve spread of productivity distribution

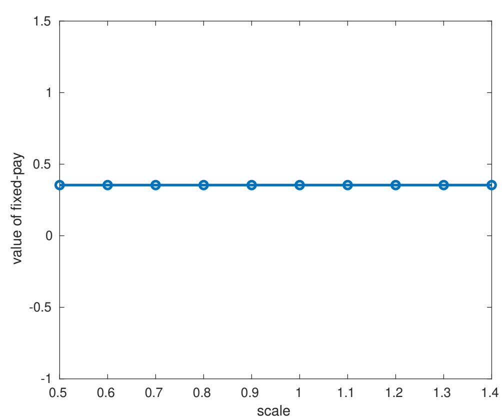
Notes: We adjust the value of the employment level at the performance-pay task of each job according to equation **??**. The x-axis denotes the value of λ. Higher λ imples a less dispersed distribution of employment distribution at the performance-pay task.



(a) Withi-job Inequality



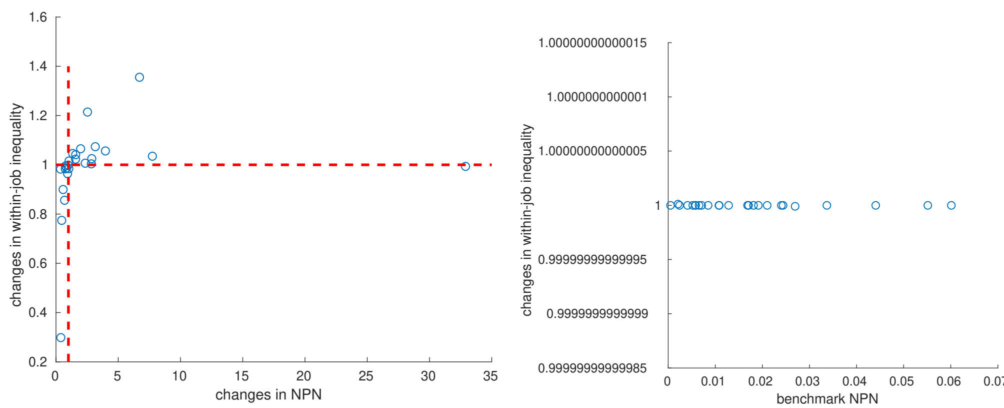
(b) Between-job Inequality



(c) Value of fixed-pay

Figure B.29: The role of ability sorting: uniformly adjusted

Notes: We uniformly scale down/up the employment level at the performace-pay task at each job. The x-axis denotes the value of the scaler. A value smaller than 1 implies a uniform reduction in the employment at the performace-pay task of each job.



(a) Mean-preserve

(b) Uniform expansion

Figure B.30: The role of ability sorting: job level

Notes: In both panels, we plot the ratio of wage inequality at each job in the counter-factual economy to that in the benchmark economy. In panel (a), the counter-factual economy is one from a mean-preserve spread of the employment distribution at the performance-pay task with $\lambda = 0.9$. In panel (b), the counter-factual economy is one with a uniform sacler of the employment at the performance-pay task, and the value of the scaler equals to 1.4.

B.3 Decompose the changes in inequality from 1990 to 2000

Table B.18: 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	0.139	0.141	0.136	0.136
(FIRE,Production)	0.167	0.139	0.167	0.139	0.167	0.140	0.166	0.166
(Trade,Production)	0.143	0.138	0.143	0.138	0.144	0.136	0.143	0.143
(Business,Clerical)	0.153	0.126	0.153	0.126	0.152	0.131	0.152	0.144
(FIRE,Clerical)	0.126	0.118	0.126	0.118	0.126	0.116	0.126	0.128
(Business,Production)	0.160	0.144	0.160	0.144	0.162	0.142	0.160	0.212
(Goods,Clerical)	0.144	0.129	0.144	0.129	0.150	0.120	0.144	0.144
(Trade,Sales)	0.211	0.174	0.211	0.174	0.213	0.173	0.210	0.208
(Transport,Clerical)	0.151	0.128	0.151	0.128	0.153	0.124	0.151	0.151
(Goods,Production)	0.152	0.140	0.168	0.212	0.174	0.167	0.171	0.184
(Transport,Production)	0.170	0.152	0.170	0.152	0.173	0.145	0.170	0.217
(Trade,Professional)	0.166	0.144	0.166	0.144	0.166	0.144	0.166	0.177
(Business,Professional)	0.234	0.189	0.234	0.189	0.236	0.218	0.230	0.165
(Trade,Manager)	0.231	0.168	0.231	0.168	0.232	0.168	0.230	0.228
(Business,Manager)	0.222	0.160	0.222	0.160	0.225	0.176	0.219	0.204
(Business,Sales)	0.237	0.183	0.237	0.183	0.225	0.191	0.237	0.237
(Goods,Sales)	0.176	0.177	0.176	0.177	0.176	0.177	0.176	0.176
(Goods,Professional)	0.153	0.106	0.153	0.106	0.153	0.100	0.151	0.128
(Transport,Professional)	0.204	0.162	0.134	0.162	0.132	0.164	0.134	0.205
(FIRE,Professional)	0.158	0.135	0.158	0.135	0.157	0.084	0.158	0.162
(FIRE,Manager)	0.212	0.171	0.212	0.171	0.211	0.170	0.211	0.214
(Goods,Manager)	0.215	0.160	0.215	0.160	0.216	0.142	0.211	0.155
(Transport,Sales)	0.264	0.183	0.264	0.183	0.286	0.169	0.264	0.294
(FIRE,Sales)	0.344	0.237	0.344	0.237	0.346	0.248	0.343	0.336
(Transport,Manager)	0.252	0.153	0.252	0.153	0.259	0.192	0.250	0.239
overall within	0.207	0.158	0.185	0.166	0.187	0.160	0.185	0.190
between job	0.021	0.019	0.030	0.024	0.032	0.029	0.023	0.025

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 11 can be re-written as follows:

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

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. $\blacksquare$

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 $j \geq k$. $\blacksquare$

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:

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

∎

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 $k < n-1$. ∎

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 utilies 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:

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

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