Educational Mismatch and the Earnings Distribution

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Running Head: Mismatch and the Earnings Distribution

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Abstract

This paper focuses on the interrelationship between educational mismatch and earnings taking three new approaches. First, we examine decompositions of the mismatch wage gap, finding that characteristics explain less than half of the mismatch penalty. Second, we use unconditional quantile regression to examine the mismatch penalty across the earnings distribution, showing that the penalty shrinks as the position in the earnings distribution increases. Third, we decompose the differentials using quantile decompositions. Different reasons for mismatch show heterogeneity in our results, with larger penalties for being mismatched due to working conditions, location, family, and no available job.

1. Introduction

College students invest in their education with the assumption that the knowledge and skills they acquire in their degree will be useful and demanded in the labor market. Yet research finds that there is a mismatch between the human capital workers acquire through education and the human capital required for the job. Estimates vary, but generally about 15 to 30% of workers are educationally mismatched in developed economies (e.g. Chevalier 2003; Wolbers 2003; Bender and Roche 2013).

While there is some debate over the causes of mismatch, there is consistent and robust empirical evidence that mismatch is correlated with adverse labor market outcomes. These include lower job satisfaction (e.g. Bender and Heywood 2006; Craft, Baker, and Finn 2017), more turnover (e.g. Wolbers 2003; Bender and Heywood 2009), and lower pay (e.g. Chevalier 2003; Bender and Heywood 2009).

This paper investigates the latter issue by focusing on the interrelationship between educational mismatch and earnings. While much of the educational mismatch literature defines mismatch as overeducation, meaning the difference between an individual's level of schooling and the average schooling among all workers in their occupation, this paper defines mismatch as a measure self-reported job relatedness. Using National Survey of College Graduates (NSCG) data on U.S. workers with at least a bachelor's degree, we use the answer to a key subjective question "To what extent was your work on your principal job related to your highest degree?" to estimate wage penalties between workers who respond that their work is related to their highest degree and workers who respond that their work is only somewhat related or not related to their highest degree. We estimate a 7% wage penalty for workers whose degrees are somewhat related to their job, and a 22% wage penalty for workers whose degrees are not related to their job on average, *ceteris paribus*. For the latter group, wage penalties vary greatly depending on the reason for the worker's mismatch. For example, workers who are mismatched due to seemingly involuntary reasons, such as location, family responsibilities, and limited job availability, incur large penalties exceeding 30%. However, if a worker chooses to work in a job that is unrelated to his or her education because it provides them higher pay or a career change, the penalty is much smaller.

These findings, discussed in more detail below, are fairly representative of the earnings penalties found in the literature. We start our analysis with a decomposition of the earnings differential to estimate the proportion of the penalty that is attributable to observed characteristics versus unobserved characteristics. Similar to McGuinness and Pouliakas (2017), we estimate an Oaxaca-style decomposition to analyze the earnings differential between matched and mismatched workers, although they look at overeducation while we focus on job relatedness. We estimate that observed characteristics, such as gender, age, occupation, and industry, explain less than half of the differential. In addition, observed characteristics explain a greater portion of the differential for males relative to females.

Following the traditional Oaxaca decomposition, the paper uses two new approaches to add to the current literature on educational mismatch. First, we examine the mismatch penalty across the earnings distribution employing unconditional quantile regression using the recentered influence function (RIF) method proposed by Firpo, Fortin, and Lemieux (2009). Similar to some of the previous literature, among workers with jobs that are not related to their highest degree, the penalty decreases as the position in the earnings distribution increases, differing somewhat by gender. As an addition to the literature, we also investigate the penalty by the reason for mismatch, finding that arguably involuntary reasons for mismatch generate substantial penalties, particularly at the bottom of the distribution.

Second, in another innovation on the mismatch literature, we use the RIF method to decompose the mismatch penalty using quantile regressions. As with the Oaxaca decomposition, we find that unobserved characteristics explain a larger portion of the differential. This finding is consistent at all positions within the earnings distribution, although observed characteristics explain a relatively higher share of the penalty at the top and bottom of the earnings distribution. Again, these decompositions vary slightly by gender and reason for mismatch.

This paper is organized as follows. First, a brief review of the literature provides a background for the research on quantile regression and educational mismatch. The data are then defined and examined for descriptive statistics and results are presented on the earnings differential decomposition, earnings differential across the earnings distribution, and the decomposition of the penalty across the earnings distribution. Finally, the results of the paper are summarized and recommendations for future work are made.

2. Literature Review

Educational Mismatch

Previous research on educational mismatch focuses on the effects of being employed in a job that is not well matched with a worker's education. There is consistent and robust empirical evidence in the economics literature that educational mismatch is correlated with adverse labor market outcomes. These include lower job satisfaction (e.g. Bender and Heywood 2006; Craft, Baker, and Finn 2017), more turnover (e.g. Wolbers 2003; Bender and Heywood 2009), and lower pay (e.g. Chevalier 2003; Bender and Heywood 2009). Given that our paper investigates the latter outcome, we focus our literature review on the educational mismatch earnings penalty and its measurement.[1]

Most of the previous research on educational mismatch defines mismatch as overeducation, meaning an individual has more years of schooling than the average years of schooling of other workers in the same occupation. In general, wage penalties are estimated for overeducated workers. For example, a meta-analysis by Groot and Maasen van den Brink (2000) shows that the over-educated experience a 14% earnings penalty. Chevalier (2003) uses UK data to estimate a 5-11% penalty for mismatched workers who have similar unobserved skills as matched workers and a 22-26% penalty for mismatched workers with lower skill endowments as matched workers.

Similar to our paper, other studies investigate a different measure of educational mismatch defined by how closely an individual's job relates to their education and its effect on earnings. Borghans and de Grip (2000), Bender and Heywood (2009), and Bender and Roche

[1] We also do not review the literature on mismatch and careers. It may be that mismatch is expected early or late in careers for a variety of reasons that could come about from an efficiently operating market. Research on this can be found in, for example, Hersch (1995) or Bender and Heywood (2011) among others.

(2013) find that working in a job unrelated to one's field of education is associated with significantly diminished earnings, and these penalties increase with the severity of mismatch.[2] However, these studies above examine the penalty using standard linear regression methods, essentially estimating the penalty at the conditional mean. More recently, economists have started to examine mismatch penalties conditional on the position in the earnings distribution. Thus, a brief review of quantile regression and its application to educational mismatch follows.

Quantile Regression

Previous research that estimates wage equations finds that wages vary significantly across the distribution and therefore estimation of wage determinants using ordinary least squares (OLS) can provide biased results. Seminal papers focus on measuring the returns to education. Buchinsky (1994 and 1998) implements quantile regression to estimate the returns to skills, i.e., the return to education and the return to experience, across the wage distribution. Buchinsky finds that relative to median regression, OLS underestimates the returns to skills, and the returns to skills increase across the wage distribution. That is, workers at the bottom of the wage distribution experience smaller returns to education and experience, and workers at the top of the wage distribution experience higher returns to education and experience.

In a novel paper using twins data, Arias, Hallock, and Sosa-Escuderoz (2000) estimate the returns to education using instrumental variables quantile regression. The authors regard the wage distribution as a reflection of the range of unobservable ability, so that people at the bottom

[2] The latter two papers use datasets from the National Survey Foundation (Survey of Doctorate Recipients and National Survey of College Graduates, respectively). Both datasets include the same self-reported question on the relatedness between the respondent's job and highest degree.

of the wage distribution are believed to have less ability and people at the top of the wage distribution are believed to have more ability. Accordingly, they argue that education and unobserved ability have a complementary relationship, and given the additional indirect effect of education on human capital, education helps high-ability individuals more.

While these important quantile regression studies focus on measuring the returns to education across the earning distribution, subsequent research expands on the usefulness and other applications of quantile regression. Yu, Lu, and Stander (2003) is a highly-cited paper that summarizes the motivation and many applications of quantile regression. Recently, quantile regression has been applied to research on educational mismatch. The results from these papers, which mainly measure the effect of mismatch on wages in developed economies, are mixed.

Evidence from Spain (Budría and Moro-Egido 2008) and Northern Ireland (McGuinness and Bennett 2007) show a mismatch penalty that narrows as the position in the earnings distribution increases. However, in an opposing paper, Hernández and Serrano (2012) find that the mismatch penalty in Spain is larger for high-wage workers in the upper part of the distribution, implying that it is not unobservable characteristics, but rather educational mismatch itself driving the wage inequality.[3]

In summary, further analysis is warranted to better understand the interrelationship between the relatedness of a worker's job and their education and the worker's earnings,

[3] Other papers focus on the role of educational mismatch on wage inequality. For example, Budría (2011) finds that educational mismatch does not drive the positive effect of education on wage inequality in Portugal and Europe, and Ordine and Rose (2015) argue that educational mismatch does explain some wage inequality among college graduates in Italy.

particularly in a distributional context. While the current literature agrees that mismatch is correlated with lower pay, it is conflicted on how the earnings penalty differs at different positions in the earnings distribution. We also know little of what explains the mismatch penalty, and whether it is attributable to a difference in distributions or a difference in means between matched and mismatched workers. One such paper by McGuinness and Pouliakas (2017) investigates this issue by decomposing the earnings penalty of overeducated workers in Europe. The authors find that the explained portion of the mismatch penalty is attributed to differences in human capital and job-skill requirements, and not attributed to equilibrium theories of compensating wage differentials and career mobility. While McGuiness and Pouliakas take an important step in this analysis, it does not investigate the decomposed mismatch penalty at different points in the earnings distribution.

3. Data

This paper uses the 2015 U.S. National Survey of College Graduates (NSCG) dataset from the U.S. National Science Foundation (NSF). The data are a nationally representative sample of approximately 90,000 individuals, of which we analyze approximately 60,000 people who are employed.

The NSCG asks respondents a key subjective question giving a measure of horizontal mismatch, "To what extent was your work on your principal job related to your highest degree? Closely related, somewhat related, or not related." We identify these workers as closely matched, moderately mismatched, and severely mismatched, respectively.[4] If workers are

[4] The literature on mismatch uses a number of different measures for mismatch. Since this one is subjective, a referee pointed out that it would be good to see if it correlated with more objective measures of mismatch – such as ones that

severely mismatched, the NSCG asks them follow-up questions about the most important reason for working in a field that is not related to their highest degree. Reasons include pay and promotion opportunities, working conditions, job location, change in career or professional interests, family-related reasons, job not available, and other.[5] We differentiate these reasons into two categories: reasons prompting what is more likely an involuntary job change including job location, family-related reasons and a job not being available, and reasons prompting what is more likely a voluntary job change including pay or promotion, working conditions, and a career change.

Table 1 presents rates of mismatch, rates for the reasons of severely mismatched workers, and mean and median earnings by mismatch type. It is interesting to note that there is an association between increasing mismatch and lower mean and median earnings for the overall sample as well as in both the female and male samples.

(Table 1 here)

In addition to the educational mismatch variables, the dataset provides a standard set of socioeconomic variables. The following analysis restricts the data to full-time workers who report positive earnings in order to examine workers in career-type jobs only.

4. Results

look at the dispersion of different jobs for a degree field (e.g. Altonji, Blom, and Meghir 2012). We found that there is a statistically significant correlation between the subjective measure we use and an increase in dispersion of jobs associated with a degree field. The authors thank the referee for making this point and these results are available from the authors upon request.

[5] Due to the ambiguity around the "other" reason for severe mismatch, our remaining analysis does not present results on this particular reason. We focus on the first six reasons as they allow us to draw more meaningful conclusions from them. However, the "other" reason category is included in all regressions using the reasons for mismatch and are available upon request.

Mismatch Penalty using OLS

First, we examine the mismatch penalty using the traditional approach, OLS. Log hourly earnings are regressed on indicators for moderate mismatch, severe mismatch, and a standard set of covariates, including gender, age, age squared, race, marital status, U.S. citizenship, experience, experience squared, tenure, tenure squared, highest degree, main task, disability status, employment sector, firm size, and region.

Similar to previous research, we find fairly substantial earnings penalties using OLS as seen in Table 2. Relative to matched workers, *ceteris paribus*, moderate mismatch is associated with a nearly 8% penalty and severe mismatch is associated with a 24% penalty.[6] These penalties differ only slightly by gender with a slightly higher penalty for men who are severely mismatched. For severely mismatched workers, the mean earnings penalty varies depending on the most important reason for their mismatch, as shown in the separate regression results in the bottom panel of Table 2. Mismatched workers with the largest penalties of 38% or more are mismatched because of arguably involuntary reasons, e.g., job location, family-related reasons and a job not being available. However, when workers are mismatched due to pay or promotion or a career change, they incur much smaller earnings penalties, not much different than those who are moderately mismatched. Overall, this finding supports the hypothesis that workers will incur a higher earnings penalty if they are pushed into a mismatched job, and a lower earnings penalty if they chose to take a mismatched job because it provided higher pay, better working conditions, or more career opportunities. For men, the penalties by the different reasons are greater than for women.

[6] Results below are all in log points. To convert to percentage differences, we use the formula: $e^{\beta} - 1$.

(Table 2 here)

Decomposing the Mismatch Penalty

Given that the mismatch penalty is large and statistically significant, we then examine the proportion of the differential that is explained versus unexplained. That is, we attempt to answer the question: can the mismatch penalty be explained by observed characteristics such as education and occupation field or is it the unobserved characteristics, captured in the estimated coefficients, which drive the gap? Thus, we use an Oaxaca-style decomposition to decompose the wage differential between the matched versus the moderately and severely mismatched.[7]

Table 3 summarizes the Oaxaca-style decomposition results. Comparing matched workers to moderately and severely mismatched workers, the observed characteristics explain only 13% of the penalty, and with little difference across genders. In general, educational qualifications and experience seem to drive the explained portion of the mismatch penalty, supporting the findings of McGuiness and Pouliakas (2017), who decompose the earnings differential for overeducated workers in Europe. The remaining differential, accounting for over 80% of the mismatch penalty, is driven by unobserved characteristics. It is the varying returns to observed characteristics, such as the returns to education and experience that explains the majority of the penalty. These varying returns can be interpreted as involuntary reasons for mismatch (for example, discrimination or a lack of adequate graduate level jobs in the labor

[7] Given that there are three categories (matched, moderately mismatched, and severely mismatched) that measure the match between the worker's highest degree and job, we also decompose the wage differential between the matched and the moderately mismatched versus the severely mismatched. The result is similar to the decomposition of the matched versus the moderately and severely mismatched, and for simplicity, we leave it out of the paper, but the results are available from the authors.

market) or the internal barriers that workers put on themselves such as voluntary choices or lack of ambition.

(Table 3 here)

Indeed, some evidence of this can be found in Table 4, where we calculate decompositions between the matched and those mismatched because of pay or because of no job being available where the former reason for mismatch is arguably more ‘voluntary’ than the latter. The results there suggest that, not only is the differential smaller for those who are severely mismatched due to pay (as expected), but that the ‘explained’ part of the decomposition is relatively higher for this group of workers (27% overall, 39% for females and 23% for males). For those whose mismatch is attributed to a job not being available, worker characteristics do not explain much of the differential (no more than 22%).

(Table 4 here)

The Earnings Distribution and the Mismatch Penalty using Unconditional Quantile Regression

As mentioned in the literature review, more recent research on mismatch examines earnings penalties across the earnings distribution. We offer two unique additions to this literature. First, given our finding of substantial heterogeneity in the voluntary and involuntary reasons for mismatch and their effects on earnings, we investigate the effect of these reasons across the earnings distribution. Second, newer methods of quantile regressions allow for decomposing differences in earnings across the distribution into characteristics and returns components. In order to do the latter, rather than use the standard Buchinsky (1994, 1998) form of quantile regression, we use a newer form of quantile regression proposed by Firpo, Fortin, and Lemieux

(2009).[8] The reason for this is because we eventually want to decompose the earnings differentials between the matched and mismatched for each percentile, rather than at the mean, as done in the standard Oaxaca-Blinder decomposition reported above. As detailed by Firpo, Fortin, and Lemieux (2009), the problem with using standard quantile techniques in a decomposition is that the difference that is decomposed is unconditional. While in OLS, this is no problem since the mean unconditional differential in earnings is the same as the conditional differential, this will not be true at each percentile in the earnings distribution. Firpo, Fortin, and Lemieux (2009) propose a method using RIF that allows for estimating unconditional differences at each percentile that can then be used to generate standard decompositions.[9]

Before turning to the regressions, it is interesting to look at the rates of mismatch across the distribution, reported in the top panel of Table 5 in the first two columns. Overall the top panel shows that the rate of being moderately mismatched is relatively constant across the distribution – typically about a quarter of the sample. However, the rates of being severely mismatched are greatest at the bottom end of the distribution where 31.3% are severely mismatched, compared to less than seven percent in the upper decile.

(Table 5 here)

Figure 1 illustrates the mismatch penalty across the earnings distribution for all workers estimated from quantile regressions using the Firpo, Fortin, and Lemieux (2009) RIF method. Moderate mismatch imposes a relatively small penalty of around 10% that narrows slightly as

[8] We also estimate the mismatch penalty using the more conventional (conditional) quantile regression method by Buchinsky (1994, 1998). The results are similar to the penalties estimated using the RIF method in that the pattern of the penalty across the distribution is the same, and the conditional estimates were only slightly smaller compared to the RIF estimates.

[9] The RIF estimates were generated by the ‘`rifreg`’ ado file provided by Nicole Fortin at her website: http://faculty.arts.ubc.ca/nfortin/datahead.html

one moves up the earnings distribution, consistent with the small changes in the rates of moderate mismatch across the distribution. The penalty for severely mismatched workers is quite different. At the bottom part of the distribution, where the rates are highest, there are also the greatest penalties. That penalty decreases, greater than 40% in the bottom decile, nearly 20% at the median and 10% in the upper decile. However, severely mismatched worker's earnings do not catch up to the earnings of workers who are only moderately mismatched at any point. Therefore, we conclude that while educational mismatch does come with an earnings penalty and this penalty shrinks as workers earn more (as found in McGuinness and Bennett 2007 and Budría and Moro-Egido 2008), it does not dissipate completely, even for the top earners in the sample.

(Figure 1 here)

Given that we estimate small gender differences in the Oaxaca results, we split the sample by gender to examine any differences. The bottom panels of Table 5 suggest that the rates of moderate mismatch are not all that different across genders. On the other hand, the rate of severe mismatch, while falling across the distribution for both genders, is slightly higher for males than females at the bottom end of the distribution, but lower at the upper end of the distribution.

In the RIF quantile regressions in general, the patterns are consistent across genders - see Figures 2 and 3. The penalty associated with moderate mismatch is relatively small and does not change much at any point in the distribution, where the penalty for severe mismatch is very large at the bottom of the distribution and falls as one moves up the distribution. However while the patterns are consistent, the relative penalties are different. For moderately mismatched workers, females tend to have a slightly greater penalty across the distribution. On the other hand, for the severely mismatched, the penalty is consistently higher among men, similar to the relative rates of severe mismatch.

(Figures 2 and 3 here)

Next, we draw upon the NSCG's question that asks severely mismatched workers the reason they work in a field that is not related to their educational field. Descriptive statistics are found in the right-hand columns of Table 5. While the rates of most of the reasons fall as wages increase, being severely mismatched because of 'pay and promotion' and 'career change' remain relatively important even at the upper end of the distribution. For example, combined they are 8.7 percentage points of the overall 31.3 percentage point rate of severe mismatch while at the top end of the distribution they are 4.7 percentage points of the 6.6 percentage point rate of severe mismatch.

Controlling for covariates in the quantile regressions allows us to see the penalties attributed to the six reasons for severe mismatch. Figure 4 shows the mismatch penalties across the earnings distribution for each reason. The penalties follow the same general shape, substantially larger penalties at the bottom of the distribution, declining as wages increase. However, the sizes of the penalties indicate considerable differences in penalties according to different reasons for mismatch. Unsurprisingly, when workers are mismatched due to pay and promotion opportunities, they experience the smallest penalties that range from more than 20% at the bottom of the distribution to generating higher than matched earnings at in the uppermost percentiles. Changes in career are also associated with smaller penalties that range from about 30% to near parity.

(Figure 4 here)

Workers who are mismatched for what we categorize as involuntary reasons, including location, family-related reasons, and job unavailability incur the largest penalties, particularly the last two. Some interesting findings by reason follow. When workers are mismatched due to family-related reasons, they incur penalties from more than 70% less than matched workers in the bottom half of the earnings distribution, although the penalty narrows significantly in the upper half of the distribution. Similar patterns occur with severe mismatch due to job unavailability and, to a lesser extent, job location. Thus, the reasons that are relatively more prominent at the bottom end of the distribution, i.e., conditions that are relatively involuntary, carry the largest penalties. On the other hand, those which are relatively more common at the upper end of the distribution, i.e., conditions that are relatively voluntary, carry the lowest penalties.[10] Not surprisingly, mismatched workers who choose a job outside of their education because it provides pay and promotion opportunities are barely penalized, and the penalty does not change much across the distribution. The effect of mismatch due to job conditions is associated with a penalty that ranges from 60% at the bottom of the earnings to distribution to 20% for workers in the top half of the distribution. While we consider this reason to be a voluntary choice for mismatch, its penalty falls in between the higher penalties associated with involuntary reasons and the lower penalties associated with voluntary reasons.

Decomposing the Mismatch Penalty across the Earnings Distribution

To investigate how much observed characteristics explain the penalty for workers at different earnings levels, we decompose the mismatch penalty at each percentile in the earnings

[10] Again, we split the sample by gender, this time investigating gender differences by the reason for mismatch across the earnings distribution. The results do indicate some differentials by gender, but the differences are not often statistically significant (results available from the authors).

distribution. To start, we decompose the mismatch penalty for the full sample comparing the closely matched and the not closely matched (that is, the closely matched and the moderately or severely mismatched) – see Figure 5. In general, the observed characteristics play relatively little role in the differential, typically accounting for about 3-4 percentage points of the overall differential. Given that the differential falls over the distribution, the relative share explained by observables does increase somewhat, but it is still always less than half of the differential.[11]

(Figure 5 here)

Finally, we employ the six reasons to decompose the mismatch penalty across the earnings distribution, comparing those who are matched and those who are severely mismatched because of the specified reason. Figure 6 shows a panel of six graphs, each one representing the decomposed mismatch penalty due to one of the six reasons for mismatch at each percentile of the earnings distribution.

(Figure 6 here)

The decompositions differ by reason. For most reasons, including pay, working conditions, career change, and family responsibilities, observed characteristics explain about a quarter of the mismatch penalty with some variation over the earnings distribution showing. But for workers mismatched due to location and a job not being available, observed characteristics explain a smaller portion of the mismatch penalty that is closer to about 15 to 20% across the earnings distribution.

5. Conclusion

[11] As in the previous footnote, splitting the sample by gender shows little qualitative difference in terms of the relative contribution of characteristics and returns. The results are available from the authors.

While there has been a good deal of research on the earnings penalty for educational mismatch, it has primarily examined differences at the mean level of earnings. This paper is the first to extend the analysis to examine the penalties across the earnings distribution using the unconditional quantile regression method. It is also the first to decompose the earnings differentials for mismatch penalties into 'explained' and 'unexplained' components to examine whether incomparability in earnings is mostly due to differences on average or in the distribution and to identify whether the reason for mismatch impacts the penalty across the distribution.

Using data from a large, nationally representative dataset of highly educated workers in the US, we find that worker characteristics explain a relatively small proportion of the earnings differentials, particularly for involuntary types of mismatch. In addition, quantile regressions suggest particularly large mismatch penalties among the low paid and for workers who are mismatched for involuntary reasons including a job not being available, family reasons, or job location. On the other hand, more voluntary forms of mismatch such as mismatch due to pay or a career change have substantially lower penalties. Like with the decomposition at the means, observed characteristics seem to play a relatively small role in explaining the overall differential at most points in the earnings distribution.

As there has been little research done on the distributional aspects of mismatch, the results from this paper suggest a number of interesting avenues for future research. For example, the sample of highly educated workers is quite selected, and it would be interesting to see if the results would be replicated in a more broadly representative sample of workers. Individual heterogeneity could also play a part in the results and the use of panel estimation would be an interesting extension. Finally, this research has only focused on the labor supply side of the market. Bringing in the labor demand side by including firm characteristics would add an interesting dimension to the research.

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Table 1. Descriptive Statistics for Selected Variables by Gender

Rates of mismatch	Full	Female	Male
Closely Matched	62.0%	62.0%	61.9%
Moderately Mismatched	25.8	24.5	26.8
Severely Mismatched	12.2	13.5	11.3
Rates of the reasons for severe mismatch			
Pay	29.5%	26.4%	32.1%
Conditions	9.0	9.6	8.5
Location	7.2	7.7	6.8
Career	19.0	18.5	19.3
Family	7.8	10.0	5.9
No job	20.2	20.8	19.7
Other	7.4	7.1	7.6
Mean Annual Pay			
Closely Matched	$42,938	$36,621	$47,419
Moderately Mismatched	39,736	34,151	43,362
Severely Mismatched	31,711	28,224	34,666
Median Annual Pay			
Closely Matched	$37,019	$32,308	$40,866
Moderately Mismatched	34,615	30,220	38,462
Severely Mismatched	25,641	23,558	27,885

Data are for 60,423 full-time workers from the 2015 NSCG.

Table 2. Selected Results from OLS Regression

Variable	Full	Female	Male
Moderately mismatched	-0.079*** (0.004)	-0.079*** (0.007)	-0.077*** (0.006)
Severely mismatched	-0.280*** (0.006)	-0.247*** (0.009)	-0.300*** (0.008)
Reasons for severe mismatch			
Pay and promotion opportunities	-0.106*** (0.010)	-0.059*** (0.015)	-0.140*** (0.013)
Working conditions	-0.269*** (0.017)	-0.199*** (0.024)	-0.319*** (0.025)
Location	-0.381*** (0.019)	-0.362*** (0.026)	-0.387*** (0.028)
Career change	-0.171*** (0.012)	-0.151*** (0.017)	-0.181*** (0.017)
Family-related	-0.469*** (0.019)	-0.426*** (0.023)	-0.493*** (0.030)
No job available	-0.464*** (0.012)	-0.406*** (0.017)	-0.508*** (0.017)
Other reason	-0.434*** (0.019)	-0.385*** (0.028)	-0.465*** (0.026)

Data are for 60,423 full-time workers from the 2015 NSCG. Results are from a log hourly earnings regression. Regressions control for gender, age, age squared, race, marital status, U.S. citizenship, experience, experience squared, tenure, tenure squared, broad degree field, highest degree, main task, disability status, employment sector, firm size, and region.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3. Oaxaca-style Decomposition Results: Matched workers versus moderately and severely mismatched workers

	Full	Female	Male
Total differential	0.167***	0.160***	0.172***
	(0.005)	(0.007)	(0.006)
Explained	0.021***	0.025***	0.023***
	(0.003)	(0.005)	(0.004)
% of Differential	13%	16%	13%
Unexplained	0.145***	0.135***	0.149***
	(0.004)	(0.007)	(0.006)
% of Differential	87%	84%	87%

Data are for 60,423 full-time workers from the 2015 NSCG. Results are from an Oaxaca decomposition that uses a log hourly earnings regression. Regressions control for gender, age, age squared, race, marital status, U.S. citizenship, experience, experience squared, tenure, tenure squared, broad degree field, highest degree, main task, disability status, employment sector, firm size, and region. Standard errors are in parentheses. The closely matched group is the reference wage structure.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4. Oaxaca-style Decomposition Results for Reasons of Pay and Job Not Available

	Full		Female		Male	
	Pay	No Job	Pay	No Job	Pay	No Job
Total differential	0.155***	0.593***	0.095***	0.521***	0.199***	0.633***
	(0.013)	(0.015)	(0.018)	(0.019)	(0.017)	(0.022)
Explained	0.042***	0.121***	0.037***	0.114***	0.046***	0.110***
	(0.007)	(0.008)	(0.010)	(0.011)	(0.009)	(0.011)
% of Differential	27%	20%	39%	22%	23%	17%
Unexplained	0.113***	0.472***	0.058***	0.407***	0.153***	0.523***
	(0.012)	(0.014)	(0.017)	(0.018)	(0.017)	(0.021)
% of Differential	73%	80	61%	78%	58%	83%

Data are for 60,423 full-time workers from the 2015 NSCG. Results are from an Oaxaca decomposition that uses a log hourly earnings regression. Regressions control for gender, age, age squared, race, marital status, U.S. citizenship, experience, experience squared, tenure, tenure squared, broad degree field, highest degree, main task, disability status, employment sector, firm size, and region. Standard errors are in parentheses. The closely matched group is the reference wage structure.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5. Means of Reasons for Mismatch at different parts of the wage distribution

	Moderately Mismatched	Severely Mismatched	Pay and Promotion	Working Conditions	Location	Career Change	Family-related	No Job Available	Other reason
Full									
0-10th pctile	25.0%	31.3%	4.6%	2.8%	2.8%	4.1%	3.9%	9.9%	3.2%
11th-25th pctile	27.4	17.2	4.6	1.7	1.3	2.9	1.3	4.2	1.3
26th-50th pctile	26.1	9.4	3.5	0.9	0.6	2.1	0.5	1.3	0.6
51st-75th pctile	26.1	7.8	2.9	0.7	0.6	1.8	0.4	1.0	0.4
76th-90th pctile	25.1	6.6	2.7	0.5	0.4	1.7	0.3	0.8	0.3
>90th pctile	23.5	6.6	3.0	0.4	0.3	1.7	0.3	0.5	0.3
Female									
0-10th pctile	25.9	29.3	3.8	3.6	3.1	4.0	4.5	8.6	2.6
11th-25th pctile	25.5	16.5	4.0	1.8	1.3	2.7	1.3	4.2	1.3
26th-50th pctile	24.0	9.9	3.5	0.9	0.6	2.2	0.8	1.4	0.6
51st-75th pctile	24.1	8.2	3.0	0.8	0.5	1.9	0.7	1.0	0.3
76th-90th pctile	23.7	7.6	2.8	0.8	0.4	2.0	0.6	0.7	0.4
>90th pctile	23.0	7.6	3.6	0.7	0.5	1.7	0.5	0.2	0.5
Male									
0-10th pctile	24.0	33.7	5.6	3.1	2.4	4.3	3.1	11.3	3.8
11th-25th pctile	29.8	17.9	5.2	1.6	1.2	3.0	1.2	4.2	1.4
26th-50th pctile	27.6	9.1	3.4	0.8	0.7	2.0	0.4	1.2	0.6
51st-75th pctile	27.3	7.6	2.8	0.7	0.7	1.7	0.3	1.0	0.4
76th-90th pctile	25.7	6.2	2.7	0.4	0.4	1.5	0.2	0.8	0.2
>90th pctile	23.6	6.3	2.9	0.4	0.2	1.7	0.3	0.6	0.3

Figure 1. Mismatch Penalty at Each Percentile of the Earnings Distribution for All Workers

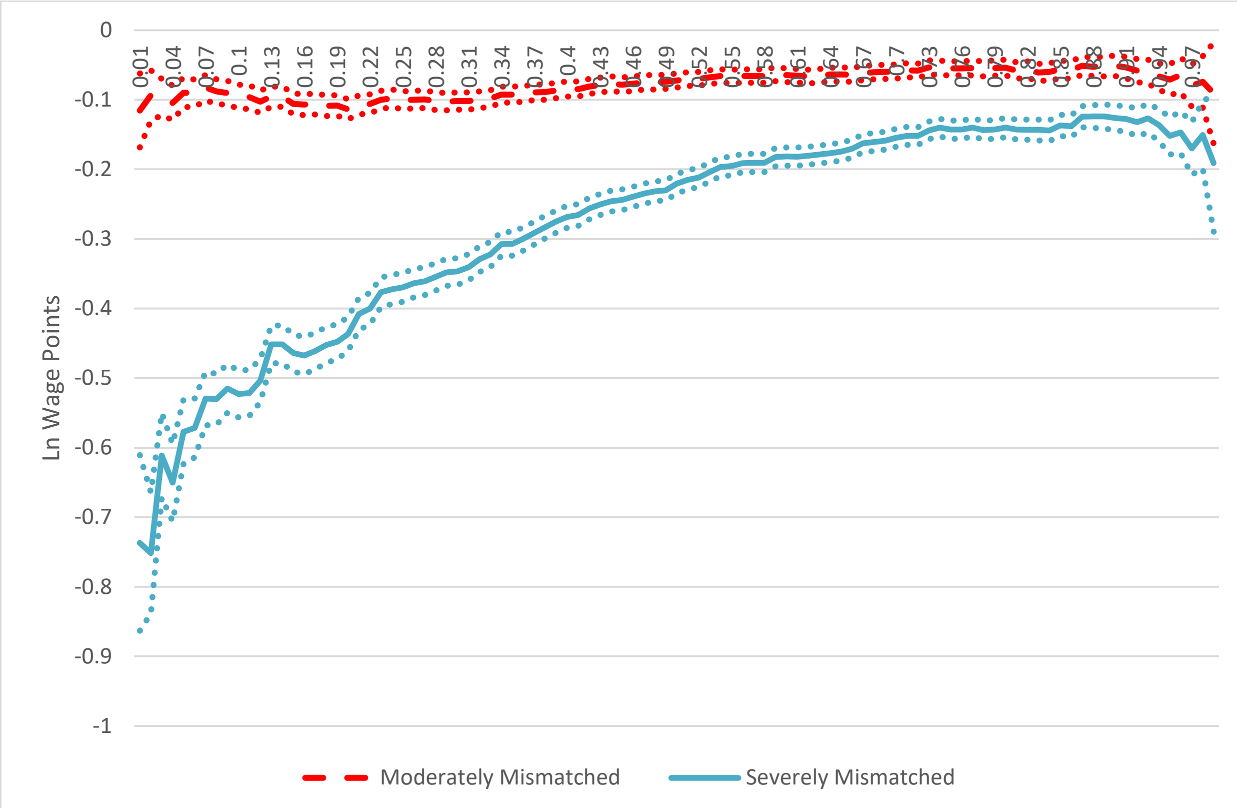

Figure 2. Mismatch Penalty at Each Percentile in the Earnings Distribution for Males

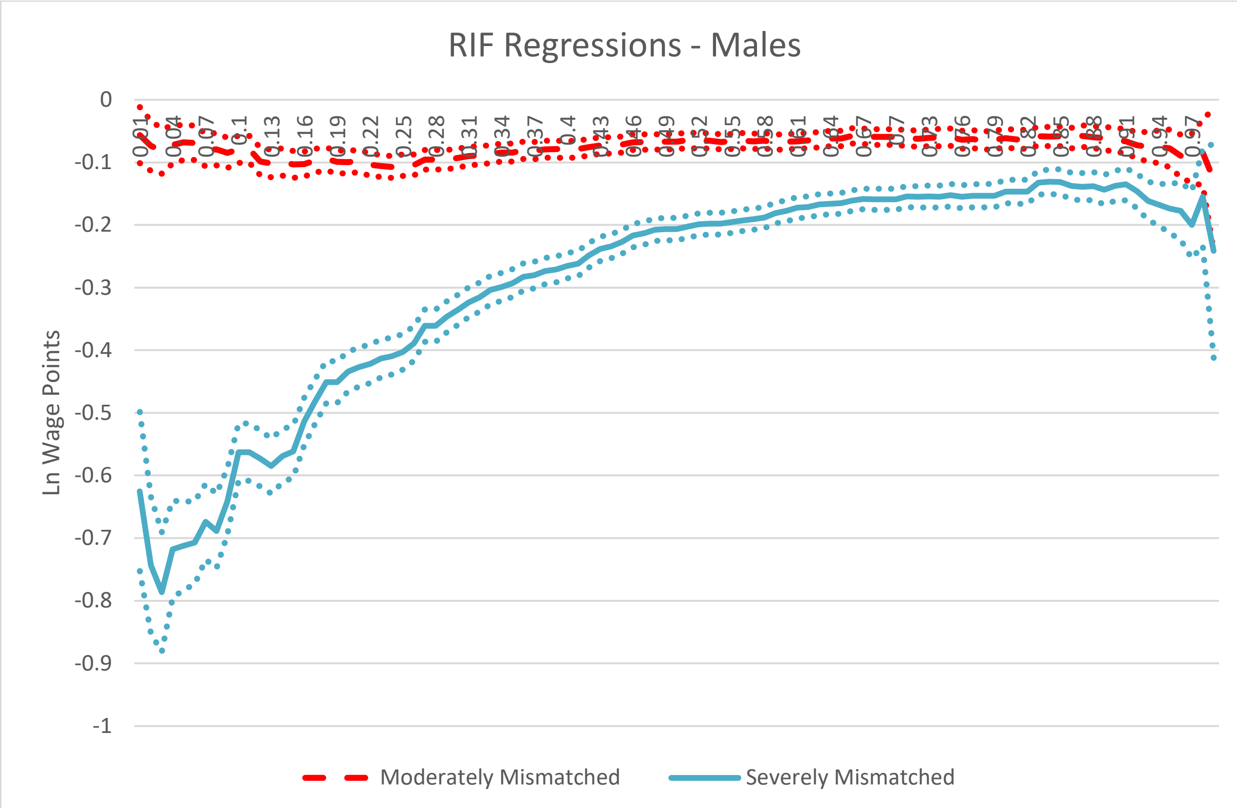

Figure 3 Mismatch Penalty at Each Percentile in the Earnings Distribution for Females

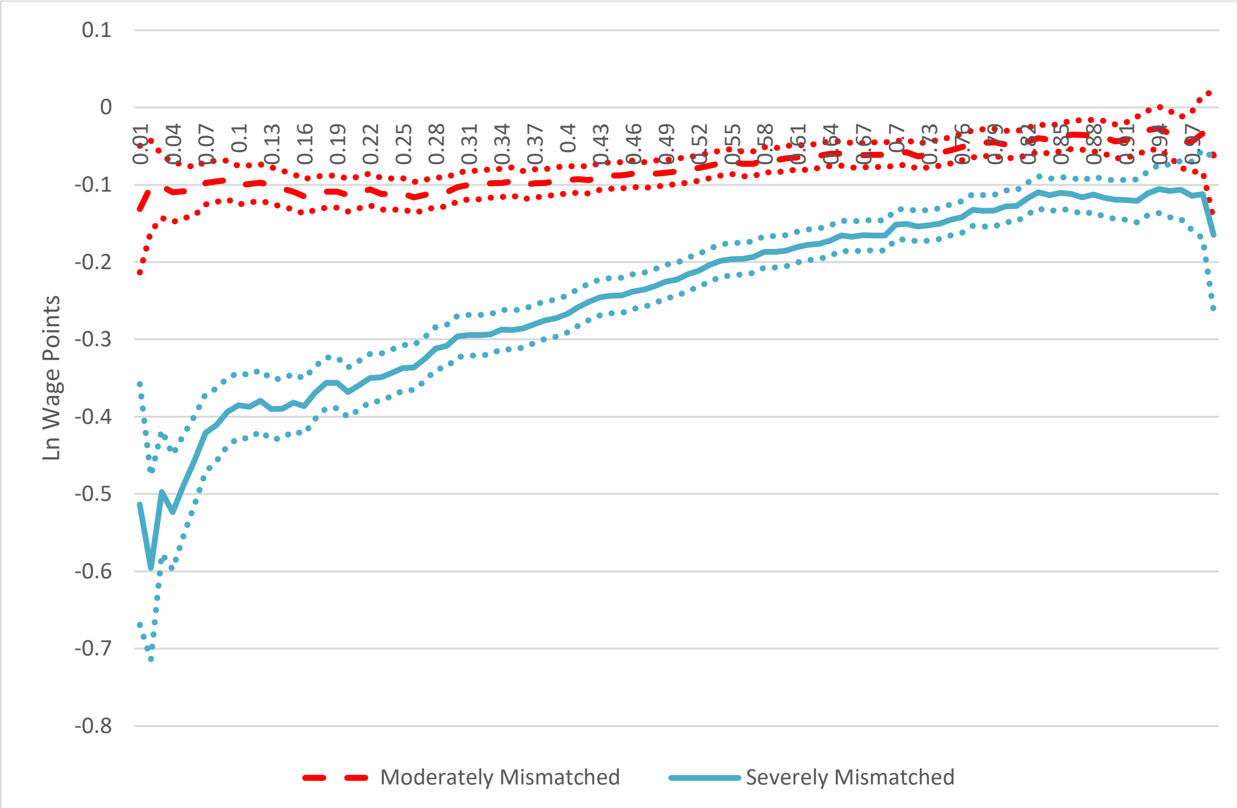

Figure 4. Mismatch Penalty by Reason at Each Percentile in the Earnings Distribution for All Workers

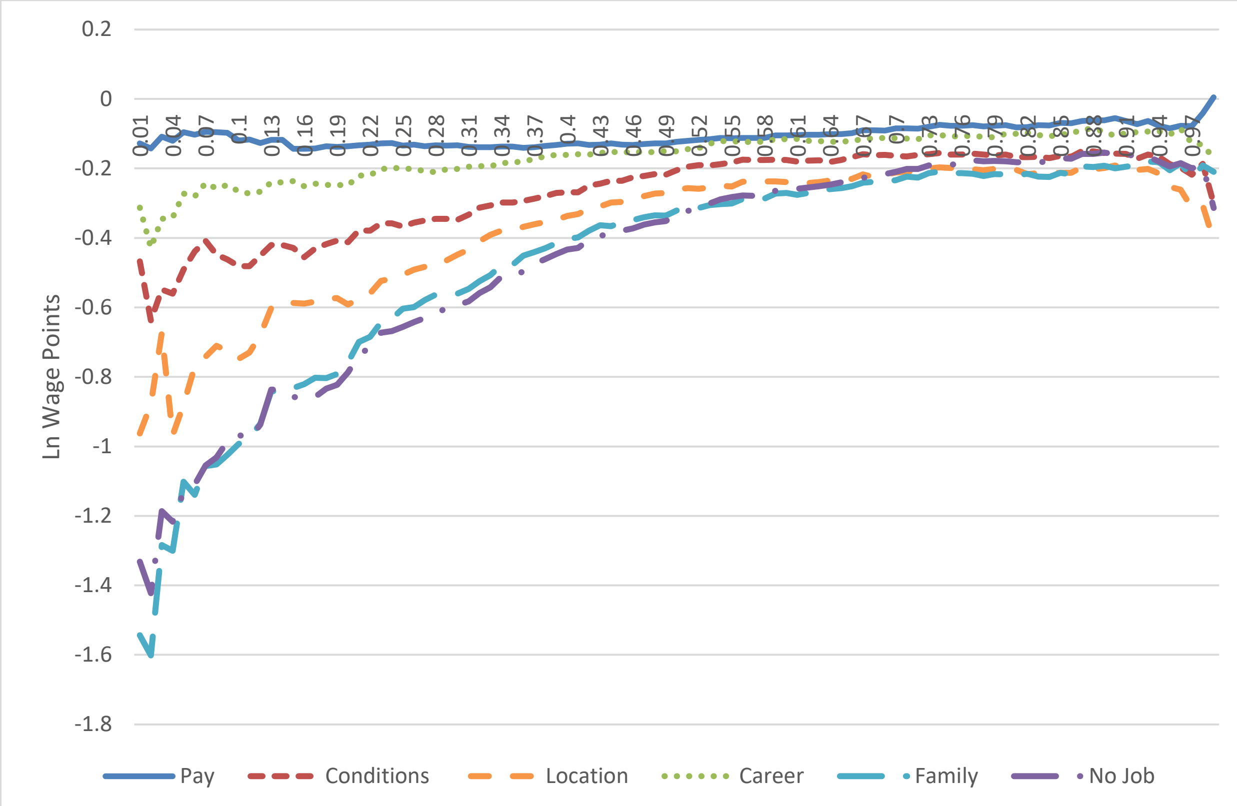

Figure 5. Decomposition of Mismatch Penalty at Each Percentile in the Earnings Distribution for All Workers

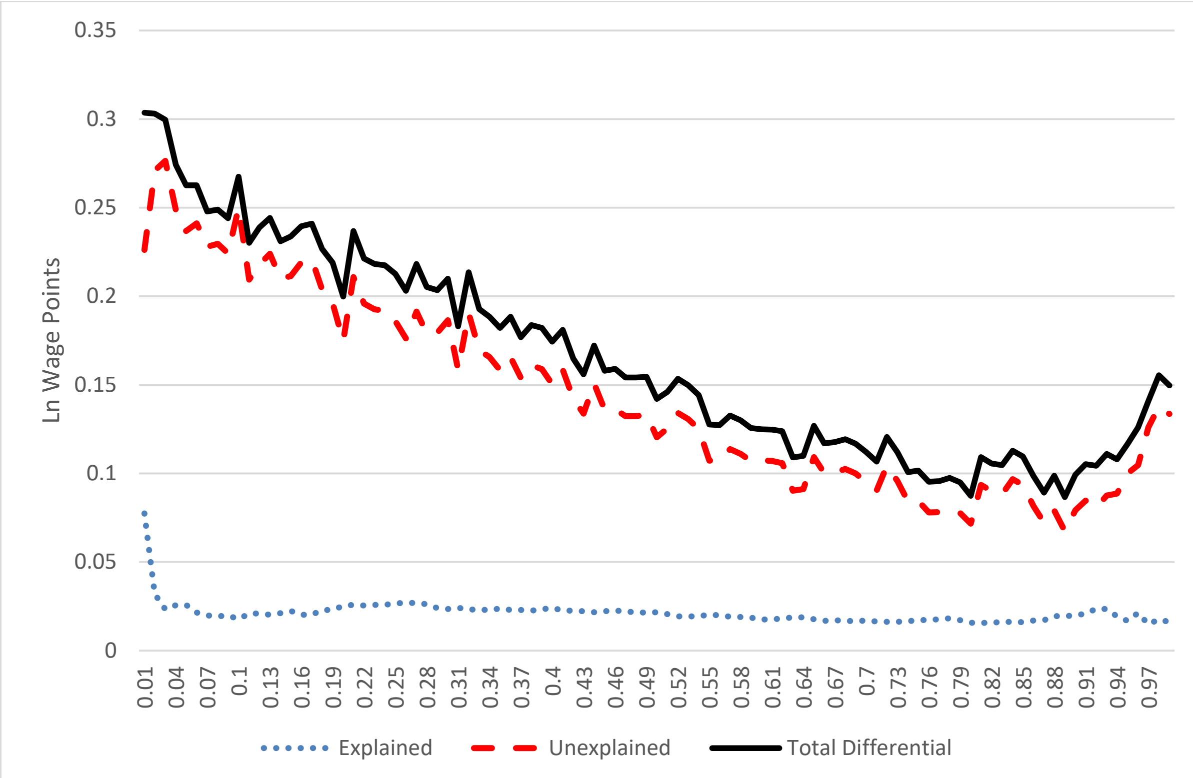

Figure 6. Decomposition of Mismatch Penalty at Each Percentile in the Earnings Distribution by Reason