Published in *Education Economics*, Vol. 19, iss. 3, July 2011: 253-74.

Educational Mismatch and the Careers of Scientists

Keith A. Bender John S. Heywood

Department of Economics and Graduate Program in Human Resources and Labor Relations
University of Wisconsin-Milwaukee, Milwaukee, Wisconsin USA

Abstract

Previous research confirms that many employees work in jobs not well matched to their skills and education, resulting in lower pay and job satisfaction. While this literature typically uses cross-sectional data, we examine the evolution of mismatch and its consequences over a career, by using a panel dataset of scientists in the US. The results show that both the incidence of mismatch and its negative consequences appear concentrated among those late in careers. This suggests that past studies of mismatch may exaggerate the degree of inefficiency in labor market matching.

Keywords: educational mismatch, panel data, science and engineering careers

JEL: J24, J44

Correspondence: Keith A. Bender, Department of Economics, University of Wisconsin-Milwaukee, P.O. Box 413, Milwaukee, WI 53201 USA; kabender@uwm.edu; (414) 229-4761.

Acknowledgements
The authors thank the US National Science Foundation (NSF) for access to the restricted data. However, the use of the NSF data does not imply NSF endorsement of the research methods or conclusions contained in this paper. The authors also thank participants in the inaugural IWAEE conference and two reviewers for helpful comments.

Educational Mismatch and the Careers of Scientists

1. Introduction

Recent empirical research has shown that a mismatch between the skills that workers have and the skills required in jobs results in adverse economic outcomes.[1] Mismatch has been shown to be negatively correlated with earnings (e.g. Bender and Heywood 2009; Robst 2007a and 2007b; Chevalier 2003; Borghans and de Grip 2000; Groot and Maasen van den Brink 2000), positively correlated with quits and job change (e.g. Bender and Heywood 2009; Wobers 2003; Allen and van der Velden 2001), and negatively correlated with job satisfaction (e.g. Baker *et al*. 2010; Bender and Heywood 2006; Moshavi and Terborg 2003; Belfield and Harris 2002). Several theoretical conjectures have been offered to explain why these adverse outcomes persist in equilibrium. First, government subsidies of higher education may lead to an oversupply of highly educated workers (Freeman 1976). Second, persistent informational asymmetries may exist between workers and firms about skill requirements (Tsang and Levin 1985; Malamud 2009). Third, institutional characteristics of the labor market, such as internal labor market considerations, can cause earnings to be based on observable characteristics of the worker and job and not directly on productivity (Thurow 1975). Yet, these conjectures seem, in part, *ex post* rationalizations as standard labor market theory would suggest that the disadvantages of mismatch would shrink or vanish as more information became available causing decisions on educational investments and match quality to improve.

The research confirming the adverse consequences of mismatch focuses primarily on cross sectional data. We follow a handful of more recent studies in focusing on panel data.

---

[1] See Hartog (2000) for a review of studies examining over-education, a form of mismatch in which the worker has more education than required for the job, and see Robst (2007a) for a discussion of general mismatch in which the worker's education is simply not relevant for the job.

Moreover, we are particularly interested in using panel techniques to explore the consequences and determinants of mismatch at different parts of a career. There are several compelling reasons for doing this. First, it informs the true consequences of mismatch. Even substantial initial negative consequences of mismatch could be modest in aggregate if they are quickly diminished by improving match quality or if the negative consequences attenuate rapidly. Second, it informs the competing theoretical conjectures by investigating the extent to which any movement toward equilibrium actually exists. Third, it informs our understanding of careers. This is of particular importance in the science- and engineering-based careers we investigate in which human capital requirements change rapidly often in response to frequent technological change. Reinvestment in rapidly depreciating skills becomes neither personally nor socially desirable as the length of the payback periods shrinks. Thus, late career mismatch may be both anticipated and not indicate large scale social inefficiency.

This paper examines these issues using the Survey of Doctoral Recipients (SDR), a micro panel dataset of U.S. workers who have received their PhD in a science or engineering discipline. We explore the likelihood of mismatch over a career and when in a career its consequences are most negative. We also explore the determinants of mismatch and the factors that cause mismatched workers to become matched. Finally, we explore the pattern in the reasons for mismatch by discipline, by period of career, and by gender. On balance, the evidence suggests that mismatch is more likely late in career, that it is harder to return to a job that matches a worker's education late in career and that the negative consequences of mismatch are greater late in career.

2. Background

In addition to the cross-section evidence on the negative consequences of mismatch, there is an emerging longitudinal literature to which we contribute. This literature grapples with the persistence and causes of mismatch. Thus, one view is that the mismatched have unmeasured characteristics that may be associated with negative outcomes and that mismatch is an indicator but not a cause of these outcomes. Using Australian longitudinal data, McGuiness and Wooden (2009) identify mismatched workers (over-skilled in their case) as moving rapidly between jobs, lacking in any additional confidence that they will find a better match and, indeed, finding "most remain either in jobs rarely where their skills are not adequately utilized or exit the workforce entirely." (p. 284) In this view, the mismatched may simply be workers of lower ability who never achieve the match their education would imply. This view can be contrasted with the reading of the UK longitudinal data by Lindley and MacIntosh (2008) who suggest that "over-education is a temporary phenomenon at the start of individuals' careers" and that examination of the transmission mechanisms reveals significant movement out of over-education. Yet, they do identify a minority of individuals for whom over-education is a reasonably permanent state extending over many years.[2]

Estimates of the consequences of mismatch also show variation. Verhaest and Omey (2009) show that over-education (as measured by a job analysis approach) has substantially smaller negative consequence on earnings for Flemish school leavers in panel estimates than in cross-section estimates. Nonetheless, the penalty remains statistically significant and there is a hint that the size of the penalty drops with years of work experience. Dolton and Siles (2008) examine the graduates of a single UK university using panel estimates but using an instrumental variable approach to correct for the measurement bias that is typically compounded in such

[2] While these studies examine, respectively, over skilling and over education, see Mavromaras *et al*. (2010) for an attempt to compare Australia and Britain on both the extent of over-skilling and its wage penalty.

estimates. Their ultimate panel estimates of the wage penalty for over-education look very similar in size to those from their cross-section suggesting that low ability may not be the primary source of the wage penalty.

These studies use very different samples and different measures of mismatch. In our sample of PhD holders in engineering and science, we focus on a measure of how closely the job is related to the doctoral degree. Thus, the educational level is held constant but the field of that education varies. The questions on mismatch probe whether or not the current job utilizes and reflects the doctoral education. Examining mismatch among these workers is crucial for several reasons. First, substantial governmental resources are devoted to educating these workers and improving their diversity. Yet, the growth in U.S. university students pursing advanced science degrees has slowed and trained scientists increasingly abandon scientific careers (Preston 2004). High degrees of mismatch may signal wasted governmental and, hence, societal resources. Second, managers of the highly skilled remain concerned with maximizing the productivity of their scientific workforce and mismatch has been shown to reduce job satisfaction and, potentially productivity, among research and development workers (Kim and Oh 2002). Third, the workers we examine play a crucial role in innovation and creating technological progress and their efficient deployment may be particularly critical. In this view mismatch may represent not only a loss in current efficiency but also reduced prospects for future growth.

While documenting the extent of mismatch and its consequences is important, understanding the causes and timing of mismatch is critical and has been understudied. From a market point of view, if initial (early career) mismatch rates are high and persist, this more likely evidences inefficiency in the functioning of the labor market. However, if mismatch emerges late in careers it is unlikely to reflect markets working inefficiently and could indicate just the opposite. In occupations with substantial and frequent changes in skill requirements, the skill sets learned while earning a PhD will depreciate over time. Moreover, reinvesting in the latest skills may not be economically sensible late in a career as the costs exceed the benefits. Thus, individuals may efficiently move from research oriented jobs to management-oriented ones (e.g. becoming a dean in a university or a manager in government or business). These transitions would be sensible when optimizing over a short remaining expected work life but would still get reported as mismatch. Thus, we posit a substantial theoretical and policy difference between early career mismatch that persists (likely inefficient) and late career mismatch in an era of rapidly changing skill requirements (likely efficient).

More generally, the labor economics literature is clear that many firms employ older workers but will not hire older workers (Hutchens 1986). This reflects a potentially efficient use of upward sloping age earnings profiles as a career incentive device to build loyalty and increase worker effort (Lazear 1979, 1981). A well-recognized consequence of such devices, is that older workers become less likely to find career jobs late in life once displaced from an original career job (Daniel and Heywood 2007; Heywood *et al*. 2010). Firms using such devices can afford neither to hire an older worker immediately into the reward phase of such profiles nor to start them over again at the beginning of such profiles (Heywood and Siebert 2009). Thus, independent of older workers' willingness to invest in recent skills, those mismatched late in life are less able to become properly matched. As these older mismatched workers are being compared to older workers in the reward phase of their earnings profile, the negative consequences of mismatch may be particular severe. Nonetheless, the presence of such older mismatched workers need not be evidence of inefficiency if the alternative is to abandon upward sloping age earnings profiles that generate efficient lifetime effort. Thus, to the extent that deferred compensation represents an important market phenomenon, it would result in older workers being mismatched for longer periods as they cannot easily find alternative career jobs.

Because of this inability to change jobs to find a better match, older workers will face larger relative penalties for mismatch given their position in the upward sloping age earnings profile.

Rapidly depreciating human capital combined with short pay back periods and the potential of efficient upward sloping age earnings profiles allows a series of predictions. First, older workers are more likely to be mismatched as they have less incentive to reinvest in rapidly changing skills. Second, mismatched older workers are less likely to move out of mismatch both because it requires such reinvestment and because firms with deferred compensation contracts would be unwilling to hire them into career jobs. Third, the penalty associated with mismatch will be greater for older workers as they become mismatched and possibly out of career jobs during the reward phase of deferred compensation contracts.

To the extent these predictions are confirmed, mismatch would appear less socially wasteful than might otherwise be the case Put differently, if young workers are less likely to be mismatched and if mismatched, they suffer small penalties and are fairly quickly matched, the concern over mismatches between education and jobs should be minimal. In turn, perhaps, less emphasis should be given to the government role in subsidizing education and the inefficiency of labor market matching and more emphasis should be given to what happens to workers and skills over the course of their careers.[3]

3. Data

The data for this analysis comes from the SDR conducted by the National Opinion Research Center on behalf of the US National Science Foundation. Started in 1993, the SDR is a longitudinal survey of a nationally representative sample of individuals who have received their

[3] Again, recognize that we our estimates reflect on the consequences of the mismatch between education and skills not specifically on the consequences of over- or under-education. See Robst (2008) for a comparison of the consequences of mismatch and of over-education.

PhD in a (hard or social) science, math, or engineering (SME) field who currently reside in the US. The initial survey, as well as new cohorts of new SME PhDs, comes from the NSF's Survey of Earned Doctorates. The survey is conducted roughly every two years and included in this study are data from the 1993, 1995, 1997, 1999, 2001, 2003 and 2006 waves. (See Bender and Heywood 2009, or http://sestat.nsf.gov for more details of the survey.)

The survey includes a wealth of information including data on socio-demographic, educational, and job characteristics.[4] Central to this study, in each survey, a question is asked that indicates the (self-reported) match between a person's job and his or her education. Specifically, the question asks: "Thinking about the relationship between your work and your education, to what extent is your work related to your doctoral degree?" The possible responses are "closely related," "somewhat related" and "not related." Those scientists working in jobs not related to their education are presumably using less of the knowledge, training and skills learned in that education. In this critical sense they may be identified as mismatched.

We will first summarize the pattern of which workers are mismatched and then present panel estimates the earnings consequences of mismatch. We will discuss the reasons for mismatch and estimate the determinants of moving into and out of mismatch. We will be sensitive to differences in out patterns by gender and by the three broad types of fields in our sample, hard science (including math), social science and engineering. We recognize that the likelihood of mismatch, the reasons for mismatch and the consequences of mismatch may differ critically among these separate samples and we have sufficient observations, as we will make clear, to provide reasonable estimates within each of these subsamples as well as for the sample as whole.

[4]Although there is a public use version of the data available, we need to employ a restricted data version of the survey, since information such as salary, detailed discipline of education and job, and race are masked in the public use version. More information about both versions of the survey can be found at the SESTAT website, or http://sestat.nsf.gov.

4. Results

Rates of mismatch

Table 1 gives the rate of mismatch for the different samples in the data. We note the large size of over 200,000 observations across the seven waves. The full sample (pooled over all waves) shows that more than two-thirds of the respondent observations report that their job is closely related to their education and eight percent indicate that the job and education are not closely related. The yearly pattern hints that mismatch has increased slightly over time. In 1997 the match rate was 69.3 percent, and it falls to 64.5 percent by 2006. It remains unclear whether this decline is due to the aging of the sample or a general increase in mismatch (we return to this issue in our estimation). Males are more likely than females to be somewhat or very mismatched (25.5 percent compared to 22.5 percent and 8.3 percent to 7 percent). Workers with a social science degree are more likely to be matched compared to those with a hard science/math or engineering degree as might be anticipated if more technical skills depreciate more quickly resulting in mismatch later in career. Finally, and unsurprisingly, workers in academia are much more likely to be matched, while nearly 50 percent of workers in the business sector report some degree of mismatch (see Bender and Heywood, 2009, for more on differences by sector of the economy).

(Table 1 about here.)

In order to explore the role of career, we use several approaches. First, at the bottom of Table 1, we examine the percentages of mismatch by career stages: 'Early in Career' (10 years or less since degree), 'Middle of Career' (11 to 24 years since degree) and 'Late in Career' (25 or more years since degree). These percentages reveal that those early in their career are more likely to be closely matched (71.3 percent compared to 66.3 and 63.1 percent) and less likely to be severely mismatched (5.9 percent compared to 8.5 and 10.2 percent). In a bit more detail, in

Figure 1, we use the pooled sample to examine the proportion of workers who are in the three match categories at different ages. In general it seems that the lowest rates of mismatch do happen at young ages with over 70 percent reporting a close educational match until their late 30's. Indeed, rates of educational mismatch start at relatively low levels and gradually climb to about 10 percent in the early to mid 70s.

(Figure 1 about here.)

However, individuals may start their PhDs some years after their college education. This, combined with the heterogeneity in the length of time in the completion of a PhD, suggests it might be more informative to examine the relationship between educational mismatch and the number of years since an individual's PhD degree. Figure 2 has these results. The general pattern is similar. If anything, the decrease in those closely matched is faster than in Figure 1. At the start of careers 75 percent of workers report being matched but toward the end of careers this drops to only 45 percent of workers. The associated increase in mismatch is not only among the most mismatched, but the share in the middle mismatch category also increases. These figures indicate that much of the mismatch may be late in a career and may, as a consequence, not be as reflective of labor market inefficiency. We will provide estimations that account for other determinants later when we examine transitions between mismatch statuses. These estimates will support the increase in mismatch late in career.

(Figure 2 about here.)

The earnings consequences of mismatch

Most of the previous literature uses cross sectional data to find a decrease in earnings of 10-20 percent associated with mismatch (see Robst 2007a, for example). This subsection examines whether these findings are robust to using fixed effects estimation. Table 2 reports selected results for the worker fixed effect models estimated for the different subsamples listed in the first column. The first row presents the critical results from the full sample. Workers who are somewhat mismatched suffer a decrease in log wages of 0.024 or slightly more than two percent. Workers who are very mismatched suffer a decrease in log wage of nearly 0.114 roughly in line with cross-sectional estimates (Robst 2007; Bender and Heywood 2009). These fixed effect estimates hold constant the individual specific earnings component and use the variation in match status across individuals to provide the earnings coefficients. Thus, the critical sample size becomes not the number of overall observations but the number of transitions in match status which introduce this variation. As shown in the third column of Table 2, there exist over 30,000 transitions in mismatch status over the 13 years of the panel. We note that one consequence of the fixed effect estimates is that only time varying parameters add to the estimations summarized in Table 2.

(Table 2 about here.)

Breaking our sample into males and females and estimating separate fixed effect estimates within each subsample generates only modest gender difference in the salary reduction for the somewhat mismatched. Yet, the influence of severe mismatch appears about three percentage points greater for women. Returning the gender together but breaking out broad disciplinary subsamples also shows some differences. The separate estimates on the samples of workers with PhDs in the Social Sciences and of workers with PhDs in Engineering show no statistically significant reduction in salary, *ceteris paribus*, for being somewhat mismatched. On the other hand, those with degrees in the Hard Sciences and Math have a reduction of almost four percent for being somewhat mismatched. This last group also has the largest reduction in salary for severe mismatch – approximately 14 percent. This compares with approximately 11 percent for Social Scientists and a relatively small six percent for Engineers.

Broadly then, the results remain in the ballpark of previous studies, even after controlling for fixed effects. The earnings penalties appear to be largest for hard scientists and smallest for engineers. At a minimum, these new results make it unlikely that previous results stemmed largely from sorting in which the inherently less able (those with lower earnings potential) were more likely to be mismatched. The apparent absence of such strong sorting would tend to discount the idea that mismatch happens to a selected sample and be more supportive of the possibility that it is often part of a career cycle. We note that the number of transitions, even within our subsamples, is large enough that it is unlikely that our results flow from a few influential outlying observations.

The results from Figures 1 and 2 indicate that rates of mismatch increase with age or years since degree. We now focus on the earnings penalty early in careers and late in careers. As we've suggested, mismatch late in career may be economically rational as human capital accumulated during graduate education can depreciate meaning that skill sets can become out of date and new investments do not pay for themselves. This may naturally lead to jobs that are no longer related to education. If this results in separation from a career track job, it may have more serious consequences for older workers who otherwise would be in the reward phase of an upward sloping age earnings profile.

Table 3 contains results for panel estimates of earnings penalties for those early in their career (ten years or less since degree) or late in their career (25 years or greater since degree). Again, we provide estimates on the full sample and for separate samples by gender and by broad degree field group. The full sample results indicate that being mismatched later in one's career carries a greater penalty. For being somewhat mismatched, the penalty is less than two percent for those in the early career stage, but it is about five percent for those in the later stages of their career. While the penalty increases for a more severe mismatch, the gap also grows with a penalty of around five percent for those early in career but of nearly twenty percent for those late in career. The gender specific results mirror generally this pattern. Interestingly, there seems to be little difference across genders for those early in their careers, while being slightly mismatched has the stronger penalty for late career women and more severe mismatch has the stronger penalty for males in their late career. The results by broad field group are interesting as it is clear that hard scientists face significant earnings penalties in both early and later career while all three fields face earnings penalties in late career. Together with the larger penalties in late career compared to early career for hard scientists, this provides further evidence that the influence of mismatch is concentrated in late career. Again, these panel estimates hold constant the worker fixed effects meaning that the estimates are generated by the within-worker variation in earnings as they change mismatch status. Nonetheless, our number of transitions is adequate to assure reasonable estimates. While the later career stage has fewer observations, it is clear that number of transitions is not proportionately smaller. In other words, those in late career face a higher chance of a transition helping to boast the number of transitions during that period.

(Table 3 about here.)

Reasons for mismatch

Determinants

Table 4 reports fixed effects (conditional) logit results for those early and late in careers. Since the mismatch variable has three values and the fixed effects logit only allows for a binary dependent variable, there are two specifications of the dependent variable here. The first, denoted as ‘Any Mismatch’, equals one if the mismatch variable indicates that the worker’s education relates to their job (partly matched) or that the education is not at all related to the job (very mismatched). The second, denoted ‘Very Mismatched’, equals one if the mismatch variable indicates only that the job and education are not at all related (thus, a more severe form of mismatch).

(Table 4 about here.)

Focusing on the former, we observe that controlling for fixed effects, moving into the government or business sector generates more mismatch compared to moving into the academic sector, but only for those early in their career. Relative to primarily doing research, other main activities such as management, computers, or other nonteaching duties, generates more mismatch in either sector. This effect is similar across career stages. Such evidence fits with the notion that those moving out of research, which tends to happen later in a career, move into mismatch. Along a similar theme, an additional year since degree increases the chance of mismatch. Moreover, this influence emerges with a stronger marginal effect on mismatch among those late in their career. Those who become disabled late in their career are also more likely to be mismatched, while there is little effect for those early in the career. The results are largely similar when examining movement into the most mismatched category in the final two columns. We emphasize that as these are conditional logit estimates, the worker dimensions that do not vary by time such as gender, race and the broad field of degree cannot be part of this estimation.

Reasons for severe mismatch

Workers in the survey who report that their job and education are not at all related also identify the most important reason that their job and education are not at all related. The options for response include pay and promotion opportunities, working conditions (hours, equipment, working environment), job location, change in career or professional interests, family-related reasons, job in degree field not available, and an 'other' category. While it is left to the researcher to interpret exactly what might be implied by each response, it is valuable to explore the pattern of responses in light of our hypotheses.

Table 5 examines the relative frequency of the reasons for mismatch and does so for those early and late in careers by various subsamples. In general, the most frequent reasons for mismatch regardless of the career stage is being mismatched due to ‘pay and promotion’, ‘career’, and ‘no job’. Those in the early part of the career, however, are slightly more likely to be mismatched because of pay and promotion (22.1 compared to 19.3 percent) and also somewhat more likely to report that no job is available (26.7 compared to 18.3 percent). On the other hand, those at the end of their career are much more likely (38.9 compared to 25.6 percent) to report that their career (career stage?) is causing them to be mismatched. This would be consistent with progression in one’s career away from one’s education toward management or other tasks. Thus, mismatches are concentrated late in careers and the major reason given for mismatch at that time is the career itself, a reason much less likely to be given early in career. Family reasons are less likely to explain mismatch late in career and mismatch due to location or other reasons show little variation by career stage.

(Table 5 about here.)

There exists some variation across the samples. Women are more likely to report being mismatched because of family reasons regardless of the stage of the career, compared to men. They are also less likely than men to say that pay and promotions are the main reason for mismatch. Academics are more likely to say that their mismatch is due to their career (particularly for those late in their career), while those in business are more likely to say that pay and promotions are the main reason, particularly early in the career. Interestingly those in government late in career have a relatively high percentage of the mismatched saying that there was no job available. While there are differences by broad degree type for those early in the career (hard scientists and engineers are mismatched due to pay and promotion and career while social scientists are more likely to say that there is no job available), there are fewer differences late in careers.

We now return to our panel estimates of earnings to incorporate the reasons for mismatch. Recall that the reasons for mismatch are only given for those who identify a severe mismatch. Thus, our fixed effects log earning equations include the one general dummy for being somewhat mismatched and then a series of mutually exclusive dummies indicating the primary reason for severe mismatch where all the coefficients are relative to those who are fully matched. The results are shown in Table 6 which mimics our early results for Table 3 although the subsamples are now shown across the columns. Each subsample is as before and, again, they are divided into early and late in career. Thus, the numbers of transitions generating the aggregate variations in mismatch status are identical to those shown in Table 3. The current difference is that the single composite measure of severe mismatch is broken down into the causes of that severe mismatch. This implies that the variation for the individual reasons for mismatch is generated by the number of transitions into or out of that cause. Thus, variation can be caused by aggregate variation, a move into severe mismatch and by changes in the cause of mismatch among those reporting mismatch.

(Table 6 about here.)

The full sample results in the first column of Table 6 make clear that the cause of mismatch that behaves least like the others is that for pay and promotion. While there is variation in magnitudes across the other causes, they all tend to generate negative and statistically significant coefficients that are larger in late career than in early career. There exists no influence on earnings for being mismatched for reasons of pay or promotion. This hints that some workers may willing accept severe mismatch to pursue pay and promotion. The alternative may well be less severe mismatch and the pay reduction or eventual severe mismatch for other reasons with the greater pay reduction. Indeed, the influence of this cause of severe mismatch can even be positive in some subsamples. Women and engineers actually enjoy a double digit log earnings advantage when mismatched for reasons of pay and promotion early in the career suggesting even greater willingness to accept mismatch. Men suffer a disadvantage late in career even when mismatched even for these reasons but it is the smaller than the disadvantage associated with any other cause of mismatch late in career.

The other cause that seems most muted in its influence of mismatch on earnings is mismatched for career reasons. Here there is never a significant disadvantage early in career but one typically develops by late career. This hints some workers early in their career may be mismatched but don't pay a penalty as those around them who are matched may still be investing in human capital and not capturing the return on their match, say in post-doctoral or other training positions. Nonetheless, the general pattern for all causes other than pay and promotion is a reduction in earnings that emerges as large late in career.

Mismatch and transitions into and out of mismatch

In this subsection we focus on the transitions between match statuses that have generated our earlier earnings penalties. In starting we emphasize our early point, shown with the mean proportions, that mismatch is more common later in the career. To provide that emphasis we use the available controls and simply estimate the determinants of being mismatched. We take as a dependent variable the dichotomous indicator of being mismatched (either somewhat or severely) and estimate a logit within each of the now familiar samples. In each estimate, the crucial comparison is that across career stage. We compare the influence of the broad middle career and of the late career with the early career influence on being mismatched. The marginal effects of this comparison are shown in column 1 of Table 7. In the full sample, those in middle career are a statistically significant 3.3 percentage points more likely to be mismatched than those early in career. Those in late career are an even larger 7.5 percentage points more likely to be mismatched. Not only is the second point estimate statistically different from zero but it is statistically different from the estimate for those in middle career. It is also a meaningfully large estimate as the total share of observations reporting mismatch is 32.3 percent.

(Table 7 about here.)

There exists interesting variation across our subsamples but the broad message does not change. The likelihood of mismatch grows for both men and women with their career stage. The size of that growth is larger for women as they are more likely to be mismatched in late career than are men. The extent of mismatch and growth in mismatch over the career is particularly large for those in hard sciences but the concentration of mismatch in late career is clear for both social scientists and engineers as well.

Having established more concretely our earlier point about the importance of career stage, we now examine the transition of those who are mismatched moving back to a match. This examination can shed light on the efficiency of the labor market in creating matches. If the probability of moving out of mismatch is low, the inefficiency would be greater all else equal. Yet, for a given probability of moving out of mismatch, the distribution of that probability remains important. Again, if probabilities are much lower for those late in career we are less concerned about inefficiency and suspect we may be observing the consequences of upward sloping age earnings profiles reflecting deferred compensation.

To examine these transitions we start with workers when we first observe them in mismatch (either somewhat or severe) and we follow them for three subsequent waves (typically six years from initial identification) and observe how many of them become matched. The columns on the left hand side of Table 8 show us the the share of those moving from any mismatch to fully matched. The full sample figure shows us that 53.1 percent of those mismatched move to a match within the observation window suggesting a fair amount of movement. While the likelihood of making such a transition does not monitonically decline with career stage, it is highest in early career. In other words, relative to other career stages, those in early career are mostly likely eliminate their mismatch. This remains true in each of subsamples. Social scientists are the most likely to move to matched from mismatched with hard scientists are generally the least likely.[5] The gender differences appear modest.

(Table 8 about here.)

We now estimate the determinants of transitioning from mismatch to match using the available controls and doing so within each of our samples. The dichotomous variable of having made the transition within the three years is the dependent variable in logit estimates. The independent variables include career stage (middle and late relative to early) and the other explanatory variables such as main work activity, years since degree, race, disability status, citizenship status, marital status and region of residence. We take these explanatory variables at the stage of initial observation of a mismatch. The results are shown in the second column of Table 7 and largely support what was shown in the simple proportions. In the full sample, it is the early stage workers who are most likely move from mismatch into match. This sits beside the fact that the early stage began with the fewest mismatched workers. The difference in transition probability between the early stage and the other two stages is particularly large for women and particularly small for engineers.

A second set of transitions provides a fuller picture. We now augment our estimate of the determinants of mismatch with one of determinants of transitions into mismatch. This reverses

---

[5] Attrition into retirement may be influencing the observed patterns. Indeed, separate estimates by the authors show that among those late in career, the mismatched are more likely to retire, even after controlling for demographic characteristics, salary, broad degree field, employment sector, and main job activity (results available from the authors). The fact that the mismatched are more likely to retire biases upward the share of workers who eventually report a match from the selected sample that remain employed.

the procedure we just described by starting with workers when we first observe them as matched and following them for three waves to observe how many of them become mismatched. As shown on the right hand side of Table 7, the full sample mean probability of making a transition to mismatch conditional upon being matched seems to decline modestly with career stage but this is not consistent across the subsamples. It appears to be generated largely by the hard scientists.

We again take the making of a transition as the dependent variables in logit estimation using the available controls and estimating within each of the samples. In the full sample, the pattern evident in the sample statistics vanishes as there is not an evident pattern over career stage. Yet, this hides offsetting patterns among the broad fields. Hard scientists appear more likely to make the move away from being matched, conditional on being initially matched, in the early stage of their careers. Together with the evidence that this is also the career stage in which hard scientists are more likely to move into a match, conditional on being mismatched, it suggests a lot of churning or change in status early in career for hard scientists. Yet, we emphasize that despite the pattern of the transitions, it remains the case that there are the fewest total mismatches for hard scientists in the early stage. The transition out of being matched shows a different pattern for engineers and social scientists (to a lesser extent). They are less likely to move out of being matched early in career compared to the other career periods.

While we have not been presenting the many full estimates behind the coefficients summarized in Table 7 because presenting all of them would be prohibitively long, they are available from the authors. However, we do include the full sample estimates of the two transitions probabilities in Appendix Table 1. They reveal the pattern by career stage summarized in Table 8 but are worth briefly discussing to focus on the other controls. Perhaps most important is that engineers are less likely to make the move to being matched compared to social scientists and that hard scientists are even less likely to make the move to being matched compared to social scientists. Similarly, engineers and hard scientists are both much more likely to transition out of being matched. This pattern supports the view that high technology fields with rapidly depreciating skills make moving into mismatch more likely and regaining a match less likely. Women are less likely to find a match once mismatched. They are also more likely to become mismatched once matched. The racial patterns seem less easily explicable with Blacks and Hispanics being more likely to find a match once mismatched and yet Blacks, Asians and Hispanics all being more likely to become mismatched once matched. This pattern suggests more churning among statuses for racial minorities than for Whites.

We note that transitions between statuses may be associated with changes in jobs or employers. While we think these changes are at least as much an effect of growing mismatch as a cause, we included additional indicators in the estimates summarized in the Appendix Table 1 (available from the authors). We use indicators in each wave of whether or not the employee is in the same job and whether or not the employee is with the same employer. Thus, there are four possibilities in each wave, the workers is with the same employer in the same job, with the same employer but in a different job, with a new employer doing the same job or with a new employer doing a different job. In our estimates of the transition probabilities we found a clear pattern but it did not influence the pattern of other results. Changes in mismatch status in either direction are associated with a new job either with the old or with a new employer. Changes in employer but keeping the same job are not associated with an increased chance of status change. This seems sensible as the question that forms the dependent variable directs workers to compare their education with their job and so job changes appear to be associated with changes in mismatch status.

While this picture of differences in mismatch and mismatch transitions over career stages is shaded, several points deserve restatement. First, it is clear from the sample statistics and our estimations that mismatch is most likely late in the career and least likely early in a career. Second, the ability to transition back into being matched once mismatched is greatest early in the career. Third, the transitioning into mismatch once matched differs by broad flied. For engineers and social scientists, such transitions are least likely in early career while for scientists it is most likely in early career. Thus, while the pattern of churning among hard scientists must be noted, the overall pattern appears to support our broad hypothesis showing that mismatch is more prevalent late in career and that mismatch early in a career is more likely to be resolved into a match. Finally, we note that hard scientists and engineers are both less likely to transition into a match once mismatched and more likely to transition into mismatch once matched when compared to social scientists.

5. Conclusions

The literature on both over-education and mismatch is large yet only a few studies have examined their consequences and determinants in a panel framework. Our examination does not measure over-education but does examine the degree of mismatch between education and the current job. It adds value by making use of the panel framework. This framework allows testing whether the results from the cross-sectional estimates are robust and, critically, allows examining what happens to educational mismatch over workers' careers. Again, while mismatch among our sample of PhD scientists may include those who are over-educated, this study has examined a concept that is not vertical (too little or too much education) but is simply about the quality of the match between education and the job.

The results make clear that mismatch is more likely late in careers. The respondents themselves have the option of identifying that their career or career stage is a reason for mismatch. A far larger share of workers makes this identification late in career than early in career. These findings are consistent with much of mismatch being a consequence of career evolution. Moreover, while the panel estimates confirm an earnings penalty from mismatch, the penalties are much larger, several times larger, for those late in their career. Those who are mismatched early in career are substantially more likely to move into match than are those mismatched in middle or late career. In general, the incidence, consequences and duration of mismatch are disproportionately associated with workers late in their career. These findings are consistent with the view that mismatch may not be as large an indicator of inefficiency as broad general statistics would imply. Instead, it is concentrated late in career and may reflect both the natural evolution of those careers and perhaps the use of deferred compensation as an efficient incentive device.

We recognize that our findings are limited by a sample that focuses on those for whom career issues may be paramount. Moreover, the scientific workforce likely faces more rapidly changing human capital requirements and faster depreciation than do typical workers. In addition, the highly educated workers in our sample may be more likely to find themselves in long-term employment relationships that make use of deferred compensation schemes. Thus, it remains an open question whether these findings generalize. Nonetheless, our examination stresses that mismatch may mean fundamentally different things at different points in a career. Recognizing this emphasizes our point that broad levels of mismatch and greater inefficiency need not always go together. Late career mismatch can be a byproduct of labor markets working appropriately from a full career prospective.

References

Allen, J. and R. van der Velden. 2001. Education mismatches versus skill mismatches. *Oxford Economic Papers* 53: 434 – 52.

Baker, J.G., R.K. Craft, and M.G. Finn. 2010. Advantages and disadvantages: job satisfaction of science and engineering baccalaureates completing doctoral verses professional degrees. Southern Utah University, Department of Economics, Working Paper.

Belfield, C.R. and R.D.F. Harris. 2002. How well do theories of job matching explain variations in job satisfaction across educational levels? Evidence for UK graduates. *Applied Economics* 34: 535 – 48.

Bender, K.A. and J.S. Heywood. 2006. Job satisfaction of the highly educated: The role of gender, academic tenure, and comparison income. *Scottish Journal of Political Economy*, 53, no. 2: 253-79.

Bender, K.A. and J.S. Heywood. 2009. Educational mismatch among Ph.D.s: Determinants and consequences. In *Science and engineering careers in the United States: An analysis of markets and employment*, ed. by R.B. Freeman and D.F. Goroff, Chicago, IL: University of Chicago Press and National Bureau of Economic Research, pp. 229-55.

Borghans, L. and A. de Grip (eds). 2000. *The overeducated worker*, Cheltenham, UK: Edward Elgar.

Chevalier, A. 2003. Measuring over-education. *Economica* 70: 509 – 31.

Daniel, K. and J.S. Heywood. 2007. The determinants of hiring older workers: UK evidence. *Labour Economics* 19: 197 – 222.

Dolton, P.J. and M.A. Siles. 2008. The effects of over-education on earnings in the graduate labour market. *Economics of Education Review* 27: 125 – 39.

Freeman, R. 1976. *The over-educated American*, New York: Academic Press.

Groot, W. and H.M. van den Brink. 2000. Over-education in the labor market: A meta-analysis," *Economics of Education Review* 19: 149 – 58.

Hartog, J. 2000. Over-education and earnings: Where are we, where should we go? *Economics of Education Review* 19: 131 – 147.

Heywood, J.S., U. Jirjahn and G. Tsertsvardze. 2010. Hiring older workers and employing older workers: German evidence. *Journal of Population Economics* 23: 595 – 615.

Heywood, J.S. and W.S. Siebert. 2009. Understanding the labour market for older workers," IZA Working Paper No. 4033.

Hutchens, R.M. 1986. Delayed payment contracts and a firm’s propensity to hire older workers," *Journal of Labor Economics* 4: 439 – 57

Kim, B. and H. Oh. 2002. Economic compensation compositions preferred by R&D personnel of different R&D types and intrinsic values. *R&D Management* 32: 47 – 59.

Lazear, E. 1979. Why is there mandatory retirement? *Journal of Political Economy* 87: 1261 – 84.

Lazear, E. 1981. Agency, earnings profiles, productivity and hours restrictions. *American Economic Review* 71: 606 - 20.

Lindley, J. and S. McIntosh. 2008. A panel data analysis of the incidence and impact of over-education. Sheffield Economic Research Paper Series, No. 2008009.

McGuinness, S. and M. Wooden. 2009. Overskilling, job insecurity and career mobility. *Industrial Relations* 48: 265 – 87.

Malamud, O. 2009. Discovering one’s talent: Learning from academic specialization. NBER Working paper 15522.

Mavromaras, K., S. McGuinness, N. O'Leary, P. Sloane and Y.K. Fok. 2010. The problem of overskilling in Australia and Britain. *Manchester School* 78: 219 – 41.

Moshavi, D. and J. R. Terborg. 2002. The job satisfaction and performance of contingent and regular customer service representatives: A human capital approach. *International Journal of Service Industry Management* 13: 333 – 47.

Robst, J. 2008. Overeducation and college majors: Expanding the definition of mismatch between schooling and jobs. *Manchester School* 76: 349 – 68.

Robst, J. 2007a. Education and job match: The relatedness of college major and work. *Economics of Education Review* 26: 397 – 407.

Robst, J. 2007b. Education, College Major and Job Match: Gender Differences in the Reason for Mismatch. *Education Economics* 15: 159 – 175.

Tsang, M.C. and H. Levin. 1985. The economics of overeducation. *Economics of Education Review* 4: 93 – 104.

Thurow, L. 1975. *Generating inequality,* New York, NY: Basic Books.

Verhaest, D. and E. Omey. 2009. Overeducation and earnings: Some further panel-data evidence. Hogeschool-Universiteit Brussels, Economics and Management Research Paper 2009/08.

Wolbers, M. 2003. Job mismatches and their labor-market effects among school-leavers in Europe. *European Sociological Review* 19: 249 – 66.

Table 1: Rates of educational match and mismatch across samples

Sample	Fully matched	Somewhat matched	Severely mismatched
Full	67.3%	24.7%	8.0%
Wave			
1993	67.3	25.1	7.6
1995	68.2	34.1	7.8
1997	69.3	23.4	7.3
1999	68.4	24.1	7.6
2001	68.1	24.3	7.7
2003	65.8	25.3	8.9
2006	64.5	26.8	8.8
Male	66.3	25.5	8.3
Female	70.5	22.5	7.0
Hard science	64.0	26.9	9.1
Social science	76.7	17.6	5.6
Engineering	61.4	30.3	8.4
Academic	81.4	15.7	3.0
Government	62.7	29.8	7.6
Business	53.1	33.5	13.4
Early career	71.3	22.8	5.9
Middle career	66.3	25.3	8.5
Late career	63.1	26.8	10.2

Notes: Data are from 1993-2006 SDR. The percentages are weighted by SDR sample weights. The full sample has 200,574 observations over 60,676 separate workers.

Table 2: Panel estimates of the effect of mismatch on (log) earnings, by gender and degree field

	Coefficient on		
Sample	Somewhat matched	Severely mismatched	# observations (# transitions)
Full sample	-0.024*** (-4.49)	-0.116*** (-9.37)	200,574 (30,597)
Female	-0.030*** (-2.61)	-0.139*** (-5.18)	56,394 (8,017)
Male	-0.022*** (-3.67)	-0.108*** (-7.87)	144,180 (22,580)
Hard science	-0.038*** (-5.50)	-0.142*** (-8.98)	115,296 (18,684)
Social science	0.004 (0.31)	-0.109*** (-3.36)	49,889 (5,681)
Engineering	-0.015 (-1.50)	-0.058** (-2.39)	35,389 (6,232)

Notes: Each row represents a separate regression based on a different sample. Coefficients are relative to a worker reporting that education and job are closely related. Other time-varying controls include marital status, disability indicator, sector of employment (academic, business or government), citizenship, main activity at work (research, teaching, computer, management, and other), years since degree, and regional indicators. Standard errors are clustered for individuals and t-statistics are in parentheses under coefficient estimates. *, **, *** indicate 1%, 5%, and 10% significance, respectively.

Table 3. Panel estimates of earnings penalties for mismatch by career stage, gender, and degree field

Sample	Somewhat matched	Severely mismatched	# observations (# transitions)
Early career			
Full sample	-0.018** (-2.39)	-0.054*** (-3.51)	83,660 (10,308)
Female	-0.019 (-1.30)	-0.077* (-1.93)	30,792 (3,632)
Male	-0.019** (-2.21)	-0.069*** (-3.52)	52,868 (6,676)
Hard science	-0.030*** (-3.00)	-0.121*** (-4.73)	45,292 (5,918)
Social science	-0.016 (-0.71)	-0.054 (-0.97)	19,227 (1,636)
Engineering	0.002 (0.17)	0.015 (0.50)	19,141 (2,754)
Late career			
Full sample	-0.054*** (-3.55)	-0.199*** (-5.96)	39,886 (7,565)
Female	-0.115** (-2.58)	-0.111 (-1.40)	5,367 (1,035)
Male	-0.045*** (-2.81)	-0.211*** (-5.81)	34,519 (6,530)
Hard science	-0.059*** (-3.10)	-0.210*** (-5.11)	24,646 (4,955)
Social science	-0.033 (-0.95)	-0.169* (-1.84)	10,100 (1,402)
Engineering	-0.060 (-1.60)	-0.181** (-2.48)	5,140 (1,208)

Notes: Each row is a separate regression based on a different sample. 'Early Career' is ten or fewer years since degree. 'Late Career' is 25 or greater years since degree. Coefficients are relative to a worker reporting that their education and job are closely related. Other time varying controls include marital status, disability indicator, sector of employment (academic, business or government), citizenship, main activity at work (research, teaching, computer, management, and other), years since degree, and regional indicators. Standard errors are clustered for individuals and t-statistics are in parentheses under coefficient estimates. *, **, *** indicate 1%, 5%, and 10% significance, respectively.

Table 4. Determinants of mismatch within career stages: fixed effect (conditional) logit

	Any mismatch		Severely mismatched	
Variable	Early career	Late career	Early career	Late career
Government sector	0.532***	0.175	0.557***	0.136
	(5.07)	(0.94)	(2.66)	(0.45)
Business sector	0.596***	0.191	0.650***	0.216
	(8.28)	(1.45)	(5.05)	(1.16)
Main activity: teaching	-0.111	-0.204*	-0.256	-0.429*
	(-1.14)	(-1.68)	(-1.08)	(-1.79)
Main activity: management	0.600***	0.589***	0.798***	0.461***
	(9.01)	(6.82)	(6.76)	(3.33)
Main activity: computers	0.484***	0.692***	0.767***	-0.018
	(5.99)	(3.39)	(5.83)	(-0.09)
Main activity: other	0.606***	0.638***	0.878***	0.421***
	(7.88)	(6.29)	(6.70)	(2.74)
Years since degree	0.023***	0.047***	0.038***	0.039***
	(3.21)	(6.12)	(2.75)	(3.13)
Disability	0.035	0.201**	0.266	0.091
	(0.32)	(2.08)	(1.27)	(0.59)
Naturalized citizen	0.282	0.315	0.135	-0.927
	(0.75)	(0.62)	(0.19)	(-1.02)
Noncitizen	0.128	0.844	-0.128	-0.979
	(0.33)	(1.18)	(-0.18)	(-0.95)

Notes: Other time varying variables controlled for but not reported are: marital status, discipline of current job, and region of residence. Reference groups include: employed in academic sector, main work activity is research, and citizenship status. Panel estimates are clustered for individuals. Numbers in parentheses are t-statistics. *, **, *** indicate 1%, 5%, and 10% significance, respectively.

Table 5. Most important reasons for severe mismatch at different career stages

Sample	Pay and promotion	Working conditions	Location	Career	Family	No job	Other
Early Career							
Full	22.1%	5.1%	4.6%	25.6%	8.1%	26.7%	7.7%
Female	17.7	7.0	5.1	26.1	13.8	22.8	7.6
Male	24.3	4.2	4.4	25.4	5.2	28.7	7.8
Academic	13.5	5.0	4.3	32.0	8.9	24.3	11.9
Government	17.9	5.5	5.0	22.6	9.2	25.4	14.4
Business	25.5	5.1	4.7	23.9	7.7	27.7	5.5
Hard science	22.1	5.0	4.3	27.3	8.0	25.6	7.7
Soc science	18.9	6.0	3.4	18.5	12.0	32.4	8.8
Engineering	24.2	4.7	6.3	26.7	5.7	25.5	7.0
Late career							
Full	19.3	4.9	5.2	38.9	4.6	18.3	8.7
Female	13.6	5.5	5.1	37.6	13.6	17.2	7.5
Male	20.3	4.7	5.3	39.2	3.0	18.5	8.9
Academic	18.5	4.9	5.1	46.2	4.8	12.0	8.5
Government	14.5	3.4	6.1	34.2	6.1	26.0	9.6
Business	20.2	5.0	5.1	37.5	4.4	19.0	8.6
Hard science	19.5	4.7	4.6	38.1	5.0	19.7	8.3
Soc science	17.2	5.3	5.8	41.4	3.0	15.3	12.0
Engineering	20.8	5.1	7.7	40.0	4.9	14.7	6.8

Notes: SDR respondents only record most important reasons for mismatch when they are severely mismatched. Sample sizes for the 'Early career' and 'Late career' for the full sample are 4,832 and 4,118, respectively. No sample size for any subsample is below 402.

Table 6. Fixed effects log earnings regressions for reasons for severe mismatch by sample

		Sample					
Variable	Career Stage	Full	Female	Male	Hard science	Social science	Engineering
Somewhat matched	Early career	-0.017** (-2.28)	-0.018 (-1.24)	-0.018** (-2.13)	-0.029*** (-2.90)	-0.016 (-0.69)	0.002 (0.20)
	Late career	-0.053*** (-3.57)	-0.113** (-2.54)	-0.044*** (-2.75)	-0.055*** (-2.92)	-0.033 (-0.95)	-0.062* (-1.66)
Pay and promotion	Early career	0.033 (1.19)	0.114* (1.72)	-0.001 (-0.04)	-0.035 (-1.05)	0.037 (0.35)	0.142*** (2.95)
	Late career	-0.075 (-1.49)	0.130 (0.88)	-0.096* (-1.80)	-0.082 (-1.31)	0.036 (0.26)	-0.142 (-1.33)
Working conditions	Early career	-0.200*** (-2.74)	-0.269** (-2.14)	-0.132* (-1.72)	-0.178* (-1.87)	-0.422** (-2.26)	-0.048 (-0.38)
	Late career	-0.501*** (-5.12)	-0.763** (-2.47)	-0.452*** (-4.51)	-0.569*** (-4.60)	-0.498* (-1.87)	-0.199 (-1.55)
Location	Early career	-0.042 (-1.30)	-0.007 (-0.14)	-0.061 (-1.47)	-0.098** (-1.96)	0.038 (0.40)	0.037 (0.97)
	Late career	-0.195** (-2.52)	-0.149 (-0.78)	-0.203** (-2.42)	-0.209** (-2.24)	-0.259 (-1.43)	-0.088 (-0.56)
Career	Early career	-0.038 (-1.19)	-0.057 (-0.95)	-0.028 (-0.76)	-0.064 (-1.39)	0.008 (-0.09)	-0.006 (-0.14)
	Late career	-0.159*** (-4.22)	-0.135 (-1.36)	0.163*** (-3.98)	-0.156*** (-3.32)	-0.205** (-1.98)	-0.126* (-1.77)
Family	Early career	-0.186*** (-3.06)	-0.171* (-1.81)	--0.190*** (-2.84)	-0.324*** (-4.01)	0.060 (0.51)	-0.059 (-0.46)
	Late career	-0.411* (-1.95)	0.019 (0.12)	-0.696** (-2.12)	-0.363 (-1.50)	-0.160 (-0.62)	-0.800 (-1.11)
No job	Early career	-0.101*** (-3.84)	-0.080 (-1.41)	-0.115*** (-3.96)	-0.117*** (-3.10)	-0.104 (-1.46)	-0.076** (-2.18)
	Late career	-0.197*** (-4.20)	-0.040 (-0.31)	-0.227*** (-4.53)	-0.186*** (-3.29)	-0.183 (-1.38)	-0.278** (-2.45)
Other reason	Early career	-0.188*** (3.51)	-0.250* (-1.83)	-0.163*** (-3.42)	-0.326*** (-3.93)	-0.017 (-0.19)	-0.033 (-0.42)
	Late career	-0.439*** (-5.04)	-0.386 (-1.36)	-0.440*** (-4.90)	-0.565*** (-4.26)	-0.245* (-1.66)	-0.173 (-1.07)

Notes: These estimations are mirrors of those in Table 3 with the exception of breaking out the cause of severe mismatch.
* statistical significance at 10% ** statistical significance at 5% *** statistical significance at 1%

Table 7: Logit regressions of matching, marginal effects

Sample	Variable	Probability of mismatch	Any mismatch to fully matched	Fully matched to any mismatch
Full sample	Middle career	0.034***	-0.068***	0.001
		(7.73)	(-6.37)	(0.16)
	Late career	0.077***	-0.055***	-0.004
		(12.48)	(-3.59)	(-0.33)
Female	Middle career	0.017**	-0.083***	0.008
		(2.44)	(-3.99)	(0.57)
	Late career	0.084***	-0.090**	-0.007
		(6.01)	(-2.13)	(-0.24)
Male	Middle career	0.040***	-0.063***	-0.002
		(7.52)	(-5.06)	(-0.23)
	Late career	0.079***	-0.049***	-0.005
		(11.19)	(-2.91)	(-0.41)
Hard science	Middle career	0.041***	-0.105***	-0.029***
		(6.51)	(-7.71)	(-3.02)
	Late career	0.090***	-0.073***	-0.028**
		(10.54)	(-3.85)	(-2.09)
Social science	Middle career	0.026***	-0.067***	0.028**
		(4.08)	(-2.74)	(2.23)
	Late career	0.052***	-0.095**	0.015
		(5.41)	(-2.46)	(0.73)
Engineering	Middle career	0.011	0.048**	0.058***
		(1.01)	(1.96)	(2.79)
	Late career	0.065***	0.002	0.066**
		(3.94)	(0.05)	(1.98)

Notes: Coefficient estimates have been converted into marginal effects. Respondents must be in the sample for at least three waves after the mismatch occurs. Other variables controlled for (where applicable) in all subsamples: gender, race, marital status, field of PhD, sector of employment, disability status, marital status, region of residence, citizenship status and main activity. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Numbers in parentheses under marginal effects are t-statistics.

Table 8: Percent of workers who change in and out of fully matched by career stage

	Any mismatch to fully matched				Fully matched to any mismatch			
	Part of career stage				Part of career stage			
Sample	Any	Early	Middle	Late	Any	Early	Middle	Late
Full sample	53.1	57.5	49.3	52.2	34.4	35.0	34.3	32.0
Female	54.1	58.5	48.2	50.8	33.6	33.9	33.3	30.7
Male	52.8	57.0	49.6	52.3	34.7	35.5	34.6	32.1
Hard scienc	51.6	58.0	46.4	51.6	36.1	37.6	35.3	32.9
Soc science	58.2	62.4	55.6	55.1	25.7	24.3	27.8	24.5
Engineering	53.6	53.5	54.4	51.6	42.0	40.7	45.3	42.3

Note: The sample consists of those workers who can be observed for three waves following their initial observations as mismatched.

Appendix Table 1. Selected results from logit regressions of matching

Variable	Any Mismatch to Fully Matched	Fully Matched to Any Mismatch
Middle career	-0.068***	0.001
	(-6.37)	(0.16)
Late career	-0.055***	-0.004
	(-3.59)	(-0.33)
Female	-0.032***	0.028***
	(-2.78)	(3.63)
Black	0.076***	0.059***
	(3.39)	(3.71)
Hispanic	0.107***	0.043**
	(4.74)	(2.75)
Asian	-0.011	0.069***
	(-0.68)	(5.58)
Other race	0.039	0.011
	(0.82)	(0.35)
Divorced	0.017	0.039***
	(0.94)	(2.98)
Widowed	0.001	-0.066*
	(0.02)	(-1.70)
Never married	-0.040***	0.030***
	(-2.78)	(3.10)
Disability	-0.032	-9.4E-5
	(-1.54)	(-0.01)
Hard science	-0.074***	0.096***
	(-5.80)	(11.69)
Engineer	-0.037**	0.115***
	(-2.22)	(9.49)
Government Sector	-0.089***	0.096***
	(-5.30)	(7.66)
Business Sector	-0.175***	0.149***
	(-15.61)	(18.15)
#obs	12,793	23,971
(% transition)	(53.1%)	(34.4%)

Notes: Coefficient estimates have been converted into marginal effects. Respondents must be in the sample for at least three waves after the mismatch occurs. Reference groups are: male, white nonHispanic, currently married, no disability, social science degree, and academic sector. Other variables controlled for all subsamples: region of residence, citizenship status and main activity. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Numbers in parentheses under marginal effects are t-statistics.

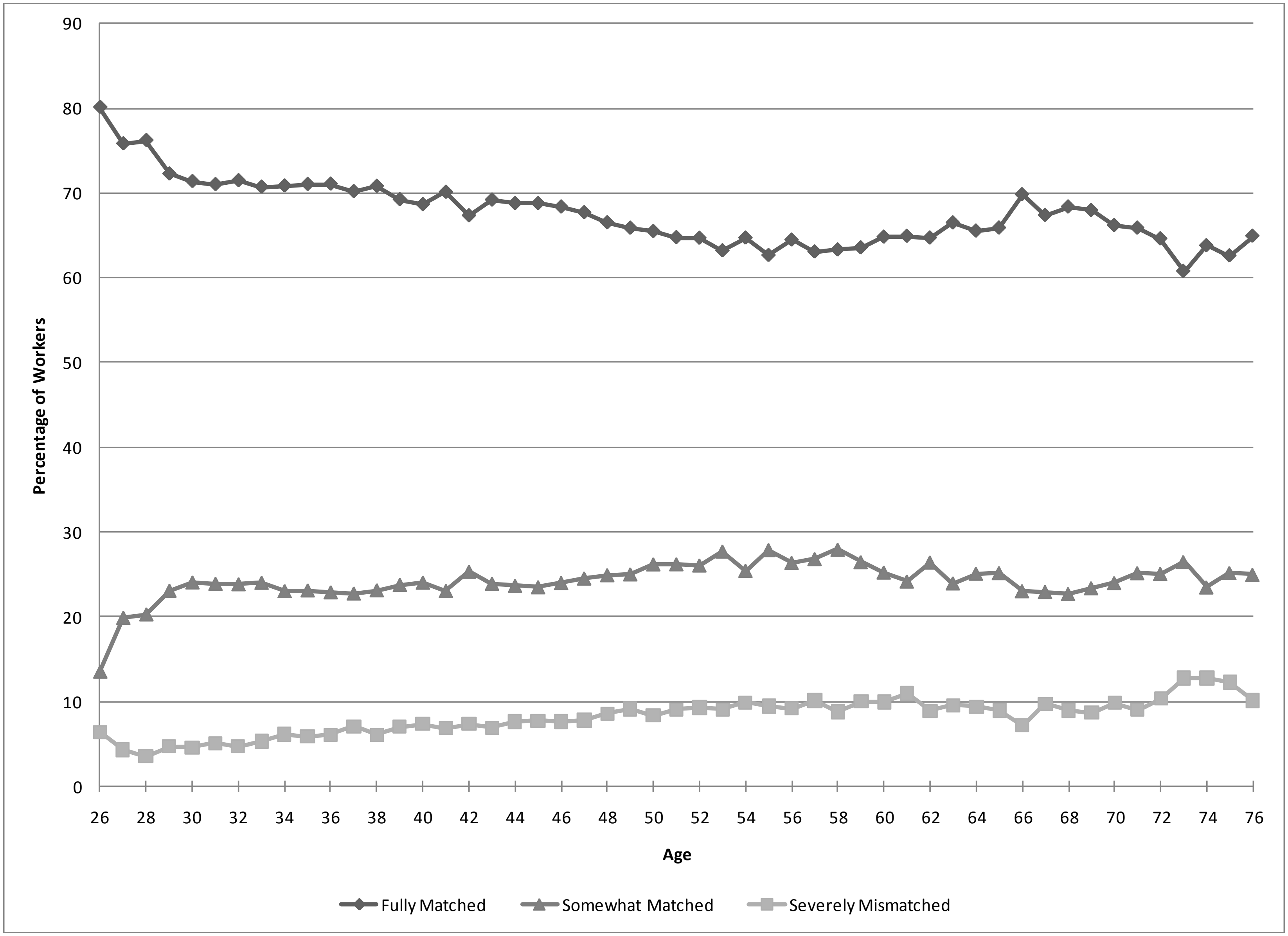

Figure 1. Rates of educational match and mismatch by age

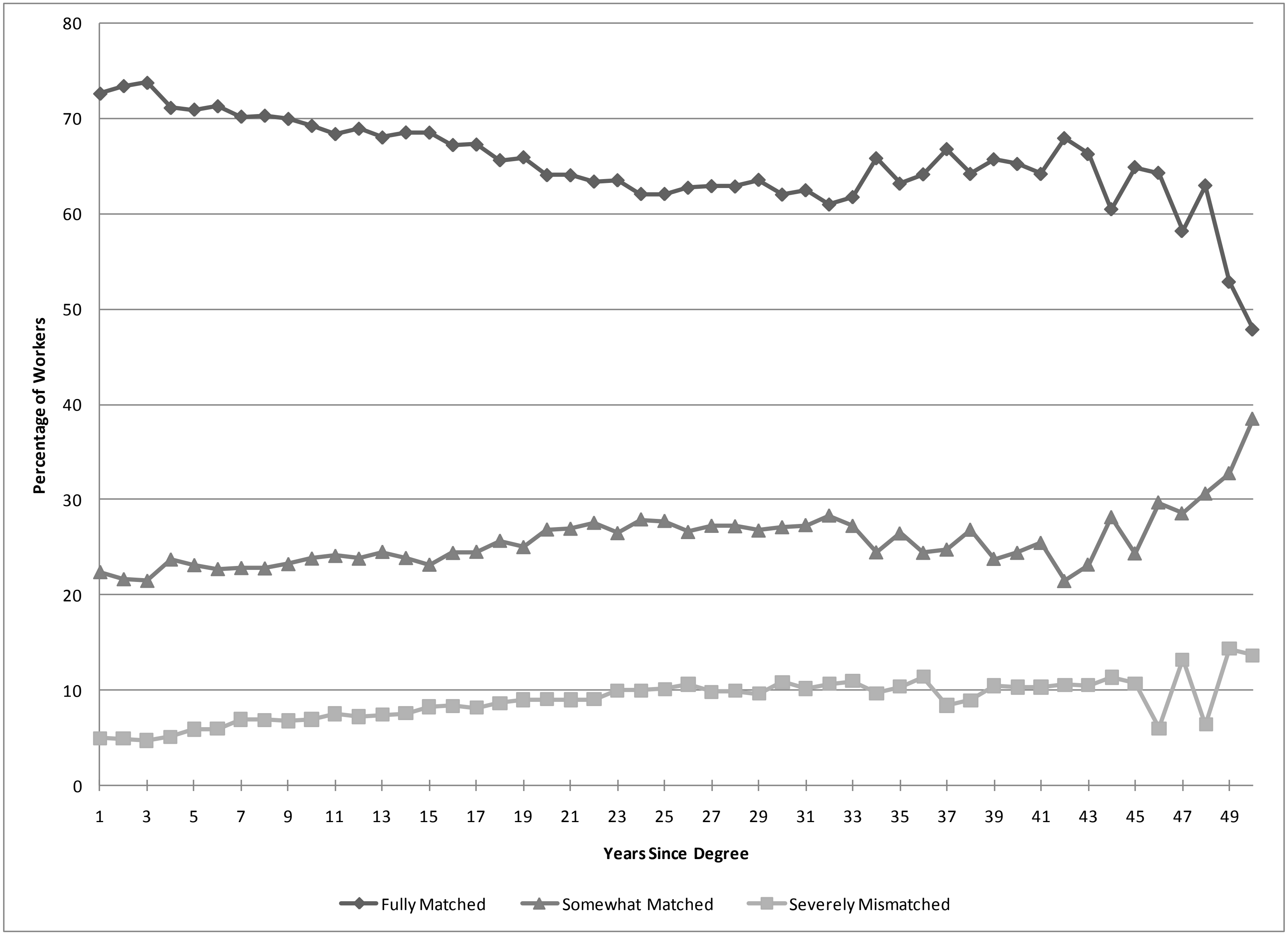

Figure 2. Rates of educational match and mismatch by years since degree