Forthcoming, *Economics of Education Review*, 2013

Educational Mismatch and Self-Employment

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Abstract

Previous research on educational mismatch concentrates on estimating its labor market consequences but with a focus on wage and salary workers. This paper examines the far less studied influence of mismatch on the self-employed. Using a sample of workers in science and engineering fields, results show larger earnings penalties for mismatch among the self-employed but no diminution in job satisfaction. Moreover, the reasons for mismatch among the self-employed differ dramatically by gender.

Keywords: educational mismatch, self-employment, earnings, job satisfaction

JEL Codes: I2, L26, J24

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Version: 21 January, 2013

1. Introduction

The public and private costs of education are huge, causing economists, policy makers, and the public to be concerned about whether or not workers utilize the skills acquired during education in the labor market. Responding to this concern, researchers examine the causes and effects of mismatches in the skills required for the job and the skills acquired during education. While mismatch can be in the type of skills or simply the quantity (over- or under-education), the research finds that mismatch generates lower earnings, lower job satisfaction, and higher turnover, *ceteris paribus*. These findings appear robust to differences in country, time period, or whether the data analysis is cross-sectional or panel in nature.

Thus, while the effects of mismatch are fairly well established, the research so far has focused only on wage and salary workers, meaning that there has been no research to date on the relationship between mismatch and self-employment. Since self-employment is often seen as a driver of economic growth and particularly in employment growth (see for example, Birch 1987, and Neumark, Wall & Zhang 2008, for the US; Burges 1991, for Australia; Audretsch & Fritsch 2003, for Germany although Haltiwanger, Jarmin, & Miranda 2010, offers a contrasting view), the study of how mismatch interacts with self-employment enriches our understanding of both educational mismatch and this critical area of policy interest.

2. Educational Mismatch Brief Literature Review

Previous research on educational mismatch focuses on the effects of being employed in a job that is not well matched with a wage and salary worker's education. For example, there is a robust finding that mismatch is correlated with lower earnings (e.g. Chevalier 2003; Borghans & de Grip 2000; Groot & Maassen van den Brink 2000). Other researchers (e.g. Wolbers 2003;

Allen & van der Velden 2001) have found mismatch to be positively correlated with quits and job turnover, while others (Bender & Heywood 2006; Moshavi & Terborg 2003; Belfield & Harris 2002) have found that it is correlated with lower job satisfaction. Results tend to hold even in the case of panel data (e.g. Mavromaras & McGuinness 2012; Bender & Heywood 2011; Mavromaras, McGuinness, O'Leary, Sloane, & Fok 2010; McGuinness & Wooden 2009; Verhaest & Omey 2009; Lindley & MacIntosh 2008). In general, it also does not seem to qualitatively matter whether one is considering vertical mismatch ('too much' or 'too little' education) or horizontal mismatch (whether the skills match the job being done), although the magnitudes of the consequences of mismatch are different depending on how one defines mismatch.[1]

One area not considered in the mismatch literature so far is whether there are differences across different types of employment – namely whether there are differences across wage and salary jobs or self-employment jobs. The research mentioned above is not explicit about the kinds of jobs where mismatch might occur and whether the effects of mismatch might differ across types of employment. Indeed, the seemingly closest related paper is one by Nordin, Persson & Rooth (2010) which uses Swedish data to examine mismatch at the occupational level, but that paper does not explicitly examine the self-employed.

Why might educational mismatch occur for the self-employed? Certainly part of the story might be the reason for self-employment. If it is voluntary, then it may be a way to find a better educational match if one is not available in the wage and salary sector. This might generate lower mismatch for the self-employed. On the other hand, mismatch might be higher if

[1] Why these effects are generated is an open question. Several explanations have been given in the literature: government subsidies of education may lead to an oversupply of the highly educated (Freeman 1976), informational asymmetries may exist about skills requirements (Tsang & Levin 1985; Malamud 2009), and institutional characteristics of the labor market may mask productivity and so workers are paid on observable characteristics (such as education) that are assumed to be correlated with productivity (Thurow 1975).

workers self-employ because they have difficulties in obtaining a wage and salary job or if there are compensating differentials to self-employment that overcome a good educational match in a wage and salary job. Additionally, some of the self-employment literature finds that entrepreneurs are 'jacks-of-all-trades' types with skills in many fields (Lazear 2004), which may explain why they work in a field that differs from their educational background.

Research also shows that the self-employed in the US tend to have higher levels of education than wage and salary workers (Hipple 2004) and are, thus, more likely to be overeducated. Perhaps this partially explains the finding by Hamilton (2000) that the self-employed have lower earnings, *ceteris paribus*, although it does not square with the findings by Evans & Leighton (1987; 1989) that the returns to education are higher for self-employed men, compared to men employed in wage and salary jobs. Further adding to this complication is the finding (e.g. Murillo, Rahona-Lopez & Salinas-Jimenez 2012) that the returns to education are lower among the mismatched. Since, to our knowledge, no paper actually examines the rates and effects of mismatch among the self-employed, our research presented below is a first step in directly analyzing the interrelationship of mismatch and self-employment.

3. Data

In this paper we utilize a dataset from the US National Science Foundation (NSF) comprising of workers who have obtained at least a bachelor's degree in a hard or social science, technology, engineering, or mathematics (STEM) field and/or are currently working in that field. The data come from the 2003 wave of the public use version of the National Survey of College Graduates (NSCG), the only wave of the public use NSCG that identifies the self-employed.[2]

[2] The data are available from the NSF's Scientists and Engineers Statistical Data System at http://www.nsf.gov/statistics/sestat/.

Central to this analysis is the following question asked in the dataset – "Thinking about the relationship between your work and your education, to what extent is your work related to your highest degree? Closely related, somewhat related, or not at all related." For those workers who are in jobs not closely related to their education, we assume that they are using less of the knowledge, training, and skills learned in that education and, therefore, indicate a level of mismatch between their education and job.[3] Indeed, we will refer to these categories as 'matched', 'moderately mismatched', and 'severely mismatched' below.[4] The dataset also contains standard socio-economic variables such as gender, race and ethnicity, age, earnings, etc. Furthermore in the NSCG, we can identify whether the worker is self-employed (either as an incorporated or nonincorporated business). In the results below, we restrict the sample to just full-time workers who report positive earnings for two reasons. First, omission of part-time workers follows the previous self-employment literature (e.g. Evans & Leighton 1989; Hundley 2000), and second, it allows us to focus on those who are in career type jobs.[5]

Table 1 is a simple look at any differences between the rates of educational mismatch by self-employed and wage and salary status and gender. Overall, the self-employed are less likely than wage and salary workers to be matched, since only 57.3 percent are matched, compared to 63 percent of wage and salary workers. While the percentage of workers who are moderately mismatched are the same, the rates of severe mismatch are higher for the self-employed by nearly six percentage points.

[3] Thus, we are not defining mismatch vertically (that is as in over- or under-education) as is done in much of the literature, but horizontally. This is partially driven by the data, but is also due to the fact that this sample is drawn for those with at least a college education. Thus, it is likely that the vertical mismatch will be in the direction of over-education.

[4] There is some debate in the mismatch literature about the use of subjective measures of mismatch (as we have here) versus more objective measures (such as comparing actual education and the average education for an occupation). Generally, however, similar labor market impacts are found using either measure.

[5] Appendix Table A1 contains the descriptive statistics for the sample, split by employment sector and by gender.

Because previous research (e.g. Leoni & Falk 2010 and Hundley 2000) indicates big differences in self-employment by gender, we also split our sample by gender. While the bottom of Table 1 shows higher rates of mismatch for the self-employed, regardless of gender, the magnitudes do differ across genders. Female wage and salary workers are more likely to be matched than female self-employed workers by over eleven percentage points (and, interestingly, more likely to be matched than male wage and salary workers by just over four percentage points). Conversely, female self-employed workers are 10.9 percent more likely to be severely mismatched. In comparison, male self-employed workers are severely mismatched only slightly more than four percentage points more – less than half the difference of female self-employed and wage and salary workers.

To get a sense of how labor market outcomes vary by job type and level of mismatch, Table 2 contains sample statistics for annual earnings and job satisfaction by gender. For the full sample, self-employed matched workers have much higher earnings than wage and salary workers. However, the penalty for being mismatched is much greater among the self-employed, since those who are severely mismatched have only about 53 percent of the salary of matched self-employed workers ($56,706 compared to $106,799). In the wage and salary sector, the mismatch-wage gap is only 77.7 percent ($57,070 compared to $73,460). In particular, it is wage and salary women who take the highest percentage penalty as those who are severely mismatched have annual earnings only 58.8 percent of the salary of the fully matched (compared to a gap of 82.2 percent for self-employed women who are severely mismatched). It is also interesting to note that the average salary for self-employed workers who are matched exceeds the average salary of matched wage and salary workers for both males and females, although the average salary for severely mismatched self-employed workers is less than the average salary of severely mismatched wage and salary workers.

Another common labor market outcome examined in this literature is how job satisfaction varies by mismatch status. In general, and consistent with the self-employment literature, the self-employed express greater job satisfaction overall, although this extends to both genders (with little difference between the genders) and, importantly here, across all mismatch categories. Indeed, the pattern is very different than found for the annual earnings. The difference in the proportion who are very satisfied between self-employed and wage and salary workers is almost ten percentage points for the matched but is 11.3 percentage points among the severely mismatched. Similar patterns are found across both genders.

Of course, there are many factors which may play into these differences, and thus we turn to multivariate regression methods to explore further the interactions of mismatch and self-employment. (Note that all regressions are clustered at the occupational level.)

4. Results

Following the literature on mismatch, we examine two areas with respect to mismatch and self-employment. First, we look at the factors correlated with mismatch and whether these differ across job types. Second, we look at the effects of mismatch on two labor market outcomes common in this literature – earnings and job satisfaction.

4.1. Determinants of Mismatch

In this analysis, we examine the factors correlated with mismatch, meaning that the mismatch indicator is the dependent variable. We order the dependent variable from matched to severely mismatched and use an ordered probit to estimate the determinants of mismatch. The marginal effects of these estimates on the probability of being in the severely mismatched category are summarized in Table 3.[6] Before turning to the self-employment results, we observe that compared to white workers, Asian workers are more likely to be mismatched while Hispanic workers are less likely to be mismatched, a finding not dissimilar to Battu & Sloane (2003) who examine British data. Mismatch is increasing in age, although does not seem to have the inverted U-shape with age as found in other studies (e.g. Bender & Heywood 2011), although it is consistent with the idea that human capital depreciates over the career particularly for workers in STEM fields. Workers who are married or have higher levels of education are also less likely to be mismatched, while US citizens are more likely to be mismatched than noncitizens, although this is likely affected by immigration policy.

Since Table 1 indicates differences by gender and the previous literature on mismatch shows important differences by gender (see for example, Groot & Maaseen van den Brink 2000), we interact the self-employment indicator with gender to allow for a differential impact by gender. *Ceteris paribus*, wage and salary females are 3.0 percent less likely to be in the severely mismatched category (out of a predicted probability of 12.3 percent), compared to wage and salary men. Furthermore, males who are self-employed are 2.6 percent more likely to be in the most severely mismatched category than males employed in wage and salary jobs. However, the biggest marginal effects are found for self-employed women, who are 7.5 percent more likely to be in the severely mismatched category, a relatively large marginal effect, given the predicted probability of just over twelve percent. These results are expected as we saw a strong correlation between mismatch and being self-employed without controlling for other factors. They also are

[6] This paper presents selected results. Full regression results are available for all estimations from the authors upon request.

consistent with our hypothesis that self-employment offers both an involuntary solution to mismatched workers who cannot find a job in the wage and salary sector and a voluntary option for workers who want to pursue new interests or benefit from a more flexible working arrangement.

Another way to look at the determinants of mismatch is to examine the answer to the question, “What is the most important reason for working in an area outside the field of your highest degree?” Percentages of responses for this question by gender and employment sector are given in Table 4. In general, most of the reasons are similar across employment sectors.[7] The exceptions include mismatch being more likely to occur for pay and promotion opportunities in the wage and salary sector than in the self-employment sector. On the other hand, the self-employed are more likely to be mismatched due to working conditions (particularly for males) and for family reasons (particularly for females). These results are consistent with previous findings (e.g., Boden 1996, Connelly 1992 and Hundley 2000) for the determinants for self-employment.

To check the robustness of the findings above, three further sets of regressions are estimated. First, one might be concerned about the heterogeneity of jobs found among the self-employed. This heterogeneity is an important part of the self-employment literature (e.g. Hundley 2000) and might take several forms. For women who are utilizing self-employment as an option that provides better ‘work-life balance’ (e.g. Connelly 1992), we include a set of variables to measure whether workers have children between the ages of six and eleven and whether the effects of these vary by self-employment status. Previous labor market experiences might also impact choices about being self-employed and the degree of mismatch. A variety of

[7] This contrasts with other research using this data that finds differences in the reasons for severe mismatch for scientists with doctoral degrees by gender (Bender & Heywood 2009) and in different parts of careers (Bender & Heywood 2011).

variables are used to control for these factors including whether the current job and/or employer is the same or different from the worker's job two years ago, and whether the worker was unemployed, retired, or a full-time student two years previous to the 2003 survey. Including these with interactions with self-employment will give a sense of whether this heterogeneity is important in the interaction between self-employment and mismatch.

The results of this exercise are found in Table 5. Interestingly, while many of the heterogeneity measures themselves are statistically significant, there is no significant change in the basic story found in Table 3. Workers with children aged six to eleven are less likely to be severely mismatched, especially when they are self-employed. Changing jobs, being previously unemployed, or previously retired increases the probability of severe mismatch, but not differentially by self-employment status. Importantly, the first three coefficients remain almost exactly the same as in Table 3 – wage and salary women are 3.3 percent less likely to be in severely mismatched compared to wage and salary men and self-employed men are 2.8 percent more likely to be severely mismatched compared to wage and salary men. Marginal effects are the highest for self-employed women, who are 5.7 percent more likely to be severely mismatched than wage and salary men, 2.9 percent more likely to be severely mismatched than self-employed men, and nine percent more likely to be severely mismatched than wage and salary women.

A second potential problem concerns the career paths of workers (Bender & Heywood 2011). While an initial job placement might show a close match, as workers move up in management, they may well be using skills other than those learned while in college. However, this is a different form of mismatch – one that is likely a voluntary form of mismatch and a normal progression of a career. Unfortunately, we cannot account for this directly since we do not have panel data, but we do have information as to whether a worker is a manager.[8] Taking these managers out of the dataset and re-estimating the determinants model results in virtually no change in the key self-employment variables. While full results are available from the authors, compared to wage and salary men, self-employed men are 2.6 percent more likely to be mismatched, wage and salary women are 3.0 percent less likely to be mismatched, and self-employed women are 7.5 percent more likely to be mismatched, where all marginal effects are statistically significant. (There are no appreciable differences when the heterogeneity controls are added as with the results with managers included.)

One final robustness check concerns endogeneity. As mentioned above, one reason the people may choose self-employment is because of being mismatched in a wage or salary job, meaning that mismatch may affect the choice of becoming self-employed. Key to dealing with this is finding appropriate instruments. While the data do not contain many good candidates, we use two potential instruments: 1) the number of published articles (grouped at zero, 1-10, 11-20, and 21 plus)[9] on the argument that research will be less likely to be necessary in self-employment and 2) the month that the highest degree was awarded on the argument that firms will hire entry level jobs cyclically and so wage and salary jobs will not be as available in nonstandard graduation months (such as May, June, or December). Unfortunately, there are generally no good ways to estimate an endogenous system where one dependent variable (here, mismatch) is ordinal and the other is binary, particularly for any tests of weak instruments and the exogeneity of the instruments (i.e. a test for overidentification). Thus, we change our estimation strategy a bit to estimate a probit regression of mismatch (where the moderately and severely mismatched are combined into one group). Selected results for this probit regression

[8] This information is taken from the respondent's minor occupation group.

[9] The results below are robust to differences in the specification of this variable – whether it is entered linearly, with a quadratic term or in log form. Full results are available from the authors.

are given in the first column of Table 6 where marginal effects of a simple probit are recorded to compare with earlier reported results. The coefficient estimate is slightly larger than in the ordered probit results in Table 5 but it is measured less precisely since it is now not significant, although the self-employment/female interaction is still significant. The second column of Table 6 contains results from a linear probability model (used by estimating the 'ivreg2' command in Stata). Note at the bottom of the table, the number of published papers instruments are statistically significant and negative (in relation to those who publish no papers) in the self-employment regression as expected. The month awarded instruments also show a cyclicality with it being less likely to be self-employed in May and August, two of the most traditional months for graduation. Fortunately, the inclusion of these instruments generate a test statistic that is far away from the Stock & Yogo (1995) cutoff of an F-stat of 10 for weak instruments. In addition, the overidentification test indicates that they generally perform well as instruments (the p-value on the statistic is only 0.1805). In terms of the estimate, the resulting coefficient on self-employment jumps dramatically, although this is a total effect of the treatment. Taking the average treatment effect, the marginal effect is approximately 0.196 which is still relatively large. However, it is important to note, that the control for endogeneity is not making the effect of self-employment go away – if anything it is becoming more pronounced. Of course, it is important to realize that this specification is not the optimal one both because it is a linear probability model and because we are unable to control for the self-employment – female interaction, but it does suggest that endogeneity is not biasing the estimated effect too much.

Assuming, then, that the instruments are valid as indicated in the linear probability model tests, we estimate a recursive bivariate probit model, using the same set of instruments. As before, the marginal effects are still positive – with self-employment increasing the probability of mismatch by over five percentage points. Interestingly gender plays a smaller, although still statistically significant role, decreasing the probability by just under 0.5 percentage points. The interaction of gender and self-employment also continues to be positive and statistically significant, although, again the effect is only nominal. Thus, while there are some changes in the point estimates, the relationships between self-employment and mismatch seem to be relatively robust to endogeneity corrections.

4.2. Effects of Mismatch

As in the educational mismatch literature, we examine two potential outcomes. First, we consider whether there is a correlation between educational mismatch and (log) annual earnings by gender. Table 7 contains the percentage earnings differentials by job type and mismatch status compared to wage and salary workers who are fully matched.[10] The first two columns indicate that there is little statistically significant influence on earnings for those who are matched in the wage and salary sector and those who are slightly mismatched, although earnings are substantially lower if the wage and salary worker is severely mismatched (by 22.3 and 17.4 percent for men and women, respectively).[11] Stronger differences by gender emerge when we

[10] That the self-employed have incentives to underreport earnings is well-known in the literature (e.g. Aronson 1991), and unfortunately, there is no way to verify if this is a significant problem in this particular dataset. The earnings question does ask to report salary before deductions, but this may not have any effect on the rate of underreporting. The effect of this bias should be that self-employed earnings will look relatively worse compared to wage and salary workers than is actually the case. However, key here is not so much the earnings difference between self-employed and wage and salary workers, but the penalty associated with mismatch across the two sectors. It is harder to think about why, for example, the underreporting of income among the self-employed would vary by mismatch status. Since we are looking at mismatch differentials by sector, much of the underreporting bias should be netted out.

[11] Point estimates of the effect of mismatch on earnings vary widely depending upon the country analyzed, the econometric method used, and the definition of mismatch (either horizontal or vertical). Cross-sectional data using horizontal definitions of mismatch generally indicate a differential in the range of 5 to 10% (see for example Table 5 in Hartog 2000). On the other hand, papers using panel data (e.g. Bauer 2002, or Mavromaras, Sloane & Wei 2012) generally find smaller differentials in the range of 2 to 5%. Few papers use the type of mismatch indicator that we use, since we are not measuring a difference in years needed for a job. However, our results are

look at the self-employed, however. Compared to wage and salary matched workers, *ceteris paribus*, self-employed matched workers earn 0.8 percent more for males and 3.3 percent less for females (although only the latter is even marginally significant). Being somewhat mismatched now is associated with lower earnings, particularly for females (18.5 percent lower, compared to 9.2 percent lower for males). Being severely mismatched is associated with much lower earnings: 44.4 and 36.2 percent for males and females, respectively, a reduction similar in scale as the severely mismatched wage and salary workers. As before, including the 'heterogeneity' indicators of the presence of children and previous labor force status does little to change the patterns above (available from the authors).

Table 8 repeats the log earnings regression but disaggregates the severely mismatched category into the main reasons for mismatch by gender and job type. As in Table 7, being matched in a self-employment job generates slightly higher earnings for men and slightly lower earnings for women, compared to matched wage and salary workers of those genders, *ceteris paribus*, and some mismatch impacts the self-employed more than wage and salary workers (particularly for women with an 18.4 percent discount). While almost all of the reasons for severe mismatch generate lower earnings across both genders and job types, there is a good deal of differences in the effect on earnings across different reasons. For example, being severely mismatched because of pay and promotion opportunities results in only a modest decrease in earnings for wage and salary men (4.4 percent) and a somewhat higher decrease for self-employed men (10.2 percent). For wage and salary women, being severely mismatched because of pay and promotion actually generates higher earnings of 2.9 percent and shows almost no difference in pay for self-employed women, although neither are statistically significant. Other

in line with findings in research by Bender & Heywood (2009) who use a similar mismatch question for workers with a PhD and Robst (2007) who uses the 1993 version of the NSCG.

reasons, however, generate substantially larger and statistically significant differentials. For example, if a worker is severely mismatched because there is no job available, earnings are lower by about 40 percent for both male and female wage and salary workers. For the self-employed, earnings are 71.3 and 58.2 percent lower for females and males, respectively. Overall, the reasons for severe mismatch are associated with substantially lower earnings for the self-employed than for similar wage and salary workers.[12]

In addition to the correlations between earnings and mismatch, the literature often focuses on whether there are any correlations between job satisfaction and mismatch.[13] Indeed, one would expect that job satisfaction will be lower for those who are mismatched. For example, papers by Allen & van der Velden (2001) and Badillo-Amador, Lopez-Nicolas & Vila (2012) find that mismatch generally reduces job satisfaction, although panel estimates by Mavromaras *et al.* (2012) find that heterogeneity controls can substantially reduce the negative effects attributed to mismatch. Thus, we estimate a job satisfaction equation, using an ordered probit to predict the effect of mismatch on job satisfaction. The predicted probabilities of being in the highest job satisfaction category are given in the top panel of Table 9 for the basic results and the bottom panel of Table 9 with the reasons for severe mismatch broken out relative to being a matched wage and salary worker with the respective gender.[14]

[12] As in the previous table, controls for the heterogeneity indicators give no substantive differences in the pattern of the results. These results are available upon request.

[13] There is great debate among economists about the efficacy of using subjective well-being data such as job satisfaction – as summarized well in the recent paper by MacKerron (2012). For example, Bertrand & Mullainathan (2001) argue that there is experimental evidence that subjective responses are not consistent and that one can, thus, model subjective well-being measures as variables measured with error. On the other hand, a number of economists argue that subjective well-being measures offer a complementary and important alternative unit of analysis since it summarizes, in the case of job satisfaction, for example, the 'value of the whole package of both monetary and nonmonetary returns from (workers') jobs according to their own personal preferences and expectations' (Fabra & Comison 2009, p. 601). Here, given that job satisfaction is an important theme in the context of educational mismatch and we wish to place this research in that area, we offer estimates of mismatch on job satisfaction by self-employment sector for comparison with the literature.

[14] Again, the inclusion of the heterogeneity indicators does not affect the pattern of results presented in Table 9.

In Panel A, we find the common result that increased mismatch generates lower probabilities of being satisfied in one's job for wage and salary workers of either gender. For males, the probability drops by 13.1 and 18.5 percent for the somewhat mismatched and the severely mismatched, while for females, there are similar reductions in the probabilities by 11.3 and 17.2 percent.[15] Likewise for both genders, there is a small increase in job satisfaction for being self-employed and matched (4.1 and 5.4 percentage points for men and women, respectively), as found in previous studies of the job satisfaction of the self-employed (e.g. Blanchflower & Oswald 1998 and Andersson 2008).

Interestingly, however, the decline in the probability of job satisfaction is not as sharp for mismatch as for wage and salary workers. Some of this is because of the increased probability in job satisfaction cause by just being self-employed, but even conditional on that, the decline in the probability is less steep – about half of the comparable probabilities for wage and salary workers.

In Panel B of Table 9, we estimate the marginal effects on the probability of being in the highest job satisfaction category by the various reasons given for mismatch. There is little difference in comparison to Panel A for the change in the probability for the somewhat mismatched and the self-employed, but as before, we see substantial heterogeneity in the job satisfaction probabilities for the different reasons by employment sector as Bender & Heywood (2006) also find. Among the wage and salary workers job satisfaction is quite low for mismatch due to location, family, and no job available for both genders, with each having over a 20 percent reduction in the probability of being in the highest job satisfaction category (although the point estimates are somewhat smaller for women). For the self-employed, however, the reduction in the probability is less than the reduction for wage and salary workers. Indeed, it is often the case

[15] All of these are substantial reductions in the probability given the predicted probability of being in this category is 0.46.

that the change is less than the reduction in the probability for workers who experience some mismatch for either gender. For example, the reduction in the probability for males who are somewhat matched and wage and salary or self-employed are 13.1 and 6.9 percent, respectively. However, there are no statistically significant differences between matched wage and salary male workers and self-employed workers who are severely mismatched due to pay and promotion opportunities, working conditions, location, and change in career interests. For women the pattern is similar except for those mismatched for pay and promotion, which generates a significantly lower probability of being satisfied in their jobs.

Thus, the effects of educational mismatch seem contradictory – associated with lower earnings but without a corresponding reduction in job satisfaction. What might be driving these results? It is difficult to be sure with these data, but a possible explanation is that workers of both genders are generating compensating differentials from self-employment. Previous research (e.g. Benz & Frey 2008; Connelly 1998) indicates that self-employment allows, for example, greater flexibility in hours or scheduled working time than wage and salary jobs. Self-employed workers, thus, are willing to have lower earnings in order to have these positive job attributes. Likewise, if a worker is going to have lower earnings because of educational mismatch, it is rational for them to choose self-employment as a way to generate higher job satisfaction, relative to the same level of mismatch in the wage and salary sector.

5. Conclusion

Research on educational mismatch has focused on the causes of mismatch and the consequences of mismatch on labor market outcomes for wage and salary workers. This paper is the first to explicitly consider differences in educational mismatch and whether workers are in the wage and salary sector or are self-employed, focusing on differences between men and women in those sectors. Controlling for a list of demographic characteristics we find that the self-employed are more likely to report being mismatched, particularly if the self-employed worker is a woman. Furthermore, mismatch among the self-employed is associated with larger earnings decreases for the moderately mismatched (compared to the decrease for moderately mismatched wage and salary workers) and smaller relative earnings discounts for the severely mismatched (again compared to the discount for severely mismatched wage and salary workers). However, these declines in earnings are not associated with even further decreases in subjective well-being as measured by job satisfaction. The negative correlation between job satisfaction and severe mismatch for the self-employed is much smaller than for wage and salary workers who are severely mismatched.

This paper, however, is just a first step in this research. An important next step would be to examine these interactions in a panel context where educational mismatch might be an indicator of changing sectors. While the self-employed are shown to have greater rates of educational mismatch, it is unclear whether this was a state that occurred when the worker became self-employed or whether it occurred before or after joining this sector. Panel data would help to identify some of these patterns as workers change from one sector to another. Furthermore, it would be interesting to see, as in previous literature, whether mismatch itself generates some incentive to change jobs or sectors. Finally, data on positive job attributes of self-employment, such as hours flexibility, would be interesting to examine to see if these explain some of the mismatch-job satisfaction differences between male and female self-employed workers.

Acknowledgements

The authors wish to thank Scott Adams, Swarnjit Aurora, Scott Drewianka, John Heywood and the seminar participants of the Education and Skills Mismatches in the Labour Market 2010 Conference in Adelaide, Australia and at the University of Aberdeen, Scotland, for comments on earlier drafts of this paper. The authors also thank the US National Science Foundation for providing the data and acknowledge that the use of these data does not imply NSF endorsement of the methods or findings in the paper.

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Table 1
Rates of Mismatch by Job Type

Sample	Self-Employed	Wage & Salary
Full		
Matched	57.3%	63.0%
Moderately Mismatched	23.3	23.7
Severely Mismatched	19.4	13.3
Females		
Matched	54.2	65.6
Moderately Mismatched	21.5	21.0
Severely Mismatched	24.4	13.5
Males		
Matched	58.5	61.4
Moderately Mismatched	24.0	25.5
Severely Mismatched	17.5	13.2

Data source: Data are for 74,229 full-time workers from the 2003 NSCG.

Table 2
Annual Earnings and Job Satisfaction by Mismatch Status and Job Type

	Annual Earnings		% Very Satisfied	
Sample	Self-Emp.	W&S	Self-Emp.	W&S
Full				
Matched	$106,799	73,460	59.6%	49.9%
Moderately Mismatched	77,803	70,227	44.5	36.2
Severely Mismatched	56,706	57,070	44.5	33.2
Females				
Matched	79,830	59,138	58.9	50.2
Moderately Mismatched	54,588	57,049	42.0	37.7
Severely Mismatched	46,937	48,605	44.1	33.2
Males				
Matched	116,357	83,560	59.8	49.7
Moderately Mismatched	85,647	77,379	45.4	35.4
Severely Mismatched	61,899	62,794	44.7	33.2

Data source: Data are for 74,229 full-time workers from the 2003 NSCG.

Table 3
Determinants of Job Mismatch from Ordered Probit Regression

Variable	Marginal Effect	Variable	Marginal Effect
Self-Employed	0.023*	Age	0.002*
	(1.65)		(1.83)
Female	-0.032**	Age Squared	-1.7E-6
	(-1.92)		(-1.21)
SE*Female	0.061***	Married	-0.023***
	(3.26)		(-3.32)
Black	-0.001	Masters Degree	-0.080***
	(-0.54)		(-4.62)
Asian	0.010	Doctorate Degree	-0.098***
	(0.66)		(-4.55)
Hispanic	-0.025***	Prof. Degree	-0.125***
	(-4.86)		(-5.10)
Other Race	0.008	Citizen	0.012***
	(0.85)		(0.82)

Data source: Data are for 74,229 full-time workers from the 2003 NSCG.
Notes: The predicted probability of being in the most severely mismatched category is 0.123. The ordered probit regression also controls for academic field of the occupation, and region. Excluded variables from the groups of dummy variables are white race and highest degree: bachelors. Number in parentheses under coefficient is the asymptotic z-statistic. Standard errors are clustered on occupation. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4
Responses to Question 'Most Important Reason for Working Outside of Field'

	Self-Employed		Wage & Salary	
	Men	Women	Men	Women
Pay, promotion opportunities	29.5%	21.4%	34.9%	28.8%
Working conditions	12.5	13.7	7.6	9.5
Job location	5.8	6.2	6.6	5.8
Change in career/professional interests	22.6	19.9	20.7	20.2
Family-related reasons	8.5	21.5	5.0	11.2
Job in field not available	12.8	9.2	16.8	17.1
Other	8.4	8.1	8.5	7.4

Data source: Data are for 74,229 full-time workers from the 2003 NSCG.

Table 5
Selected Results from an Ordered Probit Mismatch Regression allowing for Heterogeneity among the Self-Employed

Variable	Marginal Effect	Variable	Marginal Effect
Self-Employed	0.028*	Different Job & Employer	0.088***
	(1.89)		(4.72)
Female	-0.033**	Unemployed in 2001	0.047***
	(-2.01)		(3.33)
SE*Female	0.057***	SE*Unemployed in 2001	0.009
	(3.23)		(0.87)
Children	-0.006**	Student in 2001	-0.005
	(-2.22)		(-0.27)
SE*Children	-0.021***	SE*Student in 2001	-0.005
	(-4.66)		(-0.20)
Different Job	0.052***	Previously Retired	0.102***
	(6.14)		(4.15)
Different Employer	-0.007	SE*Previously Retired	0.001
	(-1.08)		(0.04)

Data source: Data are for 74,229 full-time workers from the 2003 NSCG.
Notes: The predicted probability of being in the most severely mismatched category is 0.110. The ordered probit regression also controls the other controls listed in Table 3. 'Children' is a dummy variable indicating the worker has children between the ages of 6 and 11. Number under coefficient is the asymptotic z-statistic. Standard errors are clustered on occupation. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6
Corrections for Endogeneity, Selected Marginal Effects

Variable	Probit with no Endogeneity Control	Linear Probability (ivreg2)	Recursive Bivariate Probit
Self-employed	0.046	1.190***	0.0518***
	(1.53)	(13.63)	(8.42)
Female	-0.074**	-0.002	-0.0050*
	(-2.26)	(-0.27)	(-1.78)
SE*Female	0.109***		0.0059***
	(3.58)		(3.00)
Instruments in Self-Employment Regression			
#Papers 1-10		-0.053***	-0.057***
		(-14.13)	(-4.66)
#Papers 11-20		-0.101***	-0.096***
		(-9.97)	(-6.68)
#Papers 21 plus		-0.104***	-0.095***
		(-8.11)	(-4.97)
Degree Awarded in February		0.026*	0.027**
		(1.92)	(2.46)
Degree Awarded in March		0.0002	0.002
		(0.02)	(0.18)
Degree Awarded in April		-0.010	-0.019**
		(-0.91)	(-2.21)
Degree Awarded in May		-0.017**	-0.021***
		(-2.28)	(-2.98)
Degree Awarded in June		0.003	8.9E-5
		(0.33)	(0.01)
Degree Awarded in July		-0.006	-0.007
		(-0.53)	(-0.60)
Degree Awarded in August		-0.030***	-0.033***
		(-3.51)	(-6.68)
Degree Awarded in September		0.017	0.013
		(1.47)	(1.31)
Degree Awarded in October		-0.024*	-0.024**
		(-1.71)	(-2.23)
Degree Awarded in November		-0.019	-0.017
		(-1.19)	(-1.18)
Degree Awarded in December		-0.009	-0.011*
		(-1.08)	(-1.67)
Craig Donald F-stat		26.59	
Overid/exogeneity Test		17.43 (p=0.1805)	

Data source: Data are for 74,229 full-time workers from the 2003 NSCG.
Notes: All regressions include the other controls listed in Table 3. The instruments are in relation to those who have published no research papers and graduated in January. Numbers under coefficients is either t-statistics or the asymptotic z-statistic. The coefficients for the Recursive Bivariate Probit regression have been converted into marginal effects, holding all other variables at their means. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7
Estimated Percentage Earnings Differentials from Log Annual Earnings Regression

	Without Heterogeneity Controls		With Heterogeneity Controls	
Group	Men	Women	Men	Women
W&S Moderately Mismatched	-0.012	-0.010	-0.010	-0.006
	(-0.58)	(-0.34)	(-0.47)	(-0.22)
W&S Severely Mismatched	-0.223***	-0.174***	-0.211***	-0.159***
	(-3.24)	(-3.64)	(-3.29)	(-3.64)
SE Matched	0.008	-0.033	-0.002	-0.032
	(0.14)	(-0.69)	(-0.04)	(-0.66)
SE Moderately Mismatched	-0.092*	-0.185***	-0.088*	-0.171***
	(-1.67)	(-2.87)	(-1.63)	(-2.84)
SE Severely Mismatched	-0.444***	-0.362***	-0.428***	-0.330***
	(-4.89)	(-3.64)	(-4.81)	(-5.87)

Data source: Data are for 74,229 full-time workers from the 2003 NSCG.
Notes: Numbers are based on gender-specific regressions and converted into percentage earnings differentials. The comparison group is wage and salary, matched males for the male workers and wage and salary, matched females for female workers. Other controls include: age (and its square), marital status, race/ethnicity, educational degree, US citizenship, annual hours, academic field of degree, and region. 'Heterogeneity Controls' include those in Table 5. Number under coefficient is the t-statistic. Standard errors are clustered on occupation. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 8
Estimated Percentage Earnings Differentials by Reason for Severe Mismatch, Gender, and Job Type

	Men		Women	
	Self-Emp.	W&S	Self-Emp.	W&S
Matched	-0.033	(ref. group)	0.008	(ref. group)
	(-1.84)		(0.13)	
Moderately Mismatched	-0.184***	-0.009	-0.091*	-0.011
	(-2.84)	(-0.29)	(-1.65)	(-0.54)
Pay, promotion	-0.028	0.029	-0.102	-0.044
	(-0.23)	(0.54)	(-1.55)	(-0.87)
Working conditions	-0.440***	-0.236***	-0.446***	-0.342***
	(-4.00)	(-7.05)	(-6.91)	(-6.17)
Job location	-0.401***	-0.267***	-0.671***	-0.359***
	(-3.65)	(-3.57)	(-4.23)	(-5.40)
Change in career interests	-0.350***	-0.103*	-0.584***	-0.147***
	(-4.05)	(-1.84)	(-4.53)	(-2.75)
Family-related reasons	-0.477***	-0.366***	-0.420***	-0.325***
	(-12.59)	(-8.96)	(-5.21)	(-5.75)
Job in field not available	-0.582***	-0.337***	-0.713***	-0.441***
	(-5.60)	(-7.64)	(-9.98)	(-4.10)
Other reason	-0.544***	-0.319***	-0.730***	-0.428***
	(-4.59)	(-3.92)	(-5.01)	(-5.00)

Data source: Data are for 74,229 full-time workers from the 2003 NSCG.
Notes: Estimates based on converted coefficient estimates from two regressions – one for self-employed and wage and salary men and the other for self-employed and wage and salary women. The comparison group is wage and salary, matched males for the male workers and wage and salary, matched females for female workers. Results in the 'Self-Employed' column are the additional penalties (or premiums) the self-employed incur (via interaction terms). The regression also controls for age, age squared, marital status, race, highest degree, citizenship, annual hours, academic field of the occupation and region. Number under coefficient is the t-statistic. Standard errors are clustered on occupation. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 9
Ordered Probit Job Satisfaction Regressions by Gender: Marginal Effects of Being in the Highest Job Satisfaction Category

	Men		Women	
Variable	Self-Emp.	W&S	Self-Emp.	W&S
Panel A: No Reasons for Severe Mismatch				
Matched	0.041***	(ref. group)	0.053**	(ref. group)
	(3.37)		(2.24)	
Moderately Mismatched	-0.071***	-0.131***	-0.079***	-0.113***
	(-3.92)	(-10.95)	(-4.43)	(-12.91)
Severely Mismatched	-0.094***	-0.184***	-0.100***	-0.171***
	(-4.00)	(-11.30)	(-5.12)	(-8.44)
Panel B: With Reasons for Severe Mismatch				
Matched	0.041***	(ref. group)	0.054**	(ref. group)
	(3.45)		(2.26)	
Moderately Mismatched	-0.071***	-0.131***	-0.079***	-0.113***
	(-3.97)	(-10.97)	(-4.42)	(-13.03)
Pay, promotion	-0.039	-0.151***	-0.126***	-0.136***
	(-1.06)	(-11.91)	(-5.46)	(-10.51)
Working conditions	-0.010	-0.094***	-0.053**	-0.085***
	(-0.29)	(-3.90)	(-2.19)	(-4.10)
Job location	-0.078	-0.217***	-0.125*	-0.168***
	(-1.27)	(-14.18)	(-1.78)	(-4.21)
Change in career interests	-0.022	-0.081***	0.077*	-0.079***
	(-0.61)	(-7.75)	(1.70)	(-5.07)
Family-related reasons	-0.139***	-0.251***	-0.111***	-0.176***
	(-3.90)	(-10.74)	(-4.99)	(-7.10)
Job in field not available	-0.139***	-0.317***	-0.292***	-0.310***
	(-3.90)	(-13.69)	(-7.39)	(-14.45)
Other reason	-0.114***	-0.200***	-0.157***	-0.215***
	(-4.16)	(-9.14)	(-2.51)	(-4.67)

Data source: Data are for 74,229 full-time workers from the 2003 NSCG.
Notes: Predicted marginal effects are the relative change in the probability of being in the highest job satisfaction category. Estimates based on converted coefficient estimates from two regressions – one for self-employed and wage and salary men and the other for self-employed and wage and salary women. The comparison group is matched wage and salary workers by gender. The predicted probability for being in the highest job satisfaction category for either gender is about 0.46. The ordered probit regressions also control for age, age squared, marital status, race, highest degree, citizenship, annual hours, earnings, academic field of the occupation and region. Number under coefficient is the asymptotic z-statistic. Standard errors are clustered on occupation. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix Table A1
Selected Descriptive Statistics by Type of Job and Gender

	Self-Employed		Wage & Salary	
	Men	Women	Men	Women
Sample Size	7,923	3,018	38,125	25,163
% of Employment Sector	72%	28%	60%	40%
Job Satisfaction				
Very Satisfied	54%	52%	44%	45%
Somewhat Satisfied	39%	38%	46%	45%
Somewhat Dissatisfied	6%	8%	8%	7%
Very Dissatisfied	2%	2%	2%	2%
Annual Earnings				
Mean	$ 99,582	$ 66,533	$ 79,254	$ 57,281
Median	$ 75,000	$ 50,000	$ 70,000	$ 50,000
Standard Deviation	$ 96,796	$ 64,047	$ 51,724	$ 35,773
Highest Degree				
Bachelors	54%	55%	53%	51%
Masters	20%	23%	29%	36%
Doctorate	5%	5%	12%	8%
Professional	21%	17%	5%	5%

Data source: Data are for 74,229 full-time workers from the 2003 NSCG.