Measurement Sensitivity in Field-of-Study Mismatch Research

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Abstract

Using data from the National Survey of College Graduates in simple linear regression and linear probability models, I provide evidence that the predicted causes and consequences of field-of-study mismatch are highly sensitive to how one measures mismatch itself. I demonstrate that the estimated effects, such as a wage penalty, and the estimated causes, such as citizenship status, differ based on whether I use a subjective worker self-assessed measure of mismatch or an objective data-driven one. Further, the direction and magnitude of the differences point to emotional disposition as the likely cause of this sensitivity, acting as a confounding variable for subjective measures. These findings call into question what types of policies would be effective in ameliorating field-of-study mismatch, and ultimately call into question whether doing so is a worthwhile use of limited resources.

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1 Introduction

A healthy labor market and strong economy depend in large part on matching between workers' education and the jobs they perform. On the macroeconomic level, better educational matching is associated with greater returns to educational investments, lower unemployment, and higher productivity (Humal, 2013; Heijke et al., 1996). On the microeconomic level, it is associated with better performance, greater satisfaction, and higher wages and occupational status (Kim and Choi, 2018; Wolbers, 2003).

Most studies on education mismatch focus on the "vertical" form. That is, they focus on the causes and consequences of being over- or under-educated for a given position. However, a growing body of research is focusing on the "horizontal" form of this phenomenon, so-called field-of-study mismatch. Field-of-study mismatch refers to a situation in which a worker studies one field but works in another (Montt, 2015). For example, it describes an English major who works as an investment banker, or a finance major who works as a playwright.

The evidence to date suggests that field-of-study mismatch is consequential and that the recent uptick in attention is warranted. Specifically, researchers have found that field-of-study mismatch has such deleterious consequences as reduced productivity, lower wages, and diminished worker satisfaction (Montt, 2015; Robst, 2007).

Given these adverse outcomes, economists have begun to study what causes this form of mismatch. Thus far, the research suggests that individual characteristics like age, educational characteristics like highest degree type, and occupational characteristics like work type all influence the likelihood that a given worker will be mismatched (Domadenik et al., 2013; Robst, 2007; Wolbers, 2003).

However, I demonstrate that these findings must be interpreted with caution due to a serious methodological challenge. Specifically, I find that the causes and consequences of field-of-study mismatch, estimated in linear regression and linear probability models, differ based on whether I use a subjective worker self-assessment measure or a more objective data-driven one. Especially concerning is that the estimated wage penalty attenuates significantly when switching from the subjective to the objective measure, and the penalty on job satisfaction disappears entirely.

Comparing the characteristics of individuals across different measures, I find evidence that these differences are driven by the omitted variable of emotional disposition. Subjective measures appear to capture not just the degree to which an individual is matched, but also their general attitude. This explains why estimates found with it differ from those found with objective measures, which are unrelated to general disposition.

While this may seem primarily of theoretical interest, it has real-world implications. Given the estimated detrimental impacts of field-of-study mismatch, especially on wages and satisfaction, many economists studying the topic have called on policymakers to take action. However, it would be imprudent to enact policies aimed at curtailing field-of-study mismatch before truly understanding its causes and consequences. Thus, this evidence of measurement sensitivity suggests the need for caution and a sharper focus on what exactly is meant by field-of-study mismatch.

The rest of the paper is organized as follows. In Section II I explore the causes and consequences found in the literature, as well as the measurement methods used. In Section III I explain the data I use, how I capture mismatch, and the causes and consequences I intend to explore. In Section IV I explain my linear regression and linear probability models. In Section V I present the estimates from my models and highlight the differences caused by different measurement strategies. In Section VI I conduct an exploratory analysis to identify a potential cause for the differences. In Section VII I conclude.

2 Theory and Literature

Past research has found a host of negative outcomes associated with field-of-study mismatch, including lower productivity, higher turnover, and greater training costs (Kim and Choi, 2018; Montt, 2015; Wolbers, 2003; Hersch, 1991). Perhaps the most serious consequences, and certainly the ones with the greatest policy implications, are the wage and satisfaction penalties that a number of researchers have found. For wages, the very paper often cited as kick-starting this field of research, by Robst (2007), highlights lower wages as the main consequence of mismatch. A wide range of subsequent analyses have since come to the same conclusion; that field-of-study mismatch reduces salaries (Kim and Choi, 2018; Montt, 2017, 2015; Badillo-Amador and Vila, 2013; Bender and Heywood, 2011). Similarly, several papers have found that workers who are mismatched report greater dissatisfaction with their work compared to their matched counterparts

(Kim and Choi, 2018; Bender and Heywood, 2011; Hersch, 1991). This is concerning in its own right, and is especially worrying given that less satisfied workers are generally less productive, less healthy, and less committed to their job (Faragher et al., 2013; Amah, 2009; Wright et al., 2007; Sagie, 1998).

These consequences are serious if true, and make understanding the causes of this form of mismatch crucial. As a result, many studies have investigated the question of determinants. The findings can be broken down into four main categories: worker characteristics, educational characteristics, job characteristics, and macroeconomic factors.

For individual characteristics, researchers have found associations between mismatch and age, gender, citizenship status, and race (Montt, 2015; Viramontes et al., 2015; Bender and Heywood, 2011; Robst, 2007; Wolbers, 2003; Witte and Kalleberg, 1995). For educational characteristics, they have found associations between field of study, highest degree attained, parental education, and years since graduation (Sellami et al., 2018; Domadenik et al., 2013; Boudarbat and Chernoff, 2012; Wolbers, 2003; Robst, 2007). For job characteristics, researchers have reported relationships with tenure, firm size, and public versus private sector work (Boudarbat and Chernoff, 2012; Wolbers, 2003; Witte and Kalleberg, 1995). Finally, researchers have found that macroeconomic conditions at the time of graduation, particularly the unemployment rate, influence whether a given worker ends up mismatched (Montt, 2017; Verhaest et al., 2017; Montt, 2015; Wolbers, 2003).

While rarely the focus of the research listed above, the challenge of measuring field-of-study mismatch is readily apparent. No fewer than three types of measure exist, each with the aim of measuring ostensibly the same situation of mismatch as the others. Sellami et al. (2018) helpfully labels these, from most to least subjective, the worker self-assessment category, the job analysis category, and the realized match category [1].

Worker self-assessment refers broadly to measures of mismatch based on workers' assessments of their own level of match, almost always through the use of a survey. Job analysis refers to evaluation by job analysts or the researchers themselves, typically using an occupational classification method such as the International Standard Classification of Occupations. Finally, the "realized match" method entails using the data itself to determine whether an individual is matched or not. This is rarer, but can can be done in a number of ways.

[1] These terms are borrowed from Hartog (2000), who first used them to describe different ways to measure over and under-education.

For example, Viramontes et al. (2015) use the modal major of an occupation to determine whether a given worker is matched.

Were they all to capture the same phenomenon, this diversity of measures would be unremarkable. However, as I discuss in detail below, differences in estimates driven strictly by changes in measurement method suggest they capture something distinct from one another.

3 Data

3.1 National Survey of College Graduates

The data I use in this analysis comes from 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates (NSCG). The NSCG is a survey commissioned by the National Science Foundation that samples US resident adults with a bachelor's degree or higher. It includes detailed information on demographics, educational experiences, and labor market outcomes. Survey responses are collected in a trimodal fashion, with the National Science Foundation using web surveys, mail surveys, and computer-assisted telephone interviews (CATI) to collect the sample. The weighted response rate is around 70% and the data includes weights based on demographic group, highest degree type, and occupational and bachelor's degree fields (National Survey of College Graduates, 2019).

3.2 Measuring Mismatch

The purpose of this analysis is to assess whether there is a difference in the estimated causes and consequences of field-of-study mismatch depending on which measure is used. If there is a difference, the goal becomes to assess how serious it is. Thus, I use two measures of mismatch: a subjective worker self-assessment measure and a more objective and data-driven realized one.

To create the subjective measure, I follow the convention in the literature and use a straightforward survey question: "To what extent was your work on your principal job related to your highest degree." The potential responses to this question are "closely related," "somewhat related," and "not at all related." I code this into an indicator variable, counting those who responded "not at all related" as mismatched. This follows the suggestion made by Sellami et al. (2018) to group those who are somewhat matched with those who are fully matched.

For objective match, I exploit the detailed occupation and field-of-study information included in the NSCG. First, for each occupational category, I find the fields that 75% of workers in that occupation studied [2]. For example, around 75% of workers in the economist occupation studied either economics (67%) or public policy (5%). Individuals working as economists who did not study one of those two fields are classified as mismatched by this measure. I label this the objective field mismatch measure, given that it covers individuals with uncommon fields-of-study for their occupation.

I also do the inverse. I find the occupations that cover 75% of individuals who studied a given field. For example, 75% of those who studied accounting report working as either an accountant (51%), a manager (17%), or a clerk/bookkeeper (5%). I label this the objective occupation mismatch measure, given that it covers individuals with uncommon occupations for their field-of-study.

It is important to note that the percentages do not add up to 75% in either example. This is due to how I handle the so-called cutoff point; the field or occupation that brings the percentage of individuals covered to over 75%. In this analysis I exclude that point, so that individuals with that field or occupation are considered mismatched. However, the results are nearly identical when I include the cutoff point (which leads to percentages over 75%).

When building both of these objective measures I split the data by year. I do this to account for the evolving nature of fields of study and occupations over time. For example, the fields-of-study associated with computer and information scientists evolved considerably between 2003 and 2017, with a third of the most common fields in 2017 not appearing on the list of most common fields in 2003.

While I intend for this measure to be as objective as possible, there is some unavoidable subjectivity that goes into its construction. Most notably is the 75% cutoff threshold. While I chose this cutoff to mirror the 25% mismatch incidence found in previous studies (Sellami et al., 2018), it is nonetheless a subjective choice.

To the best of my knowledge, this strategy is unique. The closest approximations are the realized measures used by researchers like Viramontes et al. (2015). However, unlike my measure, previous methods generally

[2] There are 131 occupation categories and 142 field-of-study categories

rely on using the modal field-of-study to classify mismatch; if a given person studied the modal field they are matched, if they did not they are mismatched. This is a somewhat problematic method, as it not only captures mismatch, but also heterogeneity in field-of-study concentration across occupations. For example, in my data the modal field for lawyers and judges covers over 90% of workers, whereas the modal field for the sales occupation covers just 10%. These are obviously extreme examples, but they demonstrate the key issue. Not only does such a measure capture whether an individual is matched, it also captures the relative field-of-study concentration for his/her occupation.

3.3 Consequence Measures

The two most urgent and commonly cited consequences of field-of-study mismatch are wage and satisfaction penalties. For the former, I use logged salary in 2017 dollars. For the latter I use a question in the NSCG that asks "how would you rate your overall satisfaction with [your] principal job?" Possible responses are "very satisfied," "somewhat satisfied," "somewhat dissatisfied," and "very dissatisfied." I collapse this into a dummy variable equal to one if the respondent is somewhat or very satisfied and zero otherwise.

3.4 Determinant Measures

Given the richness of the NSCG, I am able to include nearly the full range of potential predictors suggested in the literature, as well as some relatively unique ones.

For individual characteristics, I have age, race, marital status, and region. I also have indicators for whether a respondent has children, is male, has a physical disability, and is a US Citizen.

For educational characteristics, I have years since graduation, highest degree type, parents' education level, and the 1994 Carnegie Classification for institution attended [3]. I also have indicators for whether the individual attended community college, whether he/she attended a private institution, and whether he/she is a "recent graduate", which I define as having graduated within 5 years of responding to the given wave of the survey. Of course, I also have the field-of-study for each respondent's highest degree, which includes 142 possible categories.

[3] The Carnegie Classification system is a framework for classifying colleges and universities in the United States. See Table 6 for the categories I use in this analysis (The Carnegie Classification of Institutions of Higher Education, 2020).

For job characteristics, I have hours worked per week, tenure, firm type, firm size, principal work activity, an indicator for whether an individual is a supervisor, and a categorical variable for whether an individual has recently changed jobs. Of course, I also have an occupation variable, which covers 131 possible occupational categories

I have a two variables that relate to macroeconomic factors. First, I have a variable indicating which wave of the survey the respondent participated in. Insofar as economic conditions differ between 2003, 2010, 2013, 2015, and 2017, this should capture variation driven by changes in overall conditions from period to period. Similarly, I include a control for the unemployment rate during the May that a given respondent graduated.

4 Modeling

To assess the measurement sensitivity of the consequences of mismatch, I use salary and satisfaction as outcome variables in a linear regression model (1) and a linear probability model (2) respectively. For each, I run a specification with the subjective measure of mismatch as the explanatory variable, a specification with objective field mismatch as the explanatory variable, and a specification with objective occupation mismatch as the explanatory variable. This allows me to compare differences in the estimated coefficients that arise strictly due to differences in the measurement method. These models can be seen in greater detail below.

$$Salary_i = \beta_0 + \beta_1 Mismatch_i + \boldsymbol{\gamma_1}\mathbf{X}_i + \boldsymbol{\gamma_2}\boldsymbol{\Upsilon}_i + \boldsymbol{\gamma_3}\boldsymbol{\Pi}_i + \epsilon_i \tag{1}$$

$$Satisfaction_i = \beta_0 + \beta_1 Mismatch_i + \boldsymbol{\gamma_1}\mathbf{X}_i + \boldsymbol{\gamma_2}\boldsymbol{\Upsilon}_i + \boldsymbol{\gamma_3}\boldsymbol{\Pi}_i + \epsilon_i \tag{2}$$

Where $\mathbf{X}_i$, $\boldsymbol{\Upsilon}_i$, and $\boldsymbol{\Pi}_i$ are vectors of individual, educational, and occupational characteristics respectively, and where each $\boldsymbol{\gamma}$ represents the corresponding coefficient vector.

I also use both forms of mismatch as the outcome variables in a separate linear probability model (3), with the set of potential predictors listed above as the explanatory variables. This allows me to assess whether the factors estimated by the model to predict mismatch differ from one measure to the next.

$$Mismatch_i = \beta_0 + \boldsymbol{\gamma_1}\mathbf{X}_i + \boldsymbol{\gamma_2}\boldsymbol{\Upsilon}_i + \boldsymbol{\gamma_3}\boldsymbol{\Pi}_i + \epsilon_i \tag{3}$$

5 Results and Implications

5.1 Preliminary Findings

Even prior to running my models, there is reason to believe that the subjective and objective measures capture something distinct from one another. First, the phi coefficients of correlation between the subjective measure and the objective ones are a negligible 0.18 and 0.20. This suggests that there exists at most a weak (though positive) association. Investigating this further, I find that almost 30% of respondents are categorized as mismatched by one measure, but not by the other (Tables 1 and 2). For example, in Table 1 we can see that 17% of individuals in my sample report being mismatched, but studied a field common for workers in their occupation. Even more surprising is that of those who are objectively mismatched, only around 30% report themselves as mismatched. Inversely, of those who report themselves as mismatched, just 40% are mismatched according to the objective measures. This is compelling evidence of a substantial disconnect in what the two measures capture.

	Subjective Match	**Subjective Mismatch**
Objective Field Match	63.0%	17.0%
Objective Field Mismatch	11.9%	8.1%

Table 1: Percent of respondents who fall into each grouping of the two mismatch categories. Subjective mismatch based on whether the respondent reports that his/her field-of-study is not related to his/her occupation. Objective field mismatch indicates whether the respondent studied one of the fields that cover 75% of workers in his/her occupation. Data from the 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates.

	Subjective Match	**Subjective Mismatch**
Objective Occupation Match	61.7%	18.3%
Objective Occupation Mismatch	10.9%	9.0%

Table 2: Percent of respondents who fall into each grouping of the two mismatch categories. Subjective mismatch based on whether the respondent reports that his/her field-of-study is not related to his/her occupation. Objective occupation mismatch indicates whether the respondent works in one of the occupations that 75% of workers with his/her major work in. Data from the 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates.

Variable	(1)	(2)	(3)
Subjective Mismatch	-0.163***		
	(0.004)		
Objective Field Mismatch		-0.068***	
		(0.003)	
Objective Occupation Mismatch			-0.068***
			(0.003)
Individual Controls	X	X	X
Educational Controls	X	X	X
Occupational Controls	X	X	X
Macroeconomic Controls	X	X	X
Adjusted R Squared	.490	.487	0.487
Observations	301846	301846	301846

Table 3: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Entries are survey-weighted linear coefficients. Outcome variable is logged annual salary in 2017 dollars. Individual controls include age, race, marital status, region, and indicators for whether a respondent has children, is male, has a physical disability, and is a US Citizen. Educational controls include field-of-study, years since graduation, highest degree type, parents' education level, the 1994 Carnegie Classification for institution attended, and indicators for whether the individual attended community college, whether he/she attended a private institution, and whether he/she is a recent graduate. Occupational controls include occupation, hours worked per week, tenure, firm type, firm size, principal work activity, and a categorical variable for whether an individual has recently changed jobs. Macroeconomic controls include indicators for survey year and a measure of unemployment at the time of graduation (U.S. Bureau of Labor Statistics, 2020). Data from the 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates.

5.2 Consequences

Running a linear regression model with logged salary (in terms of 2017 dollars) as the outcome reveals a statistically significant penalty regardless of which measure is used (Table 3). However, there is a meaningful difference in magnitude. Exponentiating the coefficients reveals that, all else equal, workers mismatched according to the subjective measure earn just 85% of what their matched counterparts do, compared to objectively mismatched workers who earn around 93%. While both measures suggest a penalty, the estimate is a full eight percentage points higher for the subjective measure. When dealing with how to allocate scarce resources, differences of this size are meaningful.

Measurement sensitivity is even more apparent when looking at satisfaction as the outcome of interest. While individuals who report being mismatched are seven percentage points less likely to say that they are satisfied at work, there is essentially no difference in the self-reported satisfaction of workers who are mismatched according to the objective measures. While the coefficient is precisely estimated and hence statistically significant on the objective occupation mismatch measure, the magnitude is so low as to be economically insignificant.

The seriousness of the measurement challenge is already apparent. Two of the most commonly cited

Variable	(1)	(2)	(3)
Subjective Mismatch	-0.071***		
	(0.002)		
Objective Field Mismatch		-0.002	
		(0.002)	
Objective Occupation Mismatch			-0.005***
			(0.001)
Individual Controls	X	X	X
Educational Controls	X	X	X
Occupational Controls	X	X	X
Macroeconomic Controls	X	X	X
Adjusted R Squared	.048	.048	0.054
Observations	303103	303103	303103

Table 4: *** p<0.01, ** p<0.05, * p<0.10. Entries are survey-weighted linear coefficients. Outcome variable is self-reported job satisfaction indicator. Individual controls include age, race, marital status, region, and indicators for whether a respondent has children, is male, has a physical disability, and is a US Citizen. Educational controls include field-of-study, years since graduation, highest degree type, parents' education level, the 1994 Carnegie Classification for institution attended, and indicators for whether the individual attended community college, whether he/she attended a private institution, and whether he/she is a recent graduate. Occupational controls include occupation, hours worked per week, tenure, firm type, firm size, principal work activity, and a categorical variable for whether an individual has recently changed jobs. Macroeconomic controls include indicators for survey year and a measure of unemployment at the time of graduation (U.S. Bureau of Labor Statistics, 2020). Data from the 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates.

and important consequences of field of study mismatch, lower wages and greater dissatisfaction, are highly sensitive to what type of measure I use. In the case of job satisfaction, whether it is affected at all depends entirely on how I measure mismatch. This calls into question whether limited resources should be dedicated to reducing the phenomenon.

If policymakers, employers, or individuals nonetheless hope to reduce the incidence of mismatch (perhaps due to the persistence of the estimated wage penalty across measures), it is important to know its determinants. However, as I detail below, the measurement challenge arises when estimating determinants as well.

5.3 Causes

The main determinants of mismatch fall into four categories: individual, educational, occupational, and macroeconomic factors. For some, such as highest degree type, I find results consistent with the literature regardless of which measure I use[4]. However, there is enough variation across measures to warrant examination.

[4]For example, I find that attainment of more advanced degrees is associated with a lower likelihood of mismatch across measures.

For individual characteristics, the estimated effects of citizenship status and race/ethnicity differ based on the measure I use (Table 5). For citizenship the difference is straightforward. Noncitizens are less likely to report being mismatched, but are more likely to be working in an occupation that is uncommon for their field of study. The relationship is a bit more complex for race/ethnicity, but differences are nonetheless clear. For example, Hispanic respondents are less likely than white non-Hispanic respondents to report being mismatched, but are more likely to objectively appear mismatched. A less stark but still clear difference is with Asian respondents, who are no more likely to report being mismatched, despite objectively appearing mismatched more often.

For educational characteristics, the estimated coefficients for years since graduation and parents' education level differ across measures (Table 6). For the former, individuals are less likely to report being mismatched the longer it has been since they graduated, but are more likely to objectively appear mismatched. For the latter, the relationship is somewhat complex and admittedly difficult to interpret in a straightforward way. Nonetheless, the relevant takeaway for the purposes of this analysis is that for certain categories, such as having a mother with only some college experience, the coefficient differs across measures, despite being precisely estimated by the same model using the same data.

For job characteristics, firm size, firm type, and work type all have different estimated relationships with mismatch depending on the measure I use (Table 7). Firm size does not appear to matter much at all for the objective measure, but appears to have a positive association with the subjective one. Individuals working in not-for-profits and state governments are less likely to feel mismatched, but are more likely to be counted as mismatched by the objective measures (as compared to the reference category of those working in unincorporated self-employment). And for work type, compared to the reference group of accounting, individuals doing nearly all other types of work are less likely to report being mismatched, but are more likely to be working in an occupation uncommon for their field-of-study.

Finally, for macroeconomic factors, the unemployment rate at graduation has a small but positive effect on the subjective measure, but a negative one on the objective measures (Table 7).

There are many ways to interpret the direction and magnitude of the coefficients in these models, and there are many interesting relationships that I do not highlight here. Instead, the purpose of this exercise is

	Subjective Mismatch		Objective Field Mismatch		Objective Occupation Mismatch	
Variable	**Estimate**	**P**	**Estimate**	**P**	**Estimate**	**P**
Age	0.009***	0.000	0.001	0.464	-0.002**	0.018
Age Squared	0.000***	0.000	0.000	0.613	0***	0.000
Children	0.003**	0.043	0.008***	0.000	0.003*	0.096
Male	-0.005***	0.001	-0.004***	0.005	-0.003*	0.056
Physical Disability	0.013***	0.000	0.003	0.269	0.005**	0.036
US Citizen	0.012**	0.019	-0.013**	0.013	-0.003	0.603
Race/Ethnicity						
Asian (and Asian/White)	0.004	0.191	0.019***	0.000	0.022***	0.000
Black, non-Hispanic	0.014***	0.000	0.019***	0.000	0.038***	0.000
Hispanic, Mexican	-0.009**	0.029	0.01**	0.020	0.033***	0.000
Hispanic, non-Mexican	-0.006*	0.051	0.02***	0.000	0.032***	0.000
American Indian/Alaskan Native	0.022*	0.050	0.046***	0.000	0.053***	0.000
Native Hawaiian/Pacific Islander	-0.035***	0.001	-0.035***	0.003	-0.061***	0.000
Multiple Race	0.012**	0.010	0.030***	0.000	0.015***	0.005
Marital Status						
Marriage-Like Relationship	0.019***	0.000	0.007**	0.023	0.004	0.185
Widowed	0.023***	0.000	0.018***	0.002	0.011	0.104
Separated	0.026***	0.000	0.024***	0.000	0.009	0.185
Divorced	0.010***	0.000	0.009***	0.000	0.005**	0.041
Never Married	0.028***	0.000	0.02***	0.000	0.013***	0.000
Region						
Middle Atlantic	0.014***	0.000	-0.005	0.140	-0.005	0.163
East North Central	0.018***	0.000	-0.006**	0.037	-0.008**	0.012
West North Central	-0.015***	0.000	-0.010***	0.004	-0.008**	0.032
South Atlantic	0.018***	0.000	-0.009***	0.002	-0.012***	0.000
East South Central	0.017***	0.000	-0.013***	0.001	-0.016***	0.000
West South Central	0.014***	0.000	0.012***	0.000	0.007**	0.043
Mountain	0.013***	0.000	-0.004	0.274	-0.005	0.208
Pacific and US Territories	0.007**	0.011	-0.001	0.634	-0.003	0.419
Other	0.073**	0.028	-0.004	0.908	0.017	0.658
Adjusted R Squared	0.278		0.319		0.261	
Observations	303097		303097		303097	

Table 5: *** p<0.01, ** p<0.05, * p<0.10. Entries are survey-weighted linear coefficients. Outcome variables are subjective mismatch (column 1), objective field mismatch (column 2), and objective occupation mismatch (column 3). Reference categories are white non-Hispanic for race, married for marital status, and New England for region. Along with variables displayed in table, educational, occupational, and macroeconomic controls are included. Educational controls include field-of-study, years since graduation, highest degree type, parents' education level, the 1994 Carnegie Classification for institution attended, and indicators for whether the individual attended community college, whether he/she attended a private institution, and whether he/she is a recent graduate. Occupational controls include occupation, hours worked per week, tenure, firm type, firm size, principal work activity, and a categorical variable for whether an individual has recently changed jobs. Macroeconomic controls include indicators for survey year and a measure of unemployment at the time of graduation (U.S. Bureau of Labor Statistics, 2020). Data from the 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates.

	Subjective Mismatch		Objective Field Mismatch		Objective Occupation Mismatch	
Variable	**Estimate**	**P**	**Estimate**	**P**	**Estimate**	**P**
Community College	0.009***	0.000	0.017***	0.000	0.015***	0.000
Private College	-0.004***	0.007	0.000	0.773	-0.007***	0.000
Recent Graduate	-0.028***	0.000	-0.020***	0.000	-0.034***	0.000
Years Since Graduation	-0.002***	0.000	0.002***	0.000	0.004***	0.000
Years Since Graduation Squared	0.000***	0.000	0.000	0.425	0.000***	0.002
Highest Degree Type						
Masters	-0.052***	0.000	-0.019***	0.000	-0.013***	0.000
Doctorate	-0.083***	0.000	-0.050***	0.000	-0.032***	0.000
Professional	-0.069***	0.000	-0.246***	0.000	-0.256***	0.000
Parents' Education Level						
Father with Some College	-0.011***	0.000	-0.003	0.129	0.004*	0.072
Father with BA	-0.007***	0.000	-0.002	0.409	0.005**	0.030
Father with Advanced Degree	-0.001	0.518	0.004*	0.052	0.013***	0.000
Mother with Some College	0.006***	0.000	-0.003*	0.065	-0.003*	0.081
Mother with BA	0.009***	0.000	0.004**	0.029	0.003	0.123
Mother with Advanced Degree	0.012***	0.000	0.014***	0.000	0.007**	0.010
Institution Type Attended						
Research University II	0.004*	0.078	0.003	0.268	0.004	0.146
Doctorate Granting I	-0.008***	0.001	0.003	0.237	0.000	0.943
Doctorate Granting II	-0.009***	0.000	0.000	0.987	0.000	0.967
Comprehensive I	0.001	0.488	-0.001	0.636	-0.001	0.789
Comprehensive II	0.001	0.853	0.007	0.100	0.021***	0.000
Liberal Arts I	-0.013***	0.001	0.001	0.816	0.008*	0.067
Liberal Arts II	0.009***	0.002	0.000	0.895	0.024***	0.000
Medical School	0.002	0.679	-0.019***	0.002	-0.032***	0.000
Other	-0.005	0.102	0.015***	0.000	0.024***	0.000
Survey Year						
2010	-0.002	0.476	0.007***	0.002	0.067***	0.000
2013	-0.002	0.289	0.006**	0.016	0.005*	0.064
2015	-0.004*	0.071	0.012***	0.000	0.016***	0.000
2017	-0.010***	0.000	0.008***	0.001	0.008***	0.002
Interactions						
2010*Recent Graduate	0.037***	0.000	0.018***	0.007	0.031***	0.000
2013*Recent Graduate	0.010	0.119	0.007	0.330	0.020***	0.007
2015*Recent Graduate	0.001	0.889	-0.017**	0.016	-0.028***	0.000
2017*Recent Graduate	0.001	0.882	-0.024***	0.001	-0.020***	0.007
Adjusted R Squared	0.278		0.319		0.261	
Observations	303097		303097		303097	

Table 6: *** p<0.01, ** p<0.05, * p<0.10. Entries are survey-weighted linear coefficients. Outcome variables are subjective mismatch (column 1), objective field mismatch (column 2), and objective occupation mismatch (column 3). Reference categories are bachelor's for highest degree type, father/mother with no college for parents' education, Research University I for institution type, and 2003 for survey year. Along with variables displayed in table, individual, occupational, and macroeconomic controls are included. Individual controls include age, race, marital status, region, and indicators for whether a respondent has children, is male, has a physical disability, and is a US Citizen. Occupational controls include occupation, hours worked per week, tenure, firm type, firm size, principal work activity, and a categorical variable for whether an individual has recently changed jobs. Macroeconomic controls include indicators for survey year and a measure of unemployment at the time of graduation (U.S. Bureau of Labor Statistics, 2020). Data from the 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates.

Variable	Subjective Mismatch Estimate	P	Objective Field Mismatch Estimate	P	Objective Occupation Mismatch Estimate	P
Hours Worked	-0.002***	0.000	-0.001***	0.000	-0.001***	0.000
Supervisor	-0.038***	0.000	-0.006***	0.000	-0.014***	0.000
Tenure	-0.002***	0.000	-0.001***	0.000	-0.002***	0.000
Tenure Squared	0.000	0.977	0.000***	0.000	0.000**	0.012
Unemployment at Graduation	0.001***	0.004	-0.001***	0.006	-0.001***	0.007
Firm Type						
Self-employed (incorporated)	0.010***	0.002	0.001	0.844	0.008**	0.022
Private For Profit	-0.015***	0.000	-0.001	0.861	-0.004	0.256
Private Not-for-Profit	-0.063***	0.000	0.015***	0.000	0.019***	0.000
Local Government	-0.085***	0.000	-0.032***	0.000	-0.038***	0.000
State Government	-0.078***	0.000	0.010**	0.013	0.009**	0.041
Active Duty US Military	0.077***	0.000	0.026***	0.003	0.04***	0.000
U.S. government (civilian employee)	-0.058***	0.000	-0.006	0.282	-0.019***	0.001
Other	0.003	0.784	-0.050***	0.000	-0.030**	0.036
Firm Size (Number of Employees)						
11-24	0.004	0.252	-0.003	0.396	0.006*	0.081
25-99	0.003	0.275	-0.002	0.503	-0.003	0.403
100-499	-0.005*	0.055	-0.014***	0.000	-0.019***	0.000
500-999	0.001	0.749	-0.001	0.748	-0.005	0.139
1000-4999	0.006**	0.037	-0.005	0.105	0.000	0.956
5000-24999	0.006**	0.033	0.000	0.995	0.001	0.786
25000+	0.022***	0.000	-0.005	0.125	-0.003	0.396
Work Type						
Basic Research	-0.01*	0.099	0.041***	0.000	0.030***	0.000
Applied Research	-0.023***	0.000	0.026***	0.000	0.038***	0.000
Computer Programming	-0.031***	0.000	0.009*	0.064	0.018***	0.001
Material Production Research	-0.022***	0.000	0.012**	0.023	0.019***	0.001
Design of Equipment, Processes, Models	-0.009*	0.050	0.009*	0.081	-0.001	0.805
Employee Relations	-0.017***	0.000	0.033***	0.000	0.034***	0.000
Management and Administration	-0.006*	0.061	0.024***	0.000	0.038***	0.000
Production, Operations, Maintenance	0.069***	0.000	0.022***	0.000	0.026***	0.000
Professional Services	-0.035***	0.000	-0.003	0.365	-0.005	0.156
Sales, Purchasing, Marketing	0.044***	0.000	0.025***	0.000	0.031***	0.000
Quality or Productivity Management	0.025***	0.000	0.029***	0.000	0.042***	0.000
Teaching	-0.024***	0.000	0.027***	0.000	0.022***	0.000
Other	0.084***	0.000	0.015***	0.000	0.026***	0.000
Job Change						
Different Employer, Different Job	0.008***	0.001	0.011***	0.000	0.018***	0.000
Different Employer, Same Job	-0.036***	0.000	-0.011***	0.000	-0.011***	0.000
Same Employer, Different Job	0.046***	0.000	0.036***	0.000	0.034***	0.000
Adjusted R Squared	0.278		0.319		0.261	
Observations	303097		303097		303097	

Table 7: *** p<0.01, ** p<0.05, * p<0.10. Entries are survey-weighted linear coefficients. Outcome variables are subjective mismatch (column 1), objective field mismatch (column 2), and objective occupation mismatch (column 3). Reference categories are self-employed (unincorporated) for firm type, 1-10 employees for firm size, accounting for work type, and "same employer same job" for job change. Along with variables displayed in table, individual, occupational, and macroeconomic controls are included. Individual controls include age, race, marital status, region, and indicators for whether a respondent has children, is male, has a physical disability, and is a US Citizen. Educational controls include field-of-study, years since graduation, highest degree type, parents' education level, the 1994 Carnegie Classification for institution attended, and indicators for whether the individual attended community college, whether he/she attended a private institution, and whether he/she is a recent graduate. Unemployment data from the Bureau of Labor Statistics (U.S. Bureau of Labor Statistics, 2020). Data from the 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates.

to highlight just how variable the findings are across different measures of mismatch, despite being estimated with extremely high precision. Thus, not only is it debatable whether it is worth committing resources to combat field-of-study mismatch, it is unclear how those resources should be used even if they were.

6 Emotional Disposition as a Potential Explanation

This finding, beyond calling to attention the need for caution, also raises the question of why these measures differ at all, let alone so significantly. Both have reasonable theoretical justifications, and neither seem clearly inferior.

One possible explanation is emotional disposition. Those unhappy with their job or life situation may also be less likely to see a relationship between their degree and the work they do, and/or may simply be more likely to respond negatively to subjective questions in general, such as ones asking them to consider their level of match. Or, inversely, those who are satisfied with their job and/or life in general may be willing to overlook incongruities between what they studied and what they do for work, or may simply answer in the affirmative to subjective questions.

To understand how this could lead to measurement sensitivity, consider the model using salary as the outcome. One way to interpret the coefficient on the subjective measure is that those who report being mismatched earn less due to said mismatch. However, if emotional disposition influences whether an individual reports mismatch, reverse causality becomes another possible explanation. Specifically, a lower salary could worsen an individual's emotional disposition, and, as a consequence, make him/her more likely to report being mismatched. If this were the case, a smaller estimated coefficient for the objective measure is to be expected, given that there is no obvious direct connection between it and disposition, and hence less chance for reverse causality.

In other words, a relationship between emotional disposition and the subjective measure of mismatch opens the door to pernicious possibilities like reverse causality and omitted variable bias, which would appear as measurement sensitivity when compared to an objective measure that is unrelated to emotional disposition.

While rarely investigated thoroughly, others have noted this as a potential confounding factor for sub-

	Objective Mismatch	Subjective Mismatch
Individual Characteristics		
Children in Household	47.7%	44.4%
Physical Disability	9.6%	11.0%
Married	66.5%	61.4%
Educational Characteristics		
Community College	47.4%	48.9%
Recent Graduate	12.8%	16.5%
Undergraduate Debt	$12,687.00	$13,877.00
Occupational Characteristics		
Salary	$72,946.00	$56,685.00
Supervisor	38.3%	30.8%
Hours Worked Per Week	40.6	38.1
Years At Firm	7.6	6.9

Table 8: Comparison between subjective and objective measure of mismatch across key metrics. Subjective mismatch based on whether the respondent reports that his/her field-of-study is not related to his/her occupation. Objective mismatch indicates whether the respondent studied one of the fields that cover 75% of workers in his/her occupation. Data from the 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates. Undergraduate debt only measured in 2013, 2015, and 2017 waves.

jective measures of mismatch. For example, Domadenik et al. (2013) explain that they use an objective measure in part because subjective measures may capture the more general feelings that one has towards his/her job or life.

To investigate whether this is the case in my data, I explore what types of individuals are classified as subjectively mismatched and compare them to those classified as objectively mismatched. Given that there is surprisingly little overlap between the two measures [5], it is reasonable to expect that these groups will differ. The key differences are highlighted in Table 8.

Across individual metrics, three features stand out. Compared to those in the objective mismatch category, individuals in the subjective mismatch category are less likely to report having children in the household, are less likely to be married, and are more likely to report having a physical disability. For educational characteristics, those in the subjective mismatch category are slightly more likely to have attended community college at some point and are much more likely to report having graduated within the previous 5 years (in relation to when they answered the survey). In addition, those in the subjective mismatch group have considerably more undergraduate debt [6]. The contrasts are particularly stark for job characteristics. Compared to those in the objective mismatch category, those in the subjective mismatch category earn significantly less,

[5] As discussed in the results section, only 30% of those who are objectively mismatched are also subjectively mismatched. Similarly, only 40% of those who are subjectively mismatched are objectively so

[6] I did not include undergraduate debt in my models since it is only available for the 2013, 2015, and 2017 waves of the NSCG.

	Objective Mismatch	Subjective Mismatch
Health Benefits	75.3%	65.7%
Pension Plan	66.6%	56.9%
Vacation Time	76.4%	68.4%

Table 9: Comparison of benefits between subjectively and objectively mismatched individuals. Subjective mismatch based on whether the respondent reports that his/her field-of-study is not related to his/her occupation. Objective mismatch indicates whether the respondent studied one of the fields that cover 75% of workers in his/her occupation. Data from the 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates.

work fewer hours per week, have been at their firm for fewer years, and are much less likely to be supervisors.

It seems possible, perhaps even likely, that individuals who differ across these metrics would also differ in unmeasured general disposition. Indeed, previous research has found that factors like marital status, salary, occupational status, and physical disability status are all associated with disposition (Pagán-Rodríguez, 2010; Bjørnskov et al., 2008; Diener and Seligman, 2004; Frey and Stutzer, 2002).

The availability of job benefits also supports the theory that emotional disposition is playing a role. Compared to those who objectively appear mismatched, those who report being mismatched are far less likely to have health insurance, a pension plan, and vacation time (Table 9). Once again, there is evidence that those without such benefits are less satisfied (Artz, 2010). As a result, these individuals may respond differently to subjective questions.

Also illuminating, though not included in my models, are the aspects of work that individuals report as important. In particular, compared to their matched counterparts, subjectively mismatched individuals are less likely to report that they find the social impact and intellectual challenge of their job somewhat or very important, by 5.5 and 4.8 percentage points respectively. However, individuals counted as mismatched by the objective measure are no more or less likely to report these features as important compared to matched individuals. Once again, this suggests that, unlike with objective mismatch, the individuals captured by the subjective measure differ not only in level of match, but also in factors related to general attitudes.

Of particular interest are those individuals for whom the measures disagree. I develop a more detailed measure of mismatch with the aim of isolating and examining such individuals. I do so by combining the subjective and objective measures.[7]

Given that these are two binary variables, combining them leads to four categories: true match, reported

[7] I use the objective field mismatch measure to save space and keep the the number of comparisons I examine reasonable. Comparisons are similar using objective occupation mismatch.

match, true mismatch, and reported mismatch. The first refers to individuals who both report being matched and who studied a field common for workers in their occupation. The second refers to individuals who report that they are matched but who studied a rare field for their occupation. The third refers to individuals who both say they are mismatched and who studied an uncommon field for their occupation. The fourth refers to individuals who report that they are mismatched but who studied a common field among workers in their occupation. A summary of how I arrive at these labels can be seen in Table 10

	Subjective Match	**Subjective Mismatch**
Objective Match	*True Match*	*Reported Mismatch*
Objective Mismatch	*Reported Match*	*True Mismatch*

Table 10: Combined categories of mismatch. Subjective mismatch based on whether the respondent reports that his/her field-of-study is not related to his/her occupation. Objective mismatch here indicates whether the respondent studied one of the fields that 75% of workers at his/her occupation studied. Data from the 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates.

As I discussed in my modeling section, 63% of individuals fall into the true match category, 12% fall into the reported match category, 8.1% fall into the true mismatch category, and 17% fall into the reported mismatch category.

Examining these categories reveals a similar pattern as above. Not only do the reported match and reported mismatch groups fundamentally differ from one another across key metrics, but those in the reported mismatch category differ in ways that suggest a worse emotional disposition (Figures 1-4). For example, they are much less likely to have benefits, less likely to be supervisors, and less likely to be married than those in the reported match category, all things researchers have found to worsen an individual's disposition (Pagán-Rodríguez, 2010; Bjørnskov et al., 2008; Diener and Seligman, 2004; Frey and Stutzer, 2002).

Interestingly, individuals in the reported match category closely mirror those who are truly matched, while those in the reported mismatch category mirror those in the true mismatch one. This suggests that the subjective component of mismatch is the key in deciding whether a given mismatched individual will differ from a matched one.

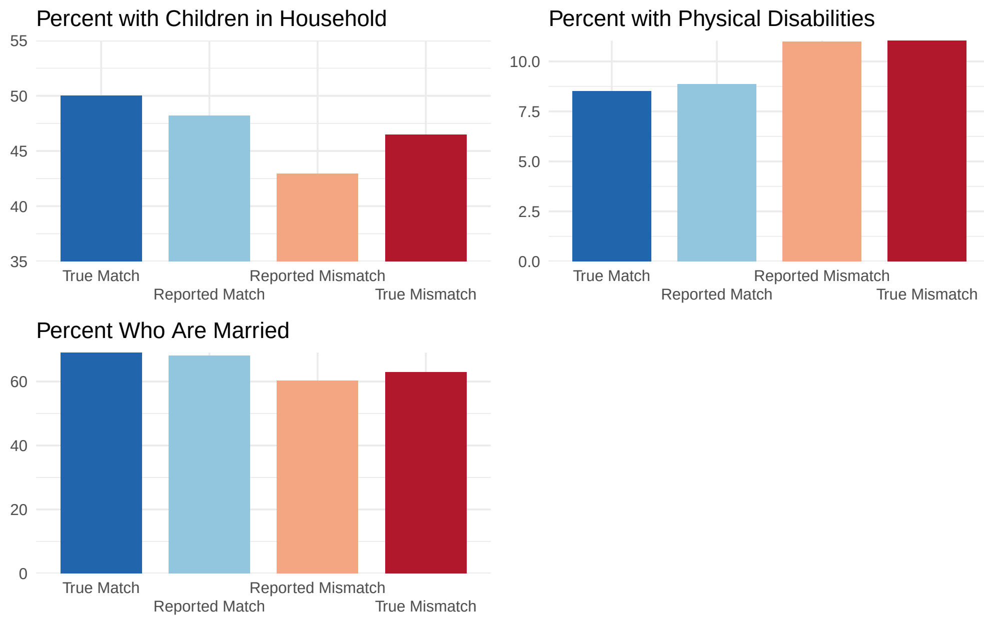

Figure 1: Percent of respondents with children in the household and percent of respondents with physical disabilities across four categories of mismatch. Dark blue indicates true match, light blue indicates reported match, light red indicates true mismatch, and dark red indicates reported mismatch. Those in the true mismatch and reported mismatch categories are less likely to have children and more likely to be physically disabled compared to those in the true match and reported match categories. Data from the 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates.

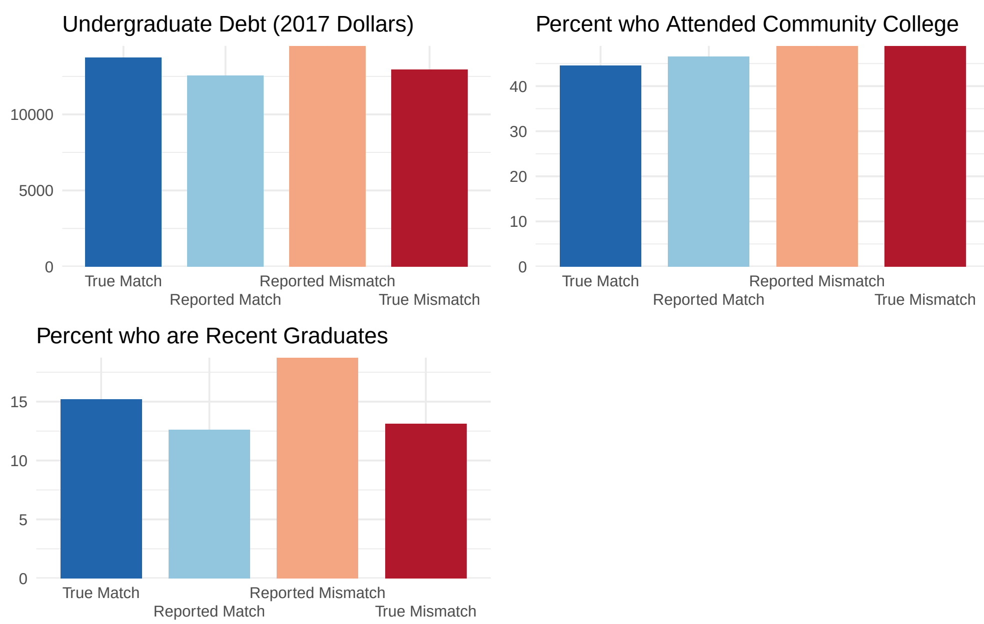

Figure 2: Clockwise: Average undergraduate debt in 2017 dollars, percent of respondents who attended community college at some point, and percent of respondents who graduated within five years of responding to the survey, across four categories of mismatch. Those in the reported mismatch category are disproportionately more likely to be a recent graduate and to have considerable student loan debt. Along with those in the true mismatch categories, these individuals are also more likely to have at some point attended community college. Data from the 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates.

Figure 3: Clockwise: Average annual salary in 2017 dollars, average hours worked per week, average number of years at firm, and percent of respondents who are supervisors, across four categories of mismatch. Those in the true mismatch and reported mismatch categories have lower salaries, work fewer hours, have less experience at their firm, and are less likely to be supervisors compared to their counterparts in the true match and reported match categories. Data from the 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates.

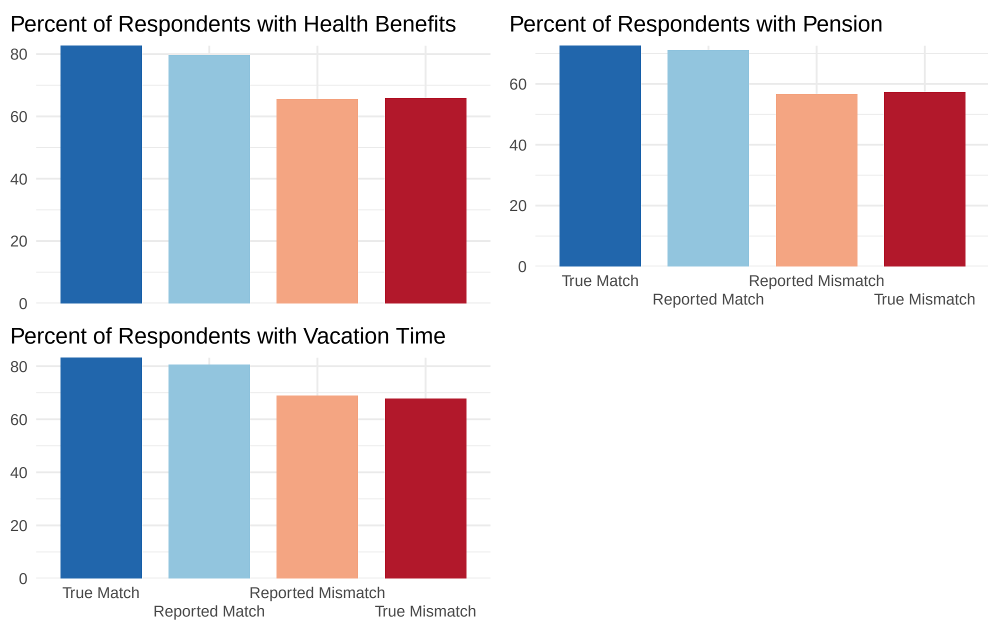

Figure 4: Clockwise: Percent of respondents with health benefits, with a pension plan, and with vacation time, across four categories of mismatch. Those in the true mismatch and reported mismatch categories are less likely to have any of these benefits compared to their counterparts in the true match and reported match categories. Data from the 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates.

The final factor that sheds light on this question is job satisfaction, perhaps the most closely related factor to disposition in my data. Looking at the relationship between self-reported job satisfaction and the four detailed mismatch categories provides further evidence that emotional disposition is indeed related to whether a given individual reports themselves as mismatched. Those who are dissatisfied with their work are disproportionately more likely to report being mismatched, even if the field they studied is common for their occupation. Similarly, those who are satisfied with their work are disproportionately more likely to report being matched, even if the field they studied is uncommon for their occupation (Figure 5). While it is challenging to isolate the direction of this effect (mismatch could be affecting satisfaction), this strongly suggests that the subjective measure of mismatch at least partially captures how a given worker feels in general, not just whether they are truly mismatched.

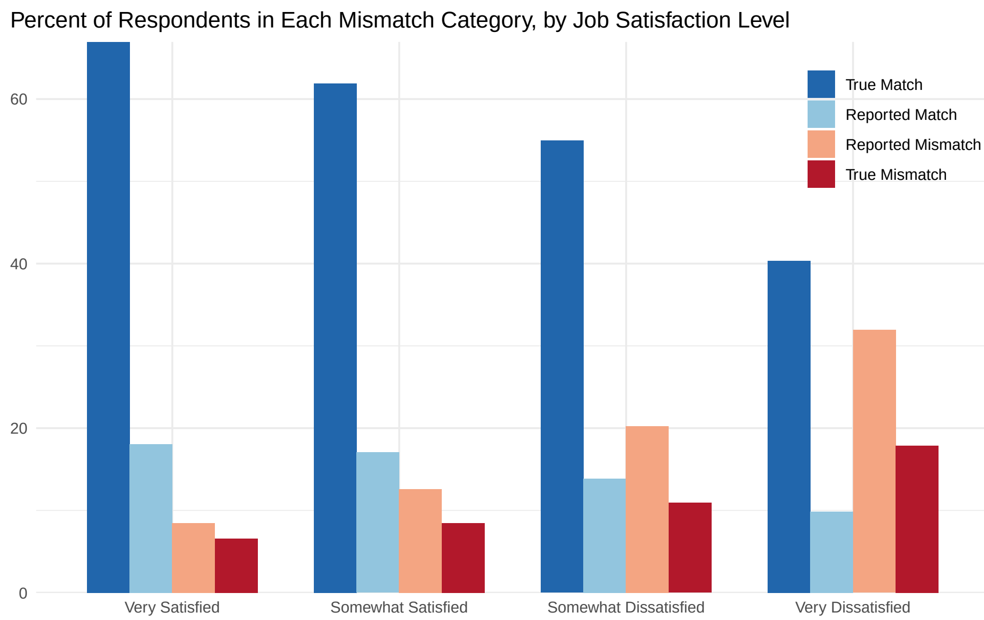

Figure 5: Percent of respondents in each category of the full mismatch measure, grouped by self-reported level of job satisfaction. Individuals in the reported mismatch category are disproportionately more likely to be dissatisfied with their job. Conversely, individuals in the reported match category are disproportionately more likely to be satisfied with their job. Data from the 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates.

Overall, this analysis both reconfirms that the subjective and objective measures capture fundamentally different individuals and sheds light on why this may be. Specifically, it suggests that the subjective mismatch measure also proxies for emotional disposition and how individuals feel about their work and life in general. This opens the door to reverse causality and omitted variable concerns, which would appear as measurement sensitivity when compared to an objective measure.

7 Conclusion

Using data from the 2003, 2010, 2013, 2015, and 2017 waves of the National Survey of College Graduates, I provide evidence that the predicted causes and consequences of field-of-study mismatch are highly sensitive to the measurement method that one uses. Specifically, I demonstrate that the estimated effect of mismatch on salary and satisfaction, as well as the estimated relationship between mismatch and individual, educational, and occupational factors, differs based on whether I use a subjective worker self-assessed measure of mismatch or an objective data-driven one.

The direction and size of these effects, as well as which characteristics relate to which measures of mismatch, point to emotional disposition as the likely cause of this sensitivity. Specifically, the subjective measure appears to capture not only whether an individual is mismatched or not, but also whether he/she has a generally positive or negative attitude. Given the likely relationship between such attitudes and factors such as salary, satisfaction, and undergraduate debt, there is a high likelihood of reverse causality and omitted variable bias. These biases are avoided with the objective measure, providing a reasonable explanation for why the estimates found using it differ from the ones found using the subjective measure.

This has real-world implications. It calls into question what types of policies would be effective in ameliorating field-of-study mismatch, and ultimately calls into question whether doing so is a worthwhile use of limited resources in the first place. Given these concerns, future research should rely on more objective measures such as job analysis and realized match, like employed by Montt (2015) and Viramontes et al. (2015).

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