THREE ESSAYS CONSIDERING THE LABOR MARKET BEHAVIOR OF YOUNG WORKERS

A Dissertation
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DOCTOR OF PHILOSOPHY

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by
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ABSTRACT

This dissertation consists of three chapters investigating labor market trends, specifically of young workers (ages 18-24). In the United States, young workers decreased their labor market participation by more than 8% from 1994-2014 and the first chapter of this research considers changing demographics and educational decisions to account for this decline. Using connected monthly Current Population Survey (CPS) data, an alternative definition of labor market attachment is considered, which accounts for *attached*, *marginally attached*, and *not attached* workers. Additionally, attending college is considered as a weak form of labor market participation. Accounting for demographic changes and varying levels of attachment by demographics, the decrease in the participation rate is decomposed into *genuine* and *demographic* changes. The finding is a *genuine* decrease of 1.5% young workers out of the labor force over the twenty year period studied. A calculation of the impact of college major choice on participation is estimated by extending the decomposition, as well as estimating a logit model on participation by college major. For males certain majors (Agriculture and English and Foreign Language) correlate with lower labor force attachment, while others (Engineering, Mathematics, and Visual and Performing Arts) correspond with higher attachment. For females, graduate degrees are the strongest indicator of attachment to the labor force and being married correlates with non-attachment to the labor force.

The second chapter of this research investigates the movement of young workers between labor market statuses. Rather than consider the stocks and percentages of workers in each state (i.e. charting the unemployment or participation rate), this paper

analyzes the flows between statuses. A contribution of this research is to consider how labor market flows are impacted by education decisions by including schooling as a labor market status. Additionally, this chapter estimates the impact that labor market movements by young workers have on fluctuations of their unemployment rate; flows between unemployment and not-in-the-labor-force, account for over forty percent of the variation in unemployment for young workers.

As young workers decide whether to participate in the labor force or continue their education, they must decide whether to forgo "on-the-job" training and experience or attend college to acquire human capital through formal education. Following the work of John Robst (2007), the third chapter of this research considers three questions: To what extent do college graduates work in fields unrelated to their most recent degree field? Which degree fields lead to greater mismatch? What is the relationship between working outside a degree field and wages?

This research first provides updated answers to these questions using data from the 2013 National Survey of College Graduates (NSCG). Additionally, this work includes new specifications of the wage penalty using parental education level, which was unavailable in Robst's data. The result indicates a wage correlation of complete mismatch between job and college major that is more than three times that of a partial mismatch. An important contribution of this paper is to address changes over time by comparing results from the NSCG data in 1993, 2003, 2010, and 2013. A significant result is that the negative association between mismatch and wages has increased by a factor of three for men and over four times for women from 1993 to 2013.

The conclusions in this research describe both structural and cyclical trends in the young worker labor market. Despite the significant proportion of young workers in the labor force, little research has been conducted using data from individuals under the age of twenty-five. This dissertation focuses on young workers because of the importance they play in the labor market, but also to motivate future research. The decisions young people make impact the labor market as well as drive individual future labor market outcomes; policy should be informed by the structural and cyclical trends presented throughout this research.

for Andre Lavallee

ACKNOWLEDGMENTS

I am grateful to my wife, Cara, for her unwavering support throughout this process. In the eight years it took to reach this point, we were married, bought two houses, and brought AJ into this world. I could not have done any of this without you- there were many sacrifices, but we had fun along the way too!

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CHAPTER 1

LABOR MARKET PARTICIPATION OF YOUNG WORKERS

1 Introduction

Young worker labor force participation in the United States has decreased over eight percentage points from 1994 to 2014 (from 73.11% to 65.02%). This equates to roughly 2.5 million fewer young workers (defined here as ages 18-24) in the labor force, and this research investigates the decline. The eight percent decrease in participation is not simply a mass departure of young workers from the labor force; using alternative definitions of labor force attachment as well as population decompositions, this research finds that eighty percent of the decrease (6.5% of the 8%) is due to either changing demographics or schooling decisions. The resulting "genuine" decrease of young worker participation is approximately 1.5% and results in almost five hundred thousand fewer young workers attached to the labor force in 2014 than in 1994.

The decline in labor force participation by young workers coincides with trends seen in the entire working age population, where participation decreased by 4% over the same time period (and only 2.3% for workers age 25 and over). The sharper decline seen in the population of young workers highlights the different labor force experience and opportunities of young and established workers.

Labor market outcomes, specifically job separation and unemployment rates, are higher for young workers than the entire population (Gervais, et al. 2014); young people are also particularly mobile (Mincer, 1986). Thus, young workers confront the decision of whether to participate in the labor market frequently, including when they initially enter the labor force. Additionally, the inclusion of full-time students in "Not in the Labor Force" status is more relevant to young workers than the population as a whole, specifically for those who intend to enter the labor force upon finishing their education.

This research differentiates between *Marginally Attached* young workers and those *Not Attached* to the labor force, including full-time student status as a marginal or weak form of labor market participation. Differentiating nonparticipation in this manner results in almost 7% marginally attached workers (with spurious labor market outcomes or in education) and a 1.6% increase in young workers who are not at all attached to the labor force from 1994-2014.

This paper's focus on labor market decisions of young workers is important because their choices affect the labor market as a whole. It is valuable to understand if the decrease in participation by young workers is cyclical or represents permanent structural changes. The participation rate of young workers does not return to trend during recoveries, which is worrisome because early labor market outcomes persist throughout lifetimes (Kahn, 2010) and if young workers leave the labor market and do not return, then a structural shift is occuring in the economy. If young workers want jobs (and are searching) and cannot find jobs, then policy should be tailored to a jobs crisis. If, instead, the labor force is shrinking because fewer young people are entering the labor market due to extending education, then the economy must adjust to fewer young workers.

More importantly, the choices by young workers early in their careers can adversely affect their future productivity and wages by reducing human capital. Despite the significant proportion of young workers (18-24 year-olds comprised 9.9% of the United States population in 2014), little research has considered the decisions of these workers as they navigate the labor market. Young workers face the decision of choosing whether to participate in the labor force and gain experience on-the-job or pursue a higher degree (and specific college major), and this decision has not received attention in the labor market literature. The labor market returns to education have been widely studied, and this research examines the decision young people make of entering the labor force or choosing an educational path.

As young workers face a job market that demands higher education levels, their decisions of whether to enter the labor market evolved from 1994 to 2014. After decomposing changes to labor force participation into *genuine* and *demographic* changes, the decompositions are extended to consider participation of workers by level of education. Last, to further study changes to participation over the twenty year period a decomposition is computed to account for changes in college majors, along with other demographic changes.

This research uses data from the Current Population Survey (CPS), which is a monthly survey produced by the Bureau of Labor Statistics (BLS). The rest of paper is organized as follows: Section 2 of this paper analyzes participation trends within the young worker labor market from 1994-2014. Section 3 provides a literature review. Section 4 describes the data used in this study. Section 5 extends the definition of labor force participation to include "marginally attached" workers. Section 6 computes compositional changes of the young worker labor market and decomposes participation into genuine and demographic changes. Section 7 extends the decomposition to consider labor force participation by levels of schooling. The last section concludes the paper.

2 The Labor Market for Young Workers

Young workers (ages 18-24) make up a significant portion of the working age population (almost 16% in 2014) and deserve consideration because young workers face different incentives than older workers.[1] Before considering trends within the young worker labor market, Figure 1.1 shows the labor force participation rate of young workers from 1994-2014. Labor force participation is defined as the percentage of the population that is active in the labor market; using definitions from the Bureau of Labor Statistics (BLS), participants in the labor market are either employed, unemployed and searching, or unemployed on tempory layoff. Those not in the labor force (NILF) could be discouraged unemployed workers who are no longer searching, students, retirees, disabled, or those not interested in working. The motivation of this research can be found in Figure 1.1 below, which shows the participation has dropped from 73.11% in 1994 to 65.02% in 2014. This research accounts for the over 8% drop in participation by considering underlying trends within the young worker population.

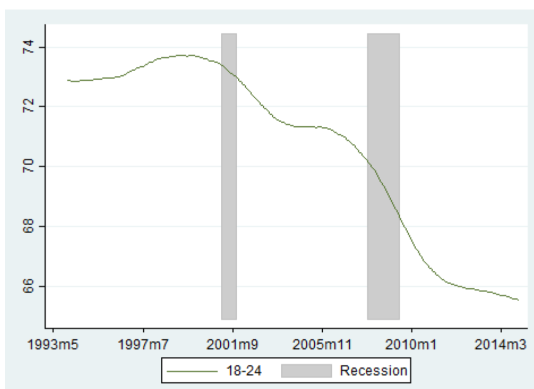


Figure 1.1: Participation in the labor market, ages 18-24.

Of note in Figure 1.1 is the cyclical pattern of particpation. The decrease in partic-

[1]Gervais, et al. analyze the labor market outcomes and occupational fit in detail.

ipation during recessions is consistent with labor market theory. The concern is that the participation rate of young workers does not return to trend during recoveries. This is worrisome because early labor market outcomes persist throughout lifetimes (Kahn, 2010) and if young workers leave the labor market and do not return, then a structural shift is occuring in the economy.

With the rise of enrollment in schooling (both high school and college), 18-24 year-olds may not be participating in the labor market because of continued education that includes the intention of joining the labor force upon graduation. This idea is explored in Section 5 by considering “Marginally Attached” workers. An alternative explanation of the decrease in participation is that the demographic composition of young people has shifted towards demographic groups with lower rates of participation. These arguments are addressed by creating counterfactual participation rates in Section 6.

The objectives and significant findings of this research focus on changes within the young worker population; the impact these changes have on the entire labor force is left to further research. The following two subsections frame the decline in labor force participation of young workers by comparing the young worker labor market to the entire labor market, then by considering changes within the young worker labor market.

Comparison of Young Workers’ Labor Market to Entire Labor Market

Participation

The labor force particpation rate for the entire United States population decreased from a high of 67.3 % in early 2000 to 62.7% by the end of 2014. Figure 1.2 below shows the participation rate of those aged 18-24 in comparison to those aged 25-34 and those over the age of 25 (which is the minimum age used in most labor market research).

Figure 1.2: Participation in the labor market by age group, 1994-2014.

	Labor Force Participation		
	1994	2014	change
18-24	73.11%	65.02%	-8.09%
25-34	83.20%	81.80%	-1.40%
25+	66.66%	64.41%	-2.25%

Table 1.1: Changes in participation by age group.

There are many commonly discussed reasons for the decline in labor force participation, but many are not relevant to young workers. Specifically, the overall decrease has been explained by the aging baby boomer population (which has increased the number of retirees and thus non participants), and the rising number of disabled persons (Fujita, 2014). These trends should increase the difference between the participation rate of young workers and that of the rest of the population, but as Figure 1.3 shows, that gap has decreased since 1994. This continues to indicate that the decrease in participation of young workers has been sharper than the rest of the population.

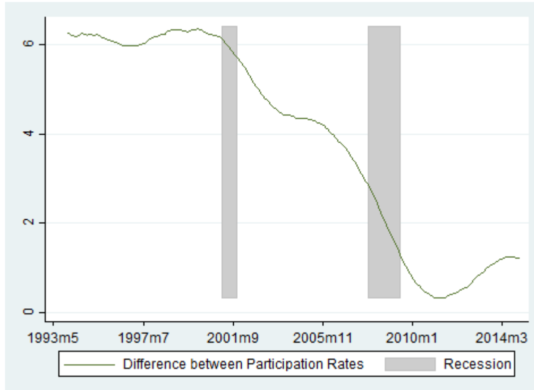
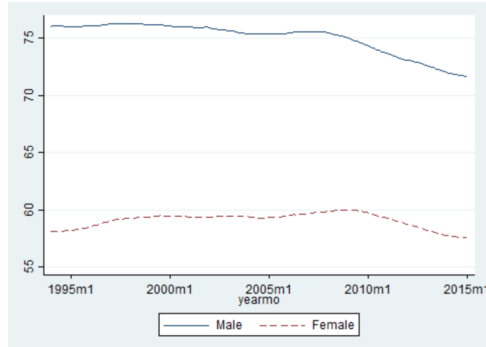


Figure 1.3: Difference between participation rates of young workers and ages 25 and older.

Another commonly discussed rationale for the decreasing participation rate is a decrease in working women over the past twenty years (after a large rise in the preceding thirty years). The graphs in Figure 1.4 compare the male and female participation rates of those ages 18-24 and for ages 25 and older. From 1994-2014, the gender participation gap- defined as the difference between male and female participation- has decreased more for young workers than the rest of the working age population. Differences in participation by gender within the 18-24 population will be discussed in the next section, but the differences (shown in Figure 1.5) indicate that the gender participation gap decreased more for 18-24 year olds (down 5.93%) than the rest of the population (down 3.75%).

There are two other common explanations for the decrease in labor market participation. The rise in education (and college enrollement) has taken many young people out of the labor force. This is a central consideration of this research and will be discussed in significant detail in Subsection 2.2.2, and is a common theme throughout this research.

(a) 18-24



(b) 25+

Figure 1.4: Labor market participation by gender.

Figure 1.5: Difference in participation rates by gender.

The final explanation for the decline in labor force participation is that unemployed workers become discouraged and stop searching for a job. These workers subsequently drop out of the labor force. The next subsection specifcally considers trends in unemployment for both young workers and labor market as a whole.

Unemployment

The labor market participation rate directly drives the unemployment rate. Since the unemployment rate is calculated by dividing the number of unemployed workers by the number of workers participating in the labor force, the connection between unemployment and participation is important. If an employed worker separates from employment and leaves the labor force, then the unemployment rate would increase, but if an unemployed worker leaves the labor force, then the unemployment rate decreases. During the recovery since the Great Recession, the participation rate- for both young workers and the entire population- has decreased, while the unemployment rate has also decreased, implying more unemployed workers leaving the labor force than employed workers.

Figure 1.6 shows the unemployment rate over the past twenty years for both young workers and for the population over age 25. Most relevant to this research is that while young workers generally participate more than those older than 25 (Figure 1.2), the unemployment rate is consistently higher for young workers.

Figure 1.6: Unemployment rates by age group.

While both unemployment rates move together, the difference between the two does vary. Figure 1.7 traces the difference between the two unemployment rates over time. During both recessions over the past twenty years, the difference between the unemployment rates has spiked (up almost 2 percentage points in the early 2000's and about 4 percentage points during the Great Recession).

Additionally, the difference returns to trend after the counter-cyclical spike. The interpretation here is that young workers are impacted (negatively) by recessions more extremely and immediately than older workers. This is consistent with much of the literature that younger workers are the first to lose their job in a recession.

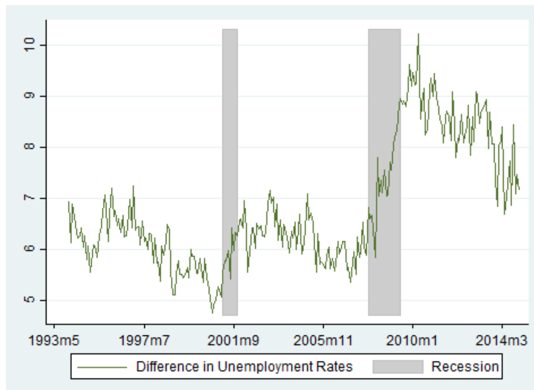


Figure 1.7: The difference between unemployment rates over the past twenty years.

A simple regression between the difference in unemployment rates of young workers and the labor market as a whole tests the significance for the change observed in Figure 1.7 (results reported in Table 1.2).

Variable	**Coefficient**	**(Std. Err.)**
monthlyGDPchange	-1.386	(0.363)
Intercept	7.074	(0.107)

Table 1.2: Estimation results : difference in unemployment rate

The recessions that occured during the 2000s impacted young workers differently than the rest of the labor force. The objectve of this research is to examine changes in behavior and composition of young workers in the labor market. While some behaviors mirror those of the labor market as a whole, others are unique to young workers. Other analyses (discussed in the literature review of Section 3) consider the labor market as a whole, or just workers over the age of 25, but the conclusions formed in this section motivate a deeper examination of the young worker labor market.

The next section begins the analysis of trends within the young worker population by considering changes in participation of subgroups of young workers.

Changes Within the Young Worker Labor Market

Differences in Labor Participation Rates by Gender and Race and Ethnicity

One initial explanation of the decrease in participation of young workers is changing demographics. Two forces combine within demographic groups to influence the aggregate labor market behavior of young workers: population trends and participation trends. While all subpopulations- defined in this research as gender, race and ethnic group, age, and education- within the young worker labor market have had varying experiences over the time period considered, they all (with very few exceptions) participate at a lower rate in 2014 than they did in 1994. While the subsets of young workers considered in this research show downward trends in participation, not all change monotonically.

Population trends by each subgroup will be detailed in Section 6 when changes in participation are decomposed to account for the changing demographics. The calculation of "counterfactual" participation rates- using 1994 populations with 2014 participation and vice versa- deciphers between the *demographic* and *genuine* changes within each subpopulation's participation rates. Looking solely at participation rates, the table below considers differences in participation between 1994 and 2014 of young workers by gender and race and ethnic group using data from the Current Population Survey.[2] As seen in Table 1.3, subpopulations of young workers have clearly changed their labor force participation at varying rates over this time period. The following graphs continue to break down labor force participation by worker characteristics.

[2]See data appendix C for detailed procedure for defining subgroups.

Participation by Demographic, ages 18-24	1994	2014	change
Overall	73.11%	65.02%	-8.09%
gender			
Male	78.07%	66.85%	-11.22%
Female	68.22%	63.17%	-5.05%
race and ethnicity			
White	77.00%	68.07%	-8.93%
Black	63.07%	60.27%	-2.80%
Hispanic	69.46%	64.77%	-4.69%
Asian	52.85%	47.79%	-5.06%
Other	63.46%	64.08%	+0.62%

Table 1.3: Changes in participation by demographics, ages 18-24.

The graph in Figure 1.8 below displays labor market participation rates of young workers by gender from 1994 to 2014. Young female workers increased their participation in the late 1990s and saw a decrease during and around the recession in 2001. That increase accounted for, young female workers decreased participation over the enitre time period by about 5 percentage points (from 68.22% to 63.17%), while young male participation decreased by over 11 percentage points (from 78.07% to 66.85%). Given that the distribution of gender in the population barely changes, this decrease in the participation gap begins to explain the driving forces behind the overall decline in participation.

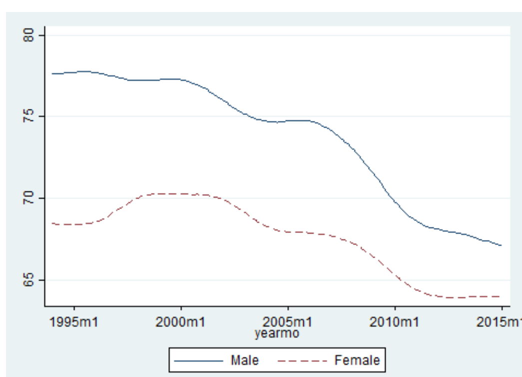
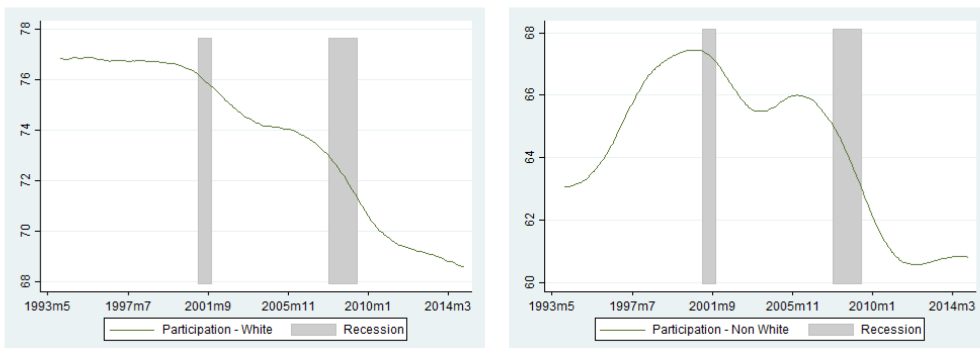


Figure 1.8: The participation rate of 18-24 year-olds by gender.

Nonwhite young workers increased their labor market participation from the late 1990s until the recession in 2001, but over the twenty-year period, this subgroup's participation in the labor market decreased by 3.5 percentage points (from 64.79% to 61.27%); much of the decrease in participation occured during the Great Recession (see Figure 1.9b). Labor market participation for young white workers mirrors that of the entire labor force as they decreased participation almost 9 percentage points (from 77.00% to 68.07%) with increased declines during and immediately following both recessions covered by the data set. Unlike nonwhites, whites do not seem to have any returns to trend following recessions.

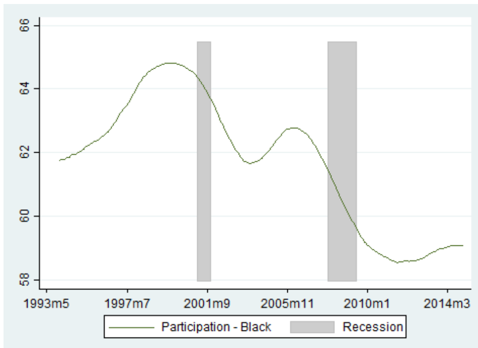


(a) white (b) nonwhite

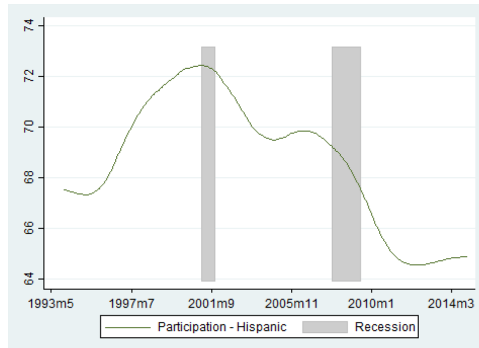
Figure 1.9: Labor market participation by race and ethnicity, ages 18-24.

The participation of young nonwhite workers in the labor market can be broken down further. The graphs in Figure 1.10 below chart labor market participation from 1994-2014 for individuals identifying as black, hispanic, asian, and other. The exact percent changes can be found in Table 1.3. While overall young worker participation dropped 8.09%, young white workers decreased participation by 8.93% from 1994-2014. Meanwhile, young black, hispanic and asian workers decreased participation by 2.80%, 4.69% and 5.06% respectively. As noted earlier, these decreases are not all monotonic.

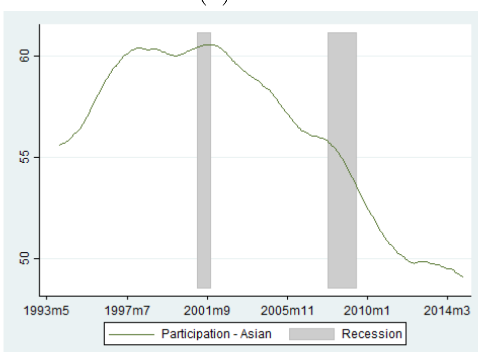
Young black, hispanic, and “other” workers increased their participation after the recession in 2001 and again slightly after the Great Recession.



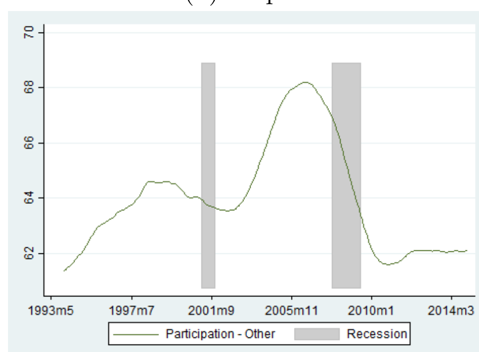
(a) Black



(b) Hispanic



(c) Asian



(d) other

Figure 1.10: Young worker labor market participation by race and ethnicity, ages 18-24.

The changes shown in the preceding figures show that young worker particiaption has changed in different ways for various demographic groups. These changes impact the overall participation rate of young workers in proportion to their changes in population, which vary dramatically. Specifically (as is described thoroughly in Section 6.1) the population of whites decreased almost thirteen percentage points, while the population of hispanics increased almost eight percentage points. Combined with the corresponding differences in participation shown above, these changes motivate the decomposition of changes in the young worker labor force participation rate computed in Section 6.

The next section extends the subpopulation breakdown to include education, which is specifically relevant to young workers.

Labor Force Participation by Education

Education trends impact the decisions of young workers. The decision of whether to begin to participate in the labor market or continue to accumulate human capital through schooling is critical for young workers' future labor market outcomes. Specifically, future job prospects and wages both hinge on previous labor market experience and education. This research considers the decision to participate in the labor force by education level and in Section 5, full-time schooling is analyzed as a marginal labor force status.

For 18-24 year olds, education level can be difficult to define accurately because of partial completion and current enrollment. For example, should a full-time college student be defined as a high school graduate (highest level of completion) or as having "some college?" Traditional CPS definitions do not differentiate for enrolled students, so for this research current full-time enrollment is taken into consideration. This research considers eight separate levels of education. They are shown in Table 1.4 below.

Level	Definition
No High School	Did not complete high school and currently not enrolled full-time
In High School	Currently enrolled in high school full-time
High School Degree	Earned high school degree and no college experience
Some College	Some college courses taken and not currently enrolled in college
In College	Currently enrolled in college full-time
College Degree	Earned bachelor's degree (B.A., A.B., B.S)
In Graduate School	Curently enrolled in graduate school
Graduate Degree	Earned graduate or professional degree

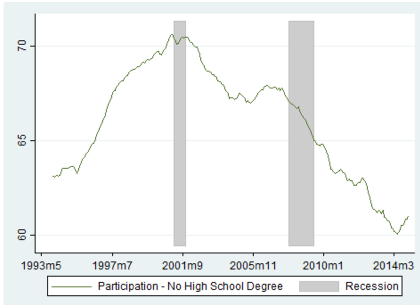
Table 1.4: Education levels defined for use in this research.

Labor force participation by education level for young workers can be seen in Table 1.5 and in Figure 1.11. Although not all education levels decreased monotonically, nearly all education levels (except males with a graduate degree and females with no high school degree) decreased in participation over the past twenty years; specific changes are shown in Table 1.5.

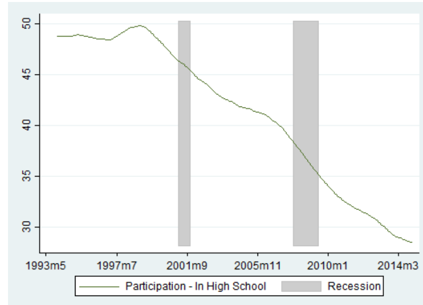
Table 1.5 contains many interesting trends that deserves consideration. The almost 2% decrease in participation of those with a college degree and almost 3% decrease of those with a Graduate Degree imply that even once an individual graduates with a degree, they do not enter the labor market. Given the widely noted increase in college attainment over the past twenty years, this change indicates a structural departure of individuals who chose to extend their education. Section 7 of this research specifically considers the labor force participation of college graduates, high school graduates and those without a high school degree.

Appendix A compares the participation of workers ages 18-24 to workers ages 25-34, who have more generally completed their formal education. Additionally, Section 6.3 decomposes the percentage of young people by education to consider whether young people truly participate in more schooling in 2014 than in 1994 or if this is a result of changing racial and ethnic make-up.

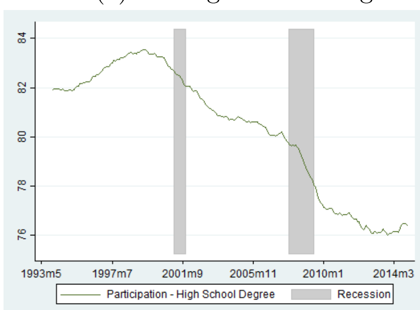
The data in Table 1.5 is broken down by gender to highlight some glaring differences in the changes over the twenty year period. There are two major takeaways. First, men without a high school degree participated in the labor force over 11 percentage points less, while women without a high school degree increased their participation by over 6 percentage points. Meanwhile, the percentage of the population of young workers without a high school degree (and not currently enrolled) decreased by over 6 percentage points over the twenty year period.



(a) No High School Degree



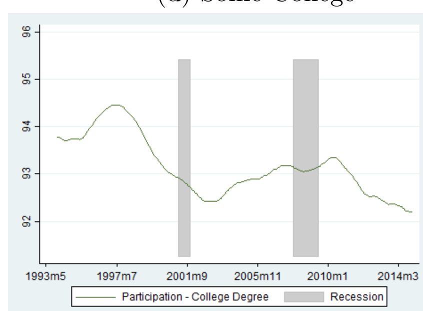
(b) In High School



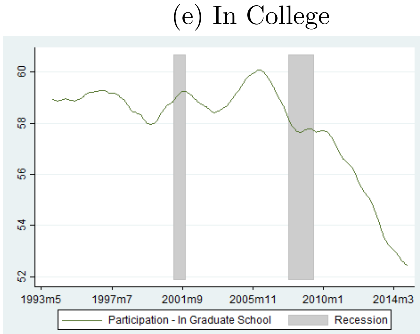
(c) High School Degree

(d) Some College

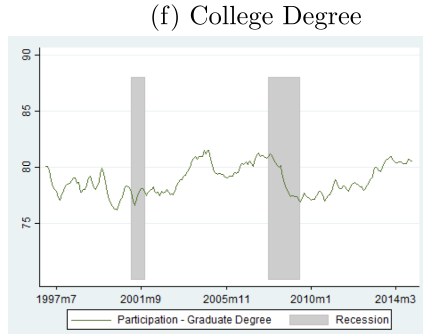
(e) In College



(f) College Degree



(g) In Graduate School



(h) Graduate Degree

Figure 1.11: Labor market participation by education, ages 18-24.

Participation by Education, ages 18-24			
	1994	2014	change
all			
No High School	64.18%	60.97%	-3.21%
In High School	47.81%	27.51%	-20.30%
High School	81.91%	75.86%	-6.05%
Some College	88.83%	83.72%	-5.11%
In College	59.14%	49.38%	-9.76%
College	93.99%	92.07%	-1.92%
In Graduate School	59.64%	52.72%	-6.92%
Graduate Degree	82.29%	79.32%	-2.97%
Male			
No High School	80.42%	68.79%	-11.63%
In High School	48.34%	26.13%	-22.21%
High School	90.12%	81.41%	-8.71%
Some College	93.07%	87.20%	-5.87%
In College	57.76%	46.45%	-11.31%
College	94.78%	93.10%	-1.68%
In Graduate School	53.56%	48.81%	-4.75%
Graduate Degree	83.53%	83.55%	+0.02%
Female			
No High School	45.09%	51.17%	+6.08%
In High School	47.07%	29.30%	-17.77%
High School	73.11%	68.81%	-4.30%
Some College	85.12%	80.42%	-4.70%
In College	60.37%	51.99%	-8.38%
College	93.38%	91.29%	-2.09%
In Graduate School	64.87%	55.22%	-9.65%
Graduate Degree	81.37%	76.50%	-4.87%

Table 1.5: Changes in participation by education, ages 18-24.

Table 1.6 displays the change in population distribution of those ages 18-24 by education level. The decomposition in Section 6 accounts for the changing population and demographic trends to determine the impact of each on the overall participation rate.

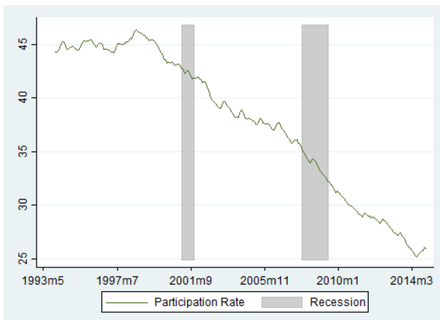
The second gender-specific trend of note is the decrease in participation of women with college and graduate degrees. While the decomposition in Section 7 will further analyze college graduates, it is important to note that there has been an increase in the number of women with a college or graduate degree from 1994 to 2014 (Table 1.6).

There are policy considerations (which are not directly addressed in this reserach) if just over three quarters of women with a college or graduate degree participate in the labor force.

	Population by Education, ages 18-24		
	1994	2014	change
all			
No High School	14.60%	8.29%	-6.31%
In High School	5.60%	6.51%	+0.91%
High School	28.29%	25.15%	-3.14%
Some College	17.42%	17.20%	-0.22%
In College	25.59%	31.88%	+6.29%
College	6.20%	7.53%	+1.33%
In Graduate School	1.90%	2.61%	+0.71%
Graduate Degree	0.39%	0.82%	+0.43%
Male			
No High School	15.90%	9.16%	-6.74%
In High School	6.55%	7.28%	+0.73%
High School	29.47%	27.94%	-1.53%
Some College	16.38%	16.65%	+0.27%
In College	24.20%	29.87%	+5.67%
College	5.40%	6.42%	+1.02%
In Graduate School	1.77%	2.02%	+0.25%
Graduate Degree	0.33%	0.65%	+0.32%
Female			
No High School	13.33%	7.41%	-5.92%
In High School	4.66%	5.73%	+1.07%
High School	27.13%	22.32%	-4.81%
Some College	18.44%	17.75%	-0.69%
In College	26.97%	33.92%	+6.95%
College	6.98%	8.64%	+1.66%
In Graduate School	2.02%	3.21%	+1.19%
Graduate Degree	0.44%	0.99%	+0.55%

Table 1.6: Changes in population by education, ages 18-24.

The decline in participation of those young people with high school and college degrees is worrisome and indicative of a structural change in the labor force. Additionally, the sharp decrease of participation of those enrolled in schooling deserves consideration. The labor force participation of those ages 18-24 enrolled in high school and college full-time dropped over 20% and almost 10%, respectively. This decline corresponds to many fewer young workers in the labor force since full-time enrolment in high school and college went up almost 1% and over 6%, respectively. Figures 1.12a and 1.12b display the change in labor force participation over the twenty year period 1994-2014 for young workers enrolled in school full-time.



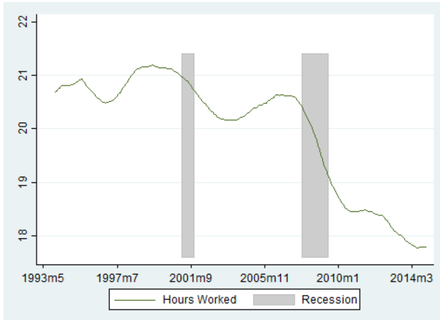
(a) High School

(b) College

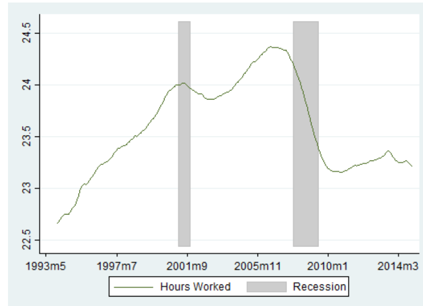
Figure 1.12: Labor market participation for those enrolled full-time, ages 18-24.

Clearly, participation dropped for young people enrolled in schooling full-time. In addition, those young workers who continued to work worked fewer hours. Figures 1.13a and 1.13b chart the change in hours worked for full-time high school and college students. The dramatic declines in hours worked for full-time students during the Great Recession may be a result of changing preferences for young people, or a cut back of hours offered. Both trends seen in Figures 1.12 and 1.13 point to the continued decrease in labor force participation of young workers.

Accounting for the change in participation for those enrolled full-time- while taking note of the change in population- results in 1.32% ($-20.30\% \times 6.51\%$) fewer and 3.11% ($-9.76\% \times 31.88\%$) fewer young workers due to the decrease in participation of enrolled high school and college students, respectively.



(a) High School



(b) College

Figure 1.13: Hours worked for those enrolled full-time, ages 18-24.

The trends explored in this section provide a motivation for a detailed study of the labor market of young workers. Section 6 quantitatively considers how changes in the labor market decisions of specific subgroups impact the young worker labor market as a whole. That consideration consists of decomposing the young worker participation rate based on shifting demographics to create a *genuine* and a *demographic* participation rate. Both Sections 6 and 7 detail the changes in the composition of the labor market to account for the 8 percentage point decrease in participation, and begin to answer the questions posed above to consider how much of the shifts seen in the young worker labor market are cyclical and how many are structural.

Before considering the labor market data for young workers, the next section provides a literature framework for this research.

3 Literature Review

There is a vast literature surrounding labor market participation, but most of the research considers only those above age 25. The first portion of the relevant literature presented here outlines notable research on labor market participation and previous decompositions of changes in the labor force (primarily unemployment). This serves as the basis of much of the methodology presented in Section 6. The second strand of literature reviewed is of young workers and education.

Labor Market Participation

Much of the labor market research focuses on the determinants and dynamics of the unemployment rate. As described earlier in this research, participation in the labor market plays a critical role in the unemployment rate and while many authors make note of the participation rate, few investigate participation itself.

A recent empirical piece by Fujita (2014) expresses the importance of considering the decrease in Labor Force Participation. Fujita examines Current Population Survey microdata to determine if the decrease in the United States's unemployment rate after the Great Recession (October 2009 to December 2013) is driven by discouraged workers leaving the labor force- and thus "unemployment has been declining for the wrong reason." (Fujita, 2014) Fujita finds that the decrease in participation started in the early 2000s, which is consistent with the data presented in the preceding section. Fujita's main contribution to the literature is that he finds that the retirement of baby boomers is driving the decrease in participation.

Not central to Fujita's paper, but relevant to this research is that he also finds that nonparticipation due to schooling has been steadily increasing. He finds that the main driver for not participating "other than disability and retirement comes from the increase in those who do not want a job because they are in school." (Fujita, 2014) Fujita notes that he does not find a clear cyclical pattern relative to business cycles in terms of nonparticipation due to schooling. Thus for the labor market as a whole, Fujita's analysis points to a structural change in the labor force.

While Fujita (among other authors) consider the level of participation, Elsby, et al. (2015) analyze the importance of the participation margin. That is, they consider how flows into and out of labor market statuses vary over the business cycle. They find a "substantial cyclicality in worker flows between unemployment and nonparticipation." (Elsby, et al., 2015) Their research delves deeper into the question of participation by considering flows into and out of unemployment, which can be masked when looking only at the level and not considering potential offsetting flows into and out of unemployed status. The authors find that "during recessions, unemployed workers are less likely to flow out of the labor force, and nonparticipants are more likely to flow into unemployment." Additionally, they find that about one third of the fluctuations in the unemployment rate are due to movements on the participation margin.

Most relevant to this research is the authors' handling of what they decribe as "spurious transitions." These misleading transitions include when respondents are defined as unemployed and not looking for work in one month, then unemployed and searching the next, and in the third are again unemployed and not looking. This transitions, the authors argue, is due to misidentifying or miscoding individuals' labor market status. The authors label a person with the labor force history described above as "NUN," which is the combination of abreviations for the Not in the Labor Force (N) and Unemployed (U). The authors handle these potentially false transitions by recoding or "de-NUNifying" their data. Elsby, et al. find that these "deNUNified" transitions "line up closely with theose implied by the Abowd and Zellner (1985) correction." The research in this paper utilizes this methodology in Section 5, when defining a worker's attachment to the labor force. When considering a person's participation over four consecutive months, a person in the labor force for the first two months, out for the third, and back in for the fourth month is considered *attached* to the labor market and the "spurious transition" out of the labor market is omitted following the logic of Elsby, et al. who consider this a classification or reporting error.

Decomposing the Labor Force

Empirical trends in unemployment vary for different subgroups of the population. Research by Perry (1970) and Gordon (1982) found that changes in the the age and sex composition of the labor force impacted the unemployment rate. Summers (1986) considered how the changing education profile of the labor force impacts the unemployment rate. Summers found that increased education in the 1960s and 1970s did not decrease the unemployment rate as he modeled, and concluded other forces of demographic changes have "increased the size of the rise in unemployment that must be explained." (Summers, 1986)

Research into the compositional effects was continued in 1998 by Shimer. He was motivated by the baby boomer generation's progress through the labor market. Shimer (1998) found that "the changing age structure of the population reduced the unemployment rate by more than 75 basis points" due to the aging of the baby boomers, thus creating relatively fewer young workers.

The methodology of Shimer is extended in this research to consider dynamics within the population of young workers, not only the population as a whole. From 1994-2014, the demographic make-up of young workers (see subsection 6.1) changed significantly, which did influence the participation rate. The relevance of Shimer's work to this research is to distinguish for young workers how much of the decrease in participation is due to genuine changes in choices and how much is due to demographic trends.

Section 6 of this research continues the work of decomposing the labor market to account for changes in population and participation among various demographic groups.

Young Workers

In a 1978 paper and again as a chapter in a volume published in 1982, Clark and Summers consider the *Dynamics of Youth Unemployment*. The authors describe two perspectives of the youth labor market that resulted in high unemployment rates. The traditional view was that the problem was job availability for young workers, while a "newer" view saw job transitions and turnover as the explanation of high unemployment. Clark and Summers used CPS data from 1976 to consider labor market transitions and found that the "youth jobless problem is attributable to a small group of young people who remain out of work a large portion of the time." (Clark and Summers, 1982) Of most relevance to this research, Clark and Summers find that unemployment spells for young workers mostly end when the worker leaves the labor force. The authors do not give consideration to how long the indiviudal remains out of the labor force.

In the same volume published in 1982, Feldstein and Ellwood reach a different conclusion than Clark and Summers. They consider only teenage males and find that unemployment is not a serious problem, since unemployment spells "end within one month when these boys find work or stop looking for work." (Feldstein and Ellwood, 1982) The authors focus on unemployed young people and do not explicitly consider those not in the labor force. They do, however, ask similar questions to those of this research. They specifically set out to determine how many teenagers that were not employed were actually "unemployed but too discouraged to look" as opposed to being "students" or "seeking part-time work." (Feldstien and Ellwood, 1982) This research approaches these questions not by looking only at those unemployed, but mainly at those who choose not to participate in the labor force at all.

The two perspectives offered by the research just mentioned shed light on the population of young workers, but they offer only a snaphot. That is, they do not look at trends over time and how those trends (i.e. demographic changes) impact the young worker labor market and the labot market as a whole.

As noted earlier, the impact of young workers shifting the age structure of the labor market as a whole was considered in 1998 by Shimer. Shimer's result that "the declining age profile for unemployment" is the motivating factor of increasing unemployment was modeled by Gervais, et al. in 2014. These authors analyze the labor market for young workers to confirm that labor market outcomes differ for varying age groups. An important finding by these authors is that young worker unemployment is higher because they are more likely to separate from their job, as opposed to not being able to find jobs. The authors are able to capture age differences in both job finding and job separation rates in their model. They take into consideration how young workers learn about their best matches by sampling occupations early in their careers and learn about their "true calling." If a match is not their true calling, then the worker and firm choose to separate. The theoretical work by Gervais, et al. also motivates this research since the authors make the case for the impact of early career labor market outcomes.

Education

Inherent in this research is human capital accumulation by young workers. In 1962, Gary Becker proposed a theory of human capital investment including both educational attainment and on-the-job training and subsequent returns. The trade-off between entering the labor force and continuing education depends on an individual's ability to pay and opportunity cost of a prospective job. (Bowen and Finegan, 1969) Dellas and Sakellaris (2003) found college enrollment was countercyclical as individuals substituted "between human capital accumulation and other economic activities." Kantrowitz (2010) also found a countercyclical trend of college enrollment. In terms of labor force participation, these authors' story indicates that participation in the labor force is cyclical, but, as was shown in Section 2, participation did not return to trend during economic recoveries.

A separate strand in the literature connects educational systems to labor market outcomes. Allmendinger (1989) finds that an individual's educational system "shapes career trajectories- specifically, the likelihood of changing jobs." Buddin (2012) connects educational attainment to labor force outcomes including unemployment and wages. Buddin notes that high school graduation rates have decreased from their 1970's peak and that college graduation rates are "stable or declining," and there exist "gaps in educational success by race, gender, and student achievement." (Buddin, 2012)

Connecting the two strands is recent research on labor force participation. Juhn and Potter (2006) note that the rise in educational attainment has increased the *education premium*, thus raising the "negative implications... of being a high school drop out" and wages relative to each educational attainment. Aaronson, et al. (2014) account for changing demographics of the labor force by considering educational attainment as a demographic variable along with age, gender, and race and ethnic group. While these authors concentrate on the labor force as a whole, they do consider young workers and compute counterfactual participation rates by fixing college enrollment rates by subgroup at their 1985 rates and using the participation trends of young people since that date. This exercise accounts for "about one-half of the decline in participation for this group." (Aaronson, et al, 2014) This technique is similar to the decomposition computations presented in Sections 6 through 8. Before these counterfactual participation rates are computed, the following section describes the data used in this research.

4 Data

The main data set used in this paper is the Current Population Survey (CPS), which is a monthly survey produced by the United States Bureau of Census for the Bureau of Labor Statistics (BLS). The CPS is used to calculate the monthly unemployment report by surveying households for four consecutive months followed by eight months out of the sample, then four more consecutive monthly surveys. There are approximately one hundred fifty thousand observations per month, including all members of each household older than age fifteen. The survey data used in this paper are from 1994 through 2014. There was a significant redesign of the CPS in 1994, so beginning at this date allows consistency throughout all variables used in this research, some of which were not available before the 1994 redesign. The data used here were downloaded from the NBER website in March 2014 and January 2015; any changes to the data since that time have not been incorporated in the data set.

The CPS data provides many useful pieces of information beyond standard personal characteristics. Specifically, each person in the sample is given an official labor market status, defined as Employed, Unemployed-on layoff, Unemployed-looking, Not in Labor Force (NILF)-retired, NILF-disabled, and NILF-other. Beyond calculating monthly employment numbers for the BLS, these labor force definitions- along with individual level data- allow researchers to analyze characteristics of those in each labor market status.

Due to minor changes in the CPS, each variable is not available for each month for all age groups. Thus, each portion of this research uses a certain subset of the entire data set described in this section. Each analysis in Sections 5 through 7 notes the specifc subset of the data used.

Constructing the Data Set

The analysis done in Section 5 of this research necessitates a linked panel to track individuals from one period to another. This section describes the construction of the twenty-year panel data set used in this research. The CPS data provided by the BLS is in the form of monthly files.[3] While the micro level data is not linked month-to-month, certain variables facilitated the matching of individuals while they were surveyed for four consecutive months.

The methodology to connect data from month to month included creating individual identifiers to match individuals, then to stack the monthly data to create a panel. This process was created using a framework of files created by Jesse Rothstein's 2011 research on unemployment. Each household in a monthly CPS file is assigned two identification numbers by the BLS: hrhid and hrhid2. These were merged to create a unique household identifier.[4] Next, a personal identifier was created using the household identifier, the state of the individual, the person's line number, and the person's month in the CPS sample.

The individual identifiers were constructed for each monthly data set, then stacked into one data set containing over 6.7 million observations. The stacking created multiple minor obstacles, since as the survey evolved over the twenty year period many variable names were changed and coding was varied. The solution used in this research was to relabel and recode variables within each monthly data set by hand before stacking. The complete list of variables used and specific labeling changes used are provided in Appendix B.

Once the panel was created, individuals were linked by connecting their personal

[3] Jean Roth's data files on the National Bureau of Economic Research were the source of the monthly raw data files and extraction .do files.

[4] The data from 1994 to 2004 did not contain the hrhid2 variable, so one was created by merging three variables: hrsample (sample identifier), hrsersuf (serial suffix), and huhhnum (household number).

identifier described above and the year and month of the observation. The next step involved checking for discrepencies in age, sex, education and race and ethnic group as well as checking for duplicates. Unique individuals were unlinked if needed and duplicates were replaced, amounting to removal of just .76% of total observations.

With the panel in place, distinct variables were created to utilize the information provided in the CPS individual data. Specifically, years of education from the CPS is broken into sixteen categories. The levels were simplified into five groups for this research: less than high school graduation, high school diploma or GED, some college (including Associate Degrees), college completion, and advanced degree. The CPS breaks marriage into six categories, including whether the spouse is present or absent and whether a non married person was widowed, separated, divorced, or never married; to simplify this data, a dummy variable was created indicating the individual was married. Dummy variables were created for specific races and ethnic groups [5] (white, black, hispanic, and asian) as well as non-white. Additionally region and metropolitan living are included as variables.[6]

Adding Education as a Labor Market Status

The CPS classifies participants' status in the labor force as either Employed and at work, Employed absent from work, Unemployed on layoff, Unemployed and searching, Not in the Labor Force (NILF) retired, NILF disabled, and NILF other. Relative to participating in the labor force, the two employed statuses are straightforward. The two unemployed designations refer to people on temporary layoff and implies that they are expecting to return to work shortly, and thus would be participating the the labor

[5] See Appendix B for details on data for race and ethnic group.

[6] Because of changes being made to the CPS, metropolitan living was not identified for surveys completed in June, July, or August of 2005. All other months included this variable.

force. A person designated as "Unemployed and searching" refers to one who does not have a job and is actively seeking employment, again this person would be considered participating in the labor force.

The NILF statuses deserve a bit more consideration. The first two (retired and disabled) are straightforward and should be classified as not participating; the status of "NILF other" deserves closer examination. Traditionally, the NILF other designation refers to someone who is a discouraged worker or separated from the labor force. A discouraged worker may have previously been considered unemployed, but is no longer looking for a job even though they would like one. Additionally, someone labeled NILF other may be separated from the labor force because of a spouse or parental support, along with a myrad of other reasons, one being a full-time student.

For young people, Not in the Labor Force can have many different meanings. Along with the traditional explanations above, a young person who is not in the labor force could be in school. Additionally, if a recent high school or college graduate does not immediately find a job, they may consider taking time off before entering the job market. For young people, those categorized as "NILF other" can have stark differences relevant to engagement with the labor market, but be labeled the same. For that reason, the data used in this research differ from official labor force categories.

For the data used in this research, individuals are considered to be in the four categories shown in Table 1.7. The first two categories are defined as is customary in the labor market literature. To determine the status of employed, both "employed and at work" and "employed and absent from work" were combined. Then, both "unemployed on layoff" and "unemployed and searching" were combined to form the unemployed status. The unique aspect of the data set used here is that those not in the labor force were separated into those who reported being full-time students and those that do not. Individuals who were officially "employed" or "unemployed" and also full-time students were not included in this status. Once the labor force status "Student" was added, the remaining persons were listed as Not in the Labor Force.

Status	Abbreviation
Employed	E
Unemployed	U
Full-Time Student	S
Not in the Labor Force	N

Table 1.7: Labor force participation statuses used in this paper.

The figure below shows the distribution of traditional labor market statuses and the statuses used in this data set for young workers in 2014. The distribution of young workers among labor force status as reported in the CPS (first row), official labor force status (second row), and distribution including education as a distinct labor force status (bottom row).

Employed at work 56.16%	Employed absent 1.64%	Unemployed on layoff 0.51%	Unemployed looking 7.36%	NILF Other 32.14%	NILF Retired 0.27%	NILF disabled 1.92%
Employed 57.80%		Unemployed 7.87%		Not in the Labor Force 34.33%		
Employed 57.80%		Unemployed 7.87%		Student (fulltime) 21.33%	Not in the Labor Force 13.01%	

Figure 1.14: The distribution of young workers by labor market status in 2014.

A unique aspect of this research, which is presented in Section 5, is that nonparticipation of young workers shrinks significantly- from 34.33% to 13.01% in 2014- once full-time students are removed from the NILF designation. As Section 5 describes, defining Schooling as a labor market status has significant relevance to labor force trends seen over the twenty year period covered in this research. Specifically, when considering an individual's attachment to the labor market, despite not working or searching, being a full-time student represents a commitment to the labor market and not dropping out of the labor market entirely. The labor market status designations presented above are used throughout this research, unless specifically noted.

National Survey of College Graduates

In addition to the CPS data, this research utilizes the National Survey of College Graduates (NSCG) to examine the behavior of young college graduates, specifically how their major impacts labor market outcomes. The data set surveys college graduates and is designed to consider the relationship between college outcomes and career outcomes. The NSCG is used in this reserach to determine the impact of college major on labor force participation. Specifically, the decomposition done in Section 6 with the CPS data is extended to include subcategories based on college major in Section 8.

The NSCG is a longitudinal survey and was conducted biennially (sometimes triennially), with cycles beginning in 1993, 2003, and 2010. Because of the proximity to the dates used with the CPS data, this research uses the 1993 and 2013 surveys. The data from the NSCG used in this research considers survey responses that were selected from the 1990 census who noted they earned a bachelor's degree (or higher). The subsequent in-cycle surveys are not used in this research, because they target science and engineering majors in order to consider the relationship between STEM majors and career outcomes. The 1993 and 2013 datasets are representative of the college-educated population and appropriate weightings are provided by the National Science Foundation[7]. The final 1993 sample consists of 75,327 men and 48,266 women and the 2013 sample consists of 47,497 men and 39,753 women[8].

A notable drawback of the NSGC is that there have been substantial changes in

[7]Further details can be found at http://www.nsf.gov/statistics/srvygrads/
[8]Data was acquired in November 2015 from http://sestat.nsf.gov/datadownload/

the design and sampling methods of the data set. Additionally, there are some inconsistencies of variables in the data set. While these issues do not directly impact results presented here, the main drawback is the difference in sample size between the two main data sets used. Additionally, unlike the CPS the NSCG contains a relatively smaller sample size. Those drawbacks noted, the NSCG will provide this research with data on the labor market status of college graduates, along with the relevant demographic data and college major. Not only will this analysis serve as a robustness check to the CPS data, but considering the impact of major on labor market participation is novel to this research.

5 Labor Market Attachment

Labor market attachment is formally defined as a binary distinction: attached (participating) or unattached (not participating). Monthly CPS survey data can be used to expand and extend the binary definition above. Specifically, the stock of individuals defined as nonparticipants in the labor market contains not just discouraged workers or those who choose not to work, but also students and retirees. This section of research aims to broaden the definition of Labor Force Attachment.

This research utilizes the panel aspect of the CPS data set described in Section 4 to track the labor market status of individuals over consecutive months. This alleviates two issues with the standard definition of Labor Force attachment. First, by linking labor market status for consecutive months, a broader picture of labor market attachment can be considered, as opposed to a snapshot of one point in one month. For instance, an individual may be unemployed for three months before becoming unattached because of Unemployment Insurance expiration; that individual's labor market attachment is different from an individual who is unattached for four consecutive months, yet in the fourth month both are considered unattached. To remedy this issue, this research considers a third level of labor force attachment: Marginally Attached.

The second issue with standard considerations of labor force attachment this research addresses is classification errors. There can be a fine line between an unemployed worker who wants to work and has not searched during the month (officially Not In the Labor Force) and someone who searches slightly and responds "yes" to having searched during the month (and is officially Unemployed and in the Labor Force). Abowd and Zeller (1985) estimate that these classification errors, specifically "incorrectly classified unemployed individuals have averaged more than 10%." The authors also note that classification errors of employed individuals are less than 1%. This research addresses this issue by following a procedure used by Elsby, et al. (2015), which is more practical than previous research.[9] Elsby, et al. (2015) used their method to reclassify and correct labor force status errors. This research builds on Elsby, et al. by using their reclassification procedure to consider what information four consecutive Labor Force statuses relay about a worker's attachment to the labor market. The next section describes this methodology in detail.

Last, this section is novel because it reconsiders the attachment of individuals in full-time schooling, which is particularly important for young workers. When considering why young workers' labor market participation has decreased, an important consideration is how committed to the labor market young workers are. Subsection 5.3 addresses this concern by reclassifying education.

[9] Chapter 2 of this dissertation discusses- then utilizes- the Abowd and Zellner Correction

Defining Labor Force Attachment

This section provides an alternative measure of *participation in* and *attachment to* the labor force. This section uses a subset of the linked CPS data, which includes only individuals linked for four consecutive months. Because a significant number of individuals could not be linked due to a survey change in 1995, this section considers changes over the period 1997-2014. During each month, individuals in the data set are labeled according to their labor force status: Employed (E), Unemployed (U), or Not In the Labor Force (NILF). In this linked panel,they can now be given a code for their labor market status over the four month period. The letters are used to create a four letter status code, such as EEUU for a worker who is employed for the first two months, then unemployed for the second two months.

For the purposes of this section, both officially Employed (E) and Unemployed (U) statuses are labeled as Participating and recoded to correspond to the letter P. Then, the individual noted above with labor force code EEUU would be recoded to PPPP.

Before beginning the analysis of consecutive monthly statuses, it is valuable to note that the resricted sub-sample of the data used here (i.e. individuals linked for four consecutive months) may have deficiencies. Specifically, there may be an underlying reason individuals are not tracked for consecutive months by the CPS data. An individual who has relocated may not have four consecutive surveys and be omitted from this sub-sample. Additionally, there may be an underlying characteristic of individuals who do not respond to the survey for four consecutive months, which could bias results using in this sub-sample.

With those drawbacks acknowledged, the resulting data consists of 491,632 individuals over the twenty year sample. Each individual has a four-letter code corresponding to each four consecutive months' labor market participation status. Next, each of the sixteen resulting combinations must be mapped to a Labor Market Attachment. The three categories used here are Attached, Not Attached, and Marginally Attached.[10]

Many combinations of labor market statuses are easily mapped to Attachment levels, while others are not as clear. The example used above of EEUU (recoded as PPPP) for a worker who is employed for the first two months, then unemployed for the second two months is clearly attached to the labor force. Alternatively, someone classified as UUNU, and thus PPNP when recoded, deserves discussion. Following Elsby, et al. (2015) any "sequences of transitions that involve a reversal of a transition from unemployment to nonparticiaption and vice versa" are recoded to eliminate "transition reversals." Elsby, et al. refer to this process as "deNUNifying" since an individual classified as NILF, then unemployed, then NILF again would have the U notation reversed to N. In the example above, UUNU would be reclassified as UUUU.

"DeNUNifying" eliminates many issues, but some four month statuses need refinement to be clearly defined. For instance, a freelance worker may be defined as Employed one month, then not in the labor force during the second, and repeats for the next two months. Thus, a code of "PNPN" or "PNNP" may not clearly indicate full attachment to the labor force, but also would not indicate a worker who is completely unattached from the labor force. Inconsistent participation in the labor market is definined here as *Marginal Attachment* to the labor force.

As noted by Elsby, et al. (2015) and of relevance here is the fact that this exercise is not meant to define a correction formula to be applied to past and future classifications or a probabalistic measure for the accuracy of a classification. Instead, this "correction" for classification errors will help to determine if the "recoding of transitions that are more likely to reflect measurement error" impacts the standard definition of labor force

[10] Classifying as only Attached and Not Attached (akin to Participation and Nonparticipation) can be vague (i.e. PNNP), but is attached as an exercise in Appendix D.

attachment. (Elsby, et al. 2015) Certainly this method will miss some true transitions between unemployment and nonparticipation, but unlike the work by Elsby, et al., this research is not focused on the transitions, rather what the four month progression of statuses say about a worker's participation and attachment to the labor force.

Table 1.8 below lists all sixteen four period status combinations by level of attachment to the labor force. The percent of the entire population is included for reference.

Attachment	four month code	% of population
Attached		
	PPPP	52.42%
	NPPP	3.17%
	PNPP	1.85%
	PPNP	1.53%
MarginallyAttached		
	PNPN	0.66%
	NPNP	0.55%
	NNPP	2.16%
	PPNN	2.13%
	PPPN	2.80%
	NNNP	1.97%
	NPPN	0.73%
	PNNP	1.00%
Not Attached		
	NNNN	23.51%
	PNNN	3.03%
	NPNN	1.27%
	NNPN	1.24%

Table 1.8: Labor force attachment by consecutive four month statuses.

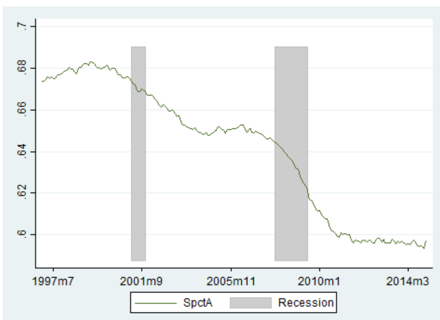
Given the definitions presented above, Table 1.9 displays the percent of young workers classified as Attached, Marginally Attached, and Not Attached to the labor force in 1997 and 2014, with corresponding changes. Time series graphs of labor force attachment over the past twenty years appear in the following subsection. The change in *Marginally Attached* young workers is small, so the decline in *Attached* young workers from 1997 to 2014 is due to almost nine percent more young workers being *Not Attached* to the labor market.

Labor Force Attachment, ages 18-24	1997	2014	change
Attached	67.72%	58.97%	-8.75%
Marginally Attached	11.85%	11.99%	+0.14%
Not Attached	20.42%	29.04%	+8.62%

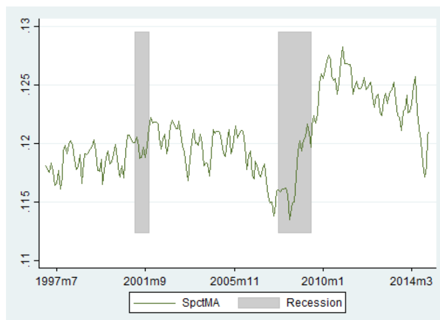
Table 1.9: Labor force attachment, ages 18-24.

Changes in Attachment

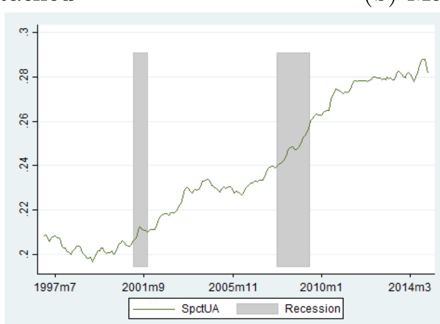
Using the definitions presented above, the graphs below chart the labor force attachment of young workers from 1994 through 2014.[11]



(a) Attached



(b) Marginally Attached



(c) Not Attached

Figure 1.15: Time series of labor force attachment, ages 18-24.

[11] Analagous graphs for individuals ages 25-34 is provided in Appendix A.2 as a comparison.

One trend seen in Figure 1.15 is that *Attachment* seems to move cyclically, meaning that there are major declines during recessions. To test this, Table 1.10 displays results of a regression specification with a time trend, monthly dummy variables (not displayed), and monthly change in GDP. The results confirm that Attachment, while decreasing over time, decreases as GDP decreases.

	Attached		**Marginally**		**Not Attached**	
Variable	**Coefficient**	**(Std.Er.)**	**Coefficient**	**(Std.Er.)**	**Coefficient**	**(Std.Er.)**
Time trend	-0.050**	(0.002)	0.003**	(0.001)	0.047**	(0.002)
monthlyGDPchange	-1.100*	(0.499)	0.152	(0.312)	0.947*	(0.454)
Significance levels :	† : 10%	$*$: 5%	$**$: 1%			

Table 1.10: Regression estimation results of labor force attachment, ages 18-24.

Meanwhile, the percent of *Not Attached* workers consistently increases over the twenty year period and does have a significant cyclical component. Finally, *Marginal Attachment* seems to see a major increase during the Great Recession, but that result is not statistically significant.

Along with the cyclicality of these time series graphs, the major conclusion of redefining labor force attachment and charting the changes in attachment from 1997-2014 is the rapid and consistent rise in the level of young workers not attached to the labor force. A relevant number to note here is the percentage of young workers that are in some way attached to the labor force. This is 1 minus the Not Attached value (or the sum of Attached and Marginally Attached). Since Not Attached increased 8.62%, that is the relevant drop in attachment, or participation, and that number is consistent in magnitude to the decline in traditionally defined participation.

As explained throughout this paper, there are many explanations for this trend, most notably for those age 18-24 is education. The next section expands the definition of Marginally Attached to consider schooling.

Including Education

The preceeding analysis of young worker attachment to the labor force showed a steep increase in those Not Attached. As noted throughout this paper, the labor force participation of young workers is particularly impacted by schooling. As described in Section 4, a contribution of this research is to consider education as a labor force status. Thus individuals in the data set are coded as "E" for employed, "U" for unemployed, "S" for full-time students[12], and "N" for Not In the Labor Force.

In the linked panel data set used in this section, individuals are recoded as "P" for Participating for workers officially Employed and Unemployed, while those with "S" and "N" labels remain. The three possible labor force statuses are linked to create a four letter status code.

There are 81 possible codes when including schooling. The definitions of *Attached* and *Not Attached* are only slightly changed from the previous section to include individuals with only one month of schooling. Table 1.11 lists the additional combinations for *Attached* and *Not Attached*, and the remaining 65 *Marginally Attached* codes are omitted for space.

[12]Who are not employed or unemployed.

Attachment	four month code	
Attached		
	PPPP	SPPP
	NPPP	PSPP
	PNPP	PPSP
	PPNP	PPPS
Not Attached		
	NNNN	SNNN
	PNNN	NSNN
	NPNN	NNSN
	NNPN	NNNS

Table 1.11: Labor force attachment by consecutive four month statuses, including schooling.

Given the definitions presented above, Table 1.12 displays the percent of young workers classified as Attached, Marginally Attached, and Not Attached to the labor force in 1997 and 2014, with corresponding changes. Figure 1.16 shows the time series graphs of labor force attachment from 1997-2014, and as before results of a regression including a time trend and monthly GDP change is displayed in Table 1.13.

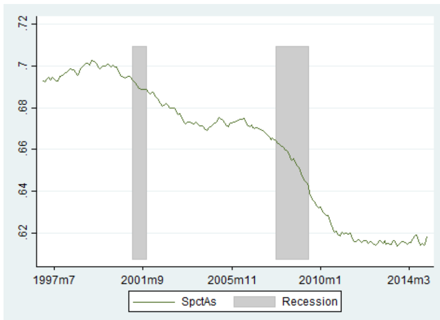
Labor Force Attachment, ages 18-24	1997	2014	change
Attached	69.10%	60.56%	-8.54%
Marginally Attached	23.58%	30.48%	+6.90%
Not Attached	7.32%	8.96%	+1.64%

Table 1.12: Labor force attachment (including schooling), ages 18-24.

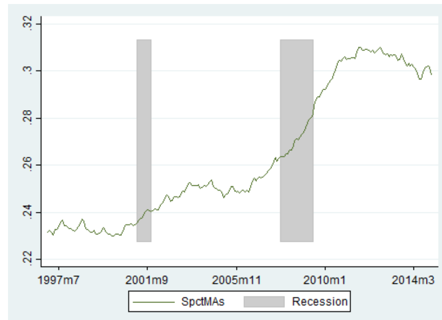
	Attached		**Marginally**		**Not Attached**	
Variable	**Coefficient**	**(Std.Er.)**	**Coefficient**	**(Std.Er.)**	**Coefficient**	**(Std.Er.)**
Time trend	-0.050**	(0.002)	0.046**	(0.002)	0.004**	(0.001)
monthlyGDPchange	-1.086*	(0.514)	0.960†	(0.508)	0.125	(0.239)
Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%						

Table 1.13: Regression estimation results of labor force attachment with schooling, ages 18-24.

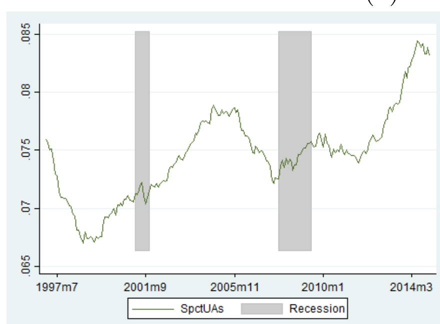
The results shown in Tables 1.12 and 1.13 and Figure 1.16 show that the decrease in Labor Force Attachment of young workers is not due to leaving the labor force. Instead, a recent increase in *Marginal Attachment* to the labor force due to changes in education decisions drive the decrease in Labor Force Attachment.



(a) Attached



(b) Marginally Attached



(c) Not Attached

Figure 1.16: Time series of labor force attachment, including schooling, ages 18-24.

The percentage of those Not Attached to the labor force increased by 1.64 percentage points, which is just shy of 7 percentage points lower than the calculation not including education. Thus, including education, which is a marginal or passive form of participation in the labot market, accounts for about 7 percentage points of the total decline in participation of young workers.

Additionally, including education as a marginal form of labor force attachment removes any significant cyclical trend from those not attached to the labor force. This result starkly contrasts trends seen in the reported levels of labor force non-participation, which were discussed in Section 2.

Expanding the definitions of attachment to the labor force certainly helps to explain much of the decrease in participation in the labor force The next two sections of this research work to quantify how participation trends combine with demographic trends of young workers to continue to account for the more than 8% decrease in their labor force participation.

6 Decomposition of Young Worker Labor Market

The decline of labor force participation among young workers shown in Section 2 can be partly described in terms of structural changes to the composition of the labor market. Specifically, from 1994 to 2014, the makeup of the labor market by gender, race and ethnicity, and education has changed. This section considers whether the changes in the overall young worker labor market are due to changes within these subgroups or changes of the relative composition of each subgroup.

While the composition of the labor market has changed, so have the participation rates of each subgroup. In some cases, these changes amplify, resulting in higher overall participation rates for young workers. In other cases, the changing composition causes population changes and participation rate changes to cancel each other out or leave the change to the entire labor market ambiguous.

The empirical exercise below decomposes the labor market for young workers to determine the source of the aggregate trends discussed in Section 2. The first decomposition is of the participation rate, then participation in schooling is decomposed. The decompositions considered here are by gender, age, and race and ethnic group as well as education.

Population Trends of the Young Worker Labor Market

The first step in decomposing the labor force for young workers is considering changes in the make-up of the labor force. The data used below are from the CPS data described in Section 4 using the years 1994 and 2014 and weighted by the CPS final individual weights. The decompositions of the young worker labor market in this section are based on age, sex, and race and ethnicity. Section 2 described changes in participation, and the subsequent data describe population trends.

The population of young workers in the CPS survey data in 1994 consisted of 49.64% males and 50.36% females. Twenty years later, the distribution changed slightly to 50.34% males and 49.66% females.

The racial makeup of young workers has changed over this twenty year period.[13] In terms of population trends, the CPS data from 1994 consists of 68.15% white workers and 31.85% were non-white. In 2014, 55.19% workers were white and 44.81% were non-white. The table below shows more detailed changes to the population of those age 18-24 by race and ethnic group from the CPS.[14]

Population by Race and Ethnic Group, ages 18-24			
	1994	2014	change
White	68.15%	55.19%	-12.96%
Black	14.22%	14.44%	+0.22%
Hispanic	13.57%	21.37%	+7.80%
Asian	3.15%	5.26%	+2.11%
Other	.91%	3.74%	+2.83%

Table 1.14: Changes in population by race and ethnicity, ages 18-24.

[13] The question as to whether the racial makeup of young workers has changed or if their willingness to identity as a different race (mostly non-white) has changed is not considered in this research, but warrants discussion and further research.

[14] See appendix B for details on data for race and ethnic groups.

The make-up of the young worker labor market by education was displayed in Table 1.6 of Section 2. The educational attainment of individuals age 18-24 has clearly shifted over the past twenty years. Most notable is the decrease in those without a high school degree (down 6.31%) and those with only a high school degree (down 3.14%). As expected, many more 18-24 year-olds are in college or have obtained a college degree. While this research does not consider changes in college completion rates, Appendix A provides demographic and participation data of 25-34 year-olds as a comparison.

Decomposition of Labor Force Participation

The previous section described changes to the young worker labor market based on demographic trends. Changes in participation within those sub groups were presented in Section 2. This section explains the calculations to decompose the labor market participation rates, which quantify the impacts of the aforementioned changes to young workers.

The process works as folows. First, divide the young worker labor force into subgroups, $i \in I$. Let $w_t(i)$ be the fraction of workers in group i of the entire population of young workers at time t. Then $\sum_{i \in I} w_t(i) = 1$ for all t. Next, define $p_t(i)$ as the participation rate of group i at time t, then the aggregate participation rate, P_t, at time t is $P_t = \sum_{i \in I} w_t(i) p_t(i)$.

The overall labor force participation rate decrease as $p_t(i)$ decreases or as populations trends shift towards subgroups with lower participation. That is, the weight, $w_t(i)$, could increase for group i with a small level of participation, $p_t(i)$ and simultaneously the weight could decrease for i with large participation.

Following Shimer's (1998) terminology, the *genuine* change in participation is the change in participation if demographics remain the same from t_0 to t_1, assuming that if demographics stay the same, each $p_t(i)$ follows the same path from t_0 to t_1. So, from time t_0 to t_1, the genuine participation can be written as

$$P^G_{t_0,t_1} = \sum_{i \in I} w_{t_0}(i) p_{t_1}(i).$$

The *demographic* change in participation is the amount participation has changed because of demographic shifts. For example, the overall participation rate could be lower because there are more young workers in subgroups that have lower participation rates. Thus, considering only demographic changes from time t_0 to t_1, the demographic participation rate can be written as

$$P^D_{t_0,t_1} = \sum_{i \in I} w_{t_1}(i) p_{t_0}(i).$$

The following subsections use participation rates from years $t_0 = 1994$ and $t_1 = 2014$ and subgroups consisting of varying ages, sexes, and race and ethnic groups, as well as education.

Decomposition of Participation: Age, Sex, and Race and Ethnicity

To decompose the labor markets defined above, young workers were broken into seventy sub groups. The first breakdown was by age, the second by sex. As described in Section 4.1, the young workers were seperated into five categories based on race and ethnicity: white, black, Hispanic, Asian, and other.

The resulting decomposition finds the *genuine* participation rate, using the 1994 weightings and 2014 participation rates, to be 65.80%, which is 0.78% higher than the reported 2014 participation rate of 65.02%, but still more than 7% lower than the participation rate of 73.11% in 1994.

The *demographic* participation rate, using the 2014 weightings and 1994 participation rates, is is 71.58%, which is 6.55% higher than the reported 2014 participation rate of 65.02%, but only 1.53% lower than the participation rate in 1994 of 73.11%.

The result of this decomposition is that the decrease in labor market participation is genuine. That is, the 8 percentage point decline in the participation rate is due to behavioral changes by young workers. This indicates a structural change as individuals make different decisions in 2014 than twenty years prior. While changing demographics of young workers have shifted, the real driving factor of decreasing participation in the labor force is the decisions.

The figure below displays the *genuine* participation rates along with the actual participation rate for young workers from 1994-2014.

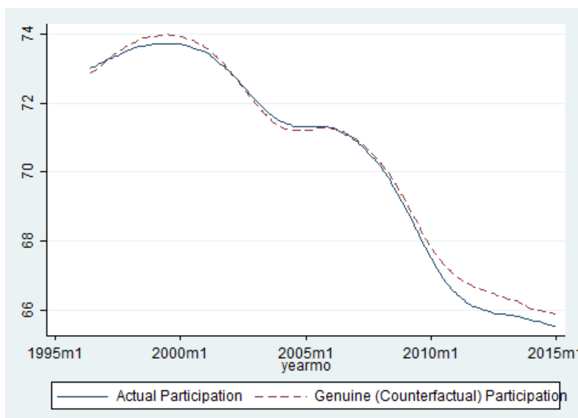


Figure 1.17: The participation and counterfactual participation rates of young workers.

Decomposition of Participation in Schooling

The genuine decline in participation rate as shown in the preceding subsection implies that young people are making different decisions in 2014 than they did in 1993. As noted throughout this research, changes in education decisions directly impact the decision of young workers not to participate in the labor force. The analysis presented in this section can easily be extended to consider participation in schooling. The decomposition calculations in this section use the same demographic subgroups as earlier, but rather than participation in the labor market, full-time participation in schooling (defined as full-time high school or college) is considered.

Define $s_t(i)$ as the participation rate in schooling of group i at time t. The aggregate participation rate in schooling, S_t, at time t is $S_t = \sum_{i \in I} w_t(i) s_t(i)$. The participation rate in schooling may increase as $s_t(i)$ increases or as subgroups with higher participation rates grow. Using the same terminology presented earlier, the *genuine* change in participation in schooling is defined as if demographics remained the same, with the assumption that if demographics stayed the same, each $s_t(i)$ would have followed the same trend from t_0 to t_1. From time t_0 to t_1, the genuine participation in schooling can be written as

$$S^G_{t_0,t_1} = \sum_{i \in I} w_{t_0}(i) s_{t_1}(i).$$

The alternative to the genuine change is the *demographic* change in participation in schooling. As described above, demographic change is the change in participation in schooling resulting from demographic shifts. Thus, considering only demographic changes from time t_0 to t_1, the participation in schooling rate can be written as

$$S^D_{t_0,t_1} = \sum_{i \in I} w_{t_1}(i) s_{t_0}(i).$$

The overall participation in schooling for young workers ages 16-24 can be seen in Figure 1.18 below.

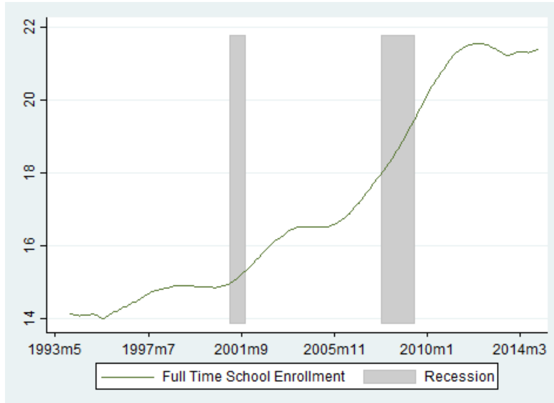


Figure 1.18: The participation rate in schooling from 1994-2014, ages 16-24.

The resulting *genuine* participation rate in schooling, using the 1994 weightings and 2014 participation in schooling rates, is 21.43%, which is only 0.28% lower than the actual 2014 rate of 21.71%, and about 8% higher than the rate of 13.57% in 1994. Thus, the change is entirely genuine.

As a confirmation of the genuine increase in young workers participating in schooling, the *demographic* participation rate in schooling, using the 2014 weightings and 1994 schooling rates, is 13.92%, which is 7.79% lower than the actual 2014 rate of 21.71%, but only 0.35% higher than the schooling rate in 1994 of 13.27%. Again, this confirms that the rise in participation in schooling is almost entirely genuine for young people ages 18-24.

Combined with the above analysis of participation, the results of this section show that, accounting for the demographic changes, there was a true decrease in the participation rate of young workers. Additionally, of those not participating in the labor market, there was a genuine increase in the number of young people enrolled in schooling. The next section considers participation by level of education by analyzing changes in poulation demographics as well as labor force participation.

7 Labor Force Participation by Level of Schooling

In Section 2.2.2, both labor market participation and the population distribution of young workers was broken down by education level. This section extends the computation of a counterfactual *genuine* participation rate from Section 6 to consider how the changing demographics and participation rates have changed within each level of schooling.

Of interest is the change of participation within young workers without a high school degree. As noted in Section 2, males without a high school degree decreased labor force participation by 11.63%, while women without a high school degree increased their participation by 6.08%. The decomposition computed in the next subsection helps to account for these changes.

Young workers with a high school degree decreased participation by just over 6% from 1994-2014, with men decreasing their participation more than women (8.71% compared to 4.30%). Again, the decomposition calculated below accounts for this change and incorporates changing racial and ethnic demographics as described in the previous section.

Finally, this secion considers trends within young workers who have graduated from college. A noteworthy change in participation (as seen in Table 1.5 in Section 2) is the roughly 2% decline in participation of college graduates. This section considers young college graduates ages 25-29, since this age group is more likely to have finished its education and begun to participate in the labor market.

Decomposition of Participation of Young Workers with No High School Degree

This section decomposes the participation rate of young workers without a high school degree by considering changing demographics, specifically the composition of age, sex, and race and ethnicity. The participation rate for those without a high school degree decreased from 63.62% in 1994 to 61.38% in 2014.

Using the methodology described in Section 6.2 to decompose the participation rates of young workers without a high school degree, the resulting decomposed *genuine* participation rate, using the 1994 weightings and 2014 participation rates, is 61.40%, which is 0.02% higher than the reported 2014 participation rate of 61.38%, and 2.22% lower than the participation rate of 63.62% in 1994.

The *demographic* participation rate, using the 2014 weights and 1994 participation rates, is 63.32%, which is 1.94% higher than the reported 2014 participation rate of 61.38%, and 0.30% lower than the participation rate in 1994 of 63.62%.

The result is that, for this subgroup of young workers, the changing demographic composition does not account for much of the decrease in labor force participation. Instead, the decrease in the labor force participation rate of those without a high school degree is almost all *genuine* changes in labor market decisions.

The figure below displays the *genuine* participation rate along with the actual participation rate for young workers from 1994-2014.

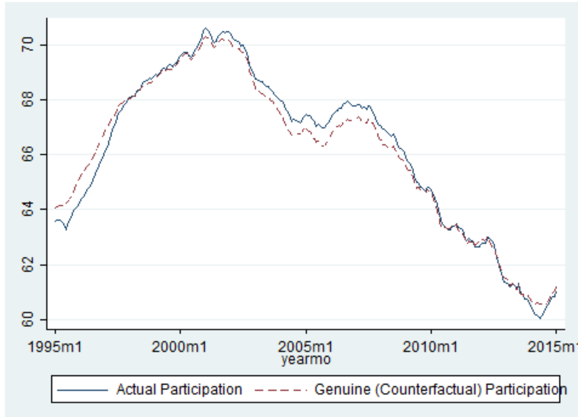


Figure 1.19: The participation rate of young workers without a high school degree.

Decomposition of Participation of Young Workers with a High School Degree

This section decomposes the participation rate of young workers with a high school degree by considering changing demographics, specifically the composition of age, sex, and race and ethnicity. Using the methodology described in Section 6.2 to decompose the participation rates of young workers with a high school degree, the resulting decomposed *genuine* participation rate, using the 1994 weights and 2014 participation rates, is 75.27%, which is 0.20% higher than the reported 2014 participation rate of 75.07%, and 5.25% lower than the participation rate of 80.52% in 1994. This means that had the composition of high school graduates not changed over the past twenty years, then the labor force participation rate would still have decreased by over five percent.

The *demographic* participation rate, using the 2014 weightings and 1994 participation rates, is 79.64%, which is 4.57% higher than the reported 2014 participation rate of 75.07%, and 0.88% lower than the participation rate in 1994 of 80.52%.

While the change in demographic composition of high school graduates has certainly changed, the decomposition of participation rates shows a distinct genuine decrease and a moderate decrease resulting from the changing composition of those young workers with a high school degree.

The figure below displays the *genuine* participation rates along with the actual participation rate for young workers from 1994-2014.

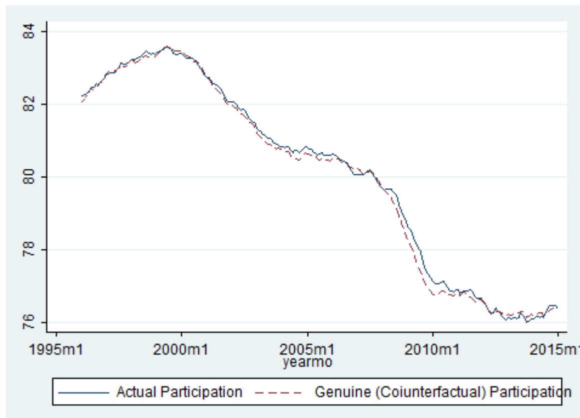


Figure 1.20: The participation rate of young workers with a high school degree.

Decomposition of Participation of Young Workers with a College Degree

This section decomposes the participation rate of college graduates by considering changing demographics, specifically the composition of age, sex, and race and ethnicity. Since many young people from age 18 to 24 are in college and thus not participating, this section considers ages 25-29, as this age group is more likely to have finished its education.[15]

The graph below displays the participation rate of college graduates from 1994-2014. The participation rate has decreased for those with a college degree, but not monotonically.

[15]Using CPS data from 2014, 18.56% of 22-25 year olds were enrolled in school full-time, and 8.92% of 26-29 year olds.

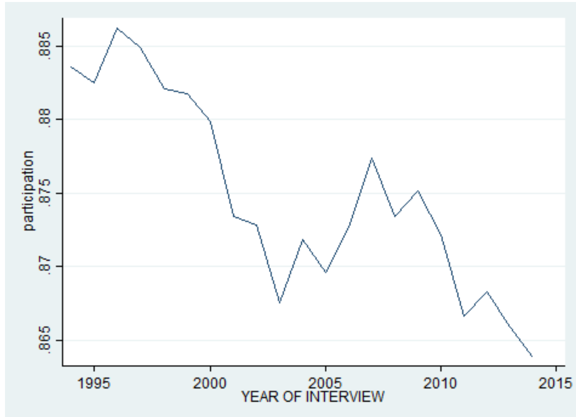


Figure 1.21: The participation rate of college graduates.

Using the methodology described in Section 6.2 to decompose the participation rates of college graduates ages 25-29, the resulting *genuine* participation rate, using the 1994 weights and 2014 participation rates, is 87.10%, which is 1.25% higher than the reported 2014 participation rate of 85.85%, and 3.39% lower than the participation rate of 90.49% in 1994. This means that, had the composition of college graduates not changed over the past twenty years, then the labor force participation rate would still have decreased by over three percent.

The *demographic* participation rate, using the 2014 weights and 1994 participation rates, is 88.89%, which is 3.04% higher than the reported 2014 participation rate of 85.85%, and 1.60% lower than the participation rate in 1994 of 90.49%.

While the change in demographic composition of college graduates has changed, the decomposition of participation rates shows a distinct genuine decrease. The figure below displays the *genuine* participation rates along with the actual participation rate for young workers from 1994-2014.

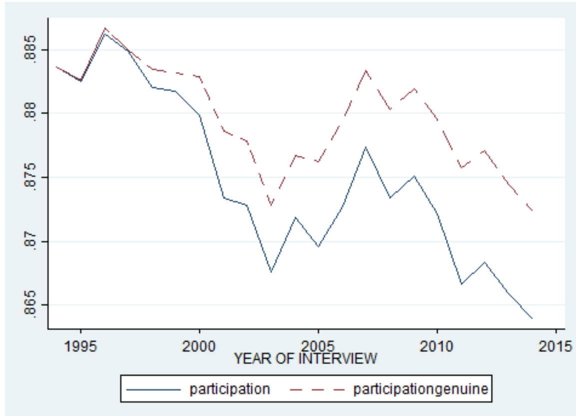


Figure 1.22: The participation and genuine participation rates of young workers with college degree.

8 Participation by College Major

This section of research utilizes data from the National Survey of College Graduates, which includes individuals' college major. The decompositions done in the previous sections are extended to include workers' undergraduate college major. First, trends in major choice from 1993 to 2013 are summarized, as well as participation by college major.

As noted in Section 4.3, the dates used in this section from the National Survey of College Graduates span twenty years from 1993-2013, which closely align with the dates of the CPS data used throughout the rest of this research. The definition of young workers in this section is ages 25-29, since these age groups are more likely to have finished their education and have begun to spend time in the labor market.

Once population trends have been considered, the decomposition including college major along with age, sex, and race and ethnicity is conducted to analyze the *genuine* and *demographic* participation rates. Before calculating the decomposition of labor force participation, this section considers the changes in college major selection from 1993-2013. The table below displays the distribution of majors over the twenty year period for those ages 25-29.

	Population by Major, ages 25-29		
	1993	2013	change
all			
STEM	28.51%	29.49%	+0.98%
Business	26.33%	17.78%	-8.55%
Social Science	16.57%	20.08%	+3.51%
Arts and Humanities	16.56%	20.11%	+3.55%
Other Majors	12.13%	12.55%	+0.42%
Male			
STEM	36.05%	36.69%	+0.64%
Business	27.88%	19.67%	-8.21%
Social Science	16.42%	18.71%	+2.29%
Arts and Humanities	12.84%	18.56%	+5.72%
Other Majors	6.82%	6.68%	-0.14%
Female			
STEM	22.19%	24.29%	+2.10%
Business	25.03%	16.41%	-8.62%
Social Science	16.70%	21.07%	+4.38%
Arts and Humanities	19.49%	21.22%	+1.73%
Other Majors	16.58%	17.01%	+0.43%

Table 1.15: Changes in population by college major, ages 25-29.

The distribution of college majors shows that graduates from STEM fields remained relatively consistent over the twenty year period. Business majors decreased over eight percentage points over this time period. Since these results include only undergraduate college majors, individuls who go on to receive an MBA or other professional business degree are not considered a "business" major unless their undergraduate degree was specifically labeled business or business management. College students majoring in Social Science and Arts and Humanities both increased, while the numer of other majors (including education) remained roughly the same. There was a larger increase in STEM majors among females than males. Additionally, the distribuion of other majors vary by gender. Less than half as many males as females tend to choose other majors, and the percentage decreased for males while it increased slightly for females, extending this difference.

Participation by Major

As described earlier in Table 1.5 from Section 2, the rate of participation in the labor force for young college graduates (18-24) decreased almost two percent over the twenty year period from 1994-2014. The age group considered in this section is older (25-29) and, generally, beyond the traditional age of college students. The participation rate from the NSCG data shows a decrease of slightly more than one percent over the twenty year time period spanned by the data. That decrease is not prevalent within each major category. In fact, participation in the labor force by those in some major categories have increased, while others decreased. The specific changes in labor force participation rates are shown in the table below.

The next section combines the population and participation trends to decompose the changes into *genuine* and *demographic* labor force participation rates by college major, along with age, sex, and race and ethnic group using the same methodology of previous sections.

	Participation by Major, ages 25-29		
	1993	2013	change
overall	93.34%	92.27%	-1.07%
all			
STEM	92.71%	90.20%	-2.51%
Business	96.10%	91.34%	-4.76%
Social Science	91.94%	91.22%	-0.72%
Arts and Humanities	92.73%	95.40%	+2.67%
Other Majors	91.56%	95.07%	+3.51%
Male			
STEM	94.73%	93.27%	-1.46%
Business	98.57%	95.20%	-3.37%
Social Science	94.76%	93.76%	-1.00%
Arts and Humanities	96.80%	98.29%	+1.49%
Other Majors	97.33%	98.04%	+0.71%
Female			
STEM	89.96%	86.85%	-3.11%
Business	93.79%	87.99%	-5.80%
Social Science	89.66%	89.60%	-0.06%
Arts and Humanities	90.49%	93.58%	+3.09%
Other Majors	89.57%	94.27%	+4.70%

Table 1.16: Changes in participation by college major, ages 25-29.

Decomposition of Labor Force Participation Including College Major

Using the methodology presented in Section 6.2, but accounting for college major, this section decomposes the labor force participation rate. The participation rate of college graduates ages 25-29 in the NSCG in 1993 was 93.34% and in 2013 it was 92.27%.

The resulting decomposed *genuine* participation rate, using the 1993 weightings and 2013 participation rates, is 93.10%, which is 0.74% higher than the actual 2013 participation rate of 92.27%, and 0.24% lower than the participation rate of 93.34% in 1993. This means that had the composition of college graduates not changed over the past twenty years, then the labor force participation rate would have only slightly changed.

The *demographic* participation rate, using the 2013 weightings and 1993 participation rates, is 91.00%, which is 1.27% lower than the actual 2013 participation rate of

92.27%, and 2.34% lower than the participation rate in 1993 of 93.34%. This result implies that new choices of majors, along with demographic changes of the population of college graduates, drives much of the change in participation of young college graduates. The next subsection extends this analysis to examine which majors, in 2013, correlate with labor force participation.

Probability of Participation by Major

An extension of the decomposition is to consider which majors lead young workers to participate in the labor force. This section tests empirically which majors lead to a higher likelihood of participation by testing a logit regression, with participation as the dependent variable:

$$Pr(Participate)_{ij} = X_{ij}\beta + Z_j\alpha.$$

The subscript i indexes individuals and j indexes degree field. The variable *Participate* is a dummy variable for whether individual i particpated in the Labor Force. X_{ij} represents individual demographic variables and Z_j represents each degree field. Separate regressions are run for males and females. Table 1.17 displays the estimation results.

The interpretation of the coefficients presented in Table 1.17 is the amount of increase in the predicted log odds that an individual participates in the labor force for a one unit increase in the variable. For each college major (represented by a dummy variable), the coefficient represents the increase in the predicted log odds of participating in the labor force for being in that major.

	Men		Women	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
Age	11.977**	(3.770)	3.115	(3.686)
Age sqrd.	-0.223**	(0.070)	-0.058	(0.068)
White	-0.255	(0.508)	0.605	(0.501)
Black	-0.916	(0.835)	0.802	(0.659)
Asian	-0.771	(0.520)	0.018	(0.506)
Hispanic	-0.090	(0.530)	1.024†	(0.559)
Never Married	-0.659*	(0.302)	0.791**	(0.257)
Disabled	-0.552	(0.427)	-0.349	(0.382)
Foreign born US citizen	-0.733†	(0.408)	0.023	(0.291)
Foreign born non-US citizen	-0.838*	(0.375)	-1.177**	(0.332)
Degree type				
Masters	0.959**	(0.250)	0.960**	(0.237)
Professional	0.897	(0.709)	1.681*	(0.828)
Doctoral	2.524**	(0.604)	2.998**	(0.828)
Degree field				
Agricultural Sciences	-1.218	(0.866)	-1.629*	(0.778)
Architecture	0.052	(0.974)	-0.815	(0.881)
Biological Sciences	-2.608**	(0.634)	-2.751**	(0.579)
Business and Management	-0.787	(0.766)	-1.952**	(0.700)
Communications	0.867	(1.267)	-0.508	(0.952)
Computer Science	0.397	(0.739)	-1.605*	(0.725)
Education	0.416	(1.047)	-0.943	(0.747)
Engineering	-0.515	(0.668)	-1.853**	(0.604)
Engineering-related Technology	0.857	(0.871)	-1.951*	(0.875)
English and Foreign Languages	-1.538	(1.139)	-2.052*	(0.815)
Health Professions	-1.767*	(0.711)	-1.715**	(0.592)
Home Economics	-2.455†	(1.272)	-2.927**	(1.019)
Law/Prelaw/Legal Studies	-0.947	(0.880)	1.341†	(0.794)
Liberal Arts	-1.237	(0.970)	-0.168	(1.030)
Mathematics	-0.252	(0.705)	-0.823	(0.695)
Philosophy/Religion/Theology	0.414	(1.242)	-3.694**	(1.046)
Physical Sciences	-1.233†	(0.730)	-1.976**	(0.742)
Psychology	-1.223†	(0.679)	-2.159**	(0.587)
Public Affairs	-0.780	(1.063)	-1.675†	(0.962)
Social Science	-1.052	(0.642)	-2.147**	(0.624)
Visual and Performing Arts	2.967**	(0.868)	-1.858*	(0.748)
Intercept	-155.204**	(50.254)	-38.873	(49.959)

	Men	Women
N	9269	10464
Log-likelihood	-402380.01	-934241.723
$\chi^2_{(34)}$	238.491	203.636

Significance levels : † : 10% $*$: 5% $**$: 1%

Table 1.17: Estimation results of logit model on participation, ages 25-29.

The degree level (Masters, Professional, or Doctoral) correlates with higher likelihood of participation. For males, Biological Sciences, Health Professions, and Home Economics correlate with less likelihood of participation, while Visual and Performing Arts is the only major with a significant and positive correlation with participation. For females, Biological Science, Business, Engineering, English Language, Home Economics, Philosophy, Psychology, and Social Science all correlate with lower participation. Law and Legal Studies are the only major with a positive correlation with participation for females.

An important note here is that the relationships between college major and participation is not necessarily causal. A latent variable, such as ability could play a factor where students that are more likely to participate in the labor force self select into certain majors. That caveat acknowledged, the relationship between what majors correspond with participation in the labor force has value in that it sheds light on the sorting process as well as the decisions young workers make in their early years in the labor force.

Probability of Attachment by Major

Following the logic presented throughout this research that education decisions impact the participation margin for young workers, this section considers participation to be inclusive of those enrolled full-time in schooling. As an extension of the previous section, this subsection tests empirically which majors lead to a higher likelihood of *attachment*[16] to the labor force by testing a logit regression, with attachment as the dependent variable:

[16]Attachment, as used here, includes all young workers employed, unemployed and searching, and enrolled full-time in a degree granting program

$$Pr(Attachment)_{ij} = X_{ij}\beta + Z_j\alpha.$$

As before, the subscript i indexes individuals and j indexes degree field. The variable *Attachment* is a dummy variable for whether individual i was formally particpating in the Labor Force or fully enrolled in a degree granting program. X_{ij} represents individual demographic variables and Z_j represents each degree field. Separate regressions are run for men and women.

The interpretation of the coefficients presented in Table 1.18 is the amount of increase in the predicted log odds that an individual is attached to the labor force for a one unit increase in the variable. For each college major (represented by a dummy variable), the coefficient represents the increase in the predicted log odds of attachment for being in that major.

For men, having a Masters or Doctorate degree correlates with higher likelihood of attachment, while for females any type of advanced degree correlates with higher likelihood of attachment. In terms of specific majors, for males, Agricultural Science and English and Foreign Language with less likelihood of attachment, while Engineering, Mathematics, and Visual and Performing Arts are the only majors with a significant and positive correlation with attachment. For women, no majors correlate with a greater likelihood of attachment and many majors do correlate with a lower likelihood of attachment. It seems the greatest predictors for female labor market attachment is never having been married and having an advanced degree.

	Men		Women	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
Age	15.502*	(6.656)	4.383	(5.986)
Age sqrd.	-0.293*	(0.123)	-0.082	(0.109)
White	-0.179	(1.050)	0.952	(0.584)
Black	-1.791	(1.274)	0.994	(0.857)
Asian	-1.461	(0.993)	0.591	(0.600)
Hispanic	1.534	(1.112)	1.743*	(0.700)
Never Married	-1.269**	(0.467)	1.520**	(0.516)
Disabled	-1.099*	(0.508)	-0.364	(0.635)
Foreign born US citizen	-0.561	(0.775)	0.420	(0.465)
Foreign born non-US citizen	-1.066	(0.799)	-1.085**	(0.370)
Degree type				
Masters	1.877**	(0.596)	0.783**	(0.301)
Professional	-0.495	(0.916)	2.506**	(0.657)
Doctoral	2.866*	(1.121)	2.219**	(0.830)
Degree field				
Agricultural Sciences	-2.006†	(1.065)	-3.549**	(1.243)
Architecture	1.812	(1.580)	-2.431*	(1.231)
Biological Sciences	-0.438	(0.998)	-3.589**	(1.083)
Business and Management	-0.501	(0.948)	-4.215**	(1.165)
Communications	0.735	(1.523)	-2.819*	(1.370)
Computer Science	0.953	(1.017)	-4.133**	(1.182)
Education	0.000	(0.000)	-3.022*	(1.182)
Engineering	1.606†	(0.964)	-4.127**	(1.087)
Engineering-related Technology	0.894	(1.230)	-4.089**	(1.274)
English and Foreign Languages	-2.065†	(1.182)	-4.249**	(1.265)
Health Professions	0.769	(1.302)	-3.479**	(1.074)
Home Economics	0.000	(0.000)	-5.461**	(1.344)
Law/Prelaw/Legal Studies	-0.401	(1.036)	-0.686	(1.257)
Liberal Arts	-1.742	(1.210)	-2.665†	(1.376)
Mathematics	2.181†	(1.195)	-2.695*	(1.191)
Philosophy/Religion/Theology	0.000	(0.000))	-6.227**	(1.358)
Physical Sciences	0.610	(1.006)	-3.975**	(1.240)
Psychology	-0.363	(1.007)	-3.892**	(1.084)
Public Affairs	-1.123	(1.587)	-1.374	(1.496)
Social Science	-0.456	(0.975)	-4.334**	(1.118)
Visual and Performing Arts	3.919**	(1.411)	-3.237*	(1.383)
Intercept	-198.419*	(89.584)	-53.028	(81.844)

	Men	Women
N	9034	10485
Log-likelihood	-160212.943	-648862.373
$\chi^2_{(34)}$	137.345	190.869

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Table 1.18: Estimation results of logit model on attachment, ages 25-29.

9 Conclusion

This research set out to account for the 8 percentage point decrease in young worker labor force participation. The decomposition in Section 6 showed that 1.53 percentage points of the decrease can be accounted for by changes to the demographic composition of young workers. Using analagous calculations, the *genuine* decline in participation is more than 7%.

Using alternate definitions of participation, specifically classifying workers as *attached*, *marginally attached*, and *not attached* to the labor force, this research attributes about eighty percent of the decrease (6.5% of the 8%) in labor force participation to changes in education decisions of young workers. In the same calculations, 1.64 percentage points are not accounted for by education decisions; this research considers this the true, and persistent, decrease of labor force participaiton of young workers from 1994 to 2014.

A notable conclusion of redefining non-participation is that when considering full-time students as *Marginally Attached*, the level of *Not Attached* workers does not show a cyclical trend. This contrasts the cyclical trend seen in the reported binary participation and non-participation rates.

This research finds that college graduates genuinely participate 3.39 percentage points less (from a nominal decrease of 4.64%) in 2014 than in 1994. Additionally, decisions by full-time enrolled high school and college students to work less results in decreases of 1.32 and 3.11 percentage points, respectively.

Continuing to consider changes in decisions of young workers, college major choice, and the implication to labor force participation and attachment, was described in Section 8. The conclusions of this portion of research is that for males, certain majors (Agriculture and English and Foreign Language) correspond with lower attachment, while others (Engineering, Mathematics, and Visual and Performing Arts) correspond to higher attachment. For females, graduate degrees are the strongest indicator of attachment to the labor force and being married corresponds with non-attachment to the labor force. These results motivate future consideration into the decisions that young people make regarding their college major and ultimately their labor market choices.

This research opens opportunities for many further studies. Specifically, time use is not considered for those young workers not participating in the labor force; this is the largest avenue for future research. Additionally, the payoff to extended education and the penalties for not participating early in a young worker's career is not directly considered here.

The trade-off between formal schooling as human capital accumulation and on-the-job training has certainly changed over time. Ability-to-pay for continued education is higher due to increased accessibility to student loans, thus decreasing the opportunity cost of college. Combined with a scarcity of jobs during the two most recent recessions, and young workers have less incentive in 2014 to enter the labor market than they did twenty years earlier. Their choices, as documented in this research, provide motivation for policy to consider the structural changes to the labor force.

CHAPTER 2

LABOR MARKET FLOWS OF YOUNG WORKERS

1 Introduction

Labor market outcomes differ between young workers (ages 18-24) and prime age workers, including separation and unemployment rates (Gervais, et al., 2014). Transition flows between labor market states drive many of the fluctuations within standard labor market measurements (referred to here as the "stocks") and off-setting flows can mask underlying trends. This paper seeks to measure the movements of young workers between labor market states and quantify the impact each flow has on the overall stocks, with a focus on the unemployment rate.

The purpose of an approach focusing on labor market transitions is to eliminate off-setting flows and differentiate between changes due to business cycles and structural trends. Each separate flow provides insight into the labor force transformation over time and response to economic shocks. As workers move between labor market statuses, some may leave unemployment, for instance, and move into employment, while some leave unemployment and leave the labor force altogether. Both transitions decrease the "stock" of unemployed workers, but each scenario is the result of a distinct change in the labor market; the literature refers to this situation as the "stock flow fallacy."

Subsequently, policy responses should differ depending on which "flow" responds adversely to a shock. Specifically, if the flow from unemployment to employment (referred to as the *job finding rate*) drives fluctuations in unemployment, then unemployment insurance incentives should focus on returning workers to work. If changes to flows from employment or unemployment out of the labor force (to "not in the labor force") drive unemployment such that the unemployment rate remains constant as workers leave the labor force, then policy should focus on the participation margin. And if flows into schooling are impacted by economic shocks, then incentives (both returns to schooling and ability to pay considerations) should be evaluated.

Ultimately, looking at the stocks of unemployed workers or the number of workers participating in the labor force does not provide a complete picture of the labor market. This is particularly true for young workers, who move between labor market states more frequently than the working age population (Gervais, et al., 2014).

Measuring the direction of flows each period gives a more accurate picture of changes within the labor market over time. A second example of the "stock flow fallacy" occurs if the labor maket improves and many workers leave the unemployed state and become employed while simultaneously many may enter unemployed from not-in-the-labor- force (NILF). The stock of those in the unemployed state could potentially stay the same, while the labor market becomes stronger.

Focusing on the unemployment rate of young workers, this paper measures the impact that labor market flows have on fluctuations in the unemployment rate of young workers by decomposing the variances between labor market flows, participation flows, and changes in the unemployment rate. Movements between unemployment and not-in-the-labor-force account for over forty percent of the variation in the unemployment rate of young workers. Flows between employment and unemployment are obviously important for describing the cyclicality of unemployment, but this result indicates that considering participation decisions is also crucial to understanding unemployment rate variation.

For young workers, participation decisions are impacted by educational choices. This decision is particularly critical for future labor market outcomes, as young workers need to decide between gaining experience "on-the-job" or further their human capital by pursuing a higher degree. This research extends work by Elsby, et al. (2015) on flows between labor market statuses by considering young workers, and more specifically, the impact that educational decisions have on flows between labor market states by including schooling as a labor market status.

This paper uses matched monthly data from the Current Population Survey (CPS) to track consecutive monthly labor market statuses. Individuals are linked in consecutive months, enabling this research to consider multiple variations of standard labor market statuses, which are particularly important for young workers. Section 3 displays the monthly transitions between labor market statuses for young workers between standard labor market statuses. In addition, education is included as a labor market status and flows between employment, unemployment, full-time schooling and not-in-the-labor force are considered. Adding education as a labor force status for young workers helps to account for the decision many newly unemployed young people face: unemployment or back to school.

The chapter is organized as follows. Section 2 describes the data used in this study, including corrections for classification errors. Section 3 displays the flows between labor market statuses, considers compositional changes, and adds a classification of young workers that are full-time students. Section 4 considers how young worker participation flows impact the fluctuations of unemployment. The last section concludes the paper.

2 Data

The data set used in this paper is derived from the Current Population Survey (CPS), which is a monthly survey produced by the United States Bureau of Census for the Bureau of Labor Statistics (BLS). The CPS is used to calculate the monthly labor force statistics (including the unemployment rate) by surveying American households, resulting in approximately one hundred fifty thousand observations per month, including all members of each household older than age fifteen. Households are included in the survey for four consecutive months, followed by eight months out of the sample, then four more consecutive months in the survey. The data used in this paper are from 1994 through 2014. There was a significant redesign of the CPS in 1994, so beginning at this date allows consistency throughout all variables used in this research, including the microlevel individual data described in Section 3. The data used here were downloaded from the NBER website in March 2014 and January 2015; any changes to the data since that time may not be incorporated in the data set.

The CPS data provides many useful pieces of information beyond standard personal characteristics. Specifically, each person in the sample is given an official labor market status, defined as Employed, Unemployed-on layoff, Unemployed-looking, Not in Labor Force (NILF)-retired, NILF-disabled, and NILF-other. Beyond calculating monthly employment numbers for the BLS, these labor force definitions- along with individual micro level data- allow researchers to analyze characteristics of those in each labor market status.

Constructing the Data Set

The goals of this research necessitate a means to track individuals from one month to another. This section describes the construction of the twenty year linked data set used in this research. The CPS data provided by the BLS is in the form of monthly files.[17] While the micro level individual data is not linked month-to-month, certain variables facilitated the matching of individuals while they were surveyed for consecutive months.

The methodology used here of creating individual identifiers, matching individuals and stacking the data to create a panel was created using a framework of files created by Jesse Rothstein's 2011 research on unemployment.

Each household in a monthly CPS file is assigned two identification numbers by the BLS: hrhid and hrhid2. These were merged to create a unique household identifier.[18] Next, a personal identifier was created using the household identifier, the state of the individual, the person's line number, and the person's month in the CPS sample.

The individual identifiers were constructed for each monthly data set, then stacked into one data set containing over 6.7 million observations. The stacking created multiple minor obstacles, which mostly amounted to relabeling variables as the survey methods and definitions evolved. The complete list of variables used and specific labeling changes used are provided in Appendix B.

Once the initial panel was created, individuals were linked by connecting their personal identifier described above and the year and month of the observation. The next step involved checking for discrepencies in sex, race, education and age; unique individuals were unlinked if needed. Using Stata's ability to search for duplicates, just over fifty thousand observations were flagged and removed as duplicates, amounting to just .76% of total observations.

[17] Jean Roth's data files on the National Bureau of Economic Research were the source of the monthly raw data files and extraction files.

[18] The data from 1994 to 2004 did not contain the hrhid2 variable, so one was created by merging three variables: hrsample (sample identifier), hrsersuf (serial suffix), and huhhnum (household number).

Including Education as a Labor Market Status

The CPS classifies participants' labor force participation as either Employed and at work, Employed absent from work, Unemployed on layoff, Unemployed and searching, Not in the Labor Force (NILF) retired, NILF disabled, and NILF other. The first two statuses are straightforward and the Unemployed designations refer to someone on temporary layoff and implies that they are expecting to return to work shortly. A person designated as Unemployed and searching refers to one who does not have a job and is actively seeking employment. The first two NILF statuses are straightforward, and the status of NILF other deserves some explanation. Traditionally, the NILF other designation refers to someone who is a discouraged worker or separated from the labor force. A discoraged worker may have previously been considered unemployed, but is no longer looking for a job even though they would like one. CPS refers to such a person as NILF. Additionally, someone labeled NILF other may be separated from the labor force because of a spouse or family member's support, or a myrad of other reasons.

For young people, not-in-the-labor force can mean many different things. Along with the traditional explanations above, a young person that is not in the labor force could be in school. Additionally, if a recent high school or college graduate does not immediately find a job, they may consider taking time off before entering the job market. For young people, those categorized as NILF other can have stark differences. For that reason, the data used in this research contains a distinction from official labor force categories.

Status	Abbreviation
Employed	E
Unemployed	U
Full-Time Student	S
Not in the Labor Force	N

Table 2.1: Labor force participation statuses used in this paper.

For the data used in this research, people are considered to be in the four categories shown in Table 2.1. The first two categories are defined as is custom in labor market literature. To determine the status of employed, both “employed and at work” and “employed and absent from work” were combined. Then, both “unemployed on layoff” and “unemployed and searching” were combined to form the unemployed status. The unique aspect to the data set used here is that those not in the labor force were separated into those who reported being full-time students and those that did not. So, the labor force status ”Student” was added, and the remaining persons were listed at not-in-the-labor force.

The figure below shows the distribution of traditional labor market statuses and the statuses used in this data set for young workers in 2014. The distribution of young workers among labor force status as reported in the CPS (first row), official labor force status (second row), and distribution including education as a labor force status (bottom row).

<table>
<tr><td>Employed
at work
56.16%</td><td>Employed
absent
1.64%</td><td>Unemployed
on layoff
0.51%</td><td>Unemployed
looking
7.36%</td><td>NILF
Other
32.14%</td><td>NILF
Retired
0.27%</td><td>NILF
disabled
1.92%</td></tr>
<tr><td colspan="2">Employed
57.80%</td><td colspan="2">Unemployed
7.87%</td><td colspan="3">Not in the Labor Force
34.33%</td></tr>
<tr><td colspan="2">Employed
57.80%</td><td colspan="2">Unemployed
7.87%</td><td>Student (fulltime)
21.33%</td><td colspan="2">Not in the Labor Force
13.01%</td></tr>
</table>

Figure 2.1: The distribution of young workers by labor market status in 2014.

Calculating Gross Flows

In order to analyze the impact of young workers on the composition of the labor market, the first step is to use the CPS data to calculate flows into and out of each labor market state. The traditional labor market statuses (employed, unemployed, not-in-the-labor force) are labeled in the individual CPS data, so linked individuals can be labeled as to their status in two consecutive months. This is refered to as "gross flows" of the CPS data, which is available from the BLS, but the data set used here includes the detailed microdata available in each monthly survey as opposed to just the number of movements.

The process for determing flows from one labor force status to the other exploited the linked CPS data files described earlier. Since individuals were tracked from month to month, each observation either is linked to a previous month, or that month is the person's first (or fifth if the individual is in their second rotation) in the sample. So for each observation that was in the previous month their labor force status was noted. Using traditional labor force statuses, nine distinct flows were created. Using E to represent employed, U to represent unemployed, and N to represent NILF the following are the flows from last month to this month: EE, EU, EN, UE, UU, UN, NE, NU, and NN. So an observation listed EN was employed the previous month and not in the labor force the following month. Observation with the same letter (EE, UU, and NN) continued in the same status as the previous month.

With four labor force statuses to include full-time schooling, the result was sixteen different combinations for consecutive months. Using S to represent student the following are the flows from last month to this month: EE, EU, ES, EN, UE, UU, US, UN, SE, SU, SS, SN, NE, NU, NS, and NN. So an observation listed ES was employed the previous month and a student the following month.

Table 2.2 below shows the distribution of flows from 2014. Rows list a worker's current status and columns list the previous month's status. Rows add to one. Trends over time are displayed and described in Section 3.

	Employed (E)	Unemployed (U)	Student (S)	NILF (N)
Employed (E)	EE 84.6%	EU 2.3%	ES 10.3%	EN 2.8%
Unemployed (U)	UE 21.9%	UU 47.1%	US 12.2%	UN 18.8%
Student (S)	SE 8.4%	SU 1.9%	SS 82.2%	SN 7.4%
NILF (N)	NE 7.1%	NU 7.7%	NS 25.1%	NN 60.2%

Table 2.2: Labor force participation status used in this paper with 2014 percentage in parentheses.

Corrections for Classification Errors

A drawback of the data used in this research is the potential for misclassification of labor market status. Since this research is interested in flows from month to month, classification errors can lead to "spurious" transitions. For instance, if an individual is misclassified as Not in the Labor Force (NILF), but is actually unemployed and is properly coded in other monthly surveys results in potentially two non-existent flows: one out and another back into the labor force. This section describes the Abowd and Zellner (1985) correction of classification errors.

Abowd and Zellner (1985) estimated the likelihood of classification errors by examining CPS reinterview surveys[19]. They concluded that almost 10% of individuals who were classified as NILF were actually unemployed. Their measurements of original status and the status determined on reinterview are displayed in Table 2.3 below.

[19] Reinterview surveys are no longer available from the BLS.

	Status determined on Reinterview		
	Employed	Unemployed	NILF
Original Status			
Employed	98.78	1.91	0.50
Unemployed	0.18	88.57	0.29
NILF	1.03	9.52	99.21

Table 2.3: Abowd and Zellner (1985) estimates of classification errors.

In order to calculate corrected transition probabilities, consider the relationship between measured stocks of labor market status and their "true" values:

$$\begin{bmatrix} \hat{E} \\ \hat{U} \\ \hat{N} \end{bmatrix}_t = \underbrace{\begin{bmatrix} 1-\epsilon_{UN}-\epsilon_{EN} & \epsilon_{UE} & \epsilon_{NE} \\ \epsilon_{EU} & 1-\epsilon_{UE}-\epsilon_{UN} & \epsilon_{NU} \\ \epsilon_{EN} & \epsilon_{UN} & 1-\epsilon_{NE}-\epsilon_{NU} \end{bmatrix}}_{\mathrm{E}} \begin{bmatrix} E \\ U \\ N \end{bmatrix}_t , \tag{2.1}$$

where ϵ_{ij} is the probability that an individual with true market state i is misclassified as state j. These values, as estimated by Abowd and Zeller (1985) are shown in Table 2.3.

In order to calculate the corrected flows from the flows found in the CPS data, let N_t be the matrix of the count of individuals flowing between each labor market state:

$$\boldsymbol{N_t} = \begin{bmatrix} EE & UE & NE \\ EU & UU & NU \\ EN & UN & NN \end{bmatrix}_t . \tag{2.2}$$

Following Poterba and Summers (1986), the measured flows described earlier can be corrected to represent their true counterpart using the relation $\hat{N}_t{=}EN_tE'$ and inverting results in:

$$\boldsymbol{N_t} = \boldsymbol{E^{-1}}\boldsymbol{\hat{N}_t}(\boldsymbol{E}^{-1})' \tag{2.3}$$

The reinterview surveys used by Abowd and Zellner are no longer released by the BLS. Thus in order to utilize this correction, a necessary assumption is that classification errors are constant over time and that they do not differ for young workers. An argument against using the Abowd and Zellner correction is that young workers may change their labor state more frequently than the rest of the population, and many true movements will be corrected. Without updated interview data, it is difficult to accurately gauge the validity of this argument. Also, CPS interview technique has improved since Abowd and Zellner's study; this improvement may offset the more fluid young worker labor market or work to render the correction irrelevant to the more recent young worker data.

With those caveats in mind, this research presents corrrected flows using the methodolgy described above with the classification errors, ϵ_{ij}, found by Abowd and Zellner. The corrected flows are also used in the decomposition of variance of the unemployment rate. In the work that follows, the original and corrected flows both exhibit corresponding trends with similar qualitative results.

3 Flows Between Labor Market Statuses

The percentage of young workers in each labor market status at any one time (shown in Figure 2.1 for 2014) provides a snapshot of the labor market. Charting a time series of the labor market statuses over time provides a glimpse of trends and cyclicality, but does not account for offsetting trends described earlier. To account for the "stock flow fallacy," this section charts and describes the time series of movements between labor market statuses, specifically for young workers.[20] This section consists of three

[20] A replicaiton of flows for prime aged workers is provided in Appendix D and serves as a replication of the work of Elsby, etal. (2015).

subsections; first, flows from traditional labor market statuses are displayed, followed by flows including schooling as a labor force status for young workers. Last, those enrolled in full-time schooling are excluded from the transitions. Descriptions of notable results gleaned from the time series graphs are provided throughout this section.

This paper uses two letters to indicate each flow: the first denotes starting status and second is status in the next period. So, a move from unemployment to employment would be denoted as UE, while EN would indicate a move from employment out of the labor force.

Certain labor market flows are of particular importance and changes in these flows have potential policy implications. Specifically, the flow "EU" (from employment to unemployment) is called the separation rate and "UE," similarly is the job-finding rate. As shown in the analysis that follows, these flows changed significantly from 1994-2014 for young workers, and are impacted by the business cycle, while other flows can be used to describe structural changes to the young worker labor market.

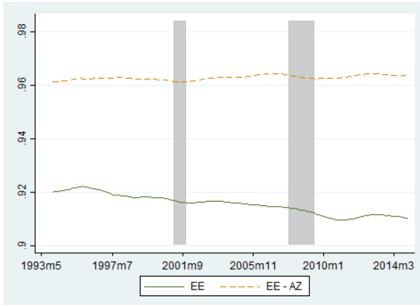
Young Worker Flows Between Labor Market Statuses

The first set of figures show flows of young workers who were employed during the previous month. Figure 2.2(a) charts the percent of employed young workers that remain employed. The complement (one minus this number) would represent the job separation rate. From 1994-2014, this rate decreased approximately one percentage point.

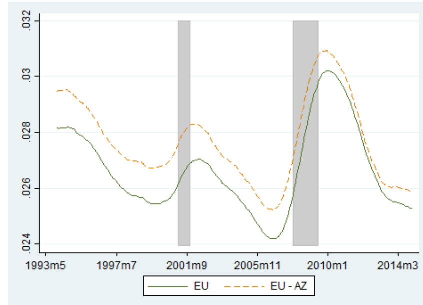
The percent of employed young workers that became unemployed the following month can be seen in Figure 2.2(b). Predictably, this flow increased significantly during each recession, but then recoverd and in 2014 was below the flow twenty years earlier. There are two explanations for the countercyclicality. The first follows the prediction of the Diamond-Mortensen-Pissarides (DMP) Model that unemployment rises during recessions (or negative shocks). The second rationale for the increase during the Great Recession is the extension of unemployment insurance benefits; this paper does not consider unemployment benefits explicitily, so this discussion is left for future work. The most important takeaway from Figure 2.2(b) is the strong countercyclicality. In terms of the goals of this paper, flows of young workers from employment to unemployment are clearly cyclical.

The rate at which employed young workers leave the labor force are shown in Figure 2.2(c). Over the twenty year period, there is a consistent increase, resulting in approximately one and a half percentage point increase. During the Great Recession, there was a decrease in the frequency of employed young workers leaving the labor force, corresponding with the increase of those moving into unemployment. Presumably, extended unemployment benefits and eligibility factored into these transition decisions. Rothstein (2011) quantifies this trend for the general population by accounting for the impact of UI benefits on job search.

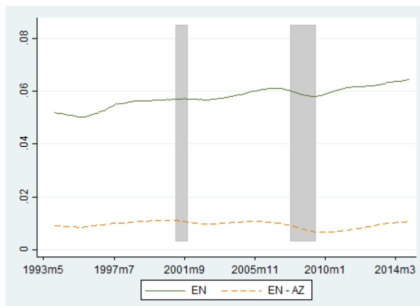
Figure 2.3 displays the flows from unemployment from 1994-2014. Of particular interest in these time series graphs is the procyclicality of those moving from unemployment to employment (the job finding rate of unemployed) and the counter cyclicality of those remaining unemployed. UE flows are clearly procyclical with the business cycle, as the rate of those leaving unemployment for employment drops significantly during recessions and begins to return to trend after the recession ends. It is important to note that there was not a full return to trend, causing a seeming decline in this flow from 1994 to 2014.



(a) EE



(b) EU



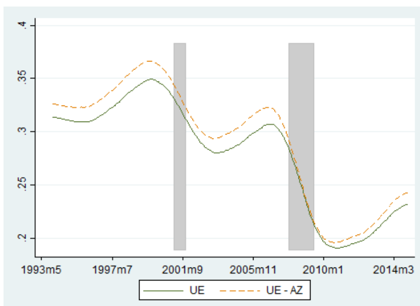
(c) EN

Figure 2.2: Time series of flows out of employment status.

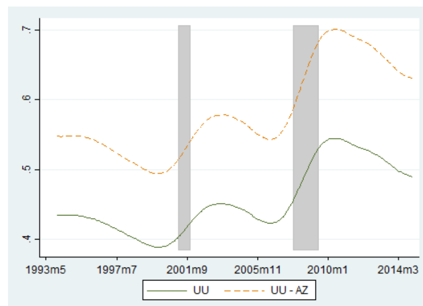
Similarly, Figure 2.3(b) shows the flow of those remaining in the unemployed state from one period to the next. Again, these flows follow the business cycle and are clearly countercyclical. Both of the flows from unemployment fit the traditional story and the DMP model. The increase in the rate of workers remaining in the unemployed state is due to the drop in the job-finding rate and increases and extensions in unemployment benefits during recessions. Rothstein (2011) provides a detailed accounting of the impact of increased Unemployment Insurance benefits on unemployment.

The twenty-year trend of unemployed workers leaving the labor force (UN rate) increases almost three percentage points, and similar to the transition out of employment, there is a large decline of young workers leaving the labor force from the unemployed state during the Great Recession. The corresponding explanation is likely due to increasing unemployment insurance benefits and relaxed requirements for those benefits. The result is more young workers remaining in the unemployed state and raising the unemployment rate. The decomposition of variances done in Section 4 accounts for the impact of these flows on changes in the unemployment rate.

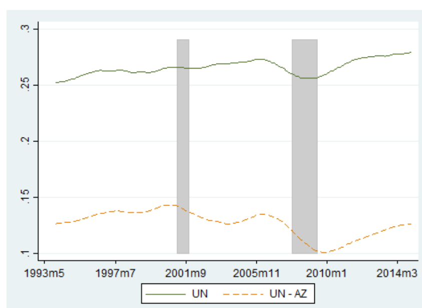
The movement from participation to non-participation (both EN flows from Figure 2.2(c) and UN flows seen in Figure 2.3(c)) is impacted by the choices young workers make regarding education. As shown in the next section, distinguishing schooling from other not-in-the-labor-force states impacts the trends seen in the EN and UN flows.



(a) UE



(b) UU



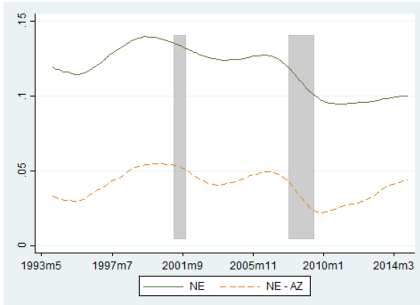
(c) UN

Figure 2.3: Time series of flows out of unemployment status.

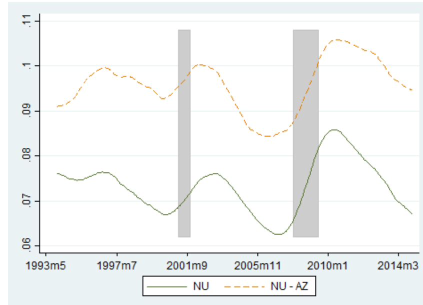
The flows of those not in the labor force can be seen in Figure 2.4. Both flows into employment and into unemployment can be considered as flows into the labor force- or from non-participation to participation. Individuals entering the labor force and becoming employed immediately increased in the mid-1990s, then displayed a procyclical trend. During the Great Recession, the NE rate decreased three percentage points from 12% to 9%. There is a slight increase seen during following the two recessions within the data set.

Also of interest are flows into unemployment; these flows are countercyclical which may be counter-intuitive. That is, if one follows the story of discouraged workers leaving the labor force, this contradicts that concept. Flows into unemployment- and presumably searching- are countercyclical meaning that in recessions (and immediately following) this flow rises, so people re-enter the labor force. Elsby, et al (2015) provide a potential explanation for the increase in NU transitions in the "added worker effect," which accounts for non-participants beginning to search to replace wages (due to a decrease in wages or job loss) of another household memeber. Elsby, et al. break down this countercyclical rentry flow and find that more men than women are likely to reenter the labor force, combined with the number of married couples and the "added worker effect" seems to only provide a portion of the explanation of the rise of the NU flow during recessions.

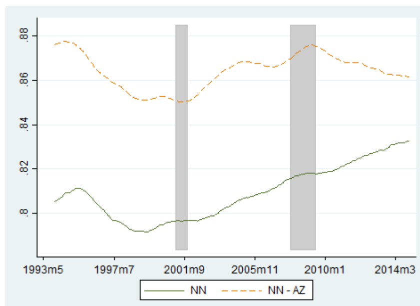
The rate of young workers remaining out of the labor force from one month to the next decreased slightly in the mid-1990s, but increased almost four percentage points over the twenty year period.



(a) NE



(b) NU



(c) NN

Figure 2.4: Time series of flows out of NILF status.

Composition Changes

The data used in this research are from 1994-2014. Over that twenty-year time period, the composition of young workers has evolved. The distribution of demographic traits, specifically gender and race and ethnicity, within the population of young workers has changed.[21] This section considers how changes in the flows presented above are impacted by changes in the composition of young workers.

The graphs in Figure 2.5 below display a "genuine" flow rate from 1994-2014, which holds demographic trends constant over the twenty year period.[22] These "genuine" flow rates decompose demographic trends to show true changes to the flow rates. The size

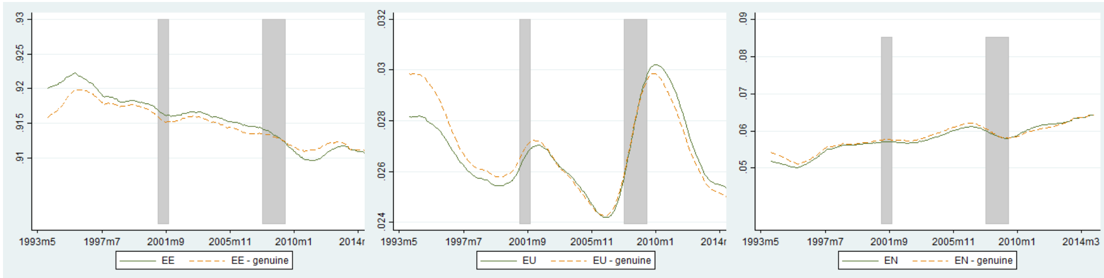
[21] See Chapter 1 of this Dissertation for detailed demographic shifts.
[22] For a detailed explination of the process, see Chapter 1 of this Dissertation

of the subpopulations are held constant while the flow level within each subgroup varies over time. The demographic variables accounted for in this section are age, gender, and race and ethnicity.

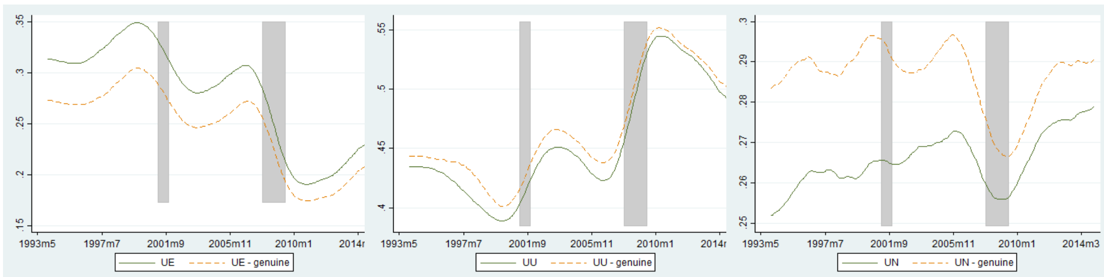
Figure 2.5 below shows each flow rate with the corresponding decomposed flow rate (dotted line).[23] The figures show only slight differences between aggregrate flows and those adjusted for compositional changes (the scale of each graph exaggerates the slight differences). Certainly the composition of young workers changed from 1994 to 2014, but the movements of young workers as a whole represent how flows progressed over the twenty year period studied.

The impact of demographic compositional changes of the young worker population do not impact major trends of flows over the twenty year period studied. There are two subtle changes to note, which both occur during the Great Recession. Specifically, the flow from unemployment to not-in-the-labor-force (Figure 2.5(f)) decreased more sharply before and during the Great Recession when removing demographic factors. Second, the flow from not-in-the-labor-force into unemployment (Figure 2.5(g)) did not increase as fast during the Great Recession. Both results indicate that demographic changes only served to emphasize trends, not reverse or drive the changes discussed in the previous section.

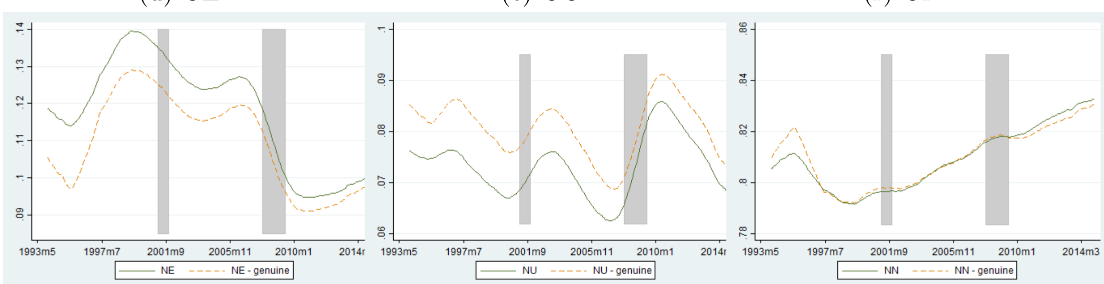
[23] The gap at the beginning of each graph (in 1994) is due to differences in smoothing due to the calculation of each composition.



(a) EE (b) EU (c) EN



(d) UE (e) UU (f) UN



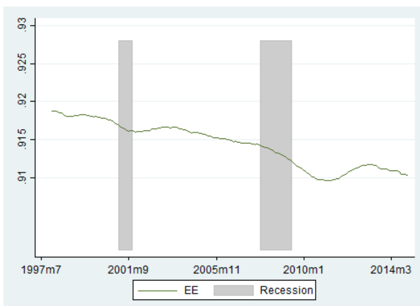
(g) NE (h) NU (i) NN

Figure 2.5: Time series of flows and decomposed genuine flows.

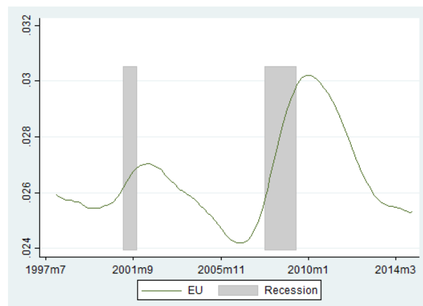
Flows With Schooling

One contribution of this research to the current literature is the addition of schooling as a labor market status, since education decisions are critical for young workers. Similar to the previous section, the following figures consider flows between traditional labor market statuses as well as in and out of schooling. Table 2.2 in Section 2.3 provides a snapshot of the percentage of flows from each status in 2014.

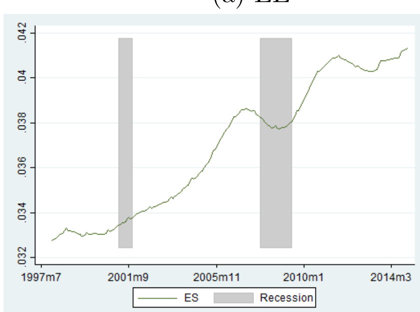
The first set of figures below show the flows of young workers from employment, while considering that some workers leave employment (voluntarily or not) to attend school full-time. In Figures 2.6(a) displays the time series of the percentage of young workers remaining in the employed state and Figure 2.6(b) shows the countercyclical flows of young workers from employment to unemployment. These graphs are identical to the corresponding figures in Figure 2.2, since the only change was separating sub-catagories of those NILF.



(a) EE



(b) EU



(c) ES

(d) EN

Figure 2.6: Time series of flows out of employment status, including schooling.

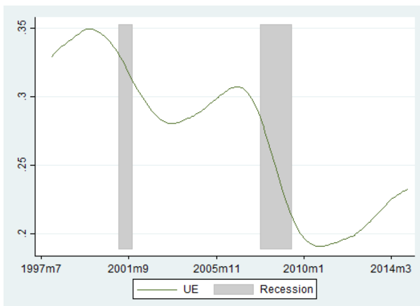
The flow from employment to schooling is shown in Figure 2.6(c); this flow rose about one and a half percentage points from 1994-2014 and dipped slightly during the Great Recession. This rate increased during the recovery. Figure 2.6(d) shows the flow from employment out of the labor force. This flow increased during the early 2000s leading up the Great Recession, then dropped significantly during the Great Recession. This is where separating individuals leaving employment for schooling and leaving for other reasons creates a notable distinction.

Earlier, Figure 2.2(c) described a consistent upward trend of employed workers leaving the labor force with approximately a one and a half percentage point increase over the twenty years studied. Figure 2.6(d) shows the EN transitions excluding young workers leaving for school. The result is a procyclical trend of the EN flow dropping during recessions and increasing during recoveries, most notably increasing half a perentage point from 2010 to 2014. The result is a negligible change in employed workers leaving the labor force, excluding education, from 1994 to 2014.

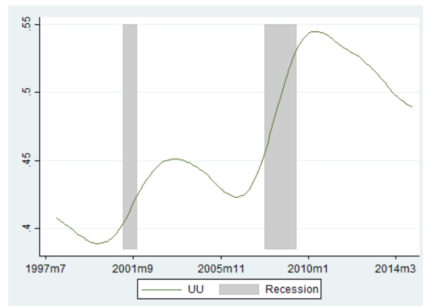
If we consider education “weak” labor force attachment- that is young people leave the formal labor market to gain skills presumably with the intention of returning- then there has not been a mass exodus of young workers from the labor force. Instead, because of incentives (including cost and returns to schooling) more young workers have decided to leave employment and go back to school.

Figure 2.7 displays the time series of flows of young workers out of the unemployment status. Figure 2.7(a) shows the flow from unemployment into employment and Figure 2.7(b) shows those remaining unemployed. Again, these flows are identical to their counterparts in the previous section and Figure 2.3.

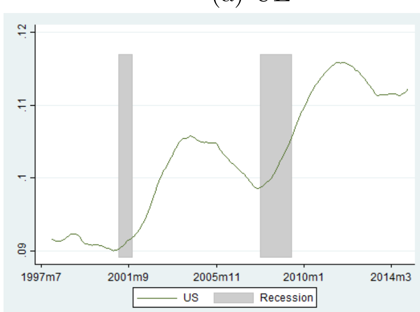
In Figure 2.7(c), the flow from unemployment to schooling has risen over three percentage points from 1994 to 2014. This increase includes a slight drop leading up to the Great Recession. The countercyclicality in Figure 2.7(c) deserves more study, as the rise in those young workers moving from unemployed to schooling could be the efficient result of changed incentives (i.e. lower job prospects based on current skills), or could be the result of expiring unemployment benefits, or a response to student loan rates and availability. The jump in the "US" flow during and following recessions seems to maintain at the higher rate (with a slight dip before the Great Recession). Because the data set contains only two recessions, definitive conclusions cannot be drawn, but there is a clear increase of over three percentage points in the movement from unemployed to full-time schooling.



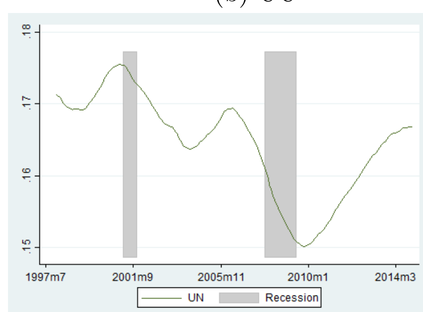
(a) UE



(b) UU



(c) US



(d) UN

Figure 2.7: Time series of flows out of unemployment status, including schooling.

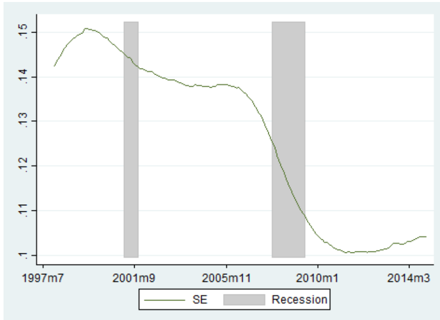
The takeaway from Figure 2.7(d) of the flow of workers from unemployment to out of the labor force is similar to that of Figure 2.3(c); both UN flows show significant declines during recessions and increases during recoveries. The relationship between unemployment and non-participation- and the corresponding impact on the unempoyment rate- motivate the measurement of the impact of the fluctuations in flows and fluctuations of the unemployment rate.

Figure 2.8 shows the time series of flows out of full-time student status. Figure 2.8(a) displays the flow into employment, which decreased signifcantly during the Great Recession. This flow is representative of the rate at which a student moves directly from school to employment. It has dropped from a high of over 15% in the late 1990's to stabilize around 10% after 2010.

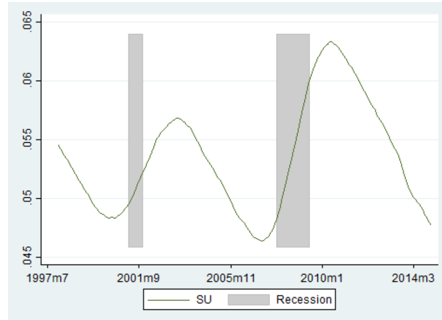
Figure 2.8(b) indicates a cyclical pattern of students moving directly into unemployment from schooling. This rate jumped during both the recession of the early 2000s and the Great Recession then began a return to trend. The expansion of unemployment benefits during recessionary periods may be the cause, though this transition is interesting in that students who recently graduated are not eligible for unemployment insurance benefits.

Figure 2.8(c) displays a relatively consistent increase in the "flow" of students remaining in school from one period to the next. There is an upward trend during the Great Recession and a slight dip in 2014.

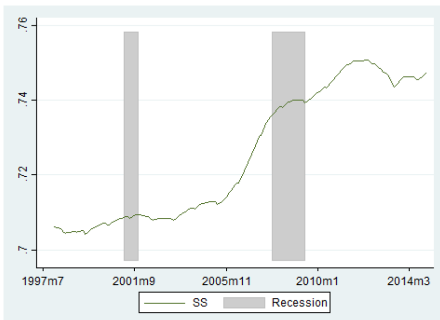
The transition rate from full-time student to Not in the Labor Force (Figure 2.8(d)) increased almost two percentage points, but has spiked in the years following the recovery. This trend is likely the result of the difficulty for young (and less experienced) workers to find a job- as indicated by Figure 2.8(a).



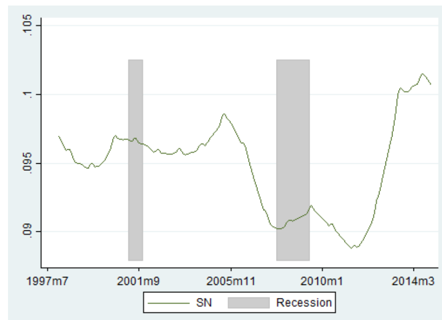
(a) SE



(b) SU



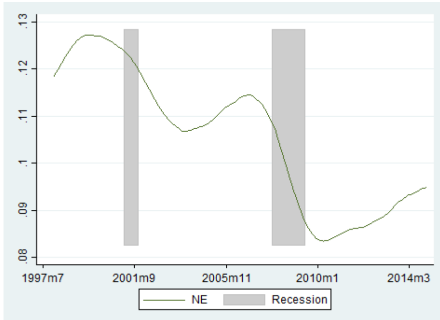
(c) SS



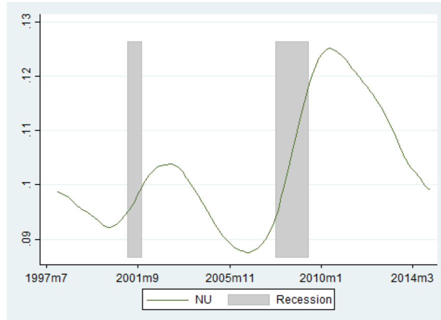
(d) SN

Figure 2.8: Time series of flows out of full-time student status.

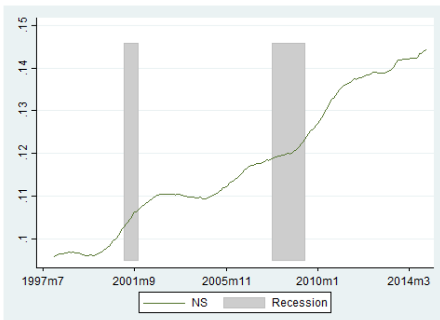
The time series of flows out of the Not in Labor Force status- or looking reversely, the flows back into the labor force- can be seen in Figure 2.9. Specifically, Figure 2.9(a) displays the flow of those not in the labor force that go directly into employment. There is a clear procyclical trend here, as young workers move directly into employment less frequently during recessions. This result is consistent with Figure 2.4(a). Figure 2.9(b) shows a countercyclical rate of flows into unemployed status, so removing full-time students from the NILF designation does not provide insight into the increase in participation during recessions.



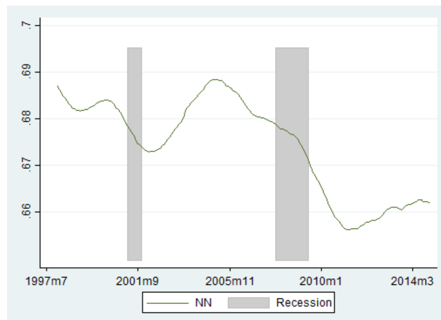
(a) NE



(b) NU



(c) NS



(d) NN

Figure 2.9: Time series of flows out of not in the labor force status, including schooling.

The rate of young workers flowing from not in the labor force into full-time student status is shown in Figure 2.9(c). This rate has consistently risen over seven percentage points from 1994-2014 and does not indicate any form of cyclicality. The result of an increased flow from not in the labor force and into schooling is another indication of a changing labor market. A human capital story might best explain this structural trend, and is left to future work.

Figure 2.9(d) shows the flow of those remaining out of the labor force. Interestingly, this rate has dropped when accounting for education separate from not participating in the labor force. Note the difference between Figure 2.4(c), which includes schooling from NILF and Figure 2.9(d), which does distinguish between schooling and NILF. In the former, those remaining NILF from one period to the next is increasing (and thus decreasing participation). Meanwhile, in the latter, those remaining NILF decreased from 1994-2014. This indicates that if we consider schooling as a means of weak participation or contribution to the labor force, then Figure 2.9(d) represents an increase in participation of young workers.

The conclusion to draw from the flows presented in this section is that while the young worker labor market is subject to both cyclical and structural changes, participation as traditionally defined does not capture trends in educational decisions. Flows between traditional labor market statuses (Employment and Unemployment, specifically) are cyclical and subject to business cycle trends consistent with DMP Models and labor market literature. Meanwhile, flows of young workers relative to schooling (most noteably into employment and remaining in school) are indicative of a structural change in the labor force. This structural trend should be addressed with specific policies tailored to young workers, specifically unemployment benefits and educational incentives. Last, when schooling is removed from NILF, the particiaption story can be viewed quite differently. Specifically, the rate of young workers remaining completely removed from productive labor market states from month to month has actually *decreased* five percentage points from 1994-2014.

Demographic Characteristics of Individuals Leaving Participation for Schooling

The previous subsection described the movements between labor force statuses, including full-time schooling. This section analyzes the microdata of individuals moving from employment and unemployment states and into full-time schooling.

Specifically, individuals who move from participation in traditional labor market states (i.e. employment and unemployment or ES and US, respectively) into full-time schooling are described below. Flows into schooling have both increased from 1994 to 2014 with slight cyclicality[24] and Table 2.4 below displays demographic characteristics of individuals who flow into full-time schooling. Thus, this section seeks to answer the question of "Who moves from participating in traditional labor force states into full-time student status?"

Demographic information, including gender, race and ethnicity, and education are shown for both 1994 and 2014. The education status is the individual's current level, not an indication of what level they are entering. Presumably an individual with some college is re-entering college, and an individual with a high school degree is pursuing some form of post-secondary education.

	ES		US	
	1994	**2014**	**1994**	**2014**
gender				
male	51.32%	49.40%	55.57%	54.07%
female	48.68%	50.60%	44.43%	45.93%
race and ethnicity				
white	75.59%	61.45%	54.21%	41.52%
black	11.95%	10.73%	25.44%	20.89%
hispanic	6.68%	17.09%	14.00%	26.32%
asian	4.24%	6.10%	4.64%	6.09%
other	1.54%	4.63%	1.71%	5.18%
Education				
no high school	13.26%	11.16%	33.57%	18.53%
high school	20.91%	21.32%	19.78%	26.26%
some college	60.42%	61.43%	44.29%	49.90%
college	5.13%	5.72%	2.36%	5.31%
graduate	0.28%	0.37%	0.0%	0.0%

Table 2.4: Demographic characteristics of individuals moving into full-time student status.

Most notably, the movements into schooling changed in terms of the race and ethnicity composition. The percentage of people identifying with hispanic ethnicity that

[24]see Figures 2.6 and 2.7

left the active labor force and moved into full-time schooling increased from 1994 to 2014.

Another notable change is the composition of education levels for those leaving employment and unemployment for full-time schooling. The number of young people with no high school degree who returned for a high school degree decreased, but this is likely due to the increase in high school completion from 1994 to 2014.[25] The largest increase in individuals leaving labor force participation for full-time schooling is those without a college degree. The percentage of unemployed workers without a college degree returning to school increased over twelve percentage points (from 64.07% to 76.16%).

4 Measuring the Impact of Flows on Unemployment Rate

The unemployment rate is calculated by dividing the number of unemployed workers by the number of workers participating in the labor force, and thus the labor market participation rate directly drives the unemployment rate. Flows between labor market states clearly change the stocks and consequently the oft noted labor market rates. This section quantifies the contribution of each flow to changes of the unemployment rate.

Figure 2.10 shows the unemployment rate from 1994-2014 for both young workers (18-24 years old) and for the population over age 25. The unemployment rate for young workers is significantly higher than the rest of the population.

[25] See Section 2.2.2 in Chapter 1 of this Dissertation for a breakdown of population changes by education level.

Figure 2.10: Unemployment rates by age group.

The unemployment rate has fluctuated for both age groups from 1994-2014, with a countercyclical movement during recessions and return to trend during recoveries. During the recovery since the Great Recession, the participation rate- for both young workers and the entire population- has decreased, while the unemployment rate has also decreased, implying more unemployed workers leaving the labor force than employed workers. This concept motivates the decomposition of unemployment fluctuations presented below.

Decomposition of Variance of Unemployment Rate

This section follows the three-state decomposition of unemployment fluctuations methodology presented in Section 5.1 of Elsby, et al. (2015). Isolating young workers in this research helps to describe the impact of labor market movements that are particular to young workers.

Elsby, et al. (2015) decompose the time series variance of each labor market stock into "parts accounted for by each of the respective flow hazards... using analytical approximations to a partial-adjustment representation of labor market dynamics." The work in this section provides a summary and replication of the work of Elsby, et al. (2015). First, a Markov chain can be used to map labor force stocks to flows,

$$\begin{bmatrix} E \\ U \\ N \end{bmatrix}_t = \begin{bmatrix} 1-\rho_{EU}-\rho_{EN} & \rho_{UE} & \rho_{NE} \\ \rho_{EU} & 1-\rho_{UE}-\rho_{UN} & \rho_{NU} \\ \rho_{EN} & \rho_{UN} & 1-\rho_{NE}-\rho_{NU} \end{bmatrix}_t \begin{bmatrix} E \\ U \\ N \end{bmatrix}_{t-1} . \tag{2.4}$$

In Equation 2.4, ρ_{ij} indicates the discrete time flows from state i to state j, which can be measured using CPS data and were displayed in previous sections. Normalizing the population to be the civilian working age population, then $E_t + U_t + N_t = 1$ [26] and Equation 2.4 can be simplified as

$$\underbrace{\begin{bmatrix} E \\ U \end{bmatrix}_t}_{s_t} = \underbrace{\begin{bmatrix} 1-\rho_{EU}-\rho_{EN}-\rho_{NE} & \rho_{UE}-\rho_{NE} \\ \rho_{EU}-\rho_{NU} & 1-\rho_{UE}-\rho_{UN}-\rho_{NU} \end{bmatrix}_t}_{\tilde{P}_t} \underbrace{\begin{bmatrix} E \\ U \end{bmatrix}_{t-1}}_{s_{t-1}} + \underbrace{\begin{bmatrix} \rho_{NE} \\ \rho_{NU} \end{bmatrix}_t}_{q_t} . \tag{2.5}$$

Then the steady state, $\bar{s}_t$, of the Markov chain is $\bar{s}_t = (I - \tilde{P}_t)^{-1} q_t$. Elsby et al. (2013) describe how changes in flow hazard rates f_{ij} over time impact the discrete time flows, which ultimately impact the path of labor market states over time. Writing the change in labor market states Δs_t as

$$\Delta s_t = (s_t - \bar{s}_t) - (s_{t-1} - \bar{s}_{t-1}) + \Delta \bar{s}_t. \tag{2.6}$$

Combining with the reduced form of Equation 2.5,

[26] E_t, U_t, and N_t are shares of the population that are employed, unemployed, and not in the labor force, respectively.

$$(s_t - \bar{s}_t) = \tilde{P}_t(s_{t-1} - \bar{s}_t) = \tilde{P}_t(s_{t-1} - \bar{s}_{t-1}) - \tilde{P}_t\Delta\bar{s}_t. \tag{2.7}$$

Substituting Equation 2.7 into Equation 2.6,

$$\Delta s_t = -(I - \tilde{P}_t)(s_{t-1} - \bar{s}_{t-1}) + (I - \tilde{P}_t)\Delta\bar{s}_t. \tag{2.8}$$

Rewriting the second part of Equation 2.7 as $\tilde{P}_t(s_{t-1} - \bar{s}_{t-1} - \Delta\bar{s}_t)$ so $(s_{t-1} - \bar{s}_{t-1} - \Delta\bar{s}_t) = \tilde{P}_t^{-1}(s_t - \bar{s}_t)$, and combining with Equation 2.6 and simplifying results in

$$\Delta s_t = (\tilde{P}_t - I)\tilde{P}_t^{-1}(s_t - \bar{s}_t). \tag{2.9}$$

Combining Equation 2.8 with Equation 2.9, we can write the change in labor market states as

$$\Delta s_t = (I - \tilde{P}_t)\Delta\bar{s}_t + (I - \tilde{P}_t)\tilde{P}_{t-1}(I - \tilde{P}_{t-1})^{-1}\Delta s_{t-1}. \tag{2.10}$$

For simplicity, let $A_t = (I - \tilde{P}_t)$ and let $B_t = (I - \tilde{P}_t)\tilde{P}_{t-1}(I - \tilde{P}_{t-1})^{-1}$, so Equation 2.10 can be rewriten as $\Delta s_t = A_t\Delta\bar{s}_t + B_t\Delta s_{t-1}$.[27] Equation 2.10 can be iterated backwards on lagged changes to the steady state to Δs_0, the change to labor market stocks from the first period:

$$\Delta s_t = \sum_{k=0}^{t-1} C_{k,t}\Delta\bar{s}_{t-k} + D_t\Delta s_0 \tag{2.11}$$

with $C_{k,t} = \prod_{n=0}^{s-1} B_{t-n}A_{t-k}$ and $D_t = \prod_{k=0}^{t-1} B_{t-k}$.

The changing continuous time flow hazards f_{ij} from state i to state j, impact

[27] From Elsby, et al. (2015) A_t "captures the changes in labor market stocks that are driven by comtemporaneous changes in the flow transition rates which shift the flow steady state $\bar{s}_t$" and B_t "summarizes the transmission of past changes in transition rates onto current labor market state."

the changes in stock of each state, s_t, and ultimately impact the movement of the steady state, $\bar{s}_t$. Elsby, et al. (2015) connect these changes by taking a first order approximation of $\bar{s}_t$ around f_{ij_t}, the lagged flow of hazard rates:

$$\Delta \bar{\boldsymbol{s}}_{\boldsymbol{t}} \approx \sum_{i \neq j} \frac{\partial \bar{\boldsymbol{s}}_{\boldsymbol{t}}}{\partial f_{ij_t}} \Delta f_{ij_t}. \tag{2.12}$$

The partial derivatives can be computed by considering the Markov chain in continuous time with flow hazards f_{ij} analagous to Equation 2.5,

$$\dot{\boldsymbol{s}}_{\boldsymbol{t}} = \underbrace{\begin{bmatrix} f_{EU} - f_{EN} - f_{NE} & f_{UE} - f_{NE} \\ f_{EU} - f_{NE} & -f_{UE} - f_{UN} - f_{NU} \end{bmatrix}_t}_{\tilde{F}_t} \boldsymbol{s}_{\boldsymbol{t}} + \underbrace{\begin{bmatrix} f_{NE} \\ f_{NU} \end{bmatrix}_t}_{g_t}. \tag{2.13}$$

Then the steady state of the Markov chain is $\bar{\boldsymbol{s}}_{\boldsymbol{t}} = -\tilde{F}^{-1} g_t$ and partial derivatives can be easily computed.

The ultimate goal for this research is to decompose the variation in labor market states, specifically unemployment, into contributions from flows into and out of that state. Combining the previous result with Equation 2.11, the variance, $var(\Delta s_t)$ can be represented symbolically as,

$$var(\Delta s_t) \approx \sum_{i \neq j} cov(\boldsymbol{\Delta s_t}, \sum_{k=0}^{t-1} C_{k,t} \frac{\partial \bar{\boldsymbol{s}}_{\boldsymbol{t-k}}}{\partial f_{ij_{t-k}}} \Delta f_{ij_{t-k}}) \tag{2.14}$$

To calculate the contribution of variance in unemployment rate accounted for by each flow, we can use Equation 2.14. Specifically, to calculate the share of variance in unemployment contributed by changes in movement from unemployment to not-in-the-labor-force, we can use:

$$\beta_{UN}^{U} = \frac{cov(\Delta U_t, \sum_{k=0}^{t-1} C_{k,t} \frac{\partial \bar{\mathbf{s}}_{\boldsymbol{t-k}}}{\partial f_{UN_{t-k}}} \Delta f_{UN_{t-k}})}{var(\Delta U_t)} \tag{2.15}$$

Last, note that the decomposition in Equation 2.15 uses U_t, which is the fraction of the civilian working age population, not unemployment rate. Thus, the final step to calculate the relevant share of variance to the share in variation of the unemployment rate, let $u_t = \frac{U_t}{L_t}$, where $L_t = E_t + U_t$ is the labor force participation rate, so changes in the unempoyment rate can be derived using

$$\Delta u_t \approx (1 - u_{t-1}) \frac{\Delta U_t}{L_{t-1}} - u_{t-1} \frac{\Delta E_t}{L_{t-1}}. \tag{2.16}$$

The following section presents the results of applying the above decomposition of variance of the unemployment rate.

Results

The table below displays the results of the decomposition described above. The share of variance of the unemployment rate that is accounted for by each flow is shown. For young workers and workers ages 25-59, the decomposition closely describes unemployment rate fluctuations, since the residual variances are small. Excluding full-time students from the calculation (and movements between labor market status and full-time students) does not accurately describe unemployment fluctuations, as the residual variance is over thirty-three percent unadjusted and over sixty-five percent for the Abowd-Zellner adjustment.

The results for workers ages 25-59 from 1994-2012 is similar to the results of Elsby, et al. (2015) who used samples beginning in 1967 and 1978. In order to compare age groups- and the impact of flows on fluctuations of their respective unemployment rates-the overlapping years from both samples were used: 1994-2012.[28]

Data	ages	Share of Variance							Total Between		
		EU	UE	NU	UN	EN	NE	residual	U and E	U and N	E and N
Unadjusted	18-24	17.6	40.6	9.6	34.1	7.9	-2.9	-6.8	58.2	43.6	4.9
Abowd-Zellner	18-24	25.2	34.6	10.6	17.6	17.6	-10.8	4.5	59.8	28.1	6.8
Unadjusted	25-59	22.8	32.5	17.9	23.9	-0.1	0.3	2.8	55.3	41.8	0.2
Abowd-Zellner	25-59	27.6	39.8	10.5	24.3	0.2	-0.7	-1.7	57.4	34.8	-0.5

Table 2.5: Decomposition of variance (1994-2012) of monthly change.

Using the unadjusted data for young workers, almost one-fifth of the variation in the unemployment rate can be described by employment to unemployment movements, while double that rate can be accounted by unemployment to employment movements. While almost sixty percent of the cyclicality of unemployment rate of young workers can be attributed to movements between employment and unemployment, the impact of EU and UE movements are distributed differently for young workers than the overall population analyzed by Elsby, et al. (2015). Despite the difference, the conclusion remains the same that the job finding and job loss movements are critical to explaining the cyclical behavior of unemployment.

The participation margin, specifically movements between unemployment and not-in-the-labor-force, accounts for over forty percent of unemployment variation. This result is consistent for both young workers and those ages 25-59. While movements between employment and unemployment are obviously important for describing the cyclicality of unemployment, this result clearly shows that considering participation decisions is also crucial to understanding unemployment rate variation.

Elsby, et al. (2015) found the impact of "flows between employment and non-participation is negligible." For young workers in the unadjusted data, this is not the

[28]Data directly from Elsby, et al. replication files were used to calculate results for those age 25-59.

case. Eight percent of the variation in unemployment can be described by movements of young workers between employment and not-in-the-labor-force. While this result is not robust to the Abowd and Zellner (1985) transformation,[29] it is valuable to consider this movement.

5 Conclusion

This research into the labor market flows of young workers confirms conventional wisdom of procyclical job finding rates and countercyclical job loss rates. Taking the analysis further, movement between labor market participation, both employment and unemployment, as well as not-in-the-labor force display cyclical and structural trends. These flows, and changes to these flows over the twenty-year period studied, reveal many opposing and complementing movements. These results provide a fuller account of the labor market and avoid the "stock-flow" fallacy of considering only labor market states.

Fluctuations in flows are crucial to understanding the changes seen in the stocks (most notably unemploymant and participation) over time and through the business cycle. Policies that focus on the job-finding rate to reduce unemployment may be overstated. The impact of the UE and EU-flows explain sixty percent of the variation in umenployment. Over forty percent of the variation was accounted for by movements between unemployment and NILF. Additionally, the flow of young workers from employment to NILF contributed about five percent of the variation in the unemployment rate. This result is not the case for the prime working age population, implying participation flows from employment are more relevant to young workers than older workers.

[29] Note that the Abowd and Zellner (1985) transformation used data on classification errors of the entire population from a different time period, so any conclustions drawn using this transformation should be taken with these considerations.

For young workers, the flows presented in Section 3 were broken down to consider movements to and from full-time schooling. Accounting for schooling decisions, flows from employment to not-in-the-labor-force and the rate of those remaining out of the labor force exhibit different trends. Specifically, both EN and NN flows increased steadily from 1994-2014, but removing full-time schooling from being classified as NILF displayed cyclical trends, including returns to trend during recoveries.

Future research can quantify participation movements including schooling decisions for young workers, including the impact on unemployment and participation rates of young workers and the entire labor market. Additionally, considering how movements between labor market statuses of young workers manifest over lifetime labor market outcomes would provide insight into these important decisions.

CHAPTER 3

MISMATCH BETWEEN JOB AND COLLEGE MAJOR

1 Introduction

What is the relationship between human capital accumulation through formal education and a worker's job? This paper considers the relationship between a worker's college major and their job. Total undergraduate enrollment increased by 46% from 13 million 1990 to over 20 million 2013,[30] indicating more individuals are acquiring human capital through formal schooling and this research adds valuable insight into the importance of college major choice.

Recent research has workerd to explain the causal relationship between the quality of a worker-occupaiton match. Lise and Postel-Vinay (2015) consider the cost of mismatch over multidimensions, specifically cognitive, manual, and interpersonal skills and conclude that the "cost of skill mismatch is very high for cognitive skills." (Lise and Postel-Vinay, 2015) When individuals consider the choice between formal education and on-the-job training, insight into the ability of different majors to create a close match with a job is valuable. This paper helps to identify majors that result in better (and worse) levels of job match.

Following the work of John Robst (2007), this paper considers three central ques-

[30]National Center for Education Statistics

tions: To what extent do college graduates work in fields unrelated to their most recent degree field? Which degree fields lead to greater mismatch? What is the relationship between working outside a degree field and wages? This paper updates the answers to Robst's questions using 2013 data. In addition to updating Robst's research with current data, this paper utilizes information on individuals' parent's education level, which was not available in the 1993 data. The purpose of using this information is to attempt to control for unobserved ability.

Early research on the match between a worker's education and job primarily focuses on the individual's length of schooling. P. J. Sloane (2003) considered mismatch by differentiating between the level of schooling and type. Robst (2007) built on Sloane's distinction and examined "whether the field of study in college is related" to a worker's current job. Some college majors provide more general skills (such as Liberal Arts), while others provide job specific skills (such as Computer Science and Library Science). Differentiating between job mismatch from different fields of study provides valuable information on the relationship between human capital acquired through formal education and occupational skills.

An additional contribution of this paper is to observe the differences in mismatch between 1993 to 2013 to shed light on changes to the labor and education markets, as well as returns to schooling. An noteworthy conclusion is that relationship between wages and both complete and partial mismatch has increased significantly over this twenty year period, in some cases by over four times.

A final consideration of this paper is the level of mismatch between workers over and under the age of forty. Younger workers are better matched than older workers. This result may imply that colleges are better preparing students for specific jobs or this result could be a signal of persistent unobserved ability.

This paper is organized as follows. Section 2 summarizes relevant Human Capital theory, which motivates this research. Next, the data and methodology are described. Section 4 presents results using 2013 data. Section 5 compares the results of this research to Robst's conclusions using 1993 data,[31] then compares young and old workers. Section 6 concludes the paper.

2 Theory

This section describes the literature surrounding returns to schooling and education level required for an individuals's job. Duncan and Hoffman (1981) extended the traditional Mincer wage equation with an augmented wage equation, which included overeducation. Recent papers by Guvenen, et al. (2015), and Lise and Postel-Vinay (2015) work to determine wage effects of mismatch between workers and occupations by considering a wide array of mismatched factors.

Relavent theory of human capital is described the the next subsection, followed by a brief description of the literature concerning the level of match between a worker and their occupation based on education.

Human Capital and Mismatch

Human capital acquisition can come in the form of formal education or on-the-job training and experience. Investments in formal education are made with the expectation of increased wages. Jobs have some level of required schooling and any additional education by the worker is considered "overeducation." Individuals may acquire "overeducation" for many reasons, including utility of schooling and future returns. Additionally, Robst (2007) suggests "overeducation merely represents a substitution of skills." That

[31]A replication of Robst's results are presented in Appendix F.

is, overeducation may mask other deficiencies in human capital, for instance ability.

The wage returns to schooling can be considered to contain two components: returns to required schooling and returns to surplus schooling. The overeducation literature highlights that returns to overeducation are smaller than returns to required schooling (Duncan and Hoffman, 1981), and Bauer (2002) describes the smaller returns to overeducation as a compensation effect for unmeasurable factors like ability.

Overeducation can be further classified as *overqualified* and *overskilled* (Chevalier et al., 2009). Overqualified workers take jobs that do not require as much schooling as they have. An illustrative example would be a teacher required to have a Master's degree to be certified, then any additional degrees (PhD, MBA, etc.) would qualify as overqualified. This mismatch may be part of an efficient labor market, where workers take jobs with the hope of promotion or a change of job. Overskilled workers create inefficiencies where workers are not required or unable to use their knowledge, skill, or experience (Green and McIntosh, 2007). An example would be an engineer becoming a mathematics teacher. Both forms of overeducation result in mismatch between a worker and their job.

The connection between overeducation and mismatch centers upon the labor market inefficiencies that result from the expansion and extension of education, specifically college education, that boomed in the 1970's. If extended education leads to greater match and higher wages, then the investment (both private and public) may be justified.

A separate story of mismatch is that it is part of an efficient labor market process where workers either sample jobs to find an appropriate match (Gervais, 2014) or take a job that they are overqualified for early in their careers to "move up the ladder" as they gain on-the-job-training and promotion. Sicherman and Galor (1990) describe overeducation as a process leading to promotion. This theory would predict that older workers would be more closely matched than younger workers; this hypothesis is tested in Section 5.2.

Recent research by Lise and Postel-Vinay (2015) considers “multidimensional” skill and occupation matching by building an on-the-job search model, including skill acuisition and transferability. The authors main findings are that “the cost of skill mismatch is very high for cognitive skills,” which are slower to adjust (relative to manual skills). This result enforces the importance of matching formal education to a job, and this paper helps to identify majors that result in better (and worse) majors.

College major choice itself has been analyzed based on multiple factors including potential lifetime earnings (Berger, 1988 and Webber, 2014), graduation rates (Montarquette, et al., 2002), and non-price preference (Easterlin, 1995). The research of Robst also examines the potential cost (in wages) of majors with high likelihood of mismatch.

Robst

This paper builds on the work of Robst’s 2007 analysis of “the relatedness of college major and work” by updating the data source and comparing results over time. Robst considers three questions in his research. First is to what extent do college graduates work in fields unrelated to their most recent degree field. Second, he considers which fields lead to greater mismatch. Last, he considers what the affect is of working outside a degree field has on earnings. Robst proposes four hypothesis based on the human capital and mismatch literature, all of which are relevant to this research.

First, Robst suggests that mismatch is more likely a result of education that provides “general skills and less likely among graduates of majors providing occupation specific skills.” The specific type of mismatch considered in this paper is that of college major to occupation. The choice of choosing a college major results in a certain set of skills that a student will enter the job market with. A relevant assumption that individuals select a college major expecting to work in a relevent field, implies that working in a job outside a college major is akin to a change in occupation. Robst's theory is that some majors provide more transferable skills than others. This hypothesis is tested in Section 4.2, which computes the likelihood of being mismatched by college major.

Robst's second hypothesis is that workers that are not well matched earn less than those that are matched. He defends this idea by noting that skills learned in a college degree program which are relevant help workers to be more productive and thus earn more.

The third and fourth hypotheses of Robst's research are related to wage effects within and across degree fields. He suggests that "wage declines are greater for graduates when fewer skills transfer" to their job, meaning that skills may not transfer the same to all occupations. Last, Robst considers that "majors that teach occupation specific skills" correlate stronger (negatively) to wages. These hypotheses will be formally tested in Section 4 of this paper.

3 Data and Methodology

National Survey of College Graduates

This research utilizes the National Survey of College Graduates (NSCG). The data set surveys college graduates and is designed to consider the relationship between college outcomes and career outcomes. The NSCG is a longitudinal survey and was conducted biennially (sometimes triennially), with cycles beginning in 1993, 2003, and 2010. This research uses the 1993, 2003, 2010, and 2013 surveys.[32]

The data from the NSCG used in this research considers survey responses that were

[32] Data was acquired accessed in November 2015 from http://sestat.nsf.gov/datadownload/

selected from the 1990 and 2010 census who noted they earned a bachelor's degree (or higher). The subsequent in-cycle surveys are not used here, because they target science and engineering majors in order to consider the relationship between STEM majors and career outcomes. The 1993 and 2013 datasets are representative of the college-educated population and includes weightings provided by the National Science Foundation.[33] The final 1993 sample consists of 75,327 men and 48,266 women and the 2013 sample consists of 47,497 men and 39,753 women.

This paper uses general demographic variables, as well as reported salary (annualized), most recent and highest college degree. In an attemp to control for ability, data on parental education is used. Specifically, the NSCG provides background on the highest level of education for both the respondent's mother and father (or female and male guardians).

Most important to the central questions of this paper, the respondent's answer the following question: "To what extent was your work on your principal job... related to your highest degree?" Responses to this question include "closely related, somewhat related, and not related."

A notable drawback of the NSGC is that there have been substantial changes in the design and sampling methods. This does not directly impact results presented here; the main impact is the difference in sample size between the two main data sets used.

Methodology

In order to measure the likelihood of mismatch between college major and occupation, responses to the question "To what extent was your work on your principal job... related to your highest degree?" were ranked whether they were *matched*, *partially matched* or

[33]Further details can be found at http://www.nsf.gov/statistics/srvygrads/

completely mismatched. Since these responses are ordinal, we use an ordered logit regression:

$$Pr(Mismatch)_{ij} = X_{ij}\beta + Z_j\alpha + \epsilon_{ij}. \tag{3.1}$$

The subscript i indexes individuals and j indexes degree field. X_{ij} represents demographic variables and Z_j represents each degree field. Separate regressions are run for males and females.

The benefit of an ordered logit regression used here is to utilize the ordinal nature of the dependent variable. A logit regression could be run on "mismatch," but results from Equation 3.1 will give the likelihood of being "more" mismatched by degree field.

To consider the relationship between working outside a degree field and earnings an OLS regression is run on the log of wages:

$$LnW_i = \beta X_{ij} + \alpha Z_j + \delta Partial_{ij} + \mu Complete_{ij} + \epsilon_i. \tag{3.2}$$

Here, X_{ij} and Z_j are definied as above. *Partial* indicates that an individual reported they are partially mismatched, and *complete* indicates that an individual reports being in a job unrelated to their college major. The correlation between mismatch and wages does not necessarily imply causation. The coefficients δ and μ may contain the impact of unobserved ability on both being mismatched and wages. In order to try to control for unobserved ability, included in the demographic controls is a variable indicating parental education. This variable has been shown to correlate well with ability in human capital literature, most notably Card (1995).

With the potential of ability bias still lurking, it is worth noting that the correlation between certain majors, levels of mismatch, and wages can help describe the underlying sorting between college majors, occupations, and wages.

The last specification considered in this paper is used to estimate how wage effects vary by major. The specification includes interaction variables between complete mismatch and degree field.

$$LnW_i = \beta X_{ij} + \alpha Z_j + \gamma_j Major_j * Complete_{ij} + \epsilon_i. \tag{3.3}$$

This specification isolates the relationship that individual majors have on being mismatched. That is, γ_j can be interpreted as the wage penalty for being mismatched varied by major. A major that provides specific human capital should result in a negative wage effect to working outside the major, while a major that provides transferable human capital would have less of a penalty for being mismatched. Thus γ_j is expected to be more negative the more specific skills taught within major j and the less transferable to a job outside the major field.

4 Results

This section answers the three questions posed in this research: To what extent do college graduates work in fields unrelated to their most recent degree field? Which degree fields lead to greater mismatch? What the affect of working outside a degree field has on earnings? The subsections below provide answers to these questions using data from the 2013 NSCG.

The Extent of Mismatch

Table 3.1 below displays individuals' responses to the question "To what extent was your work on your principal job... related to your highest degree?"

Of college graduates, 54% report that their highest field of study is closely related to their job, 25% report that their degree field is somewhat related to their job, and 20% report that their field of study is not related to their current job. More females than men report that their field of study is closely related to their job.

	Closely Related	Somewhat Related	Not Related
Overall	54.42%	25.36%	20.22%
gender			
Male	52.53%	27.68%	19.79%
Female	56.30%	23.06%	20.64%
race			
White	54.07%	25.95%	19.98%
Black	51.37%	25.79%	22.84%
Hispanic	56.22%	22.00%	21.77%
Asian	58.00%	23.28%	18.72%

Table 3.1: Match between worker's job and most recent degree field.

Likelihood of Being Mismatched by College Major

The extent of mismatch by college major can be seen in Table 3.2. The ordered logit regression gives the odds (fourth and seventh columns) that an individual is in a "worse" mismatch level. The interpretation of the coefficients and odds is the relative likelihood of mismatch compared to computer science (the omitted category).[34] The only major with a significantly less likelihood of mismatch than computer science is Health Studies for men and Education and Health Studies for women. The highest likelihoods of mismatch from a major are in the fields of Home Economics, Liberal Arts, Parks/Recreation/Fitness Studies, English and Foreign Languages, and Social Sciences for men. For women, Parks/Recreation/Fitness Studies and Liberal Arts have the highest likelihood of mismatch.

The majors corresponding with higher levels of mismatch are majors that, at least

[34]This is following the specification used by Robst (2007).

anecdotally, teach more general skills than occupation specific skills. Meanwhile, Health Studies, which has lower rates of mismatch, tend to focus on skills that apply to specific health based occupations.

Consistent with Robst's findings from data twenty years earlier, higher degrees (Masters, Doctoral, and Professional) all result in lower likelihood of mismatch, and workers that have never been married are more likely to be mismatched. Demographic results show almost no significance to mismatch, with only marriage status being significant predictor of mismatch for both males and females. Considering race and ethnicity, there was no significant correlation with job mismatch for either males or females, which is a result that differs from the 1993 data. The full estimation results can be seen in Table 3.2 below.

	Men			Women		
	Coefficient	**(Std. Err.)**	**Odds**	**Coefficient**	**(Std. Err.)**	**Odds**
Age	-0.016	(0.015)	0.984	0.002	(0.016)	1.001
Age sqrd.	0.000^{*}	(0.000)	1.000	0.000	(0.000)	1.000
Disabled	0.090	(0.078)	1.094	-0.042	(0.091)	0.959
Black	0.005	(0.118)	1.005	0.107	(0.104)	1.113
Asian	0.123	(0.092)	1.131	-0.103	(0.109)	0.902
Native	0.034	(0.647)	1.035	-0.156	(0.396)	0.856
Hispanic	-0.086	(0.113)	0.918	-0.134	(0.102)	0.875
Foreign born US citizen	0.164^{*}	(0.083)	1.178	0.065	(0.096)	1.067
Foreign born non-US citizen	0.013	(0.111)	1.013	0.295^{*}	(0.127)	1.343
Never Married	0.340^{**}	(0.075)	1.405	0.316^{**}	(0.070)	1.372
Degree						
Masters	-0.704^{**}	(0.055)	0.495	-0.936^{**}	(0.057)	0.392
Professional	-2.409^{**}	(0.196)	0.090	-2.182^{**}	(0.231)	0.113
Doctoral	-1.873^{**}	(0.086)	0.154	-1.818^{**}	(0.101)	0.162
Degree field						
Agricultural Sciences	0.680^{**}	(0.258)	1.974	0.317	(0.232)	1.373
Architecture	-0.157	(0.171)	0.855	0.235	(0.264)	1.265
Biological Sciences	0.938^{**}	(0.120)	2.555	0.393^{*}	(0.159)	1.481
Business Management	0.611^{**}	(0.102)	1.842	0.382^{*}	(0.155)	1.465
Communications	1.151^{**}	(0.167)	3.161	0.549^{**}	(0.185)	1.732
Education	0.364^{*}	(0.144)	1.439	-0.469^{**}	(0.165)	0.626
Engineering	0.194^{*}	(0.094)	1.214	$0.273^{\dagger}$	(0.163)	1.314
Engineering-related Technology	0.514^{**}	(0.156)	1.672	0.229	(0.238)	1.257
English and Foreign Languages	1.467^{**}	(0.207)	4.306	0.815^{**}	(0.201)	2.259
Health Professions	-0.323^{*}	(0.148)	0.724	-0.965^{**}	(0.157)	0.381
Home Economics	2.089^{**}	(0.687)	8.077	0.794^{**}	(0.304)	2.212
Law/Prelaw/Legal Studies	0.915^{**}	(0.221)	2.450	0.902^{**}	(0.267)	2.465
Liberal Arts	1.942^{**}	(0.265)	6.973	1.194^{**}	(0.136)	3.300
Library Sciences	-1.147	(0.733)	0.318	0.009	(0.173)	1.009
Mathematics	0.418^{**}	(0.117)	1.519	0.074	(0.185)	1.077
Parks/Recreation/Fitness studies	1.663^{**}	(0.298)	5.275	1.413^{**}	(0.388)	4.108
Philosophy/Religion/Theology	1.016^{**}	(0.238)	2.762	1.003^{**}	(0.325)	2.726
Physical Sciences	0.777^{**}	(0.116)	2.175	0.638^{**}	(0.230)	1.893
Psychology	-0.108	(0.108)	0.898	0.602^{**}	(0.157)	1.826
Public Affairs	0.925^{**}	(0.288)	2.522	0.999^{**}	(0.238)	2.716
Social Science	1.421^{**}	(0.107)	4.141	0.712^{**}	(0.154)	2.038
Visual and Performing Arts	0.732^{**}	(0.195)	2.079	0.606^{**}	(0.208)	1.833
N	47497			39753		

Table 3.2: Ordered Logit results. **indicates significance at 1% level, *indicates significance at 5% level, †indicates significance at 10% level.

Wage Effects by College Major Mismatch

The extent to which mismatch between college major and occupation correlates with wages can be seen in Table 3.3. The results of the regression of Equation 3.2 show the connection between working in or out of the degree field and wages. The specific demographic variables included in the specification shown in Table 3.3 include variables available in both the 1993 and 2013 NSCG to ensure results are comparable in Section 5. The results displayed are robust to an alternative specification including parental education; results of this specification can be seen in Appendix G.

For both men and women, working completely out of their field and partially outside of their field correlates with lower reported wages than those working within their field. The magnitude of the impact for partial and complete mismatch shows that complete mismatch and lower wages is correlated stronger than partial mismatch and lower wages. Similar to the results of Robst (2007), these results indicate that the more transferable skills are from a major to the current job, the smaller the relationship with lower wages. Conversely, this indicates that non-transferable skills from majors to occupations correspond with lower wages.

In order to compare how being outside of a specific major degree field corresponds with wages, Table 3.4 displays the coefficients of interactions between being mismatched and college major. The coefficients can be interpreted as the wage penalty for being mismatched for each degree. A major that provides specific human capital should correspond with a larger (negative) correlation with wages, while a major that provides transferable human capital would have less of a negative relationship with wages. The more negative the coefficient is, the more specific skills are taught within that major and thus the less transferable to a job outside the major field.

	Men		Women	
	Coefficient	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
mismatch				
Complete	-0.430**	(0.034)	-0.410**	(0.034)
Partial	-0.140**	(0.024)	-0.118**	(0.028)
demographics				
Experience	0.010**	(0.001)	0.015**	(0.001)
Training Program	0.183**	(0.022)	0.262**	(0.025)
Disabled	-0.222**	(0.037)	-0.137**	(0.041)
Black	-0.230**	(0.055)	-0.013	(0.040)
Asian	-0.025	(0.029)	0.072†	(0.043)
Native	-0.137	(0.094)	0.013	(0.120)
Hispanic	-0.158**	(0.035)	-0.073†	(0.039)
Foreign born US citizen	0.015	(0.028)	-0.002	(0.045)
Foreign born non-US citizen	-0.098**	(0.036)	-0.099†	(0.054)
Never Married	-0.392**	(0.028)	-0.013	(0.026)
Degree Type				
Masters	0.162**	(0.023)	0.156**	(0.024)
Professional	0.549**	(0.055)	0.660**	(0.042)
Doctor	0.305**	(0.027)	0.475**	(0.036)
major				
Agricultural Sciences	-0.310**	(0.067)	-0.414**	(0.127)
Architecture	-0.302**	(0.059)	-0.325**	(0.084)
Biological Science	-0.279**	(0.038)	-0.371**	(0.054)
Business Management	-0.050	(0.032)	-0.080	(0.051)
Communications	-0.230**	(0.073)	-0.276**	(0.082)
Education	-0.696**	(0.056)	-0.658**	(0.054)
Engineering	0.062*	(0.025)	0.133*	(0.052)
Engineering-related Technology	-0.087†	(0.051)	-0.083	(0.098)
English and Foreign Languages	-0.529**	(0.105)	-0.447**	(0.080)
Health Professions	-0.126**	(0.043)	-0.251**	(0.048)
Home Economics	-0.019	(0.139)	-0.541**	(0.138)
Law/Prelaw/Legal Studies	-0.337**	(0.070)	-0.326**	(0.065)
Liberal Arts	-0.251*	(0.099)	-0.382**	(0.090)
Library Sciences	-0.410*	(0.202)	-0.515**	(0.132)
Mathematics	-0.110**	(0.039)	-0.270**	(0.069)
Parks/Recreation/Fitness Studies	-0.711**	(0.172)	-0.540**	(0.165)
Philosophy/Religion/Theology	-0.807**	(0.097)	-0.635**	(0.154)
Physical Sciences	-0.160**	(0.039)	-0.223**	(0.071)
Psychology	-0.214**	(0.051)	-0.186**	(0.049)
Public Affairs	-0.456**	(0.134)	-0.216	(0.157)
Social Science	-0.194**	(0.039)	-0.389**	(0.054)
Visual and Performing Arts	-0.722**	(0.095)	-0.567**	(0.089)
Intercept	11.225**	(0.032)	10.739**	(0.052)
N	47269		39554	
R sqrd.	0.224		0.155	

Table 3.3: The wage effects of mismatch. **indicates significance at 1% level, *indicates significance at 5% level, †indicates significance at 10% level.

The strongest negative correlation to wages for working outside the field of study for males was Library Science, and Business, Computer Science, Mathematics, Engineering and Health Professions also had high negative correlations between being mismatched and wages. These majors have specific jobs or occupations associated with the degree, so working outside that field (and not utilizing the skills gained in those majors) generates a large penalty. For females, the largest significant negative relationship was for Computer Science majors, while Architecture, Business, Engineering and Engineering-related Technology, Mathematics and Health Professions majors also had large negative correlations between working outside those fields of study and wages.

	Men		Women	
	Coefficient	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
*Mismatch * degree field*				
Agricultural Sciences	0.032	(0.110)	-0.588**	(0.219)
Architecture	-0.315	(0.267)	-0.789**	(0.234)
Biological Sciences	-0.209**	(0.064)	-0.296**	(0.075)
Business Management	-0.519**	(0.058)	-0.620**	(0.077)
Communications	-0.394†	(0.214)	-0.478**	(0.155)
Computer Science	-0.728**	(0.096)	-0.939**	(0.140)
Education	-0.390†	(0.199)	-0.240**	(0.088)
Engineering	-0.510**	(0.048)	-0.546**	(0.106)
Engineering-related Technology	-0.417**	(0.131)	-0.931**	(0.221)
English and Foreign Languages	0.325*	(0.165)	-0.023	(0.133)
Health Professions	-0.692**	(0.091)	-0.825**	(0.086)
Home Economics	0.224	(0.228)	0.296	(0.220)
Law/Prelaw/Legal Studies	-0.325**	(0.107)	-0.459**	(0.111)
Liberal Arts	-0.268	(0.167)	-0.259†	(0.151)
Library Science	-0.945**	(0.338)	-1.174	(1.006)
Mathematics	-0.538**	(0.128)	-0.712**	(0.155)
Parks/Recreation/Fitness Studies	-0.179	(0.384)	-0.328	(0.321)
Philosophy/Religion/Theology	0.028	(0.175)	-0.353	(0.320)
Physical Sciences	-0.366**	(0.103)	-0.297†	(0.158)
Psychology	0.166†	(0.098)	0.212†	(0.116)
Public Affairs	-0.604	(0.472)	-0.264	(0.215)
Social Science	-0.154*	(0.064)	-0.325**	(0.073)
Visual and Performing Arts	-0.228	(0.207)	0.273†	(0.148)
N	47269		39554	
R squared	0.282		0.197	

Table 3.4: The wage effects of mismatch for working outside the degree field. **indicates significance at 1% level, *indicates significance at 5% level, †indicates significance at 10% level.

5 Changes Over Time

The National Survey of College Graduates was published by the National Science Foundation in 1993, 2003, 2010, and 2013. This section considers how the andwers to three major questions considered by this research have changed between 1993 to 2013. Additionally, Section 5.2 extends the analysis to consider workers ages 20-39 as subsets of the 1993 and 2013 data sets that do not overlap, in order to consider how individual choices in majors and occupations, may impact mismatch.

Differences from 1993 to 2013

Extent of Mismatch

The figure below charts the percent of respondents that identify their job as being closely related to their most recent college major. A greater rate of women consistently report a close match between their job and major, but, over time this gap has decreased.

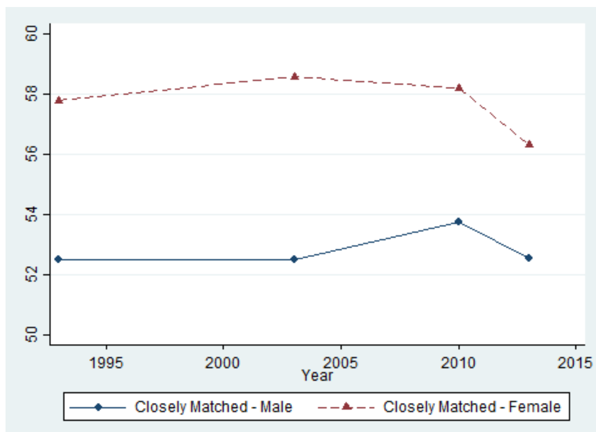
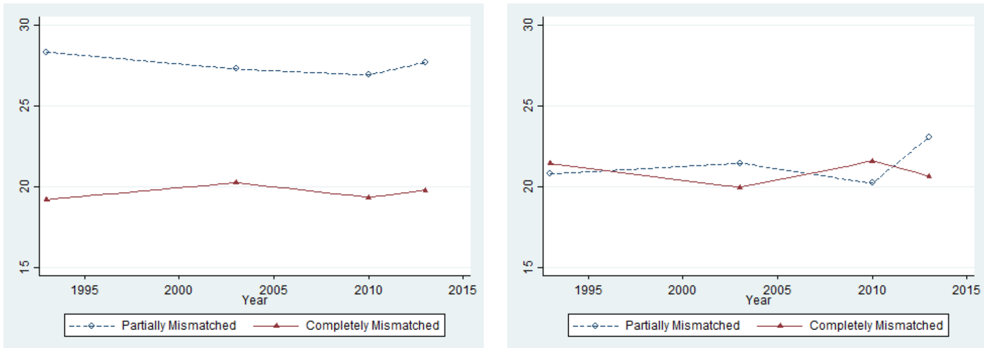


Figure 3.1: Percent with complete match, by gender.

Figure 3.2 displays the percent of men and women who report their job and college major are *Partially Mismatched* and *Completely Mismatched*. For men, the percent of those reporting their job is somewhat related is consistently about eight percentage points higher than those reporting their job is not related to their college major. For women, the percentage reporting being *Partially Mismatched* and *Completely Mismatched* has fluctuated. In 1993, more women reported their job was not related to their college major, but in 2013, more women reported that their job was somewhat related to their college major. Table 3.5 below lists the distributions of responses for men and women over the twenty year period.



(a) male

(b) female

Figure 3.2: Level of mismatch, by gender.

	Closely Related	Somewhat Related	Not Related
men			
1993	52.49%	28.31%	19.20%
2003	52.49%	27.27%	20.24%
2010	53.76%	26.89%	19.35%
2013	52.53%	27.68%	19.79%
women			
1993	57.78%	20.79%	21.43%
2003	58.57%	21.45%	19.97%
2010	58.19%	20.22%	21.59%
2013	56.30%	23.06%	20.64%

Table 3.5: Match between worker's job and most recent degree field.

Comparing the results that Robst published in 2007 with data from 1993 to the results presented in the preceeding section shows a few notable changes in how mismatch between major degree field and occupation impact labor market outcomes. Replicated results using the NSCG from 1993 are provided in Appendix F.

The prevalence of partial and complete mismatch between 1993 and 2013 shows minimal changes. There is a a decrease of 0.33% fewer closely related matches between degree field and occupation and that decrease corresponded to an increase in partial matches by 0.26% and a slight decrease of 0.07% fewer complete mismatches. By gender, there was a 1.48% decrease in females reporting closely related matches, while males increased the rate of closely related matches by 0.04%. The major shift of female match was 2.27% more somewhat related matches, corresponding to the decrease in close matches and the decrease of 0.79% fewer complete mismatches by females. Meanwhile, males experienced a 0.63% decrease in somewhat related matches, and had an increase of 0.59% complete mismatches between degree and occupation.

Mismatch by Degree Field

The results of Equation 3.1 using data from 1993 and 2013 show the changes in the factors of mismatch. One notable difference is the signifcance of race in 1993, but lack of significance in 2013. Additionally, in the 1993 data, foreign born individuals were more likely to be mismatched, while in 2013 only male foreign born US citizens and female non-US citizens were more likely.

In terms of specific college majors that result in mismatch, the results in Table 3.2 can be used to group majors by likelihood of mismatch. The results (both odds and coefficients) can be interpreted as the relative likelihood of being mismatched relative to the omitted category, Computer Science. The results can effectively rank majors by level of mismatch, and while one major's relative ranking to its immediate neighbors may not be significant, majors can be placed into "bins" of likelihood of match.[35]

Comparing the results of the two ordered logit results (Tables 3.2 and F.2 in the Appendix), Psychology is one major that has male graduates who are better matched in 2013 than 1993. For males, relative to other majors, Law and Pre Law studies have more mismatch in 2013 than 1993.

[35]As a robustness check, Appendix H provides results of a logit model with *complete* mismatch as the dependent variable.

Wage Penalty

The relationship between wages and mismatch was relevant and significant in Robst's work, and continued to be in 2013. The availability of a control for unobserved ability in the 2013 estimation means that the magnitude of the measurements from 1993 and 2013 cannot be compared, but the relation between *partial* and *complete* mismatch can. The data presented in Table 3.6 below shows that in both 1993 and 2013, the penalty for complete mismatch is between three and five times as much as partial mismatch.

	Men		Women	
	1993	**2013**	**1993**	**2013**
mismatch				
complete	-0.125**	-0.430**	-0.095**	-0.410**
	(0.008)	(0.034)	(0.008)	(0.034)
partial	-0.030**	-0.140**	-0.014†	-0.118**
	(0.006)	(0.024)	(.007)	(0.028)

Table 3.6: The wage effects of mismatch separated by age. The specification includes the same demographic variables and major distinctions as shown in Table 3.3. **indicates significance at 1% level, *indicates significance at 5% level, †indicates significance at 10% level.

While noting which majors correlate with greater levels of mismatch (Table 3.2), the penalty for working outside a specific major was estimated using Equation 3.3 with results shown in Table 3.4. The theory is that individuals who study majors that teach occupation specific skills will face a greater wage penalty for being outside their major. Meanwhile, an individual who studied in a field that provided broad skills would realize less of a penalty for being outside their degree field.

Estimations of Equation 3.3 from 1993 and 2013 provide an empirical measurement of how penalties incurred for working outside each major changed over the twenty year period. Notable changes include a high penalty for Law and Pre-Law majors for both males and females in 1993, and a relatively smaller penalty in 2013. In 2013, male Library Science majors working outside their major field had a large penalty, which was not significant in 1993. Additionally, female Architecture majors face a large significant penalty in 2013 that was not significant in 1993. For both males and females in 2013, the penalty for working outside the Mathematics and Engineering fields was large relative to other majors and in 1993, while there was still a significant wage penalty for these majors, the penalty was smaller relative to other majors.

These results suggest that fields of studies with higher mismatch penalties in 2013 teach more specific skills than they did twenty years earlier.

Changes Over the Life Cycle

This secton describes how young and older workers are impacted by mismatch. The section partitions the data set into workers under the age of forty and at or above the age of forty. Table 3.7 displays the distribution of levels of mismatch by gender and young and older wokers.

	Closely Related	Somewhat Related	Not Related
Overall	54.42%	25.36%	20.22%
19-39	55.00%	25.43%	19.57%
40+	54.05%	25.31%	20.64%
Male	52.53%	27.68%	19.79%
19-39	53.14%	27.50%	19.36%
40+	52.18%	27.79%	20.04%
Female	56.30%	23.06%	20.64%
19-39	56.55%	23.69%	19.75%
40+	56.11%	22.59%	21.30%

Table 3.7: Match between worker's job and most recent degree field.

The extent of mismatch is lower for workers under the age of forty. Workers under the age of forty report their occupation as being more closely related to their occupation by about one percent. More younger females than older reported that their job was *somewhat related* to their degree, while men over the age of forty reported higher partial relatedness of their degree. Both younger males and females report less complete mismatch than those over the age of forty.

This result may be the effect of unobserved ability, where low ability workers are less likely to have a quality match and that impact persists. That is, any high ability workers that are mismatched as young workers change jobs as they progress through the life cycle to better matches.

Wage Effects by Age

As workers move through the life cycle, human capital acquired in formal education and through on-the-job training are related to wages. Table 3.8 below breaks down the relationship between wages and partial and complete mismatch by age groups, using the specification of Equation 3.2. The correlations presented between as *partial* and *complete* mismatch do not assume causation. Instead, the approximately double wage "penalty" for older workers being mismatched is likely related to self-selection and unobserved ability.

As workers progress through their career, they have opportunities to create stronger matches by changing jobs (Gervais, 2014). Assuming ability and mismatch are also correlated, then older workers that are still mismatched should have a stronger negative correlation with wages. The idea here is that higher ability workers were able to find a match between their job and skills learned through college education early in their career.

	Men		Women	
	19-39	**40+**	**19-39**	**40+**
mismatch				
partial	-0.077*	-0.156**	-0.078*	-0.125**
	(0.037)	(0.029)	(.039)	(0.039)
complete	-0.253**	-0.478**	-0.341**	-0.438**
	(0.050)	(0.041)	(0.047)	(0.047)

Table 3.8: The wage effects of mismatch separated by age. The specification includes the same demographic variables and major distinctions as shown in table 3. **indicates significance at 1% level, *indicates significance at 5% level, †indicates significance at 10% level.

Younger Workers

To extend the preceding analysis, the 1993 and 2013 data sets are partitioned by age to look specifically at workers under the age of 30. Additionally, this breakdown excludes any individual overlaps of the two data sets since they are twenty years apart. The results in this section, the likehood of being mismatched by major and wage effect of complete and partial mismatch, provide insight into the younger worker labor market as well as the labor market as a whole.

The extent of mismatch of young workers by college major can be seen in Table 3.9. The ordered logit regression presents the log-likelihood of individuals being mismatched by college major for workers ages 19-29 in 2013.

For young workers, the wage penalties for being partially and completely mismatched are shown in Table 3.10. An interesting result is that for males ages 20-29 in 2013, there was not a significant wage penalty for being mismatched. This result reinforces the data in Table 3.8 that older workers face a sharper wage penalty for being mismatched.

	Men		Women	
	Coefficient	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
Age	1.783	(1.458)	-0.206	(1.218)
Age sqrd.	-0.034	(0.027)	0.005	(0.023)
Disabled	-0.032	(0.226)	-0.188	(0.305)
Black	1.061^{**}	(0.387)	0.760^{**}	(0.272)
Asian	0.533^{*}	(0.241)	0.048	(0.328)
Native	-1.927^{*}	(0.841)	0.471	(0.362)
Hispanic	-0.016	(0.294)	-0.034	(0.250)
Foreign born US citizen	-0.050	(0.202)	-0.319	(0.433)
Foreign born non-US citizen	-1.089^{**}	(0.264)	0.078	(0.299)
Never Married	0.327^{*}	(0.144)	0.307^{*}	(0.142)
Degree				
Masters	-0.950^{**}	(0.191)	-0.816^{**}	(0.181)
Professional	-1.858^{**}	(0.710)	-3.472^{**}	(0.788)
Doctoral	-1.188^{*}	(0.497)	-2.094^{**}	(0.529)
Degree field				
Agricultural Sciences	-0.196	(0.607)	0.841	(1.054)
Architecture	0.068	(0.454)	0.289	(0.974)
Biological Sciences	$0.506^{\dagger}$	(0.300)	0.689	(0.834)
Business Management	$0.592^{\dagger}$	(0.312)	0.973	(0.846)
Communications	$0.724^{\dagger}$	(0.380)	0.633	(0.866)
Education	-0.401	(0.574)	-0.450	(0.871)
Engineering	-0.230	(0.256)	0.529	(0.842)
Engineering-related Technology	0.461	(0.333)	0.523	(1.047)
English and Foreign Languages	1.133^{*}	(0.507)	1.539	(0.966)
Health Professions	0.130	(0.504)	-0.748	(0.837)
Home Economics	5.374^{**}	(1.245)	1.071	(1.116)
Law/Prelaw/Legal Studies	0.266	(0.510)	2.212^{*}	(1.074)
Liberal Arts	1.884^{*}	(0.785)	0.833	(0.927)
Library Sciences	-16.736^{**}	(0.699)	2.040^{*}	(0.882)
Mathematics	0.411	(0.294)	0.811	(0.902)
Parks/Recreation/Fitness studies	1.842^{**}	(0.581)	0.672	(1.563)
Philosophy/Religion/Theology	0.422	(0.962)	2.187	(1.409)
Physical Sciences	0.089	(0.321)	1.117	(0.911)
Psychology	-0.204	(0.245)	-0.073	(0.168)
Public Affairs	1.483^{**}	(0.426)	1.662	(1.040)
Social Science	1.654^{**}	(0.282)	1.355	(0.841)
Visual and Performing Arts	$0.923^{\dagger}$	(0.488)	1.468	(0.933)
N	9219		10018	

Table 3.9: Ordered Logit results, ages 19-29. **indicates significance at 1% level, *indicates significance at 5% level, †indicates significance at 10% level.

	Men		Women	
	1993	**2013**	**1993**	**2013**
mismatch				
partial	-0.041*	-0.013	-0.059**	-0.152*
	(0.018)	(0.076)	(.017)	(0.065)
complete	-0.121**	-0.245*	-0.176**	-0.334**
	(0.026)	(0.113)	(0.023)	(0.071)

Table 3.10: The wage effects of mismatch of young workers in 1993 and 2013. The specification includes the same demographic variables and major distinctions as shown in table 3. **indicates significance at 1% level, *indicates significance at 5% level, †indicates significance at 10% level.

6 Conclusion

The research on mismatch between skills and occupation is unanimous that mismatched workers earn less than well matched workers. This research supports the most recent literature considering multidimensional skill matching by investigating the impact a worker's college major has on their reported level of match.

A major conclusion of this research is that the relationship between both partial and complete mismatch and lower wages increased from 1993 to 2013. The implication is that the penalty for working outside a degree field may be increasing. Even if mismatch is the result of an unobserved ability, the increasing penalty should motivate students to choose wisely.

When an individual chooses a college major they are investing in human capital that they hope to earn a return on in a job that utilizes their skills. Some majors provide general skills (Liberal Arts, for instance) and subsequently have a higher likelihood of mismatch, but an insignificant wage penalty on that mismatch. Majors that provide occupation specific skills (such as Health Professions and Library Science) have a low incidence of mismatch, but large penalties for working outside the field of study. The results presented in this paper are useful to both prospective students and well as higher education institutions, when allocating resources, specifically time and money.

Females are more closely matched in 2013 than twenty years earlier, while males report the same level of complete job and college major match. Section 5.1 compared results from 1993 and 2013 and found that some majors (Psychology for males) are better matched while others (Law) have more mismatch. This may be the result of more students working within these majors or a lack of jobs within these fields; the distinction is left for further study.

In terms of wage penalties for working outside certain major fields, Law and Pre-Law incurred a higher relative penalty in 2013 (from 1993) along with Mathematics and Engineering. These results suggest that fields of studies with higher penalties for mismatch teach more specific skills than they did twenty years earlier.

Throughout this research, an individual's most recent college major was used to define their college major. An extension of this research could consider only Bachelor's Degrees and likelihood of future mismatch. A theory in support of more general majors is that undergraduate majors that provide general skills may be indicative of certain Graduate degrees that lead to a strong match (or strong wages). Additionally, focusing the methodology used in this paper to consider only Graduate and Professional degrees would provide insight into the returns of certain degree fields.

A last extension of this research is to consider the non-wage returns to each college major, which could provide insight into major choice. For instance, the difficulty of earning each degree is not considered in this research and could provide motivation for college major choice, as could the non-wage returns to a job with low levels of match.

Ultimately, insight into the returns of college majors, as well as both the likelihood and penalties associated with working outside a degree field provide individuals with valuable information when making human capital accumulation decisions.

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Appendix A

LABOR FORCE PARTICIPATION OF WORKERS, AGES 25-34

This section is included as a comparison to the participation of young workers ages 18-24. The idea is that the workers discussed here are relatively early into their career and in many ways similar to the population discussed in this paper. That said, individuals included in this section's data have for the most part have completed their education, thus serving as a reference point for the results in this research. The participation rate from 1994-2014 for workers ages 25-34 is shown in the figure below.

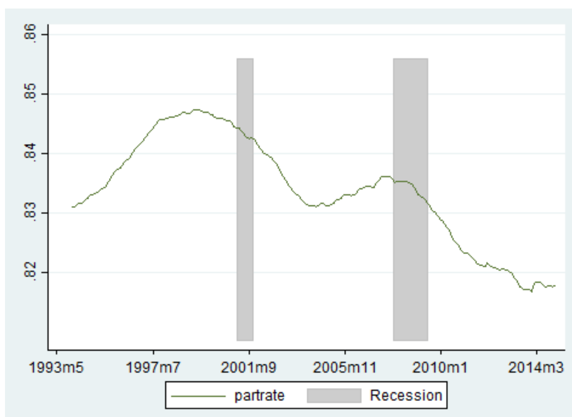


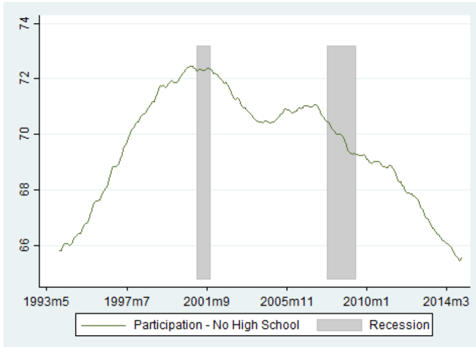
Figure A.1: Participation in the labor market, ages 25-34.

Labor Force Participation by Education

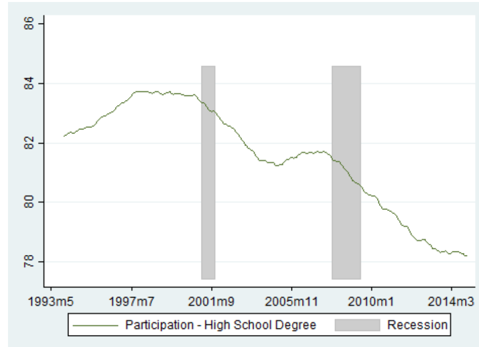
The table below details the changes in educational attainment. The graphs of Figure A.2 on the following page chart the participation rates of each level of educational attainment.

	Population by Education, ages 25-34		
	1994	2014	change
all			
No High School	13.13%	9.74%	-3.39%
High School	34.74%	25.82%	-8.92%
Some College	27.86%	28.80%	+0.94%
College	18.98%	25.12%	+6.14%
Graduate Degree	5.30%	10.52%	+5.22%
Male			
No High School	14.15%	10.65%	-3.50%
High School	35.49%	29.55%	-5.94%
Some College	26.04%	27.71%	+1.67%
College	18.49%	23.22%	+4.73%
Graduate Degree	5.83%	8.86%	+3.03%
Female			
No High School	12.14%	8.85%	-3.29%
High School	34.00%	22.17%	-11.83%
Some College	29.63%	29.86%	+0.23%
College	19.45%	26.97%	+7.52%
Graduate Degree	4.78%	12.15%	+7.37%

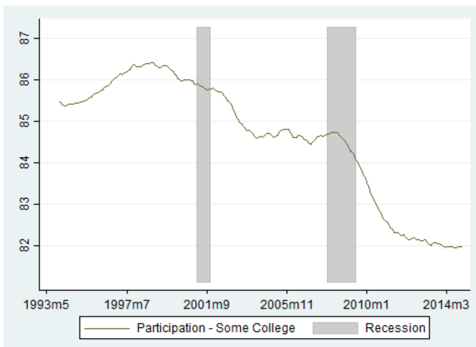
Table A.1: Changes in population by education, ages 25-34.



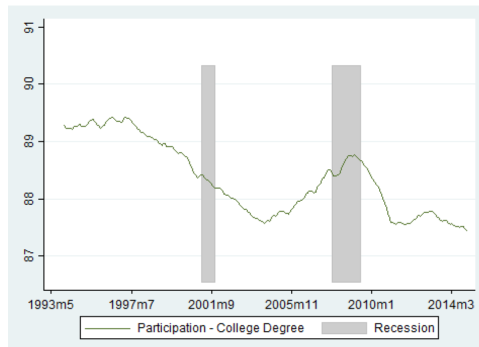
(a) No High School Degree



(b) High School Degree



(c) Some College



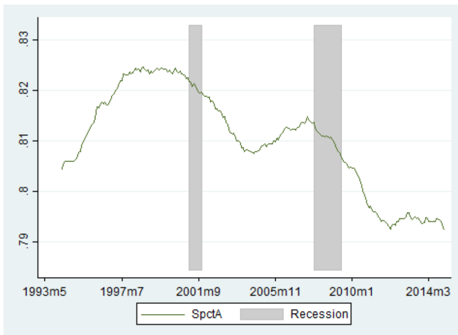
(d) College Degree

(e) Graduate Degree

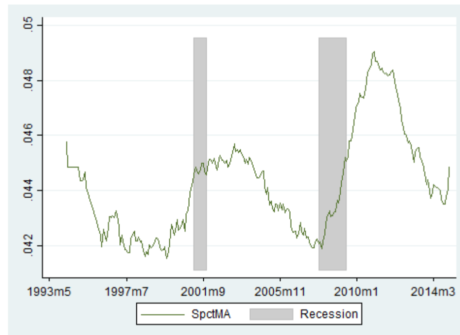
Figure A.2: Labor market participation by education, ages 25-34.

Attachment

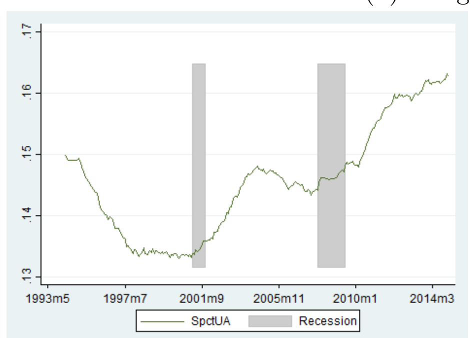
The graphs below replicate the analysis in Section 1.5 of Chapter 1 for individuals ages 25-34.



(a) Attached



(b) Marginally Attached



(c) Not Attached

Figure A.3: Time series of labor force attachment, ages 25-34.

Appendix B

CURRENT POPULATION SURVEY DATA

Current Population Survey data variable names		
Variable	CPS data name	alternate variable name (years)
Demographic		
Age	peage	prtage (2014)
Marital Status	pemaritl	
Sex	pesex	
State	gtmetsta	gemetsta(1994-2004)
Race	ptdtrace	perace (1994-2004)
Hispanic	pehspnon	prhspnon (1994-2002)
Region of the Country	gereg	
Education		
Education Level	peeduca	
Full-time student	peschft	
Enrolled in school last week	peschenr	
LaborMarketVariables		
Labor Force Status	pemlr	
Employment status with discouraged worker	prempnot	
Duration of unemployment	prunedur	
Does respondent want a job	prwntjob	
Discouraged	prdisc	
When last worked	pelklwo	
Reason for unemployment	pruntype	
Industry	prmjind1	
Class of worker	prcow1	
Retirement status	puretot	
Disability status	pudis	
Administrative		
Household ID	hrhhid	
Household Identifier 2	hrhhid2	did not exist 1994-2004[36]
Person line number	pulineno	
Month	hrmonth	
Year	hryear4	hryear(1994-1997)
Month in sample	hrmis	
Longitudinal link	hrlonglk	
Final outcome code	hufinal	
Longitudinal weight	pwlgwgt	
Final weight	pwsswgt	
Allocation code	pxmlr	

Appendix C

DEFINITION OF RACE AND ETHNICITY IN THE CURRENT POPULATION SURVEY

The CPS asks respondents to choose their race from the following categories: White, Black, American Indian, Asian, Pacific Islander, other. For the purpose of the decompositions calculated in Section 6 of Chapter 1, this reasearch also included information from another CPS question asking whether or not the respondent was hispanic; this question was independent from the question about race. To construct the racial and ethnic definitions used in this research (and listed in the table below), any respondent that answered "yes" to being hispanic was listed as hispanic, while the response to the question about race was used for everyone who responded "no" to being hispanic. While also maintaining the full list of races and ethnicities, the top four responses (White, Black, Hispanic, Asian) were defined and the remaining responses were combined as "other" for computational simplification.

Race and Ethnicities used for the purpose of this research
White
Black
Hispanic
Asian
Other

By no means is this methodology considered exhaustive or conclusive, rather a procedure to gather as much information from the survey data as possible.

Appendix D

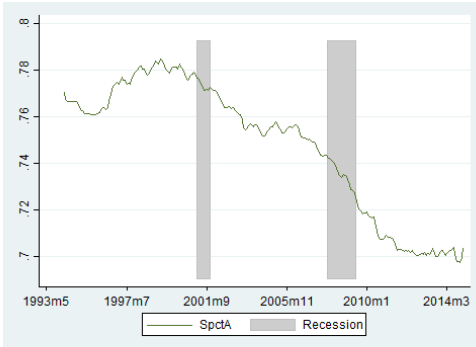
BINARY LABOR FORCE ATTACHMENT

The table below lists all sixteen four period status combinations described in Section 5 of Chapter 1 divided into either Attached or Not Attached. As a default, combinations that include two months of participation are included as attached.

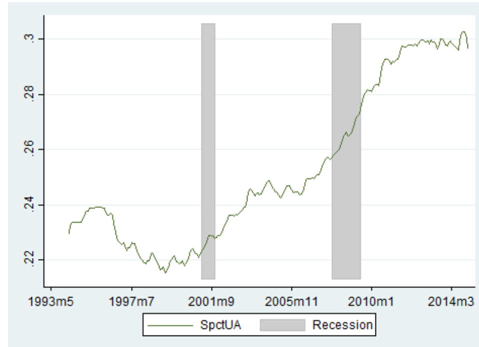
Attachment	four month code
Attached	
	PPPP
	NPPP
	PNPP
	PPNP
	PNPN
	NPNP
	NNPP
	PPPN
	NPPN
	PNNP
	PPNN
Unattached	
	NNNN
	PNNN
	NPNN
	NNPN
	NNNP

Table D.1: Labor force attachment by consecutive four month statuses.

The resulting trends are shown in Figure D.1 on the following page.



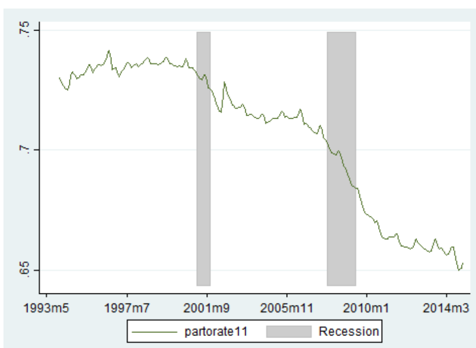
(a) Attached



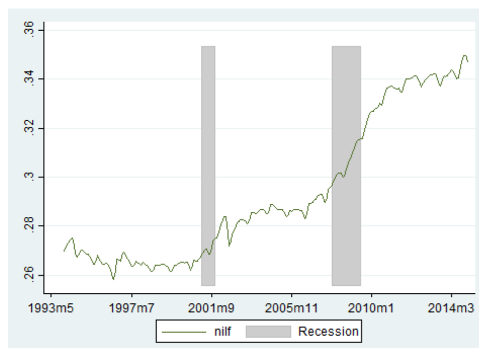
(b) Not Attached

Figure D.1: Time series of labor force attachment.

As a means of comparison, the time series of the customary definitions of Particiaption and Not in the Labor Force are displayed in Figure D.2.



(a) Participation



(b) Not in the Labor Force

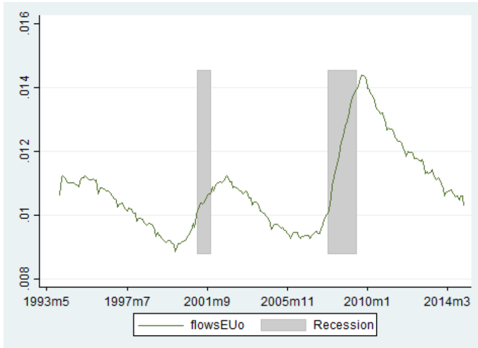
Figure D.2: Time series of labor force participation and NILF.

Appendix E

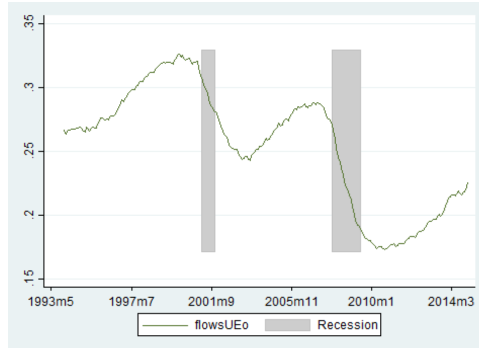
REPLICATING LABOR MARKET FLOWS

The purpose of this section is simply to replicate the flows constructed by Elsby et al. (2015). Specifically, the following graphs replicate the monthly flows of Figure 2 of Elsby, et al. (2015). While the date range of the two data sets differs, the overlap is consistent. Note that Elsby et al. (2015) also use adjusted flows to correct for potential misreporting of labor market status, this research does not.

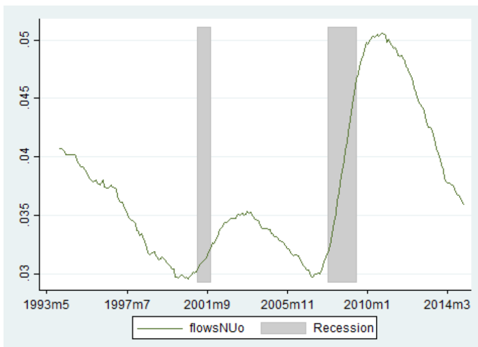
Comparing the replication results, the data and methodology used in this paper succeeds in matching the work of Elsby, et al. (2015). The graphical differences include the discrepencies in dates used. Elsby, et al. use 1968 through 2010, while the data used in this paper cover 1994 through 2014.



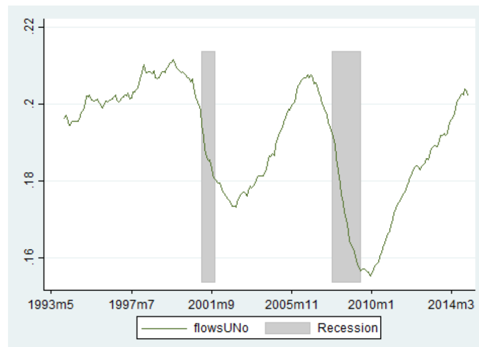
(a) EU



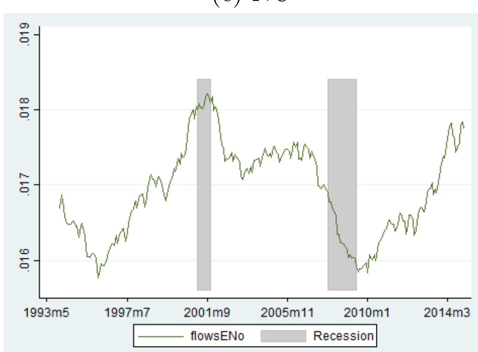
(b) UE



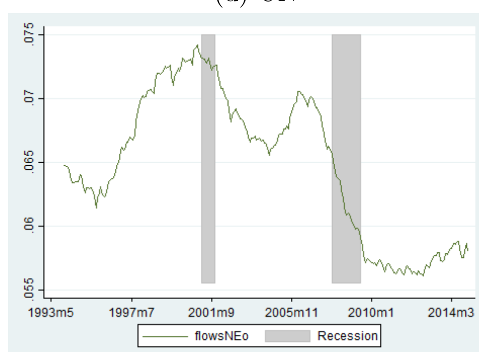
(c) NU



(d) UN



(e) EN



(f) NE

Figure E.1: Monthly flow transition probabilities (unadjusted)

Appendix F

REPLICATION OF ROBST (2007), USING 1993 DATA

The data shown below replicates the findings of Robst, 2007. For comparison, only data that was available in both the 1993 and 2013 data are included[37], so the coefficient values differ.

	Closely Related	Somewhat Related	Not Related
Overall	54.75%	25.10%	20.15%
gender			
Male	52.49%	28.31%	19.20%
Female	57.78%	20.79%	21.43%
race			
White	54.61%	25.47%	19.92%
Black	56.44%	22.49%	21.07%
Hispanic	57.07%	22.44%	20.49%
Asian	53.68%	23.51%	22.81%

Table F.1: Match between worker's job and most recent degree field, 1993.

Of college graduates, 54% report that their highest field of study is closely related to their job, 25% report that their degree field is somewhat related to their job, and 20% report that their field of study is not related to their current job. More females than men report that their field of study is closely related to their job.

[37] Training was not included in the 2013 data, so that data was omitted here

Likelihood of being mismatched by College Major, 1993

	Men			Women		
	Coefficient	**(Std. Err.)**	**Odds**	**Coefficient**	**(Std. Err.)**	**Odds**
Age	0.051^{**}	(0.007)	1.052	0.041^{**}	(0.009)	1.042
Age sqrd.	0.000^{**}	(0.000)	1.000	0.000^{**}	(0.000)	1.000
Disabled	0.023	(0.038)	1.023	$0.080^{\dagger}$	(0.046)	1.083
Black	-0.041	(0.036)	0.960	-0.170^{**}	(0.031)	0.844
Asian	0.114^{**}	(0.035)	1.121	0.101^{**}	(0.040)	1.106
Native	$-1.98^{\dagger}$	(0.106)	0.138	-0.069	(0.106)	0.933
Hispanic	-0.101^{**}	(0.038)	0.904	-0.171^{**}	(0.042)	0.843
Foreign born US citizen	0.144^{**}	(0.030)	1.155	0.260^{**}	(0.037)	1.297
Foreign born non-US citizen	0.245^{**}	(0.044)	1.278	0.441^{**}	(0.053)	1.554
Never Married	0.204^{**}	(0.029)	1.226	0.203^{**}	(0.029)	1.225
Masters	-0.851^{**}	(0.024)	0.427	-0.992^{**}	(0.029)	0.371
Professional	-1.986^{**}	(0.082)	0.137	-2.961^{**}	(0.123)	0.052
Doctor	-2.006^{**}	(0.045)	0.135	-1.787^{**}	(0.069)	0.167
Degree Field						
Agricultural Studies	0.824^{**}	(0.106)	2.280	0.981^{**}	(0.187)	2.667
Architecture	-0.107	(0.115)	0.899	0.526^{**}	(0.191)	1.692
Biological Sciences	1.168^{**}	(0.073)	3.216	0.825^{**}	(0.099)	2.282
Business Management	0.710^{**}	(0.058)	2.034	0.630^{**}	(0.086)	1.878
Communications	0.999^{**}	(0.086)	2.716	0.968^{**}	(0.100)	2.633
Education	0.809^{**}	(0.067)	2.246	$0.158^{\dagger}$	(0.087)	1.171
Engineering	0.388^{**}	(0.059)	1.474	0.534^{**}	(0.105)	1.706
Engineering-related Technology	0.461^{**}	(0.076)	1.586	0.555^{**}	(0.176)	1.742
English and Foreign Languages	1.643^{**}	(0.088)	5.171	1.207^{**}	(0.095)	3.343
Health	-0.673^{**}	(0.095)	0.510	-0.722^{**}	(0.094)	0.486
Home Economics	1.633^{**}	(0.391)	5.119	0.906^{**}	(0.109)	2.474
Law/Prelaw/Legal Studies	0.615^{**}	(0.094)	1.850	0.962^{**}	(0.134)	2.617
Liberal Arts	1.922^{**}	(0.136)	6.835	1.194^{**}	(0.136)	3.300
Library Sciences	$-0.700^{\dagger}$	(0.357)	0.497	0.009	(0.173)	1.009
Mathematics	1.062^{**}	(0.074)	2.892	0.759^{**}	(0.107)	2.136
Parks/Recreation/Fitness Studies	1.354^{**}	(0.156)	3.873	0.938^{**}	(0.169)	2.555
Philosophy/Religion/Teology	0.840^{**}	(0.098)	2.316	0.976^{**}	(0.149)	2.654
Physical Sciences	1.048^{**}	(0.071)	2.852	0.825^{**}	(0.122)	2.282
Psychology	1.355^{**}	(.074)	3.877	0.946^{**}	(.093)	2.575
Public Affairs	1.170^{**}	(0.115)	3.222	1.307^{**}	(0.152)	3.695
Social Science	1.686^{**}	(0.063)	5.398	1.173^{**}	(0.088)	3.232
Visual and Performing Aerts	1.052^{**}	(0.088)	2.863	0.974^{**}	(0.100)	2.649
Intercept	1.856^{**}	(0.169)	6.398	1.687^{**}	(0.205)	5.403
Intercept	3.379^{**}	(0.169)	29.341	2.788^{**}	(0.206)	16.248

Table F.2: Ordered logit results of mismatch, 1993. **indicates significance at 1% level, *indicates significance at 5% level, †indicates significance at 10% level.

	Men		Women	
	Coefficient	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
mismatch				
Complete	-0.125**	(0.008)	-0.095**	(0.008)
Partial	-0.030**	(0.006)	-0.014†	(0.007)
demographics				
Age	0.052**	(0.002)	0.031**	(0.002)
Age sqrd.	-0.001**	(0.000)	0.000**	(0.000)
Disabled	-0.074**	(0.010)	-0.058**	(0.012)
Black	-0.141**	(0.008)	-0.044**	(0.006)
Asian	-0.057**	(0.008)	0.020*	(0.009)
Native	-0.141**	(0.021)	-0.063**	(0.023)
Hispanic	-0.079**	(0.008)	-0.005	(0.009)
Foreign born US citizen	0.001	(0.007)	0.020*	(0.009)
Foreign born non-US citizen	-0.050**	(0.011)	-0.079**	(0.013)
Never Married	-0.130**	(0.007)	-0.007	(0.007)
work and training				
Experience	0.015**	(0.001)	0.016**	(0.000)
Training	0.085**	(0.006)	0.077**	(0.007)
Masters	0.106**	(0.006)	0.156**	(0.006)
Professional	0.476**	(0.014)	0.504**	(0.018)
Doctoate	0.277**	(0.009)	0.349**	(0.013)
major				
Agricultural Sciences	-0.248**	(0.025)	-0.241**	(0.054)
Architecture	-0.096**	(0.022)	-0.084*	(0.042)
Biological Sciences	-0.146**	(0.017)	-0.203**	(0.022)
Business Management	0.002	(0.013)	-0.076**	(0.019)
Communications	-0.114**	(0.021)	-0.165**	(0.024)
Education	-0.288**	(0.014)	-0.331**	(0.019)
Engineering	0.096**	(0.013)	0.133**	(0.023)
Engineering-related Technology	-0.021	(0.018)	-0.023	(0.047)
English and Foreign Languages	-0.186**	(0.023)	-0.231**	(0.022)
Health Professions	0.033†	(0.017)	-0.073**	(0.019)
Home Economics	-0.145	(0.119)	-0.331**	(0.028)
Law/Prelaw/Legal Studies	-0.104**	(0.019)	-0.177**	(0.028)
Liberal Arts	-0.099*	(0.040)	-0.113**	(0.034)
Library Sciences	-0.343**	(0.043)	-0.343**	(0.026)
Mathematics	0.018	(0.018)	-0.099**	(0.027)
Parks/Recreation/Fitness Studies	-0.267**	(0.030)	-0.374**	(0.040)
Philosophy/Religion/Theology	-0.554**	(0.020)	-0.420**	(0.043)
Physical Sciences	-0.010	(0.016)	-0.064*	(0.028)
Psychology	-0.155**	(0.019)	-0.222**	(0.021)
Public Affairs	-0.089**	(0.028)	-0.054	(0.034)
Social Sciences	-0.098**	(0.015)	-0.214**	(0.020)
Visual and Performing Arts	-0.265**	(0.020)	-0.293**	(0.024)
Intercept	9.425**	(0.046)	9.726**	(0.052)
N	70955		39800	
R sqrd.	0.266		0.224	

Table F.3: The wage effects of mismatch by college major mismatch.

Wage Penalty by College Major Mismatch, 1993

	Men		Women	
	Coefficient	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
*Mismatch * degree field*				
Agricultural Sciences	-0.046	(0.062)	0.053	(0.115)
Architecture	$-0.142^{\dagger}$	(0.075)	-0.013	(0.096)
Biological Sciences	-0.007	(0.029)	-0.084^{*}	(0.038)
Business Management	-0.243^{**}	(0.015)	-0.238^{**}	(0.021)
Communications	-0.110^{*}	(0.044)	-0.145^{**}	(0.037)
Computer Science	-0.140^{*}	(0.055)	-0.522^{**}	(0.116)
Education	0.019	(0.021)	$-0.028^{\dagger}$	(0.017)
Engineering	-0.236^{**}	(0.024)	-0.269^{**}	(0.055)
Engineering-related Technology	-0.138^{**}	(0.053)	-0.102	(0.129)
English and Foreign Languages	0.003	(0.041)	-0.009	(0.027)
Health Professions	-0.294^{**}	(0.051)	-0.219^{**}	(0.038)
Home Economics	0.107	(0.221)	-0.055	(0.048)
Law/Prelaw/Legal Studies	-0.173^{**}	(0.049)	-0.258^{**}	(0.053)
Liberal Arts	-0.078	(0.076)	-0.006	(0.060)
Library Science	0.294^{**}	(0.091)	-0.040	(0.094)
Mathematics	-0.152^{**}	(0.041)	-0.168^{**}	(0.058)
Parks/Recreation/Fitness Studies	0.118^{*}	(0.058)	-0.040	(0.082)
Philosophy/Religion/Theology	0.149^{**}	(0.041)	0.071	(0.091)
Physical Sciences	-0.122^{**}	(0.030)	-0.183^{**}	(0.058)
Psychology	0.037	(0.036)	0.014	(0.029)
Public Affairs	$-0.128^{\dagger}$	(0.066)	-0.113	(0.072)
Social Science	-0.063^{**}	(0.018)	-0.045^{*}	(0.020)
Visual and Performing Arts	$-0.064^{\dagger}$	(0.033)	-0.074^{*}	(0.032)
N	70955		39800	
R squared	0.271		0.230	

Table F.4: The wage effects of mismatch for working outside the degree field. **indicates significance at 1% level, *indicates significance at 5% level, †indicates significance at 10% level.

Appendix G

ALTERNATE WAGE EQUATION WITH MISMATCH

	Men		Women	
	Coefficient	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
Partial	-0.131**	(0.023)	-0.108**	(0.028)
Complete	-0.406**	(0.032)	-0.400**	(0.033)
Age	0.121**	(0.007)	0.094**	(0.007)
Age sqrd.	-0.001**	(0.000)	-0.001**	(0.000)
Experience	0.030**	(0.005)	0.029**	(0.004)
Experience sqrd.	-0.001**	(0.000)	0.000**	(0.000)
Training Program	0.153**	(0.021)	0.239**	(0.025)
Disabled	-0.210**	(0.036)	-0.127**	(0.042)
Black	-0.229**	(0.054)	-0.018	(0.040)
Asian	-0.023	(0.029)	0.061	(0.045)
Native	-0.179	(0.117)	-0.003	(0.126)
Hispanic	-0.165**	(0.035)	-0.097*	(0.039)
Foreign born US citizen	-0.006	(0.028)	-0.020	(0.046)
Foreign born non-US citizen	-0.109**	(0.037)	-0.109†	(0.057)
Never Married	-0.239**	(0.027)	0.051†	(0.026)
Parent's Education	0.003*	(0.001)	0.002	(0.001)
Masters	0.153**	(0.022)	0.148**	(0.024)
Professional	0.586**	(0.053)	0.626**	(0.043)
Doctor	0.321**	(0.027)	0.482**	(0.037)
Agricultural Sciences	-0.261**	(0.065)	-0.373**	(0.131)
Architecture	-0.257**	(0.058)	-0.285**	(0.085)
Biological Science	-0.240**	(0.036)	-0.312**	(0.055)
Business Management	-0.028	(0.032)	-0.055	(0.051)
Communications	-0.221**	(0.072)	-0.237**	(0.084)
Education	-0.669**	(0.054)	-0.577**	(0.054)
Engineering	0.083**	(0.026)	0.157**	(0.052)
Engineering-related Technology	-0.073	(0.051)	-0.081	(0.097)
English and Foreign Languages	-0.514**	(0.101)	-0.394**	(0.080)
Health Professions	-0.104*	(0.042)	-0.185**	(0.049)
Home Economics	0.112	(0.107)	-0.426**	(0.131)
Law/Prelaw/Legal Studies	-0.309**	(0.065)	-0.281**	(0.065)
Liberal Arts	-0.250**	(0.089)	-0.325**	(0.087)
Library Sciences	-0.452*	(0.205)	-0.446**	(0.117)
Mathematics	-0.090*	(0.038)	-0.213**	(0.070)
Parks/Recreation/Fitness Studies	-0.683**	(0.168)	-0.497**	(0.164)
Philosophy/Religion/Theology	-0.709**	(0.090)	-0.519**	(0.143)
Physical Sciences	-0.137**	(0.040)	-0.188**	(0.069)
Psychology	-0.194**	(0.049)	-0.177**	(0.048)
Public Affairs	-0.390**	(0.123)	-0.180	(0.155)
Social Science	-0.163**	(0.039)	-0.319**	(0.055)
Visual and Performing Arts	-0.698**	(0.088)	-0.502**	(0.088)
Intercept	8.483**	(0.154)	8.746**	(0.161)
R sqrd.	0.283		0.187	

Table G.1: The wage effects of mismatch with alternate specification of Equation 3.2 in Chapter 3.

Appendix H

LOGIT RESULTS ON COMPLETE MISMATCH

Variable	**Coefficient**	**(Std. Err.)**
age	-0.020	(0.021)
age2	0.000*	(0.000)
disabled	0.076	(0.102)
black	0.023	(0.157)
asian	0.256†	(0.131)
native	0.597	(0.642)
hispanic	0.134	(0.134)
forUS	0.190†	(0.111)
forNUS	0.199	(0.159)
nevermarried	0.464**	(0.096)
masters	-0.887**	(0.082)
professional	-2.393**	(0.253)
doctor	-2.149**	(0.152)
agriculture	0.870**	(0.317)
architecture	-0.297	(0.259)
biology	1.116**	(0.175)
business	0.320†	(0.168)
communications	0.951**	(0.244)
education	0.715**	(0.201)
engineering	-0.160	(0.163)
engineeringtech	0.439†	(0.241)
englanguage	1.599**	(0.278)
health	0.130	(0.208)
homeec	1.948†	(1.002)
law	1.256**	(0.266)
liberalarts	1.892**	(0.322)
library	-0.111	(0.768)
math	0.090	(0.196)
parks	1.471**	(0.405)
philosophy	1.434**	(0.267)
physics	0.679**	(0.184)
psychology	-0.142	(0.143)
public	0.852*	(0.373)
socials	1.437**	(0.163)
visart	0.978**	(0.237)
Intercept	-1.958**	(0.500)
N	47497	
Log-likelihood	-9690294.588	
$\chi^2_{(35)}$	848.027	

Table H.1: Estimation results : logit results on complete mismatch.