# The Consequences of Initial Skill Mismatch for College Graduates: Evidence from Online Job Postings*

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**Abstract**

In this paper, we study how skill-specific initial labor market conditions affect early career outcomes of college graduates. Exploiting data on the near-universe of online job postings in the U.S. between 2010 and 2016, we build a new measure of skill mismatch which captures how well an individual's college major matches the occupational composition of local labor demand around the time of graduation. Intuitively, a college graduate experiences skill mismatch when only a small fraction of online job postings in her city are suitable for her major in the year she graduates. Exploiting variation in skill mismatch across majors, cities and graduation cohorts, we find that a one standard deviation increase in our measure leads to a 3 percent decline in initial wages. Skill mismatch is also associated with a greater probability of being initially unemployed or employed in a part-time job, as well as a lower probability of being employed in a college occupation or one of the top occupations by college major. While the effects on unemployment, part-time employment and employment in college occupations gradually fade over time, the effects on wages and major-occupation fit persist up to 6 years after graduation. Our findings highlight the importance of having the right skills in the right place at the right time.

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# 1 Introduction

A number of studies have documented the long-term impact of graduating from college during times of high unemployment (Kahn, 2010; Oreopoulos et al., 2012; Altonji et al., 2016). Cohorts who enter the labor market during downturns are more likely to be unemployed, more likely to start their career in worse jobs, and earn lower wages on average compared to cohorts who face more favorable economic conditions at entry. While these initial differences typically dissipate over time, some of them can persist for many years after graduation. These findings illustrate the cost of recessions for individual workers, and contribute to our understanding cross-cohort income inequality by highlighting the role of initial labor market conditions. They also shed light on the forces underlying career dynamics. In particular, the speed and the extent to which individuals who graduate during bad times are able to catch up with their more fortunate counterparts—as well as the channels through which they bridge the gap (e.g. by changing jobs vs. on the job)—provide important clues that can inform various theories of career progression.[1]

Another important finding is that average effects of graduating during a recession mask substantial heterogeneity across college graduates. Notably, studies have found large disparities in the size and persistence of these effects across graduates from different fields of study. Graduates with high-paying majors tend to fare better than graduates with low-paying majors, both in the short-run and the long-run. While the differential impact of downturns across college majors could in principle reflect differential exposure, and subsequent response, to a common shock, it seems likely that graduates with different skills actually face different labor market conditions at entry. After all, there are not only large earnings differentials across college majors (Altonji et al., 2012), but there is also evidence that these gaps exhibit substantial variation across time (Altonji et al., 2014) and space (Phelan and Sander, 2017).

In this paper, we directly explore this possibility by studying how *skill-specific* initial labor market conditions affect early career outcomes of college graduates. To answer this question, we exploit data on the near-universe of online job postings in the U.S. since 2010 and construct a new measure of "skill mismatch," which essentially captures how well the skills that are embedded in college majors match the skills that are demanded by local employers in a given city and given year. Intuitively, college graduates with a specific major experience skill mismatch when only a small fraction of job openings in their local labor market are suitable for their major in the year that they graduate.[2] For instance, a finance major who graduated in Detroit in 2013 will have experienced skill mismatch if there were relatively few job openings for financial occupations in that area at the time. Our empirical strategy consists in comparing individuals who faced different initial labor market conditions, as measured by skill mismatch, based on when and where they graduated, but also what field they majored in. This additional layer of variation allows us

[1] Leading examples include job search models, models of human capital accumulation, employer learning models, and models of long-term wage contracts.

[2] In our baseline definition, we quantify the suitability between majors and occupations using occupational employment shares by college major, but we will also show alternative results based on college major wage premiums by occupation.

to control for cohort-location-specific factors, and implicitly compare individuals who faced the same overall labor market conditions, but whose skills were more or less in the demand when they graduated.

We find that skill mismatch leads to worse initial outcomes for college graduates: they are more likely to be unemployed or employed in a part-time job, less likely to be employed in an occupation that typically requires a college degree, less likely to be employed one of the top occupations for their college major, and they earn lower wages. In terms of magnitude, a one standard deviation increase in our skill mismatch measure—roughly equivalent to the average difference between a major in music and drama and a major in physics, or alternatively the difference between having a STEM degree in Providence, RI as opposed to San Francisco, CA in 2016—leads to a 0.4 percentage point increase in the probability of being unemployed, a 0.8 percentage point increase in the probability of being employed in a part-time job, and a 1 percentage point decrease in the probability of being employed in a college occupation, a 1.8 percentage point decrease in the probability of being employed in one of the top 5 occupations by college major, and a 3 percent decline in hourly wages among individuals 1-2 years out of college.

While the effects on unemployment, part-time employment and employment in college occupations gradually fade over time, the effects on wages and major-occupation fit persist up to 6 years after graduation. These medium-run effects are substantial: the wage and major-occupation fit penalties associated with a one standard deviation increase in initial skill mismatch are 2.6 percent and 1.6 percentage points respectively among individuals 5-6 years out of college. Focusing on wages, we also find that low-paying majors are more sensitive to skill mismatch than high-paying majors, and that the medium-run effects are largely driven by initial skill mismatch rather than skill mismatch experienced in subsequent years. This last result, combined with the persistent effect of skill mismatch on major-occupation fit, suggests that early career human capital accumulation plays an important role. All in all, our findings highlight the importance of having the right skills in the right place at the right time.

As mentioned already, our paper is closely related to the literature on the long-term effects of initial labor market conditions, as measured by local or national unemployment rates. Analyzing cohorts of white males in the National Longitudinal Survey of Youth who graduated from college during the 1980s, Kahn (2010) finds that initial economic conditions have a negative and persistent effect on wages. Using Canadian administrative data covering a large number of cohorts of male college graduates, Oreopoulos et al. (2012) find similar, though less persistent, effects on earnings. Exploiting the richness of their university-employer-employee linked data, they also document heterogeneity in the speed and nature of the recovery process across more or less disadvantaged college graduates. College graduates with high predicted earnings, based on their major and the school they attended, fully recover within a few years, mostly through job mobility. On the other hand, college graduates with low predicted earnings never fully recover, and their recovery mostly take place within the firm. Liu et al. (2016) show using administrative data from Norway that early career "skill mismatch"—which in their study refers to college graduates obtaining jobs in industries that are ill-suited for their college major—is an important driver of both the short-term and long-term earnings effects of graduating during times of high unemployment. More recently, Altonji et al. (2016) reexamine the long-term effects of initial labor market conditions in the U.S. using pooled data on cohorts who graduated between 1974 and 2011. They find similar patterns of negative wage effects at entry that gradually fade over time, and show that high-paying majors are less affected than than low-paying majors.

While the patterns documented in this paper might seem similar, it is important to emphasize that our estimates are effectively *net* of the impact of initial labor market conditions common across college majors (both local and national), including unemployment rates. In that sense, our findings are fundamentally distinct from those in the existing literature. To show how this leads to new insights, we revisit the effects of initial unemployment rates in our sample, and find that they are less persistent and weak predictors of major-occupation fit.

Given that the term "skill mismatch" has been used by others in different ways, it is also worth distinguishing our concept of skill mismatch with alternative ones in the literature. Perhaps the most common notion of skill mismatch is one of match quality between workers and their current occupation, based on the dissimilarity between workers' ability profile and the task content of their occupation. Various studies have explored how skill mismatch affects wage growth and job mobility over the life cycle (Guvenen et al., 2015; Lise and Postel-Vinay, 2016; Fredriksson et al., forthcoming). Another related concept is "mismatch unemployment," which refers to a misallocation between job seekers and vacancies (Şahin et al., 2014; Marinescu and Rathelot, forthcoming). More specifically, mismatch unemployment occurs when a planner could theoretically reduce aggregate unemployment by reallocating workers across segments of the economy, as defined by locations, industries or occupations (or some combination of the three). Therefore, these papers either assume that workers are homogeneous, or that they can only work in specific occupations or industries. Most closely related to our paper is the concept of "skill remoteness" introduced in Macaluso (2017), which refers to a mismatch between the skill profile of recently laid-off workers and local labor demand. However, whereas we infer workers' skills based on their college major (i.e. skills acquired in school), Macaluso (2017) infers workers' skills based on the task content of their previous occupation (i.e. skills acquired on the job). Moreover, local labor demand is proxied using an area's occupational structure, whereas we directly measure the skills demanded by local employers using the occupational composition of online job postings.

The remainder of the paper is organized as follows. We begin by describing the data sources used in the empirical analysis in Section 2. In Section 3, we outline our empirical strategy. In Section 4, we present our main results. Section 5 contains a broader discussion of the results. Finally, Section 6 concludes.

## 2 Data

### 2.1 Burning Glass Technologies

The primary data source in this paper is a database of online job ads provided by Burning Glass Technologies (BGT), an employment analytics and labor market information firm. Burning Glass maintains a database covering the near-universe of online job postings in the U.S. by regularly scraping information from over 40,000 online jobs boards and company website, providing a real-time snapshot of the labor market. Online job postings data is widely used by state and local workforce agencies, higher education institutions and employers to learn about the latest trends in the labor market, complementing more traditional sources on vacancies such as the Job Openings and Labor Turnover Survey (JOLTS) maintained by the Bureau of Labor Statistics.[3]. More recently, these data sources have been increasingly used in academic research, for example to study routine-biased technological change over the business cycle (Hershbein and Kahn, 2016), the returns to skill requirements (Deming and Kahn, 2018), and monopsony in the labor market (Azar et al., 2017, 2018).

Figure 1 plots the total number of online job postings in Burning Glass and the total number of job openings in JOLTS at a quarterly frequency since 2010. Although there is a significant level difference between these two series—which is partly due to how job openings and job postings are defined—they otherwise track each other quite closely over time.[4] There is however a key difference between Burning Glass and JOLTS. Because not all jobs are posted online, the distribution of online job postings is not necessarily representative of actual distribution of vacancies in the economy. Perhaps unsurprisingly, jobs that are posted online tend to be higher-skill jobs. Carnevale et al. (2014) estimate that, while between 60 and 70 percent of all jobs are posted online, the coverage for jobs that require at least a Bachelor's degree is closer to 80-90 percent.

Table 1 compares the industry composition in JOLTS and Burning Glass. Clearly, some industries are overrepresented in Burning Glass, most notably manufacturing, finance, education, and healthcare. Other industries, which tend to employ a greater number of low-skill workers, are underrepresented (e.g. construction, accommodation and food services, government). Since occupations are not available in JOLTS, Table 2 compares the occupational composition of online job postings in Burning Glass to the occupational composition of employment in the American Community Survey in terms of 2-digit Standard Occupational Classification (SOC) codes. Consistent with the previous table, some occupations are overrepresented in BGT, including business and financial occupations, computer and math occupations, and healthcare occupations, while others are underrepresented, such as education occupations, construction occupations, and production occupations. The fact that Burning Glass is more representative of college-type jobs is actually

[3]JOLTS is a nationally-representative survey of roughly 16,000 randomly-sampled establishments conducted each month, and not only measures vacancies but also hires and separations.

[4]JOLTS defines *active* job openings as positions that are open on the last business day of the month, could start within 30 days, and are subject to active recruiting efforts. BGT identifies *new* job postings using a 60-day window tolerance. That is, during the data collection process, any job posting is flagged as a duplicate if it has the same characteristics as one which was originally identified less than 60 days ago.

convenient for our setting since we are primarily interested in the job opportunities that college graduates face when they enter the labor market.

One major advantage of Burning Glass over JOLTS is the size and scope of the data. Burning Glass contains over 145 million unique job postings covering the period 2010 to 2016. For each job posting, Burning Glass extracts a variety of information, including the employer, the occupation, the industry, the location, and various job requirements (e.g. education, experience). The granularity of the data allows us to get a more detailed picture of labor demand and conduct analyses at a very fine level, both in terms of geography and sectors of the economy. For the purpose of this study, we only exploit the occupation associated with the job (6-digit SOC), the Metropolitan Statistical Area (MSA) in which the job is to take place, as well as the year in which the job ad was posted. As we describe in Section 3.1, we use this information to compute the occupational composition of online job postings for every MSA-year pair, which will serve as our proxy for the types of skills demanded by local employers in the construction of our skill mismatch measure. Despite its richness, the main drawback of Burning Glass is that it only goes as far back as 2010, which effectively restricts the number of graduating cohorts we are able study in the analysis.[5]

### 2.2 American Community Survey

To measure employment outcomes of college graduates, we use data from the 2010-2016 American Community Surveys (ACS) 1% samples (Ruggles et al., 2017). The ACS is a large-scale household survey of the U.S. population, and contains detailed information on respondents' demographic characteristics, employment status, income and geographic location. Crucially for our purposes, since 2009 the ACS has asked respondents who hold a 4-year Bachelor's degree about their college major. In this paper, we will use college majors as a summary measure of the skills that individuals have acquired while in school. College majors are typically associated with a specific curriculum and therefore a specific set of skills. As certain skills tend to be valued in certain jobs more than others, college majors implicitly contain useful information regarding the set of suitable occupations for a given college graduate. For example, nursing majors presumably possess the necessary skills to become registered nurses or enter related healthcare occupations. One important advantage of college majors over alternative measures of skills, such as current/previous occupations or ability profiles, is that they are available for a large sample of the population, regardless of current or past employment status. This means we can not only study individuals who have never held a job before, but the large sample sizes in the ACS enable us to fully exploit the granularity of the Burning Glass data.

In the analysis, we focus on college graduates with 1 to 6 years of potential experience—defined as the *estimated* number of years since graduation (see below)—who graduated between 2010 and 2015, either hold a Bachelor's or Master's degree, are not currently enrolled in school,

[5] Data is technically available for 2007, but our analysis relies on knowing individuals' college major, which is only available in the American Community Survey since 2009.

and currently reside in one of the 294 MSAs that are identifiable in the ACS.[6] The potential experience and graduation year restrictions are dictated by the fact that Burning Glass only goes as far back as 2010, and the fact that 2016 is the latest ACS release.[7] We exclude individuals with 0 years of potential experience since the reference period for the income question in the ACS is the past 12 months (relative to the time of the survey), so that income for those individuals could potentially reflect income earned while in school. We exclude individuals with professional or doctoral degrees for two reasons: (1) program duration—and hence year of graduation—is harder to determine for those individuals (see below), and (2) the ACS only measures undergraduate fields of study, which might be a worse proxy of skills for people with graduate degrees.[8] Lastly, we focus on MSAs since urban areas have better coverage in the Burning Glass data. Given that most college graduates live in MSAs anyway (roughly 85 percent), this choice only results in a minimal loss of sample size. In Section 4.6, we show that we obtain very similar results using states as the unit of geography instead.[9]

The main limitation of the ACS is that it is mostly intended to capture the current situation of respondents, and therefore contains little information on past experiences. In our context, this means we cannot know for sure when and where individuals graduated from college. Following Altonji et al. (2016), we impute MSA at graduation using current MSA of residence, and approximate the year of graduation using the year individuals were most likely aged 22 in May, which is year of birth plus 22 for individuals born in the first two quarters of the year and year of birth plus 23 for everyone else. For individuals who hold a Master's degree, year of graduation is year of birth plus 24 or 25 depending on quarter of birth given that Master's programs typically last two years.

Appendix Table A1 displays basic summary statistics for college graduates with 1 year of potential experience. Recent college graduates are more likely to be female than male (57 percent), are majority non-Hispanic whites (67 percent in 2016, down from 73 percent in 2011), and roughly one out of five graduate also holds a Master's degree. We organized college majors in the ACS into 56 categories, loosely following the classification in Altonji et al. (2016). Appendix Table A2 displays college major shares for college graduates with 1 year of potential experience. In 2016, the five most common majors were "Psychology," "Communications," "Biological sciences," "Computer science and IT," and "Accounting." The composition of college majors has been fairly stable since 2011, with the largest gains occurring in "Computer science and IT" and "Fitness, nutrition, and leisure," and the largest losses occurring in "Business management and administration" and "Elementary education."

[6] In order to focus on the non-institutional civilian population, we exclude from the sample: (1) individuals confined to institutional group quarters, (2) unpaid family workers, and (3) individuals on active military duty.

[7] Note that our sample is unbalanced in terms of potential experience: in 2011, we only observe the 2010 graduation cohort; in 2012, we observe the 2010 and 2011 graduation cohorts, and so on.

[8] The results are robust to excluding individuals with Master's degrees as well (see Section 4.6).

[9] We could also use the concept of commuting zones (CZ) to approximate local labor markets, but one drawback is that the ACS does not allow you to uniquely identify the CZ of residence for individuals living in sparsely populated areas.

# 3 Empirical Strategy

## 3.1 Measure of Skill Mismatch

The key novelty in this paper is how we measure initial skill-specific labor market conditions. We introduce a new measure of skill mismatch, which is meant to capture how well the skills that are embedded in college majors match the skills that are demanded by local employers in a given city and given year. Essentially, skill mismatch is low for a particular college graduate when there are many suitable job opportunities for someone with her college major in her local labor market in the year she graduates, and high otherwise. As an example, consider an individual who graduated from college in 2010 in Chicago with a major in accounting. Because many accounting majors go on to become accountants, this individual presumably had good job prospects if accountants happened to be in high demand in Chicago in 2010. Of course, accountant is not the only suitable occupation for accounting majors, many of them are employed as financial managers for example. However, few of them end up being employed as chemists. Therefore, the relative number of vacancies in Chicago in 2010 for accountants or financial managers vs. chemists is ultimately what determines the extent to which this accounting major experienced skill mismatch at graduation.

In practice, our measure combines two ingredients: (1) a metric of fit between each college major and each occupation, and (2) the occupational distribution of online job postings, which is MSA and year-specific. Formally, skill mismatch for college major $m$ in MSA $\ell$ at time $t$ is defined as one minus the weighted average of the match coefficient between major $m$ and every occupation $k$, where the weights correspond to the share of online job postings in MSA $\ell$ at time $t$ that are for occupation $k$:[10]

$$\text{skill mismatch}_{m\ell t} = 1 - \sum_k \text{share of job postings}^{\text{BGT}}_{\ell t}(\text{occ}_k) \times \text{match}(\text{major}_m, \text{occ}_k) \tag{1}$$

To determine the extent to which a particular occupation $k$ is suitable for college major $m$, our baseline definition uses the share of workers with college major $m$ that are employed in occupation $k$ nationally, based on pooled 2009-2016 ACS data:

$$\text{match}(\text{major}_m, \text{occ}_k) = \frac{\text{emp}(\text{occ}_k)}{\sum_k \text{emp}(\text{occ}_k)}\bigg|\text{major}_m \tag{2}$$

The underlying assumption is that occupation $k$ is a good fit for major $m$ if a large share of workers with major $m$ are employed in occupation $k$, a kind of "revealed preference" argument.[11] In Section 4.6, we will show results using an alternative definition of skill mismatch which uses college major wage premiums by occupation instead.

[10] We use 4-digit SOC codes as our concept of occupations to compute skill mismatch because it is the most granular classification available in both the ACS and Burning Glass (109 distinct codes).

[11] To avoid any mechanical correlation between our measure of skill mismatch and the outcomes of interest, we restrict the sample to individuals aged 32 or older to compute employment shares (college graduates with a Master's degree and 6 years of potential experience are at most 31).

To facilitate the interpretation of our skill mismatch measure, we normalize it to have a mean of zero and a standard deviation of one across all college majors, MSAs and years. Table 3 shows average skill mismatch by college major between 2010 and 2016. In general, high-paying majors such as those in health and STEM fields seem to be in high-demand and are characterized by low skill mismatch (see Appendix Table A3 for a ranking of majors in terms of wages). In contrast, low-paying majors, such as those in arts and humanities are characterized by high skill mismatch. Of course, these differences are partly due to the fact that certain jobs are overrepresented in Burning Glass. However, as explained in the next section, our empirical strategy will control for national differences in skill mismatch across college majors, and instead rely on within-MSA cross-major variation and within-major cross-MSA variation in skill mismatch. To get a sense of the cross-sectional variation in skill mismatch, Figure 2 plots average skill mismatch by MSA (across all college majors), and Appendix Tables A4-A7 document the cross-MSA distribution of average skill mismatch by college major group for the four largest major groups: "Science, math, and technology," "Business," "Social sciences," and "Health and medicine." The key takeaway from these tables and figures is that there is a tremendous amount of variation in skill mismatch, but that most of it is across college majors and across MSAs rather than over time.

While the intuition behind our concept of skill mismatch is clear, one might wonder whether it truly captures something meaningful about skill-specific labor market conditions. As suggestive evidence, we show that it is correlated with two important labor market outcomes, unemployment rates and mean hourly wages, both across college majors on average and within majors across MSAs. Appendix Figures A1 and A2 plot average skill mismatch by college major against corresponding national unemployment rates and mean hourly wages, where the latter are based on recent college graduates aged 22-31. In every year, skill mismatch is positively correlated with unemployment rates and negatively correlated with mean hourly wages. In other words, majors characterized by high skill mismatch are also characterized by high unemployment rates and low wages, as we would have hoped. Next, Appendix Figures A3 and A4 plot average skill mismatch by MSA against corresponding unemployment rates and mean hourly wages, separately for each of the four largest college major groups. Within each major group, skill mismatch is positively correlated with MSA-specific unemployment rates (with the notable exception of "Health and Medicine"), and negatively correlated with MSA-specific mean hourly wages. Overall, these figures demonstrate that skill mismatch is predictive of adverse labor market outcomes, both when comparing individuals with different college majors and individuals with the same major but in different cities. It is worth noting that there seems to be a tighter relationship between skill mismatch and wages than between skill mismatch and unemployment rates. We now turn to our empirical strategy, which allows us to explore the effect of skill mismatch on labor market outcomes, both short-term and medium-term, in a more formal regression framework.

### 3.2 Empirical Specification

Our empirical strategy follows the literature on the long-term impact of graduating during a recession in that we compare outcomes of individuals who faced different initial labor market conditions—as measured by skill mismatch—depending on when and where they graduated, and allowing the effects to vary with potential experience. However, a unique feature of our context is that skill mismatch, unlike unemployment rates, also varies by college major. This allows us to exploit within-MSA cross-major variation, and implicitly compare individuals who graduated in the same city at the same time and therefore faced the same overall labor market conditions, but experienced different skill-specific labor market conditions by virtue of having different college majors.

Formally, consider an individual $i$ with potential experience $e \in \{1, \dots, 6\}$, residing in MSA $\ell$ at time $t \in \{2011, \dots, 2016\}$, who graduated from college in $g \in \{2010, \dots, 2015\}$ with a major in $m$.[12] Our main empirical specification is given by:

$$y_{iem\ell gt} = \alpha_{mg} + \gamma_{\ell g} + \lambda_t + \varphi_e + \beta_e \cdot \text{skill mismatch}_{m\ell g} + \theta \cdot X_{it} + \varepsilon_{iem\ell gt} \tag{3}$$

where $\lambda_t$ are year fixed effects, $\varphi_e$ are potential experience fixed effects, and $X_{it}$ are individual-level control variables.[13] For expositional purposes, the potential experience fixed effects $\beta_e$ are combined into three groups: 1-2 years, 3-4 years, and 5-6 years (the main potential experience fixed effects $\varphi_e$ are left in individual years). The major-cohort fixed effects $\alpha_{mg}$ control for major-specific labor market conditions at the time of graduation that are common across MSAs. Among others, these fixed effects capture cross-major level differences in skill mismatch that may stem from the non-representativeness of Burning Glass in terms of occupations. The MSA-cohort fixed effects $\gamma_{\ell g}$ control for MSA-specific labor market conditions at the time of graduation that are common across college majors. In particular, these fixed effects absorb local overall unemployment rates, which have been the focus of the literature so far.

The ability to interpret $\beta_e$ as the causal effect of skill mismatch hinges on several assumptions. First, we need to assume that students do not strategically graduate in years when demand for their major is high. This concern is somewhat alleviated by the fact that we assign skill mismatch based on *predicted* year of graduation rather *actual* year of graduation. Furthermore, studies have concluded that selective timing of graduation is unlikely to be a major factor (Oreopoulos et al., 2012; Liu et al., 2016; Altonji et al., 2016). Second, we need to assume that students do not self-select into college majors which they anticipate to be in high demand in the future *in their local labor market*. There are a two key reasons why this might be a reasonable assumption: (1) students would need to correctly anticipate (local) labor demand conditions 4 years in advance, which seems unlikely in light of the evidence on students' expectations about future earnings

[12] The ACS asks respondents to list a primary and secondary field of study. Throughout the paper, college majors refer to primary field of study.

[13] Individual-level controls include a female indicator, race fixed effects (Hispanic, Black, Asian, other race), an indicator for being foreign-born, an indicator for having Master's degree and an indicator for being a double major.

(Betts, 1996; Arcidiacono et al., 2012; Wiswall and Zafar, 2015b), and (2) studies have shown that, while future labor market prospects do matter, individual preferences and expected performance probably play a more prominent role in driving college major choices (Arcidiacono, 2004; Beffy et al., 2012; Stinebrickner and Stinebrickner, 2014; Wiswall and Zafar, 2015a).[14] Third, we need to assume that college graduates do not sort into MSAs based on local labor demand conditions. Although some studies offer encouraging evidence in other contexts (Oreopoulos et al., 2012; Liu et al., 2016), this is probably the biggest concern for our interpretation of the results, exacerbated by the fact that we cannot observe where people went to college. In Section 4.6, we try to address this concern in several different ways. Finally, on the labor demand side, we also need to assume that job postings are exogenous to the supply of college graduates, both in terms of timing and occupations. However, it seems reasonable to conjecture that employers post vacancies primarily based on their business needs at the time, and that there are few substitution possibilities between different occupations.

# 4 Results

## 4.1 Employment, Unemployment and Labor Force Participation

In Table 4, we start by looking at how skill mismatch affects the probability of being employed, unemployed or out of the labor force. We also split employment into part-time and full-time work, where part-time is defined as working less than 35 hours a week. The first row shows that skill mismatch has a negative effect on the probability of being initially employed and a positive effect on the probability of being initially unemployed. In terms of magnitude, a one standard deviation increase in skill mismatch—which is roughly equivalent to the average difference between a major in music and drama and a major in physics (see Table 3), or alternatively the difference between having a STEM degree in Providence, RI as opposed to San Francisco, CA in 2016 (see Appendix Table A4)—reduces the probability of being employed by 0.6 percentage points and raises the probability of being unemployed by 0.4 percentage points for individuals 1-2 years out of college. Columns (2) and (3) show that these effects reflect a simultaneous decline in full-time employment and (smaller) rise in part-time employment.

The second and third rows reveal that, while the positive effects on part-time employment and unemployment gradually fade over time (i.e. with experience), the negative effect on employment remains roughly constant. As a result, for individuals with 5-6 years of potential experience, the negative employment effect is associated with a greater probability of being out of the labor force rather than being unemployed.

[14] Relatedly, there is evidence that college major choice varies over the business cycle (Blom et al., 2017), though it is unclear whether these findings extend to local skill-specific labor market conditions.

## 4.2 Occupations

Next, we explore the effect of skill mismatch on occupations. Poor initial labor market conditions may not only increase the risk of not finding a job among young college graduates, but also force some of them to settle for worse jobs. This is a common finding in the literature (e.g., Oreopoulos et al., 2012). In Table 5, we examine the effect of skill mismatch on the probability of being employed in an occupation that typically requires a college degree and, following Altonji et al. (2016), the probability of being employed in one of the top 5 or top 10 occupations by college major, conditional on being employed.

We define "college" occupations in two complementary ways: (1) based on educational requirements in the Department of Labor's Occupational Information Network (O*NET) database (Abel et al., 2014), or (2) based on education levels observed in the ACS (Clark et al., 2016). In the O*NET version, we define college occupations as those for which a majority of respondents in the O*NET surveys indicated that they require one.[15] In the ACS version, we define college occupations as those for which the most common education level among incumbent workers is a Bachelor's degree or more. The top 5 or top 10 occupations by college major are determined based on employment shares in the ACS. As in Section 3.1, for each college major, we compute the occupational distribution among workers who hold that major, and identify the 5 or 10 most common jobs. Appendix Table A8 lists the top 3 occupations for each college major.[16]

As can be seen from Panel D in Appendix Table A1, about two thirds of college graduates are initially employed in college occupations, while respectively 35 percent and 45 percent of recent college graduates are employed in one of the top 5 and top 10 occupations associated with their college major. Appendix Table A3 shows that there is a tremendous amount of variation in these outcomes across college majors, with high-paying majors typically faring better than low-paying ones. For example, 86 percent of electrical engineering majors start their career in a college job, and 62 percent of them in one of the top 5 occupations. In contrast, the corresponding numbers for psychology majors are 59 percent and 20 percent respectively.

The estimates in Table 5 show that skill mismatch has negative effect on the probability of being employed in a college occupation or one of the top occupations by college major. A one standard deviation increase in skill mismatch reduces the probability of being initially employed in a college occupation by 1 percentage point, and reduces the probability of being initially employed in a top 5 or top 10 occupation by 1.8 percentage points. However, while the effect on college employment is half as large 5-6 years after graduation, the effect on major-occupation fit stays unchanged. The fact that workers who experience initial skill mismatch are more likely to be "stuck" in occupations that do not fit their college major could potentially reflect human capital depreciation.

[15] For each occupation, O*NET surveys incumbent workers and occupational experts to understand the nature of the job, including educational requirements. Rather than a unique education level, O*NET reports the distribution of responses (e.g. 55% Bachelor's degree and 45% Associate's degree).

[16] The only difference with Section 3.1 is how we classify occupations: to compute occupational outcomes in this section we the use Census occupational classification from Dorn (2009) instead of 4-digit SOC. It is worth noting that "Manager and administrators, n.e.c." happens to be the most common occupation in the U.S. under this scheme (around 5% of employment), which is why it is one of the top occupations for many college majors.

## 4.3 Earnings and Wages

We now turn to the effect of skill mismatch on earnings and wages. Hourly wages are computed by dividing annual wage income by the product of weeks worked last year and usual hours worked per week. Nominal income and wages are then converted into 2014 dollars using the Personal Consumption Expenditures chain-type price index released by the Bureau of Economic Analysis (BEA). In addition, we adjust income and wages for cost-of-living differences across MSAs using the BEA's Regional Price Parity index. Finally, we winsorize the distribution of real earnings and real wages at the top and bottom percentiles separately by year to neutralize the influence of outliers.

Table 6 shows the effect of skill mismatch on log earnings and log wages, conditional on having positive income. Skill mismatch has a negative and lasting impact on income and wages. In the first two years after graduation, a one standard deviation in skill mismatch is associated with a 5 percent decline in annual income, which partly reflects a decline in hours (see column (3) in Table 4), and a 3 percent decline in hourly wages. Strikingly, even 5-6 years after graduation, these penalties remain large and statistically significant, at -3.4 percent and -2.6 percent respectively. In contrast, the literature on the long-term effects of initial unemployment rates tend to find wage effects that decay at a faster rate. In Section 4.5, we estimate the effect of unemployment rates in our sample and show that they are indeed less persistent. Given the results in the previous section, a natural question is how much of the wage effects reflect major-occupation mismatch, since being employed in one of the top 5 or top 10 occupations by college major is associated with a 15 percent wage premium on average. However, a simple back-of-the-envelope calculation suggests that only about 14 percent of the wage effect can be attributed to major-occupation fit. We return to this point in Section 5, where we take stock of all the results.

Figure 3 illustrates heterogeneity in the wage effects across college major groups. Specifically, we estimate a single regression (3) where the dependent variable is log hourly wages, and interact initial skill mismatch not only with potential experience fixed effects but also with major group fixed effects. The figure plots the resulting OLS estimates and corresponding 95% confidence intervals for the 8 college major groups (roughly in increasing order). The largest wage declines, occur among the four lowest-paying major groups: "Arts and humanities," "Public and social services," "Multi/interdisciplinary studies" and "Social sciences." There are also negative and statistically significant wage declines among high-paying major groups such as business or STEM, both of which are important drivers of the average effects, given that they can account for around 40 percent of all college graduates. Interestingly, the wage effects among graduates with degrees in health care majors are close to zero and precisely estimated. The fact that low-paying majors are more affected by initial (skill-specific) labor market conditions is broadly consistent with the findings in Oreopoulos et al. (2012) and Altonji et al. (2016). Another interesting feature of Figure 3 is that the wage effects seem to be persistent across all majors, whereas one might have expected some differences in convergence patterns.

### 4.4 The Effect of Current vs. Initial Labor Market Conditions

As discussed in Oreopoulos et al. (2012), the medium-run estimates we have documented so far can be thought of as the effect of initial skill mismatch *plus* the weighted sum of the effect subsequent skill mismatch, to the extent that they are correlated with initial skill mismatch.[17] In this section, we explore how much of the medium-run effects is due to initial skill mismatch. We start by augmenting our main specification (3) with the effect of *current* skill mismatch interacted with potential experience fixed effects (also grouped into 2-year bins):

$$
\begin{aligned}
y_{iem\ell gt} = \alpha_{mg} + \gamma_{\ell g} + \lambda_t + \varphi_e + \beta_e \cdot \text{skill mismatch}_{m\ell g} \\
+ \delta_e \cdot \text{skill mismatch}_{m\ell t} + \theta \cdot X_{it} + \varepsilon_{iem\ell gt}
\end{aligned} \tag{4}
$$

Table 7 shows the resulting estimates. Columns (1) and (2) illustrate that, although both current and initial skill mismatch have negative effects, what matters for earnings and wages is initial skill mismatch. Figure 4 plots the wage results from column (2) using individual instead of grouped years of potential experience, and leads to a similar conclusion. The patterns for the other outcomes are slightly more mixed, with the effects for individuals with 3-4 years of potential experience seemingly being driven by current rather than initial skill mismatch while the opposite being true for individuals with 5-6 years of potential experience. However, the fact that skill mismatch is strongly serially correlated implies that it might be difficult to disentangle these two effects. In more restrictive models where current and initial skill mismatch are not interacted with potential experience fixed effects, only the coefficients corresponding to initial skill mismatch are statistically significant.

In order to dig deeper into the wage results, we estimate the effect of initial skill mismatch *net* of all subsequent skill mismatch, analogous to the exercise proposed in Oreopoulos et al. (2012). This involves controlling for the full history of skill mismatch that individuals face over the first 6 years of potential experience, allowing skill mismatch at every stage to have persistent effects. Because estimates can get noisy, we follow Oreopoulos et al. (2012) and average skill mismatch across consecutive years. Let skill mismatch$_{m\ell,01}$ denote the skill mismatch for major $m$ in MSA $\ell$ averaged across the year of graduation and the year following graduation. Define skill mismatch$_{m\ell,23}$ and skill mismatch$_{m\ell,45}$ analogously. We then estimate the following model:

$$
\begin{aligned}
\log \text{wage}_{iem\ell gt} = \alpha_{mg} + \gamma_{\ell g} + \lambda_t + \varphi_e + \beta_{e,01} \cdot \text{skill mismatch}_{m\ell,01} \\
+ \beta_{e,23} \cdot \text{skill mismatch}_{m\ell,23} \\
+ \beta_{e,45} \cdot \text{skill mismatch}_{m\ell,45} + \theta \cdot X_{it} + \varepsilon_{iem\ell gt}
\end{aligned} \tag{5}
$$

where $\beta_{e,y_1y_2} = 0 \;\; \forall e < y_2$. Figure 5 plots the estimates from our main specification (3) (baseline), the estimates from specification (5) where we only include the effect of skill mismatch$_{m\ell,01}$ (no

[17] Skill mismatch exhibits strong serial correlation: within MSA-major pairs 1 year apart, the Pearson correlation coefficient is 0.95 on average. The corresponding 5-year correlation coefficient is 0.9 on average.

history), and the estimates from specification (5) without any restrictions (full history). First, note that averaging skill mismatch across years 0 and 1 of potential experience yields estimates that are extremely similar to the baseline estimates. Second, the effect of initial skill mismatch net of subsequent skill mismatch are not too dissimilar to the baseline estimates, except for potential experience year 4. One reason why the estimate are less precise for more experienced individuals is the unbalanced nature of our sample. The estimate for 6 years of potential experience is only based on individuals who graduated in 2010 and are observed in the 2016 ACS. Similarly, the estimate for 5 years of potential experience is based on the 2010 and 2011 graduation cohorts, observed in 2015 and 2016 respectively. Hopefully, as more data becomes available in the ACS, this exercise will yield a clearer picture. But overall, our takeaway from the results in this section is that skill mismatch experienced in the year of graduation seems to be an important driver of our main results.

### 4.5 The Effect of Skill Mismatch vs. Overall Unemployment Rates

In order to contrast our findings on the effect of skill-specific labor market conditions with findings in the literature on the effect of overall labor market conditions, we directly estimate the effect of initial unemployment rates in our sample. Specifically, we estimate models of the following form:

$$y_{iem\ell gt} = \alpha_{mg} + \gamma_\ell + \lambda_t + \varphi_e + \beta_e \cdot \text{unemp}_{\ell g} + \theta \cdot X_{it} + \varepsilon_{iem\ell gt} \tag{6}$$

where $\text{unemp}_{\ell g}$ are MSA-cohort-specific unemployment rates extracted from the Bureau of Labor Statistics' Local Area Unemployment Statistics. Aside from replacing skill mismatch with unemployment rates, the only other difference relative to our main specification (3) is that we control for MSA fixed effects $\gamma_\ell$ instead of MSA-cohort fixed effects.

Table 8 displays the resulting estimates. The first row shows that unemployment rates have a negative impact on initial labor market outcomes. Among individuals with 1-2 years of potential experience, a one percentage point increase in the local unemployment rate reduces earnings by 2.4 percent and wages by 0.9 percent. It also raises the probability of being unemployed by 0.5 percentage points and reduces the probability of being employed in a college occupation by 0.5 percentage points. Although we examine a different period, the magnitude of the estimates are in line with the literature. Studying U.S. college graduating classes of 1974-2011, Altonji et al. (2016) find using a similar empirical exercise that a one percentage point increase in the Census division-cohort-specific unemployment rate leads to a 2.9 percent decline in earnings and a 1 percent decline in wages among individuals with 1 year of potential experience.

What really stands out in Table 8 is how fast the impact of unemployment rates fades with experience. While the effects are only slightly smaller and still statistically significant for individuals with 3-4 years of potential experience, they essentially vanish after 5 years.[18] Another interesting

[18]The estimates in the second and third row of Table 8 are also similar to the corresponding ones in Altonji et al. (2016).

feature is that unemployment rates are poor predictors of major-occupation fit, as can be seen from the last two columns. These qualitative patterns stand in stark contrast to our main findings, which shows that skill-specific labor market conditions have fundamentally different consequences for college graduates. This is due to the fact that unemployment rates and skill mismatch capture distinct sources of variation. To illustrate this point, Appendix Table A9 augments specification (6) with our skill mismatch measure interacted with potential experience fixed effects. Both the coefficients for unemployment rates and skill mismatch are virtually indistinguishable from the corresponding ones in Tables 4-6 and Table 8.

## 4.6 Robustness Checks

### Alternative Sample Restrictions

Our main results are robust to a variety of alternative sample restrictions. First, many studies restrict attention to men (Kahn, 2010; Oreopoulos et al., 2012), presumably to abstract away from the fact that career dynamics may differ across men and women, for example due to birth-related career interruptions among women. Table 9 shows the main results for men and women separately. Although the estimates differ slightly in magnitude, the patterns are broadly similar. It is worth noting that the wage effects are slightly more negative for men, with a 2.9 percent wage penalty in response to a one standard deviation increase in skill mismatch for men with 5-6 years of potential experience versus a corresponding 1.7 percent wage penalty for women. In addition, skill mismatch has a persistent, albeit small, effect on the probability of being unemployed for men, whereas women are largely unaffected. Some of these differences could reflect the fact that men and women sort into different college majors and that majors are differentially sensitive to skill mismatch as we showed in Figure 3. Another common empirical choice in the literature is to focus on individuals with exactly a 4-year Bachelor's degree. We include individuals with a Master's degree in our baseline sample, but results excluding them are extremely similar (see Appendix Table A12).

As Appendix Table A10 shows, there is a substantial amount of variation in the number of online job postings per capita across MSAs, ranging from fewer than 1 for every 100 individuals in San Juan, PR, to 15 for every 100 individuals in San Francisco, CA, in 2016. Therefore, one might be concerned about the accuracy of our skill mismatch measure in smaller cities. In Appendix Table A11, we restrict the sample to the top 100 MSAs in terms of online job postings per capita, and find very similar results.

### Alternative Definition of Skill Mismatch

In our baseline definition of skill mismatch, we use employment shares (2) to determine how well an occupation "matches" a particular college major. However, employment shares may be a poor measure of major-occupation fit in certain cases. As an example, consider history majors. Although not shown in Appendix Table A8, the fifth most common occupation for individuals with this major is "Retail salespersons and sales clerks." Arguably, this is not because history majors possess skills that are essential for a sales clerk position, but probably simply reflects the fact that many of them end up in low-skill jobs.

To address this concern, we construct an alternative measure of skill mismatch in which employment shares are replaced with a different notion of major-occupation fit: college major wage premiums by occupation. For each occupation, we regress log hourly wages of college-educated workers currently employed in that occupation on demographic controls and college major fixed effects.[19] The estimated college major fixed effects then serve as a proxy for how "valuable" the set of skills embedded in college majors are in a specific occupation. We borrow this idea from Liu et al. (2016), who use an analogous procedure to assess the fit between college majors and industries. Skill mismatch is then defined as in equation (1) except that the match between college majors and occupations is given by wage premiums instead of employment shares:

$$\widetilde{\text{match}}(\text{major}_m, \text{occ}_k) = \text{wage premium}(\text{major}_m)|\text{occ}_k \tag{7}$$

The rationale is that occupations associated with large wage premiums are a good fit for a particular college major. Coming back to the example above, while the 4-digit SOC code 4120 encompassing sales clerks ranks 12th in terms of employment shares among history majors, it only ranks 81st in terms of wage premiums (out of 109 4-digit SOC occupations). While college major wage premiums capture something distinct from employment shares, they are nonetheless positively correlated with one another, as we would expect. As a result, the baseline and alternative measures of skill mismatch are also positively correlated (correlation coefficient of 0.29). This is illustrated graphically in Appendix Figure A5, which plots average skill mismatch by college major under both definitions, separately by year.

Appendix Table A13 shows the main results using the alternative measure of skill mismatch. Although the magnitude of the estimates differs—in part because a one standard deviation increase in skill mismatch has a different interpretation under this alternative definition—the basic patterns are the same: there are negative persistent effects on wages, the probability of being employed and the probability of being employed in one of the top occupations by college major.

**Endogenous Migration**

As mentioned in Section 2.2, one of the main drawback of using the ACS is that it contains little information about past location. As a result, we must impute individuals' MSA at graduation using the MSA they currently reside in. This could potentially be a poor approximation, especially for individuals several years out of college. Moreover, this raises the concern that we might be overstating the impact of skill mismatch if individuals endogenously sort into MSAs.

[19] As with employment shares, we restrict the sample to individuals aged 32 or older to avoid any mechanical correlation between the outcomes and our measure of skill mismatch. Moreover, for each occupation, we convert the corresponding major wage premiums into "shares" (by normalizing them by the sum of all wage premiums), to account for the fact that certain jobs tend to pay more on average. This normalization has no bearing on the results.

We try to mitigate this concern in three different ways. First, we can simply focus on individuals with 1 year of potential experience, excluding those who migrated from a different state in the last year. For this subpopulation, we can at least be confident that we are accurately estimating the short-term effects of skill mismatch. The estimates in Appendix Table A14 are quite close to the corresponding estimates in the first rows of Tables 4-6, with the exception of part-time employment and employment in non-college occupations, which are smaller and statistically insignificant.

Alternatively, following others (e.g., Charles et al., forthcoming), we can restrict the sample to individuals born in the state they currently reside in, for which mobility is probably less of a concern. Incidentally, this restriction also excludes foreign-born college graduates who exhibit higher mobility rates, presumably because they have fewer social ties to specific areas. The resulting estimates in Appendix Table A15 reveal slightly smaller effects but broadly similar patterns. For example, the wage coefficient for 5-6 years of potential experience is half as large as the corresponding baseline estimate in Table 6, but still statistically significant. On the other hand, the effects on major-occupation fit are not persistent for this subpopulation.

Finally, we can use states instead of MSAs as the unit of geography, which at least addresses the threat within-state cross-MSA migration. This comes at the price of less cross-sectional variation in skill mismatch, but a slightly larger sample size since we can include individuals who do not live in MSAs. Appendix Table A16 shows the resulting estimates, which are remarkably similar to the baseline estimates.

**Exploiting Time Variation in Skill Mismatch**

Our main regression specification (3) features MSA-cohort fixed effects, which control for location-specific factors common across college majors, as well as major-cohort fixed effects, which control for major-specific factors common across MSAs. In principle, we could also include major-MSA fixed effects to control for time invariant location-major-specific factors. For example, certain schools might have a better track record at producing certain kinds of majors than other schools, due to the quality of instruction or the quality of research facilities. In turn, if local employers tend to heavily hire—and therefore advertise for—graduates from these fields, this would push us towards finding that low skill mismatch is associated with better outcomes. By "saturating" the regression with major-MSA fixed effects, identification of the main effects relies heavily on within-MSA variation in skill mismatch across cohorts.

The resulting estimates for log wages are shown in column (4) of Table 10, and show *positive* but statistically insignificant coefficients. The estimates for the other outcomes are also small and insignificant (not shown). The results are however fully robust to the inclusion of major-state fixed effects and major group-MSA fixed effects, as can be seen from column (3). In contrast to the saturated regression, this specification still exploits cross-sectional variation, both within-MSA across college majors belonging to the same major group and within-major across MSAs in the same state.

In light of these results, one might therefore be tempted to conclude that the main results presented in Section 4 are simply driven by cross-sectional variation in the quality of college majors. However, there are two reasons why time variation in the occupational composition of online job postings is hard to interpret and potentially misleading. First, the sophisticated algorithm used by Burning Glass to scrape job ads from various online sources is being constantly improved. In particular, it is getting better at capturing low-skill jobs, creating a spurious shift in the composition of online job postings. Second, and more importantly, the extent to which various sectors of the economy hire workers online has also changed over time. Consider the transportation and warehousing industry. Table 1 shows that the share of online job postings in Burning Glass for this industry has tripled over the last few years, from 3.78 percent in 2010 to 10.88 percent in 2016. In contrast, the corresponding share of job openings in JOLTS has only increased from 2.74 percent to 3.55 percent over the same period. This can also been seen in Table 2, where the shares of online job postings for transportation and material moving occupations has risen from 3.95 percent to 10.45 percent between 2010 and 2016, while employment in these occupations has been relatively stable in the ACS at around 6 percent. Therefore, the sharp rise of transportation jobs in Burning Glass probably reflects a shift in the way this industry hires new workers, rather than a real shift in labor demand.

Addressing the representativeness of Burning Glass over time is a challenging task. Following Şahin et al. (2014), one option is to assume that the industry composition of job openings in JOLTS reflects the true composition of job openings in the economy and adjust the composition of online job postings in Burning Glass accordingly. For each industry-year pair $(j, t)$, we compute the JOLTS adjustment factor which equalizes the industry composition in JOLTS and Burning Glass:

$$\text{share of job openings}_t^{\text{JOLTS}}(\text{ind}_j) = \text{JOLTS adjustment}_{jt} \times \text{share of job postings}_t^{\text{BGT}}(\text{ind}_j) \tag{8}$$

We can then scale the MSA-year-specific occupational shares in the definition of skill mismatch (1) by first computing shares at the occupation-industry level, scaling them by the industry-specific JOLTS adjustment factor, and summing over all industries for each occupation $k$:

$$\widetilde{\text{share of job postings}}_{\ell t}^{\text{BGT}}(\text{occ}_k) = \sum_j \text{share of job postings}_{\ell t}^{\text{BGT}}(\text{occ}_{kj}) \times \text{JOLTS adjustment}_{jt} \tag{9}$$

To get a sense of what this adjustment does, the last three columns in Table 2 display the JOLTS-adjusted occupational composition of online job postings in Burning Glass, i.e. equation (9) where occupation-industry shares are computed at the national rather than MSA level. While it is impossible to know the true occupational composition of job openings, the JOLTS-adjusted shares do get closer to employment shares in the ACS on average, although not for every occupation (e.g. "Office and Administrative Support Occupations").

Columns (5) and (6) in Table 10 show the regression results for log wages using this JOLTS-adjusted measure of skill mismatch, respectively without and with major-MSA fixed effects. The estimates are extremely similar to the corresponding estimates in columns (1) and (4). This is perhaps not so surprising given that we include major-cohort fixed effects, which effectively account for the fact that some majors tend to have lower skill mismatch than others on average due to the occupational composition of job postings in Burning Glass. Therefore, a national-level adjustment is unlikely to make much of a difference.

In principle, we could do a finer adjustment if JOLTS data was available at an MSA level.[20] However, the fundamental problem is that the adjustment can only be done at the industry level. The simple example in Appendix Table A17 illustrates why. Suppose that there are only two industries in the economy: IT and construction. Within IT, there are two types of jobs: software developers and database administrators. Similarly, within construction, the two types of jobs are construction managers and construction workers. For simplicity, suppose that there are 100 job openings in the economy in 2010, distributed according to column (4). The number of job openings increases to 120 in 2016, but the increase is proportional across jobs so that the composition of job openings in column (5) stays unchanged. Columns (6) and (7) show the corresponding number and composition of job postings in Burning Glass, where differences stem from the fact that not all jobs are posted online and the fact that IT and high-skill jobs are overrepresented in Burning Glass. However, between 2010 and 2016, the composition of jobs in Burning Glass shifts from IT towards construction, and from construction managers towards construction workers (within the construction sector). Based on column (7), one would conclude that labor demand has shifted away from IT, with a particularly strong increase in the demand for construction workers. Of course, these changes are spurious and simply reflect changes in the extent to which different industries hire workers online as well as improvements in Burning Glass' data collection technology.

The question now is whether an industry-level adjustment can solve this issue. Columns (8)-(12) apply the JOLTS adjustment as described above, again assuming that JOLTS perfectly captures job openings in the economy. The are two things to notice from the resulting JOLTS-adjusted shares in column (13). First, because the relative representativeness of software developers versus database administrators in Burning Glass has not changed over time, the JOLTS-adjusted shares are accurate for those two jobs. However, because this is not the case for construction managers versus construction workers, the shares for those two jobs are still off in both periods, even though their sum is now correct. Therefore, based on the JOLTS-adjusted shares we would still conclude that labor demand has shifted away from construction managers towards construction workers. This illustrates the fundamental challenge in trying to exploit time variation in the occupational composition of online job postings, and why we should perhaps not put too much stock in the estimates in Table 10 that try to do that.

[20] The lowest level of geography in JOLTS is Census regions, but they are not available at the industry level (at least in the public data).

## 5 Discussion

In this section, we discuss what our findings imply for models of career dynamics. Two alternative mechanisms are often proposed as potential explanations for the presence of persistent wage effects in response to poor initial labor market conditions. The first class of models are job search models in which workers continuously make draws from some underlying wage distribution, slowly climbing the job ladder by obtaining better jobs. As argued in Oreopoulos et al. (2012), in order to generate persistent wage effects in response to a temporary deterioration in the wage distribution, the basic framework needs to be augmented with job mobility costs that are increasing with age or tenure. Assuming the existence of such costs, workers who start their career in worse jobs are at risk of being stuck at the bottom of the job ladder as time goes by. Mobility costs that are increasing with age can originate from several sources, including firm-specific human capital and family-related constraints. Oreopoulos et al. (2012) argue that a search model along those line is consistent with their findings, in particular the fact that part of the recovery process takes the form of mobility from lower towards higher-quality employers, especially for college graduates with high predicted earnings.

The second class of models are models of human capital accumulation, in which wage growth over the life cycle stems from the accumulation productivity-enhancing human capital over time, either at the firm, industry or occupation level. In those models, differential career paths as a function of initial labor market conditions can be attributed to starting jobs with differential opportunities for human capital accumulation, with lower-level jobs implicitly associated with lower rates of human capital accumulation.

Since we do not have longitudinal data on workers, we cannot directly explore how much of our effects are driven by job (im)mobility and thereby provide direct evidence in favor of (or against) the job search hypothesis in the context of skill mismatch. Nevertheless, we argue that the human capital story offers a simple and intuitive explanation for our findings. In particular, it is consistent with one piece of evidence we have documented: namely the impact of skill mismatch on major-occupation fit. We posit that college majors are associated with a certain mix of skills and that different occupations make use of those skills with different intensities. Human capital accumulation is then a function of how well those skills are exploited on the job.[21] Therefore, to the extent that major-occupation fit is an indicator of how well skills acquired in school are exploited in a certain occupation, then the fact that skill mismatch has a negative effect on initial major-occupation fit would seem to support this hypothesis. Our finding that skill mismatch experienced in the year of graduation seems to be crucial is also consistent with this story. The importance of starting jobs for subsequent wage growth has been emphasized by Devereux (2002), and Kinsler and Pavan (2015) have shown that working in an occupation related to one's major is associated with a significant wage premium. Moreover, as mentioned in the introduction, Liu et al. (2016) find that initial major-industry fit can explain a large portion of the long-term im-

[21] One could also imagine that skills depreciate over time if unused. This basic premise is similar to the one in Lise and Postel-Vinay (2016).

pact of recessions among Norwegian college graduates. Shedding further light on this particular mechanism is something we are exploring in ongoing work.[22]

Before concluding, we end with a brief policy note. Our findings provide useful insights in the context of initiatives geared towards helping students make more informed college major choices. In recent years, policymakers have made efforts to increase transparency in higher education by making data available to the public on cost and performance metrics of higher education institutions. A prominent example is the U.S. Department of Educations College Scorecard, which provides information on tuition costs, financial aid, graduation rates, and earnings of past students for nearly every college or university in the United States. Concurrently, a literature has emerged exploring the effectiveness of these kinds of initiatives, particularly when it comes to college major decisions (Hastings et al., 2015; Wiswall and Zafar, 2015b; Baker et al., 2017). Our findings on the effect of skill mismatch illustrate that what matters for future labor market prospects is the interaction of field of study *and* location. Therefore, average earnings by college major should be made available at subnational levels if possible for maximum informativeness.

## 6 Conclusion

A number of recent studies have documented the persistent effects of graduating from college during times of high unemployment, and how these effects vary across graduates from different fields of study. In this paper, we explore a related question: how do skill-specific initial labor market conditions affect early career outcomes of college graduates? Exploiting data on the near-universe of online job postings in the U.S. between since 2010, we construct a new measure of skill mismatch which captures how well the skills that are embedded in college majors match the skills that are demanded by local employers in a given city and given year. Intuitively, college graduates with a specific major experience skill mismatch when only a small fraction of job openings in their local labor market are suitable for their major in the year that they graduate. Conceptually, this additional layer of variation implicitly allows us to compare individuals who faced the same overall labor market conditions, but whose skills were more or less in demand when they graduated.

We find that skill mismatch leads to worse initial outcomes for college graduates: they are more likely to be unemployed or employed in a part-time job, less likely to be employed in a college occupation, less likely to be employed in one of the top occupations for their college major, and they earn lower wages. While the effects on unemployment, part-time employment and employment in college occupations gradually fade over time, the effects on wages and major-occupation fit persist up to 6 years after graduation. These medium-run effects are substantial: a one standard deviation increase in initial skill mismatch leads to a 1.6% point decline in the probability of being employed in one of the top 5 occupations by college major and a 2.6% decline in hourly

[22]One promising direction is to further investigate heterogeneity in the effect of skill mismatch across college majors, as major-specific human capital accumulation may be more important for some majors than others.

wages, 6 years after graduation. This contrasts with the effects of overall unemployment rates at graduation—the focus of past studies—which completely dissipate within 4 years of graduation in our sample.

Our findings highlight the importance of having the right skills in the right place at the right time. In particular, the persistent effects on major-occupation fit, combined with the fact that initial skill mismatch seems to matter more for wages than skill mismatch experienced in subsequent years, suggest that early career human capital accumulation is a key determinant of college graduates' long-term career path. From a policy perspective, our findings suggest that efforts to inform students' college major choices should keep in mind the interaction between college majors and locations.

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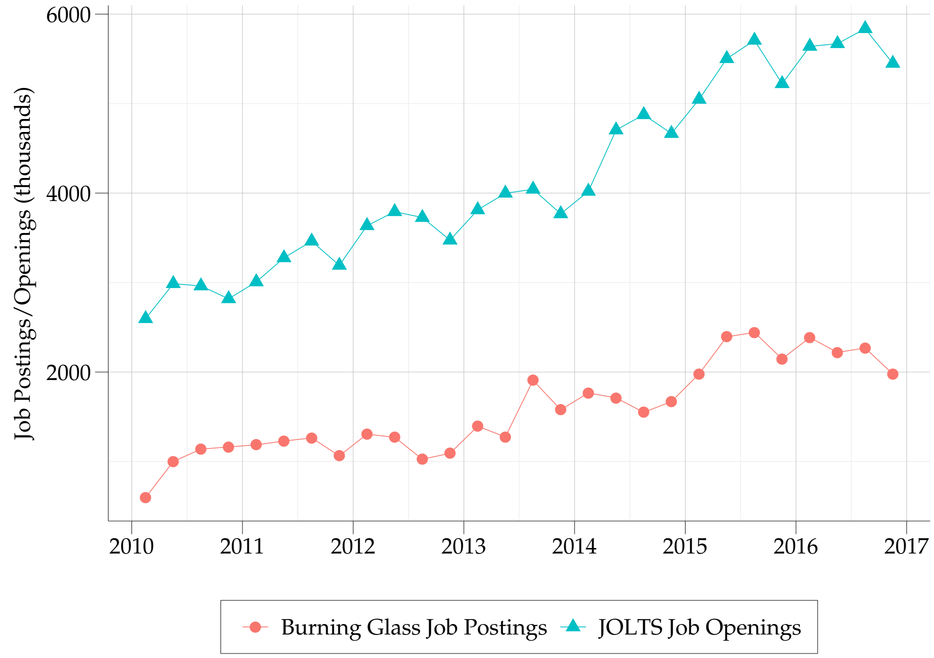
Figure 1 — Quarterly Job Postings/Openings: JOLTS vs. Burning Glass, 2010-2016

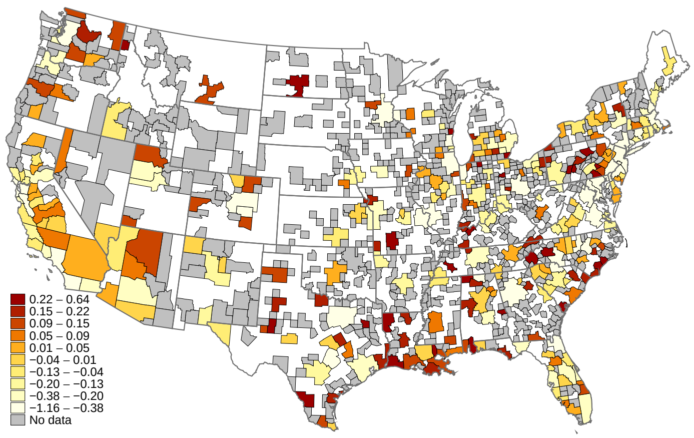



*Notes:* Monthly job posting and job opening counts are averaged by quarter.

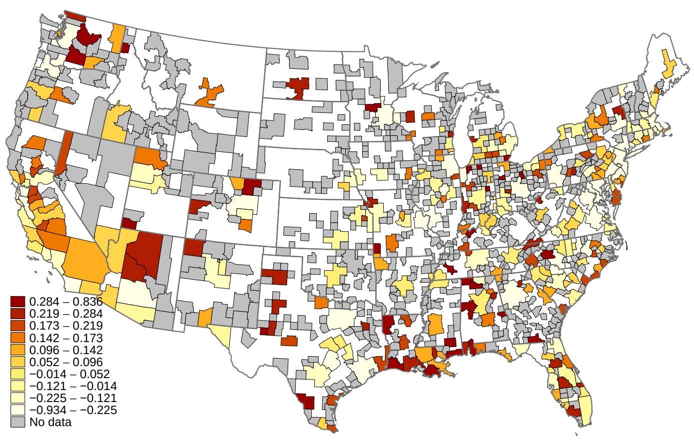
*Source:* Job Openings and Labor Turnover Survey, Burning Glass Technologies.

Figure 2 — Average Skill Mismatch By MSA, 2010-2016

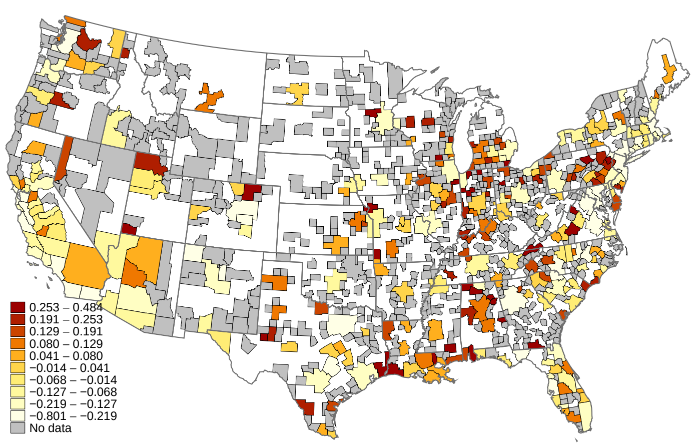
Panel A: 2010




Panel B: 2013



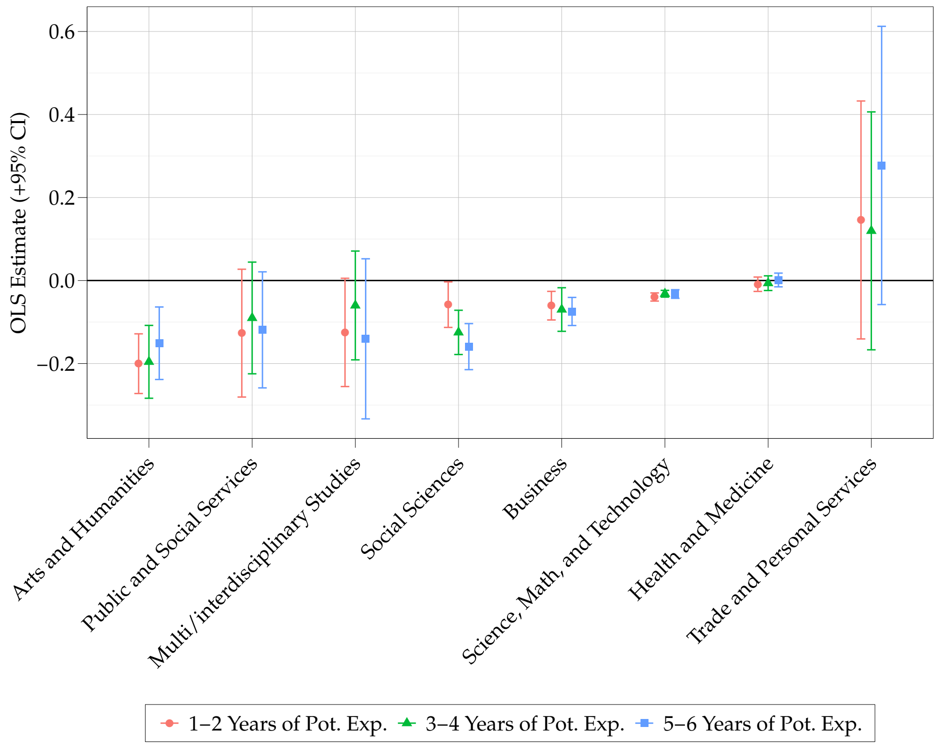

Panel C: 2016




*Notes:* Each map plots skill mismatch averaged across college majors (unweighted) for each of the 294 MSAs in the ACS, organized into year-specific deciles.

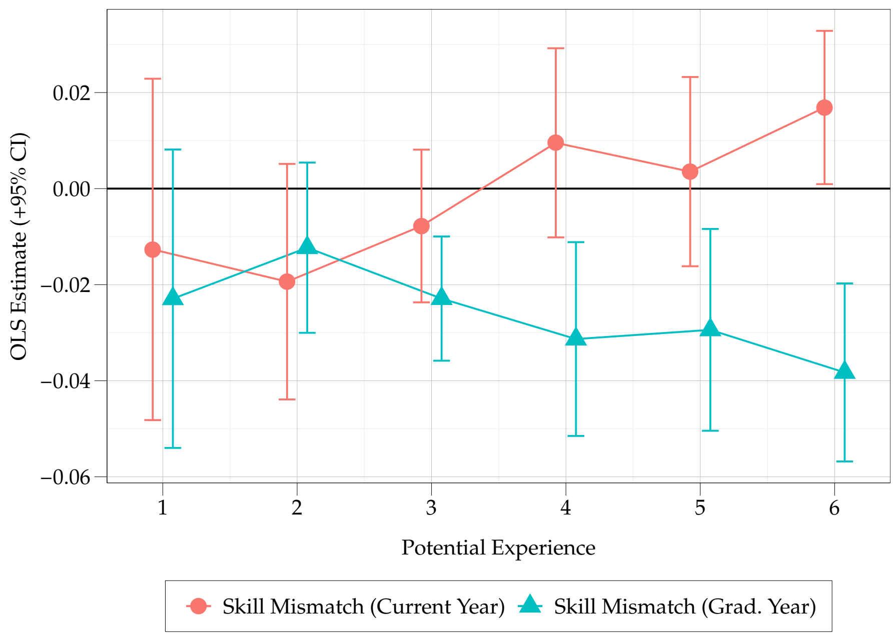
*Source:* American Community Survey, Burning Glass Technologies.

Figure 3 — The Effect of Skill Mismatch on Wages: Heterogeneity By College Major Group



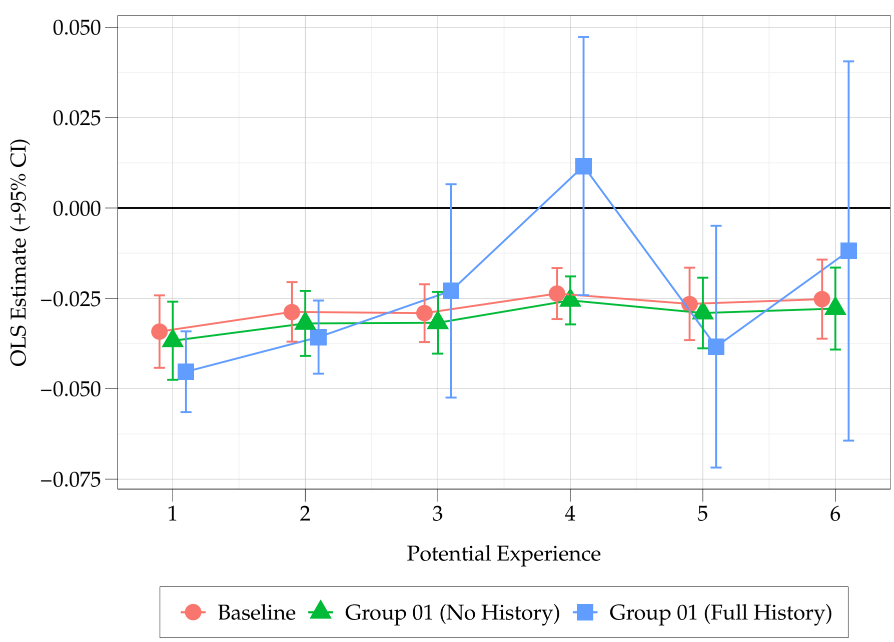

*Notes:* Each dot/triangle/square represents the OLS coefficient corresponding to the interaction between skill mismatch, a potential experience group (see legend) and one of the eight college major groups ($x$-axis) in regression (3) where the dependent variable is log hourly wage. The vertical error bars represent the corresponding 95% confidence intervals.

Figure 4 — The Effect of Skill Mismatch on Wages: Current vs. Graduation Year




*Notes:* Each dot/triangle represents the OLS coefficient corresponding to the interaction between skill mismatch in current or graduation year (see legend) and a potential experience dummy ($x$-axis) in regression (4) where the dependent variable is log hourly wage. The vertical error bars represent the corresponding 95% confidence intervals.

Figure 5 — The Effect of Skill Mismatch on Wages: Baseline vs. Full History




*Notes:* Each dot/triangle/square represents the OLS coefficient corresponding to the interaction between skill mismatch and a potential experience dummy ($x$-axis) in regression (3) or (5) (see legend) where the dependent variable is log hourly wage. The vertical error bars represent the corresponding 95% confidence intervals.

Table 1 — Industry Composition: JOLTS vs. Burning Glass, 2010-2016

| | Job opening/job posting shares (%) | | | | | |
|---|---|---|---|---|---|---|
| | JOLTS | | | Burning Glass | | |
| JOLTS industry | 2010 | 2013 | 2016 | 2010 | 2013 | 2016 |
| Mining and Logging | 0.57 | 0.51 | 0.22 | 0.72 | 0.59 | 0.23 |
| Construction | 2.53 | 3.01 | 3.36 | 0.91 | 1.15 | 1.24 |
| Manufacturing | 6.49 | 6.75 | 6.05 | 9.41 | 9.58 | 8.26 |
| Wholesale Trade | 2.91 | 3.30 | 3.26 | 0.98 | 1.08 | 0.82 |
| Retail Trade | 9.26 | 11.65 | 10.98 | 9.66 | 12.13 | 11.27 |
| Transportation, Warehousing and Utilities | 2.74 | 3.49 | 3.55 | 3.78 | 4.98 | 10.88 |
| Information | 2.76 | 2.46 | 1.49 | 4.40 | 3.87 | 3.54 |
| Finance and Insurance | 6.20 | 5.63 | 4.43 | 9.51 | 9.53 | 8.69 |
| Real Estate and Rental and Leasing | 1.13 | 1.43 | 1.37 | 3.31 | 2.42 | 1.88 |
| Professional and Business Services | 18.79 | 17.70 | 19.63 | 18.95 | 15.67 | 14.61 |
| Educational Services | 2.00 | 1.70 | 1.75 | 5.02 | 5.90 | 4.44 |
| Health Care and Social Assistance | 16.80 | 15.57 | 17.69 | 21.54 | 19.35 | 22.00 |
| Arts, Entertainment, and Recreation | 1.18 | 1.55 | 1.50 | 0.84 | 0.95 | 0.74 |
| Accommodation and Food Services | 8.76 | 11.55 | 11.79 | 5.99 | 7.40 | 7.44 |
| Other Services | 4.76 | 3.71 | 3.74 | 2.14 | 2.46 | 1.73 |
| Government | 13.12 | 9.99 | 9.19 | 2.84 | 2.94 | 2.22 |

*Notes:* Job postings belonging to the industry "Agriculture, Forestry, Fishing and Hunting" (NAICS code 11) are excluded from the Burning Glass sample before computing industry shares in this table since JOLTS does not cover agricultural establishments.

*Source:* Job Openings and Labor Turnover Survey, Burning Glass Technologies.

Table 2 — Occupational Composition: American Community Survey vs. Burning Glass, 2010-2016

| | | Employment/job posting shares (%) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | ACS | | | Burning Glass | | | Burning Glass (JOLTS-adjusted) | | |
| SOC code | SOC occupation group | 2010 | 2013 | 2016 | 2010 | 2013 | 2016 | 2010 | 2013 | 2016 |
| 11-0000 | Management Occupations | 9.67 | 9.82 | 10.30 | 12.00 | 11.40 | 9.90 | 12.16 | 11.28 | 10.13 |
| 13-0000 | Business and Financial Operations Occupations | 4.67 | 4.80 | 4.85 | 7.45 | 7.50 | 6.97 | 7.01 | 6.57 | 6.08 |
| 15-0000 | Computer and Mathematical Occupations | 2.47 | 2.67 | 2.96 | 14.58 | 11.58 | 10.00 | 12.01 | 9.40 | 8.28 |
| 17-0000 | Architecture and Engineering Occupations | 1.81 | 1.84 | 1.84 | 3.10 | 3.05 | 2.44 | 3.04 | 2.87 | 2.35 |
| 19-0000 | Life, Physical, and Social Science Occupations | 0.88 | 0.86 | 0.88 | 1.12 | 1.03 | 0.99 | 1.40 | 1.11 | 1.11 |
| 21-0000 | Community and Social Service Occupations | 1.70 | 1.64 | 1.74 | 1.06 | 1.12 | 1.01 | 1.38 | 1.26 | 1.17 |
| 23-0000 | Legal Occupations | 1.18 | 1.16 | 1.12 | 1.00 | 1.23 | 0.54 | 0.98 | 1.38 | 0.67 |
| 25-0000 | Education, Training, and Library Occupations | 6.24 | 6.08 | 5.98 | 1.96 | 2.58 | 2.21 | 1.51 | 1.48 | 1.58 |
| 27-0000 | Arts, Design, Entertainment, Sports, and Media Occupations | 1.87 | 1.92 | 2.01 | 2.64 | 2.90 | 2.29 | 2.37 | 2.64 | 2.19 |
| 29-0000 | Healthcare Practitioners and Technical Occupations | 5.50 | 5.60 | 5.97 | 12.32 | 9.78 | 13.95 | 13.18 | 10.43 | 14.26 |
| 31-0000 | Healthcare Support Occupations | 2.51 | 2.59 | 2.34 | 2.48 | 2.04 | 2.13 | 2.54 | 2.04 | 2.07 |
| 33-0000 | Protective Service Occupations | 2.25 | 2.21 | 2.08 | 0.91 | 1.02 | 1.11 | 1.59 | 1.61 | 1.93 |
| 35-0000 | Food Preparation and Serving Related Occupations | 5.68 | 5.84 | 5.89 | 3.26 | 4.45 | 4.31 | 5.30 | 7.68 | 7.50 |
| 37-0000 | Building and Grounds Cleaning and Maintenance Occupations | 4.00 | 4.02 | 3.93 | 1.09 | 1.19 | 1.08 | 1.21 | 1.40 | 1.48 |
| 39-0000 | Personal Care and Service Occupations | 3.58 | 3.72 | 3.77 | 1.60 | 2.44 | 1.30 | 2.02 | 2.89 | 1.81 |
| 41-0000 | Sales and Related Occupations | 11.08 | 10.82 | 10.49 | 12.78 | 13.22 | 12.16 | 12.66 | 13.76 | 13.29 |
| 43-0000 | Office and Administrative Support Occupations | 13.91 | 13.36 | 12.83 | 10.61 | 11.67 | 10.83 | 9.68 | 10.47 | 10.20 |
| 45-0000 | Farming, Fishing, and Forestry Occupations | 0.73 | 0.70 | 0.68 | 0.05 | 0.07 | 0.06 | 0.04 | 0.06 | 0.07 |
| 47-0000 | Construction and Extraction Occupations | 5.06 | 4.99 | 5.03 | 1.00 | 1.07 | 1.03 | 1.16 | 1.35 | 1.52 |
| 49-0000 | Installation, Maintenance, and Repair Occupations | 3.30 | 3.20 | 3.09 | 2.78 | 3.04 | 2.75 | 3.12 | 3.44 | 3.42 |
| 51-0000 | Production Occupations | 5.91 | 6.01 | 5.79 | 2.24 | 2.69 | 2.49 | 2.04 | 2.29 | 2.38 |
| 53-0000 | Transportation and Material Moving Occupations | 6.01 | 6.15 | 6.42 | 3.95 | 4.94 | 10.45 | 3.53 | 4.61 | 6.31 |

*Notes:* ACS employment shares are based on all individuals aged 16 or older. JOLTS-adjusted job posting shares are calculated according to (9), using occupation-industry shares at the national rather than MSA level. Job postings belonging to the industry "Agriculture, Forestry, Fishing and Hunting" (NAICS code 11) are excluded from the Burning Glass sample before computing JOLTS-adjusted occupational shares in this table since JOLTS does not cover agricultural establishments.

*Source:* American Community Survey, Burning Glass Technologies.

Table 3 — Average Skill Mismatch by College Major, 2010-2016

| | Average skill mismatch | | | | | | | | | Average skill mismatch | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| College major | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2010-16 | College major | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2010-16 |
| Nursing | -5.33 | -4.13 | -3.90 | -3.00 | -3.41 | -5.34 | -6.13 | -4.46 | Sociology | 0.15 | 0.17 | 0.17 | 0.19 | 0.18 | 0.15 | 0.18 | 0.17 |
| Medical and health services | -2.27 | -1.78 | -1.66 | -1.26 | -1.39 | -2.26 | -2.57 | -1.88 | All other social sciences | 0.17 | 0.16 | 0.16 | 0.20 | 0.20 | 0.16 | 0.20 | 0.18 |
| Computer science and IT | -1.93 | -2.18 | -2.27 | -1.62 | -1.42 | -1.74 | -1.25 | -1.77 | Agricultural sciences | 0.19 | 0.13 | 0.20 | 0.20 | 0.22 | 0.20 | 0.22 | 0.19 |
| Medical support | -1.25 | -0.99 | -1.12 | -0.76 | -0.79 | -1.18 | -1.27 | -1.05 | Public administration | 0.18 | 0.14 | 0.14 | 0.20 | 0.24 | 0.20 | 0.27 | 0.20 |
| Physics | -0.60 | -0.76 | -0.80 | -0.45 | -0.35 | -0.51 | -0.26 | -0.53 | Family and consumer sciences | 0.20 | 0.23 | 0.24 | 0.20 | 0.17 | 0.18 | 0.18 | 0.20 |
| Mathematics | -0.47 | -0.59 | -0.64 | -0.37 | -0.29 | -0.42 | -0.20 | -0.42 | Human resources | 0.22 | 0.16 | 0.15 | 0.19 | 0.24 | 0.20 | 0.27 | 0.21 |
| Electrical engineering | -0.44 | -0.63 | -0.66 | -0.30 | -0.19 | -0.33 | -0.06 | -0.37 | Social work | 0.17 | 0.23 | 0.22 | 0.25 | 0.23 | 0.17 | 0.18 | 0.21 |
| Multidisciplinary or general science | -0.39 | -0.32 | -0.30 | -0.18 | -0.20 | -0.38 | -0.39 | -0.31 | History | 0.24 | 0.21 | 0.23 | 0.22 | 0.23 | 0.23 | 0.26 | 0.23 |
| Biological sciences | -0.35 | -0.26 | -0.25 | -0.09 | -0.11 | -0.31 | -0.33 | -0.24 | Area, ethnic, and civilization studies | 0.22 | 0.22 | 0.22 | 0.25 | 0.26 | 0.24 | 0.28 | 0.24 |
| All other engineering | -0.28 | -0.44 | -0.46 | -0.18 | -0.10 | -0.21 | 0.00 | -0.24 | Linguistics | 0.26 | 0.27 | 0.26 | 0.27 | 0.26 | 0.25 | 0.28 | 0.26 |
| Engineering technologies | -0.23 | -0.36 | -0.38 | -0.15 | -0.09 | -0.18 | -0.01 | -0.20 | Fine arts | 0.27 | 0.30 | 0.30 | 0.24 | 0.21 | 0.26 | 0.31 | 0.27 |
| Fitness, nutrition, and leisure | -0.25 | -0.16 | -0.10 | -0.07 | -0.12 | -0.25 | -0.31 | -0.18 | English literature | 0.30 | 0.30 | 0.30 | 0.30 | 0.31 | 0.30 | 0.34 | 0.31 |
| Accounting | -0.16 | -0.25 | -0.29 | -0.27 | -0.03 | -0.18 | 0.00 | -0.17 | All other physical sciences | 0.32 | 0.25 | 0.24 | 0.36 | 0.39 | 0.34 | 0.42 | 0.33 |
| Marketing | -0.22 | -0.24 | -0.18 | -0.18 | -0.14 | -0.11 | -0.04 | -0.16 | Journalism | 0.34 | 0.34 | 0.35 | 0.36 | 0.39 | 0.39 | 0.45 | 0.37 |
| General business | -0.15 | -0.20 | -0.16 | -0.14 | -0.08 | -0.11 | -0.02 | -0.12 | Film and visual arts | 0.40 | 0.42 | 0.41 | 0.37 | 0.35 | 0.39 | 0.44 | 0.40 |
| Business mgmt and administration | -0.10 | -0.16 | -0.14 | -0.10 | -0.02 | -0.06 | 0.03 | -0.08 | Music and drama | 0.45 | 0.45 | 0.44 | 0.42 | 0.42 | 0.44 | 0.48 | 0.44 |
| Economics | -0.10 | -0.17 | -0.15 | -0.10 | -0.01 | -0.06 | 0.05 | -0.08 | Environmental studies | 0.44 | 0.40 | 0.41 | 0.47 | 0.48 | 0.45 | 0.50 | 0.45 |
| Finance | -0.06 | -0.15 | -0.14 | -0.10 | 0.06 | -0.02 | 0.11 | -0.04 | Civil engineering | 0.46 | 0.31 | 0.33 | 0.48 | 0.54 | 0.49 | 0.61 | 0.46 |
| Psychology | -0.07 | -0.01 | 0.00 | 0.07 | 0.05 | -0.06 | -0.06 | -0.01 | Philosophy and religion | 0.51 | 0.49 | 0.50 | 0.51 | 0.50 | 0.46 | 0.48 | 0.49 |
| All other business | 0.01 | -0.04 | -0.01 | 0.01 | 0.07 | 0.06 | 0.13 | 0.03 | Hospitality | 0.51 | 0.49 | 0.59 | 0.46 | 0.47 | 0.58 | 0.50 | 0.51 |
| Chemistry | 0.05 | 0.03 | 0.03 | 0.16 | 0.18 | 0.10 | 0.16 | 0.10 | Legal studies | 0.52 | 0.51 | 0.50 | 0.49 | 0.54 | 0.54 | 0.58 | 0.53 |
| Communications | 0.07 | 0.06 | 0.09 | 0.11 | 0.13 | 0.12 | 0.17 | 0.11 | All other education | 0.63 | 0.63 | 0.61 | 0.53 | 0.45 | 0.52 | 0.47 | 0.55 |
| Mechanical engineering | 0.09 | -0.08 | -0.08 | 0.15 | 0.21 | 0.17 | 0.33 | 0.11 | General education | 0.66 | 0.67 | 0.65 | 0.55 | 0.45 | 0.55 | 0.49 | 0.57 |
| International relations | 0.09 | 0.05 | 0.06 | 0.12 | 0.17 | 0.13 | 0.22 | 0.12 | Criminal justice and fire protection | 0.61 | 0.58 | 0.58 | 0.59 | 0.59 | 0.56 | 0.58 | 0.58 |
| Political science | 0.12 | 0.08 | 0.10 | 0.13 | 0.16 | 0.14 | 0.21 | 0.13 | Precision production and industrial arts | 0.63 | 0.54 | 0.58 | 0.61 | 0.63 | 0.62 | 0.65 | 0.61 |
| Liberal arts and humanities | 0.14 | 0.15 | 0.16 | 0.14 | 0.13 | 0.12 | 0.14 | 0.14 | Elementary education | 0.81 | 0.82 | 0.78 | 0.66 | 0.54 | 0.68 | 0.60 | 0.70 |
| Chemical engineering | 0.11 | -0.01 | -0.01 | 0.18 | 0.25 | 0.20 | 0.34 | 0.15 | Architecture | 0.78 | 0.75 | 0.76 | 0.75 | 0.76 | 0.77 | 0.82 | 0.77 |
| Commercial art and graphic design | 0.16 | 0.21 | 0.19 | 0.09 | 0.05 | 0.17 | 0.25 | 0.16 | Library science | 0.84 | 0.83 | 0.83 | 0.83 | 0.83 | 0.83 | 0.89 | 0.84 |
| Total | -0.04 | -0.04 | -0.03 | 0.05 | 0.07 | -0.02 | 0.02 | 0 | Total | -0.04 | -0.04 | -0.03 | 0.05 | 0.07 | -0.02 | 0.02 | 0 |

*Notes:* Skill mismatch is defined according to equation (1), and normalized to have a mean of zero and standard deviation of one (across all college majors, MSAs and years). This table shows average skill mismatch, separately by college major and by year.

Table 4 — The Effect of Skill Mismatch on Employment, Unemployment and Labor Force Participation

| | Dependent variable: | | | | |
|---|---|---|---|---|---|
| | Employed | | | | |
| | Any | Part-time | Full-time | Unemployed | Out of labor force |
| | (1) | (2) | (3) | (4) | (5) |
| Skill mismatch × 1-2 years of potential exp. | -0.006*** | 0.008*** | -0.014*** | 0.004*** | 0.002 |
| | (0.001) | (0.002) | (0.002) | (0.001) | (0.001) |
| Skill mismatch × 3-4 years of potential exp. | -0.006*** | 0.003** | -0.008*** | 0.003*** | 0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Skill mismatch × 5-6 years of potential exp. | -0.008*** | 0.000 | -0.008*** | 0.002** | 0.005*** |
| | (0.001) | (0.002) | (0.002) | (0.001) | (0.001) |
| MSA × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ |
| College major × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ |
| Potential experience FEs | ✓ | ✓ | ✓ | ✓ | ✓ |
| Individual controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.061 | 0.052 | 0.074 | 0.031 | 0.072 |
| Observations | 162,508 | 162,508 | 162,508 | 162,508 | 162,508 |

*Notes:* Individual controls include an indicator for being female, race fixed effects (Hispanic, Black, Asian, other race), an indicator for being foreign-born, an indicator for having a Master's degree and an indicator for being a double major. Observations are weighted by Census sampling weights. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table 5 — The Effect of Skill Mismatch on Occupations

| | Dependent variable: | | | |
|---|---|---|---|---|
| | Employed in college/top 5/top 10 occupation | | | |
| | College (O*NET) | College (ACS) | Top 5 | Top 10 |
| | (1) | (2) | (3) | (4) |
| Skill mismatch × 1-2 years of potential exp. | -0.010*** | -0.008*** | -0.018*** | -0.017*** |
| | (0.002) | (0.002) | (0.003) | (0.004) |
| Skill mismatch × 3-4 years of potential exp. | -0.006*** | -0.005*** | -0.016*** | -0.016*** |
| | (0.002) | (0.002) | (0.004) | (0.004) |
| Skill mismatch × 5-6 years of potential exp. | -0.004** | -0.003* | -0.016*** | -0.018*** |
| | (0.002) | (0.002) | (0.005) | (0.004) |
| MSA × cohort FEs | ✓ | ✓ | ✓ | ✓ |
| College major × cohort FEs | ✓ | ✓ | ✓ | ✓ |
| Year FEs | ✓ | ✓ | ✓ | ✓ |
| Potential experience FEs | ✓ | ✓ | ✓ | ✓ |
| Individual controls | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.124 | 0.132 | 0.173 | 0.136 |
| Observations | 146,566 | 146,566 | 146,566 | 146,566 |

*Notes:* Sample excludes the non-employed. Individual controls include an indicator for being female, race fixed effects (Hispanic, Black, Asian, other race), an indicator for being foreign-born, an indicator for having a Master's degree and an indicator for being a double major. Observations are weighted by Census sampling weights. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table 6 — The Effect of Skill Mismatch on Earnings and Wages

| | Dependent variable: | |
|---|---|---|
| | Log annual income | Log hourly wage |
| | (1) | (2) |
| Skill mismatch × 1-2 years of potential exp. | -0.049*** | -0.031*** |
| | (0.005) | (0.004) |
| Skill mismatch × 3-4 years of potential exp. | -0.036*** | -0.027*** |
| | (0.005) | (0.004) |
| Skill mismatch × 5-6 years of potential exp. | -0.034*** | -0.026*** |
| | (0.006) | (0.005) |
| MSA × cohort FEs | ✓ | ✓ |
| College major × cohort FEs | ✓ | ✓ |
| Year FEs | ✓ | ✓ |
| Potential experience FEs | ✓ | ✓ |
| Individual controls | ✓ | ✓ |
| $R^2$ | 0.181 | 0.199 |
| Observations | 150,844 | 150,844 |

*Notes:* Sample excludes individuals with no wage income. Individual controls include an indicator for being female, race fixed effects (Hispanic, Black, Asian, other race), an indicator for being foreign-born, an indicator for having a Master's degree and an indicator for being a double major. Observations are weighted by Census sampling weights. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table 7 — The Effect of Skill Mismatch in Current vs. Graduation Year

| | Dependent variable: | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | Employed | | | Occupations | | | |
| | Log income | Log wage | Any | Part-time | Unemployed | College (O*NET) | College (ACS) | Top 5 | Top 10 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Skill mismatch (grad. year) × 1-2 years of potential exp. | -0.037** | -0.016* | -0.007 | 0.006 | 0.004 | -0.006 | -0.005 | -0.016** | -0.009 |
| | (0.017) | (0.009) | (0.004) | (0.004) | (0.002) | (0.006) | (0.006) | (0.007) | (0.006) |
| Skill mismatch (grad. year) × 3-4 years of potential exp. | -0.024*** | -0.027*** | -0.004 | -0.004 | 0.003* | 0.000 | 0.002 | -0.007 | -0.004 |
| | (0.006) | (0.006) | (0.003) | (0.003) | (0.001) | (0.005) | (0.005) | (0.005) | (0.005) |
| Skill mismatch (grad. year) × 5-6 years of potential exp. | -0.044*** | -0.033*** | -0.007** | 0.007 | -0.001 | -0.007 | -0.004 | -0.020*** | -0.019*** |
| | (0.012) | (0.009) | (0.003) | (0.005) | (0.002) | (0.004) | (0.004) | (0.007) | (0.006) |
| Skill mismatch (current year) × 1-2 years of potential exp. | -0.014 | -0.018 | 0.001 | 0.003 | 0.001 | -0.005 | -0.004 | -0.003 | -0.009 |
| | (0.021) | (0.012) | (0.004) | (0.005) | (0.002) | (0.007) | (0.007) | (0.009) | (0.008) |
| Skill mismatch (current year) × 3-4 years of potential exp. | -0.016* | -0.000 | -0.003 | 0.008*** | 0.000 | -0.008 | -0.009* | -0.010* | -0.014** |
| | (0.008) | (0.005) | (0.003) | (0.003) | (0.002) | (0.005) | (0.005) | (0.006) | (0.006) |
| Skill mismatch (current year) × 5-6 years of potential exp. | 0.012 | 0.008 | -0.001 | -0.009 | 0.004* | 0.003 | 0.000 | 0.005 | 0.001 |
| | (0.014) | (0.007) | (0.004) | (0.007) | (0.002) | (0.004) | (0.004) | (0.005) | (0.006) |
| MSA × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| College major × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Potential experience FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Individual controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.181 | 0.199 | 0.061 | 0.052 | 0.031 | 0.124 | 0.132 | 0.173 | 0.136 |
| Observations | 150,844 | 150,844 | 162,508 | 162,508 | 162,508 | 146,566 | 146,566 | 146,566 | 146,566 |

*Notes:* Individual controls include an indicator for being female, race fixed effects (Hispanic, Black, Asian, other race), an indicator for being foreign-born, an indicator for having a Master's degree and an indicator for being a double major. Observations are weighted by Census sampling weights. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table 8 — The Effect of Overall Unemployment Rates at the MSA Level in Graduation Year

| | Dependent variable: | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | Employed | | | Occupations | | | |
| | Log income | Log wage | Any | Part-time | Unemployed | College (O*NET) | College (ACS) | Top 5 | Top 10 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Unemployment rate (%) × | -0.024*** | -0.009** | -0.010*** | 0.005** | 0.005*** | -0.006** | -0.005* | -0.005 | -0.001 |
| 1-2 years of potential exp. | (0.007) | (0.004) | (0.002) | (0.002) | (0.001) | (0.003) | (0.003) | (0.004) | (0.003) |
| Unemployment rate (%) × | -0.014** | -0.008** | -0.005*** | 0.002 | 0.004** | -0.005** | -0.004 | -0.005 | -0.004 |
| 3-4 years of potential exp. | (0.005) | (0.004) | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) |
| Unemployment rate (%) × | -0.003 | -0.003 | -0.003 | -0.002 | 0.001 | -0.002 | -0.001 | -0.002 | -0.001 |
| 5-6 years of potential exp. | (0.005) | (0.004) | (0.002) | (0.002) | (0.001) | (0.002) | (0.003) | (0.004) | (0.003) |
| MSA FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| College major × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Potential experience FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Individual controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.169 | 0.187 | 0.050 | 0.040 | 0.020 | 0.112 | 0.120 | 0.164 | 0.126 |
| Observations | 140,041 | 140,041 | 151,104 | 151,104 | 151,104 | 136,092 | 136,092 | 136,092 | 136,092 |

*Notes:* Individual controls include an indicator for being female, race fixed effects (Hispanic, Black, Asian, other race), an indicator for being foreign-born, an indicator for having a Master's degree and an indicator for being a double major. Observations are weighted by Census sampling weights. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table 9 — The Effect of Skill Mismatch on Males vs. Females

| | Dependent variable: | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | Employed | | | Occupations | | | |
| | Log income | Log wage | Any | Part-time | Unemployed | College (O*NET) | College (ACS) | Top 5 | Top 10 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Panel A: Men | | | | | | | | | |
| Skill mismatch × | -0.054*** | -0.035*** | -0.008*** | 0.006*** | 0.005*** | -0.004 | -0.004 | -0.023*** | -0.018*** |
| 1-2 years of potential exp. | (0.006) | (0.005) | (0.002) | (0.002) | (0.001) | (0.004) | (0.004) | (0.004) | (0.004) |
| Skill mismatch × | -0.036*** | -0.030*** | -0.007*** | -0.001 | 0.003** | -0.001 | -0.000 | -0.020*** | -0.017*** |
| 3-4 years of potential exp. | (0.008) | (0.005) | (0.002) | (0.002) | (0.001) | (0.003) | (0.003) | (0.004) | (0.004) |
| Skill mismatch × | -0.032*** | -0.029*** | -0.005*** | -0.002 | 0.003** | -0.000 | 0.002 | -0.019*** | -0.017*** |
| 5-6 years of potential exp. | (0.008) | (0.006) | (0.002) | (0.002) | (0.001) | (0.003) | (0.003) | (0.004) | (0.004) |
| $R^2$ | 0.219 | 0.225 | 0.066 | 0.084 | 0.054 | 0.149 | 0.156 | 0.170 | 0.139 |
| Observations | 65,686 | 65,686 | 69,559 | 69,559 | 69,559 | 64,052 | 64,052 | 64,052 | 64,052 |
| Panel B: Women | | | | | | | | | |
| Skill mismatch × | -0.042*** | -0.026*** | -0.002 | 0.011*** | 0.002* | -0.014*** | -0.010*** | -0.012** | -0.014*** |
| 1-2 years of potential exp. | (0.008) | (0.007) | (0.003) | (0.003) | (0.001) | (0.004) | (0.003) | (0.005) | (0.004) |
| Skill mismatch × | -0.033*** | -0.019*** | -0.003 | 0.007*** | 0.001 | -0.010*** | -0.007** | -0.010* | -0.014*** |
| 3-4 years of potential exp. | (0.005) | (0.004) | (0.002) | (0.002) | (0.001) | (0.003) | (0.003) | (0.006) | (0.004) |
| Skill mismatch × | -0.025*** | -0.017*** | -0.006* | 0.001 | -0.000 | -0.007*** | -0.007** | -0.011 | -0.018*** |
| 5-6 years of potential exp. | (0.005) | (0.004) | (0.004) | (0.003) | (0.001) | (0.003) | (0.003) | (0.008) | (0.005) |
| $R^2$ | 0.171 | 0.199 | 0.103 | 0.059 | 0.041 | 0.139 | 0.146 | 0.208 | 0.168 |
| Observations | 85,158 | 85,158 | 92,949 | 92,949 | 92,949 | 82,514 | 82,514 | 82,514 | 82,514 |

*Notes:* Individual controls include race fixed effects (Hispanic, Black, Asian, other race), an indicator for being foreign-born, an indicator for having a Master's degree and an indicator for being a double major. Observations are weighted by Census sampling weights. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

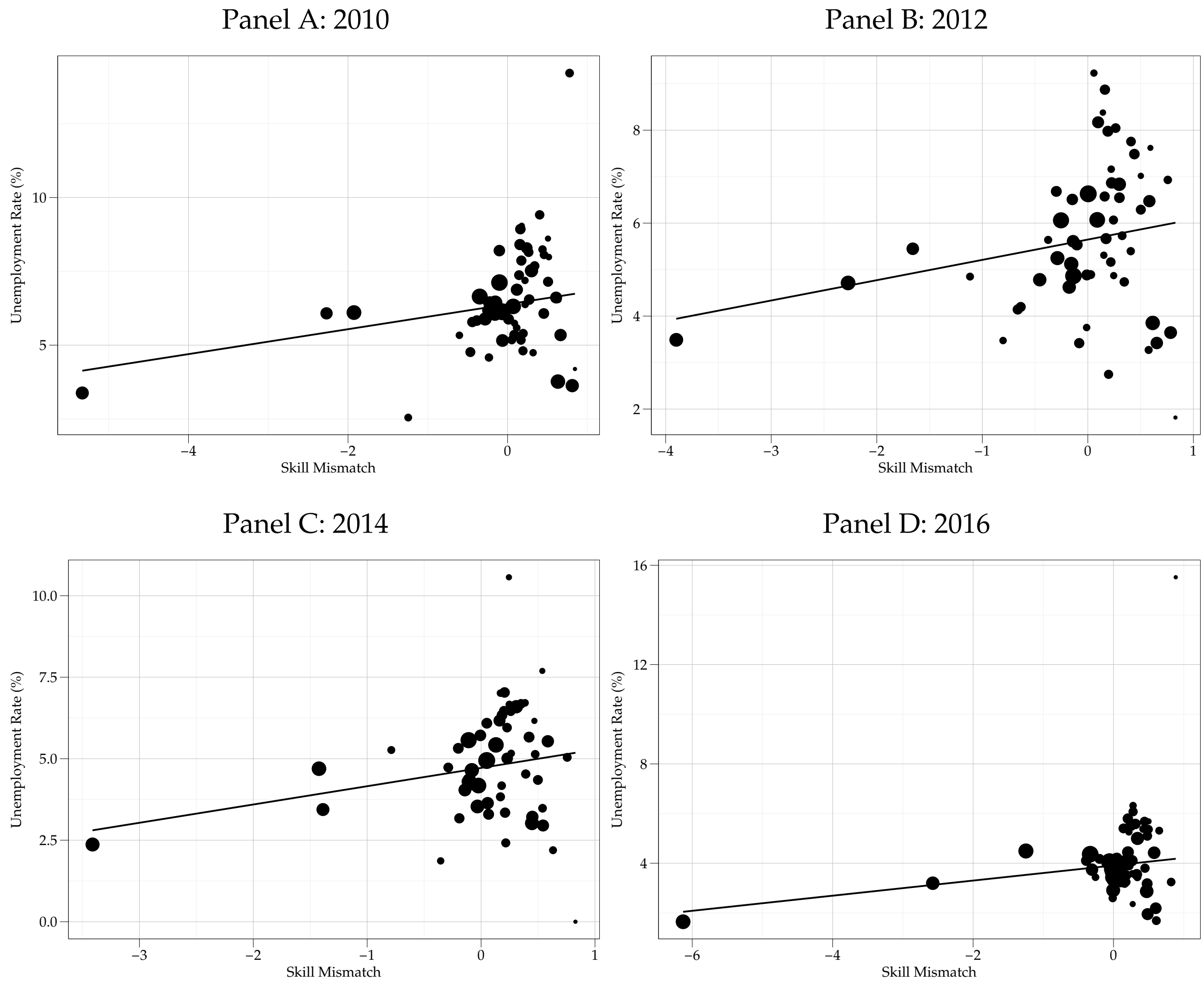
Table 10 — Wage Regressions: Alternative Specifications

| | Dependent variable: Log hourly wage | | | | | |
|---|---|---|---|---|---|---|
| | Baseline | | | | JOLTS-adjusted | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Skill mismatch × | -0.031*** | -0.030*** | -0.035*** | 0.013 | -0.035*** | 0.008 |
| 1-2 years of potential exp. | (0.004) | (0.004) | (0.004) | (0.014) | (0.006) | (0.010) |
| Skill mismatch × | -0.027*** | -0.028*** | -0.031*** | 0.017 | -0.031*** | 0.013 |
| 3-4 years of potential exp. | (0.004) | (0.004) | (0.004) | (0.014) | (0.006) | (0.011) |
| Skill mismatch × | -0.026*** | -0.028*** | -0.032*** | 0.017 | -0.029*** | 0.014 |
| 5-6 years of potential exp. | (0.005) | (0.004) | (0.005) | (0.013) | (0.007) | (0.010) |
| MSA × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| College major × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FEs | ✓ | | ✓ | ✓ | ✓ | ✓ |
| MSA × year FEs | | ✓ | | | | |
| College major × year FEs | | ✓ | | | | |
| College major × state FEs | | | ✓ | | | |
| College major group × MSA FEs | | | ✓ | | | |
| College major × MSA FEs | | | | ✓ | | ✓ |
| Potential experience FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Individual controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.199 | 0.212 | 0.234 | 0.273 | 0.199 | 0.273 |
| Observations | 150,844 | 150,844 | 150,844 | 150,844 | 150,844 | 150,844 |

*Notes:* The JOLTS-adjusted measure of skill mismatch is described in Section 4.6. Individual controls include an indicator for being female, race fixed effects (Hispanic, Black, Asian, other race), an indicator for being foreign-born, an indicator for having a Master's degree and an indicator for being a double major. Observations are weighted by Census sampling weights. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

# Appendix Figures and Tables

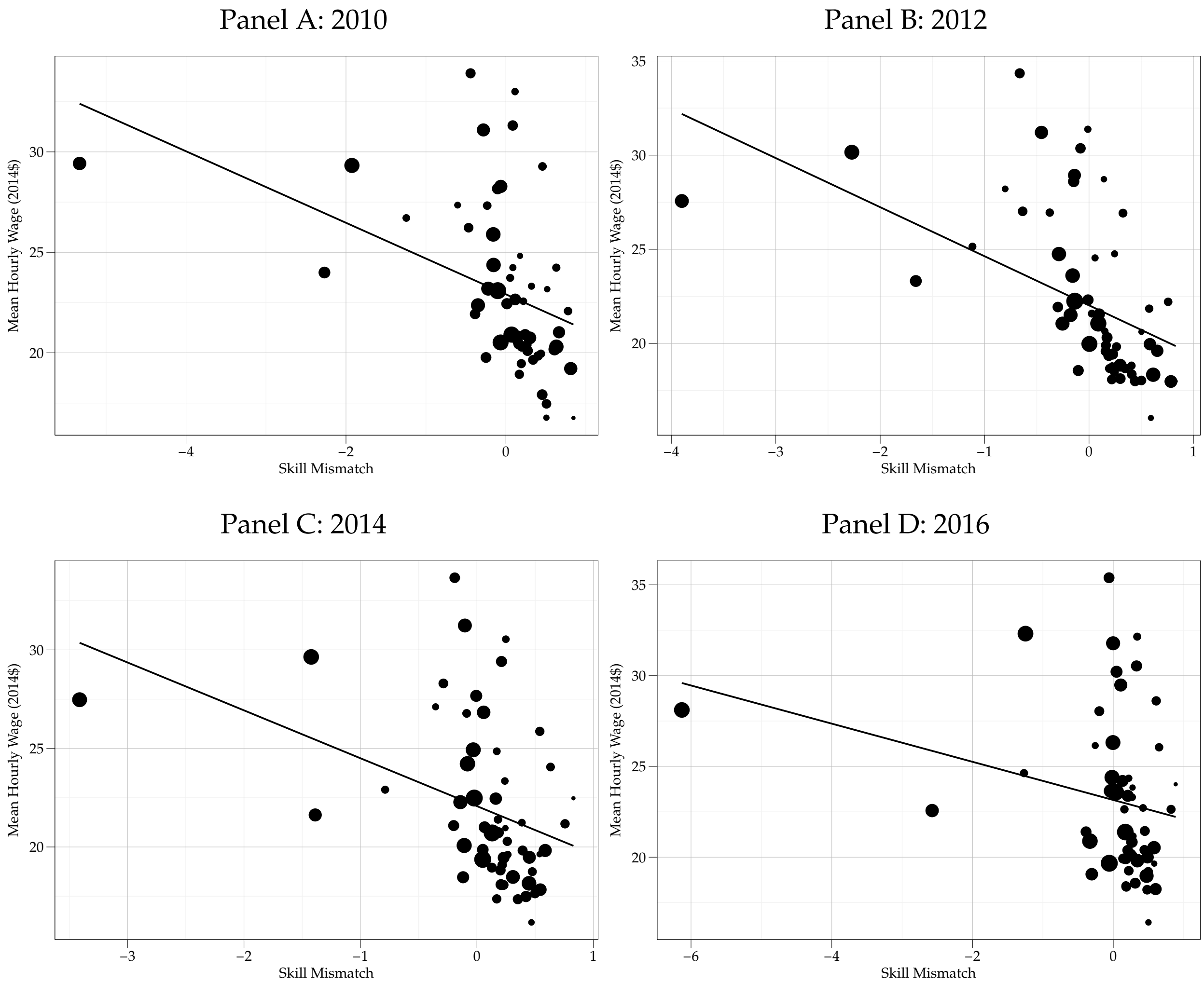
Figure A1 — Average Skill Mismatch vs. Unemployment Rates Across College Majors, 2010-2016




*Notes:* Each dot represents average skill mismatch (*x*-axis) and the national unemployment rate (*y*-axis) for one of the 56 college majors. National unemployment rates are based on recent college graduates aged 22 to 31 with a Bachelor's or Master's degree. The size of each dot is proportional to the number of recent college graduates holding the corresponding major nationally, and the solid line represents the slope from a weighted linear regression.

*Source:* American Community Survey, Burning Glass Technologies.

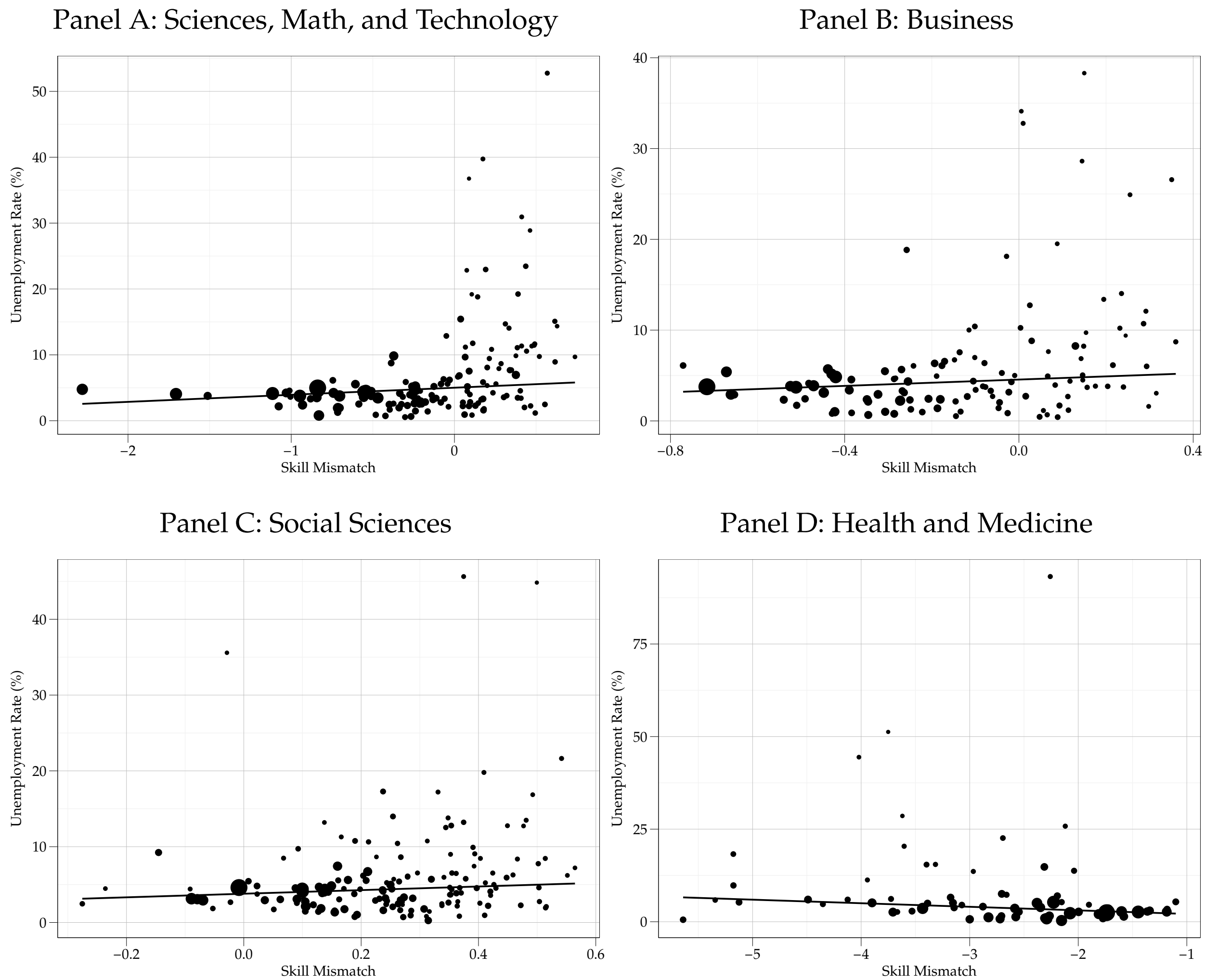
Figure A2 — Average Skill Mismatch vs. Mean Hourly Wage Across College Majors, 2010-2016




*Notes:* Each dot represents average skill mismatch ($x$-axis) and the mean hourly wage ($y$-axis) for one of the 56 college majors. Mean hourly wages at the national level are based on recent college graduates aged 22 to 31 with a Bachelor's or Master's degree, earning a positive wage, and not attending school. The size of each dot is proportional to the number of recent college graduates holding the corresponding major nationally, and the solid line represents the slope from a weighted linear regression.

*Source:* American Community Survey, Burning Glass Technologies.

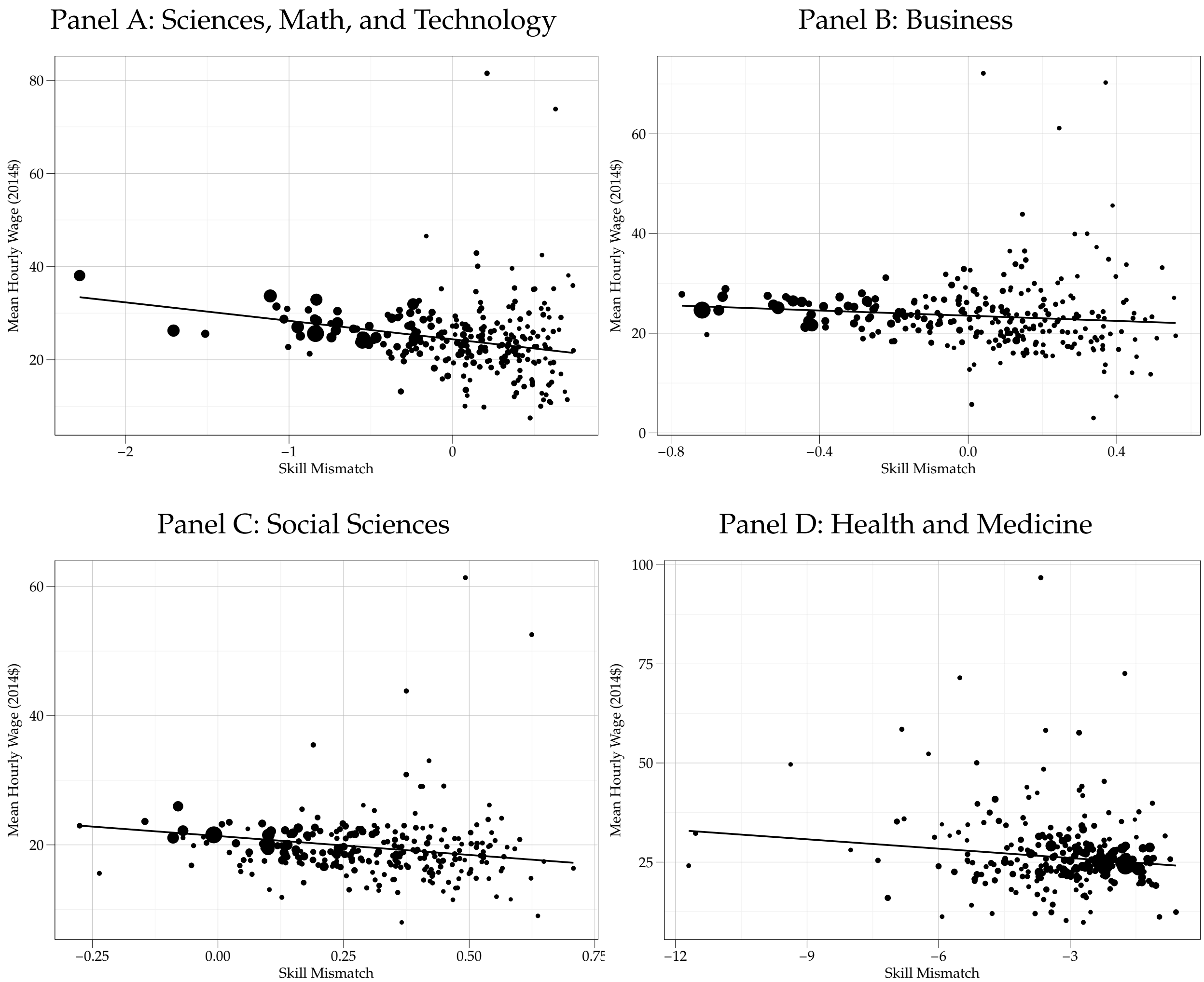
Figure A3 — Average Skill Mismatch vs. Unemployment Rate Across MSAs, 2016




*Notes:* Each dot represents average skill mismatch ($x$-axis) and the unemployment rate ($y$-axis) for a specific college major group (panel) and a specific MSA. Unemployment rates at the MSA level are based on recent college graduates aged 22 to 31 with a Bachelor's or Master's degree. The size of each dot is proportional to the number of recent college graduates holding a major belonging to the corresponding major group and living in the corresponding MSA, and the solid line represents the slope from a weighted linear regression.

*Source:* American Community Survey, Burning Glass Technologies.

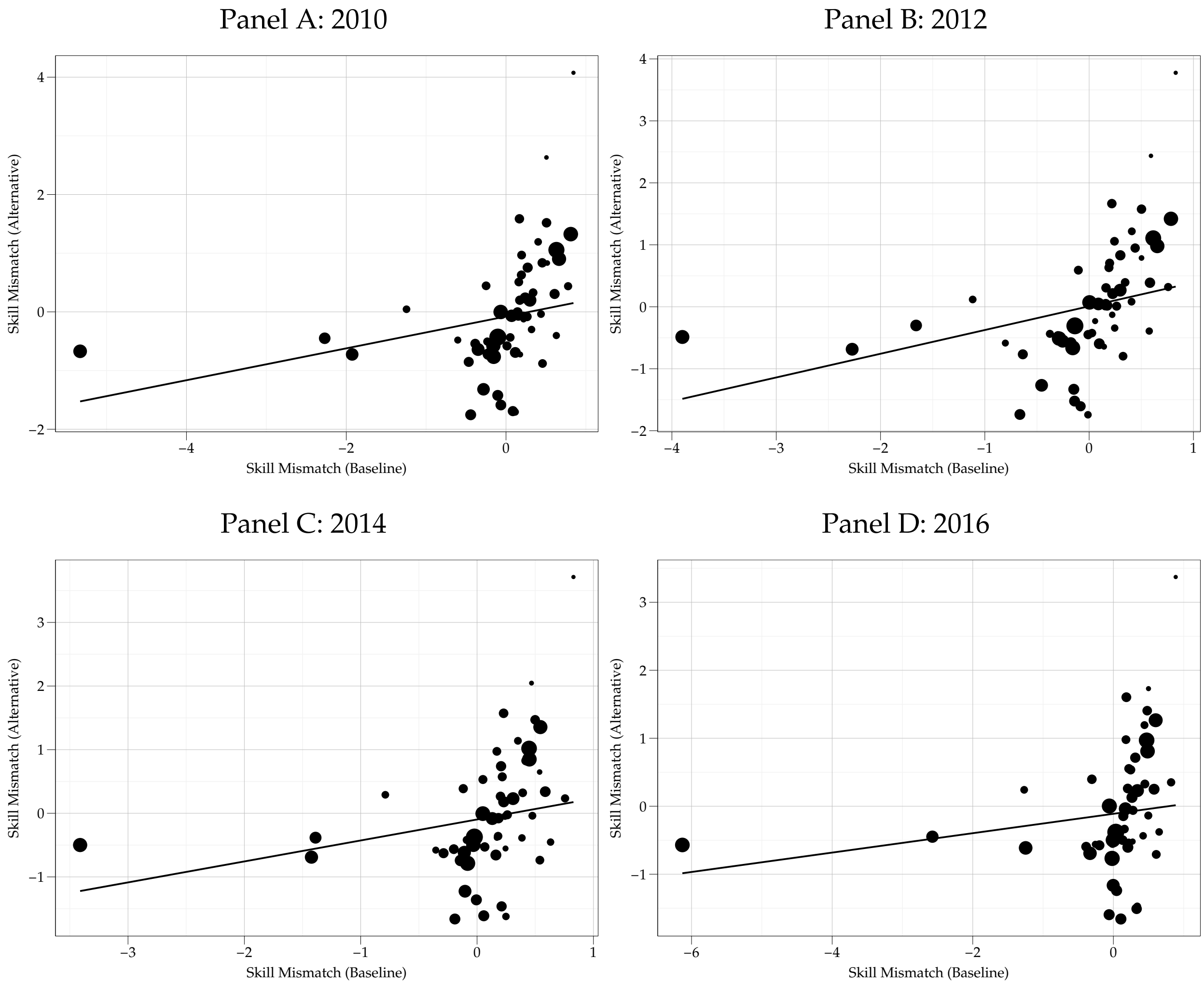
Figure A4 — Average Skill Mismatch vs. Mean Hourly Wage Across MSAs, 2016




*Notes:* Each dot represents average skill mismatch ($x$-axis) and the mean hourly wage ($y$-axis) for a specific college major group (panel) and a specific MSA. Mean hourly wages at the MSA level are based on recent college graduates aged 22 to 31 with a Bachelor's or Master's degree, earning a positive wage, and not attending school. The size of each dot is proportional to the number of recent college graduates holding a major belonging to the corresponding major group and living in the corresponding MSA, and the solid line represents the slope from a weighted linear regression.

*Source:* American Community Survey, Burning Glass Technologies.

Figure A5 — Average Skill Mismatch By College Major: Baseline vs. Alternative Definition, 2010-2016




*Notes:* Each dot represents average skill mismatch for one of the 56 college majors. The baseline definition of skill mismatch ($x$-axis) uses employment shares (2) to assess the match between college majors and occupations, while the alternative definition of skill mismatch ($y$-axis) uses wage premiums (7) instead. The size of each dot is proportional to the number of recent college graduates holding that major nationally, and the solid line represents the slope from a weighted linear regression.

*Source:* American Community Survey, Burning Glass Technologies.

Table A1 — Summary Statistics Among Recent College Graduates, 2011-2016

| | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|
| Panel A: Demographics | | | | | | |
| Age | 23.91 | 23.93 | 23.90 | 23.89 | 23.91 | 23.94 |
| Female | 0.575 | 0.585 | 0.577 | 0.583 | 0.569 | 0.570 |
| Hispanic | 0.057 | 0.057 | 0.057 | 0.069 | 0.060 | 0.070 |
| Black | 0.074 | 0.084 | 0.085 | 0.087 | 0.081 | 0.087 |
| Asian | 0.095 | 0.100 | 0.108 | 0.105 | 0.115 | 0.110 |
| Other race | 0.043 | 0.057 | 0.055 | 0.061 | 0.063 | 0.062 |
| Master's degree | 0.175 | 0.192 | 0.172 | 0.171 | 0.187 | 0.197 |
| Double major | 0.128 | 0.117 | 0.112 | 0.119 | 0.117 | 0.117 |
| Foreign born | 0.100 | 0.111 | 0.104 | 0.111 | 0.112 | 0.109 |
| | | | | | | |
| Panel B: Migration | | | | | | |
| Born in different state than current state of residence | 0.440 | 0.434 | 0.430 | 0.429 | 0.433 | 0.427 |
| Migrated in MSA within the last year | 0.128 | 0.119 | 0.108 | 0.127 | 0.119 | 0.120 |
| | | | | | | |
| Panel C: Employment status | | | | | | |
| Employed | 0.878 | 0.893 | 0.892 | 0.884 | 0.895 | 0.901 |
| Employed part-time (less than 35 hours/week) | 0.150 | 0.143 | 0.151 | 0.156 | 0.145 | 0.135 |
| Unemployed | 0.062 | 0.055 | 0.054 | 0.055 | 0.048 | 0.044 |
| | | | | | | |
| Panel D: Occupations (conditional on employment) | | | | | | |
| Employed in college occupation (O*NET) | 0.640 | 0.640 | 0.650 | 0.649 | 0.654 | 0.674 |
| Employed in college occupation (ACS) | 0.590 | 0.603 | 0.607 | 0.625 | 0.625 | 0.639 |
| Employed in top 5 occupation for own college major | 0.357 | 0.364 | 0.355 | 0.352 | 0.354 | 0.356 |
| Employed in top 10 occupation for own college major | 0.468 | 0.475 | 0.471 | 0.466 | 0.462 | 0.475 |
| | | | | | | |
| Panel E: Income (MSA price parity-adjusted 2014$) | | | | | | |
| Annual wage income | 30,573 | 30,874 | 30,846 | 29,711 | 31,945 | 33,585 |
| Hourly wage | 17.14 | 16.95 | 16.66 | 16.56 | 17.25 | 18.09 |

*Notes:* Recent college graduates are defined as having 1 year of potential experience. Non-college occupations and top occupations by college major are defined in Section 4.2.

Table A2 — College Major Shares Among Recent College Graduates, 2011-2016

| College major | Share (%) 2011 | Share (%) 2016 | College major | Share (%) 2011 | Share (%) 2016 |
|---|---|---|---|---|---|
| *Arts and humanities:* | *11.85* | *10.83* | *Science, math, and technology:* | *18.55* | *23.05* |
| English literature | 3.57 | 3.05 | Biological sciences | 4.47 | 4.95 |
| Music and drama | 1.56 | 1.70 | Computer science and IT | 2.70 | 4.23 |
| Fine arts | 1.61 | 1.48 | All other engineering | 2.76 | 3.16 |
| Commercial art and graphic design | 1.84 | 1.38 | Mechanical engineering | 1.45 | 1.87 |
| Film and visual arts | 1.23 | 1.15 | Mathematics | 1.01 | 1.27 |
| Philosophy and religion | 1.12 | 1.04 | Electrical engineering | 1.08 | 1.25 |
| Linguistics | 0.93 | 1.03 | Environmental studies | 0.79 | 1.17 |
| | | | Civil engineering | 0.92 | 1.01 |
| *Business:* | *21.70* | *18.78* | Agricultural sciences | 0.52 | 1.00 |
| Accounting | 3.18 | 3.89 | Chemistry | 0.57 | 0.71 |
| General business | 3.85 | 3.58 | All other physical sciences | 0.32 | 0.57 |
| Business mgmt and administration | 5.07 | 3.52 | Architecture | 0.48 | 0.55 |
| Marketing | 3.57 | 3.25 | Chemical engineering | 0.43 | 0.48 |
| Finance | 3.11 | 2.63 | Physics | 0.29 | 0.44 |
| All other business | 2.45 | 1.66 | Engineering technologies | 0.78 | 0.40 |
| Human resources | 0.47 | 0.26 | | | |
| | | | *Social sciences:* | *31.27* | *28.87* |
| *Health and medicine:* | *6.17* | *6.53* | Psychology | 6.27 | 6.07 |
| Nursing | 3.20 | 3.13 | Communications | 5.36 | 5.80 |
| Medical and health services | 2.62 | 2.97 | All other education | 3.45 | 2.84 |
| Medical support | 0.35 | 0.44 | Political science | 2.54 | 2.74 |
| | | | General education | 2.21 | 1.87 |
| *Multi/interdisciplinary studies:* | *6.07* | *6.98* | Economics | 2.24 | 1.83 |
| Fitness, nutrition, and leisure | 1.92 | 3.10 | All other social sciences | 1.16 | 1.61 |
| Multidisciplinary or general science | 1.55 | 1.47 | History | 2.00 | 1.57 |
| Liberal arts and humanities | 1.12 | 1.08 | Elementary education | 2.49 | 1.52 |
| Family and consumer sciences | 0.89 | 0.94 | Sociology | 1.80 | 1.35 |
| Area, ethnic, and civilization studies | 0.59 | 0.38 | Journalism | 1.26 | 1.20 |
| | | | International relations | 0.46 | 0.43 |
| *Public and social services:* | *3.88* | *4.29* | Library science | 0.03 | 0.04 |
| Criminal justice and fire protection | 2.34 | 2.51 | | | |
| Social work | 1.16 | 1.33 | *Trades and personal services:* | *0.51* | *0.67* |
| Legal studies | 0.17 | 0.26 | Precision production and industrial arts | 0.38 | 0.57 |
| Public administration | 0.20 | 0.19 | Hospitality | 0.13 | 0.10 |

*Notes:* Recent college graduates are defined as having 1 year of potential experience.

Table A3 — Summary Statistics by College Major Among Recent College Graduates

| | Average outcomes | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Employed | | | Occupations (conditional on employment) | | | | | |
| College major | Any | Part-time | Unemployed | College (O*NET) | College (ACS) | Top 5 | Top 10 | Annual income | Hourly wage |
| Electrical engineering | 0.88 | 0.04 | 0.04 | 0.87 | 0.86 | 0.62 | 0.67 | 55,056 | 28.93 |
| Mechanical engineering | 0.92 | 0.05 | 0.05 | 0.84 | 0.83 | 0.5 | 0.65 | 49,113 | 24.93 |
| Public administration | 0.90 | 0.14 | 0.08 | 0.62 | 0.47 | 0.07 | 0.26 | 37,815 | 24.93 |
| Computer science and IT | 0.88 | 0.09 | 0.04 | 0.78 | 0.76 | 0.59 | 0.64 | 45,470 | 24.43 |
| All other engineering | 0.90 | 0.06 | 0.04 | 0.83 | 0.82 | 0.47 | 0.58 | 48,354 | 24.31 |
| Chemical engineering | 0.94 | 0.08 | 0.03 | 0.85 | 0.83 | 0.4 | 0.52 | 49,328 | 24.25 |
| Nursing | 0.91 | 0.14 | 0.04 | 0.87 | 0.86 | 0.87 | 0.88 | 37,122 | 22.18 |
| Civil engineering | 0.96 | 0.05 | 0.02 | 0.86 | 0.83 | 0.64 | 0.7 | 44,747 | 22.07 |
| Precision production and industrial arts | 0.88 | 0.12 | 0.09 | 0.62 | 0.6 | 0.32 | 0.37 | 43,208 | 21.43 |
| Mathematics | 0.86 | 0.13 | 0.07 | 0.84 | 0.81 | 0.39 | 0.5 | 38,608 | 21.15 |
| Accounting | 0.93 | 0.07 | 0.04 | 0.84 | 0.82 | 0.66 | 0.76 | 42,930 | 20.64 |
| Physics | 0.84 | 0.13 | 0.06 | 0.88 | 0.85 | 0.29 | 0.35 | 38,415 | 20.29 |
| Medical support | 0.81 | 0.21 | 0.10 | 0.39 | 0.35 | 0.4 | 0.61 | 34,559 | 19.76 |
| Finance | 0.91 | 0.07 | 0.05 | 0.72 | 0.66 | 0.37 | 0.53 | 38,921 | 19.54 |
| Engineering technologies | 0.89 | 0.11 | 0.06 | 0.65 | 0.62 | 0.29 | 0.41 | 34,142 | 19.40 |
| Economics | 0.90 | 0.08 | 0.06 | 0.73 | 0.69 | 0.26 | 0.47 | 37,969 | 18.64 |
| Medical and health services | 0.89 | 0.17 | 0.04 | 0.68 | 0.6 | 0.24 | 0.37 | 32,824 | 18.20 |
| General business | 0.90 | 0.10 | 0.05 | 0.57 | 0.53 | 0.3 | 0.43 | 34,215 | 17.80 |
| General education | 0.93 | 0.13 | 0.03 | 0.83 | 0.81 | 0.62 | 0.72 | 30,264 | 17.07 |
| Library science | 0.90 | 0.20 | 0.00 | 1 | 1 | 1 | 1 | 30,872 | 16.84 |
| Political science | 0.87 | 0.13 | 0.08 | 0.55 | 0.54 | 0.19 | 0.29 | 29,237 | 16.67 |
| Linguistics | 0.85 | 0.18 | 0.05 | 0.65 | 0.58 | 0.15 | 0.3 | 26,746 | 16.67 |
| Business mgmt and administration | 0.90 | 0.10 | 0.05 | 0.57 | 0.52 | 0.27 | 0.42 | 31,732 | 16.55 |
| All other business | 0.89 | 0.12 | 0.06 | 0.53 | 0.49 | 0.26 | 0.35 | 31,264 | 16.52 |
| Architecture | 0.88 | 0.10 | 0.07 | 0.69 | 0.68 | 0.57 | 0.65 | 30,181 | 16.43 |
| All other physical sciences | 0.92 | 0.17 | 0.06 | 0.66 | 0.63 | 0.24 | 0.34 | 29,522 | 16.38 |
| International relations | 0.88 | 0.14 | 0.06 | 0.7 | 0.66 | 0.21 | 0.31 | 28,873 | 16.31 |
| Social work | 0.93 | 0.11 | 0.03 | 0.76 | 0.74 | 0.6 | 0.67 | 29,008 | 16.10 |

*Notes:* Recent college graduates are defined as having 1 year of potential experience. Non-college occupations and top occupations by college major are defined in Section 4.2. Annual income and hourly wages are expressed in MSA price parity-adjusted 2014 dollars.

Table A3 (cont.): Summary Statistics by College Major Among Recent College Graduates

| | Average outcomes | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Employed | | | Occupations (conditional on employment) | | | | | |
| College major | Any | Part-time | Unemployed | College (O*NET) | College (ACS) | Top 5 | Top 10 | Annual income | Hourly wage |
| Chemistry | 0.87 | 0.13 | 0.06 | 0.7 | 0.65 | 0.23 | 0.33 | 29,002 | 16.05 |
| Marketing | 0.93 | 0.11 | 0.04 | 0.58 | 0.53 | 0.38 | 0.47 | 31,002 | 15.91 |
| Human resources | 0.87 | 0.09 | 0.07 | 0.65 | 0.59 | 0.46 | 0.53 | 32,078 | 15.74 |
| Multidisciplinary or general science | 0.86 | 0.17 | 0.06 | 0.56 | 0.51 | 0.13 | 0.24 | 27,145 | 15.44 |
| Journalism | 0.92 | 0.19 | 0.05 | 0.66 | 0.64 | 0.31 | 0.43 | 26,800 | 15.43 |
| All other education | 0.91 | 0.18 | 0.04 | 0.8 | 0.79 | 0.63 | 0.73 | 27,247 | 15.36 |
| Elementary education | 0.93 | 0.17 | 0.03 | 0.78 | 0.77 | 0.68 | 0.77 | 26,677 | 15.36 |
| Biological sciences | 0.83 | 0.18 | 0.05 | 0.61 | 0.52 | 0.16 | 0.24 | 25,466 | 15.13 |
| Commercial art and graphic design | 0.87 | 0.19 | 0.07 | 0.67 | 0.66 | 0.56 | 0.67 | 26,788 | 15.06 |
| All other social sciences | 0.86 | 0.20 | 0.09 | 0.51 | 0.47 | 0.14 | 0.24 | 25,499 | 15.04 |
| Agricultural sciences | 0.90 | 0.10 | 0.04 | 0.41 | 0.36 | 0.23 | 0.34 | 28,006 | 15.03 |
| History | 0.87 | 0.21 | 0.06 | 0.53 | 0.48 | 0.25 | 0.31 | 25,853 | 14.84 |
| Communications | 0.91 | 0.15 | 0.05 | 0.6 | 0.57 | 0.26 | 0.42 | 27,053 | 14.79 |
| Area, ethnic, and civilization studies | 0.91 | 0.18 | 0.05 | 0.63 | 0.58 | 0.24 | 0.34 | 24,518 | 14.67 |
| Family and consumer sciences | 0.89 | 0.17 | 0.05 | 0.64 | 0.62 | 0.29 | 0.41 | 24,323 | 14.63 |
| Fitness, nutrition, and leisure | 0.91 | 0.21 | 0.05 | 0.56 | 0.51 | 0.23 | 0.39 | 24,975 | 14.56 |
| Psychology | 0.88 | 0.20 | 0.06 | 0.59 | 0.56 | 0.23 | 0.32 | 24,984 | 14.35 |
| Criminal justice and fire protection | 0.91 | 0.17 | 0.05 | 0.38 | 0.32 | 0.26 | 0.36 | 24,815 | 14.25 |
| Sociology | 0.89 | 0.16 | 0.06 | 0.58 | 0.54 | 0.2 | 0.29 | 25,854 | 14.16 |
| English literature | 0.86 | 0.20 | 0.07 | 0.57 | 0.55 | 0.22 | 0.34 | 23,618 | 14.02 |
| Liberal arts and humanities | 0.81 | 0.20 | 0.07 | 0.52 | 0.48 | 0.26 | 0.32 | 21,970 | 13.69 |
| Environmental studies | 0.87 | 0.17 | 0.08 | 0.49 | 0.43 | 0.15 | 0.23 | 22,654 | 13.57 |
| Philosophy and religion | 0.86 | 0.23 | 0.06 | 0.55 | 0.54 | 0.22 | 0.36 | 22,789 | 13.26 |
| Film and visual arts | 0.89 | 0.29 | 0.06 | 0.5 | 0.49 | 0.11 | 0.37 | 21,678 | 13.19 |
| Legal studies | 0.92 | 0.20 | 0.02 | 0.5 | 0.38 | 0.29 | 0.43 | 26,308 | 13.08 |
| Fine arts | 0.88 | 0.24 | 0.07 | 0.46 | 0.45 | 0.22 | 0.37 | 21,480 | 12.89 |
| Music and drama | 0.88 | 0.31 | 0.07 | 0.51 | 0.48 | 0.2 | 0.36 | 20,021 | 12.49 |
| Hospitality | 0.89 | 0.12 | 0.11 | 0.14 | 0.14 | 0.47 | 0.63 | 24,513 | 11.92 |

*Notes:* Recent college graduates are defined as having 1 year of potential experience. Non-college occupations and top occupations by college major are defined in Section 4.2. Annual income and hourly wages are expressed in MSA price parity-adjusted 2014 dollars.

Table A4 — Distribution of Skill Mismatch Across MSAs: Science, Math, and Technology, 2010-2016

| | College major group: Science, math, and technology | | | | | |
|---|---|---|---|---|---|---|
| | 2010 | | 2013 | | 2016 | |
| | Panel A: Percentiles | | | | | |
| 90th | 0.49 | | 0.47 | | 0.56 | |
| 75th | 0.32 | | 0.35 | | 0.43 | |
| 50th | 0.06 | | 0.12 | | 0.18 | |
| 25th | -0.35 | | -0.27 | | -0.16 | |
| 10th | -1.04 | | -0.75 | | -0.53 | |
| | Panel B: Rank (40 largest MSAs) | | | | | |
| 1 | Riverside-San Bernardino-Ontario, CA | 0.15 | Riverside-San Bernardino-Ontario, CA | 0.32 | Riverside-San Bernardino-Ontario, CA | 0.38 |
| 2 | Las Vegas-Henderson-Paradise, NV | -0.04 | San Juan-Carolina-Caguas, PR | 0.07 | Las Vegas-Henderson-Paradise, NV | 0.04 |
| 3 | San Juan-Carolina-Caguas, PR | -0.10 | Las Vegas-Henderson-Paradise, NV | 0.04 | San Juan-Carolina-Caguas, PR | -0.05 |
| 4 | Providence-Warwick, RI-MA | -0.32 | Miami-Fort Lauderdale-West Palm Beach, FL | -0.23 | Providence-Warwick, RI-MA | -0.13 |
| 5 | Miami-Fort Lauderdale-West Palm Beach, FL | -0.40 | Orlando-Kissimmee-Sanford, FL | -0.27 | Indianapolis-Carmel-Anderson, IN | -0.18 |
| 20 | Detroit-Warren-Dearborn, MI | -1.04 | Chicago-Naperville-Elgin, IL-IN-WI | -0.78 | St. Louis, MO-IL | -0.51 |
| 21 | Milwaukee-Waukesha-West Allis, WI | -1.04 | Philadelphia-Camden-Wilmington, PA-NJ-DE-MD | -0.81 | Chicago-Naperville-Elgin, IL-IN-WI | -0.54 |
| 36 | New York-Newark-Jersey City, NY-NJ-PA | -1.77 | San Francisco-Oakland-Hayward, CA | -1.36 | Austin-Round Rock, TX | -1.03 |
| 37 | Seattle-Tacoma-Bellevue, WA | -1.79 | Charlotte-Concord-Gastonia, NC-SC | -1.42 | Charlotte-Concord-Gastonia, NC-SC | -1.08 |
| 38 | San Francisco-Oakland-Hayward, CA | -2.12 | Austin-Round Rock, TX | -1.43 | San Francisco-Oakland-Hayward, CA | -1.11 |
| 39 | Washington-Arlington-Alexandria, DC-VA-MD-WV | -2.33 | Washington-Arlington-Alexandria, DC-VA-MD-WV | -1.70 | Washington-Arlington-Alexandria, DC-VA-MD-WV | -1.71 |
| 40 | San Jose-Sunnyvale-Santa Clara, CA | -3.55 | San Jose-Sunnyvale-Santa Clara, CA | -2.84 | San Jose-Sunnyvale-Santa Clara, CA | -2.28 |

*Notes:* Skill mismatch is defined according to equation (1), and normalized to have a mean of zero and standard deviation of one (across all college majors, MSAs and years). This table shows average skill mismatch for college majors belonging to the group "Science, math, and technology", separately by MSA and by year. Panel A shows percentiles of the distribution of average skill mismatch across MSAs, separately by year. Panel B shows average skill mismatch for the 40 largest MSAs (in terms of population), separately by year.

## Table A5 — Distribution of Skill Mismatch Across MSAs: Business, 2010-2016

| | College major group: Business | | | | | |
|---|---|---|---|---|---|---|
| | 2010 | | 2013 | | 2016 | |
| | Panel A: Percentiles | | | | | |
| 90th | 0.24 | | 0.17 | | 0.37 | |
| 75th | 0.15 | | 0.08 | | 0.25 | |
| 50th | -0.01 | | -0.02 | | 0.12 | |
| 25th | -0.24 | | -0.21 | | -0.08 | |
| 10th | -0.48 | | -0.46 | | -0.30 | |
| | Panel B: Rank (40 largest MSAs) | | | | | |
| 1 | Riverside-San Bernardino-Ontario, CA | -0.11 | Riverside-San Bernardino-Ontario, CA | 0.02 | Riverside-San Bernardino-Ontario, CA | 0.13 |
| 2 | Virginia Beach-Norfolk-Newport News, VA-NC | -0.17 | Las Vegas-Henderson-Paradise, NV | -0.08 | Virginia Beach-Norfolk-Newport News, VA-NC | -0.02 |
| 3 | Las Vegas-Henderson-Paradise, NV | -0.18 | Virginia Beach-Norfolk-Newport News, VA-NC | -0.12 | Las Vegas-Henderson-Paradise, NV | -0.10 |
| 4 | San Antonio-New Braunfels, TX | -0.25 | Orlando-Kissimmee-Sanford, FL | -0.27 | Providence-Warwick, RI-MA | -0.12 |
| 5 | Providence-Warwick, RI-MA | -0.30 | Indianapolis-Carmel-Anderson, IN | -0.28 | Sacramento–Roseville–Arden-Arcade, CA | -0.17 |
| 20 | Miami-Fort Lauderdale-West Palm Beach, FL | -0.50 | Minneapolis-St. Paul-Bloomington, MN-WI | -0.46 | San Diego-Carlsbad, CA | -0.31 |
| 21 | St. Louis, MO-IL | -0.52 | Sacramento–Roseville–Arden-Arcade, CA | -0.47 | Denver-Aurora-Lakewood, CO | -0.32 |
| 36 | San Francisco-Oakland-Hayward, CA | -0.88 | San Francisco-Oakland-Hayward, CA | -0.73 | Charlotte-Concord-Gastonia, NC-SC | -0.54 |
| 37 | Chicago-Naperville-Elgin, IL-IN-WI | -0.93 | Washington-Arlington-Alexandria, DC-VA-MD-WV | -0.75 | San Jose-Sunnyvale-Santa Clara, CA | -0.65 |
| 38 | San Jose-Sunnyvale-Santa Clara, CA | -0.94 | Charlotte-Concord-Gastonia, NC-SC | -0.78 | San Francisco-Oakland-Hayward, CA | -0.66 |
| 39 | Washington-Arlington-Alexandria, DC-VA-MD-WV | -0.95 | San Jose-Sunnyvale-Santa Clara, CA | -0.82 | Washington-Arlington-Alexandria, DC-VA-MD-WV | -0.67 |
| 40 | New York-Newark-Jersey City, NY-NJ-PA | -1.02 | New York-Newark-Jersey City, NY-NJ-PA | -0.97 | New York-Newark-Jersey City, NY-NJ-PA | -0.72 |

*Notes:* Skill mismatch is defined according to equation (1), and normalized to have a mean of zero and standard deviation of one (across all college majors, MSAs and years). This table shows average skill mismatch for college majors belonging to the group “Business”, separately by MSA and by year. Panel A shows percentiles of the distribution of average skill mismatch across MSAs, separately by year. Panel B shows average skill mismatch for the 40 largest MSAs (in terms of population), separately by year.

Table A6 — Distribution of Skill Mismatch Across MSAs: Social Sciences, 2010-2016

| | College major group: Social sciences | | | | | |
|---|---|---|---|---|---|---|
| | 2010 | | 2013 | | 2016 | |
| | Panel A: Percentiles | | | | | |
| 90th | 0.52 | | 0.49 | | 0.53 | |
| 75th | 0.44 | | 0.43 | | 0.44 | |
| 50th | 0.33 | | 0.32 | | 0.35 | |
| 25th | 0.20 | | 0.19 | | 0.20 | |
| 10th | 0.05 | | 0.05 | | 0.09 | |
| | Panel B: Rank (40 largest MSAs) | | | | | |
| 1 | San Juan-Carolina-Caguas, PR | 0.36 | San Juan-Carolina-Caguas, PR | 0.39 | San Juan-Carolina-Caguas, PR | 0.37 |
| 2 | Las Vegas-Henderson-Paradise, NV | 0.32 | Las Vegas-Henderson-Paradise, NV | 0.34 | Milwaukee-Waukesha-West Allis, WI | 0.32 |
| 3 | Virginia Beach-Norfolk-Newport News, VA-NC | 0.30 | Virginia Beach-Norfolk-Newport News, VA-NC | 0.31 | Indianapolis-Carmel-Anderson, IN | 0.31 |
| 4 | Pittsburgh, PA | 0.28 | Orlando-Kissimmee-Sanford, FL | 0.28 | Orlando-Kissimmee-Sanford, FL | 0.31 |
| 5 | San Antonio-New Braunfels, TX | 0.26 | Riverside-San Bernardino-Ontario, CA | 0.27 | Cincinnati, OH-KY-IN | 0.29 |
| 20 | Phoenix-Mesa-Scottsdale, AZ | 0.13 | Houston-The Woodlands-Sugar Land, TX | 0.13 | Atlanta-Sandy Springs-Roswell, GA | 0.15 |
| 21 | Sacramento–Roseville–Arden-Arcade, CA | 0.12 | Providence-Warwick, RI-MA | 0.12 | Tampa-St. Petersburg-Clearwater, FL | 0.14 |
| 36 | Minneapolis-St. Paul-Bloomington, MN-WI | -0.09 | Austin-Round Rock, TX | -0.09 | New York-Newark-Jersey City, NY-NJ-PA | -0.01 |
| 37 | New York-Newark-Jersey City, NY-NJ-PA | -0.14 | Washington-Arlington-Alexandria, DC-VA-MD-WV | -0.12 | Boston-Cambridge-Newton, MA-NH | -0.07 |
| 38 | Washington-Arlington-Alexandria, DC-VA-MD-WV | -0.18 | New York-Newark-Jersey City, NY-NJ-PA | -0.12 | San Francisco-Oakland-Hayward, CA | -0.08 |
| 39 | San Francisco-Oakland-Hayward, CA | -0.18 | Boston-Cambridge-Newton, MA-NH | -0.14 | Washington-Arlington-Alexandria, DC-VA-MD-WV | -0.09 |
| 40 | San Jose-Sunnyvale-Santa Clara, CA | -0.24 | San Jose-Sunnyvale-Santa Clara, CA | -0.15 | San Jose-Sunnyvale-Santa Clara, CA | -0.15 |

*Notes:* Skill mismatch is defined according to equation (1), and normalized to have a mean of zero and standard deviation of one (across all college majors, MSAs and years). This table shows average skill mismatch for college majors belonging to the group "Social sciences", separately by MSA and by year. Panel A shows percentiles of the distribution of average skill mismatch across MSAs, separately by year. Panel B shows average skill mismatch for the 40 largest MSAs (in terms of population), separately by year.

Table A7 — Distribution of Skill Mismatch Across MSAs: Health and Medicine, 2010-2016

| | College major group: Health and medicine | | | | | |
|---|---|---|---|---|---|---|
| | 2010 | | 2013 | | 2016 | |
| | Panel A: Percentiles | | | | | |
| 90th | -1.18 | | -0.63 | | -1.60 | |
| 75th | -1.97 | | -1.01 | | -2.27 | |
| 50th | -2.72 | | -1.54 | | -3.04 | |
| 25th | -3.78 | | -2.10 | | -4.10 | |
| 10th | -5.10 | | -2.77 | | -5.31 | |
| | Panel B: Rank (40 largest MSAs) | | | | | |
| 1 | San Juan-Carolina-Caguas, PR | 0.10 | San Juan-Carolina-Caguas, PR | -0.12 | San Juan-Carolina-Caguas, PR | -0.15 |
| 2 | San Jose-Sunnyvale-Santa Clara, CA | -0.29 | Cincinnati, OH-KY-IN | -0.43 | Minneapolis-St. Paul-Bloomington, MN-WI | -1.18 |
| 3 | Washington-Arlington-Alexandria, DC-VA-MD-WV | -0.79 | Pittsburgh, PA | -0.49 | Columbus, OH | -1.24 |
| 4 | San Diego-Carlsbad, CA | -0.82 | Columbus, OH | -0.59 | Cincinnati, OH-KY-IN | -1.34 |
| 5 | San Francisco-Oakland-Hayward, CA | -0.89 | Washington-Arlington-Alexandria, DC-VA-MD-WV | -0.60 | San Jose-Sunnyvale-Santa Clara, CA | -1.37 |
| 20 | Denver-Aurora-Lakewood, CO | -2.01 | Orlando-Kissimmee-Sanford, FL | -1.15 | Dallas-Fort Worth-Arlington, TX | -2.29 |
| 21 | Seattle-Tacoma-Bellevue, WA | -2.04 | Austin-Round Rock, TX | -1.16 | St. Louis, MO-IL | -2.31 |
| 36 | Kansas City, MO-KS | -2.88 | Las Vegas-Henderson-Paradise, NV | -1.93 | San Antonio-New Braunfels, TX | -3.39 |
| 37 | Phoenix-Mesa-Scottsdale, AZ | -3.04 | Virginia Beach-Norfolk-Newport News, VA-NC | -1.98 | Houston-The Woodlands-Sugar Land, TX | -3.43 |
| 38 | Providence-Warwick, RI-MA | -3.19 | Riverside-San Bernardino-Ontario, CA | -2.05 | Tampa-St. Petersburg-Clearwater, FL | -3.71 |
| 39 | Nashville-Davidson–Murfreesboro–Franklin, TN | -3.28 | Tampa-St. Petersburg-Clearwater, FL | -2.22 | Riverside-San Bernardino-Ontario, CA | -3.90 |
| 40 | Tampa-St. Petersburg-Clearwater, FL | -3.46 | San Antonio-New Braunfels, TX | -2.38 | Providence-Warwick, RI-MA | -4.49 |

*Notes:* Skill mismatch is defined according to equation (1), and normalized to have a mean of zero and standard deviation of one (across all college majors, MSAs and years). This table shows average skill mismatch for college majors belonging to the group "Health and medicine", separately by MSA and by year. Panel A shows percentiles of the distribution of average skill mismatch across MSAs, separately by year. Panel B shows average skill mismatch for the 40 largest MSAs (in terms of population), separately by year.

Table A8 — Top 3 Occupations by College Major

| College major | Top 3 occupations: 1 | 2 | 3 |
|---|---|---|---|
| Accounting | Accountants and auditors | Managers and administrators, n.e.c. | Financial managers |
| Agricultural sciences | Farmers (owners and tenants) | Managers and administrators, n.e.c. | Sales supervisors and proprietors |
| All other business | Managers and administrators, n.e.c. | Sales supervisors and proprietors | Accountants and auditors |
| All other education | Primary school teachers | Secondary school teachers | Managers in education and related fields |
| All other engineering | Managers and administrators, n.e.c. | Computer software developers | Engineers and other professionals, n.e.c. |
| All other physical sciences | Managers and administrators, n.e.c. | Geologists | Computer software developers |
| All other social sciences | Managers and administrators, n.e.c. | Primary school teachers | Computer systems analysts and computer scientists |
| Architecture | Architects | Managers and administrators, n.e.c. | Designers |
| Area, ethnic, and civilization studies | Managers and administrators, n.e.c. | Primary school teachers | Subject instructors, college |
| Biological sciences | Managers and administrators, n.e.c. | Primary school teachers | Registered nurses |
| Business mgmt and administration | Managers and administrators, n.e.c. | Accountants and auditors | Sales supervisors and proprietors |
| Chemical engineering | Managers and administrators, n.e.c. | Chemical engineers | Engineers and other professionals, n.e.c. |
| Chemistry | Managers and administrators, n.e.c. | Chemists | Primary school teachers |
| Civil engineering | Managers and administrators, n.e.c. | Civil engineers | Engineers and other professionals, n.e.c. |
| Commercial art and graphic design | Designers | Managers and administrators, n.e.c. | Painters, sculptors, craft-artists and print-makers |
| Communications | Managers and administrators, n.e.c. | Managers and specialists in mktg advertising and PR | Primary school teachers |
| Computer science and IT | Computer software developers | Computer systems analysts and computer scientists | Managers and administrators, n.e.c. |
| Criminal justice and fire protection | Police and detectives, public service | Managers and administrators, n.e.c. | Guards and police, excluding public service |
| Economics | Managers and administrators, n.e.c. | Other financial specialists | Accountants and auditors |
| Electrical engineering | Managers and administrators, n.e.c. | Computer software developers | Electrical engineers |
| Elementary education | Primary school teachers | Managers in education and related fields | Kindergarten and earlier school teachers |
| Engineering technologies | Managers and administrators, n.e.c. | Computer systems analysts and computer scientists | Computer software developers |
| English literature | Primary school teachers | Managers and administrators, n.e.c. | Subject instructors, college |
| Environmental studies | Managers and administrators, n.e.c. | Foresters and conservation scientists | Primary school teachers |
| Family and consumer sciences | Primary school teachers | Managers and administrators, n.e.c. | Social workers |
| Film and visual arts | Managers and administrators, n.e.c. | Primary school teachers | Photographers |
| Finance | Managers and administrators, n.e.c. | Other financial specialists | Accountants and auditors |
| Fine arts | Designers | Managers and administrators, n.e.c. | Primary school teachers |

*Notes:* The top 3 occupations by college major are defined in terms of employment share, based on pooled 2009-2016 ACS data and the sample of individuals aged 32 or older with a Bachelor's or Master's degree.

Table A8 (cont.): Top 3 Occupations by College Major

| College major | Top 3 occupations 1 | 2 | 3 |
|---|---|---|---|
| Fitness, nutrition, and leisure | Managers and administrators, n.e.c. | Primary school teachers | Dieticians and nutritionists |
| General business | Managers and administrators, n.e.c. | Sales supervisors and proprietors | Accountants and auditors |
| General education | Primary school teachers | Secondary school teachers | Managers in education and related fields |
| History | Managers and administrators, n.e.c. | Primary school teachers | Sales supervisors and proprietors |
| Hospitality | Cooks | Managers and administrators, n.e.c. | Funeral directors |
| Human resources | Personnel, HR, training and labor relations specialists | Managers and administrators, n.e.c. | Human resources and labor relations managers |
| International relations | Managers and administrators, n.e.c. | Managers and specialists in mktg, advertising and PR | Management analysts |
| Journalism | Editors and reporters | Managers and administrators, n.e.c. | Managers and specialists in mktg, advertising and PR |
| Legal studies | Legal assistants and paralegals | Managers and administrators, n.e.c. | Secretaries and stenographers |
| Liberal arts and humanities | Primary school teachers | Managers and administrators, n.e.c. | Sales supervisors and proprietors |
| Library science | Librarians | Primary school teachers | Managers in education and related fields |
| Linguistics | Primary school teachers | Managers and administrators, n.e.c. | Secondary school teachers |
| Marketing | Managers and administrators, n.e.c. | Salespersons, n.e.c. | Managers and specialists in mktg, advertising and PR |
| Mathematics | Managers and administrators, n.e.c. | Computer software developers | Computer systems analysts and computer scientists |
| Mechanical engineering | Managers and administrators, n.e.c. | Mechanical engineers | Engineers and other professionals, n.e.c. |
| Medical and health services | Pharmacists | Physical therapists | Speech therapists |
| Medical support | Clinical laboratory technologies and technicians | Dental hygienists | Radiologic technologists and technicians |
| Multidisciplinary or general science | Managers and administrators, n.e.c. | Primary school teachers | Registered nurses |
| Music and drama | Musicians and composers | Teachers, n.e.c. | Managers and administrators, n.e.c. |
| Nursing | Registered nurses | Managers of medicine and health occupations | Health and nursing aides |
| Philosophy and religion | Clergy and religious workers | Managers and administrators, n.e.c. | Primary school teachers |
| Physics | Managers and administrators, n.e.c. | Computer software developers | Computer systems analysts and computer scientists |
| Political science | Managers and administrators, n.e.c. | Primary school teachers | Sales supervisors and proprietors |
| Precision production and industrial arts | Managers and administrators, n.e.c. | Airplane pilots and navigators | Chief executives, public administrators and legislators |
| Psychology | Managers and administrators, n.e.c. | Vocational and educational counselors | Primary school teachers |
| Public administration | Managers and administrators, n.e.c. | Police and detectives, public service | Chief executives, public administrators and legislators |
| Social work | Social workers | Managers and administrators, n.e.c. | Vocational and educational counselors |
| Sociology | Managers and administrators, n.e.c. | Social workers | Primary school teachers |

*Notes:* The top 3 occupations by college major are defined in terms of employment share, based on pooled 2009-2016 ACS data and the sample of individuals aged 32 or older with a Bachelor's or Master's degree.

Table A9 — The Effect of Skill Mismatch vs. Overall Unemployment Rates at the MSA Level in Graduation Year

| | Dependent variable: | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | Employed | | | Occupations | | | |
| | Log income | Log wage | Any | Part-time | Unemployed | College (O*NET) | College (ACS) | Top 5 | Top 10 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Unemployment rate (%) × | -0.024*** | -0.009** | -0.010*** | 0.005** | 0.005*** | -0.006** | -0.005* | -0.005 | -0.001 |
| 1-2 years of potential exp. | (0.007) | (0.004) | (0.002) | (0.002) | (0.001) | (0.003) | (0.003) | (0.004) | (0.003) |
| Unemployment rate (%) × | -0.014** | -0.008** | -0.005*** | 0.002 | 0.004** | -0.005** | -0.004 | -0.005 | -0.004 |
| 3-4 years of potential exp. | (0.005) | (0.004) | (0.002) | (0.002) | (0.001) | (0.002) | (0.003) | (0.003) | (0.003) |
| Unemployment rate (%) × | -0.003 | -0.003 | -0.003 | -0.002 | 0.001 | -0.002 | -0.001 | -0.002 | -0.001 |
| 5-6 years of potential exp. | (0.005) | (0.004) | (0.002) | (0.002) | (0.001) | (0.002) | (0.003) | (0.004) | (0.003) |
| Skill mismatch × | -0.049*** | -0.032*** | -0.005*** | 0.008*** | 0.004*** | -0.009*** | -0.008*** | -0.019*** | -0.017*** |
| 1-2 years of potential exp. | (0.005) | (0.004) | (0.001) | (0.002) | (0.001) | (0.002) | (0.003) | (0.003) | (0.003) |
| Skill mismatch × | -0.038*** | -0.028*** | -0.006*** | 0.003** | 0.003*** | -0.006*** | -0.005*** | -0.015*** | -0.015*** |
| 3-4 years of potential exp. | (0.005) | (0.004) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.004) | (0.004) |
| Skill mismatch × | -0.035*** | -0.027*** | -0.007*** | -0.000 | 0.002* | -0.004* | -0.003 | -0.018*** | -0.019*** |
| 5-6 years of potential exp. | (0.006) | (0.005) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.004) | (0.004) |
| MSA FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| College major × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Potential experience FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Individual controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.170 | 0.188 | 0.050 | 0.041 | 0.020 | 0.112 | 0.120 | 0.165 | 0.126 |
| Observations | 140,041 | 140,041 | 151,104 | 151,104 | 151,104 | 136,092 | 136,092 | 136,092 | 136,092 |

*Notes:* Individual controls include an indicator for being female, race fixed effects (Hispanic, Black, Asian, other race), an indicator for being foreign-born, an indicator for having a Master's degree and an indicator for being a double major. Observations are weighted by Census sampling weights. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table A10 — Distribution of Online Job Postings Per Capita Across MSAs, 2010-2016

| | 2010 | | 2013 | | 2016 | |
|---|---|---|---|---|---|---|
| | | | Panel A: Percentiles | | | |
| 90th | | 0.05 | | 0.08 | | 0.10 |
| 75th | | 0.04 | | 0.07 | | 0.08 |
| 50th | | 0.03 | | 0.05 | | 0.07 |
| 25th | | 0.02 | | 0.04 | | 0.05 |
| 10th | | 0.02 | | 0.03 | | 0.04 |
| | | | Panel B: Rank (40 largest MSAs) | | | |
| 1 | San Jose-Sunnyvale-Santa Clara, CA | 0.09 | San Jose-Sunnyvale-Santa Clara, CA | 0.12 | San Francisco-Oakland-Hayward, CA | 0.15 |
| 2 | Washington-Arlington-Alexandria, DC-VA-MD-WV | 0.07 | San Francisco-Oakland-Hayward, CA | 0.11 | Denver-Aurora-Lakewood, CO | 0.15 |
| 3 | Boston-Cambridge-Newton, MA-NH | 0.06 | Boston-Cambridge-Newton, MA-NH | 0.10 | San Jose-Sunnyvale-Santa Clara, CA | 0.15 |
| 4 | San Francisco-Oakland-Hayward, CA | 0.06 | Denver-Aurora-Lakewood, CO | 0.10 | Portland-Vancouver-Hillsboro, OR-WA | 0.14 |
| 5 | Denver-Aurora-Lakewood, CO | 0.06 | Washington-Arlington-Alexandria, DC-VA-MD-WV | 0.09 | Washington-Arlington-Alexandria, DC-VA-MD-WV | 0.13 |
| 20 | Milwaukee-Waukesha-West Allis, WI | 0.04 | Philadelphia-Camden-Wilmington, PA-NJ-DE-MD | 0.06 | Dallas-Fort Worth-Arlington, TX | 0.10 |
| 21 | Nashville-Davidson–Murfreesboro–Franklin, TN | 0.04 | Phoenix-Mesa-Scottsdale, AZ | 0.06 | San Diego-Carlsbad, CA | 0.09 |
| 36 | Houston-The Woodlands-Sugar Land, TX | 0.03 | Providence-Warwick, RI-MA | 0.05 | Miami-Fort Lauderdale-West Palm Beach, FL | 0.06 |
| 37 | Virginia Beach-Norfolk-Newport News, VA-NC | 0.03 | Miami-Fort Lauderdale-West Palm Beach, FL | 0.05 | San Antonio-New Braunfels, TX | 0.06 |
| 38 | Miami-Fort Lauderdale-West Palm Beach, FL | 0.03 | San Antonio-New Braunfels, TX | 0.04 | Houston-The Woodlands-Sugar Land, TX | 0.06 |
| 39 | Riverside-San Bernardino-Ontario, CA | 0.02 | Riverside-San Bernardino-Ontario, CA | 0.03 | Riverside-San Bernardino-Ontario, CA | 0.05 |
| 40 | San Juan-Carolina-Caguas, PR | 0.00 | San Juan-Carolina-Caguas, PR | 0.00 | San Juan-Carolina-Caguas, PR | 0.00 |

*Source:* Burning Glass Technologies.

Table A11 — Robustness: Top 100 MSAs in Terms of Online Job Postings Per Capita

| | Dependent variable: | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | Employed | | | Occupations | | | |
| | Log income | Log wage | Any | Part-time | Unemployed | College (O*NET) | College (ACS) | Top 5 | Top 10 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Skill mismatch × | -0.053*** | -0.036*** | -0.009*** | 0.007*** | 0.005*** | -0.003 | -0.002 | -0.015*** | -0.014** |
| 1-2 years of potential exp. | (0.008) | (0.005) | (0.002) | (0.002) | (0.001) | (0.004) | (0.003) | (0.006) | (0.006) |
| Skill mismatch × | -0.035*** | -0.026*** | -0.009*** | 0.001 | 0.003*** | 0.000 | 0.001 | -0.014*** | -0.014*** |
| 3-4 years of potential exp. | (0.006) | (0.003) | (0.002) | (0.002) | (0.001) | (0.003) | (0.003) | (0.005) | (0.005) |
| Skill mismatch × | -0.035*** | -0.025*** | -0.011*** | 0.000 | 0.003** | 0.002 | 0.004 | -0.015* | -0.016*** |
| 5-6 years of potential exp. | (0.007) | (0.004) | (0.003) | (0.002) | (0.002) | (0.003) | (0.003) | (0.008) | (0.006) |
| MSA × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| College major × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Potential experience FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Individual controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.179 | 0.205 | 0.065 | 0.050 | 0.027 | 0.121 | 0.129 | 0.177 | 0.137 |
| Observations | 80,842 | 80,842 | 86,571 | 86,571 | 86,571 | 78,771 | 78,771 | 78,771 | 78,771 |

*Notes:* Sample restricted to top 100 MSAs in terms of online job postings per capita (separately by year). Individual controls include an indicator for being female, race fixed effects (Hispanic, Black, Asian, other race), an indicator for being foreign-born, an indicator for having a Master's degree and an indicator for being a double major. Observations are weighted by Census sampling weights. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table A12 — Robustness: Exclude Master's Degree Holders

| | Dependent variable: | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | Employed | | | Occupations | | | |
| | Log income | Log wage | Any | Part-time | Unemployed | College (O*NET) | College (ACS) | Top 5 | Top 10 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Skill mismatch × | -0.052*** | -0.035*** | -0.002 | 0.009*** | 0.004*** | -0.015*** | -0.013*** | -0.020*** | -0.018*** |
| 1-2 years of potential exp. | (0.005) | (0.005) | (0.002) | (0.002) | (0.001) | (0.003) | (0.004) | (0.004) | (0.004) |
| Skill mismatch × | -0.035*** | -0.027*** | -0.002 | 0.002 | 0.002 | -0.011** | -0.010** | -0.014*** | -0.015*** |
| 3-4 years of potential exp. | (0.007) | (0.006) | (0.001) | (0.002) | (0.001) | (0.004) | (0.004) | (0.005) | (0.004) |
| Skill mismatch × | -0.032*** | -0.026*** | -0.004** | -0.000 | 0.002 | -0.011*** | -0.010*** | -0.017*** | -0.021*** |
| 5-6 years of potential exp. | (0.007) | (0.006) | (0.002) | (0.002) | (0.001) | (0.003) | (0.003) | (0.005) | (0.004) |
| MSA × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| College major × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Potential experience FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Individual controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.168 | 0.173 | 0.061 | 0.056 | 0.037 | 0.104 | 0.111 | 0.179 | 0.138 |
| Observations | 116,913 | 116,913 | 126,080 | 126,080 | 126,080 | 113,369 | 113,369 | 113,369 | 113,369 |

*Notes:* Sample excludes individuals who hold a Master's degree. Individual controls include an indicator for being female, race fixed effects (Hispanic, Black, Asian, other race), an indicator for being foreign-born and an indicator for being a double major. Observations are weighted by Census sampling weights. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table A13 — Robustness: Alternative Definition of Skill Mismatch

| | Dependent variable: | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | Employed | | | Occupations | | | |
| | Log income | Log wage | Any | Part-time | Unemployed | College (O*NET) | College (ACS) | Top 5 | Top 10 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Skill mismatch × | -0.147*** | -0.064** | -0.030*** | 0.027*** | 0.013* | 0.005 | 0.008 | -0.056** | -0.045* |
| 1-2 years of potential exp. | (0.030) | (0.031) | (0.011) | (0.009) | (0.007) | (0.018) | (0.017) | (0.026) | (0.024) |
| Skill mismatch × | -0.135*** | -0.064** | -0.036*** | 0.010 | 0.014* | 0.011 | 0.010 | -0.054** | -0.047* |
| 3-4 years of potential exp. | (0.030) | (0.030) | (0.010) | (0.009) | (0.007) | (0.017) | (0.016) | (0.026) | (0.024) |
| Skill mismatch × | -0.124*** | -0.061** | -0.044*** | 0.004 | 0.011* | 0.017 | 0.014 | -0.060** | -0.055** |
| 5-6 years of potential exp. | (0.030) | (0.030) | (0.010) | (0.010) | (0.007) | (0.018) | (0.016) | (0.027) | (0.025) |
| MSA × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| College major × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Potential experience FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Individual controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.180 | 0.198 | 0.061 | 0.052 | 0.031 | 0.124 | 0.132 | 0.173 | 0.135 |
| Observations | 150,844 | 150,844 | 162,508 | 162,508 | 162,508 | 146,566 | 146,566 | 146,566 | 146,566 |

*Notes:* The alternative definition of skill mismatch is described in Section 4.6. Individual controls include an indicator for being female, race fixed effects (Hispanic, Black, Asian, other race), an indicator for being foreign-born, an indicator for having a Master's degree and an indicator for being a double major. Observations are weighted by Census sampling weights. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table A14 — Robustness: Restrict to "Non-Movers" with 1 Year of Potential Experience

| | Dependent variable: | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | Employed | | | Occupations | | | |
| | Log income | Log wage | Any | Part-time | Unemployed | College (O*NET) | College (ACS) | Top 5 | Top 10 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Skill mismatch | -0.040*** | -0.034*** | -0.006* | 0.002 | 0.005*** | -0.007 | -0.004 | -0.022*** | -0.020*** |
| | (0.014) | (0.009) | (0.004) | (0.003) | (0.002) | (0.005) | (0.004) | (0.006) | (0.006) |
| MSA × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| College major × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Individual controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.206 | 0.224 | 0.108 | 0.117 | 0.089 | 0.195 | 0.206 | 0.246 | 0.207 |
| Observations | 30,795 | 30,795 | 32,886 | 32,886 | 32,886 | 29,586 | 29,586 | 29,586 | 29,586 |

*Notes:* Sample excludes individuals with more than 1 year of potential experience and individuals who migrated from a different state in the last year (i.e. "movers"). Individual controls include an indicator for being female, race fixed effects (Hispanic, Black, Asian, other race), an indicator for being foreign-born, an indicator for having a Master's degree and an indicator for being a double major. Observations are weighted by Census sampling weights. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table A15 — Robustness: Exclude Individuals Born Out-of-State

| | Dependent variable: | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | Employed | | | Occupations | | | |
| | Log income | Log wage | Any | Part-time | Unemployed | College (O*NET) | College (ACS) | Top 5 | Top 10 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Skill mismatch × | -0.025*** | -0.013*** | -0.005** | 0.005* | 0.004*** | -0.009*** | -0.008** | -0.011*** | -0.009** |
| 1-2 years of potential exp. | (0.005) | (0.005) | (0.002) | (0.003) | (0.001) | (0.003) | (0.004) | (0.003) | (0.004) |
| Skill mismatch × | -0.014** | -0.011** | -0.005*** | -0.000 | 0.002 | -0.006 | -0.005 | -0.003 | -0.004 |
| 3-4 years of potential exp. | (0.007) | (0.004) | (0.002) | (0.002) | (0.001) | (0.004) | (0.003) | (0.004) | (0.004) |
| Skill mismatch × | -0.013* | -0.013** | -0.004* | -0.006** | 0.002 | -0.006 | -0.005 | -0.003 | -0.004 |
| 5-6 years of potential exp. | (0.008) | (0.005) | (0.002) | (0.003) | (0.001) | (0.005) | (0.004) | (0.005) | (0.006) |
| MSA × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| College major × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Potential experience FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Individual controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.191 | 0.202 | 0.056 | 0.065 | 0.049 | 0.139 | 0.147 | 0.192 | 0.154 |
| Observations | 81,277 | 81,277 | 86,096 | 86,096 | 86,096 | 78,952 | 78,952 | 78,952 | 78,952 |

*Notes:* Sample excludes individuals born in a different state than their current state of residence (this includes the foreing-born by definition). Individual controls include an indicator for being female, race fixed effects (Hispanic, Black, Asian, other race), an indicator for having a Master's degree and an indicator for being a double major. Observations are weighted by Census sampling weights. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table A16 — Robustness: State-Level Regressions

| | Dependent variable: | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | Employed | | | Occupations | | | |
| | Log income | Log wage | Any | Part-time | Unemployed | College (O*NET) | College (ACS) | Top 5 | Top 10 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Skill mismatch × | -0.052*** | -0.033*** | -0.007*** | 0.011*** | 0.004*** | -0.011** | -0.009** | -0.015*** | -0.015*** |
| 1-2 years of potential exp. | (0.007) | (0.006) | (0.002) | (0.003) | (0.001) | (0.005) | (0.004) | (0.004) | (0.005) |
| Skill mismatch × | -0.038*** | -0.027*** | -0.006*** | 0.004 | 0.003*** | -0.006 | -0.006 | -0.013*** | -0.014** |
| 3-4 years of potential exp. | (0.006) | (0.006) | (0.002) | (0.003) | (0.001) | (0.004) | (0.004) | (0.005) | (0.006) |
| Skill mismatch × | -0.035*** | -0.027*** | -0.010*** | -0.000 | 0.002* | -0.004 | -0.005 | -0.015** | -0.016*** |
| 5-6 years of potential exp. | (0.009) | (0.007) | (0.002) | (0.003) | (0.001) | (0.003) | (0.003) | (0.006) | (0.006) |
| State × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| College major × cohort FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Potential experience FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Individual controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $R^2$ | 0.162 | 0.183 | 0.046 | 0.037 | 0.018 | 0.114 | 0.122 | 0.164 | 0.126 |
| Observations | 177,043 | 177,043 | 190,714 | 190,714 | 190,714 | 172,090 | 172,090 | 172,090 | 172,090 |

*Notes:* In this table, skill mismatch is defined at the state level (rather than MSA level), and the sample includes individuals who live outside of MSAs. Individual controls include an indicator for being female, race fixed effects (Hispanic, Black, Asian, other race), an indicator for being foreign-born, an indicator for having a Master's degree and an indicator for being a double major. Observations are weighted by Census sampling weights. Robust standard errors in parentheses, clustered at the state level. *** 1%, ** 5%, * 10% significance.

Table A17 — JOLTS Adjustment: Stylized Example

| Year | Occupation | Industry | Real vs. BGT vacancies | | | | JOLTS adjustment | | | | Adjusted |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Real vacancies | Real vacancy share | BGT vacancies | BGT vacancy share | BGT industry share | JOLTS vacancies | JOLTS industry share | JOLTS adjustment factor | BGT vacancy share |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| 2010 | Software Developer | IT | 30 | 30% | 15 | 45.5% | 75.8% | 50 | 50% | 0.66 | 30% |
| 2010 | Database Administrator | IT | 20 | 20% | 10 | 30.3% | | | | | 20% |
| 2010 | Construction Manager | Construction | 30 | 30% | 6 | 18.2% | 24.2% | 50 | 50% | 2.06 | 37.5% |
| 2010 | Construction Worker | Construction | 20 | 20% | 2 | 6.1% | | | | | 12.5% |
| | Total | | 100 | 100% | 33 | 100% | 100% | 100 | 100% | | 100% |
| 2016 | Software Developer | IT | 36 | 30% | 24 | 38.1% | 63.5% | 60 | 50% | 0.79 | 30% |
| 2016 | Database Administrator | IT | 24 | 20% | 16 | 25.4% | | | | | 20% |
| 2016 | Construction Manager | Construction | 36 | 30% | 15 | 23.8% | 36.5% | 60 | 50% | 1.37 | 32.6% |
| 2016 | Construction Worker | Construction | 24 | 20% | 8 | 12.7% | | | | | 17.4% |
| | Total | | 120 | 100% | 63 | 100% | 100% | 120 | 100% | | 100% |

*Notes:* The numbers in this table are purely hypothetical (see Section 4.6 for details).