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Abstract

This paper analyzes whether postsecondary training programs have kept up with shifts in the occupational structure of the labor market over the past decades. I compare long-term trends in the distribution of employment, degrees, and certificates across occupation groupings using data from the Census and from the nation's largest community college system. I then estimate that an occupation's share of community college completions grows 0.53 percentage points for every percentage point increase in its share of employment. However, I show that this relationship is primarily driven by increases in student demand rather than by colleges expanding capacity.

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1 Introduction

The United States labor market underwent dramatic shifts in its occupational composition over the past few decades. Employment and wages have grown for workers at both the high and low end of the skill distribution, with declines in the middle (Acemoglu and Autor, 2011). The labor market has also seen the continued decline of industrial and manufacturing employment, and the rise of low-skill service jobs (Autor and Dorn, 2013). While the causes of these massive changes are still being debated,[1] the consequences are far-reaching, affecting income inequality, political alignments, and social indicators (Acemoglu and Autor, 2011; Autor et al., 2016; Autor, Dorn and Hanson, 2017).

It is unclear, though, if the training of workers has kept pace with these changes in labor demand. In this paper I focus on community colleges, which have been a primary source of training for middle-skill jobs and have thus acted as important drivers of upward socioeconomic mobility (Grubb, 1996; Grubb and Lazerson, 2004). Career technical education (CTE) programs are often the primary training centers for entire professions, such as registered nurses and firefighters (Van Noy et al., 2008; Lerman, 2009). However, community colleges are often criticized for their inability to keep pace with changes in the labor market (National Academies of Sciences and Medicine, 2017). The conventional wisdom, as expressed by Dougherty (1994), is that the community college sector "dances to the rhythms of the labor market, but it rarely keeps very good time." It is surprising, then, that there is scant research seeking empirical evidence for this criticism.

In this paper I study how the occupations for which community colleges train students have changed over time. I leverage administrative data encompassing all students, faculty and course offerings since 1992 at California's community colleges, the largest public education system in the country. I link program-level information on enrollment, completion, faculty hiring, and course availability to occupation-level information on employment, wages, and education levels from the Census. I first provide a descriptive view of the range and content of community college program completions, and how they overlap with employment. I then analyze whether employment changes in a particular occupation cause commensurate changes in the number of community college

[1] The two key drivers are skill-biased technological change (Autor, Levy and Murnane, 2003; Acemoglu and Restrepo, 2017) and international trade (Autor, Dorn and Hanson, 2013; Goos, Manning and Salomons, 2014). For a discussion of the relative importance of these two causes, see Autor, Dorn and Hanson (2015).

completions in programs that train students for that occupation. While the most policy relevant variable is the number of completions, the relationship between completions and employment could be driven by changes in student demand for programs or by changes in community college supply of programs. If students respond to labor market forces but community colleges do not expand their programs, for example, this may still result in a positive relationship between completions and employment, if some programs are never filled to capacity. There is evidence that, at least in California, community colleges have increased class size in certain courses due to budget cuts (Bohn, Reyes and Johnson, 2013), which may result in reductions in educational quality and thus the extent to which labor market needs are actually met. A key contribution of this paper is that the administrative data I use allow me to observe program-level information beyond completions, such as course enrollment and faculty hiring, in order to investigate these mechanisms.

I show that only half the "polarization" phenomenon documented by Acemoglu and Autor (2011) occurs for community colleges; specifically, degree and certificate completions since the early 1990s increased for occupations at the bottom of the skill distribution, but unlike employment they have not increased for occupations at the top. However, community colleges do train students in occupations that are broadly similar to those held by highly educated workers. Autor, Levy and Murnane (2003) and others have shown that demand has declined for occupations with a high intensity of routine, codifiable tasks that can be performed by a computer. Similarly, I show that the task content of community college programs resembles the task content of occupations that employ highly educated workers. However, overall trends in community college completions parallel the more general shifts seen throughout the labor market: a decline in routine tasks and a rise in abstract, non-routine and non-manual tasks.

In the main analysis I relate an occupation's share of overall employment to its share of community college completions, courses, faculty, and enrollment. A concern is that if community colleges train new workers, then growth in employment might actually be caused by college expansions. To account for this potential bias, I use an approach that leverages the historical distribution of employment in occupations, as well as national trends in employment growth, to account for occupation-level changes in demand (Bartik, 1991; Autor and Dorn, 2009; Diamond, 2016).

I find evidence of a modest link between occupational employment change and the growth of degrees and certificates. An occupation whose share of overall employment grew by one percentage point over the course of a decade saw its share of all degrees and certificates grow by approximately half a percentage point. I find that the response of program-level course enrollment to employment changes is similar to the completion response. However, I find no evidence of a response in terms of the number of course sections offered or faculty employed to teach these courses. I cannot rule out that colleges increase course capacity, perhaps leading to larger class sizes and overcrowding. This suggests that most of the connection between community colleges and the labor market comes from changes in student demand for programs in growing fields rather than colleges changing their inputs. Thus, these results support the common claim that administrative and budgetary constraints keep community colleges from adequately "dancing" to the rhythms of the labor market.

Focusing on completions, I find significant heterogeneity across occupations in this connection between employment and completions. Occupations in the production and manufacturing sector have a weaker response than other occupations. However, there were no important differences between occupations that require relatively costly training–such as in healthcare–and other occupations. I also find some heterogeneity across colleges, with larger colleges being particularly responsive to employment changes.

This paper makes several contributions to the literature. This is the first paper to explore the content of community college degrees and certificates in the context of the recent literature on labor market polarization. Because of the vocational mission of community colleges, this connection is important to understand. Second, while much of the prior literature has lamented a supposed mismatch between community college program offerings and occupation-level labor demand, in this paper I provide an explicit estimate based on an approach grounded in causal inference. Finally, a growing body of work explores the causes and consequences of student sorting across college majors, with recent work using surveys or lab settings (Baker et al., 2017; Arcidiacono, Hotz and Kang, 2012). Here I explore this issue at the community college level using information on completions and enrollment, and show that while there may be some inefficiencies, students do seem to sort into growing fields.

The rest of this paper proceeds as follows. Section 2 reviews the relevant literature. Section 3 describes the datasets as well as the matching algorithm between occupation-level employment statistics and program-level academic information. Section 4 contains a detailed descriptive analysis of how trends in community college completions compare to employment trends. Section 5 describes the regression methodology. Section 6 shows the regression results, and Section 7 concludes.

2 Literature Review

The importance of education as a driver of socioeconomic mobility has increased over the past half century. There is ample documentation of rising college wage premiums driven in part by a reallocation of labor across industries and occupations (Katz and Murphy, 1992; Goldin and Katz, 2008). In recent years, a growing body of work has shown that international trade and technological progress have led to relative increases in employment among workers with high and low education levels, at the expense of "middle-skill" workers. Likewise, the labor market has experienced an increase in demand for workers in occupations that require critical thinking and in-person interactions that cannot be easily codified by computers (Autor, Levy and Murnane, 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2017; Goos, Manning and Salomons, 2014; Autor, Dorn and Hanson, 2013).

In this context, community colleges are crucial due to their focus on training workers in specific occupations. The job training mission of the community colleges gained traction after the 1960s, spurred by federal funding written into the Vocational Education Act of 1964 and its 1968 amendments (Cohen and Brawer, 2003). Since then, CTE has become one of the primary missions of the community college, and recent evidence shows that the labor market returns to many CTE programs are quite high (Jepsen, Troske and Coomes, 2014; Stevens, Kurlaender and Grosz, 2019; Grosz, 2020). However, a tension remains between training workers in new high-growth sectors and providing basic job training as a way to fight poverty and stimulate upward economic mobility (Jacobs and Dougherty, 2006). Dougherty (1994) argues that bureaucratic and institutional factors lead community colleges to be slow and inaccurate in responding to student needs. Still, in recent years community colleges have been the recipients of large-scale funding from federal and state sources, with the explicit purpose to expand program offerings in certain industries and occupations.[2]

Nevertheless, there is little empirical evidence on the extent of the connection between community colleges and occupational growth in a causal framework. On the other hand, there is considerable work observing aggregate trends and projections for employment of workers with different skills and educational attainment (Carnevale, Smith and Strohl, 2013; Johnson, Mejia and Bohn, 2017). While informative, these types of analyses do not speak to the direct causal link between labor market changes and community college offerings.

Much more is known, however, about other drivers of changes in community college enrollment and programmatic offerings. Community colleges shrink enrollment in response to budgetary pressure, for example (Deming and Walters, 2017; Bound and Turner, 2007). There is also evidence that enrollment rises during recessions (Betts and McFarland, 1995; Barrow and Davis, 2012) as well as following local labor market downturns (Foote and Grosz, 2017; Weinstein, 2017). In recent years, a great deal of attention has been paid to the potential competition between public community colleges and the private for-profit sector (Deming, Goldin and Katz, 2012; Cellini, 2010, 2009; Cellini, Darolia and Turner, 2016; Xia, 2016). Still, the literature has not investigated community college responses to labor market changes at the program level.

There is some evidence, though, that occupation-specific employment and wage changes do affect enrollment at the four-year college level. Focusing on degrees by declared major, Bardhan, Hicks and Jaffee (2013) document heterogeneity in the extent of responsiveness between occupation-degree pairings by constructing an instrument that leverages differences in the age composition across different occupations. Similarly, Long, Goldhaber and Huntington-Klein (2015) show that for four-year college majors there is a modest alignment between degree production and labor market demand. These two papers are most similar in spirit to this paper, though they focus on four-year colleges and use a different empirical approach. However, given the well-documented mission of community colleges in providing CTE programs and training, it is more likely that there should be a tighter connection with labor market trends at the community college level than at the four-year college level.

[2] See Eyster, Durham and Anderson (2016) and Jacobson et al. (2011) for a review of specific federal workforce development and training programs housed at community colleges.

3 Data

Below I describe the main sources of data and how I match the two main datasets in order to produce an occupation-year panel.

3.1 Academic Data

The California Community Colleges system consists of 113 campuses and is the largest public higher education system in the country, enrolling over 2.6 million students annually. I use detailed administrative records from the California Community Colleges Chancellors Office (CCCCO) from 1993 to 2016, which include information at the student, college, course, and faculty levels. The key benefit of the California data is that I can observe program-level information beyond just completions.

I categorize the content of programs, courses, and faculty teaching assignments according to the Taxonomy of Programs (TOP), a system unique to the CCCCO, but almost identical to the more commonly used Classification of Instructional Programs (CIP) maintained by the National Center for Education Statistics (NCES). All community colleges in the state use the TOP, yielding a uniform categorization of the topical content of numerous variables across time within the large California community college system. There are 607 unique TOP codes.

For the majority of the analyses I rely on information about completions: degrees and certificates. Each completion is assigned a unique TOP code describing its educational content. The CCCCO data also disaggregate these completions by their type according to the number of units they required: 6-17, 18-29, 30-59, and at least 60 units. An associate's degree typically requires 60 or more units. For simplicity, for the analysis of completions I create a summary measure of "awarded units": the total number of units completed, constructed from the sum of different types of completions.[3] In robustness exercises I also consider basic counts of overall completions, as well as degrees and certificates separately.

In addition to completions, I also observe enrollment, the number of course sections, and

[3]Because each completion is in a range of possible units completioned, I take the midpoint. Thus, for the purposes of this analysis a 6-17 unit certificate consists of 9.5 units, a 18-29 unit completion consists of 23.5 units, and a 30-59 unit certificate of 44.5 units. The 60 and over certificates I categorize as 60 units, though in practice there are very few of these. I categorize associate's degrees as 60 units. Thus, the summary measure can be interpreted as a weighted sum of the number of completions, giving higher weight to longer programs.

faculty appointments, all at the course level. For courses offered, I calculate the number of total units offered across all course sections in a TOP code. This allows me to incorporate information on the capacity of programs, giving greater weight to programs that are offered over multiple course sections. Unfortunately, there is no information at the course level on enrollment capacity or caps. I calculate the number of faculty in terms of the full-time equivalent (FTE) given in the data, and in robustness checks separate out fulltime FTEs from adjunct faculty FTEs. Finally, I calculate the raw counts of students enrolled in each TOP code each term.

In a robustness exercise I also use data from the Integrated Postsecondary Educational Data System (IPEDS). I use national institution-level information since 1986 on completions of certificates and associate degrees for all subbaccalaureate non-profit colleges.

3.2 Employment Data

Data for workers come from the Census Integrated Public Use Micro Samples for the years 1980, 1990 and 2000, as well as the American Community Survey (ACS) for 2010 (Ruggles et al., 2015). The Census samples cover five percent of the US population, and the ACS sample covers one percent. I limit the sample to workers and categorize them by their education status: at most high school, some college but no baccalaureate degree, and at least a college degree. Because the academic data I use come from California, I also create a subsample of California workers.

In order to observe occupations that are consistent over time I use the occupation codes developed by Autor and Dorn (2013) for the 1980-2000 Censuses and 2005-2008 ACS, and later updated by Deming (2017) for the 2010 ACS.

3.3 Matching Academic to Employment Data

While the academic data from the CCCCO are categorized at the TOP level, the employment data from the Census and ACS are categorized at the occupation level. To crosswalk between the two, I develop a mapping, based on crosswalks created by the National Center for Education Statistics (NCES) and the Bureau of Labor Statistics (BLS), that relates the occupational codes to the educational codes. This is a process similar to that in other work that seeks to match occupations to majors (Long, Goldhaber and Huntington-Klein, 2015; Bardhan, Hicks and Jaffee, 2013).

Six-digit TOP codes, each corresponding to a “subdiscipline,” broadly correspond to the more commonly used CIP codes according to a crosswalk published by the CCCCO. The crosswalk accounts for 404 of the 607 possible TOP codes. The NCES and BLS match between CIP codes to 2000 Census occupational codes accounts for 379 TOP codes. For the 2014 academic year, these 379 matched TOP codes account for 97 percent of all degrees and certificates. The match between the CIP codes and occupation codes is many-to-many, so collapsing degrees and certificates from this match down to the occupation level would double-count degrees. In a related case Long, Goldhaber and Huntington-Klein (2015) weight each match by the share of workers in each occupation who earned each major using American Community Survey data. However, they find that weighting each match equally—the approach I use— produced similar results. The resulting panel consists of 341 occupations for which there is academic data from the CCCCO and employment data from the Census. Data Appendix A2 describes the matching process in more detail.

4 Descriptive Evidence

I begin the analysis by comparing California community college degrees and certificates to overall employment along various metrics. The analysis is descriptive, but uncovers phenomena that have not previously been documented, and also motivate the causal analysis in the next section (Loeb et al., 2017). First I consider whether community college completions have followed the well-documented pattern of polarization, whereby employment has grown at the top and bottom of the skill distribution and sagged in the middle. Then I examine the allocation of employment across broad occupational groupings. A predominant trend in the US labor market has been the rise of service-sector jobs at the expense of production and clerical jobs, which have traditionally formed the core of community college career-technical program offerings. Finally, I compare community college completions and employment along their task content. Describing the tasks that occupations require leads to useful comparisons of occupations that on face value have little in common, but may be affected in similar ways by labor market forces.[4]

[4]For all the descriptive analyses I use employment data from California, though results using national employment data are very similar and available on request. Academic data come from the California community colleges.

4.1 Skill distribution

Panel a) of Figure 1 shows the well-known image of the polarization of the US labor market. The horizontal axis shows percentiles of the 1980 skill distribution, measured as log occupational mean wages, weighted by 1980 employment. The vertical axis shows the growth of employment by each of these percentiles, measured as the change in the share of each occupation's employment from 1990 to 2010. The typical U-shape curve shows growth at the bottom and top of the skill distribution, with a decline in the middle.[5]

Panel b) of Figure 1 shows an analogous plot for the change in the distribution of California community college completions, between 1993 and 2013, by the same percentiles of the 1980 skill distribution. There are some similarities between the change in the distribution of degrees and certificates by skill percentile and that of overall employment. However, the increases at low skill levels are much bigger for degrees and certificates. Most notably, there has not been an increase in completions at the top of the skill distribution, which for degrees and certificates remains unchanged. Thus, while there may be polarization in terms of employment, the distribution of completions is only being stretched in one direction.

One implication of Figure 1 is that perhaps community college degrees and certificates should not be directly compared to the overall distribution of employment. Instead, community college students who earn CTE degrees and certificates are learning skills that move them up the skill distribution, but not quite to the same extent as a four-year college degree. The distribution of community college CTE completions is perhaps more comparable to the distribution of employment of workers with some college but less than a four-year degree.

Figure 2 shows the distribution of employment and completions, by the same percentiles of the 1980 overall skill distribution as in the previous figure. Overall employment is constructed to be uniformly distributed across each percentile, so it can be represented as a horizontal line at a density of 0.01. Not surprisingly, there is a clear difference in the distribution of workers with some college (dashed) and with a degree (dotted). The dark solid line shows the distribution of community college completions in 1993. This distribution lies somewhere between that of workers with some college and those with a college degree. The occupations for which community college

[5] A figure showing the employment change from 1980 to 2010 is almost identical

students train require much more skill than those held by workers with just some college. Of course, part of the reason for this difference is that many workers with less than a college degree do not work in occupations where they skills learned in postsecondary coursework; community colleges do not train cashiers, waiters, and receptionists, who comprised three of the largest five occupation groups for workers with some college but no baccalaureate degree in 1990.[6] Between 1990 and 2010, as shown in panel b) of Figure 2, the skill level of occupations for workers with a college degree increased, while the skill level of workers with some college decreased, as did that of community college completions.

A drawback of summarizing the labor market in terms of skill level is that there is a clear difference in the occupations that comprise the growth of employment and completions at the low end of the skill or earnings distribution. To illustrate, Figure 3 shows employment and completions for three of the largest occupations in terms of community college completions. Cosmetologists, hairdressers, and childcare workers accounted for five percent of all CTE degrees and certificates in 1993, but grew rapidly in the late 1990s and early 2000s to reach over 10 percent of all degrees and certificates by 2010. On the other hand, a primary source of employment growth for workers with some college was among nursing and home health aides, which did not see a similar rise in community college completions. Figure 3 shows that growth in employment and completions in these large occupations did not necessarily overlap, even though the overall trend in skill distribution did.

4.2 Task content of occupations

Another informative way to categorize the occupations is by their task content. The “routinization” hypothesis developed by Autor, Levy and Murnane (2003) explained how, as technology becomes cheaper, employers can substitute away from certain types of workers, while new technological innovation can complement other workers. Whether computers will substitute for or complement labor depends on whether that worker engages in tasks that substitute or complement a computer’s own abilities. Autor, Levy and Murnane (2003) point out that because computers excel at routine tasks, which can be codified as a series of instruction, workers in occupations that require these

[6] The other two largest occupations were childcare workers and health and nursing aides, which do receive training in community college.

types of tasks will be substituted for. Thus, relative demand will rise in non-routine occupations.

In this context, examining the task-content of community college degrees and certificates is a valuable contribution to this literature. This exercise gives a more nuanced perspective of the underlying structural changes the labor market has undergone, and whether community colleges have responded.

I construct measures based on combinations of work activities and work context scores from the Department of Labor's Occupational Information Network (O*NET). I follow a set of categorizations about the routine intensity of an occupation, as described in Acemoglu and Autor (2011), Autor, Levy and Murnane (2003) and Autor, Katz and Kearney (2008).[7] In addition, I follow Deming (2017) to measure the social content of occupations. Because all these scores are based on categorical scales, following Acemoglu and Autor (2011) I standardize them to have mean zero and standard deviation of one, based on the 1990 distribution of employment.[8] The scores can thus be interpreted as standard deviation differences from the 1990 overall employment distribution. A list of the ten highest scoring occupations in each task is in Appendix Table A1.

Table 1 shows employment-weighted means and standard deviations for task scores across different educational groups in 1990, as well as completion-weighted means and standard deviations for community college degrees and certificates in 1993. The means should be interpreted as standard deviation differences in task intensity relative to the 1990 overall employment distribution. In 1990 workers with at most a high school diploma worked in occupations that were less abstract-intensive and more manual and routine than the average worker, and were also less likely to work in social-intensive occupations. At the other extreme, as shown in column 3, workers with at least a college degree were much more likely than the average worker to be in abstract-intensive and social occupations.

As shown in column 4, community college degrees and certificates tended to be completioned in abstract-intensive and social occupations.The average community college completion was also less manual-intensive than the average occupation. As shown previously this places the distribution of community college completions somewhere between the distribution of employment of workers

[7] A more in-depth description of each of these task groupings, along with its component parts, is in the Data Appendix.

[8] Other work has shown that the most dramatic shifts in demand for tasks occurred in the 1980s, and thus other authors have standardized scores to the 1980 employment distribution. I standardize relative to 1990 because the comparison between the 1993 completion distribution and 1990 employment distribution is informative.

with some college and those with a college degree.

In addition to the initial differences between community college completions and overall employment it is also informative to examine trends over time. Figure 4 shows the mean task intensity for each educational grouping since 1990. For each individual panel the task intensity is standardized in the initial year.[9] This allows me to isolate just the relative changes over time, knowing that initial levels are different across the groupings.

Panels a), b), and c) show how the task intensity of employment among workers with different educational attainment evolved from 1990 to 2010. Workers with at most a high school degree or equivalent were much less likely to work in abstract and social-intensive occupations, and much more likely to work in manual ones. The opposite is true for workers with more than a college degree. The task composition of work for those with some college but no degree lies somewhere between these other two types of workers. An important trend documented by Autor and Dorn (2013), though, is that overall routine task intensity has dropped substantially.

How did the evolution of task intensity for community college completions compare? Panel d) shows that between 1993 and 2010, the composition of community college degrees and certificates changed substantially. Early declines in abstract intensity were followed by large growth starting in 2000. There was also a notable drop in both routine and manual intensive occupations. There was also modest growth in social tasks. These overall changes mirror the changes evident among college degree holders and, to a lesser extent, workers with some college. Appendix Table A2 shows task means in 2010, relative to overall employment in 2010. The means are largely similar to those in 1990.

4.3 Broad occupational groups

Finally, I investigate further whether there is overlap between employment and the occupations that community colleges train workers for. I categorize occupations into broad groups, following Autor and Dorn (2013). The first group is managerial, professional, and technical occupations, which tend to be highly skilled and paid occupations. The next group consists of administrative, retail,

[9] This is a different standardization than in Table 1, which standardized to overall employment in 1990. In Figure 4 panel a), for example, the mean task intensity is set to 0 for workers with high school or less, and in b) it is set to 0 for workers with some college.

and sales occupations, which tend to be middle-skilled white collar occupations. The third group consists of low-skill service occupations, which tend to employ workers without postsecondary education and consists of jobs in personal care, food preparation and cleaning, and protective service. The final group consists of middle- and low-skill blue collar occupations in production, manufacturing, crafts and construction. Appendix Table A13 contains a list of all the occupations and their broad grouping.

Panel a) of Figure 5 shows each occupational group's share of employment and community college degrees in 1990. The first three bars show the differences in the distribution of employment for workers with a high school degree, with some college, and with a college degree. The final bar shows the share of community college degrees and certificates in each of the broad occupational categories in 1993. Managerial and technical occupations accounted for more than half of all CTE completions, with the rest almost evenly split among the other occupational groupings. Approximately 20 percent of all community college completions were in blue-collar occupations in 1993, which is not surprising given the traditional community college focus on manufacturing and construction trades.

Panel b) of Figure 5 compares the growth of each occupational grouping since 1990. Across the board, employment in low- and middle-skill blue collar occupations declined, a trend that has been well-documented in the literature. At the same time, there has been a marked rise in low-skill service occupations in each educational grouping. As mentioned previously, while these changes have been driven by increased employment in low-skill healthcare professions for workers with some college, it has been driven by an increase in personal care certificates like cosmetology and barbering at the community colleges. The regressions in the following section are similar in spirit to this figure, and instead compare these trends while disaggregating the broad occupational groups back to the individual occupations.

5 Methods

Until now I have shown descriptive evidence for an alignment between employment changes and community college completions since 1990. In this section I describe the analytical strategy to measure the direct link between an occupation's employment and community college programs.

I focus on shifts between decennial Census years. Labor market trends like polarization and the growth of the service sector have been slow. Similarly, it is unlikely that any response from the community college sector would occur from one year to the next: colleges do not have the administrative or bureaucratic capacity to respond so quickly to such changes.

I characterize the changes in an occupation's share of educational production to changes in its share of overall employment through the following relationship:

$$\Delta y_{jt} = \alpha + \beta \Delta Emp_{jt}^{CA} + \delta_t + u_{jt} \tag{1}$$

For occupation j in year t, y_{jt} is an occupation's share of an academic variable: completions, available course units, faculty FTE's, or enrolled students. For example, this could be the fraction of all completions in year t that were in occupation j. Similarly, Emp_{jt}^{CA} is an occupation's share of employment in California. To control for occupation effects equation 1 is in ten-year differences. Since the data span three decades and the specification is expressed in changes, there are two observations for each occupation, and thus the year fixed effect δ_t is an indicator for the decade from 1990 to 2000. All regressions cluster standard errors at the occupation level. I weight regressions by 1980 Census employment at the national level.[10]

One challenge in combining the decennial Census data and the academic data is that the first available year of community college data is from the 1992-1993 academic year. Thus, I cannot observe a full decade change for 1990 to 2000. On the other hand, there is no Census data available between Census years. As a solution, in the main specifications I relate decadal changes in employment from Census to the longest intervals for which I have access in the academic data, which are seven-year changes. So, in other words, I match 1990-2000 employment changes with 1993-2000 changes in academic variables, and 2000-2010 employment changes with 2003-2010 changes in academic variables. In robustness exercises I use other intervals and also allow for lags in the response of the academic variables to employment.

The concern when estimating equation 1 is the endogeneity of changes in occupational employment with respect to shifts in the content of local educational production. For example, new community college graduates trained in an occupation may affect that occupation's share of overall

[10] I present unweighted regressions in an appendix table.

employment. To alleviate this concern, I use an instrument that isolates occupation-level demand shocks from national shocks across industries. The instrument takes the form of the standard "shift-share" approach commonly used in this literature (Bartik, 1991; Autor and Dorn, 2009, 2013; Autor, Dorn and Hanson, 2013; Diamond, 2016). The goal is to isolate changes in labor demand that come from national-level shocks to industry-level employment, such as those that come from forces like international trade, as opposed to endogenous occupation-specific shocks.

I use the instrument to predict employment across occupations within California. The instrument fixes occupation-industry shares at the beginning of the study period and allows them to grow by the national employment growth rate in each industry. The rationale is that changes in industry shares nationally will impact occupational shares in California. For example, growth in the hospital industry nationally will increase the California employment share of occupations—such as medical assistants and registered nurses—that are disproportionately present in that industry. Specifically, the instrument is defined as:

$$\widehat{Emp}_{jt}^{CA} \equiv \sum_{i=1}^{I} \left[Emp_{ij,1980}^{CA} * (g_{it,1980}^{US}) \right] \tag{2}$$

Here, $g_{it,1980}^{US}$ is industry j's growth rate between 1980 and time period t. The superscript "US" includes all non-California employment. In other words, only national shocks to employment growth are allowed to affect California employment in the instrument. Table A3 shows first stage estimates. The first column shows results of the baseline specification, which I use in most of the analyses, and the other columns show the first stage results of several robustness specifications I discuss in a later section. The employment instrument is highly predictive, with a high F statistic.

Goldsmith-Pinkham, Sorkin and Swift (2018) propose various tests to show evidence of support for the validity of the exclusion restriction. They note that the underlying variation from these instruments is the initial industry shares, and recommend testing the correlation of these shares, in my case $Emp_{ij,1980}^{CA}$, with characteristics of the occupation itself. I show these in Appendix Table A4 for the five industries with the highest mean share of employment in California. Some of the characteristics are correlated with the industry shares. As Goldsmith-Pinkham, Sorkin and Swift (2018) report, this tends to be the case even in canonical applications of the shift-share instrument. Nevertheless, the most important covariates—measures of educational composition—

seem uncorrelated with the industry shares. As a separate test, which I discuss in a later section, I show that inclusion of these covariates into the main regressions leads to almost identical results, providing further support.

6 Results

6.1 Main Results

Table 2 shows results of estimation of equation 1, relating an occupation's growth in employment share to its community college programs. Each column shows a different measure of the program's offerings: completions, faculty FTEs, courses offered, and enrollment. The first outcome is completed units, and the result suggests that occupations whose share of total employment grew one percentage point also grew their share of completions by 0.495 percentage points. A coefficient of one would suggest that increases in employment shares were associated with equal increases in completion shares. The estimate is statistically significantly different from zero—which would mean no response—and is also statistically significantly different from one—which would mean a perfectly aligned response.

Panel B of Table 2 shows the results of the two-stage least squares analysis, using the shift-share constructs as instruments. The result in column 1 is similar to the OLS result: occupations that grew one percentage point as a share of overall employment increased their share of total completions by 0.527 percentage points. Overall, these results suggest that there is a non-zero response by community colleges to changes in the labor market. It is helpful to understand the sense of scale of the effects in panel A in terms of the number of degrees. One of the fastest-growing occupations between 2000 and 2010 was health and nursing aides, whose share of overall employment grew by 0.7 percentage points over this time period. The results in Table 2 suggest that the share of degrees and certificates in these occupations would have grown by 0.37 percentage points, or about 215 associate's degrees per year.[11]

[11] In more detail, the point estimate suggests that the share of completions in this particular occupation would grow by 0.37 percentage points given its employment share grew by 0.7 percentage points. The predicted share of completions in 2010 thus becomes 2.58 percent of all completions, or 61,518 completed units. Given that there were 48,726 completed units in this occupation in 2000, the difference is 12,791 units, or the equivalent of approximately 215 associate's degrees, which are comprised of 60 units each.

Column 1 shows effects on completions, which is an important measure since it provides an estimate of the flow of newly trained workers in different occupations into the California labor market. As a measure of community college response to trends in the labor market, though, it is incomplete. The number of degrees and certificates is a function of the availability of programs as well as the interest and persistence of students in enrolling and completing credentials in these programs.

To disentangle these effects, and hone in on whether the response I observe in completions is one of community college administrators or of students, I implement the same analyses through estimating equation 1 for other measures that are available in the California dataset. I consider measures that reflect inputs to degrees and certificates, or are at least upstream from completed degrees. Column 2 shows the effect of employment changes on an occupation's share of faculty FTE's, and column 3 shows the effect on an occupation's share of course sections. For neither of these measures is there a large or precisely estimated response. Thus, I do not find evidence that colleges are systematically changing their capacity to meet changes in labor demand.

On the other hand, the final column of Table 2 shows effects on enrollment, measured in terms of enrolled units. Here I do find an effect: occupations that grew one percentage point as a share of total employment also grew as a share of total enrollment by 0.141 percentage points. This result, combined with the main results on completions rate, suggest that students are responding to changes in the labor market, while colleges are not systematically changing capacity. This is likely evidence that extra demand for courses from students is being met by increasing course capacity or the number of seats available, as opposed to opening new sections or hiring new faculty. In fact, systematic increases in class size throughout the community college sector have been well-documented (Bohn, Reyes and Johnson, 2013). Unfortunately I cannot observe course-level enrollment caps or waiting lists to provide further evidence for this finding.

The results in Table 2 are not sensitive to various different specifications. Appendix Table A6 shows that the results are qualitatively similar when not weighted. Appendix Table A7 shows the main results including additional occupation-year-level covariates, such as demographic characteristics and employment characteristics, including the ones used earlier in correlations with industry shares, in Appendix Table A4. This provides further evidence of the strength of the shift-share instrument. Appendix Table A8 redefines the key explanatory variables—employment shares—in terms of the California population with some college but less than a four-year degree. The results are also comparable to those in the main table.

In another check, I construct the instrument in a slightly different way. In the main analysis, as shown in equation 2, I fix the 1980 distribution of industry shares as the main source of variation in the shift share instrument and calculate industry growth rates relative to 1980. As a robustness exercise I instead use the distribution in the previous period. I define the instrument as:

$$\widehat{Emp}_{jt}^{CA} \equiv \sum_{i=1}^{I} \left[Emp_{ij,t-1}^{CA} * (g_{it,t-1}^{US}) \right] \tag{3}$$

where $t-1$ is defined as the previous decade's value of the variable. The last column of Table A3 shows first stage estimates, which are similar to the main specification, though slightly smaller. Table A9 shows the main coefficients using this slightly different formulation of the instrument, which are also very similar.

6.2 Intervals and Lags

The results so far relate seven-year changes in academic variables to 10-year changes in Census variables; for example, 1990-2000 employment changes and 1993-2000 completions changes. The reason for the seven-year changes is that 1993 is the first year of community college data.

Figure 6 shows how the results change depending on the interval (smaller or greater than seven years) as well as the number of lag years between the academic variables the Census variables. The lag time is important if community colleges move slower than the labor market. The figure shows estimates and confidence intervals for the four main outcome variables. Each color of estimate is a different size interval, while the horizontal axis shows the number of lag years. The default, shown in the main tables so far, is a lag of zero and an interval of seven years, corresponding to the orange circle above the zero on the horizontal axis. Moving to the right, the orange circle above the number one corresponds to academic data from 1994-2001 and 2004-2011: an interval of seven years but a lag of one year relative to the census data. Meanwhile, the green X above zero corresponds to academic data from 1994-2000 and 2004-2010.[12]

There are two key takeaways from this exercise. First, the size of the interval does not seem to

[12] Since the data do not go back before 1993, it is impossible to show intervals of 8 or 9 years at a lag of zero.

matter. Within each lag size—that is, at each point above the horizontal axis—the estimates for different interval lengths are relatively similar. However, there do seem to be important differences in the estimates depending on the lag length. Across the four panels, the lag length of three or four years results in the largest estimate. For example, the orange circle at lag of 3, corresponding to the years 1996-2003 and 2006-2013, results in the largest estimate of the effect of employment changes on completions. The pattern for different lag lengths is apparent in all the outcomes, and actually yields marginally statistically significant results for faculty employment. The figure shows that the default specification I use leads to a lower bound estimate.

6.3 Occupation Characteristics

There may be heterogeneous effects by occupation characteristics. Community colleges may expand certain programs even if employment in those particular occupations is not growing particularly fast. These changes might, in some cases, be associated with the way community college programs and departments are organized. For example, it might make sense for a college to shutter multiple manufacturing and construction programs even if employment in all of the specific fields is not declining.

Building on the earlier descriptive analysis, the first three columns of Table 3 divide occupations into professional, service, and production categories as defined by Autor and Dorn (2013). The coefficient in panel A suggests that professional occupations have a strong link between employment and completions. On the other hand, the coefficient for service occupations large but not statistically significant, and the one for production occupations is small and not statistically significant.

An important feature of the differences across community college programs is the cost to a college to run the program, as well as the additional cost in expanding it. Infrastructure-heavy fields of study, such as health and engineering, are more expensive than academic fields, but also more expensive than CTE fields like accounting and graphic design. However, apart from a few states, community colleges tend to be financed on a per-pupil basis with little differentiation by program type (Stange, 2015). In California during the time period I study the funding per student was approximately $5,000-$7,000 per full time student. Therefore, it is likely that expansion of certain community college programs may be more closely tied to the cost of running the programs than to labor market trends.

I obtained program-level data on operating expenses for one college in California in the 2014-2015 school year. The data include instructional expenditures and equipment costs, and are summarized on a per-student level based on current enrollment.[13] I categorize occupations by whether they were above or below the median per-student expenditure of $1,200. Columns 4 and 5 show that more expensive programs were not differentially responsive to the labor market than other programs.

The last two columns separate occupations by whether they grew or shrank as a share of total employment in the time period. Thus, these columns analyze whether there are symmetrical effects. The coefficient for growing occupations is larger than that for declining occupations, which provides suggestive evidence that colleges see increases in growing occupations more commonly than declines in shrinking occupations.

6.4 College and Regional Differences

As a whole, the results so far suggest that community colleges in California respond to long-term changes in the labor market. A natural question is whether certain colleges are more in tune with these changes and can respond more effectively. In order to investigate this question I create subsamples of colleges with particular attributes.

First, I categorized colleges as large or small based on whether they were above or below the median overall number of degrees and certificates each college completioned in the first year of data, 1993. The first two columns of Table 4 show the results for these two subsamples. There is a larger coefficient for larger colleges, and the p-value of the difference is 0.11. This is at least suggestive evidence that larger colleges are more responsive.

Next, I examine differences by the initial educational content of different colleges. I categorize colleges as having a high or low initial CTE share of completions based on the share of total completions that were in CTE fields in the beginning of the period. Here, colleges with high initial CTE shares show a lower response to the labor market than colleges with low ones, though this

[13]There are two important limitations of these data. First, they come from just one college; it is likely that operating costs differ across colleges. Nevertheless, I include these numbers because of the scarcity of program-level cost information. Second, the data do not include program expansion costs, which are likely quite important as college administrators decide whether to grow enrollment in certain fields.

difference is not statistically significant.

Local economic conditions may also affect how colleges adjust to the labor market. For example, there may be a difference between colleges in large urban centers and those in rural areas or smaller cities. Colleges outside of large cities may have an obligation to offer a wide range of programs, while colleges in denser areas may be able to specialize. I compared colleges in the main metropolitan areas of the state— Los Angeles County, San Diego County, and the San Francisco Bay Area—to other colleges.[14] Here, the differences are relatively small and not statistically significant.

On the other hand, I categorized colleges by their county's unemployment rate. A growing literature shows that displaced workers enter postsecondary training program to study in-demand occupations, often with the support of unemployment insurance programs themselves (Barr and Turner, 2015; Foote and Grosz, 2017). I used Local Area Unemployment Statistics and calculated each county's average unemployment rate over the entire time period, between 1990 and 2016.[15] Columns 7 and 8 of Table 4 shows the results for colleges in counties with unemployment above and below the median.[16] Colleges in high unemployment counties had a much higher connection to the labor market than counties in low unemployment counties.

6.5 Other Results

Although the analyses so far suggest that there is a reasonably strong link between occupational growth and growth in completions and enrollment, there is still a disconnect between the initial distributions, as shown earlier in the descriptive analysis. For example, panel a) of Figure 2 showed that in 1990 there was relatively more employment in lower-skill occupations than there were degrees. Similarly, panel a) of Figure 5 shows that there was a substantially higher share of completions in managerial and professional occupations than there was empoyment. In Table A5 I account for this initial mismatch by including an indicator for the initial gap between the employment share and the completions share in 1990. Specifically, I include this initial gap as a ratio and as a difference. The table shows that this initial gap is positive: occupations that were

[14] I refer to these colleges as "urban" as a shorthand, even though "rural" colleges by this definition are located in cities like Sacramento, Fresno, and Bakersfield.

[15] Results using just the 1990 unemployment rate are quite similar.

[16] I calculated the median unemployment rate among counties that had a community college. Counties that had multiple community colleges are more likely to have large urban centers and also lower unemployment rates. Thus, 81 percent of the colleges were in counties with below-median unemployment rates.

initially overrepresented in completions also grew faster. The main coefficients are unchanged, however.

Table A10 shows results of the main specification on other outcomes. Panels A-C show effects on the number of completions—as opposed to completed units—altogether and separately by associate degrees and certificates. These show that the main results actually come from changes in completions of degrees, rather than certificates. Panels D and E separate out faculty employment by adjunct and permanent, while panels F and G look at the number of sections and courses, as opposed to units. There are small and statistically insignificant coefficients for all these outcomes.

6.6 Results Using National Data

In all the analyses so far I have relied on California administrative data, which are remarkably detailed and include information not just on degree and certificates, but also on inputs to educational production. A potential drawback is that California may not be representative of national trends in the community college sector. Indeed, California has by far the largest community college system, which also benefits from stronger articulation agreements with the public four-year sector than exist in other states.

To investigate this issue further, I used information on community college degrees and certificates from the Integrated Postsecondary Education Data System (IPEDS) from the National Center for Education Statistics. I compile college-level statistics on degrees and certificates at the CIP code level since 1986, which allows me to run the main specification from Equation 1. Because the data are at the national level I cannot use the two-stage least squares estimation strategy using the shift-share instrument, and instead show OLS estimates in Table 5. The estimates are quite similar to the OLS estimates from Table 2. Of course, the estimates using IPEDS are subject to the same concerns about endogeneity as the other OLS estimates. However, this exercise serves to provide support for using California data in this paper, since the correlational trends seem similar.

7 Conclusion

In recent years community colleges have received increased attention from policymakers focused on the nation's skill gaps. However, researchers have long criticized community colleges for not doing enough to keep with the changing demands of the labor market (National Academies of Sciences and Medicine, 2017; Jacobs and Dougherty, 2006; Brint and Karabel, 1989; Dougherty, 1994). Over the past decade, especially, community colleges have seemed slow and unresponsive relative to the nimble for-profit sector. Apart from some studies of specific programs, though, or analyses of community college responses to general macroeconomic trends, there is limited quantifiable evidence of the connection between community college CTE programs and occupational employment growth.

It is particularly important to study the relationship between labor demand and training programs given growing evidence of fundamental changes in the structure of the American labor market. Much of the literature so far has focused on documenting these changes, as well as their effects. Less attention, though, has been paid to studying local policy efforts at responding to them. Program offerings at community colleges are especially important to study in this context: these institutions are important producers of skilled workers.

In the first half of this paper I describe the characteristics of community college program offerings in the context of the literature on labor market changes. This is important since, while it is implicitly understood that community colleges train students for in-demand occupations, there is very little evidence to support this basic idea. I find that there is indeed overlap between the characteristics of occupations held by middle-skill workers and those for which community colleges train students. However, I also find that there is a significant portion of workers with "some college" who work in occupations that have little overlap with community college offerings.

In the second half of the paper I ask whether the occupations that have seen the most growth over the past few decades are also the ones that have seen growth in community college degrees. In order to account for potential endogeneity bias I use an instrumental variables approach that leverages variation from the initial distribution of employment across occupations and industries as well as national occupation-specific employment growth. Using this approach I find that occupations whose share of employment grows by one percentage point see their share of degrees and certificates grow by 0.5 percentage points. This is definitely evidence of a link between community colleges and the labor market, but far from a one-to-one correspondence. I also show that some colleges, especially larger ones outside urban centers and low-unemployment areas, are more responsive than others.

This paper addresses a significant gap in the literature. There is widespread concern that the demand for workers with certain skills outpaces the supply, and community colleges are often assumed to bear part of the responsibility. However, there is little empirical evidence specifically examining whether community colleges do, in fact, expand and contract their programs to meet changes in labor demand. By matching occupation-level employment data to occupation-level academic data for California community colleges this paper takes a step towards specifically answering this question. Ultimately, I find that there is an overlap between employment demand and community college offerings, but it is imperfect. While there are numerous avenues for future research, I conclude that there is credit to arguments that both praise and criticize community colleges for their role in the labor market.

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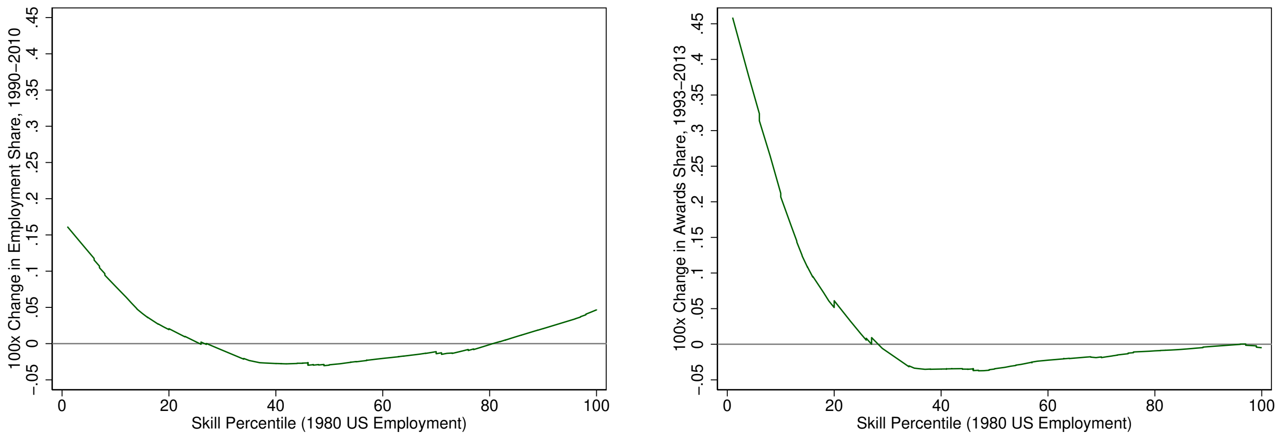
Figure 1: Employment and Completions Growth, by Skill Percentile

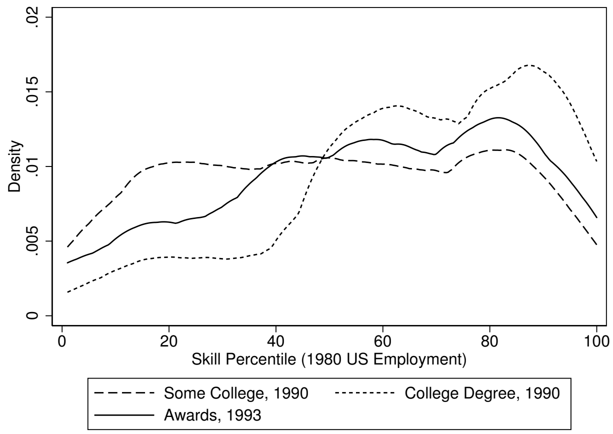


a) Changes in Employment, 1980-2010

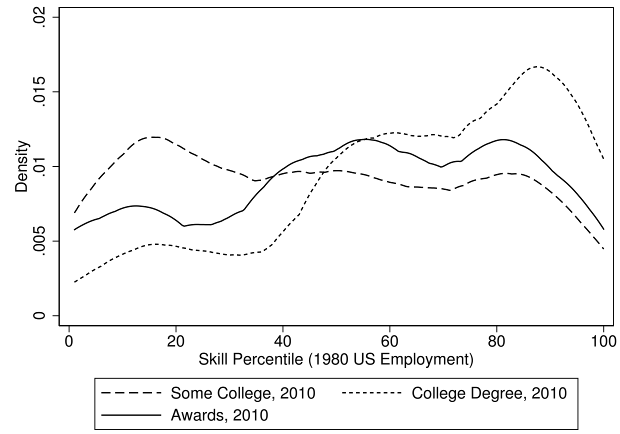
b) Change in Completions Share, 1993-2013

Notes. Horizontal axis consists of percentiles of worker wages weighted by 1980 US employment for all workers. In panel a) the vertical axis is the change in the share of workers in each percentile. In panel b) the vertical axis is the change in the share of completioned California community college degrees and certificates, in terms of units completioned.

Figure 2: Distribution of Community College Completions and Employment of Workers with Some College, by Skill Percentile



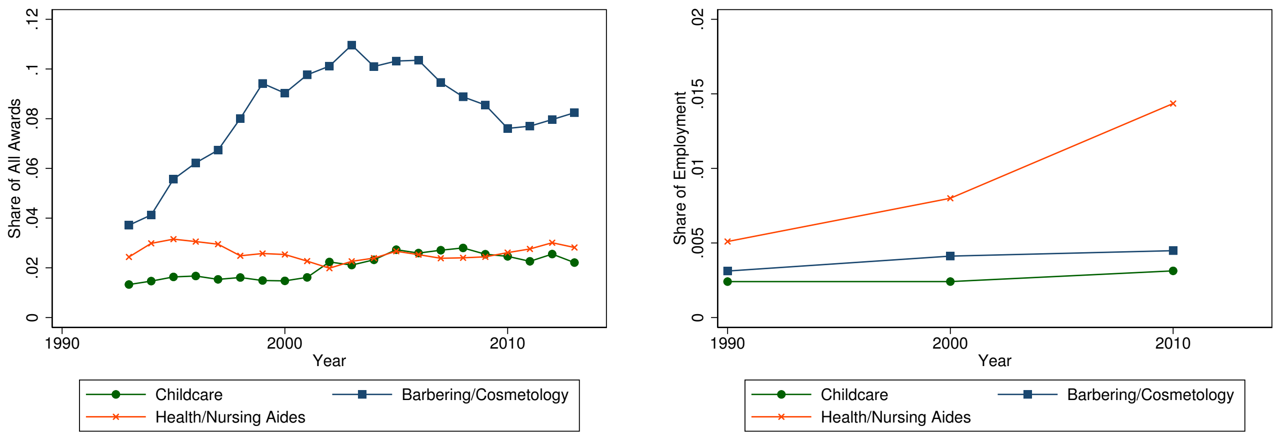
a) 1990



b) 2010

Notes. Horizontal axis consists of percentiles of worker wages weighted by 1980 US employment for all workers. Kernel densities calculated using an Epanechnikov kernel. Completions are California community college degrees and certificates, in terms of units. "Some college" refers to workers with more than a high school diploma but less than a four-year college degree.

Figure 3: Degrees and Certificates in Childcare, Cosmetology/Barbering, and Nursing/Health Aides

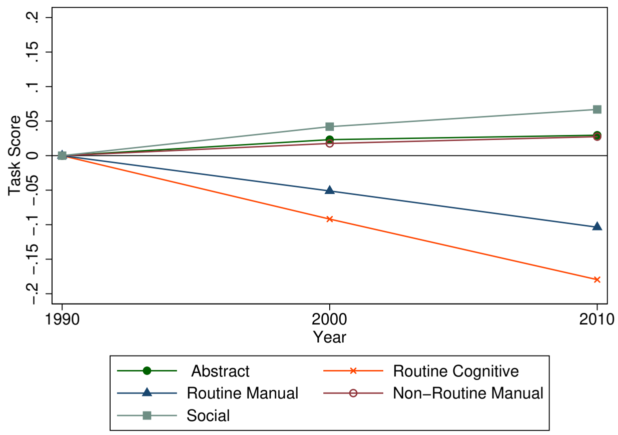


a) Community College Completions

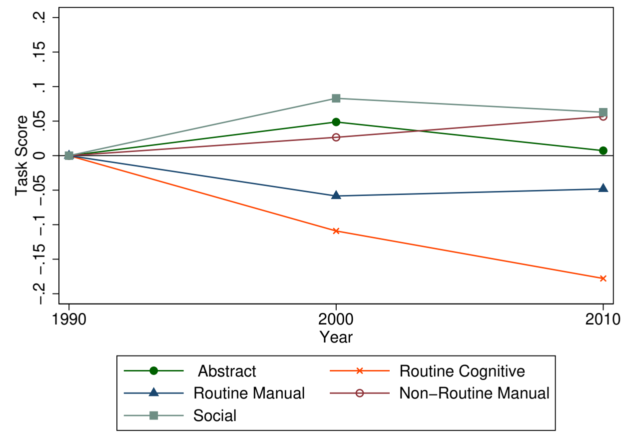
b) Workers with Some College

Notes. Figures show the share of all community college completioned units and workers in the three occupations. In the *occ1990dd* occupation codes compiled by Dorn (2009) and Deming (2017) these correspond to occupations 457 and 458 (barbers, hairdressers and cosmetologists), 468 (childcare workers), and 447 (health and nursing aides).

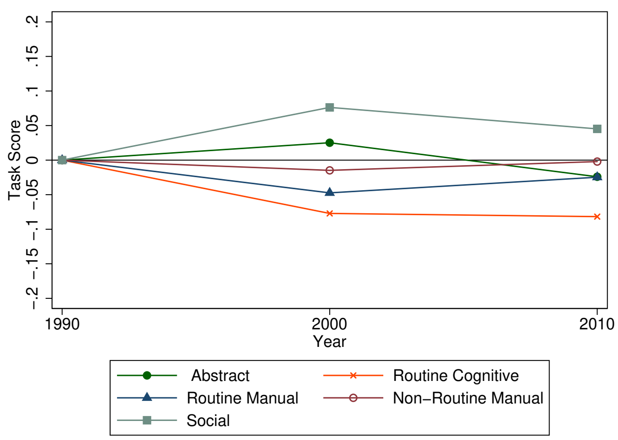
Figure 4: Mean Task Content of Employment and Completions, 1990-2013



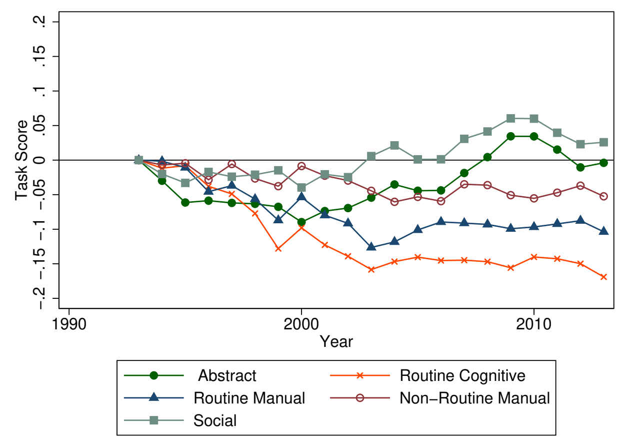
a) Workers, High School or Less



b) Workers, Some College



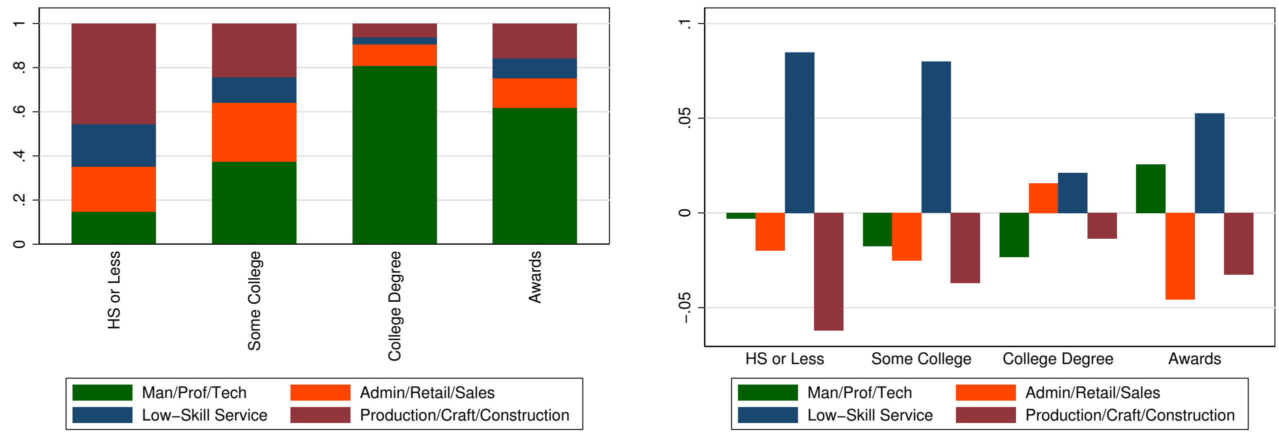
c) Workers, College Degree



d) Community College Completions

Notes. For each panel, tasks scores are standardized to have mean zero and standard deviation one when weighted by occupation-specific counts in the initial year. Mean task scores in later years are weighted to the respective occupation-specific counts. See Data Appendix for detailed information on coding of tasks in the O*NET data.

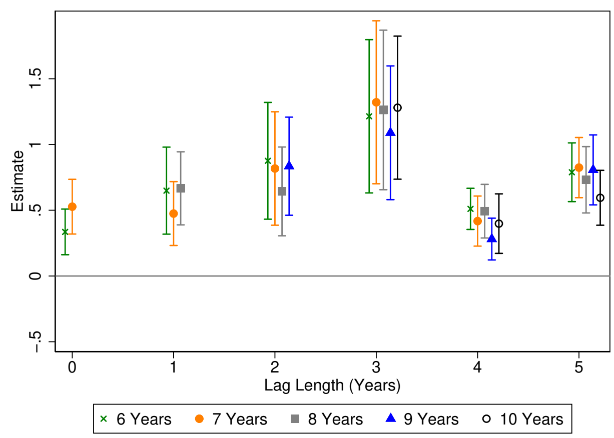
Figure 5: Employment and Completions, by Occupation Categories



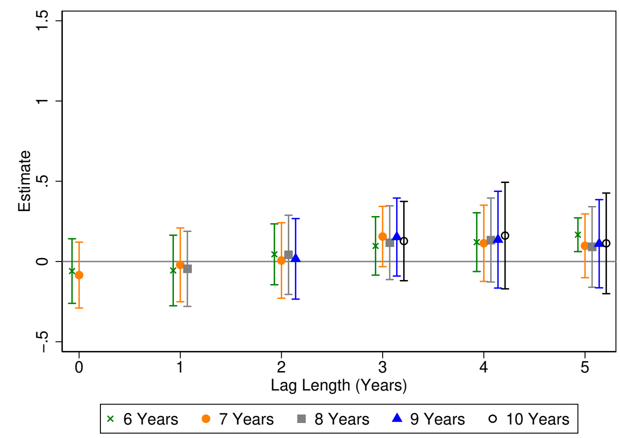
a) Employment Share by Category, 1990 b) Change in Category Share, 1990-2010

Notes. Occupation categories follow Autor and Dorn (2013). "Man/Prof/Tech" are managerial, professional, and technical occupations, and also include finance and public safety occupations. "Admin/Retail/Sales" occupations are administrative, retail, and sales, and also include clerical occupations. "Production/Craft/Construction" occupations also include machine operators, transportation, mining, farm, and assemblers. Mean completions are for 1993, not 1990.

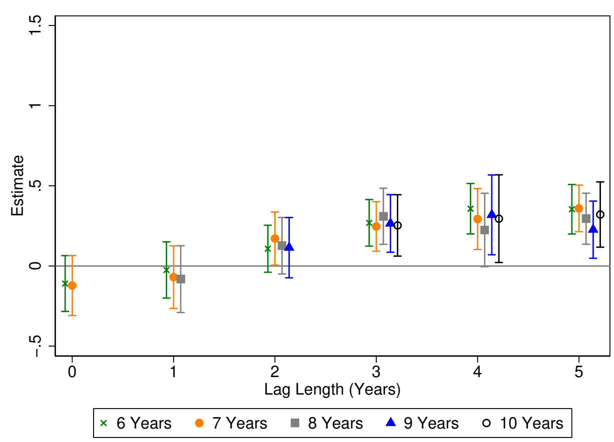
Figure 6: Effects of Employment at Different Intervals and Lags



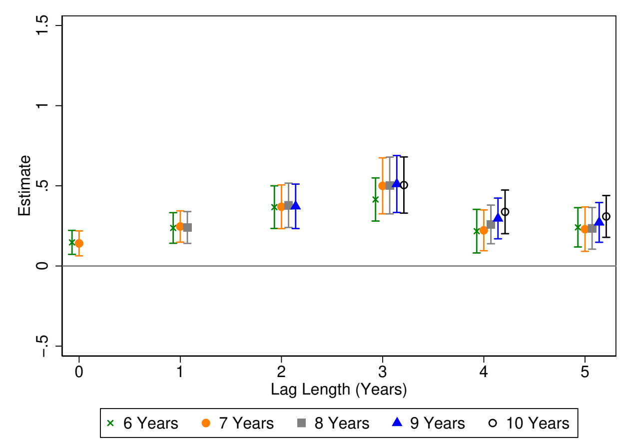
a) Completions



b) Section Units



c) Faculty FTE



d) Enrollment

Notes. Each point corresponds to the coefficient and 95% confidence interval from a separate regression estimate of equation 1. The horizontal axis refers to the number of lags at of the main independent variable–the change in employment share. The interval refers to the number of years over which the change in the dependent variable is calculated. For example, the seven year interval (orange circle) at a lag of 0 corresponds to academic data from 1993-2000 and 2003-2010. All employment data come from 1990-2000 and 2000-2010. The seven year interval (orange circle) at a lag of 1 corresponds to academic data from 1994-2001 and 2004-2011.

Table 1: Mean O*NET task measures for employment and community college completions, 1990

	(1)	(2)	(3)	(4)
	Census Employment, 1990			
	≤ High School	Some College	College Degree	Degrees & Certificates
Abstract (Non-Routine Cognitive)	-0.428	0.0349	0.878	0.276
	(0.802)	(0.916)	(0.881)	(0.951)
Routine Cognitive	0.0287	0.0972	-0.240	0.129
	(0.995)	(1.058)	(0.913)	(1.004)
Routine Manual	0.363	-0.0806	-0.695	-0.170
	(0.959)	(0.927)	(0.759)	(0.895)
Non-Routine Manual	0.301	-0.107	-0.529	-0.113
	(1.018)	(0.946)	(0.744)	(0.924)
Offshoreability	-0.100	0.0631	0.136	-0.273
	(0.935)	(1.051)	(1.031)	(1.294)
Social	-0.379	0.0595	0.769	0.368
	(0.879)	(0.962)	(0.830)	(0.987)

Notes. See Data Appendix for detailed information on coding of tasks in the O*NET data. Each task is standardized to have mean zero and standard deviation one when weighted in terms of the 1990 overall employment distribution. The table shows means and standard deviations. Mean completions are for 1993, not 1990.

Table 2: Effect of Employment Changes on Completions, College Inputs, and Enrollment

	(1)	(2)	(3)	(4)
	Completions	Course Sections	Faculty FTE	Enrollment
A. OLS				
ΔEmp	0.495***	0.0670	-0.0193	0.198*
	(0.094)	(0.224)	(0.118)	(0.083)
N	473	473	473	473
R-sq	0.135	0.004	0.011	0.080
B. 2SLS				
ΔEmp	0.527***	-0.0847	-0.122	0.141***
	(0.106)	(0.105)	(0.095)	(0.040)
N	473	473	473	473
R-sq	0.135	-0.014	-0.003	0.074

Notes. Academic data include the intervals 1993-2000 and 2003-2010. Employment data include the intervals 1990-2000, 2000-2010. Results weighted by 1980 national employment levels. Standard errors clustered at the occupation level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table 3: Effect of Employment Changes on Completions, by Occupation Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Occupation Categories			Training Cost		Relative Emp. Growth	
	Professional	Service	Production	High	Low	Positive	Negative
ΔEmp	0.470***	0.173	0.0993	0.00182	0.477***	0.798***	0.199
	(0.090)	(0.318)	(0.139)	(0.254)	(0.070)	(0.168)	(0.152)
N	168	103	208	206	237	199	280
R-sq	0.366	0.088	-0.004	0.046	0.341	0.067	0.080

Notes. Academic data include the intervals 1993-2000 and 2003-2010. Employment data include the intervals 1990-2000, 2000-2010. Results weighted by 1980 national employment levels. All results show instrumental variables estimates. Occupation categories are based on Autor and Dorn (2013). "High-Cost" occupations are those with per-student costs above the median. The final two columns separate out occupations by whether their share of employment grew or shrank during the time period. Standard errors clustered at the occupation level.
$*p < 0.05, **p < 0.01, ***p < 0.001$

Table 4: Effect of Employment Changes on Completions, by College and County Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	College Size		Vocational Share		Location		County Unemp.	
	Large	Small	High	Low	Urban	Rural	High	Low
ΔEmp	0.620***	0.292***	0.414***	0.649***	0.545***	0.515***	0.819***	0.491***
	(0.121)	(0.080)	(0.120)	(0.099)	(0.102)	(0.124)	(0.186)	(0.100)
N	479	479	479	479	479	479	479	479

Notes. Academic data include the intervals 1993-2000 and 2003-2010. Employment data include the intervals 1990-2000, 2000-2010. Results weighted by 1980 national employment levels. All results show instrumental variables estimates. Large and small colleges based on being above or below median enrollment. Vocational share based on being above or below the share of degrees and certificates in vocational programs. Urban colleges are those in the Los Angeles, San Francisco Bay, and San Diego metro areas. Standard errors clustered at the occupation level.
$*p < 0.05, **p < 0.01, ***p < 0.001$

Table 5: National-Level Results Using IPEDS Data

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Employment			Workers with Some College		
	Units	AA/AS	Certificates	Units	AA/AS	Certificates
ΔEmp	0.428**	0.322**	0.262	0.462*	0.345*	0.347
	(0.136)	(0.111)	(0.179)	(0.185)	(0.159)	(0.243)
N	592	592	592	592	592	592
R-sq	0.154	0.090	0.052	0.243	0.140	0.104

Notes. Regressions are OLS and control for year effects. Regressions weighted by 1980 employment levels. Units consist of the sum of total degrees and certificates, weighted by the number of average units per completion. Standard errors clustered at the occupation level. $*p < 0.05, **p < 0.01, ***p < 0.001$

A1 Appendix Tables and Figures

Table A1: High-Ranking Occupations, by Task Content

Abstract	Routine Cognitive
Chief executives, public administrators, and legislators	Data entry keyers
Primary school teachers	Air traffic controllers
Human resources and labor relations managers	Statistical clerks
Financial managers	Proofreaders
Computer software developers	Bookkeepers and accounting and auditing clerks
Managers in education and related fields	Explosives workers
Chemical engineers	Typists
Office supervisors	Mail clerks, outside of post office
Recreation and fitness workers	Human resources clerks, excl payroll and timekeeping
Chemists	Billing clerks and related financial records processing
Routine Manual	Non-Routine Manual
Operating engineers of construction equipment	Airplane pilots and navigators
Drillers of earth	Drillers of earth
Textile sewing machine operators	Truck, delivery, and tractor drivers
Textile cutting and dyeing machine operators	Paving, surfacing, and tamping equipment operators
Drilling and boring machine operators	Bus drivers
Rollers, roll hands, and finishers of meta	Explosives workers
Grinding, abrading, buffing, and polishing workers	Ship crews and marine engineers
Nail, tacking, shaping and joining mach ops (wood)	Millwrights
Cementing and gluing machne operators	Miners
Punching and stamping press operatives	Glaziers
Offshoreability	Social
Actuaries	Chief executives, public administrators, and legislators
Economists, market and survey researchers	Financial service sales occupations
Insurance underwriters	Managers and specialists in marketing, advert., PR
Payroll and timekeeping clerks	Sales engineers
Operations and systems researchers and analysts	Urban and regional planners
Proofreaders	Managers in education and related fields
Urban and regional planners	Dieticians and nutritionists
Purchasing managers, agents, and buyers, n.e.c.	Lawyers and judges
Mathematicians and statisticians	Advertising and related sales jobs
Financial managers	Social workers

Notes. Each group contains the names of 10 occupation codes, as categorized in Dorn (2009), with the highest score on each task composite measure. Occupations are listed in descending order of the score.

Table A2: Mean O*NET task measures for employment and community college completions, 2010

	(1) $\leq$ High School	(2) Some College	(3) College Degree	(4) Comple- tions
Abstract (Non-Routine Cognitive)	-0.521	-0.0757	0.749	0.176
	(0.799)	(0.899)	(0.860)	(0.904)
Routine Cognitive	0.00136	0.0834	-0.131	0.122
	(0.993)	(1.057)	(0.939)	(1.117)
Routine Manual	0.441	0.0283	-0.606	-0.118
	(0.953)	(0.944)	(0.789)	(0.937)
Non-Routine Manual	0.378	-0.00860	-0.491	-0.118
	(1.028)	(0.962)	(0.764)	(0.921)
Offshoreability	-0.104	-0.0254	0.170	-0.235
	(0.894)	(1.039)	(1.053)	(1.236)
Social	-0.475	-0.0382	0.666	0.284
	(0.873)	(0.942)	(0.837)	(0.950)

Notes. See Data Appendix for detailed information on coding of tasks in the O*NET data. Each task is standardized to have mean zero and standard deviation one when weighted in terms of the 2010 overall employment distribution. The table shows means and standard deviations

Table A3: First Stage Estimates

	(1) All Workers	(2) Some College	(3) Including Covariates	(4) Unweighted	(5) Decade Lag
$\Delta\widehat{Emp}$	0.713***	0.700***	0.734***	0.762***	0.605***
	(0.028)	(0.064)	(0.020)	(0.075)	(0.044)
N	479	479	479	479	479
R-sq	0.640	0.475	0.715	0.444	0.860
F	458.3	81.73	374.7	61.28	96.32

Notes. Regressions include year effects. Regressions weighted by 1980 employment unless otherwise noted. Partial F statistic displayed. Controls include share of occupation by race, gender, age, marital status, and urban areas. Data include years 1990, 2000, and 2010. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A4: Correlating Industry Shares to Occupation Characteristics, 1980

	(1) Professional Services	(2) Non-Durable Manufacturing	(3) Durable Manufacturing	(4) Retail	(5) Public Administration
White	0.0459	-0.105	-0.0740	-0.0588	0.0260
	(0.117)	(0.0894)	(0.104)	(0.0844)	(0.0545)
Black	0.0537	-0.0318	-0.0448	-0.0438	0.0246
	(0.0339)	(0.0218)	(0.0288)	(0.0229)	(0.0194)
Hispanic/Latino	-0.0775	-0.0833	0.0763	-0.107	0.00652
	(0.108)	(0.0904)	(0.0778)	(0.0721)	(0.0392)
Age under 18	0.0221	-0.00630	-0.0633	0.0225	0.104
	(0.0926)	(0.0720)	(0.125)	(0.0559)	(0.0895)
Age 18-39	0.167	-0.0286	-0.0376	-0.266	0.327
	(0.303)	(0.226)	(0.422)	(0.148)	(0.271)
Age 40-65	0.167	-0.0690	0.0334	-0.276	0.336
	(0.288)	(0.219)	(0.422)	(0.145)	(0.254)
Age over 65	0.0703	-0.0133	-0.0459	-0.0914*	0.0978
	(0.0973)	(0.0665)	(0.126)	(0.0436)	(0.0956)
Male	-0.138***	-0.0135	0.0590***	0.00340	-0.00915
	(0.0240)	(0.0119)	(0.0131)	(0.0127)	(0.00949)
US-born	0.0175	-0.138***	0.00321	-0.0250	0.0314
	(0.0446)	(0.0387)	(0.0659)	(0.0290)	(0.0247)
Married	0.0956	0.0152	-0.0226	-0.0523	0.0277
	(0.0624)	(0.0304)	(0.0381)	(0.0425)	(0.0311)
Never married	0.121	-0.0324	0.0435	-0.0941*	0.00900
	(0.0774)	(0.0391)	(0.0504)	(0.0443)	(0.0402)
Urban	0.00421	0.00227	0.0104	0.0164**	-0.00692
	(0.0115)	(0.0122)	(0.0216)	(0.00610)	(0.00792)
Share with Some College	-0.139***	-0.0150	0.00961	0.00737	0.0180
	(0.0382)	(0.0135)	(0.0146)	(0.0123)	(0.0224)
Share with No College	0.180**	-0.0233	-0.00725	-0.0509*	0.0152
	(0.0651)	(0.0137)	(0.0166)	(0.0258)	(0.0232)
N	333	333	333	333	333
R-sq	0.432	0.340	0.239	0.243	0.112

Notes. Data include 1980. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A5: Effect of Employment, Including Initial Gap

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Completions		Faculty FTE		Courses		Enrollment	
ΔEmp	0.526***	0.496***	-0.123	-0.118	-0.0846	-0.135	0.140***	0.149***
	(0.107)	(0.095)	(0.094)	(0.096)	(0.105)	(0.092)	(0.040)	(0.040)
Ratio of Awards-Employment	0.00348		0.0185*		-0.000785		0.00672	
	(0.004)		(0.009)		(0.010)		(0.007)	
Difference in Awards-Employment		3.487		1.669		-16.39		-5.191
		(1.922)		(3.977)		(9.512)		(5.663)
N	473	473	473	473	473	473	473	473
R-sq	0.135	0.145	0.029	0.003	-0.014	0.312	0.079	0.129

Notes. Ratio of completions to employment is the occupations share of total completions divided by the occupation's share of total employment, in 1980. Similarly, the difference in completions and employment is the differences in these shares in 1980. All results show instrumental variables estimates. Academic data include the intervals 1993-2000 and 2003-2010. Employment data include the intervals 1990-2000, 2000-2010. Results weighted by 1980 national employment levels. Standard errors clustered at the occupation level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A6: Effect of Employment Changes, Unweighted

	(1) Completions	(2) Course Sections	(3) Faculty FTE	(4) Enrollment
A. OLS				
ΔEmp	0.493*	0.365	0.346	0.385
	(0.207)	(0.272)	(0.273)	(0.250)
N	473	473	473	473
R-sq	0.053	0.083	0.050	0.077
B. 2SLS				
ΔEmp	0.341*	0.0698	0.160	0.151
	(0.158)	(0.155)	(0.198)	(0.117)
N	473	473	473	473
R-sq	0.048	0.029	0.035	0.048

Notes. Academic data include the intervals 1993-2000 and 2003-2010. Employment data include the intervals 1990-2000, 2000-2010. Results weighted by 1980 national employment levels. Standard errors clustered at the occupation level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A7: Effect of Employment Changes, Including Covariates

	(1) Completions	(2) Course Sections	(3) Faculty FTE	(4) Enrollment
A. OLS				
ΔEmp	0.496***	0.0696	-0.0379	0.217**
	(0.088)	(0.213)	(0.116)	(0.073)
N	473	473	473	473
R-sq	0.176	0.213	0.068	0.241
B. 2SLS				
ΔEmp	0.487***	-0.0832	-0.145	0.148***
	(0.085)	(0.124)	(0.089)	(0.033)
N	473	473	473	473
R-sq	0.176	0.196	0.053	0.232

Notes. Academic data include the intervals 1993-2000 and 2003-2010. Employment data include the intervals 1990-2000, 2000-2010. Results weighted by 1980 national employment levels. Controls include share of occupation by race, gender, age, marital status, and urban areas.Standard errors clustered at the occupation level.
$*p < 0.05, **p < 0.01, ***p < 0.001$

Table A8: Effect of Employment Changes, Workers with Some College

	(1) Completions	(2) Course Sections	(3) Faculty FTE	(4) Enrollment
A. OLS				
ΔEmp	0.401**	0.116	-0.0467	0.178
	(0.127)	(0.249)	(0.072)	(0.097)
N	473	473	473	473
R-sq	0.113	0.013	0.031	0.074
B. 2SLS				
ΔEmp	0.532**	-0.208*	-0.234*	0.0874
	(0.170)	(0.089)	(0.097)	(0.066)
N	473	473	473	473
R-sq	0.101	-0.071	-0.026	0.057

Notes. Academic data include the intervals 1993-2000 and 2003-2010. Employment data include the intervals 1990-2000, 2000-2010. Standard errors clustered at the occupation level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A9: Effect of Employment Changes, using Prior Decade Industry Distribution

	(1) Completions	(2) Course Sections	(3) Faculty FTE	(4) Enrollment
A. OLS				
ΔEmp	0.495***	0.0670	-0.0193	0.198*
	(0.094)	(0.224)	(0.118)	(0.083)
N	473	473	473	473
R-sq	0.135	0.004	0.011	0.080
B. 2SLS				
ΔEmp	0.345***	0.147	0.0170	0.239
	(0.091)	(0.351)	(0.158)	(0.129)
N	473	473	473	473
R-sq	0.123	-0.001	0.009	0.077

Notes. Academic data include the intervals 1993-2000 and 2003-2010. Employment data include the intervals 1990-2000, 2000-2010. Controls include share of occupation by race, gender, age, marital status, and urban areas. Standard errors clustered at the occupation level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A10: Effect of Employment Changes on Other Outcomes

	(1)	(2)
	OLS	2SLS
A. Completion Count		
ΔEmp	0.794***	0.759***
	(0.153)	(0.182)
N	473	473
R-sq	0.265	0.265
B. AA/AS Count		
ΔEmp	0.605***	0.424***
	(0.082)	(0.067)
N	473	473
R-sq	0.218	0.199
C. Certificate Count		
ΔEmp	0.0959	-0.0222
	(0.152)	(0.092)
N	473	473
R-sq	0.005	-0.001
D. Adjunct Faculty FTE		
ΔEmp	0.0565	0.112*
	(0.103)	(0.049)
N	473	473
R-sq	0.024	0.020
E. Permanent Faculty FTE		
ΔEmp	-0.0978	-0.348*
	(0.136)	(0.151)
N	473	473
R-sq	0.012	-0.053
F. Courses Count		
ΔEmp	-0.00984	-0.210**
	(0.135)	(0.076)
N	473	473
R-sq	0.016	-0.042
G. Sections Count		
ΔEmp	0.0698	-0.120
	(0.236)	(0.114)
N	473	473
R-sq	0.004	-0.023

Notes. Academic data include the intervals 1993-2000 and 2003-2010. Employment data include the intervals 1990-2000, 2000-2010. Results weighted by 1980 national employment levels. Standard errors clustered at the occupation level. $*p < 0.05, **p < 0.01, ***p < 0.001$

A2 Data Appendix

This appendix describes the methodology that enables me to match employment information by occupation to academic information by TOP code topic fields.

A2.1 Description of TOP codes

The Taxonomy of Programs (TOP) is a system used exclusively by the California Community Colleges to describe their programs and courses. All completions (degrees and certificates) and courses are assigned a TOP code. There are 607 6-digit TOP codes. TOP codes are 6 digits long and their structure parallels the federal Classificiation of Instructional Programs (CIP).[17] The first two digits describe the "discipline", which is a broad category, such as "Health" or "Communications." The next two digits describe the "subdiscipline." The last two digits describe "fields," which are subcategories of the subdiscipline. In practice, many subdisciplines have just one field. For example, in the Health discipline (12) there is subdiscipline of nursing (1230). Within nursing, the fields are Registered nursing (123010), Licensed vocational nursing (123020) and Certified Nursing Assistant (123030). On the other hand, the subdiscpline of athletic training and sports medicine (1228) has no fields under it.

Because colleges report in different ways, some colleges report activity in TOP codes that don't exist in the latest (6th) edition, which is the one used for the match. I recode these to the 6th edition: in most cases these recoded TOP codes are more specific fields within a general subdiscipline. In some cases, there has been substantial recoding of TOP codes, even across disciplines. Luckily, the CCCCO has a master list of TOP codes and their descriptions that I use to streamline the coding across years and across colleges. Table A11 below shows the recodings for problematic TOP codes, and notes where I recoded a TOP code to its more general subdiscipline, and where I recoded it to an unrelated TOP code.

A2.2 Matching TOP to Occupations

In cooperation with the California Department of Education and the California Department of Labor, the CCCCO produced its own crosswalk between TOP and SOC (Standard Occupation Codes). This match takes two steps. The first is a one-to-many merge from TOP to the more commonly used Classificiation of Instructional Programs 2000 (CIP). The next is a many-to-many match from CIP to Standard Occupational Classifications 2000 (SOC), which describe occupations. The result is a many-to-many merge from TOP to SOC.[18] There are 1,036 TOP-SOC combinations in the official match, for 404 TOP codes. However, I exclude TOP codes starting with "49" since these are generally meant for non-credit and remedial courses. Thus, I have 993 TOP-SOC matches for 379 TOP codes.

I also manually matched between existing crosswalks developed by the BLS and NCES. There is a published TOP-CIP crosswalk using 2000 CIP definitions. There is also a commonly used CIP2000-SOC2000 crosswalk. Of the 993 TOP-SOC combinations, 920 of 993 cases (92.6 percent) are the same as in the official CCCCO crosswalk, which is the one I use for all analyses.

I then match the SOC codes to the standardized Census occupation codes as in Deming (2017). This is a one-to-many merge, with multiple SOC codes for each occupation code. I match the academic and employment files to the crosswalk, and then collapse to create totals for each occupation code. The only decision point comes from the fact that in some cases a single TOP

[17] In fact, the TOP-CIP match is one to many.

[18] Crosswalk available here: http://www.labormarketinfo.edd.ca.gov/commcolleges/

code may match to multiple occupation codes codes. In order to avoid double-counting, I split up the TOP code evenly among its matched occupation codes (for example, if a TOP code with 10 completions matches to 2 occupation codes, each occupation code is assigned 5 completions). This avoids double-counting.[19]

[19] Bardhan, Hicks and Jaffee (2013) use this equal allotment of completions across occupation groups, although their analysis goes the opposite way, with occupations collapsed to CIP codes. Nevertheless, they also show that they find similar results using a weighted allocation across different CIP codes based on observed employment among former students for each major.

Table A11: TOP streamlining recodes

Old TOP	New TOP	Recode or General	Old TOP	New TOP	Recode or General	Old TOP	New TOP	Recode or General
10000	10100		93550	93500	general	130420	130500	recode
10110	10100		93610	93600	general	130430	130300	recode
10250	11200	recode	93620	93600	general	130440	130110	recode
11210	11200	general	93640	93600	general	130450	130600	recode
11240	11200	general	93650	93600	general	130460	130560	recode
11260	11200	general	93710	94500	recode	130470	130600	recode
11270	11200	general	94310	94300	general	130480	130400	general
11280	11200	general	94520	94500	general	130490	130400	general
11290	11200	general	94530	94500	general	130640	130600	general
11410	11400	general	94540	94500	general	130650	130600	general
11610	11600	general	94710	94700	general	140000	140100	
11630	11600	general	94810	94800	general	140110	140100	general
20000	20100		95350	95300	general	150000	150100	
20120	20100	general	95610	95640	recode	152000	150100	recode
20130	20100	general	95620	95640	recode	159900	150100	recode
20300	130200	recode	95660	95250	recode	160110	160100	general
20310	130200	recode	95710	95700	general	170000	170100	
40000	40100		95810	95800	general	170110	170100	general
50000	50100		95840	95800	general	170170	170100	general
50220	50200	general	100000	100100	general	170200	170100	recode
50410	50400	general	101000	60300	recode	180000	180100	
50420	50400	general	101110	101100	general	180100	180100	
50430	50400	general	101140	101100	general	190000	190100	
50440	50400	general	103020	103000	general	191410	191400	general
50610	50600	general	110000	110100		193000	191400	recode
50620	50600	general	120000	126000		200000	201000	
50930	50900		120100	126000	recode	210000	210200	
50980	50900		120110	126000	recode	210100	210200	recode
51010	51000	general	120120	126000	recode	210220	125000	recode
51450	51400	general	120210	120200	general	210240	210200	general
51460	51400	general	120220	120200	general	210260	125000	recode
51470	51400	general	120310	123010	recode	210300	210200	recode
60000	60100		120340	120600	recode	210410	210400	general
60300	60400	recode	120430	124030	recode	210560	210540	recode
60310	60410	recode	120530	120500	general	210700	210400	recode
60320	60420	recode	120700	122500	recode	210710	210700	general
60500	60400	recode	120730	121000	recode	210720	210700	general
70000	70100		120740	121300	recode	210730	210700	general
70110	70100		120780	121300	recode	210740	210700	general
70410	70710	recode	120910	121900	recode	210770	210700	general
70420	70710	recode	121220	122200	recode	213320	213300	general
70510	70730	recode	121510	120820	recode	219910	213310	recode
70520	70730	recode	121600	121400	recode	220000	220100	
80000	80100		122230	122200	general	300000	309900	recode
80820	80900	recode	122520	122500	general	300100	309900	recode
89900	80100	recode	123930	123080	recode	300200	130610	recode
90000	90100		124600	122200	recode	300210	130630	recode
92400	90100		125010	125000	general	300220	130630	recode
92520	95300	recode	125020	125000	general	300240	130630	recode
92540	95330	recode	127000	126200	recode	300250	130610	recode
92550	95340	recode	130000	130100		300400	300500	recode
93000	91000	recode	130210	130200	general	300500	300500	
93300	93460	recode	130220	101920	recode	300930	300900	general
93520	93500	general	130340	130330	recode	300940	300900	general
93540	93500	general	130410	130100	recode			

Note: This table shows the list of TOP codes that do contain academic information but are not listed in the crosswalk. The table notes what the new TOP code would be, as well as if the new TOP code is just the umbrella category (general) or whether there was a reasonable recoding to an altogether different TOP code.

A3 Task Groupings

I create task measures based on ones commonly used in the literature. Table A12 shows the O*NET task groupings used to create each construct. Each row corresponds to an individual work activity, work context, work ability, or social skill. Tasks 1-4 are derived from those in Acemoglu and Autor (2011), on page 1163. Offshoreability is defined in the reverse: for example, occupations with a higher value of "face-to-face discussions" are *less* offshoreable. Task 6 is derived from Deming (2017). As in Autor, Katz and Kearney (2008) I define the "abstract" tasks as non-routine cognitive; "routine" as routine cognitive and routine manual; and "manual" as routine manual. According to these larger groupings, following Autor and Dorn (2013) I define "routine task intensity" (RTI) as $RTI = ln(routine) - ln(abstract) - ln(manual)$.

Table A12: Task Groupings of O*NET Scores

1) Abstract (Non-Routine Cognitive)	
4.A.2.a.4	Analyzing Data or Information
4.A.4.a.1	Interpreting the Meaning of Information for Others
4.A.2.b.2	Thinking Creatively
4.A.4.b.5	Coaching and Developing Others
4.A.4.a.4	Establishing and Maintaining Interpersonal Relationships
4.A.4.b.4	Guiding, Directing, and Motivating Subordinates
2) Routine cognitive	
4.C.3.b.4	Importance of Being Exact or Accurate
4.C.3.b.7	Importance of Repeating Same Tasks
4.C.3.b.8	Structured versus Unstructured Work
3) Routine manual	
4.C.3.d.3	Pace Determined by Speed of Equipment
4.C.2.d.1.i	Spend Time Making Repetitive Motions
4.A.3.a.3	Controlling Machines and Processes
4) Non-routine manual	
1.A.2.a.2	Manual Dexterity
1.A.1.f.1	Spatial Orientation
4.A.3.a.4	Operating Vehicles, Mechanized Devices, or Equipment
4.C.2.d.1.g	Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls
5) Offshorability	
4.C.1.a.2.l	Face-to-Face Discussions
4.A.4.a.5	Assisting and Caring for Others
4.A.3.a.2	Handling and Moving Objects
4.A.1.b.2	Inspecting Equipment, Structures, or Material
4.A.4.a.8	Performing for or Working Directly with the Public
4.A.3.b.5	Repairing and Maintaining Electronic Equipment
4.A.3.b.4	Repairing and Maintaining Mechanical Equipment
6) Social	
2.B.1.a	Social Perceptiveness
2.B.1.b	Coordination
2.B.1.c	Persuasion
2.B.1.d	Negotiation

Note: See text for specific definition of task groupings. First column refers to the O*NET code: Prefix 1.A consists of "work abilities," 2.B is "skills", 4.A is "work activities," and 4.C is "work contexts."

A4 Occupation Groupings

I follow Autor and Dorn (2013) in categorizing occupations into broad groups. While Autor and Dorn (2013) have six groups, for further each of exposition I use four groups. These are: Management/Professional/Technical; Administrative Support and Retail Sales; Low-Skill Services; Production/Construction/Manufacturing. The first three of these are identical to those in Autor and Dorn (2013), while the fourth of my categories incorporate the remaining three categories from Autor and Dorn (2013)

Table A13: Occupation Codes and Occupation Groupings, Based on Autor and Dorn (2013)

Code	Description	Category
4	Chief executives, public administrators, and legislators	Management/Professional/Technical
7	Financial managers	Management/Professional/Technical
8	Human resources and labor relations managers	Management/Professional/Technical
9	Purchasing managers	Management/Professional/Technical
13	Managers in marketing, advert., PR	Management/Professional/Technical
14	Managers in education and related fields	Management/Professional/Technical
15	Managers of medicine and health occupations	Management/Professional/Technical
18	Managers of properties and real estate	Management/Professional/Technical
19	Funeral directors	Management/Professional/Technical
22	Managers and administrators, n.e.c.	Management/Professional/Technical
23	Accountants and auditors	Management/Professional/Technical
24	Insurance underwriters	Management/Professional/Technical
25	Other financial specialists	Management/Professional/Technical
26	Management analysts	Management/Professional/Technical
27	Personnel, HR, training, and labor rel. specialists	Management/Professional/Technical
28	Purchasing agents and buyers of farm products	Management/Professional/Technical
29	Buyers, wholesale and retail trade	Management/Professional/Technical
33	Purchasing agents and buyers, n.e.c.	Management/Professional/Technical
34	Business and promotion agents	Management/Professional/Technical
35	Construction inspectors	Management/Professional/Technical
36	Inspectors and compliance officers, outside	Management/Professional/Technical
37	Management support occupations	Management/Professional/Technical
43	Architects	Management/Professional/Technical
44	Aerospace engineers	Management/Professional/Technical
45	Metallurgical and materials engineers	Management/Professional/Technical
47	Petroleum, mining, and geological engineers	Management/Professional/Technical
48	Chemical engineers	Management/Professional/Technical
53	Civil engineers	Management/Professional/Technical
55	Electrical engineers	Management/Professional/Technical
56	Industrial engineers	Management/Professional/Technical
57	Mechanical engineers	Management/Professional/Technical
58	Marine engineers and naval architects	Management/Professional/Technical
59	Engineers and other professionals, n.e.c.	Management/Professional/Technical
64	Computer systems analysts and computer scientists	Management/Professional/Technical

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Table A13 – *Continued from previous page*

Code	Description	Category
65	Operations and systems researchers and analysts	Management/Professional/Technical
66	Actuaries	Management/Professional/Technical
68	Mathematicians and statisticians	Management/Professional/Technical
69	Physicists and astronomists	Management/Professional/Technical
73	Chemists	Management/Professional/Technical
74	Atmospheric and space scientists	Management/Professional/Technical
75	Geologists	Management/Professional/Technical
76	Physical scientists, n.e.c.	Management/Professional/Technical
77	Agricultural and food scientists	Management/Professional/Technical
78	Biological scientists	Management/Professional/Technical
79	Foresters and conservation scientists	Management/Professional/Technical
83	Medical scientists	Management/Professional/Technical
84	Physicians	Management/Professional/Technical
85	Dentists	Management/Professional/Technical
86	Veterinarians	Management/Professional/Technical
87	Optometrists	Management/Professional/Technical
88	Podiatrists	Management/Professional/Technical
89	Other health and therapy occupations	Management/Professional/Technical
95	Registered nurses	Management/Professional/Technical
96	Pharmacists	Management/Professional/Technical
97	Dieticians and nutritionists	Management/Professional/Technical
98	Respiratory therapists	Management/Professional/Technical
99	Occupational therapists	Management/Professional/Technical
103	Physical therapists	Management/Professional/Technical
104	Speech therapists	Management/Professional/Technical
105	Therapists, n.e.c.	Management/Professional/Technical
106	Physicians assistants	Management/Professional/Technical
154	Subject instructors, college	Management/Professional/Technical
155	Kindergarten and earlier school teachers	Management/Professional/Technical
156	Primary school teachers	Management/Professional/Technical
157	Secondary school teachers	Management/Professional/Technical
158	Special education teachers	Management/Professional/Technical
159	Teachers, n.e.c.	Management/Professional/Technical
163	Vocational and educational counselors	Management/Professional/Technical
164	Librarians	Management/Professional/Technical
165	Archivists and curators	Management/Professional/Technical
166	Economists, market and survey researchers	Management/Professional/Technical
167	Psychologists	Management/Professional/Technical
169	Social scientists and sociologists, n.e.c.	Management/Professional/Technical
173	Urban and regional planners	Management/Professional/Technical
174	Social workers	Management/Professional/Technical
175	Religious workers, n.e.c.	Management/Professional/Technical
176	Clergy	Management/Professional/Technical
177	Welfare service workers	Management/Professional/Technical
178	Lawyers and judges	Management/Professional/Technical

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Table A13 – *Continued from previous page*

Code	Description	Category
183	Writersandauthors	Management/Professional/Technical
184	Technical writers	Management/Professional/Technical
185	Designers	Management/Professional/Technical
186	Musicians and composers	Management/Professional/Technical
187	Actors, directors, and producers	Management/Professional/Technical
188	Painters, sculptors, craft-artists, and print-makers	Management/Professional/Technical
189	Photographers	Management/Professional/Technical
193	Dancers	Management/Professional/Technical
194	Art/entertainment performers and related occs	Management/Professional/Technical
195	Editors and reporters	Management/Professional/Technical
197	Specialists in marketing, advert., PR	Management/Professional/Technical
198	Announcers	Management/Professional/Technical
199	Athletes, sports instructors, and officials	Management/Professional/Technical
203	Clinical laboratory technologies and technicians	Management/Professional/Technical
204	Dental hygienists	Management/Professional/Technical
205	Health record technologists and technicians	Management/Professional/Technical
206	Radiologic technologists and technicians	Management/Professional/Technical
207	Licensed practical nurses	Management/Professional/Technical
208	Health technologists and technicians, n.e.c.	Management/Professional/Technical
214	Engineering and science technicians	Management/Professional/Technical
217	Drafters	Management/Professional/Technical
218	Surveryors, cartographers, mapping scientists/techs	Management/Professional/Technical
223	Biological technicians	Management/Professional/Technical
224	Chemical technicians	Management/Professional/Technical
226	Airplane pilots and navigators	Management/Professional/Technical
227	Air traffic controllers	Management/Professional/Technical
228	Broadcast equipment operators	Management/Professional/Technical
229	Computer programmers	Management/Professional/Technical
233	Programmers of numerically controlled machine tools	Management/Professional/Technical
234	Legal assistants and paralegals	Management/Professional/Technical
235	Technicians, n.e.c.	Management/Professional/Technical
243	Sales supervisors and proprietors	Management/Professional/Technical
253	Insurance sales occupations	Management/Professional/Technical
254	Real estate sales occupations	Management/Professional/Technical
255	Financial service sales occupations	Management/Professional/Technical
256	Advertising and related sales jobs	Management/Professional/Technical
258	Sales engineers	Management/Professional/Technical
269	Parts salesperson	
270	Sales workers	
274	Sales occupations and sales representatives	Administrative Support and Retail Sales
275	Sales counter clerks	Administrative Support and Retail Sales
276	Cashiers	Administrative Support and Retail Sales
277	Door-to-door sales, street sales, and news vendors	Administrative Support and Retail Sales
283	Sales demonstrators, promoters, and models	Administrative Support and Retail Sales
285	Auctioneers and sales support occupations, n.e.c.	

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Table A13 – *Continued from previous page*

Code	Description	Category
303	Office supervisors	Administrative Support and Retail Sales
308	Computer and peripheral equipment operators	Administrative Support and Retail Sales
313	Secretaries and administrative assistants	Administrative Support and Retail Sales
315	Typists	Administrative Support and Retail Sales
316	Interviewers, enumerators, and surveyors	Administrative Support and Retail Sales
317	Hotel clerks	Administrative Support and Retail Sales
318	Transportation ticket and reservation agents	Administrative Support and Retail Sales
319	Receptionists and other information clerks	Administrative Support and Retail Sales
326	Correspondence and order clerks	Administrative Support and Retail Sales
328	Human resources clerks, excl payroll and timekeeping	Administrative Support and Retail Sales
329	Library assistants	Administrative Support and Retail Sales
335	File clerks	Administrative Support and Retail Sales
336	Records clerks	Administrative Support and Retail Sales
337	Bookkeepers and accounting and auditing clerks	Administrative Support and Retail Sales
338	Payroll and timekeeping clerks	Administrative Support and Retail Sales
344	Billing clerks and related financial records processing	Administrative Support and Retail Sales
347	Office machine operators, n.e.c.	Administrative Support and Retail Sales
348	Telephone operators	Administrative Support and Retail Sales
349	Other telecom operators	Administrative Support and Retail Sales
354	Postal clerks, exluding mail carriers	Administrative Support and Retail Sales
355	Mail carriers for postal service	Administrative Support and Retail Sales
356	Mail clerks, outside of post office	Administrative Support and Retail Sales
357	Messengers	Administrative Support and Retail Sales
359	Dispatchers	Administrative Support and Retail Sales
364	Shipping and receiving clerks	Administrative Support and Retail Sales
365	Stock and inventory clerks	Administrative Support and Retail Sales
366	Meter readers	Administrative Support and Retail Sales
368	Weighers, measurers, and checkers	Administrative Support and Retail Sales
373	Material recording, sched., prod., plan., expediting cl.	Administrative Support and Retail Sales
375	Insurance adjusters, examiners, and investigators	Administrative Support and Retail Sales
376	Customer service reps, invest., adjusters, excl. insur.	Administrative Support and Retail Sales
377	Eligibility clerks for government prog., social welfare	Administrative Support and Retail Sales
378	Bill and account collectors	Administrative Support and Retail Sales
379	General office clerks	Administrative Support and Retail Sales
383	Bank tellers	Administrative Support and Retail Sales
384	Proofreaders	Administrative Support and Retail Sales
385	Data entry keyers	Administrative Support and Retail Sales
386	Statistical clerks	Administrative Support and Retail Sales
387	Teacher's aides	Administrative Support and Retail Sales
389	Administrative support jobs, n.e.c.	Administrative Support and Retail Sales
405	Housekeepers, maids, butlers, and cleaners	Low-Skill Services
408	Laundry and dry cleaning workers	Low-Skill Services
413	Supervisors, firefighting and fire prevention occupations	
414	Supervisors, police and detectives	
415	Supervisors of guards	Low-Skill Services

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Table A13 – *Continued from previous page*

Code	Description	Category
417	Fire fighting, inspection, and prevention occupations	Management/Professional/Technical
418	Police and detectives, public service	Management/Professional/Technical
423	Sheriffs, bailiffs, correctional institution officers	Management/Professional/Technical
425	Crossing guards	Low-Skill Services
426	Guards and police, except public service	Low-Skill Services
427	Protective service, n.e.c.	Low-Skill Services
433	Supervisors of food preparation and service	Low-Skill Services
434	Bartenders	Low-Skill Services
435	Waiters and waitresses	Low-Skill Services
436	Cooks	Low-Skill Services
439	Food preparation workers	Low-Skill Services
444	Miscellanious food preparation and service workers	Low-Skill Services
445	Dental assistants	Low-Skill Services
447	Health and nursing aides	Low-Skill Services
448	Supervisors of cleaning and building service	Low-Skill Services
450	Superv. of landscaping, lawn service, groundskeeping	Low-Skill Services
451	Gardeners and groundskeepers	Low-Skill Services
453	Janitors	Low-Skill Services
455	Pest control occupations	Low-Skill Services
457	Barbers	Low-Skill Services
458	Hairdressers and cosmetologists	Low-Skill Services
459	Recreation facility attendants	Low-Skill Services
461	Guides	Low-Skill Services
462	Ushers	Low-Skill Services
464	Baggage porters, bellhops and concierges	Low-Skill Services
466	Recreation and fitness workers	Low-Skill Services
467	Motion picture projectionists	Low-Skill Services
468	Childcareworkers	Low-Skill Services
469	Personal service occupations, n.e.c	Low-Skill Services
470	Supervisors of personal service jobs, n.e.c	Low-Skill Services
471	Public transportation attendants	Low-Skill Services
472	Animal caretakers, except farm	Low-Skill Services
473	Farmers, ranchers, and other agricultural managers	Production/Construction/Manufacturing
479	Farm workers, incl. nursery farming, and marine life	Production/Construction/Manufacturing
488	Graders and sorters of agricultural products	Production/Construction/Manufacturing
489	Inspectors of agricultural products	Production/Construction/Manufacturing
494	Supervisors, forestry and logging workers	Production/Construction/Manufacturing
496	Timber, logging, and forestry workers	Production/Construction/Manufacturing
498	Fishing and hunting workers	Production/Construction/Manufacturing
503	Supervisors of mechanics and repairers	Production/Construction/Manufacturing
505	Automobile mechanics and repairers	Production/Construction/Manufacturing
507	Bus, truck, and stationary engine mechanics	Production/Construction/Manufacturing
508	Aircraft mechanics	Production/Construction/Manufacturing
509	Small engine repairers	Production/Construction/Manufacturing
514	Auto body repairers	Production/Construction/Manufacturing

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Table A13 – *Continued from previous page*

Code	Description	Category
516	Heavy equipement and farm equipment mechanics	Production/Construction/Manufacturing
518	Industrial machinery repairers	Production/Construction/Manufacturing
519	Machinery maintenance occupations	Production/Construction/Manufacturing
523	Repairers of industrial electrical equipment	Production/Construction/Manufacturing
525	Repairers of data processing equipment	Production/Construction/Manufacturing
526	Repairers of household appliances and power tools	Production/Construction/Manufacturing
527	Telecom and line installers and repairers	Production/Construction/Manufacturing
533	Repairers of electrical equipment, n.e.c.	Production/Construction/Manufacturing
534	Heating, air conditioning, and refrigeration mechanics	Production/Construction/Manufacturing
535	Precision instrument and equipment repairers	Production/Construction/Manufacturing
536	Locksmiths and safe repairers	Production/Construction/Manufacturing
539	Repairers of mechanical controls and valves	Production/Construction/Manufacturing
543	Elevator installers and repairers	Production/Construction/Manufacturing
544	Millwrights	Production/Construction/Manufacturing
549	Mechanics and repairers, n.e.c.	Production/Construction/Manufacturing
558	Supervisors of construction work	Production/Construction/Manufacturing
563	Masons, tilers, and carpet installers	Production/Construction/Manufacturing
567	Carpenters	Production/Construction/Manufacturing
573	Drywall installers	Production/Construction/Manufacturing
575	Electricians	Production/Construction/Manufacturing
577	Electric power installers and repairers	Production/Construction/Manufacturing
579	Painters, construction and maintenance	Production/Construction/Manufacturing
583	Paperhangers	Production/Construction/Manufacturing
584	Plasterers	Production/Construction/Manufacturing
585	Plumbers, pipe fitters, and steamfitters	Production/Construction/Manufacturing
588	Concrete and cement workers	Production/Construction/Manufacturing
589	Glaziers	Production/Construction/Manufacturing
593	Insulation workers	Production/Construction/Manufacturing
594	Paving, surfacing, and tamping equipment operators	Production/Construction/Manufacturing
595	Roofers	Production/Construction/Manufacturing
597	Structural metal workers	Production/Construction/Manufacturing
598	Drillers of earth	Production/Construction/Manufacturing
599	Misc. construction and related occupations	Production/Construction/Manufacturing
614	Drillers of oil wells	Production/Construction/Manufacturing
615	Explosives workers	Production/Construction/Manufacturing
616	Miners	Production/Construction/Manufacturing
617	Other mining occupations	Production/Construction/Manufacturing
628	Production supervisors or foremen	Production/Construction/Manufacturing
634	Tool and die makers and die setters	Production/Construction/Manufacturing
637	Machinists	Production/Construction/Manufacturing
643	Boilermakers	Production/Construction/Manufacturing
644	Precision grinders and fitters	Production/Construction/Manufacturing
645	Patternmakers and model makers, metal and plastic	Production/Construction/Manufacturing
647	Jewelers and precious stone and metal workers	Production/Construction/Manufacturing
649	Engravers	Production/Construction/Manufacturing

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Table A13 – *Continued from previous page*

Code	Description	Category
653	Sheet metal workers	Production/Construction/Manufacturing
657	Cabinetmakers and bench carpeters	Production/Construction/Manufacturing
658	Furniture and wood finishers	Production/Construction/Manufacturing
666	Tailors, dressmakers, and sewers	Production/Construction/Manufacturing
668	Upholsterers	Production/Construction/Manufacturing
669	Shoe and leather workers and repairers	Production/Construction/Manufacturing
675	Hand molders, shapers, and casters, except jewelers	Production/Construction/Manufacturing
677	Optical goods workers	Production/Construction/Manufacturing
678	Dental laboratory and medical applicance technicians	Production/Construction/Manufacturing
684	Miscellaneous precision workers, n.e.c.	Production/Construction/Manufacturing
686	Butchers and meat cutters	Production/Construction/Manufacturing
687	Bakers	Production/Construction/Manufacturing
688	Batch food makers	Production/Construction/Manufacturing
694	Water and sewage treatment plant operators	Production/Construction/Manufacturing
695	Power plant operators	Production/Construction/Manufacturing
696	Plant and system operators, stationary engineers	Production/Construction/Manufacturing
699	Other plant and system operators	Production/Construction/Manufacturing
703	Lathe and turning machine operatives	Production/Construction/Manufacturing
706	Punching and stamping press operatives	Production/Construction/Manufacturing
707	Rollers, roll hands, and finishers of metal	Production/Construction/Manufacturing
708	Drilling and boring machine operators	Production/Construction/Manufacturing
709	Grinding, abrading, buffing, and polishing workers	Production/Construction/Manufacturing
713	Forge and hammer operators	Production/Construction/Manufacturing
719	Molders and casting machine operators	Production/Construction/Manufacturing
723	Metal platers	Production/Construction/Manufacturing
724	Heat treating equipment operators	Production/Construction/Manufacturing
727	Sawing machine operators and sawyers	Production/Construction/Manufacturing
729	Nail, tacking, shaping and joining mach ops (wood)	Production/Construction/Manufacturing
733	Misc. woodworking machine operators	Production/Construction/Manufacturing
734	Bookbinders and printing machine operators, n.e.c.	Production/Construction/Manufacturing
736	Typesetters and compositors	Production/Construction/Manufacturing
738	Winding and twisting textile and apparel operatives	Production/Construction/Manufacturing
739	Knitters, loopers, and toppers textile operatives	Production/Construction/Manufacturing
743	Textile cutting and dyeing machine operators	Production/Construction/Manufacturing
744	Textile sewing machine operators	Production/Construction/Manufacturing
745	Shoemaking machine operators	Production/Construction/Manufacturing
747	Clothing pressing machine operators	Production/Construction/Manufacturing
749	Miscellanious textile machine operators	Production/Construction/Manufacturing
753	Cementing and gluing machne operators	Production/Construction/Manufacturing
754	Packers, fillers, and wrappers	Production/Construction/Manufacturing
755	Extruding and forming machine operators	Production/Construction/Manufacturing
756	Mixing and blending machine operators	Production/Construction/Manufacturing
757	Separating, filtering, and clarifying machine operators	Production/Construction/Manufacturing
763	Food roasting and baking machine operators	Production/Construction/Manufacturing
764	Washing, cleaning, and pickling machine operators	Production/Construction/Manufacturing

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Table A13 – *Continued from previous page*

Code	Description	Category
765	Paper folding machine operators	Production/Construction/Manufacturing
766	Furnance, kiln, and oven operators, apart from food	Production/Construction/Manufacturing
769	Slicing and cutting machine operators	Production/Construction/Manufacturing
774	Photographic process machine operators	Production/Construction/Manufacturing
779	Machine operators, n.e.c.	Production/Construction/Manufacturing
783	Welders, solderers, and metal cutters	Production/Construction/Manufacturing
785	Assemblers of electrical equipment	Production/Construction/Manufacturing
789	Painting and decoration occupations	Production/Construction/Manufacturing
799	Production checkers, graders, and sorters in	Production/Construction/Manufacturing
803	Supervisors of motor vehicle transportation	Production/Construction/Manufacturing
804	Driver/sales workers and truck Drivers	Production/Construction/Manufacturing
808	Bus drivers	Production/Construction/Manufacturing
809	Taxi drivers and chauffeurs	Production/Construction/Manufacturing
813	Parking lot attendants	Production/Construction/Manufacturing
814	Motor transportation occupations, n.e.c.	Production/Construction/Manufacturing
823	Railroad conductors and yardmasters	Production/Construction/Manufacturing
824	Locomotive operators: engineers and firemen	Production/Construction/Manufacturing
825	Railroad brake, coupler, and switch operators	Production/Construction/Manufacturing
828	Ship and boat captains and operators	Production/Construction/Manufacturing
829	Sailors and deckhands, ship/marine engineers	Production/Construction/Manufacturing
834	Miscellanious transportation occupations	Production/Construction/Manufacturing
844	Operating engineers of construction equipment	Production/Construction/Manufacturing
848	Hoist and winch operators	Production/Construction/Manufacturing
849	Crane and tower operators	Production/Construction/Manufacturing
853	Excavating and loading machine operators	Production/Construction/Manufacturing
856	Industrial truck and tractor operators	Production/Construction/Manufacturing
859	Misc. material moving equipment operators	Production/Construction/Manufacturing
865	Helpers, constructions	Production/Construction/Manufacturing
866	Helpers, surveyors	Production/Construction/Manufacturing
869	Construction laborers	Production/Construction/Manufacturing
873	Production helpers	Production/Construction/Manufacturing
875	Garbage and recyclable material collectors	Production/Construction/Manufacturing
878	Machine feeders and offbearers	Production/Construction/Manufacturing
885	Garage and service station related occupations	Production/Construction/Manufacturing
887	Vehicle washers and equipment cleaners	Production/Construction/Manufacturing
888	Packers and packagers by hand	Production/Construction/Manufacturing
889	Laborers, freight, stock, and material handlers, n.e.c.	Production/Construction/Manufacturing