Do Postsecondary Training Programs Respond to Changes in the Labor Market?

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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 show long-term trends in the distribution of degrees and certificates across occupation groupings in the nation's largest community college system. Using an instrumental variables approach I then estimate that an occupation's share of community college completions grows 0.47 percentage points for every percentage point increase in its share of employment. However, I show that this relationship is primarily due to increases in student demand rather than to colleges expanding capacity.

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1 Introduction

The United States labor market has seen 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 collapse 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 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 an administrative dataset encompassing students, faculty and course offerings at California's community colleges, which comprise the largest 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 offerings, and how they overlap with employment. I then analyze whether employment changes in a particular occupation are followed by commensurate changes in community college programs that train

[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).

students for that occupation.

I show that only half the polarization phenomenon occurs for community colleges: while degree and certificate completions since the early 1990s increased for occupations at the bottom of the skill distribution, 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. A concern is that degrees and certificates are endogenously determined: 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 a "shift-share" instrumental variables approach common to studies of this type (Bartik, 1991; Autor and Dorn, 2009; Diamond, 2016). This strategy leverages both the historical distribution of employment in occupations across industries, as well as national trends in employment growth, to account for occupation-level changes in demand.

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 1 percentage point over the course of a decade saw its share of all degrees and certificates grow by 0.5 percentage points. However, I find significant heterogeneity across occupations in this connection between employment and awards. Occupations in the production and manufacturing sector have a weaker response than other occupations, as do those that require extensive manual tasks. Occupations with high social and interpersonal content grew faster in response to changes in occupational demand. There is also some heterogeneity across colleges: large colleges are particularly responsive to employment changes.

The relationship between community college completions and employment could be driven by changes in student demand or in community college supply. If students respond to labor market forces but community colleges do not expand their programs, this may still result in a positive effect on completions if some programs are never filled to capacity. A key contribution of this paper is that I can observe program-level information beyond completions in order to investigate the mechanisms for the connection between community college awards and employment. 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 hired. 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.

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 comunity 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 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, but there remains a tension between whether to train workers in new high-growth sectors or to provide 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). In recent years, a great deal of attention has been paid to the potential competition between public community colleges

[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.

and the private for-profit sector (Deming, Goldin and Katz, 2012; Cellini, 2010, 2009; 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.

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), which include information at the student, college, and course levels.

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 similar to the more commonly used Classification of Instructional Programs (CIP). 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 awards: that is, degrees and certificates. Each award is assigned a unique TOP code describing its educational content. The CCCCO data also disaggregate these awards 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. In order to discuss one metric of college outcomes, for most of the analysis on awards I use the number of credits awarded as opposed to the simple count of awards, constructed from the sum of different types of awards.[3]

In addition to awards, I also observe enrollment, the number of course sections, and faculty appointments, all at the course level. I compile the number of sections and course units offered in each TOP code in each term, as well as the number of students enrolled by TOP code. Unfortunately, there is no information at the course level on enrollment capacity or caps; instead, the number of sections, units, hours, and students enrolled is as close I can be to approximate the true capacity of program offerings at the TOP level.

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]Because each award is in a range of possible units awarded, 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 award 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. In robustness exercises I consider each degree or certificate type individually.

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 produced similar results. I use this latter approach, resulting in a panel of 341 occupation codes. 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 motivate the causal analysis in the next section (Loeb et al., 2017). First I consider whether community college awards 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 awards 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.

4.1 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 1980 to 2010. The typical U-shape curve shows growth at the bottom and top of the skill distribution, with a decline in the middle.

Panel b) of Figure 1 shows an analogous plot for the change in the distribution of California community college awards, 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 awards 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 awards 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 awards is perhaps more comparable to the distribution of employment of workers with some college.

Figure 2 shows the distribution of employment and awards, 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 awards 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 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.[4] 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 awards.

Despite this similarity, there is a clear difference in the occupations that comprise the growth of employment and completions at the low end of the skill distribution. To illustrate, Figure 3 shows employment and completions for three of the largest occupations in terms of community college awards. Cosmetologists, hairdressers, and childcare workers comprised 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 awards. Figure 3 shows that growth in employment and awards in these large occupations did not overlap, even though the overall trend in skill distribution did.

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

4.2 Broad occupational groups

In this subsection 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, 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 consts 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.

Panel a) of Figure 4 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 awards, with the rest almost evenly split among the other occupational groupings. Approximately 20 percent of all community college awards 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 4 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 expand on this analysis of the change in employment share and the change in awards share by disaggregating the broad occupational groups back to the individual occupations.

4.3 Task content of occupations

As a final descriptive piece I investigate the "routinization" hypothesis developed by Autor, Levy and Murnane (2003) to understand how technological advances, in particular, have shaped the occupational structure. In short, 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 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. Studying tasks, as opposed to skill composition or broad occupation groupings, 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).[5] In addition, I use a 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.[6] 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 award-weighted means and standard deviations

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

[6] 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 award distribution and 1990 employment distribution is informative.

for community college degrees and certificates in 1993. Since the scores are standardized to have mean zero when weighted for overall employment in 1990, the means should be interpreted as the difference in task intensity in terms of standard deviations from 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 awarded in abstract-intensive and social occupations.The average community college award was also less manual-intensive than the average occupation. As shown previously this places the distribution of community college awards somewhere between the distribution of employment of workers with some college and those with a college degree.

In addition to the initial differences between community college awards and overall employment, it is also informative to examine trends over time. Figure 5 shows the mean task intensity for each educational grouping since 1990. For each individual panel the task intensity is standardized in the initial year.[7] 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 awards compare? Panel d)

[7] This is a different standardization than in Table 1, which standardized to overall employment in 1990. In Figure 5 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.

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 evidence 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.

5 Methods

Until now I have shown descriptive evidence for an alignment between employment changes and community college awards since 1990. In this section I describe the analytical strategy to measure the direct link between occupational growth in 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, so community college responses would not be perceptible from year to year. 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 and its mean wages, through the following relationship:

$$\Delta \frac{y_{jt}}{y_t} = \alpha + \beta_1 \Delta \frac{Emp_{jt}^{CA}}{Emp_t^{CA}} + \beta_2 \Delta W_{jt} + \delta_t + u_{jt} \tag{1}$$

For occupation j in year t, y_{jt} is a measure of community college awards, Emp_{jt}^{CA} is employment in that occupation in California, and W_{jt}^{CA} is log mean annual wages, also in California. To control for occupation effects equation 1 is in first 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.[8]

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 obviously no Census data available between Census years. As a solution, in the main specifications I relate decadal changes in employment and wages 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 smaller intervals (six and fix years), and also change the base year slightly.[9]

One concern when estimating equation 1 is the endogeneity of state changes in occupational employment with respect to shifts in the content of local educational production. One plausible source of this endogeneity is reverse causality. New community college graduates trained in an occupation may affect that occupation's share of overall employment. To alleviate this and other endogeneity concerns, I use an instrument that isolates local occupation-specific demand shocks.

The instrument takes the form of the "shift-share" approach commonly used in this literature (Bartik, 1991; Autor and Dorn, 2009, 2013; Autor, Dorn and Hanson, 2013; Diamond, 2016). To predict occupation-level employment the instrument leverages the mix of occupational employment within each industry i in 1980, before the beginning of the study period. Industry-by-occupation employment then is assumed to grow at the same rate as non-California employment in these same cells:

$$\widehat{Emp}_{jt}^{CA} \equiv \sum_{i=1}^{I} \Big[Emp_{ij,1980}^{CA} * (1 + \frac{Emp_{ijt}^{US} - Emp_{ij,1980}^{US}}{Emp_{ij,1980}^{US}}) \Big] \tag{2}$$

Here, the superscript "US" includes all non-California employment. In other words, only national shocks to occupational employment are allowed to affect California employment, thus

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

[9] By changing the base year I mean, for example, relating 1990-2000 employment changes to 1994-2001 awards changes. The results are not too different.

freeing the measure of each occupation's share of total employment from concerns of endogenous shocks.

Because the main equation is expressed in shares, I scale the instrument in Equation 10 by an equivalent construct of total employment in the state.

$$\widehat{Emp}_t^{CA} \equiv \sum_{i=1}^{I} \Big[Emp_{i,1980}^{CA} * (1 + \frac{Emp_{it}^{US} - Emp_{i,1980}^{US}}{Emp_{i,1980}^{US}}) \Big] \tag{3}$$

I use a similar construct to instrument for occupational mean wages. I deconstruct occupation-level mean wages into the weighted average of mean wages by occupation-industry cells. That is, I start with the following decomposition, which states that an occupation's mean wage is the weighted average of wages within occupation-industry cells, weighted by employment in these cells:

$$W_{jt} = \sum_{i=1}^{I} \Big[W_{ijt} * \frac{Emp_{ijt}}{Emp_{jt}} \Big] \tag{4}$$

To construct the instrument for occupational wages, the "share" analog of the employment instrument is fixed wage and industry-occupation weights from 1980. The "shift" grows these wages by the change in non-California wages within these occupation-industry cells:

$$\widehat{W}_{jt}^{CA} \equiv \sum_{i=1}^{I} \Big[W_{ij,1980}^{CA} * \frac{Emp_{ij,1980}^{CA}}{Emp_{j,1980}^{CA}} * (1 + \frac{W_{ijt}^{US} - W_{ij,1980}^{US}}{W_{ij,1980}^{US}}) \Big] \tag{5}$$

In practice, for both the employment and wage instruments I calculate changes in logs. For example,

$$\frac{Emp_{ijt}^{US} - Emp_{ij,1980}^{US}}{Emp_{ij,1980}^{US}} \approx ln(Emp_{ijt}^{US}) - ln(Emp_{ij,1980}^{US}) \tag{6}$$

In sum, I create two instruments, one for an occupation's current year share of overall employment, and the other for the occupation's mean wage. Table A10 shows first stage estimates of ϕ_2 and θ_2 from the following equations:

$$\frac{Emp_{jt}^{CA}}{Emp_t^{CA}} = \phi_1 + \phi_2 \frac{\widehat{Emp}_{jt}^{CA}}{\widehat{Emp}_t^{CA}} + \xi_t + \varepsilon_{jt} \tag{7}$$

$$W_{jt}^{CA} = \theta_1 + \theta_2 \widehat{W}_t^{CA} + \zeta_t + \epsilon_{jt} \tag{8}$$

Table A10 shows that the employment instrument is really predictive, with a coefficient close to 1 and a high F statistic. The wage instrument is also very predictive.

Studies that use shift-share instruments do not tend to show support for the validity of the exclusion restriction, most likely because the shift-share measure is not a typical instrument and the exclusion restriction is difficult to describe in a meaningful way. I follow Goldsmith-Pinkham, Sorkin and Swift (2018), who note that the underlying variation from these instruments is the initial shares of, in my case, industry composition of occupations. Goldsmith-Pinkham, Sorkin and Swift (2018) recommend testing the correlation of these shares, in my case $Emp_{ij,1980}^{CA}/Emp_{j,1980}^{CA}$, and characteristics of the occupation itself. I show these in Table A3 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, in my case the most important covariates, educational composition, are most often uncorrelated with the industry shares. Moreover, in an appendix I show that inclusion of these covariates into the main regressions leads to almost identical results.

6 Results

6.1 Main Results

Table A11 shows results of estimation of equation 1, relating an occupation's growth in employment share to its growth in share of community college awards. Column 1 shows results using OLS, which suggests that occupations whose share of total employment grew one percentage point also grew their share of awards by 0.495 percentage points. A coefficient of one would suggest that increases in employment shares were associated with equal increases in award 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.

Column 2 adds changes in the mean wage, which does not substantially affect the coefficient on employment. Perhaps surprisingly, the coefficient on the wage is also small and not statistically significant. Of course, the OLS results are subject to potential bias due to reverse causality, which motivates the use of the shift-share instrumental variables approach.

Columns 3 and 4 show the reduced form effect of the shift-share instruments on awards. Column 3 suggests that the shift-share instrument is strongly correlated with employment growth. On the other hand, column 4 shows that the wage instrument is not strongly correlated with award growth.

The last two columns of Table A11 show the results of the two-stage least squares analysis, using the shift-share constructs as instruments. The result in column 5 is analogous to the OLS result in column 1, and is almost identical: occupations that grew one percentage point as a share of overall employment increased their share of total awarded units by 0.469 percentage point. The specification in column 6 is analogous to the one in column 2, and is also similar: again, the inclusion of the wage change has no significant effect on the coefficient on employment, nor is the coefficient on the wage change economically or statistically significant.

Given the descriptive discussion of the the similarities between community college program offerings and employment of workers with some college, panel B of Table A11 measures the effect on awards shares of changes in the occupational employment shares of workers with some college, as opposed to overall employment. The results are comparable to those in panel A. One noteworthy difference between the two panels is that while in panel A the OLS results are slightly larger than those with the instruments, in panel B the opposite is true. However, in neither case are the differences between the OLS result and the instrumenal variables result large or statistically significant.

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 these effects 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 A11 suggest that the share of degrees and certificates in these occupations would have grown by 0.32 percentage points, or about 200 associate's degrees per year.[10]

Although the analyses so far suggest that there is a reasonably strong link between occupational growth and awards growth, 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 4 shows that there was a substantially higher share of awards in managerial and professional occupations than there was empoyment. In Table 4 I account for this initial mismatch by including an indicator for the initial gap between the employment share and the awards 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 initially overrepresented in awards also grew faster. The main coefficients are unchanged, however.

As a robustness check, Table A4 shows that the results are similar when not weighted. Tables A6 and A7 show that the main results are robust to the size of the difference in the awards data (5, 6, or 7 years).

6.2 Occupation Characteristics

The results so far show a connection between occupational employment and degrees. These analyses do not account for the more systemic changes that have occured in the labor market over the past few decades. 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.

To investigate this issue in a more systematic way, I analyze whether certain occupations

[10] In more detail, the point estimate suggests that the share of awards in this particular occupation would grow by 0.32 percentage points given its employment share grew by 0.7 percentage points. The predicted share of awards in 2010 thus becomes 2.54 percent of all awards, or 60,564 awarded units. Given that there were 48,726 awarded units in this occupation in 2000, the difference is 11,838 units, or the equivalent of approximately 200 associate's degrees, which are comprised of 60 units each.

exhibit an especially strong or weak relationship between employment and awards. I estimate the following:

$$\Delta\frac{y_{jt}}{y_t} = \alpha + \beta_1 \Delta\frac{Emp^{CA}_{jt}}{Emp^{CA}_t} + \beta_2 \Delta\frac{Emp^{CA}_{jt}}{Emp^{CA}_t} * I(X_j = x) + \beta_3 I(X_j = x) + \delta_t + u_{jt} \tag{9}$$

where $I(X_j = x)$ is an indicator for whether an occupation j is a member of a group of occupations with characteristic x. I consider three main types of occupation characteristics: broad occupational groupings, task intensity, and operating costs to the college. For estimation I now include an instrument for the employment change $\Delta\frac{Emp^{CA}_{jt}}{Emp^{CA}_t}$ as before, and include the interaction of the instrument with the particular occupational grouping as an additional instrument, giving me two instruments for two endogenous variables.[11]

The coefficient of interest is β_2, which is the additional growth in awards share for an occupation relative to other occupations without the characteristic. The task intensity and operating cost characteristics are not mutually exclusive: one occupation can be both routine-intensive and manual-intensive, or neither.[12] Broad occupational groupings are, however, mutually exclusive.[13]

Building on the earlier analysis from Section 4.2, the first three columns of Table 5 divide occupations into professional, service, and production categories as defined by Autor and Dorn (2013). The coefficient in the second row of panel A suggests that professional occupations have a strong link between employment and awards. On the other hand, the negative coefficient in the second column shows an opposite association for service occupations. In neither case is the interaction coefficient statistically significant. On the other hand, occupations in production occupations are much less likely to have a strong relationship between employment and awards.

Columns 4-7 consider the task content of the occupation. Returning to the task scores discussed earlier, I categorized occupations by whether they were above or below zero in the 1980 employment-weighted distribution of employment. Column 4 shows that occupations with

[11] In other specifications not shown I also instrument for the wage change, and the results are quite similar. Likewise, controlling for the indicator of task intensity (that is, estimating β_3) does not affect the key interaction term, and the coefficient estimates are small and statistically insignificant.

[12] An example of the former is textile sewing machine operators, and an example of the latter is financial managers.

[13] An occupation cannot be both a service occupation and a production occupation.

a high abstract content were not any more likely to grow faster relative to occupation growth. In fact, the coefficient on the interaction term for abstract intensive occupations in panel B is slightly negative. Similarly, routine-intensive occupations were no more likely to grow faster than non-routine intensive occupations. On the other hand, occupations with a high degree of manual tasks were less likely to grow with the growth of occupations. Column 7 shows a large coefficient on the interaction term with social-intensive occupations,.

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). 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. Because colleges receive a set per-pupil allocation, of approximately $3,500 per student, I also determine whether each program operates as a net positive or negative expenditure for the college.[14] Column 8 shows that occupations that operated at a loss for the college were no more likely to have a strong relationship with the labor market. Only 53 of 259 occupations are net negative, though, which means that the identification for this interaction is not coming from a great many occupations. So, in the final column of the table I also categorize occupations by whether they were above or below the median per-student expenditure of $1,200, not net of revenue. A similar result holds: more expensive programs were not differentially responsive to the labor market than other programs.[15]

[14]There are two important limitations of these data. First, they come from just one college; it is likely that operating costs differ across colleges. 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.

[15]These estimates are of course limited by coming from one college in just one academic year, and so might not be representative of program costs at all college across all the years of the study. Nevertheless, I include these numbers because of the scarcity of program-level cost information.

6.3 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 awarded in the first year of data, 1993. The first two columns of Table 6 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. The results in panel B for employment of workers with some college, though, show a similar sign but the difference is not statistically significant.

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 awards based. Here, colleges with high initial CTE shares show a lower response to the labor market than colleges with a low one, though this 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.[16] Here, the differences are relatively small and not statistically significant.

On the other hand, I categorized colleges by their county's unemployment rate. I used Local Area Unemployment Statistics and calculated each county's average unemployment rate over the entire time period, between 1990 and 2016.[17] Columns 7 and 8 of Table 6 shows the results

[16] 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.

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

for colleges in counties with unemployment above and below the median.[18] Colleges in high unemployment counties had a much higher connection to the labor market than counties in low unemployment counties.

6.4 Inputs to Educational Production

The main measure I have used is community college degrees and certificates, summarized together in terms of awarded units. This 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 perhaps incomplete. The number of degrees and certificates is as much a function of the availability of programs as it is the interest and persistence of students in enrolling and completing credentials in these programs.

To begin to disentangle these effects, and hone in on whether the response I observe in the previous results is one of community college administrators or of students, I implement the same analyses through estimating equation 1 for other measures. In particular, I consider measures that reflect inputs to degrees and certificates, or are at least upstream from completed degrees. Column 1 of Table 7 repeats the main estimates. Column 2 shows the effect of employment changes on the number of course sections offered in each occupation.[19] The next three columns show the effects on the number of total, permanent, and adjunct faculty. For none of these measures is there a large or precisely estimated response. This suggests that there is no evidence that colleges are systematically changing their capacity to meet changes in labor demand.

On the other hand, the final column of Table 7 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 0.187 percentage points. In panel B the coefficient is statistically significant at the 10 percent level. These results, combined with the main results on awards rate, suggest that students are responding to changes in the labor

[18] 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.

[19] Course sections are measured in terms of units, to take into account different course requirements.

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).

6.5 Robustness: 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 8. The estimates are quite similar to the OLS estimates from Table A11. Of course, the estimates using IPEDS are subject to the same concerns about endogeneity and reverse causation 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 wholesale 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 "shift-share" 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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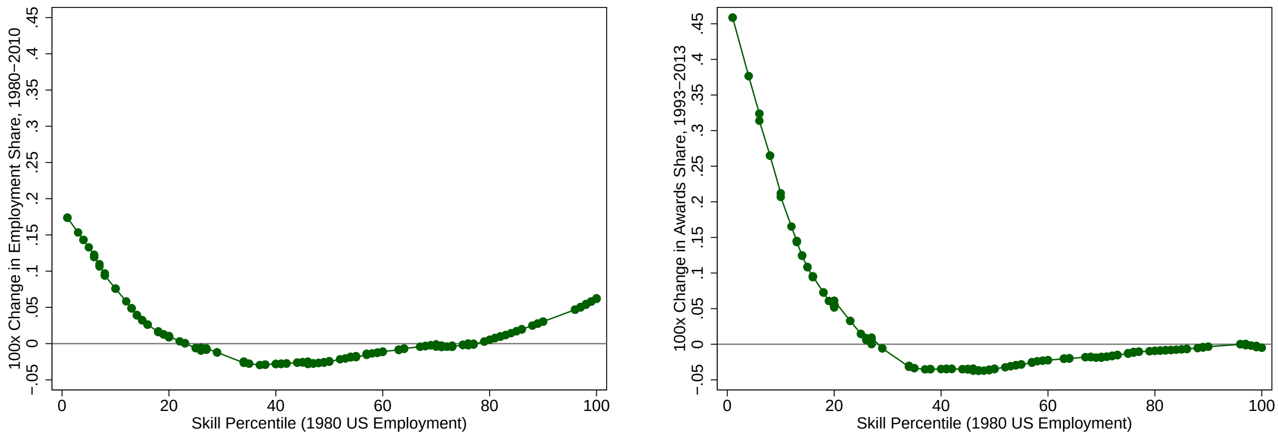
Figure 1: Employment and Awards Growth, by Skill Percentile

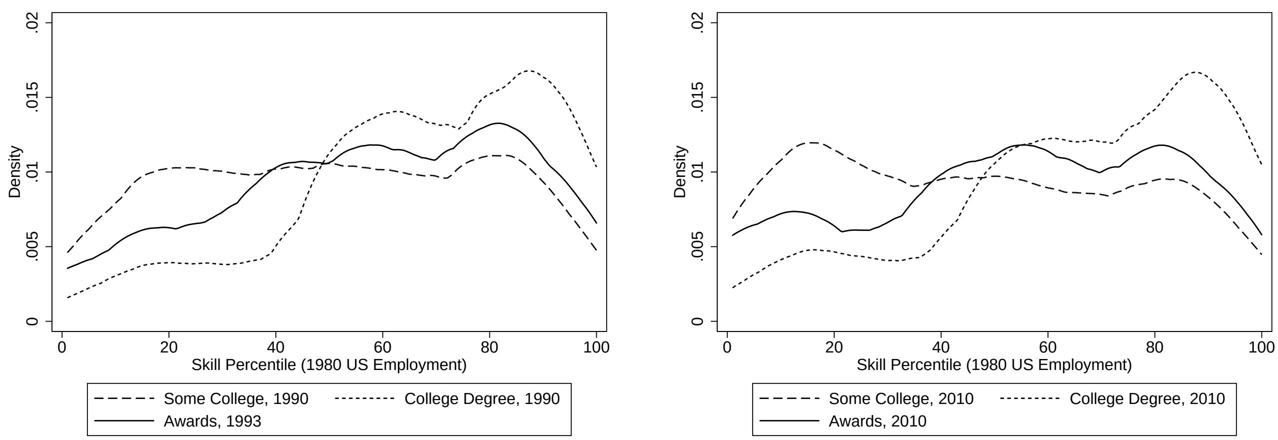


a) Changes in Employment, 1980-2010

b) Change in Awards 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 awarded California community college degrees and certificates, in terms of units awarded.

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

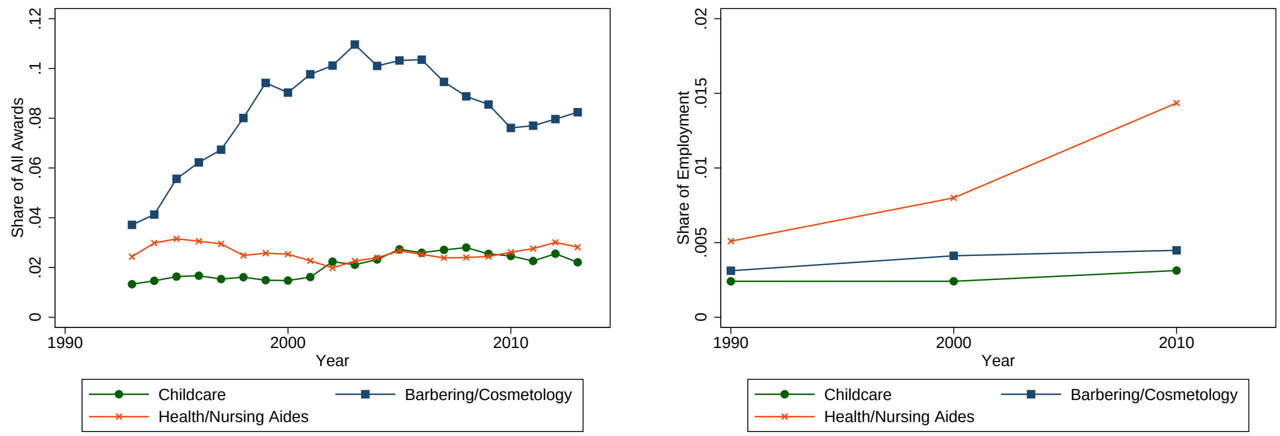


a) 1990

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. Awards 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

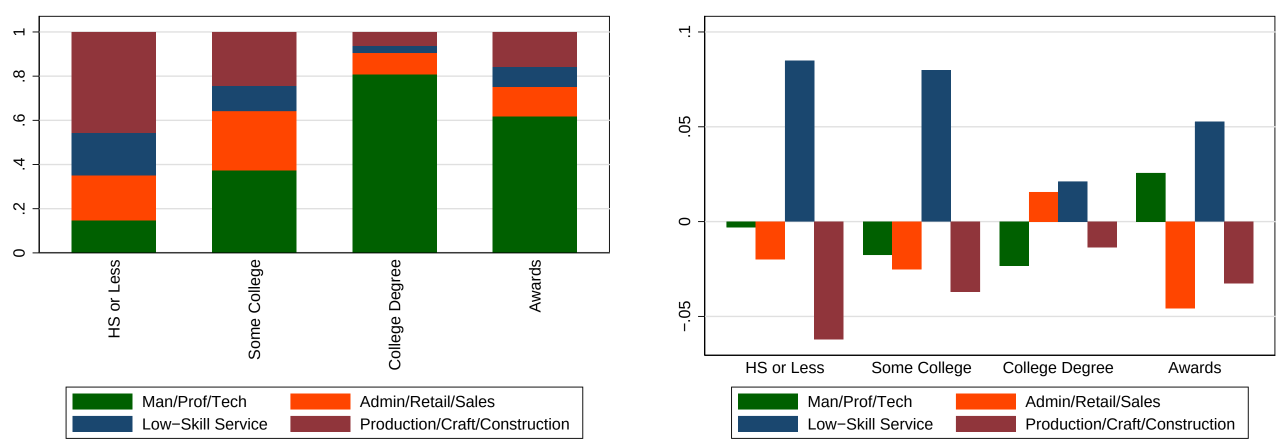


a) Community College Awards

b) Workers with Some College

Notes. Figures show the share of all community college awarded 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: Employment and Awards, by Occupation Categories

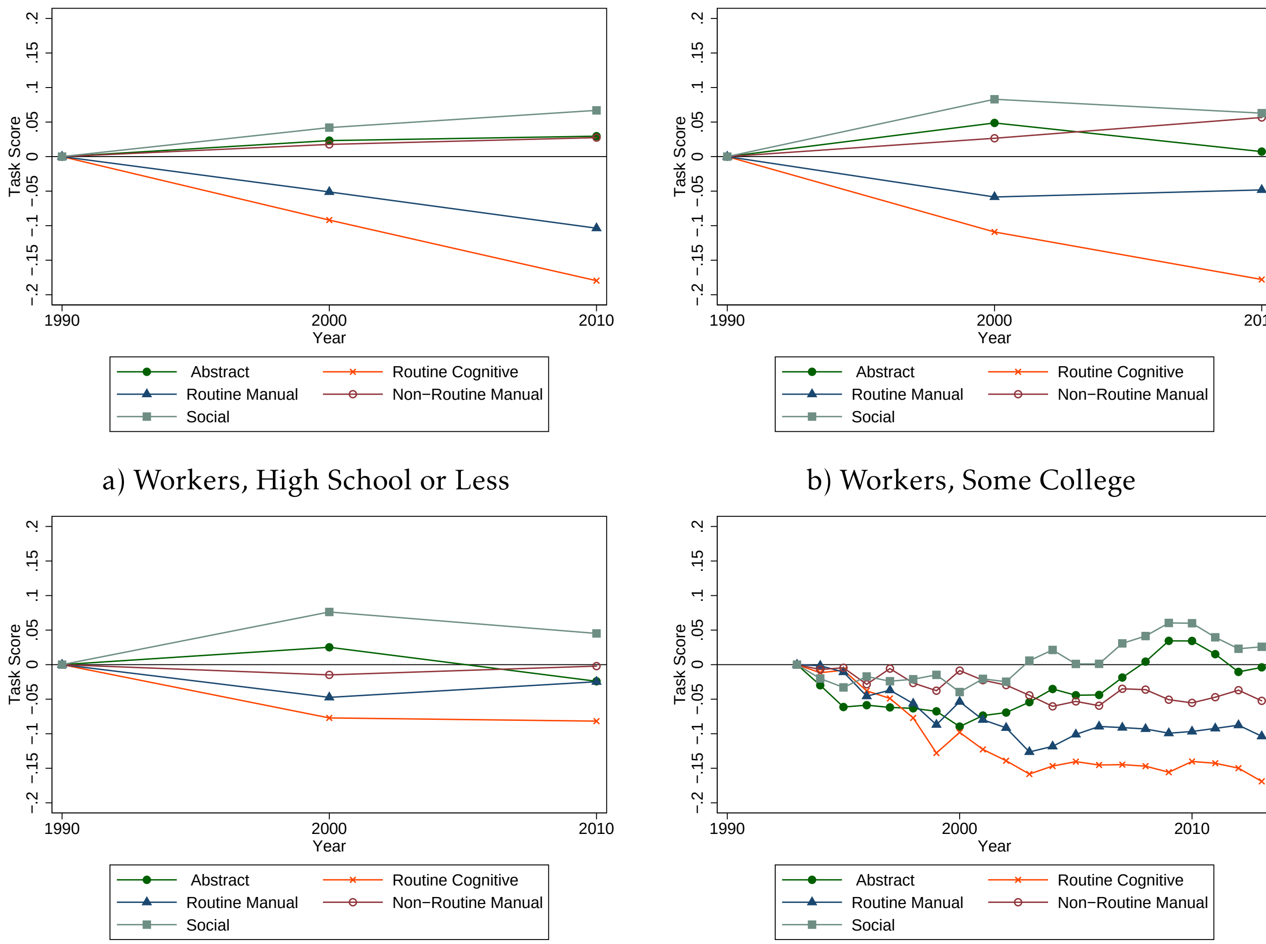


a) Employment Share by Category, 1990

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 awards are for 1993, not 1990.

Figure 5: Mean Task Content of Employment and Awards, 1990-2013



a) Workers, High School or Less

b) Workers, Some College

c) Workers, College Degree

d) Community College Awards

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.

Table 1: Mean O*NET task measures for employment and community college awards, 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 awards are for 1993, not 1990.

Table 2: First Stage Estimates

	(1)	(2)	(3)	(4)
	All Workers	Some College	All Workers	Some College
A. Instrument for Employment				
Levels	1.001***	1.011***		
	(0.0240)	(0.0361)		
Changes			1.177***	1.502***
			(0.105)	(0.178)
N	999	999	666	666
F	1735.552	786.472	125.866	71.279
B. Instrument for Wages				
Levels	0.0958***	0.128***		
	(0.0175)	(0.0150)		
Changes			0.0962***	0.125***
			(0.0252)	(0.0303)
N	997	974	664	641
F	29.976	73.062	14.549	17.005

Notes. Regressions include year effects. Regressions weighted by 1980 employment. Partial F statistic displayed. Data include years 1990, 2000, and 2010. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table 3: Effect of Employment and Wages on Units Awarded

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		Reduced Form		2SLS	
A. All Workers						
ΔEmp	0.495***	0.516***			0.469***	0.454***
	(0.094)	(0.105)			(0.085)	(0.119)
ΔW		0.0635				-0.0357
		(0.052)				(0.191)
$\Delta\widehat{Emp}$			0.608***	0.596***		
			(0.113)	(0.119)		
$\Delta\widehat{W}$				0.000152		
				(0.001)		
N	473	473	473	473	473	473
R-sq	0.135	0.148	0.106	0.106	0.135	0.116
B. Workers with Some College						
ΔEmp	0.401**	0.417**			0.452***	0.413**
	(0.127)	(0.134)			(0.126)	(0.140)
ΔW		0.0577				-0.0979
		(0.049)				(0.207)
$\Delta\widehat{Emp}$			0.764***	0.751***		
			(0.206)	(0.215)		
$\Delta\widehat{W}$				0.000157		
				(0.001)		
N	473	467	473	468	473	467
R-sq	0.113	0.126	0.119	0.119	0.111	0.034

Notes. Academic data include the intervals 1993-2000 and 2003-2010. Employment and wages 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 4: Effect of Employment on Units Awarded, Including Initial Gap

	(1)	(2)	(3)	(4)
	All Workers		Some College	
ΔEmp	0.467***	0.469***	0.451***	0.553***
	(0.086)	(0.093)	(0.126)	(0.152)
Ratio of Awards-Employment	0.00394		0.000814*	
	(0.004)		(0.000)	
Difference in Awards-Employment		3.457		6.266*
		(1.834)		(2.843)
N	473	473	473	473
R-sq	0.135	0.145	0.113	0.147

Notes. Ratio of awards to employment is the occupations share of total awards divided by the occupation's share of total employment, in 1980. Similarly, the difference in awards 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 and wages 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 5: Effect of Employment on Units Awarded, Occupation Interactions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Occupation Categories			Task Intensity of Occupation in 1980				Operating Cost	
	Prof.	Service	Production	Abstract	Routine	Manual	Social	Net Negative	High-Cost
A. All Workers									
ΔEmp	0.192	0.494***	0.498***	0.281	0.486***	0.497***	0.0982	0.471***	0.497***
	(0.205)	(0.059)	(0.075)	(0.224)	(0.064)	(0.075)	(0.113)	(0.088)	(0.063)
$\Delta Emp * I(X = x)$	0.333	-0.211	-0.405***	0.205	-0.203	-0.254*	0.413***	0.0843	-0.231
	(0.172)	(0.253)	(0.085)	(0.195)	(0.224)	(0.107)	(0.074)	(0.589)	(0.231)
N	479	479	479	479	479	479	479	445	445
R-sq	0.141	0.141	0.143	0.142	0.133	0.135	0.148	0.141	0.133
B. Workers with Some College									
ΔEmp	0.357	0.429***	0.438***	0.490	0.425***	0.448***	0.0469	0.405***	0.390***
	(0.290)	(0.051)	(0.098)	(0.377)	(0.064)	(0.101)	(0.086)	(0.099)	(0.073)
$\Delta Emp * I(X = x)$	0.120	-0.0141	-0.395***	-0.0748	-0.0208	-0.282**	0.428***	1.457	0.250
	(0.262)	(0.270)	(0.104)	(0.361)	(0.324)	(0.092)	(0.070)	(1.293)	(0.444)
N	479	479	479	479	479	479	479	445	445
R-sq	0.120	0.119	0.105	0.113	0.113	0.100	0.116	0.166	0.133

Notes. Academic data include the intervals 1993-2000 and 2003-2010. Employment and wages data include the intervals 1990-2000, 2000-2010. Results weighted by 1980 national employment levels. All results show instrumental variables estimates. Occupation categories are mutually exclusive groupings based on Autor and Dorn (2013). Task intensity variables split occupations by whether they are above or below the median in terms of that task. "Net negative" operating cost means the per-student cost is higher than the approximately $3,500 in per-student funding. "High-Cost" occupations are those with per-student costs above the median. See text for more information occupation category and task intensity groupings. Standard errors clustered at the occupation level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table 6: Effect of Employment on Units Awarded, 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
A. All Workers								
ΔEmp	0.531***	0.335***	0.393***	0.565***	0.436***	0.537***	0.785***	0.409***
	(0.088)	(0.084)	(0.098)	(0.097)	(0.083)	(0.106)	(0.200)	(0.086)
N	479	479	479	479	479	479	479	479
B. Workers with Some College								
ΔEmp	0.447***	0.377**	0.355***	0.508***	0.366**	0.521***	0.702***	0.358**
	(0.095)	(0.116)	(0.099)	(0.131)	(0.113)	(0.101)	(0.198)	(0.114)
N	479	479	479	479	479	479	479	479

Notes. Academic data include the intervals 1993-2000 and 2003-2010. Employment and wages 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 7: Effect of Employment and Wages on Awards, College Inputs, and Enrollment

	(1) Awards	(2) Sections Offered	(3) Overall Faculty	(4) Temp Faculty	(5) Permanent Faculty	(6) Enrollment
A. All Workers						
ΔEmp	0.469***	0.0261	-0.0794	0.00665	-0.166	0.187*
	(0.085)	(0.226)	(0.092)	(0.042)	(0.147)	(0.077)
N	473	473	473	473	473	473
R-sq	0.135	0.003	0.006	0.021	0.007	0.080
B. Workers with Some College						
ΔEmp	0.452***	0.156	-0.0926	-0.0769	-0.117	0.221
	(0.126)	(0.345)	(0.069)	(0.048)	(0.117)	(0.130)
N	473	473	473	473	473	473
R-sq	0.111	0.012	0.027	0.036	0.014	0.070

Notes. Faculty data are the number of full-time equivalents (FTEs) at each occupation. The number of sections includes the number of total units offered in each occupation, in terms of the number of sections of each course. All results show instrumental variables estimates. Academic data include the intervals 1993-2000 and 2003-2010. Employment and wages 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 8: 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 award. 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 awards, 2010

	(1) ≤ High School	(2) Some College	(3) College Degree	(4) Awards
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: 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 A4: Effect of Employment and Wages on Units Awarded, Unweighted

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		Reduced Form		2SLS	
A. All Workers						
ΔEmp	0.493*	0.502*			0.308*	0.312*
	(0.207)	(0.208)			(0.133)	(0.132)
ΔW		-0.00379				-0.0126
		(0.007)				(0.022)
$\Delta \widehat{Emp}$			0.426*	0.414*		
			(0.191)	(0.183)		
$\Delta \widehat{W}$				0.0000428		
				(0.000)		
N	473	473	473	473	473	473
R-sq	0.053	0.054	0.013	0.013	0.046	0.042
B. Workers with Some College						
ΔEmp	0.467*	0.467*			0.315**	0.315**
	(0.226)	(0.227)			(0.120)	(0.120)
ΔW		-0.000318				-0.00662
		(0.003)				(0.019)
$\Delta \widehat{Emp}$			0.578*	0.567**		
			(0.225)	(0.209)		
$\Delta \widehat{W}$				0.0000356		
				(0.000)		
N	473	467	473	468	473	467
R-sq	0.061	0.061	0.018	0.018	0.055	0.051

Notes. Academic data include the intervals 1993-2000 and 2003-2010. Employment and wages data include the intervals 1990-2000, 2000-2010. Results not weighted. Standard errors clustered at the occupation level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A5: Effect of Employment and Wages on Units Awarded, Including Covariates

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		Reduced Form		2SLS	
A. All Workers						
ΔEmp	0.496***	0.523***			0.453***	0.421***
	(0.088)	(0.102)			(0.078)	(0.117)
ΔW		0.0829				-0.0772
		(0.058)				(0.207)
$\Delta \widehat{Emp}$			0.581***	0.576***		
			(0.103)	(0.109)		
$\Delta \widehat{W}$				0.0000749		
				(0.001)		
N	473	473	473	473	473	473
R-sq	0.176	0.193	0.144	0.144	0.175	0.127
B. Workers with Some College						
ΔEmp	0.449***	0.463***			0.467***	0.446***
	(0.119)	(0.121)			(0.106)	(0.128)
ΔW		0.0720				-0.0601
		(0.050)				(0.185)
$\Delta \widehat{Emp}$			0.756***	0.738***		
			(0.172)	(0.168)		
$\Delta \widehat{W}$				0.000223		
				(0.001)		
N	473	467	473	468	473	467
R-sq	0.191	0.208	0.180	0.181	0.190	0.153

Notes. Academic data include the intervals 1993-2000 and 2003-2010. Employment and wages 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 A6: Main Effects, Different Intervals, All Workers

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		Reduced Form		2SLS	
Panel A. 5-Year Differences						
ΔEmp	0.236**	0.248**			0.291***	0.291*
	(0.077)	(0.082)			(0.073)	(0.113)
ΔW		0.0362				-0.00142
		(0.032)				(0.155)
$\Delta \widehat{Emp}$			0.378***	0.366***		
			(0.095)	(0.092)		
$\Delta \widehat{W}$				0.000159		
				(0.000)		
N	473	473	473	473	473	473
R-sq	0.060	0.068	0.077	0.078	0.057	0.057
Panel B. 6-Year Differences						
ΔEmp	0.292**	0.313**			0.269***	0.281**
	(0.090)	(0.100)			(0.070)	(0.107)
ΔW		0.0647				0.0295
		(0.048)				(0.173)
$\Delta \widehat{Emp}$			0.349***	0.331***		
			(0.091)	(0.095)		
$\Delta \widehat{W}$				0.000242		
				(0.001)		
N	472	472	472	472	472	472
R-sq	0.063	0.081	0.046	0.047	0.063	0.075
Panel C. 7-Year Differences						
ΔEmp	0.495***	0.516***			0.469***	0.454***
	(0.094)	(0.105)			(0.085)	(0.119)
ΔW		0.0635				-0.0357
		(0.052)				(0.191)
$\Delta \widehat{Emp}$			0.608***	0.596***		
			(0.113)	(0.119)		
$\Delta \widehat{W}$				0.000152		
				(0.001)		
N	473	473	473	473	473	473
R-sq	0.135	0.148	0.106	0.106	0.135	0.116

Notes. Academic data include the intervals noted, with the first year of the decade in the end of the period. For example, the five year differences include 1995-2000 and 2005-2010. Employment and wages 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 A7: Main Effects, Different Intervals, Workers with Some College

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		Reduced Form		2SLS	
Panel A. 5-Year Differences						
ΔEmp	0.0857	0.0920			0.185**	0.184
	(0.085)	(0.092)			(0.068)	(0.099)
ΔW		0.0222				-0.00259
		(0.036)				(0.155)
$\Delta\widehat{Emp}$			0.312**	0.297**		
			(0.109)	(0.110)		
$\Delta\widehat{W}$				0.000192		
				(0.001)		
N	473	467	473	468	473	467
R-sq	0.014	0.018	0.041	0.042	0.002	0.001
Panel B. 6-Year Differences						
ΔEmp	0.238	0.253			0.269*	0.255
	(0.129)	(0.136)			(0.121)	(0.132)
ΔW		0.0534				-0.0354
		(0.043)				(0.194)
$\Delta\widehat{Emp}$			0.454*	0.440*		
			(0.200)	(0.207)		
$\Delta\widehat{W}$				0.000172		
				(0.001)		
N	472	466	472	467	472	466
R-sq	0.052	0.066	0.055	0.055	0.051	0.026
Panel C. 7-Year Differences						
ΔEmp	0.401**	0.417**			0.452***	0.413**
	(0.127)	(0.134)			(0.126)	(0.140)
ΔW		0.0577				-0.0979
		(0.049)				(0.207)
$\Delta\widehat{Emp}$			0.764***	0.751***		
			(0.206)	(0.215)		
$\Delta\widehat{W}$				0.000157		
				(0.001)		
N	473	467	473	468	473	467
R-sq	0.113	0.126	0.119	0.119	0.111	0.034

Academic data include the intervals noted, with the first year of the decade in the end of the period. For example, the five year differences include 1995-2000 and 2005-2010. Employment and wages data include the intervals 1990-2000, 2000-2010. 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 awards (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).[20] 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 A8 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.[21] 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

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

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

(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 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 awards matches to 2 occupation codes, each occupation code is assigned 5 awards). This avoids double-counting.[22]

[22]Bardhan, Hicks and Jaffee (2013) use this equal allotment of awards 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 A8: 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 A9 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 A9: 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 Using Once-Lagged Industry Shares for Instrument

In the main analysis I use the 1980 distribution of industry shares as the main source of variation in the shift share instrument. As a robustness exercise I instead use the distribution in the previous period. For example, I define

$$\widehat{Emp}_t^{CA} \equiv \sum_{i=1}^{I} \Big[Emp_{i,t-1}^{CA} * (1 + \frac{Emp_{it}^{US} - Emp_{i,t-1}^{US}}{Emp_{i,t-1}^{US}}) \Big] \tag{10}$$

and

$$\widehat{W}_{jt}^{CA} \equiv \sum_{i=1}^{I} \Big[W_{ij,1980}^{CA} * \frac{Emp_{ij,1980}^{CA}}{Emp_{j,1980}^{CA}} * (1 + \frac{W_{ijt}^{US} - W_{ij,1980}^{US}}{W_{ij,1980}^{US}}) \Big] \tag{11}$$

where $t-1$ is defined as the previous decade's value of the variable. The two tables below show the first stage estimates and main coefficients on awards using this slightly different formulation of the instrument. The results are very similar.

Table A10: First Stage Estimates using Prior Decade Industry Distribution

	(1)	(2)	(3)	(4)
	All Workers	Some College	All Workers	Some College
A. Instrument for Employment				
Levels	1.014***	1.030***		
	(0.0104)	(0.0162)		
Changes			0.708***	0.710***
			(0.0871)	(0.100)
N	999	999	666	666
F	9566.858	4035.187	65.955	50.322
B. Instrument for Wages				
Levels	0.0962***	0.127***		
	(0.0175)	(0.0150)		
Changes			0.0968***	0.116***
			(0.0249)	(0.0314)
N	997	972	664	641
F	30.381	71.667	15.155	13.723

Notes. Regressions include year effects. Regressions weighted by 1980 employment. Partial F statistic displayed. Data include years 1990, 2000, and 2010. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A11: Effect of Employment and Wages on Units Awarded, using Prior Decade Industry Distribution

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		Reduced Form		2SLS	
A. All Workers						
ΔEmp	0.495***	0.516***			0.345**	0.441**
	(0.094)	(0.105)			(0.114)	(0.139)
ΔW		0.0635				0.241
		(0.052)				(0.289)
$\Delta \widehat{Emp}$			0.347*	0.283		
			(0.153)	(0.201)		
$\Delta \widehat{W}$				0.00101		
				(0.001)		
N	473	473	473	473	473	473
R-sq	0.135	0.148	0.055	0.063	0.123	0.039
B. Workers with Some College						
ΔEmp	0.401**	0.417**			0.250	0.357**
	(0.127)	(0.134)			(0.148)	(0.133)
ΔW		0.0577				0.261
		(0.049)				(0.297)
$\Delta \widehat{Emp}$			0.248	0.168		
			(0.172)	(0.227)		
$\Delta \widehat{W}$				0.00144		
				(0.001)		
N	473	467	473	468	473	467
R-sq	0.113	0.126	0.032	0.046	0.097	-0.039

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