THE EFFECT OF LOCAL LABOR MARKET DOWNTURNS ON POSTSECONDARY ENROLLMENT AND PROGRAM CHOICE

Andrew Foote
Center for Economic Studies
U.S. Census Bureau
Suitland, MD 20746
andrew.foote@census.gov

Michel Grosz
(corresponding author)
Bureau of Economics
Federal Trade Commission
Washington, DC 20580
mgrosz@ftc.gov

Abstract
We examine how workers invest in human capital following unanticipated local labor market downturns. We find that, on average, two-year college enrollment increases by three students within three years for every one hundred workers laid off. This rise in enrollment accounts for half the observed increase in labor force nonparticipation following mass layoffs. Completions in career-technical programs also increase, especially in short-term certificates, but vary by field of study. We find the effect on completions is strongest in fields of study with larger earnings returns.

https://doi.org/10.1162/edfp_a_00288
© 2019 Association for Education Finance and Policy
1. **INTRODUCTION**

The dynamics of worker adjustment following job loss have gained renewed interest in light of the recent Great Recession and declines in labor force participation (Office of the President 2016). Some workers regain employment quickly but many exit the labor force. Recent work has documented some of the types of labor force exits of displaced and unemployed workers, including early retirement, enrollment in disability insurance, migration, use of opioid painkillers, and even playing video games (Blanchard and Katz 1992; Coile and Levine 2007; Rege, Telle, and Votruba 2009; Aguiar et al. 2017; Krueger 2017; Foote, Grosz, and Stevens 2018).

One particularly important channel of response to labor market downturns is enrollment in postsecondary education. Workers who exit the labor force may experience significant depreciation in human capital over time, with permanent productivity and wage consequences (Albrecht et al. 1999; Görlich and De Grijp 2009). However, if these workers invest in retraining, their career prospects may improve. The federal government has invested many billions of dollars in worker retraining efforts over the past decades (Barnow and Smith 2015; Eyster, Durham, and Anderson 2016), largely with this model of human capital investment in mind. Thus, it is important to understand to what extent workers enter postsecondary institutions in bad economic times and, crucially, what fields they study. To date, most of the research documenting the relationship between job loss and postsecondary enrollment has measured the aggregate effects of large macroeconomic shocks, or has focused on particular industries or workers. Much less is known about how acute local labor demand shocks affect the extent of human capital investment, as well as which fields new students study.

In this paper, we measure the extent to which enrollment in postsecondary education, especially at community colleges, acts as a channel for worker adjustment following job displacement. We focus on community colleges because they are a primary engine of worker retraining, especially for older and nontraditional students, who are the ones most likely affected by local economic downturns. We consider enrollment effects as well as the receipt of associate degrees and certificates. We group awards by field of study and duration, with a particular focus on how response magnitudes vary across various career-technical fields.

To measure the size of the local labor demand shock, we use counts of the number of workers in a labor market directly affected in mass layoffs. Mass layoffs, defined for our purposes as an event where at least fifty workers filed unemployment claims against a single establishment within a five-week period, are a large, acute shock to employment for workers. The use of mass layoffs as a measure of local downturns is not subject to many of the methodological limitations common to studies of this kind.

This paper makes several contributions to the literature. We focus on effects at the two-year college level, in the spirit of influential analysis by Betts and McFarland (1995), but also go a step further and explore other key outcomes. Most importantly, we can separately estimate effects for completion in different fields of degree and certificate programs, such as health, information technology, and construction. Another contribution is our focus on the effect of local mass layoffs, which resolves many of the issues in the usual approach in this literature, which is to examine the effect of the unemployment rate on labor market outcomes. A third contribution is that we conduct our analyses at the labor market level, and examine local shocks. Much of the literature on
postsecondary enrollment examines the effect of macroeconomic shocks, but local shocks may have more direct effects on workers.

We find an increase in community college enrollment following mass layoff events. Our main results suggest that for every one hundred workers laid off, enrollment increases by three students within the next three years. Additionally, we find that for every one hundred workers involved in a mass layoff, there is an increase in degree completion of two students. When we examine different types of awards separately, we find the bulk of this effect is concentrated among short-term certificates, as opposed to associate’s degree programs. The implications of this work are more optimistic than those of current studies showing the effects of recent economic declines on drug abuse, worker discouragement, and adverse health outcomes. We find that the increase in enrollment following a local labor market downturn accounts for, at most, half of the increase in labor force nonparticipation from these events. This suggests that, although many workers may well exit the labor force because they feel despair, a large portion do seek retraining in order to reenter the labor force.

We also find that there is heterogeneity in the extent to which workers complete different programs following layoff events. There are much larger responses in career-technical fields than in academic fields focused on transfer to four-year colleges. Within career-technical fields, we find particularly large effects for degrees in construction and manufacturing, as well as certificate programs in allied health.\(^1\) Overall, we find a positive correlation between a particular program’s completion response to layoff events and its estimated earnings return, which we take as suggestive evidence that workers tend to retrain in high-return fields. Thus, our results suggest that when workers do enroll in college they aim to gain credentials in fast-growing fields that may lead to increased earnings.

Our findings suggest that there are a number of ways in which policy makers may be able to encourage retraining that is beneficial after job displacement. First, more information needs to be available to inform potential students about earnings by field of study. Some progress has been made on providing this information at the state level. The U.S. Census Bureau has recently started publishing earnings outcomes for a select group of institutions, but the information is not comprehensive.\(^2\) Additionally, Xia (2016) shows that for-profit schools exhibit greater responsiveness to changes in demand than community colleges, and Grosz (2020) shows that community colleges do not expand nursing programs even though the social return is large. In recent years, the federal government has invested more in training programs at the community college level, with a specific focus on displaced workers. The Trade Adjustment Assistance Community College and Career Training Grant Program (TAACCCT), for example, shows early promising results (Durham et al. 2017). These and other programs are small, though, relative to the large number of individuals needing training either due to displacement or changes in the demand for specific occupations.

The rest of this paper proceeds as follows. Section 2 reviews the previous literature on the topic, and section 3 discusses our data. To motivate our analysis, section 4

---

1. Examples of allied health programs include medical and nursing assistants, dental hygienists and assistants, emergency medical technicians, and radiologic technologists.

presents aggregate trends in postsecondary enrollment and degree receipt, as well as the geographic variation in postsecondary enrollment. Section 5 outlines our research design, and section 6 presents our results. Section 7 concludes and discusses potential directions for future work.

2. LITERATURE
A large literature has shown the adverse effects of job loss on workers. Jacobson, LaLonde, and Sullivan (1993) show that workers involved in a mass layoff lose about 25 percent of their earnings over the next six years. Additionally, Stevens (1997) shows that much of this effect can be explained by individuals losing subsequent jobs, effectively compounding the adverse effects. However, recent literature has shown that although the mean effect of job loss is quite negative, the dispersion of outcomes for displaced workers is large and can even be positive. Fallick, Haltiwanger, and McEntarfer (2012) find that more than 25 percent of workers who separate from distressed firms and experience four or more quarters of nonemployment eventually experience positive earnings growth. One potential channel for this growth is that workers increase their human capital accumulation after a separation and nonemployment spell, ultimately leading to higher earnings.

There is also a growing literature documenting labor force exit following adverse labor demand shocks. Autor, Dorn, and Hanson (2013) show that workers in areas experiencing lower labor demand because of increased trade competition drop out of the labor force at higher rates than workers in areas not exposed to this competition. Foote, Grosz, and Stevens (2018) find that after a mass layoff, about half of the adjustment in labor force size is due to nonparticipation. Yagan (2017) also shows that nonparticipation was particularly important in the Great Recession.

There is also strong evidence that postsecondary enrollment is countercyclical. Betts and McFarland (1995) find that unemployment rate increases of 1 percentage point lead to enrollment increases of 4 percentage points, and recent work uses similar designs (Nutting 2008; Clark 2011; Hillman and Orians 2013). Additionally, recent evidence shows that enrollment in the two-year and four-year sectors increased considerably because of the Great Recession (Barrow and Davis 2012), and enrollment in community colleges is particularly sensitive to labor demand changes due to globalization and offshoring (Hickman and Olney 2011). However, there is much less evidence on whether the content of what people study is affected by downturns. Nutting (2008) finds that career technical enrollment is more responsive to labor market conditions than academic enrollment at one large public university, whereas Blom, Cadena, and Keys (2015) find that students are more likely to enroll in science, technology, engineering, or mathematics (STEM) fields during a recession, especially female students.

Recent work also examines the skill-upgrading of displaced workers. Barr and Turner (2015) find that longer unemployment insurance duration and more generous unemployment insurance policies increase the likelihood of individuals to enroll in
postsecondary education. Jacobson, LaLonde, and Sullivan (2005a, 2005b) use administrative data from Washington and find that workers who enroll in schooling following a job loss have increased earnings, even for older workers, but that these earnings gains are concentrated in specific fields.

There is also growing interest in how postsecondary institutions themselves act as economic agents, and whether they respond to local changes in labor demand. This interest is partially related to the rise of two-year for-profit colleges, leading to concern about competition between the public and the private sector (Cellini 2009, 2010; Deming, Goldin, and Katz 2012).

3. DATA

This section outlines the main data sources that we use for the analysis. All the data we collect are reported at the county or subcounty level, but we aggregate the data to the commuting zone level (Tolbert and Sizer 1996). Commuting zones approximate the boundaries of a local economy according to commuting patterns, thus reducing the likelihood of confounding spillovers due to local migration and commuting. Moreover, because commuting zones are aggregations of counties, they are straightforward to use with publicly provided data.

In our context, the use of commuting zones is useful for two other reasons. First, although community colleges draw students from the local area, students are also likely to often cross county lines to attend college. This is especially probable in labor markets where counties are small. Second, many counties do not have any postsecondary institutions. Limiting the analysis to these counties would lead to biased results, since workers in counties with colleges are likely systematically different than those in counties without colleges. On the other hand, states are too large a definition of a local labor market, especially since two- and four-year colleges tend to draw students locally.

Mass Layoffs

We use mass layoff events as our key measure of local labor market downturns. Between 1996 and 2013, the Bureau of Labor Statistics (BLS) compiled monthly reports on layoffs by observing the initial claims for unemployment insurance filed by workers. The BLS identified a mass layoff event when more than fifty workers filed claims against a single establishment within a five-week period. For these events, the BLS contacted the establishment to determine whether these workers experienced a layoff of at least thirty-one days. We use these data to quantify the size of a local labor demand shock at the county level. The data are reported by county of residence and so, for each county, we measure the number of workers residing in that county who were involved in a mass layoff in a given year. These county-level data are reported at an annual frequency, and therefore our analysis is at an annual frequency as well. We aggregate these county-level counts to the commuting zone level.

---

5. Bettinger and Long (2009) find, in Ohio, the median distance between home and four-year college was twenty-six miles, and over half of students lived within fifty miles; we expect this is an upper bound for community colleges.

6. The data we use for this paper are technically tabulated “extended mass layoffs”; throughout the paper, when we use mass layoffs, this is the measure to which we are referring.
Local Labor Markets and Postsecondary Enrollment

Education Data
Our data on enrollment and degree receipt come from the Integrated Postsecondary Education Data System (IPEDS), from the U.S. Department of Education National Center for Education Statistics. IPEDS data include extensive information for all institutions of higher education that participate in federal financial aid programs, as well as some that may volunteer their own data. We focus on two measures of enrollment, overall and first-time fall enrollment counts.7

The data in IPEDS also include information on awards, both degrees and certificates. We focus on associate’s degrees and two types of certificates: one- to four-year certificates and certificates requiring less than a year.8 We examine degrees and certificates in the aggregate and by broad field of study.9 To further simplify, we categorize certain fields of study as “career-technical,” based on U.S. Department of Education classifications. IPEDS data also provide address data for every year for all institutions. We match each institution with its commuting zone and, thus, the number of layoffs in the local area.

Other work has discussed the drawbacks of using the IPEDS to measure the activity of for-profit sub-baccalaureate institutions (Cellini 2005, 2010). In particular, IPEDS tends to undercount these institutions, and is not always accurate in determining their location, which is crucial for our analysis.10 This data limitation may affect results over time, as distance and online-only education has been secularly increasing as a share of enrollment, especially for sub-baccalaureate degrees. We present results separately for for-profit colleges, with the caveat that they may be subject to measurement error.

Other Data
We supplement these main sources of data with additional information on county demographics. We use age, gender, and racial composition information from the Surveillance, Epidemiology, and End Results (SEER) program of the National Cancer Institute. We also use the SEER data to calculate the size of the working age population (ages 16–65 years). Additionally, we use the Local Area Unemployment Statistics from the BLS in order to measure the size of the labor force and the unemployment rate in the county.

4. DESCRIPTIVE EVIDENCE
Trends in Postsecondary Enrollment and Degree Receipt
To better understand how college enrollment responds to macroeconomic conditions, and how college-going rates vary geographically, in this section we present enrollment

---
7. First-time enrollment is defined as the first time a student enrolls at any university or college.
8. There is also information on bachelor’s degrees and graduate degrees, but these are not relevant to the margin we are studying. Bachelor’s degrees at community colleges are a small and relatively new phenomenon. There are also data on enrollment and degree by age but it is only required to be reported in some years, and so the data are not reliable.
9. All awards are categorized by their Classification of Instructional Program (CIP) codes maintained by the National Center for Education Statistics and updated periodically. There are over 1,300 CIP codes. To simplify matters, we group them into broader categories. Appendix table A.1 shows the grouping of CIP codes we use (all appendices are available in a separate online appendix that can be accessed on Education Finance and Policy’s Web site at www.mitpressjournals.org/doi/suppl/10.1162/edfp_a_00288).10. Cellini and Goldin (2014) estimate that IPEDS undercounts for-profit schools by a factor of two.
trends over our study period, with a particular emphasis on the dynamics of the community college sector.

Figure 1 shows first-time enrollment from 1996 to 2011, disaggregated by type of institution (four-year, two-year public, and two-year private). Two-year public enrollment increased markedly in the two most recent recessions, shown as shaded bars. In contrast, four-year enrollment has been secularly increasing since the beginning of our period, with no visible changes in the trend in response to business cycles. Also, while two-year for-profit schools have received increasing scrutiny, they make up a small portion of enrollment in IPEDS.\footnote{IPEDS does not cover the for-profit sector nearly as well, as noted in section 3.}

There are also regional differences in postsecondary and community college enrollment, as shown in the maps in figure 2, which display postsecondary enrollment by commuting zone.\footnote{As with our empirical estimates, we choose to display statistics at the commuting zone level, because many counties have no postsecondary institutions, and individuals could easily attend a school in an adjacent county. For presentation purposes, Hawaii and Alaska are not included in the maps but they are included in the analyses.} Figure 2a shows enrollment as a share of population in the commuting zone, and figure 2b shows community college enrollment as a share of total enrollment. There is some geographic variation in enrollment in postsecondary institutions across the country, though no particular pattern stands out. The variation in the community college share of postsecondary enrollment, though, is particularly striking. The West Coast and Southeast have large community college shares, as do parts of the Midwest.

There are also significant geographic differences in field of study. Figure 3 displays the share of overall community college awards in a few large fields of study. While...
career-technical education is concentrated in the Rust Belt, there is regional variation in the particular types of programs. For example, child care and cosmetology are concentrated in the South and in Southern California. On the other hand, health programs are much more broadly represented.

Overall, it is clear that community college enrollment is correlated with macroeconomic labor market conditions, and that career-technical education is an important piece of this response. In addition, there are considerable regional differences in educational access, enrollment, and attainment in the cross-section as well. We harness both of these levels of variation to estimate the causal effect of local economic shocks on two-year college enrollment and receipt of degrees and certificates.

Sample Summary Statistics

Table 1 displays summary statistics for the main variables we use for the analysis, for the years 1996 to 2013, at the commuting zone level. On average, almost 1,500 workers
Andrew Foote and Michel Grosz

Notes:
(a) Career technical education (CTE) awards as a share of total awards.
(b)–(d) Awards in the particular field as a share of all CTE awards.

Figure 3. Content of Community College Awards, 2005, Commuting Zones
Table 1. Summary Statistics, 1996–2013

<table>
<thead>
<tr>
<th>Description</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Workers in mass layoffs</td>
<td>1,445.8</td>
<td>6434.50</td>
</tr>
<tr>
<td>Workers in mass layoffs as share of labor force</td>
<td>0.00568</td>
<td>0.01</td>
</tr>
<tr>
<td>Layoffs &gt; 1% of labor force</td>
<td>0.203</td>
<td>0.40</td>
</tr>
<tr>
<td>Layoffs &gt; 5% of labor force</td>
<td>0.0235</td>
<td>0.15</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>0.0588</td>
<td>0.03</td>
</tr>
<tr>
<td>Population (1,000s)</td>
<td>365.7</td>
<td>1,047.00</td>
</tr>
<tr>
<td>Population age 18–60 years (1,000s)</td>
<td>206.4</td>
<td>602.10</td>
</tr>
<tr>
<td>Community colleges</td>
<td>2.496</td>
<td>3.85</td>
</tr>
<tr>
<td>For-profit 2-year colleges</td>
<td>5.296</td>
<td>16.61</td>
</tr>
<tr>
<td>Community college fall enrollment</td>
<td>9,407.9</td>
<td>30,888.60</td>
</tr>
<tr>
<td>For-profit fall enrollment</td>
<td>788.4</td>
<td>2,934.80</td>
</tr>
<tr>
<td>No 2-year institutions in commuting zone</td>
<td>0.0672</td>
<td>0.25</td>
</tr>
<tr>
<td>Only 2-year institutions in commuting zone</td>
<td>0.374</td>
<td>0.48</td>
</tr>
<tr>
<td>Associate’s degrees</td>
<td>1,117.1</td>
<td>2,822.40</td>
</tr>
<tr>
<td>1–4 year certificates</td>
<td>562.2</td>
<td>1,571.70</td>
</tr>
<tr>
<td>&lt;1 year certificates</td>
<td>597.2</td>
<td>2,045.50</td>
</tr>
<tr>
<td>Share of awards in career technical education</td>
<td>0.405</td>
<td>0.17</td>
</tr>
<tr>
<td>Share of awards in construction/manufacturing</td>
<td>0.0967</td>
<td>0.11</td>
</tr>
<tr>
<td>Share of awards in health</td>
<td>0.179</td>
<td>0.12</td>
</tr>
<tr>
<td>Share of awards in information technology</td>
<td>0.0284</td>
<td>0.03</td>
</tr>
<tr>
<td>Share of awards in public/protective services</td>
<td>0.0381</td>
<td>0.04</td>
</tr>
<tr>
<td>Share of awards in cosmetology/child care</td>
<td>0.0132</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Notes: Unit of observation is commuting zone by year. Means and standard deviations displayed.
Commuting zones have an average of between two and three community colleges, and around twice as many for-profit, two-year schools. Although there were more for-profit than public, two-year colleges, community colleges represented the lion’s share of two-year college enrollment. A number of commuting zones had no community colleges or for-profit two-year colleges; these commuting zones are almost exclusively in rural areas, while in a large share of commuting zones (37 percent) two-year colleges represented the only type of postsecondary institution. The last rows of table 1 show the distribution of the content of degrees and certificates across broad programmatic areas.

5. METHODOLOGY
In this section we describe our empirical strategy for estimating the effect of local labor market downturns on postsecondary enrollment and completions. We first discuss the use of local mass layoffs as a measure of labor market downturns, and how it improves upon using the unemployment rate, which is common in this literature. We then describe the main estimation equation.

Mass Layoffs and the Unemployment Rate
Much of the previous literature on local labor demand and postsecondary enrollment uses unemployment rates as the measure of labor market conditions (Betts and McFarland 1995; Clark 2011; Hillman and Orians 2013). Using unemployment rates introduces a number of possible biases into the estimation. First, this type of analysis is normally done at the state level, which may be too broad a definition of a local labor market. On the other hand, unemployment rates are measured with significant error at lower levels of geography, such as counties (Bartik 1996; Hoynes 2000; Lindo 2015). Second, the unemployment rate captures both labor supply and labor demand changes (Bartik 1996). Third, changes in the labor force, such as postsecondary enrollment, can be mechanically related to the unemployment rate—an increase in full-time enrollment may mean a decline in the size of the labor force, the denominator of the unemployment rate, if students leave employment.

Using mass layoffs as a measure of labor market shocks addresses many of the issues with the unemployment rate, for a number of reasons. First, whereas a change in educational enrollment may mechanically reduce the unemployment rate over time, enrollment does not similarly affect mass layoffs. Second, because the BLS data on mass layoffs are based on administrative records of individual firms, they do not suffer from the same small-area estimation problems as county-level unemployment rates. Therefore, because the sources of data are distinct, any measurement error present in the mass layoffs data—which arises primarily from coverage issues—is likely unrelated to measurement error in the local unemployment rate, which arises from small-area estimation problems. Third, any measurement error present in the mass layoffs data is most likely uncorrelated with the measurement error in the local unemployment rate. Lastly, as we discuss in more detail in a later section, mass layoffs represent an acute, permanent, and plausibly exogenous shock that comes from a decrease in local labor demand.
Not surprisingly, however, the unemployment rate and mass layoffs are highly correlated. A regression of the unemployment rate on the mass layoff rate over the period we study has an F-statistic of 15.\textsuperscript{13} For the main analysis, however, we focus on the reduced form effect of mass layoffs on educational outcomes, which allows us to estimate how the number of jobs lost translates into individuals enrolling in community college.\textsuperscript{14} As noted earlier, the BLS Mass Layoff Statistics represent separations that resulted in fifty or more unemployment insurance claimants. Thus, they are a good measure in our setting precisely because they account for workers who lose their jobs, do not find work, and apply for unemployment benefits.\textsuperscript{15} In other words, the number of workers involved in mass layoffs represents a group for whom job retraining is potentially the most advantageous.

**Main Methodological Approach**
Our goal is to measure the effect of local economic shocks on the educational behavior of individuals. We estimate the effect of mass layoffs on enrollment in postsecondary education. We estimate an elasticity, and allow mass layoffs to impact enrollment in more than one period, since it takes workers time to adjust. To do so, we estimate the following equation:

\[
\gamma_{ct} = \sum_{i=1}^{3} \beta_i m_{c,t-i} + \Theta X_{ct} + \gamma_c + \eta_t + \xi_c \times t + \varepsilon_{ct},
\]

where $\gamma_{ct}$ is the logged value of one of our outcomes of interest, either enrollment or awards, and $m_{c,t}$ is the logged number of workers directly affected by mass layoff events in commuting zone $c$ in year $t$. In our preferred specifications, we include three lags of the mass layoffs, because even if enrollment effects are immediate, degree receipt takes time.

In the matrix $X_{ct}$ we include a set of time-varying measures of local characteristics: age, gender, and race/ethnicity. We include commuting zone fixed effects, $\gamma_c$, to account for systematic, time-invariant differences between commuting zones, and year fixed effects, $\eta_t$, to control for national trends. We also include commuting zone-specific linear time trends, $\xi_c \times t$, and discuss their importance below. All regressions are weighted by the local labor market’s lagged total population. To address the fact that mass layoffs

\textsuperscript{13} With such high first-stage power, one potential approach to take is to use the rate of mass layoffs as an instrument for the unemployment rate. We show these results, along with the ordinary least squares version, in online Appendix B.

\textsuperscript{14} A commonly used instrument for the unemployment rate to isolate labor demand shocks is the shift-share or "Bartik" instrument (Bound and Holzer 2000; Saks and Wozniak 2011), which leverages pre-existing area-specific industry structure and changes in industry outcomes at the national level. There are a number of reasons why such a method is likely inadequate in the context we study. First, these instruments do not usually give intuition on the size of a shock relative to the local labor force. More importantly, the shift-share instruments are better suited to identifying long-run structural shocks, as opposed to the transitory, acute impact of layoffs that we study in this paper. Moreover, Bartik demand measures combine local industry structure with trends in national product and labor demand. Education may respond to both local and national business cycle conditions, but here we focus on local measures, so it is not desirable to combine local and national conditions in a single measure.

\textsuperscript{15} Most states allow displaced workers to collect unemployment benefits while enrolled in school, because it falls under retraining. For more on these policies, see Barr and Turner (2015).
may be correlated within a commuting zone over time, we cluster our standard errors at the commuting zone level.

A key element of our main estimating equation is that the coefficient $\beta_i$ is identified off deviations from labor market-specific linear time trends $\xi_c * t$. Including these trends is important: Their inclusion controls for long-run changes in economic conditions in commuting zones that are not unanticipated shocks to labor demand. If a labor market’s economy is consistently declining, for example, an increasing number of layoffs is likely and expected, which would lead workers to obtain training before the layoffs occur. Inclusion of trends allows us to identify the effect of unanticipated layoff events. A second reason to include trends is to control for long-term patterns in enrollment and degree receipt. In particular, the demographic composition of certain areas are likely changing over our time period, making the area’s population increasingly more or less likely to attend postsecondary institutions. Not controlling for these differential demographic changes would confound the effect of mass layoffs with demographic changes. The identifying assumption of equation 1 is that the number of workers laid off in a mass layoff event is exogenous conditional on labor market and time fixed effects, as well as the labor market trends.

One feature of our approach is that we estimate equation 1 at an aggregate level, as opposed to using individual-level data on job loss. Thus, we are unable to assert that the workers losing their jobs are exactly the individuals enrolling in postsecondary institutions—it may be the case that other workers are responding to slack labor market conditions and choosing to enroll in school. Additionally, there is a possibility that some students are affected because their parents lost their jobs, and choose to enroll in community college as a less expensive alternative to a four-year college (Hilger 2014). For this to be a large portion of the effect, we would expect a commensurate decline in four-year school enrollment. We do not find such an effect when estimating equation 1, which limits our concern about this issue.

As shown in much of the prior literature, there is a dramatic migration response to local economic downturns (Blanchard and Katz 1992). Although we do not explicitly estimate it here, in related work using a similar empirical design we find a migration response to mass layoffs as well (Foote, Grosz, and Stevens 2018). If some students are being induced to move across labor markets following economic shocks, this will reduce our estimates of $\beta_i$. In that sense, our estimates are a lower bound for the effect of mass layoffs on the educational enrollment of students who remain in the labor market.

6. RESULTS

Event Study Evidence of Exogeneity

Before showing the main results, in this subsection we present evidence to further motivate our use of mass layoffs as a labor demand shock. Our main estimation strategy is based off deviations from commuting zone trends, and thus we cannot visually show evidence of parallel trends as is common in a difference-in-difference approach. Instead, here we focus on commuting zones that experienced particularly large layoff events throughout the time period. The event study analysis mimics the overall estimation strategy, showing suggestive evidence that these acute shocks to the labor market were not preceded by long-term declines in our outcomes of interest.
We focus the analysis on the subset of commuting zones where at least 1 percent of the labor force was laid off in mass layoff events throughout the time period. We limit the sample in this way to facilitate the event study approach. We then estimate the following event study model:

$$y_{ct} = \alpha + \sum_{i=-4}^{3} [\beta_i I(t - T_c = i)] + \delta_t + \gamma_c + u_{ct}.$$  

(2)

We define $T_c$ as the year the labor market experienced layoffs of at least 1 percent of the labor force, and thus the indicator $I(t - T_c = i)$ takes a value of 1 when the observation is $i$ years from $T_c$. We omit the dummy for $i = 0$, so all coefficients are relative to the year of the event. We include controls for year and commuting zone.

Figure 4 shows the resulting coefficients and 95 percent confidence intervals for total fall enrollment, first-time fall enrollment, and total awards. The main objective of the analysis is to show evidence of a flat trend prior to the event, which is clear from all three panels of the figure. There do appear to be positive effects after the event, which we describe in more detail in the next subsections. However, this figure shows visual support for our use of mass layoffs as an indicator of local labor market shocks.

**Enrollment and Completions**

Table 2 shows results for first-time enrollment. We include three lags of the log layoffs variable, and also compute the total effect as the sum of the three lagged coefficients. Table 2 shows how our main result changes when adding controls. Column 1 just includes the lags of logged mass layoffs. Adding commuting zone and year fixed effects lowers the effect significantly in column 2. Inclusion of demographic controls in column 3 has little effect on the coefficients. Columns 4 and 5, however, include commuting zone-specific trends, which we argued previously are crucial for the identification strategy. Controlling for these trends does not dramatically change the first and second lag, but does make the third lag no longer statistically significant. We calculate F-statistics to test the joint significance of the trends in the regressions; these tests are always highly significant, with $p$-values well under 0.001, which suggest that it is important to control for trends in our specifications. We also show in the final column that our results are unaffected when we omit controls for demographics. These main results show that there is a positive immediate response in first-time community college enrollment following a layoff event: A 1 percent increase in the number of workers laid off leads to a 0.025 percent increase in first-time students the following year, and an additional 0.018 percent increase after two years. For the rest of the analyses we use the specification in column 4 as our preferred specification.16

Table 3 shows results for the main outcomes using our preferred specification with demographic controls and commuting zone-specific trends. The top panel shows results for community colleges and the lower panel shows the same specifications for for-profit colleges. The first column shows that a 1 percent increase in the number of workers laid off leads to an insignificant 0.01 percent increase in community college

16. We present results with all the specifications for the other main outcomes in online Appendix table A.4.
Notes: Figures display coefficients from equation 2 in the text and a 95 percent pointwise confidence interval is shown. Sample consists of 103 commuting zones that had exactly one year with mass layoffs exceeding 1 percent of the total labor force between 1995 and 2011. Outcome variables are listed below each panel. Specifications include commuting zone and year fixed effects. Standard errors are clustered at the state level.

Figure 4. Event Study Estimates of Effect of Mass Layoffs, Commuting Zones with One Event of at Least 1 Percent of the Labor Force
Table 2. Mass Layoffs and Two-Year First-Time College Enrollment

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Layoffs, t − 1</td>
<td>0.288***</td>
<td>0.0210**</td>
<td>0.0195**</td>
<td>0.0244**</td>
<td>0.0249**</td>
</tr>
<tr>
<td></td>
<td>(0.0292)</td>
<td>(0.0093)</td>
<td>(0.0097)</td>
<td>(0.0095)</td>
<td>(0.0104)</td>
</tr>
<tr>
<td>Layoffs, t − 2</td>
<td>0.126***</td>
<td>0.00855</td>
<td>0.00555</td>
<td>0.0160**</td>
<td>0.0179**</td>
</tr>
<tr>
<td></td>
<td>(0.0118)</td>
<td>(0.0070)</td>
<td>(0.0068)</td>
<td>(0.0071)</td>
<td>(0.0080)</td>
</tr>
<tr>
<td>Layoffs, t − 3</td>
<td>0.174***</td>
<td>−0.0262***</td>
<td>−0.0261***</td>
<td>−0.0118</td>
<td>−0.0106</td>
</tr>
<tr>
<td></td>
<td>(0.0168)</td>
<td>(0.0089)</td>
<td>(0.0093)</td>
<td>(0.0083)</td>
<td>(0.0078)</td>
</tr>
<tr>
<td>Total effect</td>
<td>0.5907***</td>
<td>0.0034</td>
<td>−0.001</td>
<td>0.0286</td>
<td>0.0323*</td>
</tr>
<tr>
<td></td>
<td>(0.0480)</td>
<td>(0.0180)</td>
<td>(0.0180)</td>
<td>(0.0176)</td>
<td>(0.0194)</td>
</tr>
<tr>
<td>Y-mean</td>
<td>2,138.1</td>
<td>2,138.1</td>
<td>2,138.1</td>
<td>2,138.1</td>
<td>2,138.1</td>
</tr>
<tr>
<td>Observations</td>
<td>6,882</td>
<td>6,882</td>
<td>6,882</td>
<td>6,882</td>
<td>6,882</td>
</tr>
<tr>
<td>R²</td>
<td>0.612</td>
<td>0.957</td>
<td>0.958</td>
<td>0.979</td>
<td>0.978</td>
</tr>
<tr>
<td>CZ fixed effects</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Demographics</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>CZ trends</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

Notes: Outcome variable is log first-year full time enrollment. The first column just includes lags of log mass layoffs; the second column adds commuting zone (CZ) and year fixed effects. Column 3 adds controls for the age distribution, racial makeup, and share male of the CZ, and column 4 adds CZ-specific trends. The sum of the effects is at the bottom of the table. Standard errors are clustered at the commuting zone level.

*p < 0.10; **p < 0.05; ***p < 0.01.

enrollment, with a smaller effect in subsequent years. The second column displays fall enrollment just among first-time students, which we showed earlier. We expect this response to be more pronounced than for overall enrollment, because overall enrollment includes continuing students. Indeed, the estimates in the second column of the table are almost twice as large, and the second lag is also larger and statistically significant. Additionally, this estimate likely understates the total response because it only counts students who have never attended any postsecondary institution.

The second panel of the table shows estimates for for-profit institutions. The point estimates are similar in magnitude, but the confidence intervals do not allow us to rule out large negative effects. Although the for-profit sector is a fraction of the size of the public sector, and is likely underrepresented in the IPEDS data, this is nevertheless suggestive evidence of a response. Given our lack of precision in these estimates, as well as restraint in the general literature on relying too much on for-profit college statistics in the IPEDS data, we focus on community colleges for the remainder of the paper.

The next four columns of table 3 explore the effect of layoff shocks on degree receipt. We expect the measured effects to be more muted than for enrollment because of high attrition rates in the two-year sector, as well as the lag between enrollment and degree completion (Calcagno et al. 2008). Still, the third column shows that degree and certificate receipt does respond to layoffs. A 1 percent increase in layoffs results in a 0.017 percent increase in community college awards within three years. There is a smaller effect at the for-profit level. We find no evidence of an increase in total associate’s degrees following layoffs but, perhaps not surprisingly, there are larger effects for smaller
Table 3. Mass Layoffs and Two-Year College Enrollment, Degrees and Certificates

<table>
<thead>
<tr>
<th></th>
<th>Fall Enrollment</th>
<th></th>
<th>Associate Degrees and Certificates</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total First-Time</td>
<td>Total AA/AS 1–4 Year Certificate</td>
<td>&lt;1 Year Certificate</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1) (2)</td>
<td>(3) (4)</td>
<td>(5) (6)</td>
<td></td>
</tr>
<tr>
<td>Layoffs, $t - 1$</td>
<td>0.011 (0.0076)</td>
<td>0.0029 (0.0072)</td>
<td>-0.0056 (0.0093)</td>
<td>-0.031 (0.0170)</td>
</tr>
<tr>
<td></td>
<td>0.024*** (0.0092)</td>
<td></td>
<td>(0.0170)</td>
<td>0.0079 (0.0200)</td>
</tr>
<tr>
<td>Layoffs, $t - 2$</td>
<td>0.0021 (0.0059)</td>
<td>0.014** (0.0057)</td>
<td>0.0013 (0.0076)</td>
<td>0.022** (0.0110)</td>
</tr>
<tr>
<td></td>
<td>0.016** (0.0071)</td>
<td></td>
<td>(0.0110)</td>
<td>0.038** (0.0150)</td>
</tr>
<tr>
<td>Layoffs, $t - 3$</td>
<td>-0.0017 (0.0072)</td>
<td>-0.0031 (0.0054)</td>
<td>-0.018 (0.0120)</td>
<td>0.022* (0.0110)</td>
</tr>
<tr>
<td></td>
<td>(0.0082)</td>
<td></td>
<td>(0.0110)</td>
<td>0.012 (0.0150)</td>
</tr>
<tr>
<td>Total Effect</td>
<td>0.0111 (0.0159)</td>
<td>0.017 (0.0139)</td>
<td>-0.0227 (0.0259)</td>
<td>0.0741 (0.0332)</td>
</tr>
<tr>
<td></td>
<td>0.0287 (0.0173)</td>
<td></td>
<td>(0.0322)</td>
<td>0.0584 (0.0374)</td>
</tr>
<tr>
<td>Y-mean</td>
<td>12,184.2 2,138.1</td>
<td>6,872 6,318</td>
<td>6,714 5,354</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>6,882 6,882</td>
<td>6,872 6,318</td>
<td>6,714 5,354</td>
<td></td>
</tr>
<tr>
<td>R$^2$</td>
<td>0.99 0.98</td>
<td>0.98 0.98</td>
<td>0.9 0.94</td>
<td></td>
</tr>
</tbody>
</table>

Panel B: For-Profits

<table>
<thead>
<tr>
<th></th>
<th>Layoffs, $t - 1$</th>
<th>Layoffs, $t - 2$</th>
<th>Layoffs, $t - 3$</th>
<th>Total Effect</th>
<th>Y-mean</th>
<th>Observations</th>
<th>R$^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.0095)</td>
<td>(0.0088)</td>
<td>(0.0110)</td>
<td>(0.0188)</td>
<td>1,442.9 729.6</td>
<td>4,783 4,783</td>
<td>0.98 0.98</td>
</tr>
<tr>
<td>Layoffs, $t - 1$</td>
<td>0.01 (0.0010)</td>
<td>0.01 (0.0095)</td>
<td>0.012 (0.0110)</td>
<td>0.0334 (0.0188)</td>
<td>945.5 355.9</td>
<td>4,783 4,783</td>
<td>0.98 0.98</td>
</tr>
<tr>
<td></td>
<td>0.016 (0.0100)</td>
<td>0.014 (0.0095)</td>
<td>0.011 (0.0110)</td>
<td>0.041 (0.0187)</td>
<td>423.9 486.7</td>
<td>4,783 4,783</td>
<td>0.98 0.98</td>
</tr>
<tr>
<td>Layoffs, $t - 2$</td>
<td>0.0066 (0.0085)</td>
<td>0.0071 (0.0081)</td>
<td>0.025** (0.0110)</td>
<td>0.0386 (0.0164)</td>
<td>2005 4,656</td>
<td>4,783 4,783</td>
<td>0.98 0.98</td>
</tr>
<tr>
<td></td>
<td>-0.0096 (0.0330)</td>
<td>-0.046 (0.0290)</td>
<td>-0.0074 (0.0330)</td>
<td>-0.0633 (0.0888)</td>
<td>4,656 3,773</td>
<td>4,783 4,783</td>
<td>0.98 0.98</td>
</tr>
<tr>
<td>Layoffs, $t - 3$</td>
<td>0.0045 (0.013)</td>
<td>0.011 (0.0120)</td>
<td>0.018 (0.0130)</td>
<td>0.034 (0.0265)</td>
<td>3,773</td>
<td>4,783 4,783</td>
<td>0.98 0.98</td>
</tr>
<tr>
<td></td>
<td>(0.0210)</td>
<td>(0.0120)</td>
<td>(0.0210)</td>
<td>(0.0439)</td>
<td>3,773</td>
<td>4,783 4,783</td>
<td>0.98 0.98</td>
</tr>
<tr>
<td>Total effect</td>
<td>0.0045 (0.0210)</td>
<td>0.011 (0.0120)</td>
<td>0.018 (0.0210)</td>
<td>0.034 (0.0439)</td>
<td>3,773</td>
<td>4,783 4,783</td>
<td>0.98 0.98</td>
</tr>
<tr>
<td>Y-mean</td>
<td>1,442.9 729.6</td>
<td>945.5 355.9</td>
<td>423.9 486.7</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>4,783 4,783</td>
<td>4,785 2,005</td>
<td>4,656 3,773</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R$^2$</td>
<td>0.98 0.98</td>
<td>0.98 0.98</td>
<td>0.97 0.95</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Outcome variables are listed at the top of each column, and are the log counts of the corresponding outcome. Estimates are from equation 1. Panel A shows estimates for public community colleges, and panel B shows estimates for for-profit schools. All regressions include year and commuting zone (CZ) fixed effects, commuting zone specific trends, and demographic controls. Regressions are weighted by commuting zone population. Standard errors are clustered on commuting zone. AA/AS = Associate of Arts/Associate of Science.

*p < 0.10; **p < 0.05; ***p < 0.01.

Certificate programs that take less time to complete. These programs also have fewer general education requirements than associate degree programs.¹⁷

The timing of the award response is consistent with the length of time required to finish these programs. For example, the effect on the completion of associate’s degrees, which take approximately two years of full-time study, is concentrated in the two-year lag, although not statistically significant. Completion of certificates is evenly distributed across all years.

The main result from table 3 is that there is a positive and statistically significant effect of mass layoffs on enrollment and completion in community colleges. To scale

¹⁷. Although it may seem counterintuitive that the shortest certificates show effects after two years, Ma and Baum (2016) look at graduation and certificate completion, and find that only 20 percent of certificate-seekers complete in 150 percent of the time to degree.
these effects, consider a commuting zone at the mean of the mass layoffs distribution. For 100 workers involved in a mass layoff in this commuting zone, our estimates suggest that first-time enrollment increases by approximately 2.8 students within three years. Moreover, eventual degree receipt increases by 1.9 students over the same period.

In related work using a similar methodology, sample, and time period, we find that a 1 percentage point increase in the share of the labor force laid off leads to a 0.2 percentage point decrease in the size of the labor force, of which only half can be explained through observable channels (such as migration, retirement, and enrollment in disability insurance; Foote, Grosz, and Stevens 2018). Our results on enrollment suggest that about half the workers exiting the labor force not through these channels are accounted for by increases in community college enrollment.

In these results, as well as in the ones in the next subsection, our sample changes slightly based on the outcome, because some commuting zones do not have institutions that offer certain programs or certain types of degrees or certificates. When we run our results on a consistent set of commuting zones, our results are very similar.\footnote{Additionally, for our main results we only include institutions that are consistently in the sample—some institutions only report in certain years, which causes spurious changes in enrollment and degree counts.}

In online Appendix table A.2 we repeat the same analysis for four-year college enrollment and bachelor’s degrees. These colleges, especially those offering online degrees or are non-selective, may be an alternative to two-year colleges for laid-off workers, and thus by just focusing on two-year colleges we may be underestimating the effects. However, we find small estimates that are not statistically significant.

**Field of Study**

Next, we estimate the differential responses for degree and certificate production by field of study. For this analysis we focus exclusively on awards at community colleges, and exclude for-profit colleges. Ideally, we would be able to observe enrollment in different types of degree and certificate programs. Identifying which student is enrolled in a particular program, though, is particularly difficult (Zeidenberg, Scott, and Belfield 2015). We can only observe completion by program of study, which incorporates a certain measure of endogenous differences in completion rates. Nevertheless, in all cases, we expect our estimates of the effect of mass layoffs on program-level completions to be an underestimate, both in terms of the absolute magnitude as well as in the speed of response. Thus, we believe measuring completion can shed light on how workers are responding to displacement.

Figure 5 shows the coefficient and confidence interval for the total effect summed over three lags. The first bar of figure 5a shows the aggregate award response. These awards encompass career-technical programs, as well as academic programs for students aiming to transfer. In the second and third bars we split out the academic and career-technical programs. Not surprisingly, the results are higher and also statistically significant for career-technical education awards overall, given that displaced workers are likely to enroll in these programs in order to upgrade their skills.

The next five bars of figure 5a further disaggregate the career-technical awards by the specific content of the programs. We find a large though marginally significant increase in the production of awards in construction and manufacturing fields following...
Notes: Figures show total effects of three lagged coefficients. Each box and whisker shows the result of one regression, with the point estimate and 95 percent confidence interval. CTE = career-technical education; IT = information technology.

Figure 5. Effects of Mass Layoffs on Completions, by Field of Study and Award Type
layoffs. This is perhaps surprising given the contemporaneous decline of manufacturing. However, there are a few potential explanations. First, workers laid off in mass layoff events are more likely to be in manufacturing and production fields, making them also more likely to retrain in manufacturing fields. Second, aggregating all programs of this type ignores the fact that much of the response may be in certain high-growth areas. In fact, in recent years, funding from large federal programs such as Trade Adjustment Assistance (TAA) and the Workforce Investment and Opportunity Act (WIOA) has gone specifically to high-tech manufacturing programs (U.S. Congress 2014; Eyster et al. 2017). We return to this issue in the next subsection.

Figures 5b, 5c, and 5d disaggregate the various awards by their type, which reveals heterogeneity in response beyond the lack of positive effects overall. We find strong effects for short-term certificates in health, as opposed to associate’s degrees or even long-term certificates. Short-term certificates grow almost 0.06 percent in the first year following a 1-percent increase in layoffs, and a similar size in the following year. These short-term certificates are generally for medical assisting, nursing assisting, and related fields. Prior research has found that employment in these occupations is highly countercyclical (Baughman and Smith 2012; Stevens et al. 2015), and our results suggest that training for these occupations is also countercyclical. On the other hand, it is not surprising that we find little effect for associate’s degree and long-term certificates programs. These programs tend to be oversubscribed and face large capacity constraints, so it is unlikely that additional student demand following layoff events would lead to increases in enrollment and completion in these programs (Kuehn 2007).

We find a similar pattern for awards in construction and manufacturing. There is no effect on associate’s degrees, but we do find positive responses for long certificates. There is no effect, however, on short-term certificates in construction and manufacturing.

For information technology programs the main effect seems to be concentrated in increases in associate’s degree completions, although the magnitudes are similar for one- to four-year certificates. In contrast, the only result that is significant for public and protective services is for one- to four-year certificates, which is large and statistically significant. However, these awards represented a particularly small fraction of overall awards, so while the effect is large, its importance is less clear. For other award types in public and protective services the coefficients are small and not statistically significant.

Finally, we examine the personal and family fields. Overall, we find negative and statistically insignificant results. However, we do find an increase in certificates that is statistically significant. This, as with public/protective services, is somewhat of a red herring: this group of awards represents a small share of total certificates in this category. Most of these awards require less than a year of study, for which we find small and statistically insignificant results.

Online Appendix table A.3 shows coefficients for each of the three lags that we sum up to construct these figures. Most importantly, the individual lag coefficients provide

19. There are many reasons why employment in these occupations is countercyclical—they tend to be low-income, provide low benefits, with high turnover, low job stability, and high levels of stress (Banaszak-Holl and Hines 1996; Yamada 2002).

20. We examine these two types of programs together because they are both lower-skill service occupations with low economic returns.
evidence on the timing of the responses by field of study and length of program. In particular, completion in short-term certificates occurs within one or two years of the layoff event. The only exception is for long health certificates. This makes sense, since these are often highly sought-after programs, which might have a waitlist or additional prerequisites.

**Degree Receipt Response by Expected Earnings Returns**

So far, we have documented heterogeneity in the educational production response to mass layoffs that depends on field of study. An important question is whether the fields that see the largest responses are the ones with the greatest earnings potential. A number of recent papers have measured the labor market returns to different community college programs and found a great deal of heterogeneity across field of study (Jepsen, Troske, and Coomes 2014; Liu, Belfield, and Trimble 2015; Stevens, Kurlaender, and Grosz 2019). However, how students select into different programs of study is still an open question: There is limited evidence that four-year college and community college students incorporate expected earnings returns into their choice of field (Arcidiacono, Hotz, and Kang 2012; Wiswall and Zafar 2015; Baker et al. 2018). Thus, it is important to understand whether, when faced with weak employment prospects, workers sort into fields with high earnings potential.

For this exercise we estimate our main results for programs at the four-digit CIP code level, which is a much more detailed description of programs than the two-digit codes we display in figure 5. We then match these four-digit CIP code results to program-level earnings returns from Stevens, Kurlaender, and Grosz (2019), who use comparable four-digit program codes. Most of the CIP codes match to the codes used by Stevens, Kurlaender, and Grosz, but in cases where there is no observed coefficient for a particular CIP code we do not estimate a layoff response. Stevens, Kurlaender, and Grosz disaggregate degrees based on units required, while we only have years required for certificates (one to four years or less than one year). To harmonize these definitions, we average the thirty to fifty-nine and eighteen to twenty-nine unit effects from their paper and treat that as the estimate for the one- to four-year certificate.

Figure 6 shows a scatter plot of the layoff response magnitudes (vertical axis) with the estimated return for that field and degree (horizontal axis). In figure 6a the size of the dots corresponds to the product of the average annual completions in that field and award type nationwide, and the inverse of the standard error from our estimate. Figure 6a shows that there is a weak yet positive correlation between the measures—a regression line through these data has a coefficient of 0.019 (0.016). Figure 6b shows the same data, with the dots in different shapes corresponding to the type of degree or certificate. The positive association between earnings returns and completion effects following layoffs is not necessarily limited to a particular type of award: degrees and certificates all had positive associations even though degrees tended to have larger earnings returns than certificates.22

---

21. The estimates in Stevens, Kurlaender, and Grosz (2019) come from California community colleges, though the results are broadly similar to estimates in other states (Belfield and Bailey 2017).

22. In online Appendix figure A.1 we repeat these figures but omit all statistically insignificant estimates of earnings returns. This leads to a relationship that is slightly larger in magnitude and more precisely estimated, with a coefficient of 0.032 (0.015).
These analyses show that there are considerable differences in the fields of study workers enter following local downturns, and suggestive evidence that there are larger responses for fields with higher labor market returns. This is an optimistic finding for those concerned about the role community colleges play in helping labor markets adjust in the long term. However, one broader concern is that students may not be able to enroll in high-demand, high-return programs if these programs are capacity constrained, which means that the true demand for these programs is actually higher. We also do not measure the job security of these fields, which may be another important outcome over which students maximize. We leave these questions for future research.
Table 4. Mass Layoffs and Two-Year College Enrollment, Degrees, and Certificates, Before and After 2007

<table>
<thead>
<tr>
<th>Fall Enrollment</th>
<th>Associate Degrees and Certificates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total First-Time</td>
</tr>
<tr>
<td></td>
<td>(1) (2)</td>
</tr>
<tr>
<td>Layoffs, t − 1</td>
<td>0.011 (0.0098) 0.017*** (0.0092)</td>
</tr>
<tr>
<td>Layoffs, t − 2</td>
<td>0.0043 (0.0062) 0.017** (0.0068)</td>
</tr>
<tr>
<td>Layoffs, t − 3</td>
<td>−0.0048 (0.0092) −0.016 (0.0099)</td>
</tr>
<tr>
<td>Layoffs, t − 1 × Post-2007</td>
<td>−0.00069 (0.0086) 0.019 (0.014)</td>
</tr>
<tr>
<td>Layoffs, t − 2 × Post-2007</td>
<td>−0.0066 (0.0061) −0.00046 (0.01)</td>
</tr>
<tr>
<td>Layoffs, t − 3 × Post-2007</td>
<td>0.0091 (0.0091) 0.01 (0.012)</td>
</tr>
<tr>
<td>Y-mean</td>
<td>12.184.2 2.138.1 1.664.7 1.051.7 320.8 493.3</td>
</tr>
<tr>
<td>R²</td>
<td>0.99 0.98 0.98 0.98 0.95 0.94</td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>X X X X X X</td>
</tr>
<tr>
<td>Commuting zone fixed effects</td>
<td>X X X X X X</td>
</tr>
<tr>
<td>Commuting zone trends</td>
<td>X X X X X X</td>
</tr>
</tbody>
</table>

Notes: Outcome variables are listed at the top of each column, and are the log counts of the corresponding outcome. Estimates are from equation 1, and allows the effect of mass layoffs to differ before and after 2007. All regressions include year and commuting zone fixed effects, commuting zone specific trends, and demographic controls. Regressions are weighted by commuting zone population. Standard errors are clustered on commuting zone. AA/AS = Associate of Arts/Associate of Science.

*p < 0.10; **p < 0.05; ***p < 0.01.

Other Findings

Given previous work that finds larger nonparticipation responses during the Great Recession, we may expect larger enrollment effects in this period. To estimate the size of the difference, we allow the effect of a mass layoff to differ for the years before and after the start of the Great Recession in 2007. Our results, in table 4, show minimal differences between the two periods, which suggests that the increased nonparticipation did not result in larger enrollment responses. However, one reason for this effect may have been decreases in availability of community college, as funding levels fell during the Great Recession. Another explanation for this result is that the IPEDS data do not capture online degrees or enrollment. To the extent that enrollment in these types of programs has been secularly increasing, the estimates for the later period may be a lower bound on the true effect.

As discussed earlier, there is considerable variation across the country in the availability of community colleges. This presents an important source of heterogeneity: Individuals in areas with fewer colleges may be less likely to enroll in college when laid off. Figure 7 shows estimates of the effect of mass layoffs on enrollment and community college awards, separated by the number of community colleges in the commuting zone. For both enrollment and awards, there is an upward trend in the

---

23. Table A.5 in the online appendix shows results by field of study, with similar results to those in table 3.
24. Commuting zones with more than five colleges are coded as having five.
Areas with fewer colleges might also have a smaller range of courses of study, potentially limiting the ability of workers to choose a program that will have a straightforward outlet into the labor market. To investigate this issue, we repeated the analysis in the previous subsection, estimating effects of mass layoffs on completions in each individual program; this time, however, we estimated separate effects for commuting zones with one college, commuting zones with two to four colleges, and commuting zones with at least five colleges. We then regressed the completion effect in each subset of commuting zones on the estimated return from Stevens, Kurlaender, and Grosz (2019) in that program. There is a clear positive gradient. In commuting zones with one
college, the effect was actually negative: $-0.014 \pm 0.004$. In areas with two to four community colleges, the effect was positive and small, though statistically significant: $0.031 \pm 0.008$. In areas with many community colleges, the effect was $0.105 \pm 0.06$, which is much larger but not statistically significant. This analysis is not causally identified, yet it is at least suggestive evidence that workers in “education deserts” are constrained not only in their ability to enroll in college altogether, but also in their ability to receive training in high-paying occupations.

Robustness Checks
We perform a number of robustness checks for the main results. Our main results, in table 3, have different observation counts for each outcome. This is because not every commuting zone has an institution that offers each type of degree or certificate. Online table A.6 shows the results when we limit the sample to commuting zones in which all degree and certificate types are represented. The results are almost identical to the main results, which suggests that commuting zones with limited community college offerings are not driving the results.

We also test whether there are heterogeneous effects by race and gender, and do not find any differences. These results are in online table A.7, and suggest that the effects are quite similar across demographic groups. We also disaggregate the layoff measures by age, race, and gender in online table A.8, and again find similar results across demographic groups.

In online Appendix C we show that our results are robust to specifications that change the geographic definitions of labor markets.

7. CONCLUSION
Our results show that for the average labor market, an additional one hundred workers laid off leads to three more first-time community college students within three years. When we compare this effect to earlier work using a similar methodological approach, we find that educational enrollment accounts for about half of the increase in labor force nonparticipation following a mass layoff event. This is an optimistic finding, especially relative to recent work that shows increases in nonparticipation due to opioid and other drug use during hard economic times (Hollingsworth, Ruhm, and Simon 2017).

We find suggestive evidence that workers seek degrees and certificates in fields with higher labor market returns. However, the correlation between degree receipt and labor market returns is somewhat weak. This may be because some students do not know about differences in earnings potential across different majors, as has been shown often in the literature (Wiswall and Zafar 2015; Baker et al. 2018). Some progress in producing these statistics has been made at the state and federal levels, but this information is for a select number of institutions. Alternatively, some students may not be able to enroll in high-return programs that often have capacity constraints. Programs in high-return health fields often have separate admissions requirements, and bottleneck courses often have waitlists. If community colleges were more responsive to local demand for certain courses, it may improve both completion and subsequent earnings outcomes for students. Furthermore, we only measure completion. This excludes workers who enrolled in courses and started a program but did not complete a degree in a certain
field. This latter mechanism may be important if mass layoffs push marginal students into school, or workers who have not been in school for a long time.

There are a number of potential directions for future research. Individual-level administrative data would allow us to follow the educational and labor market trajectories of laid off workers, as well as neighborhood-level effects. It is also important to investigate responses at for-profit colleges, which are not well-represented in our data. Recent evidence suggests that earnings outcomes at for-profits are not high (Cascio and Narayan 2015; Darolia et al. 2015; Deming et al. 2016; Cellini and Turner 2019), but students may still enroll in these institutions when faced with poor labor market conditions.

In sum, we find evidence that workers respond to mass layoffs by seeking short-duration degrees and certificates that are generally in fields with higher labor market returns. This is consistent with the idea that displaced workers seek to make new investments in specific human capital and that there are high opportunity costs for their time.

ACKNOWLEDGMENTS

We thank Massimo Anelli, Dave Carlson, Matt Naven, and participants at the Association for Education Finance and Policy and the Association for Public Policy and Management conferences. Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S. Census Bureau, the Federal Trade Commission, or any of its commissioners. All results have been reviewed to ensure that no confidential information is disclosed.

REFERENCES


Basso, Gaetano. 2016. Local labor markets adjustments to oil booms and busts. Unpublished paper, University of California, Davis.


