The effect of local labor market conditions on postsecondary enrollment and degree completion

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I use a recent data panel spanning the years 2001-2017 to study the effect of local-area unemployment on postsecondary enrollment and degree completion. My analysis extends the literature in several ways, most notably by (a) incorporating data well into the recent economic recovery from the Great Recession, (b) using improved (more accurate) measures of postsecondary enrollment, and (c) accounting for the attenuating effect of measurement error in calculated unemployment rates. Like in previous research, I find that postsecondary enrollment is countercyclical. I further show that the countercyclical enrollment pattern is concentrated among students in 2-year and sub-2-year degree programs. There is suggestive evidence that men are more elastic than women in their enrollment response to unemployment, and unemployment rates have long term effect on degree completion, but my estimates are too imprecise to draw strong inference.

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1. Introduction

During the great recession, the unemployment rate reached a thirty-year high (Barr and Turner, 2015). In the meantime, college enrollment increased significantly by 6.9 percent from 2006 to 2010 (Dunbar, et. al., 2011). After the great recession, from 2010 to 2017, undergraduate enrollment decreased by 7 percent during the economic recovery period (McFarland et. al., 2019). According to classic human capital theory, when the labor market experiences downturns, the reduced likelihood of finding a job and lower wage expectations decrease the opportunity cost of attending college (Becker, 1964). As a result, people become more likely to enroll (Betts and McFarland, 1995; Clark, 2011).

There is vast literature examining the effect of local unemployment rates on postsecondary enrollment at four-year universities and two-year community colleges. The results are consistent: most research finds that the effect of unemployment rates on college enrollment is positive (Betts and McFarland, 1995; Hillman and Orians, 2013; Barrow and Davis, 2012; Johnson, 2013). Furthermore, Johnson (2013) finds that female enrollment is countercyclical while male enrollment is procyclical.

I contribute to the literature by creating a new data panel of Metropolitan Statistical Areas (MSAs) containing enrollment and degree-completion data taken from the U.S. Department of Education Integrated Postsecondary Education Data Systems (IPEDS). I merge the postsecondary data with labor market data from two sources: Local Area Unemployment Statistics (LAUS) and the basic monthly Current Population Survey (CPS) (Ruggles et. al., 2020). The sample period is from 2001 to 2017, which is of sufficient length to capture the relations between local labor market conditions and college enrollment before, during and after the Great Recession.

I leverage variation in unemployment rates within MSAs over time via two-way fixed effects models (with fixed effects for MSAs and years) to estimate the effect of local unemployment rates on postsecondary education outcomes. I use fall semester full-time degree seeking and part-time degree seeking enrollment for three types of degree programs: four-year degrees (i.e., bachelor's degrees), two-year degrees (i.e. associate's degrees), and sub-two-year degree (i.e., certificates). I also estimate the effect of local unemployment rates on the attainment of these degrees to measure the long-term impact. . In addition, I break down total enrollment and degree attainment by gender to test whether men and women response to the labor market differently.

From 2000 to 2011, the number of associate's degrees and certificates conferred increased by 77 percent and 87 percent, respectively. During the same time period, the number of bachelor's degrees increased by only around 40 percent. Previous research has focuses on one specific level of postsecondary education or degree (e.g., Betts and McFarland, 1995; Hillman and Orians, 2013), or aggregated all enrollment and degrees together (e.g., Card and Lemieux,2000; Rivkin, 1995). However, at least in more recent data, the shift in the total postsecondary enrollment and attainment shares toward 2-year colleges suggests that separately examining various college pathways is worthwhile. To the best of my knowledge, my study is the first to distinctively and simultaneously evaluate the effect of the unemployment rate on enrollment and attainment of bachelor's degrees, associate's degrees, and certificates.

I also improve on the previous literature by constructing more accurate measures of postsecondary enrollment by pathway. Common practice in the literature is to use the categorical designations from IPEDS to determine the enrollment for each type of degree program and education level (Foote and Grosz, 2019; Hillman and Orians,2013). IPEDS designates a postsecondary institution as one of the following, based on the highest-level degree program that the institution offers: four-year college, two-year college, or less-than-two-year college. For example, if the highest degree program an institution provides is an associate's degree program, it is a two-year college. However, categorizing all enrollment based on the IPEDS designation is problematic. For instance, if a two-year community college introduces a single, new four-year degree program, its institution type in IPEDS switches from a two-year college to a four-year college immediately. Thus, IPEDS' categorical designation would imply that all students shift from two-year enrollment to four-year enrollment despite the fact that most students at the institution would still be pursuing two-year degrees.

To avoid the possible disadvantages that arise when using the traditional method, I develop a new degree-program-based method to measure enrollment. My new method allows me to produce more informative enrollment measured based on institution-level information about recently conferred degrees. I show that using my measures reduces the number of unrealistic sample composition shifts in the data at the institution level, and generally decreases measurement error.

Previous studies investigating the relationship between labor market conditions and college enrollment mostly use state-level, or even national-level data. Using data at such a high level of aggregation could introduce aggregation bias and miss important variation in economic conditions locally. Following Hillman and Orians (2013), I use LAUS data from Bureau of Labor Statistics (BLS) to calculate unemployment rates at MSA level. In addition, there is an emerging literature studying on gender-specific unemployment rate effect on decision making (Qian, 2008; Lindo et. al., 2018). Considering men and women may react to gender-specific local labor market conditions differently (Clark, 2011), I create gender specific unemployment rates for MSAs from the CPS data. I then extend the literature by identifying gender specific response elasticities to changing economic conditions and testing for evidence of gender segregation of labor markets.

Corroborating most of the existing literature, I find that postsecondary enrollment is counter-cyclical. I further show that two-year degree enrollment and sub-two-year degree enrollment are more responsive to local employment conditions than four-year degree enrollment. There is suggestive evidence that an increase in the unemployment rate has a long-term effect on degree completions, although statistical imprecision prevents me from drawing strong inference in this regard. In terms of associate's degree enrollment, men are more elastic than women in their response to the unemployment rate, but I find no evidence of gender heterogeneity in responsiveness for other types of enrollment. There is little evidence to reject the null hypothesis of no gender segregation in the labor market.

The remainder of the paper is organized as follows. Section 2 presents the construction of the dataset and basic descriptive statistics. Methodology and estimation results are shown in section 3 and section 4, and I conclude in section 5.

2. Data

My MSA-level data panel includes two main datasets: the education dataset and the labor market dataset. The education dataset contains enrollment and degree attainment information from IPEDS. IPEDS provide detailed information about all postsecondary institutions that receive federal financial assistance, including enrollment, degree completion, address information, etc. The local labor market dataset consists of total unemployment rates and gender specific unemployment rates taken from the BLS and CPS.

I measure full-time and part-time degree seeking enrollment and degrees awarded for all postsecondary institutions in the US and further break down enrollment and degree receipt by degree program type. I define three types of degree programs: (1) four-year degree program, i.e., bachelor's degree, (2) two-year degree program, i.e., associate's degree, and (3) sub-two-year degree program, i.e., all other certificates. In addition, I break down the enrollment and degree attainment by gender. With MSA codes provided by IPEDS for every year and every institution, I aggregate enrollment and degree attainment numbers to the MSA level.

As noted above, past studies measuring postsecondary enrollment, not limited to investigating the effect of unemployment rates, have primarily relied on a "institution based" definition of enrollment. With this approach, researchers categorically identify the postsecondary institutions by type first—i.e., four-year universities, community colleges, etc.—then extract the enrollment information and assign enrollment of a type that matches the institution. This approach can be problematic because IPEDS uses coarse categories for institutions—e.g., if an institution provides any bachelor's degree programs, IPEDS designate it as a four-year university, even if very few students are enrolled in four-year degree programs.

For research measuring postsecondary enrollment at the institution level, an observable data consequence of using the IPEDS categorizations is that when an institution adds a new degree program (or drops a program), the shift in status can result in large and inaccurate shifts in student enrollment. For example, consider the simple task of capturing state or MSA-level enrollment in bachelor's degree programs. The rise in community colleges offering at least some 4-year degree programming over time introduces excess variation in 4-year enrollment that is an artifact of the IPEDS coding structure only. This is an important problem in the data: during my data panel form 2001-2017, 1057 out of 7676 postsecondary institutions changed their institution type at least once.

One of the major goals of this paper is to evaluate different postsecondary sectors at the degree-program level, thus the traditional "institution based" method for tacking enrollment is a poor fit. To avoid the possible disadvantages that arise when using the traditional method, I develop a new degree-program-based method that calculates enrollments continuously based on information about degrees conferred. Specifically, I combine present year degree completion data with the data from the previous two years to calculate three-year average shares of all three types of degrees at each institution. By multiplying prior years' degree shares by current enrollment of full-time and part-time degree seeking students, I can calculate the number of students in each degree program more accurately.[1]

While my degree-program-based measure is an improvement over the commonly used measure based on categorical IPEDS data, it is not perfect. One way to interpret my measure is that it is a smoothed version of traditional measure. The biggest concern is that my measure misses true, immediate institutional changes in degree composition. Although such changes at scale are likely rare, they could happen. In addition, slower-moving enrollment changes that surely do happen are missed. For example, if a community college that introduces a new bachelor's degree program, my approach will take four years to capture the enrollment change. While this is an improvement over recoding all students at the community college as bachelor's enrollment from the perspective of total measurement error, there is still error.

Figure 1 illustrates the benefits of my measure. It shows enrollment at Fashion Institute of Design & Merchandising (FIDM), a two-year college, from 2001 to 2017. In 2005, IPEDS begins designating FIDM as a four-year university because it introduced at least one four-year degree program. Applying the traditional "institution based" method of measuring enrollment, all students enrolled at FIDM would be coded four-year university students beginning in 2005. However, if I use the "degree programed based" method, students at FIDM would still be counted as seeking

[1] Appendix for details.

two-year degrees in 2005, 2006 and 2007; then, after 2007, the share of four-year degrees awarded starts to increase. Notice that the share increases very slowly, and even in 2017, 12 years after the type-change in IPEDS, four-year degrees only accounted for less than 15 percent of total degrees awarded. Even though my method understates 4-year degree enrollment in the early years after FIDM makes the change, the degree of understatement is far less than the overstatement of using the traditional measure (i.e., coding all FIDM students as bachelor's enrollment in 2005 and later).

The labor market dataset contains information from two sources: unemployment rates at the MSA-level are from the Local Area Unemployment Statistics (LAUS) published by the Bureau of Labor Statistics (BLS), and I calculate gender-specific unemployment rates from the basic monthly Current Population Survey (CPS) (Ruggles et. al., 2019). LAUS contains monthly unemployment rate data for workers aged 16 and above at the county level, but does not provide gender specific unemployment rates information at the county level or MSA level. To calculate MSA level gender-specific unemployment rates, I collect the individual unemployment information provided by the CPS, and further calculate the MSA level unemployment rates. Because the enrollment of each postsecondary institution in IPEDS is reported in October, I only use the LAUS and CPS data from January to October to calculate unemployment rates to avoid time misalignment between treatments and outcomes (i.e., using treatment information measured after outcomes are captured).[2]

Table 1 shows the descriptive statistics for the main variables aggregated to the MSA level for the years from 2001 to 2017. The unit of observation is MSA by year. Columns (1), (2), and (3) are for the full sample, women, and men, respectively. The total sample size is 6527 MSAs. The mean of full-time four-year degree enrollment is 14911, which is much higher than part-time

[2] I also supplement the data panel with gender and racial composition information from the Surveillance, Epidemiology, and End Results (SEER) program of the National Cancer Institute.

four-year degree enrollment at only, 2983. However, for two-year and sub-two-year degree programs there is no significant difference between full-time and part-time enrollment. The share of female students enrolled in postsecondary institutions and who receive degrees is higher than the share of male students among all program types, consistent with the modern empirical regularity that women are more represented and more successful in higher education. The mean unemployment rate across MSAs during the sample period, calculated based on LAUS, is 6.5%, and the standard deviation is 3%.[3] After disaggregating the unemployment rate by gender, the mean unemployment rate among men is higher than the mean unemployment rate among women.

Figure 2 shows the different types of postsecondary enrollment in relation to the unemployment rate over time. Before the great recession, all types of enrollment experienced rapid growth, although the rates of increase of different degree programs vary year to year. After 2010, most types of degree program enrollment, except for full-time four-year degree enrollment, show a noticeable response to the decline of unemployment rates. Notably, full-time two-year and sub-two-year degree enrollment moves almost simultaneously with the unemployment rate.

3. Methodology

I leverage within-MSA and cross-time variation to estimate the effect of the local unemployment rate on postsecondary education outcomes using the following model:

$$y_{it} = \alpha + \beta UR_{it} + \Gamma X_{it} + \eta_i + \delta_t + \epsilon_{it} \quad (1)$$

In equation (1), y_{it} is an logged value outcome variable for MSA *i* in year *t*. Per above, I focus on two outcomes: fall enrollment, disaggregating by full-time and part-time enrollment status, and degree attainment using the three types of degrees described in the previous section. UR_{it} is the MSA level total unemployment rate and also the main variable of interest. X_{it} is a vector for

[3] The unemployment rate reported here is based on LAUS. Similar calculations using the CPS data produce very similar results.

control variables measuring time-varying MSA level demographics, including the share of population that is white and the share of the population that is female. η_i is an MSA fixed effects and δ_t is a year fixed effects. ϵ_{it} is the error term. In some specifications I further divide the full sample into two sub-samples, men and women, to test for possible effect heterogeneity by gender, i.e., whether men and women would response differently to the local labor market change. Regressions are weighted by MSA total population from the 2010 United States Census. To account for correlated errors within MSA over years, I cluster standard errors at the MSA level throughout (Bertrand, Duflo and Mullainathan, 2004).

A causal interpretation of the unemployment-rate coefficient requires the assumption that after controlling MSA fixed effects and year fixed effects, there are no dynamic unobservables correlated with both the local unemployment rate and education outcomes. A possible threat to this identifying assumption is reverse causality—in particular, a concern is that reduced enrollment could increase the measured unemployment rate by taking some individuals out of the workforce. However, given that the average ratio of college enrollment to working-age population is relatively small, at about 0.05 across MSAs, it is reasonable to believe enrollment shifts will not cause a significant change to the size of the local labor force. Moreover, in a robustness test I reduce the potential influence of this type of mechanical confounding by measuring unemployment only for workers aged 35 and above, who are unlikely to enroll in college, an show that the results are qualitatively similar to those using the full working-age population.

The extension of equation (1) shown below in equation (2) allows me to differentiate the effect of gender-specific unemployment rates and test whether the local labor market is gender segregated. The expanded version of the model is as follows:

$$y_{it} = \alpha + \beta_1 UR_{women_{it}} + \beta_2 UR_{men_{it}} + \eta_i + \delta_t + \epsilon_{it} \qquad (2)$$

In Equation (2), the recurring variables follow the same definition as in equation (1). The addition to equation (2) is that I include both the female and male unemployment rates separately. The identifying assumption is the same as in equation (1). I test the gender segregation of the labor market by examining the gender-specific coefficient. The null hypothesis is that the labor market is not gender segregated.

4. Primary Results

4.1 Enrollment

Table 2 shows the effect of the local unemployment rate on postsecondary enrollment corresponding to equation (1). Each column shows results for a different type of enrollment. Panel A shows the effect on total enrollment, panel B shows the effect on female enrollment, and panel C shows the effect on male enrollment. Each coefficient is from a separate regression and shows the effect of a one-percentage-point increase in the local area unemployment rate as measured for the working-age population corresponding to the included gender demographics.

Overall, there is strong evidence that postsecondary enrollment is counter-cyclical. Starting with panel A, the consistently positive coefficients indicate that a higher unemployment rate increases college enrollment. The coefficient in column (1) indicates that a one percentage point increase in the unemployment rate increases full time four-year enrollment by 1.65 percent (significant at the 10 percent level). The coefficient in column (1) is nominally larger than the coefficient for part-time four-year enrollment in column (2), although the bottom row in panel A shows they cannot be distinguished statistically. Column (3) and (4) shows the results for two-year enrollment. The coefficient for full-time two-year enrollment, 2.962, is large and significant at the 1 percent level. This estimate is close to the findings in previous research (Betts and Mcfarland, 1995; Hillman and Orians, 2013). The coefficient for part-time two-year enrollment is much smaller and not significant at conventional levels. The coefficients for both types of sub-two-year enrollment are large and significant, indicating that sub-two-year enrollment is more responsive to local labor market changes than other types of enrollment overall.

Panels B and C show that except for two-year enrollment, the magnitudes and significance levels of coefficients are close to corresponding results in the top panel. There exists some heterogeneity in the model of enrollment in two-year degree programs. In column (3), for full-time two-year degree program, the coefficient for male students is 3.461, which is about 1 percentage point higher than the coefficient for female students. In terms of part-time two-year degree enrollment in column (4), the estimate for female students is close to 0, though the large standard error clouds inference. The estimate for male students is 2.106 and significant at the 5 percent level. The p-values from statistical tests of equality between the effect of the unemployment rate on female and male enrollment in column (3) and column (4) are all less than 0.01. These results suggest that men are more elastic than women in their two-year degree enrollment response to unemployment. For other types of enrollment, there is no evidence suggesting that there is any significant difference between male and female students.

In summary, Table 2 shows that two-year enrollment and sub-two-year enrollment are more responsive to local unemployment rate than four-year enrollment. This finding is consistent with previous research (Dellas and Sakellaris, 2003). Within each type of enrollment, I do not find clear evidence that full-time enrollment is more responsive to the local unemployment rate than part-time enrollment, although there is suggestive evidence at all levels that this is the case. Male enrollment is more responsive than female enrollment to the unemployment rate, driven most clearly by differences in enrollment in two-year degree programs.

4.2 Degree Completions

Table 3 presents estimates of the effect of lagged local area unemployment rates on degree completions. In Columns (1), (2), and (3), I test the effect of lagged four year (year t-4) MSA level unemployment rates on the numbers of four-year degrees awarded to total students, female students, and male students, respectively. In Columns (4), (5), and (6), I test the effect of lagged two year (year t-2) MSA level unemployment rates on the numbers of two-year degree awarded to total students, female students, and male students, respectively. In Column (7), (8), and (9), I test the effect of lagged one year (year t-1) MSA level unemployment rates on the number of sub-two-year degree awarded to total students, female students, and male students, respectively.

All of the coefficients in Table 3 are positive, but few are significant at conventional levels. The exception is for sub-two-year degrees, where there is some indication of a long-term effect driven by female students. My estimates indicates that a one percentage-point increase in the unemployment rate results in a 2.475 percent increase in total sub-two-year degrees awarded one year later.[4] Overall, these results suggest some "slippage" between unemployment-induced postsecondary enrollment and degrees conferred, which is not surprising if marginally induced students are less interested in and attached to postsecondary education, but are at least suggestive of long-term impacts of unemployment rates on postsecondary attainment.

5. Robustness

In this section I consider the robustness of my findings to several modifications to the sample and key measures. I focus on the enrollment models from the previous section for brevity.

[4] In Appendix Table A3, I show the results with other model specifications, which include more lagged years. When including all four lagged years from *t-1* to *t-4*, the unemployment rate in year t-2 has moderate effects on degree awards, but standard errors for other coefficients are still too large to give useful inference. Overall, there is suggestive evidence that local unemployment rates have positive effects on future degree completions, especially for short term degrees. Because of the large standard errors, I cannot rule out large degree effects in any sectors.

5.1 Sensitivity to Outliers

To examine the sensitivity of main results to different MSA compositions, I drop the three largest MSAs in terms of population: New York metropolitan area, Los Angeles metropolitan area, and Chicago metropolitan area. These three MSAs have total populations in the 2010 Census of 19.6 million, 12.8 million and 9.5 million, which are significantly higher than the average of other MSAs, which is just 0.6 million. This has the potential to significantly skew my results due to the MSA-population weighting. Table 4 shows the results after dropping these three MSAs. The magnitudes and significant levels are very close to estimates in Table 2, except for part-time enrollment in two-year and sub-two-year degree programs. The main findings regarding full-time enrollment still hold, suggesting that my results are robust to this sample composition change.

5.2 Measuring Unemployment for ages 35+

As noted above, reverse causality could affect the identifying assumption. In this section I use the unemployment rate among workers aged 35-plus to remove the potential cofounding effect of flows between the labor force and postsecondary education among younger workers. Because the LAUS does not provide measures of the unemployment rate by age at the MSA level, I use the monthly CPS to calculate older workers' unemployment rates, pooling the data for each year from January to October. Using survey data raises the concern that additional measurement error may be introduced, especially at a low aggregated level like the MSA (Betts & McFarland, 1995). I take two steps to assess and improve the accuracy of my measures, reduce the attenuation bias, and ensure the estimation results using two different measures are comparable.

First, I compare the total unemployment rate created by CPS data to the one provided by LAUS. The unemployment rate from LAUS is calculated based on information from multiple sources, including CPS, the Current Employment Statistics (CES), and the Quarterly Census of

Employment and Wages (QCEW). Figure 3 shows the histogram of differences between the two measures (in percentage points), which are small—e.g., for just over half of the MSA observations, the difference is less than one percentage point. Although my CPS-based measures are close to LAUS measures on average and for most MSAs, there are still some extreme differences that may reflect non-negligible measurement error. To reduce the influence of measurement error and make the results more comparable, I only keep the MSAs in which the difference between the two measures is no larger than three percentage points, which I view as an indicator of higher-quality data in the MSA. Second, I bootstrap the CPS data to directly calculate the variance of the sampling error, and fit errors-in-variables (EIV) regressions to reduce attenuation bias.[5]

To test the efficacy of my approach, Appendix Tables A1 and A2 compare results corresponding to equation (1) using the LAUS and CPS measures, with the sample restricted to MSAs for which the LAUS- and CPS-based total unemployment rate estimates are within three percentage points, and using the EIV regressions for the CPS-based models. The results are similar using both datasets. Taking this baseline similarity as a point of departure, Table 5 shows results using unemployment rates among aged 35-plus workers calculated based on CPS data. The coefficients for four-year degree enrollment increase slightly, while the coefficients for two-year degree part-time enrollment and sub-two-year degree part-time enrollment decrease slightly. On the whole, the evidence suggests that any bias in my main specifications due to reverse causality is small.

6. Extensions

6.1 Comparison of Postsecondary Enrollment Measures

[5] The appendix describes the bootstrap procedure and errors-in-variables regressions in detail.

To investigate the practical significance of the measurement error issue when using the traditional "institution based" designations to measure college enrollment I compare my findings to findings using the traditional approach. If the measurement error is independent—which is a reasonable assumption but challenging to test empirically—it should not cause bias in my estimates because it is contained in the dependent variable, but just increase the variance and reduce model efficiency.

In Table 6 I estimate the same regressions as in Table 2, replacing the dependent variables constructed using my measures with the traditional, categorical measures based on IPEDS institutional designations. Compared to results in Table 2, the coefficients for full-time four-year degree enrollment and sub-two-year degree enrollment are larger, while the coefficients for two-year degree enrollment are lower, and even negative for part-time enrollment. More telling is that the standard errors explode in Table 6 compared to Table 2. Outside of the full-time, four-year degree results in column (1), all of the standard errors in Table 5 are at least twice as large as the corresponding standard errors in Table 2. For part-time two-year enrollment and part-time sub-two-year enrollment, the standard errors are almost three times larger. The high standard errors are a clear indication that constructing enrollment measures using IPEDS' institutional categorizations results in very noisy measurement and substantially reduced model efficiency.

6.2 Testing for Gender Segregation in the Labor Market?

Thus far I have estimated the effect of the total unemployment rate on total postsecondary enrollment and enrollment by gender. The total unemployment rate, to which I allow for differential gender responsiveness for both genders (i.e., it is the total unemployment rate), is fixed, so that the differences I observe can be attributed to differences in responsiveness between genders to the same conditions. In this section I expand the model as described by equation (2) to test the hypothesis that men and women are responding to different local labor markets—i.e., I test for gender segregation in the labor market.

For this analysis I again rely on the monthly CPS data, this time to calculate gender-specific unemployment rates. Per equation (2), the gender-specific rates are included simultaneously to look for evidence of differential responsiveness. Table 7 shows the results. Overall, the estimates are smaller in magnitude than the estimates for total unemployment rates in Table 2, although some of the estimates are noisy. I test the gender segregation hypothesis by testing for equality between the coefficients on the female and male unemployment rates. If the local labor market is gender segregated, then we should observe that the effect of the gender-specific unemployment rates differ significantly, but most p-values from the statistical tests are very high, except some tests for four-year enrollment. Moreover, even these estimates are not consistent with gender-segregated markets, but seem to suggest that the male unemployment rate is a stronger driver of behavior for both genders. The generally insignificant results, their direction, and the possibility of type I errors among multiple statistical tests lead to the summary conclusion that there is no evidence of gender segregation in the labor market as measured by my models.

7. Conclusion

I investigate the link between local labor market conditions and postsecondary education outcomes at the MSA level. My sample covers the years 2001 to 2017 and spans the Great Recession. I find that postsecondary enrollment is counter-cyclical: enrollment increases when the unemployment rate rises. My results are most pronounced for two-year degree enrollment and sub-two-year degree enrollment, which appear more responsive to local employment conditions than four-year degree enrollment. Within each type of enrollment, I do not find strong evidence that full-time enrollment is more responsive to unemployment rates than part-time enrollment, but there is suggestive evidence that this is the case. I also track degree outcomes corresponding to lagged unemployment rates and show suggestive evidence of positive impacts, although it is not conclusive and even an optimistic interpretation of those results suggests significant slippage between the enrollment effect and degree-production effect of unemployment fluctuations. Finally, I show that men are more elastic than women in their two-year degree enrollment response to the unemployment rate, and find no evidence to suggest this is caused by gendered segregation in the labor market.

My analysis is facilitated by a new "degree program based" measure of postsecondary enrollment that I construct for MSAs using IPEDS data. My measure produces program-specific enrollment estimates for each institution in year-*t* using the (recent) historical composition of degrees conferred at that institution and year-*t* enrollment. Relative to the standard approach of categorizing all enrollment in an institution based on the IPEDS degree-level category, my measure is less error prone and results in much more efficient estimation.

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Table 1: Summary Statistics

	Total	Women	Men
Full time 4-year enrollment	14911.32	8173.74	6743.02
	(29224.83)	(16212.40)	(13085.76)
Part time 4-year enrollment	2983.43	1716.50	1264.47
	(6884.67)	(4025.54)	(2925.85)
Full time 2-year enrollment	5096.99	2902.07	2201.48
	(13474.29)	(7735.88)	(5814.89)
Part time 2-year enrollment	5286.29	3286.29	2025.93
	(12851.93)	(7676.69)	(5263.37)
Full time sub-2-year enrollment	3101.45	1803.62	1285.82
	(6983.30)	(4003.24)	(3009.40)
Part time sub-2-year enrollment	2575.78	1445.31	1107.00
	(7062.00)	(3744.23)	(3356.30)
4-year degree conferred	7339.13	4213.66	3125.47
	(15012.64)	(8788.83)	(6260.98)
2-year degree conferred	3775.27	2290.22	1485.05
	(8670.51)	(5316.58)	(3429.65)
sub-2-year degree conferred	3788.69	2332.20	1456.49
	(8716.16)	(5379.98)	(3420.46)
Average in-state tuition and fees	9734.48	9734.48	9734.48
	(5632.68)	(5632.68)	(5632.68)
fraction of white	0.51	0.51	0.51
	(0.01)	(0.01)	(0.01)
fraction of Women	0.84	0.84	0.84
	(0.12)	(0.12)	(0.12)
unemployment rate	0.07	0.06	0.07
	(0.03)	(0.03)	(0.04)
Number of Observations	6527	6527	6527

Notes: Unit of Observation is Metropolitan Statistical Area by year. Means and standard deviations displayed. Total unemployment rate measure is calculated from LAUS data, gender-specific unemployment rate measure is calculated from CPS data.

Table 2: Effect of the unemployment rate on college enrollment

	(1)	(2)	(3)	(4)	(5)	(6)
	4-year degree enrollment		2-year degree enrollment		sub-2-year degree enrollment	
	full-time	part-time	full-time	part-time	full-time	part-time
Panel A: Total						
Unemployment Rate: β	1.648*	1.068	2.962***	1.184	4.192***	2.938*
	(0.855)	(1.245)	(0.970)	(0.948)	(0.846)	(1.579)
Observations	6257	6257	6257	6257	6257	6257
R-squared	0.981	0.973	0.974	0.973	0.970	0.957
P-value for H_0: $\beta_{\text{Full-time}} = \beta_{\text{Part-time}}$	0.534		0.098		0.294	
Panel B: Women						
Unemployment Rate: β	1.481*	0.767	2.486**	0.515	3.971***	2.847**
	(0.834)	(1.335)	(1.003)	(0.960)	(0.798)	(1.420)
Observations	6257	6257	6257	6257	6257	6257
R-squared	0.982	0.971	0.972	0.972	0.970	0.958
P-value for H_0: $\beta_{\text{Full-time}} = \beta_{\text{Part-time}}$	0.511		0.056		0.325	
Panel C: Men						
Unemployment Rate: β	1.635**	1.130	3.461***	2.106**	4.037***	3.314*
	(0.789)	(1.028)	(0.856)	(0.990)	(1.081)	(1.827)
Observations	6257	6257	6257	6257	6257	6257
R-squared	0.984	0.978	0.976	0.974	0.968	0.957
P-value for H_0: $\beta_{\text{Full-time}} = \beta_{\text{Part-time}}$	0.501		0.206		0.592	
P-value for H_0: $\beta_{\text{Women}} = \beta_{Men}$	0.526	0.468	0.006	0.001	0.923	0.630
MSA FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Control Variables	X	X	X	X	X	X
Weighted by Pop.	X	X	X	X	X	X

Notes: Robust standard errors clustered at MSA level in parentheses, control variables include share of population whites, and sex ratio. H_0: $\beta_{\text{Full-time}} = \beta_{\text{Part-time}}$ is in reference for equation (1), the null hypothesis is that the effect of unemployment rate on full-time enrollment and part-time enrollment are equal. H_0: $\beta_{\text{Women}} = \beta_{\text{Men}}$ is in reference for equation (1), the null hypothesis is that the effect of unemployment rate on female enrollment and male enrollment are equal. Regressions are weighted by 2010 MSA population.*** p<0.01, ** p<0.05, * p<0.1.

Table 3: Effect of the unemployment rate on degree completions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		4-year degree			2-year degree			sub-2-year degree	
	Total	Women	Men	Total	Women	Men	Total	Women	Men
Unemployment Rate in year t-1							2.475*	2.940**	1.339
							(1.346)	(1.360)	(1.432)
Unemployment Rate in year t-2				1.419	0.796	2.201			
				(1.333)	(1.293)	(1.376)			
Unemployment Rate in year t-4	1.472	1.374	1.859						
	(1.363)	(1.344)	(1.238)						
Observations	4768	4768	4768	5511	5511	5511	5883	5883	5883
R-squared	0.982	0.982	0.986	0.979	0.979	0.979	0.967	0.967	0.960
MSA FE	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X
Control Variables	X	X	X	X	X	X	X	X	X
Weighted by Pop.	X	X	X	X	X	X	X	X	X

Notes: Robust standard errors clustered at MSA level in parentheses, control variables include share of population whites, and sex ratio. 4-year degree includes bachelor's degree, 2-year degree includes associate's degree, and sub-2-year degree includes all kinds of certificates. Regressions are weighted by 2010 MSA population. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Effect of the unemployment rate on college enrollment, dropping three largest MSAs

	(1)	(2)	(3)	(4)	(5)	(6)
	4-year degree enrollment		2-year degree enrollment		sub-2-year degree enrollment	
	full-time	part-time	full-time	part-time	full-time	part-time
Panel A: Total						
Unemployment Rate: β	1.907**	1.422	3.141***	0.541	3.794***	1.743
	(0.931)	(1.322)	(1.003)	(0.890)	(0.703)	(1.315)
Observations	6206	6206	6206	6206	6206	6206
R-squared	0.976	0.966	0.966	0.967	0.967	0.952
Panel B: Women						
Unemployment Rate: β	1.709*	1.166	2.629**	-0.045	3.670***	1.924
	(0.908)	(1.404)	(1.031)	(0.926)	(0.735)	(1.261)
Observations	6206	6206	6206	6206	6206	6206
R-squared	0.977	0.963	0.962	0.966	0.966	0.951
Panel C: Men						
Unemployment Rate: β	1.893**	1.373	3.667***	1.394	3.556***	1.798
	(0.857)	(1.102)	(0.883)	(0.927)	(0.869)	(1.455)
Observations	6206	6206	6206	6206	6206	6206
R-squared	0.980	0.972	0.969	0.969	0.965	0.953
MSA FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Control Variables	X	X	X	X	X	X
Weighted by Pop.	X	X	X	X	X	X

Notes: Robust standard errors clustered at MSA level in parentheses, control variables include share of population whites, and sex ratio. Three largest MSAs are dropped: New York metropolitan area, Los Angeles metropolitan area, and Chicago metropolitan area. Regressions are weighted by 2010 MSA population.*** p<0.01, ** p<0.05, * p<0.1.

Table 5: Effect of the unemployment rate among senior workers on college enrollment restricting MSAs

	(1)	(2)	(3)	(4)	(5)	(6)
	4-year degree enrollment		2-year degree enrollment		sub-2-year degree enrollment	
	full-time	part-time	full-time	part-time	full-time	part-time
Panel A: Total						
Unemployment Rate: β	0.881*	0.346	2.797***	2.224*	2.901***	3.243***
	(0.511)	(0.808)	(0.907)	(1.275)	(0.628)	(1.171)
Observations	3613	3613	3613	3613	3613	3613
R-squared	0.985	0.973	0.982	0.977	0.983	0.965
Panel B: Women						
Unemployment Rate: β	0.760	0.133	2.488**	1.703	2.992***	3.274***
	(0.504)	(0.896)	(0.973)	(1.276)	(0.61)	(1.091)
Observations	3613	3613	3613	3613	3613	3613
R-squared	0.986	0.971	0.978	0.975	0.982	0.964
Panel C: Men						
Unemployment Rate: β	0.998**	0.533	3.207***	2.769**	2.783***	3.293**
	(0.481)	(0.693)	(0.832)	(1.212)	(0.789)	(1.338)
Observations	3613	3613	3613	3613	3613	3613
R-squared	0.988	0.978	0.983	0.977	0.977	0.961
MSA FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Control Variables	X	X	X	X	X	X
Weighted by Pop.	X	X	X	X	X	X

Notes: Robust standard errors clustered at MSA level in parentheses, control variables include share of population whites, and sex ratio. Unemployment rate are calculated among senior workers whose ages are greater than 35, based on CPS data. MSAs in which the difference between two unemployment rates measured by CPS data and LAUS data are no larger than three percentage points are kept. Regressions are weighted by 2010 MSA population.*** p<0.01, ** p<0.05, * p<0.1.

Table 6: Effect of the unemployment rate on college enrollment, using measures from IPEDS designation

	(1)	(2)	(3)	(4)	(5)	(6)
	4-year degree enrollment		2-year degree enrollment		sub-2-year degree enrollment	
	full-time	part-time	full-time	part-time	full-time	part-time
Panel A: Total						
Unemployment Rate: β	2.108*	1.002	1.300	-3.322	6.929***	6.946
	(1.124)	(2.111)	(1.989)	(3.930)	(2.121)	(5.726)
Observations	6257	6257	6257	6257	6257	6257
R-squared	0.962	0.945	0.906	0.892	0.926	0.894
Panel B: Women						
Unemployment Rate: β	2.054*	0.553	0.809	-3.612	6.692***	6.807
	(1.108)	(2.158)	(1.953)	(3.857)	(2.053)	(5.206)
Observations	6257	6257	6257	6257	6257	6257
R-squared	0.963	0.943	0.908	0.892	0.924	0.894
Panel C: Men						
Unemployment Rate: β	2.057*	1.400	1.990	-2.971	6.962***	10.60
	(1.048)	(1.970)	(1.898)	(3.784)	(2.615)	(7.486)
Observations	6257	6257	6257	6257	6257	6257
R-squared	0.968	0.952	0.918	0.901	0.935	0.872
MSA FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Control Variables	X	X	X	X	X	X
Weighted by Pop.	X	X	X	X	X	X

Notes: Enrollment is measured based on IPEDS designation. Robust standard errors clustered at MSA level in parentheses, control variables include share of population whites, and sex ratio. Regressions are weighted by 2010 MSA population.*** p<0.01, ** p<0.05, * p<0.1.

Table 7: Effect of by gender unemployment rate on college enrollment

	4-year degree enrollment		2-year degree enrollment		sub-2-year degree enrollment	
	full-time	part-time	full-time	part-time	full-time	part-time
Panel A: Women						
Unemployment Rate among Women: β_1	-0.200	-1.204*	0.610	0.443	1.106***	0.610
	0.375	0.687	0.554	0.601	0.401	0.581
Unemployment Rate among Men: β_2	0.636*	1.008*	1.128*	0.955	1.057**	2.115***
	0.362	0.565	0.602	0.923	0.451	0.774
Observations	3,545	3,545	3,545	3,545	3,545	3,545
R-squared	0.979	0.959	0.963	0.965	0.972	0.952
P-value for H_0: $\beta_1 = \beta_2$	0.150	0.029	0.532	0.536	0.936	0.157
Panel B: Men						
Unemployment Rate among Women: β_1	-0.141	-0.743	1.259***	1.113*	1.422***	0.337
	0.326	0.542	0.449	0.649	0.472	0.721
Unemployment Rate among Men: β_2	0.845**	0.917*	1.556***	1.281	1.097**	2.078**
	0.352	0.515	0.527	0.878	0.514	0.946
Observations	3,545	3,545	3,545	3,545	3,545	3,545
R-squared	0.983	0.97	0.969	0.967	0.965	0.948
P-value for H_0: $\beta_1 = \beta_2$	0.086	0.065	0.666	0.848	0.662	0.186
MSA FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Control Variables	X	X	X	X	X	X
Weighted by Pop.	X	X	X	X	X	X

Notes: Robust standard errors clustered at MSA level in parentheses, control variables include share of population whites, and sex ratio. H_0: $\beta_1 = \beta_2$ is in reference for equation (2), the null hypothesis is that coefficients on female unemployment rates and male unemployment rates are equal. Regressions are weighted by 2010 MSA population.*** p<0.01, ** p<0.05, * p<0.1.

Appendix Table a1: Effect of the unemployment rate (LAUS measures) on college enrollment restricting MSAs

	(1)	(2)	(3)	(4)	(5)	(6)
	4-year degree enrollment		2-year degree enrollment		sub-2-year degree enrollment	
	full-time	part-time	full-time	part-time	full-time	part-time
Panel A: Total						
Unemployment Rate: β	0.909	1.046	2.413**	1.825	3.867***	3.799**
	(0.641)	(1.172)	(1.014)	(1.269)	(0.689)	(1.56)
Observations	3613	3613	3613	3613	3613	3613
R-squared	0.985	0.973	0.982	0.977	0.983	0.965
Panel B: Women						
Unemployment Rate: β	0.812	0.816	1.99*	1.073	3.823***	3.802***
	(0.668)	(1.329)	(1.083)	(1.293)	(0.698)	(1.42)
Observations	3613	3613	3613	3613	3613	3613
R-squared	0.986	0.971	0.978	0.975	0.982	0.964
Panel C: Men						
Unemployment Rate: β	0.952	1.213	2.954***	2.584**	3.507***	3.869**
	(0.617)	(0.962)	(0.956)	(1.209)	(0.933)	(1.873)
Observations	3613	3613	3613	3613	3613	3613
R-squared	0.988	0.978	0.983	0.977	0.977	0.961
MSA FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Control Variables	X	X	X	X	X	X
Weighted by Pop.	X	X	X	X	X	X

Notes: Robust standard errors clustered at MSA level in parentheses, control variables include share of population whites, and sex ratio. Unemployment rate are calculated based on LAUS data. MSAs in which the difference between two unemployment rates measured by CPS data and LAUS data are no larger than three percentage points are kept. Regressions are weighted by 2010 MSA population.*** p<0.01, ** p<0.05, * p<0.1.

Appendix Table a2: Effect of the unemployment rate (CPS measures) on college enrollment restricting MSAs

	(1)	(2)	(3)	(4)	(5)	(6)
	4-year degree enrollment		2-year degree enrollment		sub-2-year degree enrollment	
	full-time	part-time	full-time	part-time	full-time	part-time
Panel A: Total						
Unemployment Rate: β	0.623	-0.157	2.694***	2.793*	2.99***	4.056***
	(0.522)	(0.803)	(0.962)	(1.664)	(0.734)	(1.387)
Observations	3613	3613	3613	3613	3613	3613
R-squared	0.985	0.973	0.982	0.977	0.983	0.965
Panel B: Women						
Unemployment Rate: β	0.465	-0.443	2.102**	2.116	2.793***	4.088***
	(0.562)	(0.935)	(1.012)	(1.64)	(0.739)	(1.264)
Observations	3613	3613	3613	3613	3613	3613
R-squared	0.986	0.971	0.978	0.975	0.982	0.965
Panel C: Men						
Unemployment Rate: β	0.834*	0.261	3.426***	3.546**	3.189***	4.131**
	(0.472)	(0.679)	(0.887)	(1.59)	(0.884)	(1.645)
Observations	3613	3613	3613	3613	3613	3613
R-squared	0.988	0.978	0.983	0.977	0.977	0.961
MSA FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Control Variables	X	X	X	X	X	X
Weighted by Pop.	X	X	X	X	X	X

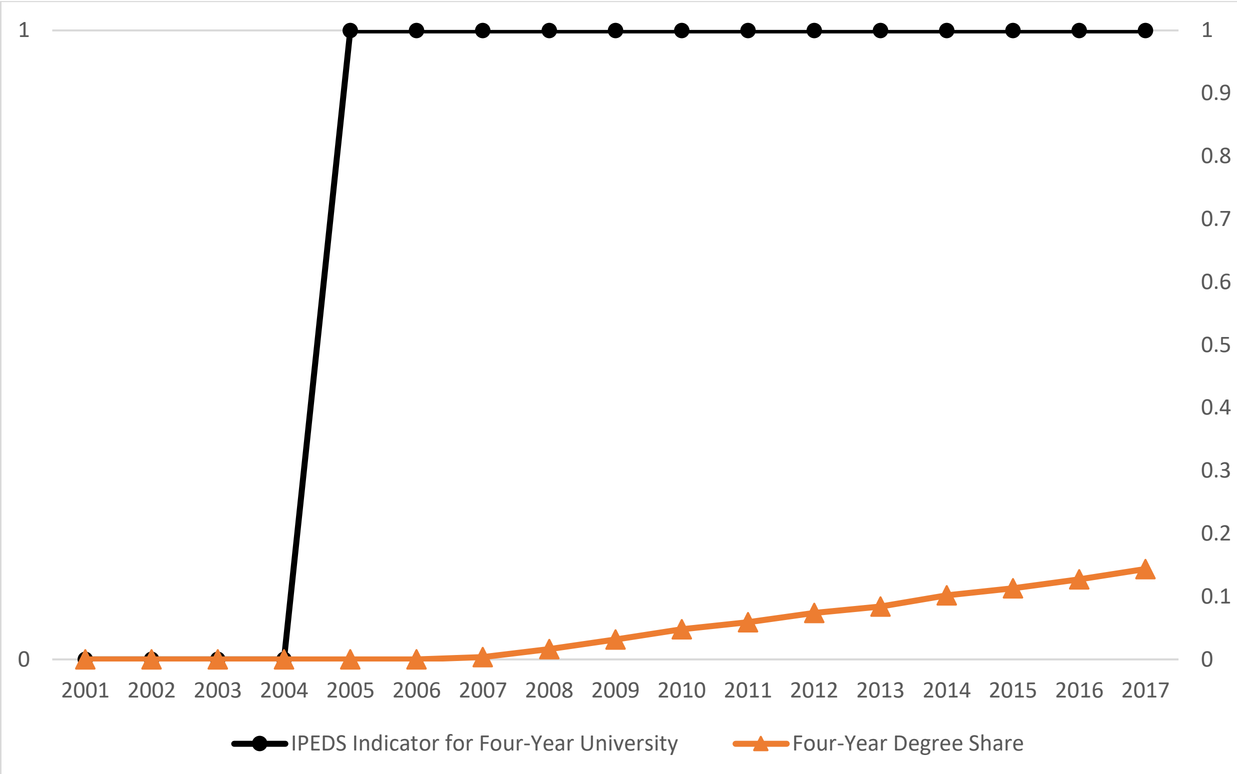
Notes: Robust standard errors clustered at MSA level in parentheses, control variables include share of population whites, and sex ratio. Unemployment rate are calculated based on CPS data. MSAs in which the difference between two unemployment rates measured by CPS data and LAUS data are no larger than three percentage points are kept. Regressions are weighted by 2010 MSA population.*** p<0.01, ** p<0.05, * p<0.1.

Appendix Table a3: Effect of the unemployment rate on degree completions

	4-year degree			2-year degree			sub-2-year degree		
	Total	Women	Men	Total	Women	Men	Total	Women	Men
Unemployment Rate in year t-1	0.354	0.248	0.226	-0.352	-0.728	0.141	2.475*	2.940**	1.339
	(0.873)	(0.849)	(0.765)	(1.570)	(1.585)	(1.495)	(1.346)	(1.360)	(1.432)
Unemployment Rate in year t-2	1.197**	1.071*	1.549***	1.689	1.355	2.092			
	(0.606)	(0.584)	(0.588)	(2.202)	(2.139)	(2.282)			
Unemployment Rate in year t-3	0.029	0.025	-0.189						
	(0.423)	(0.427)	(0.423)						
Unemployment Rate in year t-4	0.964	0.926	1.386						
	(1.283)	(1.250)	(1.166)						
Observations	4768	4768	4768	5511	5511	5511	5883	5883	5883
R-squared	0.982	0.982	0.986	0.978	0.978	0.978	0.967	0.967	0.960
MSA FE	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X
Control Variables	X	X	X	X	X	X	X	X	X
Weighted by Pop.	X	X	X	X	X	X	X	X	X

Notes: Robust standard errors clustered at MSA level in parentheses, control variables include share of population whites, and sex ratio. 4-year degree includes bachelor's degree, 2-year degree includes associate's degree, and sub-2-year degree includes all kinds of certificates. Regressions are weighted by 2010 MSA population. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Example of difference between IPEDS designations and "degree program based" method

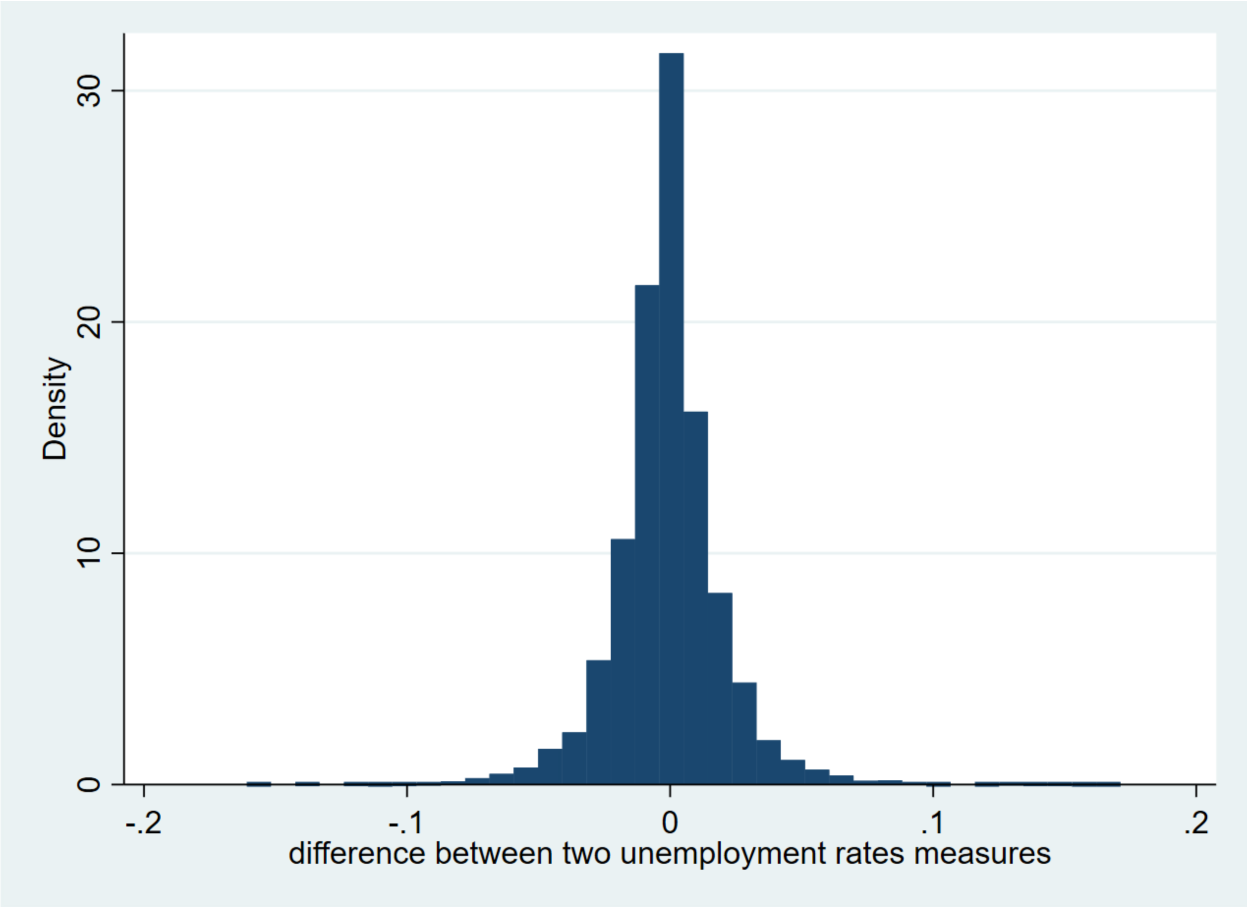


Notes: This figure compares two methods using an example of Fashion Institute of Design & Merchandising: IPEDS designations (black line) and "degree program based" method (orange line).

Figure 2: College enrollment by degree program type and unemployment rate

Notes: Figure shows total enrollment by degree program type (blue solid line) and unemployment rate (red dashed line) in US from 2001 to 2017.

Figure 3: Histogram of the difference between unemployment rates calculated by LAUS data and CPS data



Notes: Figure shows the histogram of the difference between unemployment rates calculated by LAUS data and CPS data.

Appendix

Measuring Enrollment by Program Level

I combine present year degree completion data with the same data from the previous two years to calculate three-year-average shares of three types of degrees awarded (bachelor's degrees, associate's degrees and certificates) at each institution. I then multiply these shares by the enrollment of full-time and part-time degree seeking students to calculate the number of students in each degree program.

If an institution does not have any degrees conferred in past three years, I use the nearest year's information available to impute the value. If IPEDS does not report any degree conferred information about an institution in any year, I use the type of that institution designated by IPEDS in the first year of my data sample to impute the values—this matches the standard approach (e.g., for 4-year colleges as categorized by IPEDS, I assume all students are seeking a bachelor's degree).

CPS Data Bootstrapping Procedure

The bootstrap sampling procedure is as follows: first, I randomly draw with replacement within each cell of MSA by year from original CPS data to get new sample. Then I use the new sample to calculate unemployment rates for each MSA in each year. I Repeat this 300 times, so that for each MSA in each year, I have 300 sample unemployment rates. I then Calculate the variance of the 300 unemployment rates for each MSA in each year. Then the average of the variances is the variance of sampling error.

After getting the variance of noise, I can calculate the reliability ratio of unemployment rate: $r = 1 - \frac{variance\ of\ noise}{variance\ of\ unemployment\ rate}$. When fitting the error-in-variable regressions, instead of using $(X'X)^{-1}(X'y)$, now I use $(X'X - S)^{-1}(X'y)$, where S is a diagonal matrix with elements $N(1 - r_i)s_i{}^2$, where N is the number of observations, r_i is the reliability ration of ith independent variable, and s_i^2 is the variance of ith independent variable.