MISMATCH IN LOCAL LABOR MARKETS: HOW DEMAND SHOCKS TO DIFFERENT TYPES OF JOBS AFFECT DIVERSE LOCAL LABOR MARKETS

PRELIMINARY: DO NOT CITE OR QUOTE WITHOUT PERMISSION

Timothy J. Bartik
Senior Economist
W.E. Upjohn Institute for Employment Research

November 2021

ABSTRACT

This paper estimates the effects on labor market outcomes of local labor demand shocks to different types of occupations. Occupations are divided into three groups, "high, middle, and low," with occupations differing in wages paid and education credentials required. In a wide variety of commuting zones, and for many groups, increases in mid-occupation jobs—jobs which pay relatively well compared to required credentials, such as many jobs in manufacturing—have positive effects on labor market outcomes. These positive effects tend to be stronger for more disadvantaged groups, such as groups with less education. In commuting zones with high employment rates, and for less-educated groups, increases in high-occupation jobs tend to negatively affect labor market outcomes, possibly because of effects on in-migration that push up local prices without strong direct effects on wages and employment of less-educated groups. For the less-educated group and for Black workers, and in commuting zones (CZs) which at baseline had high employment rates and low college grad percents, low-occupation demand shocks have positive outcomes. For more-educated workers, low-occupation demand shocks tend to have negative effects on real wages.

JEL Classification Codes: R23, J48

Key Words: Occupational polarization; job mismatch; local labor markets; local demand shocks; local industry targeting

Acknowledgments: I appreciate the assistance of Lillian Petrovic, Steve Yesiltepe, Shane Reed, and Claire Black. Support for this project was provided by The Pew Charitable Trusts. The views expressed herein are those of the author and do not necessarily reflect the views of The Pew Charitable Trusts.

1. INTRODUCTION

This paper estimates how different types of job growth in local labor markets affect labor market outcomes for different groups of local residents, and how these effects vary with local labor market characteristics. Does the "match" between the credentials required by different jobs, and residents' education, make a difference to how job creation affects local employment rates or wages? Does the baseline tightness of the local labor market matter? Variation in local labor market benefits might rationalize economic development strategies that target different job types, with industry targets chosen based on area characteristics.

This paper is also relevant to a national debate: what is causing recent increases in inequality? Are inequality increases due to a "polarization" of job opportunities, with job growth concentrated in either high-wage, high-education-credential jobs, or low-wage, low-education-credential jobs? What are the effects of the loss of "middle jobs," such as some manufacturing jobs, which pay relatively well compared to their credential requirements?

The dependent variables are a local labor market's changes in employment rates, real wages, and real annual earnings, from 2000 to the 2015–2019 period. These data come from the 2000 Census and the 2015–2019 American Community Survey (ACS). The local labor markets examined are the 371 commuting zones (CZs) with more than 100,000 population as of 2000, which comprise 96 percent of the U.S. population. The period examined is from business cycle peak to a period close to a business cycle peak, which arguably represents long-run trends. The various groups examined include: all persons ages 25–64; two education groups, those with less than a 4-year college degree, and those with a 4-year degree or more; two racial groups, Black persons and white non-Hispanic persons. The labor market outcomes examined are adjusted for differences in the CZ's demographic mix. Labor market outcomes also adjust for local prices.

Job type is defined by occupation. Occupations are divided into three groups: high, middle, and low, which differ in wages and education credentials, based on a grouping by Autor (2019). Demand shocks to occupation groups are measured by combining data on local industry mix, national trends in industry demand, and national trends in each industry's occupation mix. For example, a national decline in a manufacturing industry in which a CZ specializes will predict local declines in that industry, and if the industry provides many "mid jobs," will predict local declines in mid jobs. Data on industry trends and occupation mix combines information from the Upjohn Institute's WholeData series on local industry employment, derived from County Business Patterns, with occupational data by industry from the Census and ACS.

Demand shock effects are allowed to vary with two baseline (as of 2000) local characteristics: the employment rate, and the percent of 25–64 year olds with a 4-year college degree. Do demand shock effects differ if a CZ has more labor available of particular types?

The most prominent finding: mid-occupation demand shocks have positive effects, for a wide variety of groups, in many types of CZs. For the less-educated group and Black workers, in CZs with high baseline employment rates and a low baseline college grad percentage, low-occupation demand shocks also have positive effects. However, for more-educated groups, low-occupation demand shocks have negative real wage effects, which may reflect effects on in-migration and local prices without sufficient direct benefits for these more-educated groups' labor market opportunities. In CZs with high employment rates, and for less-educated groups, high-occupation demand shocks have negative effects, which may also reflect in-migration effects without direct effects on job opportunities for less-educated groups.

2. PRIOR RESEARCH

Based on prior research, demand shocks to local jobs increase local employment rates, not only in the short-run but in the long-run. A typical long-run elasticity is 0.2: a 1 percent job shock increases the local employment rate in percentage terms by 0.2 percent.[1] Local labor demand shocks also boost real wages in the short-run, but evidence on the long-run is mixed.

Why might a once-and-for-all shock to the job level in a local economy boost employment rates persistently? What might lead to this "hysteresis" effect, with a one-time event causing a permanent change in the equilibrium? One hypothesis: these hysteresis effects are due to a job shock's persistent effects on human capital, broadly defined. A short-term job shock will allow some residents to get more or better jobs. These residents will develop better job skills, and be less likely to develop mental health and substance abuse problems, get involved in crime, and have family break-ups. The children in such families may do better. Local governments may collect more tax revenue, improving public services. All these job shock effects will boost residents' productivity, making them more employable. This hysteresis argument is consistent with evidence showing effects of the local economy on mental health (Diette et al. 2018), substance abuse (Autor, Dorn, and Hanson 2019), crime (Pierce and Schott 2020), family breakups (Autor, Dorn, and Hanson 2019), child development (Bastian and Michelmore 2018, Stuart 2017) and local fiscal conditions (Charles, Hurst, and Schwartz 2018).

Local job growth's effects are progressive, but only modestly (Bartik 2020). Local job growth has percentage effects on the income of the lowest income quintile that are greater than for the highest quintile, by over two-fold. But because the highest quintile has ten-fold greater

[1] To clarify units, this is the effect on the log of the employment rate, thus in percentage terms, not percentage point terms. Bartik (2020) provides a review, and recent long-run studies include Beaudry, Green, and Sand (2014), Amior and Manning (2018) and Bartik (2021a).

income than the lowest quintile, local job growth's effects on lower-income groups are less in dollar terms. In addition, local job growth has higher effects on persons with lower education credentials (Bartik 1996, 2001). One explanation: local job growth tends to help lower-income and less-educated groups because these groups are less mobile and have more non-employed.

Research has not reached a consensus on whether local job growth has greater effects on Black workers versus white workers (Bartik 1996). Different results across studies may reflect differences in the access of Black households to job growth in diverse local areas.

What local characteristics alter local job growth's effects? A lower baseline employment rate is associated with higher effects of job growth on employment rates, in both the short-run (Austin, Glaeser, and Summers 2018; Bartik 2021b) and the long-run (Bartik 2015; Bartik 2021a). In the short-run, the elasticity is one-half greater in places at the 10th percentile of baseline employment rates, compared to those at the 90th percentile; in the long-run, the differential is greater. On the other hand, local job growth's effects on real wages appear to be higher if the local labor market is initially tighter (Bartik 2015).

For job growth's local social benefits, it is unclear how much relative weight should be placed on employment rates versus real wages. Some sparse evidence suggests greater social benefits of higher employment rates vs. real wages; for example, local suicide rates are increased more by lower employment rates than by lower incomes (Blakely, Collings, and Atkinson 2003).

What local job types matter? Some research suggests that jobs that pay relatively well, compared to the required credentials, have greater overall local labor market benefits, particularly for middle-income groups (Bartik 1996).

But no research has examined the effects of whether the new jobs match the local workforce. Match issues are important for local economic development policies. For example, in the competition for Amazon Headquarters II, some critics argued that the high-skill jobs in Amazon would not be accessible to residents. As another example, large incentives are often given to manufacturers, because these jobs often pay well relative to credential requirements.

Some research supports analyzing jobs by occupation. Macaluso (2019) finds that for workers losing jobs, a closer match between their occupation's characteristics and the local occupation mix predicts faster re-employment and higher wages. Alex Bartik (2018) finds that negative manufacturing shocks, or positive fracking shocks, have effects that differ more by occupation than industry, with effects larger for persons in manual occupations. Demaria, Fee, and Wardrip (2020) analyze what occupations offer the best odds of upward mobility.

At the national level, income inequality since the 1970s has increased. Rising income inequality since the 1970s is due in part to rising inequality across education groups. However, since 2000, there is more dispute: some studies find that education differentials have continued to increase (Hoffman, Lee, and Lemieux 2020), whereas other studies find less of a change in education differentials (Autor 2019; Gould 2020).

Black/white wage differentials have remained high. Some progress in narrowing such differentials occurred in the 1960s, but since 2000, Black wages at the median have declined relative to whites, although Black versus white wage differentials at the 90th percentile of each race have held steady (Bayer and Charles 2018).

Place differentials in employment rates, wages, and income have remained high. Historically, U.S. local economies trended towards narrower cross-area income differentials. In recent years, place disparities have been more persistent (Austin, Glaeser, and Summers 2018).

These inequality trends may in part be due to "institutional" forces: a declining real value of the minimum wages, declining unionization (Bayer and Charles 2018; Gould 2020). But these trends may also be due to changes in relative demand for different job types and relative supply of different types of workers.

One labor demand vs. supply hypothesis is David Autor's polarization hypothesis. The hypothesis: some inequality trends may be due to a polarization of job opportunities. Polarization means that labor demand has increased for jobs with high wages and high educational credentials, and for jobs with low wages and low education credentials, while labor demand has decreased for jobs which paid moderately high wages for workers with lower education credentials. These trends towards less "mid jobs" seem more acute in larger cities, and among workers with less than a college degree (Autor 2019). The argument is that this decline in mid jobs may have particularly hurt non-college graduates in larger cities,

Autor's hypothesis in part inspired this paper. Are trends in polarization in different commuting zones (CZs) correlated with labor market outcomes for different groups? Do the polarization effects vary based on CZ characteristics, such as the percent college graduates?

The model is that mid jobs have larger benefits for non-college workers. These mid jobs are accessible and relatively well-paying for non-college workers. Low jobs are accessible but pay less and elicit less labor force participation. High jobs pay well, but are not as accessible to non-college workers. Because non-college workers are less geographically mobile than college workers, non-college worker effects should dominate overall local labor market effects.

If local labor markets are initially looser (e.g., low employment rates), employment rate effects of growth in middle jobs, and perhaps other job types, should be greater. But with lower initial employment rates, the real wage effects of these local job shocks might be less. For real earnings effects, the implications of lower initial employment rates are unclear.

If local labor markets initially have fewer educated workers, local increase in high jobs may have less effects on local employment rates, and possible real wages and earnings, because these high jobs are more mismatched to the local labor supply. Because of greater matching, lower initial college grad rates may cause local increases in mid-jobs or low jobs to have greater effects on local employment rates. These differential effects may be more obvious in the groups that are matched to the labor demand shock, that is local college grads for the high-job shock, and for local non-college workers for the low-job and mid-job shocks.

Due to migration effects, positive labor demand shocks, if not well matched to a group, may affect real wages, real earnings, and employment rates negatively. For example, a high shock (low shock) may not much increase job opportunities for less-educated groups (more-educated groups), but may induce some in-migration, which would tend to increase local prices and thereby decrease real wages. The lower real wages may in turn lead to some labor supply reductions, lowering employment rates. The lower real wage and the lower employment rate will both lead to lower real earnings.

For more-educated groups, amenity effects of demand shocks may be important (Diamond 2016). More-educated groups may accept lower real wages if this is offset by higher local amenities. In-migration of more-educated workers may increase local amenities. If high-occupation demand shocks lead to more in-migration of more-educated workers, the resulting amenity increase may be a sufficient “supply-side” effect to more than offset the increased demand, resulting in some downward pressure on local real wages.

How these effects by education group extend to race is unclear. For example, Black workers may have less access to mid-jobs, so perhaps mid-job shocks have less effects on Black groups, and low-job shocks have greater effects.

3. MODEL AND DATA

This paper's model examines how different demand shocks affect the change in the natural logarithm of a CZ's labor market outcomes for different groups, adjusted for demographic mix, from 2000 to 2015–2019. The demand shocks are shocks to low-, mid-, and high-occupation jobs during this time period. Demand shocks are defined as due to the area's baseline industry mix, and national trends in industry growth and occupational demand by industry. The low, mid, and high-occupation shocks are defined so that they sum to the total share effect prediction of local job growth (Bartik 1991). These three demand shocks (low, mid, and high) are interacted with a measure of the CZ's baseline prime-age employment rate, and a measure of the CZ's baseline proportion college-educated. The interaction terms are also included directly as regressors. To ease interpretation of some coefficients, as will be detailed, the baseline college graduation rate and local employment rate are relative to appropriate national means.

This paper's model can be written as:

(1) $\ln(Y_{jz9}) - \ln(Y_{jz0}) =$

$$B_0 + B_e \times \ln(E_{z0}) + B_c \times [\ln(C_{z0}) - \ln(C_{n0})] +$$

$$B_l \times (D_{lz}) + B_{le} \times [(\ln(E_{z0})] (D_{lz}) + B_{lc} \times [\ln(C_{z0}) - \ln(C_{n0})] (D_{lz}) +$$

$$B_m \times (D_{mz}) + B_{me} \times [(\ln(E_{z0})] (D_{mz}) + B_{mc} \times [\ln(C_{z0}) - \ln(C_{n0})] (D_{mz}) +$$

$$B_h \times (D_{hz}) + B_{he} \times [(\ln(E_{z0})] (D_{hz}) + B_{hc} \times [\ln(C_{z0}) - \ln(C_{n0})] (D_{hz})$$

Here, (Y_{jz9}) and (Y_{jz0}) are some adjusted labor market outcomes for group j in CZ z at years 2015–2019 (9 subscript) or year 2000 (0 subscript). (E_{z0}) is CZ z's overall adjusted employment rate relative to the U.S. in the year 2000. (C_{z0}) and (C_{n0}) are the college grad percent of adults ages 25–64 in the year 2000 in either the CZ (subscript z) or the nation (subscript n). (D_{lz}), (D_{mz}), and (D_{hz}) are the demand shocks to low-, mid- and high-occupations in CZ z from the former to the latter period.

The CZ definitions are based on the 2010 Census and are from Fowler and Jensen (2020). Only CZs whose 2000 population exceeds 100,000 are included. In Census and ACS data, microdata observations are probabilistically assigned to CZs by mapping what proportion of the population of the Census/ACS "Public Use Microdata Area" is in a particular CZ. This amounts to adding some CZ assignment weights, which often will be 1 for many PUMAs and CZs, to the person weights that we also use in calculating CZ statistics.[2]

Labor market outcomes considered are employment rates, real median hourly wage rates, and real median annual earnings. Medians are used to reduce the influence of outliers. Real values are calculating using estimates of local prices based on Census/ACS estimates of local housing rental prices. Appendix A provides more details on these calculations.[3]

The local labor market groups considered in this paper are: everyone ages 25–64; two education groups, those ages 25–64 with less than a 4-year college degree, and those with a 4-year degree or more; two race groups, those ages 25–64 who are Black persons, and those who are white non-Hispanic persons. Local labor market outcomes for each group in each time period are adjusted to be relative to the national average, but with the demographic sub-group mix within the group held constant. Specifically, we calculate weighted averages of employment rates, median real wages, and median real annual earnings for 160 groups: four age groups (25–34, 35–44, 45–54, 55–64) by five education groups (high school dropout, high school graduate, associate degree, bachelor's degree, more than bachelor's degree) by four racial groups (white non-Hispanic, Black non-Hispanic,

[2] The use of probabilistic PUMA assignment rationalizes the minimum population size for CZs of 100,000. Below that population, the Census/ACS data does not really identify the CZ's labor market outcomes, but rather assigns a much larger area's outcomes to a smaller CZ. This is because PUMAs are defined to have a population size of around 100,000.

[3] The Appendix also provides more detail on procedures for calculating hourly wages.

Hispanic, other) by two genders. These weighted averages use, for both the CZ and the nation, the same weights, which are the weighted proportion of each sub-group in the overall group, with sub-group weights calculated for that CZ and year, and calculate the ratio of the weighted average in the CZ to the weighted average in the nation for the same time period:

(2) $Yjzt = \frac{Y_t^{Zz}}{Y_t^{Nz}} = \frac{\sum_k Sztk*Yztk}{\sum_k Sztk*Yntk}$

$Yjzt$ is the adjusted labor market outcome for either 2015–2019, or for the year 2000, with the logged difference between the two years used as a dependent variable in the estimation equations of form (1). S_{ztk} is the share of persons in the CZ who at time t are in a particular sub-group k, one of these 160 sub-groups. Y_{ztk} is the "average" labor market outcome (either the mean employment rate, or the median real wage or median real earnings) in the CZ for that time period in that particular sub-group k. Y_{ntk} is the average labor market outcome in the U.S. for that time period for that particular sub-group k. The summation, when we calculate indices for everyone ages 25–64, sums over all 160 sub-groups. In the numerator on the left-hand side of the equation, we end up with Y_t^{Zz}, which is an overall average over all 160 sub-groups of these labor market outcomes for the CZ in time period t. In the denominator, we end up with Y_t^{Nz}, which is the average that would theoretically occur if the mix of the 160 groups in the CZ at time period t were located randomly in the U.S. and then had the U.S. averages for their outcomes. Intuitively, this ratio ends up measuring average labor market outcomes for the persons in the CZ at time t, relative to what their outcomes would have been in the United States as a whole.[4]

When we instead calculate such indices for smaller groups, defined by education or race, we end up using a smaller number of weighted sub-groups. For example, for the Black group, we

[4] Why not instead use an index with uniform national weights? Because for many CZs, some of the 160 groups are not observed in the Census/ACS data, so such indices are not always feasible.

have 40 subgroups (four age groups by five education groups by two genders). For those persons with less than a four-year degree, we have 96 subgroups (four age groups by three education groups by two genders by four racial/ethnic groups).

The dependent variable then takes the natural logarithm of this relative labor market outcome for 2015–2019, and then subtracts from it the natural logarithm of this relative labor market outcome variable for 2000. The variable thus represents the logarithmic percentage change in a particular labor market outcome (employment rates, real wages per hour, real annual earnings), adjusted for demographics.

The three occupation shocks—for low-, mid-, and high-occupations—together sum to the so-called "Bartik instrument" (Bartik 1991), which predicts overall percentage growth based on the CZ's base-period industry mix, and on national industry growth rates from 1999 to 2016.[5] The Bartik instrument is defined as:

(3) $\sum_i (E_{iz0} / E_{z0}) \times [(E_{in9} - E_{in0}) / E_{in0}]$

The summation is over all industries i for each CZ z. E_{iz0} is employment in industry i in CZ z at the base time period (1999), E_{z0} is total employment in the CZ in 1999, E_{in9} is national employment in industry i in 2016, E_{in0} is national employment in industry i in 1999, and the bracketed expression is the national growth rate from 1999 to 2016 in industry i.[6] The industry data from each CZ comes from the Upjohn Institute's WholeData, which overcomes industry suppressions in County Business Patterns in over 1,000 NAICS industries for every county in the U.S., and is currently available for each year from 1998 to 2016. In regional economics, this

[5] The year 1999 is chosen rather than 2000 because the Census 2000 data on real wage rates and earnings refers to earnings and wages over the preceding year. The year 2016 is chosen because it is the last year available in WholeData, as described further below.

[6] Unlike some other researchers, I do not subtract out the own CZ from the calculation. I think it questionable that national growth is "more endogenous" than national growth after subtracting out one particular CZ. In practice, dropping one area from such calculations makes little difference.

prediction has long been known as the "share effect" in "shift-share analysis" of local area growth. The contribution of Bartik (1991) was to show that this summation over all industries was mainly driven by industries whose shares vary a lot across locations. Industries whose shares vary greatly across locations tend to be "export-base" industries that sell to a national or international market. Therefore, this share-effect prediction is a good proxy for shocks to local export-base industries due to expansions of national demand. Intuitively, the prediction assumes that as national demand expands, there is some tendency for local export-base industries to maintain their initial share of the national market in each industry.

The occupation groups used are based on a division by Autor (2019). The high-wage, high education credential occupations are three broad groups: managers and executives; professionals plus sales in finance and advertising; technicians plus fire and police occupations. The mid-wage, middle education credential occupations are: retail sales except for finance and advertising; clerical and administrative support; production and operative. The low-wage, low education credential occupations are: transportation; construction plus mechanics; services, including cleaning and protective services, personal services, and health services; farming and mining. I preferred basing my groups on Autor's classification, rather than creating from scratch my own classifications, both because his categories seemed as reasonable as any, and to avoid the temptation to manipulate the occupational classifications to get "better" results.

The demand shocks for each of the three occupational groups are the predicted change in employment by occupation, based on the CZ's baseline industry mix, national industry growth trends, and national changes in industry-occupation matrices from 2000 to 2015–2019, with these predicted occupational group changes then taken as a percentage of total baseline employment in the CZ. More specifically, the occupation demand shock is:

(4) $\sum_i (1/E_{z0}) \times [E_{izo} \times (E_{in9}/E_{in0}) \times P_{oi9} - E_{izo} \times P_{oi0}]$

In Equation (4), P_{oi9} and P_{oi0} are the national proportion of industry i's employment in occupation group o at the final time period (subscript 9), and the base time period (subscript 0). An area will have a large occupation demand shock in an occupational group if it either has a lot of fast-growing industries with above average employment shares in that occupational group, or if its industries tend to have shown greater national shifts in the share of industry employment in that occupational group. As mentioned, these three occupation shocks sum to the Bartik shock.

The cross-CZ differences in these occupation demand shocks will be driven by export-base industries, whose local shares differ across CZs. The reduced form effects of these shocks to occupation demand reflect both the direct effects of these shocks to occupation demand, and the indirect multiplier effects of these shocks on overall demand, and the occupational composition of occupational demand. For example, if a CZ happens to specialize in a manufacturing industry that does well nationally, and has an above-average share of mid-occupation jobs, the effect of an area's shock to mid-occupation jobs will reflect both the direct effect of this industry's growth, and the industry's multiplier effects. As a result of an increase in one manufacturing industry, some local manufacturing suppliers may expand. Also, the increase in these manufacturing jobs may increase demand for local retailers. The measured effect of the initial shock to mid-occupation jobs from this one manufacturing industry will also reflect all these subsequent multiplier effects on overall demand and its occupational composition.

From a local policy perspective, what matters for industry targeting is these reduced form effects. Policymakers can control the export-base industries they target, but have less influence over the resulting multiplier effects.

Industry employment numbers for the CZ and the nation are from WholeData, for 1999 and 2016.[7] Industry-occupation matrices are from the 2000 Census and the 2015–2019 ACS. Because of limitations in Census data, the industries in the industry-occupation matrix are 119 industries, mostly at the 3-digit NAICS level. The industry-occupation matrix for one of these 119 industries is assumed the same for more detailed industries within the broader industry, and combined with the more detailed WholeData. Appendix Table A15 provides an industry list.[8]

In Equation (1), some terms are differenced from a fixed variable. This allows easier interpretation of coefficients. For example, the occupational demand shock variables by themselves represent the effect of each occupational demand when the employment rate interaction term is zero (the CZ is at the national baseline employment rate), and when the college share interaction term is zero (the area's baseline college share is at the national average).

4. DESCRIPTIVE INFORMATION

Before getting to coefficient estimates, I examine national and CZ trends in key variables, to get a better sense of patterns of variation and what might drive these patterns.

---

[7] WholeData overcomes data suppressions in County Business Patterns by using CBP information on the distribution of establishments by size, and exploiting adding up constraints across industries and areas, using an algorithm by Isserman and Westerveldt (2006). Comparisons with confidential data suggest that WholeData's estimates are more accurate than alternative industry series (Carpenter, Van Sandt, and Loveridge 2021). Perhaps for this reason, the Census Bureau has increased suppressions in CBP in 2017, so WholeData currently ends in 2016. Research is underway to adapt WholeData to deal with this more extensive data suppression.

[8] Table A15 has 112 industries that are non-zero in WholeData, which excludes some industries, such as government. Seven other industries are used in some analyses of national data, which are also listed in the Appendix.

Trends in Labor Market Outcomes

The national trends in adjusted local labor market outcomes from 2000 to 2015–2019 show slight deterioration in employment rates, and modest increases in real wages and earnings. These adjusted labor market outcomes hold constant the overall local labor market shares of the 160 sub-groups at their 2015–2019 shares. As shown in Table 1, adjusted employment rates declined about 4 percent, and real wages and real earnings both went up about 1 percent.

Table 1 National Trends in Adjusted Labor Market Outcomes

	Employment Rate (%)	Real Median Wage ($)	Real annual earnings
2000	77.5	$ 24.22	$ 32,838
2015–2019	74.6	$ 24.34	$ 33,274
2000 to 2015–2019 percentage growth	−3.7	0.5%	1.3%

NOTE: Adjusted numbers based on using national weights for each of 160 sub-groups in 2015–2019 to calculate weighted averages, in 2019 prices. See text. The employment rate is also adjusted upwards for the Census's undercount relative to BLS (Clark et al. 2003), which is corrected from 2008 forward in ACS (Kromer and Howard 2011). This adjustment was the BLS vs. Census differential in April 2000 for ages 25–64 of 5.2 percentage points.

As shown in Table 2, across the 371 CZs, the logarithmic percentage change in the overall employment rate index and the real wage index show a standard deviation of 3 or 4 percent—which is considerable, indicating that some CZs show differences in growth of 6 or 8 percent. The standard deviation of growth in annual real earnings is higher, at around 11 percent.

Table 2 Changes in Local Employment Rates, Real Wages, and Real Earnings, 2000 to 2015–2019

	Employment rate	Median wage rate	Median earnings
	Adj	Adj	Adj
St. dev. for changes over 2000 to 2015–2019, across 371 CZs greater than 100K in population	3.1%	4.1%	11.4%
Correlation of change in employment rate w/ change in wage		0.146	
Correlation of change in employment rate with change in earnings			0.679
Correlation of change in wage with change in earnings			0.535

NOTE: These results are for changes in natural log of the adjusted indices for each of 371 CZs.

Changes in CZ's overall employment rates are not much correlated with changes in a CZ's real wage, indicating that these two changes may have different determinants. Both employment rate changes and real wage changes are correlated with changes in the real earnings index, with a slightly higher correlation for changes in the employment rate.

As shown in Table 3, changes over time in earnings for persons with less than a college education show a larger standard deviation than for more-educated persons. In addition, changes in earnings for Black workers show a much higher standard deviation across CZs than for white non-Hispanic workers. Disadvantaged workers are more tied to local labor market fates.

Table 3 Variation and Correlation Across Groups in 2000 to 2015–2019 Changes in Adjusted Real Earnings Across CZs

	Everyone ages 25–64	Sub-BA	BA+	Black group	White group
Standard deviation	11.4%	17.2%	8.4%	49.4%	10.7%
Correlation of Sub-BA w/ BA+		0.568			
Correlation of Black and white earnings				0.213	

NOTE: Data for everyone and different education groups is for all 371 CZs. Data involving racial groups is for 370 CZs with non-zero Black earnings cases in both 2000 and 2015–2019. The high Black variance and low correlation with white earnings gains is not just due to low sample size. Restricting sample to 300 CZs with at least 30 Black earnings cases in each time period yields: white standard deviation of 9.6 percent, Black standard deviation of 34.0 percent, and Black/white correlation of 0.246.

CZ changes in earnings for less than BA workers are moderately correlated with changes in the earnings index for BA plus workers. The correlation is weaker between Black workers and white non-Hispanic workers. The local labor market for different education groups seems more inter-related than the local labor market for different racial groups.[9]

If we look at the 69 CZs with employment greater than 1 million employment, and rank them by the change in the overall earnings index, we find that a CZ that does well overall may not do well for all sub-groups (Table 4). For example, Pittsburgh does well for everyone ages

[9] As stated in the notes to Table 3, this finding is not just due to lower sample size for Black persons.

25–64, for those with less than a BA, and for white non-Hispanic workers. But Pittsburgh's performance for the BA plus education group or for Black workers is not good. In contrast, San Francisco does well for everyone, as well as for white non-Hispanics and those with a BA or more. But San Francisco does not do well for those with less than a BA or Black workers.

Table 4 Percentage Changes in CZ Earnings Index, 2000 to 2015–2019 (%)

	Largest City in CZ	2000 population (in millions)	Everyone ages 25–64	Sub-BA education level	BA+ education level	Black group	White non-Hispanic group
Top 5	Pittsburgh	2.603	11.2	21.2	1.4	−3.2	12.7
	Manchester	1.193	9.0	13.3	8.5	2.4	9.3
	Seattle	3.942	8.8	8.1	12.0	4.3	7.8
	San Francisco	5.101	8.6	2.4	11.8	−8.4	8.7
	Oklahoma City	1.107	5.5	6.0	7.6	15.7	6.2
Bottom 5	McAllen	1.070	−8.7	−7.5	−16.8	21.4	−12.9
	Orlando	2.074	−9.4	−11.9	−6.8	−7.0	−8.5
	Detroit	5.077	−10.8	−14.7	−8.3	−15.7	−9.7
	Bakersfield	1.159	−11.4	−21.3	−1.2	−46.8	−13.4
	Miami	3.956	−12.6	−11.8	−10.9	−7.4	−10.1

Occupational Group Trends

Looking first at the national level, the data show the trend noted by Autor, away from middle occupations, and towards occupations on the low-end and especially on the high-end (Table 5). Using Census data, employment in middle occupations declines during this period.[10]

Table 5 Growth in Employment, 2000 to 2015–2019, by High, Mid, and Low Occupations

		Total	High	Mid	Low
2000	Employment(in millions)	130.9	50.3	40.7	39.8
	Percent of total employment	100.0%	38.4%	31.1%	30.4%
2015–2019	Employment(in millions)	155.9	66.7	38.9	50.3
	Percent of total employment	100.0%	42.8%	25.0%	32.3%
2000 to 2015-19 % growth, as % of total base in 2000		19.1%	12.5%	−1.4%	8.0%

NOTE: Calculations based on 2000 Census, and 2015–2019 American Community Survey.

[10] Overall percent changes in this Census/ACS comparison are biased upwards by the Census undercounting employment (relative to the CPS) in 2000 (Clark et al. 2003), and the ACS being revised from 2008 on and slightly overstating employment relative to the CPS (Kromer and Howard 2011). This is due to changes in question wording about employment status. The 2000 undercount is over 5 percent. However, the overall biases do not obviously bias the relative changes across occupation types, the focus of Table 5.

We can do a non-geographic "shift-share" decomposition of occupation trends into what is due to growth of industries with different occupation shares, and what is due to within-industry shifts in occupations.[11] The percent growth of each occupational group, as a percent of total baseline employment, can be divided into a national growth effect, a double-differential "industry share" effect, and an "industry-occupation" shift effect:

(5) National occupation growth as % of total employment =

$(1/E_b) * (\sum_i(Hfi - Hbi)$

E_b is total employment in the base period, and H_{fi} and H_{bi} are employment in a occupation group in industry i in the final period and the base period, and we sum over industries i.

(5.1) National growth effect = $\sum_i(Sbi * hfi * G)$

(5.2) Double-differential industry share effect = $\sum_i(Sbi * (hfi - hf) * (Gi - G)$

(5.3) Industry/occupation shift effect: $\sum_i(Sbi * (hfi - hbi))$

S_{bi} is the share of base period employment in industry i; h_{fi} is the share of the industry's employment in the occupation group in the final period; G is the national employment growth rate; h_f is the all-industry average of employment in the occupation group in the final period; G_i is industry i's growth rate from the base to the final period; h_{bi} is the occupation's base share in industry I employment. Expression 5 equals the sum of expressions (5.1), (5.2), and (5.3).

The national growth component shows what would have happened to occupational group growth relative to total base period employment if each industry had grown at the national rate,

[11] This "shift-share" has nothing to do with geographic shift-shares. The shares and shifts here refer to growth of industries with different occupation shares, and shifts in industry occupation shares. The geographic shares refer to national growth of industries with different local shares and the shift component is differential local growth of industries from national industry trends. Therefore, I refer in the case of the industry-occupation analysis to "industry share effects" and "industry/occupation shift effects." In addition, in the rest of this paper, when referring to geographic shift-share, I will refer to "local share effects" and "local industry shift effects."

and had the final share in each occupational group in both time periods. The double-differential industry share effect shows the differential growth in occupational employment, as a percentage of base employment, due to an industry having an occupational share that differs from the national average, combined with whether the industry grew faster or slower than the average industry. An industry can have a positive contribution by growing faster than average and having an above average occupational group share, or having a below average occupational group share and growing slower than average. Finally, the industry/occupation shift component shows the contribution to occupational group growth, as a percent of total base period employment, due to shifts over time in each industry's occupational group proportion.

Panel A of Table 6 shows the contribution of these three components to occupational growth in the nation. As shown in the table, if each industry had grown the same and occupation shares in each industry had stayed the same, each occupation would have grown. High occupational group employment grew faster than the national growth component by about 4 percent, due to an industry/occupation shift effect: occupational shares within industries shifted towards the high group. For low-group employment, growth exceeded national growth due to the industry share effect: differential industry growth of industries with different occupational shares explains the low-group's higher growth. For the middle group, both the industry share effect and the industry/occupation shift effect are important in explaining why middle group employment declined, even though overall national employment grew. Shifts in some industries went away from mid employment, and differential industry growth favored industries with less mid employment relative to those with more mid employment.

Table 6 Differential Industry Growth vs. Within-Industry Shifts as Contributors to National Trends in Job Growth by Occupation Category

Panel A: Decomposition of High, Mid, and Low Occupation Group Growth Trends by National Growth Trends vs. Industry Growth vs. Within-Industry Shifts (%)				
	Total	High	Mid	Low
2000 to 2015–2019 % growth, as % of total base in 2000	19.10	12.54	−1.41	7.97
National growth effect		8.08	5.22	5.80
Industry Share effect		0.56	−2.80	2.24
Ind/occ Shift effect		3.90	−3.83	−0.07

Panel B: Decomposition of Industry Share Effects and Ind/Occ Shift Effects by Industry Group (%)						
	Industry Share effect			Ind/Occ Shift effect		
	High	Mid	Low	High	Mid	Low
Farming and mining	0.09	0.04	−0.13	0.03	0.00	−0.03
Utilities	0.01	−0.01	0.00	0.06	−0.05	−0.01
Construction	0.04	0.03	−0.07	0.27	−0.12	−0.15
Manufacturing	0.56	−1.36	0.80	0.85	−0.80	−0.05
Wholesale trade	0.13	−0.21	0.08	0.18	−0.14	−0.03
Retail trade	0.04	−0.15	0.11	0.10	−0.13	0.03
Transportation	−0.11	−0.13	0.25	0.04	−0.13	0.09
Publishing, info	−0.24	−0.03	0.27	0.31	−0.28	−0.03
FIRE	−0.05	−0.06	0.12	0.61	−0.63	0.02
Business services	0.30	−0.28	−0.01	0.42	−0.49	0.07
Education	0.17	−0.04	−0.13	0.33	−0.28	−0.04
Health care, families and child care	0.30	−0.29	−0.01	0.41	−0.29	−0.12
Restaurants, hotels, arts	−0.50	−0.27	0.77	0.02	−0.01	−0.01
Other services	−0.06	−0.05	0.11	0.13	−0.20	0.08
Government	−0.12	0.02	0.10	0.15	−0.27	0.12
Total	**0.56**	**−2.80**	**2.24**	**3.90**	**−3.83**	**−0.07**

Panel C: Descriptors of Industry Groups' Growth Trends, Occupational Composition, and Occupational Shifts (%)								
	Industry % of total jobs, 2000	Industry growth 2000 to 2015–2019	High % 2000	Mid % 2000	Low % 2000	Change in High %, 2000 to 2015–2019	Change in Middle %, 2000 to 2015–2019	Change in Low %, 2000 to 2015–2019
Farming and mining	1.9	12.9	8.9	8.4	82.7	4.5	0.8	−5.3
Utilities	0.9	6.9	29.0	40.7	30.3	6.3	−5.0	−1.2
Construction	6.7	16.4	14.8	9.9	75.3	4.0	−1.8	−2.2
Manufacturing	14.0	−14.5	25.1	57.9	17.0	6.2	−6.4	0.2
Wholesale trade	3.6	−14.0	26.8	46.9	26.3	5.0	−4.0	−0.9
Retail trade	11.6	13.7	26.9	56.7	16.4	0.4	−0.8	0.3
Transportation	4.3	26.4	11.6	32.1	56.3	0.7	−5.7	5.1
Publishing, info	3.1	−22.8	52.0	34.4	13.6	10.5	−10.2	−0.2
FIRE	6.8	13.7	56.9	36.8	6.3	9.4	−9.9	0.5
Business services	9.2	47.9	52.7	26.0	21.3	3.9	−6.6	2.7
Education	8.7	25.5	73.9	12.2	13.9	3.6	−2.8	−0.7
Health care and families and child care	11.0	48.7	51.5	16.8	31.7	3.1	−2.3	−0.8
Restaurants, hotels, arts	7.8	47.7	19.2	13.9	66.8	0.4	−0.3	−0.1
Other services	4.8	19.2	24.0	20.5	55.5	1.5	−5.0	3.5
Government	5.6	10.5	67.8	22.7	9.5	2.9	−5.0	2.1
Total	**100.0**	**19.1**	**38.4**	**31.1**	**30.4**	**4.4**	**−6.2**	**1.8**

NOTE: Author's calculations based on 2000 Census and 2015-2019 American Community Survey.

Panel B of Table 6 breaks down the industry share and industry/occupation shift component by industry. Rather than reporting all 119 industries, the table sums the 119 industries into 15 broader industry groups. Panel C shows industry characteristics: industry growth; proportions in different occupations; shifts in occupational proportions.

For industry share effect trends, manufacturing decline is key. Manufacturing has an above average proportion of employment in mid jobs, and a below average proportion in low jobs. Therefore, its decline tends to depress mid growth, and boost low growth. Manufacturing contributed −1.36 percent to the overall share effect of −2.80 percent for mid jobs, and contributed 0.80 percent to the overall 2.24 percent share effect for low jobs.

For the industry share effect for low groups, another key industry is restaurants and bars. This industry has above average growth, and above average low jobs, which end up explaining 0.77 percent of the low group's share effect. For the low group, the decline in manufacturing, with below-average low jobs, and the increase in restaurants and bars, with above-average low jobs, together explain 1.57 percent out of the overall share effect of 2.24 percent.

For mid jobs, the industry groups of health care, restaurants and bars, and business services, all of which have above average growth, and a below average proportion of mid jobs, together contribute to a −0.84 percent share effect (−0.29 percent for health care, −0.27 percent for restaurants, −0.28 percent for business services). Together with manufacturing, these four industries contribute −2.20 percent to the total mid share effect of −2.80 percent.

For the industry/occupation shift effect, many industries shift from mid to high jobs. Important contributions are manufacturing (−0.80 percent contribution to decline of mid jobs, 0.85 percent contribution to increase in high jobs), FIRE (−0.63 percent, 0.61 percent), Business services (−0.49 percent, 0.42 percent), health care (−0.29 percent, 0.41 percent), education (−0.28 percent, 0.33 percent) and publishing and information (−0.28 percent, 0.31 percent).[12]

Occupational Group Trends by CZ

We now turn to analyzing occupational demand shocks by CZ. This is done using the Upjohn Institute's WholeData for industry data, combined with Census/ACS data on occupational group employment by industry. Demand shocks are the predicted change in occupational employment in the CZ, if each industry in the CZ expanded at its national rate, and if industry by occupation groups in the CZ changed as they did in the nation.

To set the stage, we first look at national trends in these data (Table 7), and compare them with the occupational trends previously reported in Table 6.

Table 7 Decompositions Using Census Data vs. WholeData

	Total	High	Mid	Low
Panel A: Census-based Decomposition of High, Mid, and Low Occupation Group Growth Trends by National Growth Trends vs. Industry Growth vs. Within-Industry Shifts (%)				
2000 to 2015-19 % growth, as percent of total base in 2000	19.10	12.54	−1.41	7.97
National growth effect		8.08	5.22	5.80
Share effect		0.56	−2.80	2.24
Shift effect		3.90	−3.83	−0.07
Panel B: WholeData-based Decomposition of High, Mid, and Low Occupation Group Growth Trends by National Growth Trends vs. Industry Growth vs. Within-Industry Shifts				
1999 to 2016 % growth, as percent of total base in 1999	11.45	9.46	−3.85	5.83
National growth effect		4.47	3.48	3.50
Share effect		0.91	−3.09	2.19
Shift effect		4.09	−4.23	0.14

NOTE: Panel A from prior table. Census data uses all industries, and is based on Census samples for 2000 and 2015–2019. WholeData is based on private industries only, uses administrative data, and comes from 1999 and 2016.

These WholeData calculations show similar but not identical results to the prior Census results. They differ because of differences in industry coverage, the time period considered, and different data sources.[13] But despite the differences, the WholeData also shows polarization of

[12] Note that this is non-governmental education employment.
[13] For example, as previously noted, the Census/ACS percentages are biased upwards by survey changes.

jobs, with a decline in middle jobs, and growth in both high and low occupational group jobs, with stronger growth in high jobs. Furthermore, this decline in middle jobs is due in part to differential industry growth trends, and in part due to within-industry shifts in demand for different occupations. In addition, the shift towards lower jobs is mainly due to differential growth of some industries with lots of low occupations, whereas the shift towards high jobs is mostly driven by within-industry shifts of jobs away from mid jobs and towards high jobs.

Table 8 shows descriptive statistics across the 371 CZs, including the standard deviation, both for overall growth and its components. Across the 371 CZs, overall job growth varies greatly. This job growth can be divided into a local share effect (the Bartik instrument) and a local industry shift effect. The local share effect is the predicted growth if an area's industries grew at the national average. The local industry shift effect is the remaining growth due to an area's industries growing differently than their national counterparts. The local industry share effect can be interpreted as the demand shock if the CZ's specialized industries kept their national market share as the national market for a good/service expanded or contracted—it is a

Table 8 Descriptive Statistics for Growth and Various Demand Shocks, 371 CZs, 1999 to 2016 (%)

	Mean	Median	Standard Deviation
Overall growth	8.97	6.14	17.75
Local Share effect (Bartik shock)	9.23	10.39	6.90
High group Demand shock	8.03	8.13	2.30
Differential industry growth component	4.22	4.50	2.45
Within-industry ind/occ shift component	3.81	3.85	0.46
Mid group Demand shock	−4.15	−3.64	3.21
Differential industry growth component	−0.40	0.15	2.94
Within-industry ind/occ shift component	−3.75	−3.72	0.60
Low group Demand Shock	5.35	5.41	2.03
Differential industry growth component	5.41	5.52	1.98
Within-industry ind/occ shift component	−0.06	−0.07	0.31
Local Industry Shift Effect	−0.26	−2.25	15.03

NOTE: These are unweighted statistics over 371 CZs. Overall percentage growth in jobs is divided into a component due to an area's specialized industries growing fast or slow nationally(local share effect), and a component due to industries growing faster or slower locally than nationally (last row, local industry shift effect). The local share effect is divided into three occupation shocks. Within each occupational shock, part is due to CZ having different predicted growth in industries with different occupation shares. Part is due to within-industry shifts towards or away from different occupations.

type of labor demand shock to the CZ's export base (Bartik 1991). The local industry shift effect can be interpreted as due to either labor demand or supply forces that lead to an area's industries having some competitive advantage for gaining national market share.

As is often the case for long-term growth trends, there is more variation across CZs in the local industry shift component than in the local industry share effect. However, there is still considerable variation in the share effect across CZs, the portion of growth we can most clearly identify as being demand-driven.

The table also reports descriptive statistics across the 371 CZs for occupational group demand shifters, which together sum to the total local industry share effect. The largest variation across CZs is for the mid occupation demand shifter, although there is some variation as well in the demand shifters for the other two occupation groups. For all three types of occupation group demand shifters, most of the variation across CZs is due to areas specializing in different industries that happen to have above-average or below-average proportions of employment in the three occupational groups. Relatively little is due to CZs specializing in industries that show different patterns of occupational group shifts. This may reflect that occupational group demand shifts occur across many industries, as noted before in discussing Table 6.

In Table 9, I report correlations of various growth and demand shifters across the 371 CZs. The share effect and the overall occupational demand shocks all show correlations with overall growth. Most of the occupational demand shock correlations with overall growth are due to CZs specializing in industries with different occupational employment patterns. The occupational demand shifters are all highly correlated with the overall Bartik shock, and moderately highly with each other, which raises some concern about whether the estimation will be able to accurately estimate their separate effects. Finally, each of the occupational group demand shocks are more correlated with the CZ's specialized industries having different national growth patterns and different typical occupational employment patterns, rather than due to a CZ specializing in industries that show different occupational shifts over time.

Table 9 Correlation Across 371 CZs of Various Growth and Demand Shock Measures

	Correlation with growth	Correlation w/ Bartik shock	Correlation with Mid Shock	Correlation with Low Shock	Correlation with Occupational Demand Shock
Overall growth	1.000				
Local Share effect (Bartik)	0.558	1.000			
High group demand shock	0.448	0.887	0.733	0.721	
Differential industry growth component	0.487				0.983
Within-industry ind/occ shift	−0.351				−0.234
Mid group Demand shock	0.512	0.942	1.000	0.789	
Differential industry growth component	0.517				0.985
Within-industry ind/occ shift	0.206				0.526
Low group demand shock	0.578	0.902	0.789	1.000	
Differential industry growth component	0.573				0.988
Within-industry ind/occ shift	0.127				0.234
Local Industry Shift Effect	0.925	0.200			

Finally, to get a greater feel for the patterns, Table 10 reports some data for selected "large" CZs, those over 1 million in population. All 69 of these large CZs are ranked by their occupational demand shock for the mid-group, and then the 10 top and 10 bottom CZs are reported. As can be seem, the top 10 CZs have a mid-group shock of close to zero, whereas the bottom 10 have a negative shock greater (in absolute value) than −5 percent. The top CZs generally tend to be faster growing than the bottom CZs, and have larger demand shocks for the other occupation groups. However, this pattern is not rigid, so there is considerable variation in the mid-group that is independent of what is going on with other occupation groups.

Table 10 CZs Larger than 1 Million in Population, Ranked by Predicted Demand Shock to Mid-occ Group, Top 10 and Bottom 10

Population of CZ in 2000, in millions	Largest County	State	Largest City	Overall job growth (%)	High shock (%)	Mid shock (%)	Low shock (%)
Top 10							
1.413	Clark County	NV	Las Vegas	42.8	8.6	0.6	12.4
1.268	San Joaquin County	CA	Stockton	15.7	9.0	−0.1	10.2
1.472	Orleans Parish	LA	New Orleans	−2.9	11.0	−0.8	8.1
1.085	Virginia Beach city	VA	VA Beach	8.9	10.1	−0.9	6.5
1.063	Honolulu County	HI	Honolulu	20.9	10.0	−1.0	9.2
4.415	Fairfax County	VA	DC	52.4	16.7	−1.1	6.3
1.017	Mobile County	AL	Mobile	1.9	7.9	−1.4	5.2
1.159	Kern County	CA	Bakersfield	31.4	9.6	−1.5	8.1
3.943	King County	WA	Seattle	20.4	10.6	−1.7	6.1
1.071	Hidalgo County	TX	McAllen	56.3	10.0	−1.8	10.3
Bottom 10							
16.374	Los Angeles County	CA	LA	11.3	8.0	−5.5	5.7
1.343	Kent County	MI	Grand Rapids	5.4	7.1	−5.5	4.1
2.396	Hillsborough County	FL	Tampa	9.9	7.3	−5.6	4.2
2.393	Santa Clara County	CA	San Jose	9.1	8.9	−5.7	4.6
1.096	Monroe County	NY	Rochester	2.1	8.9	−5.7	5.2
1.907	Milwaukee County	WI	Milwaukee	0.4	8.5	−6.2	5.0
1.583	Providence County	RI	Providence	5.6	8.1	−6.6	6.1
1.162	Berks County	PA	Allentown	12.9	7.5	−6.6	5.0
1.872	Mecklenburg County	NC	Charlotte	21.5	6.8	−7.6	3.8
1.284	Guilford County	NC	Greensboro	−5.3	6.6	−9.7	4.0

Descriptive Statistics for Key Dependent and Independent Variables in Regressions

Finally, before proceeding to the regression estimates, I present descriptive statistics for the key dependent and independent variables in the regressions, in Table 11. As mentioned, because the labor market variables are weighted mean indices of relative employment rates, real wages, and real earnings relative to the U.S., a value of 1 means the area has similar labor market outcomes to the U.S. as a whole. For the dependent variables, which take the change over time in the natural logarithm of these indices, these measure the log percentage change in labor market outcomes in the CZ, relative to the U.S. average. For the ln(employment rate index) used as an interaction term, this means that for a CZ whose index is at the U.S. average, this interaction term will be zero. The ln(college graduate) variable used as an interaction term subtracts out the natural logarithm of the national mean of this variable for 2000; this national mean is 26.5

Table 11 Descriptive Statistics for Key Regression Variables Across 371 CZs, 1999/2000 to 2015–2019 (%)

Group	Variable	Mean	Standard deviation	Percentile 10th	25th	50th	75th	90th
Everyone 25–64	Change in ln(emp rate index), 2000 to 2015–2019	−1.5	3.1	−5.5	−3.2	−1.1	0.5	1.9
	Change in ln(real wage index), 2000 to 2015–2019	2.5	4.1	−2.6	−0.2	2.3	5.2	7.4
	Change in ln(real earnings index), 2000 to 2015–2019	−1.0	11.4	−14.2	−7.4	−0.1	5.3	12.4
Less than BA	Change in ln(emp rate index), 2000 to 2015–2019	−1.6	3.8	−6.6	−3.8	−1.3	1.2	2.6
	Change in ln(real wage index), 2000 to 2015–2019	4.7	4.7	−1.0	1.6	4.5	7.8	10.2
	Change in ln(real earnings index), 2000 to 2015–2019	−0.8	17.2	−21.3	−10.0	0.7	8.9	19.7
BA	Change in ln(emp rate index), 2000 to 2015–2019	−1.1	2.4	−4.0	−2.5	−0.8	0.5	1.6
	Change in ln(real wage index), 2000 to 2015–2019	−0.3	5.7	−7.4	−4.0	−0.1	3.2	6.2
	Change in ln(real earnings index), 2000 to 2015–2019	−0.6	8.4	−10.2	−6.0	−0.4	4.1	9.5
Black workers	Change in ln(emp rate index), 2000 to 2015–2019	0.1	24.5	−18.4	−7.0	−1.5	5.0	18.8
	Change in ln(real wage index), 2000 to 2015–2019	3.1	22.0	−18.7	−3.5	3.5	10.5	22.4
	Change in ln(real earnings index), 2000 to 2015–2019	−0.3	49.4	−48.8	−18.5	1.1	15.5	36.1
White workers	Change in ln(emp rate index), 2000 to 2015–2019	−1.0	2.9	−5.0	−2.8	−0.8	1.0	2.4
	Change in ln(real wage index), 2000 to 2015–2019	2.7	4.1	−2.6	−0.1	2.5	5.3	7.8
	Change in ln(real earnings index), 2000 to 2015–2019	−0.9	10.8	−14.5	−7.1	−0.3	5.6	12.5
Everyone 25–64	ln(emp rate index), 2000	−1.2	5.9	−7.4	−3.9	−0.4	2.5	4.9
Everyone 25–64	ln(college grad rate in CZ) minus ln(grad rate in U.S.), 2000	−27.4	31.4	−68.9	−50.9	−27.1	−2.4	14.4
Demand shock for occupations, 1999 to 2016	High	8.0	2.3	5.3	6.5	8.1	9.6	10.6
	Mid	−4.1	3.2	−8.5	−5.7	−3.6	−2.1	−0.6
	Low	5.3	2.0	2.8	4.2	5.4	6.5	7.4

NOTE: As described in text, indices are ratio of weighted means across up to 160 demographic groups to U.S. for same time period, weighted using the period's local weights. Value of 1 for index indicates area at national average. The college grad rate variable subtracts out ln(0.265), where 26.5 percent is national mean college grad rate in 2000 for 25–64-year olds. As described in text, demand shocks are change in demand for different groups of occupations, based on industry shares in each CZ, industry growth trends, and industry-occupation matrices for 2000 and 2015–2019. All statistics use 371 CZ observations, except the Black variables are for 370 for real earnings and 369 for real wages, due to no observations for Black workers in the omitted CZs. All statistics for the CZs are unweighted.

percent. Therefore, for a CZ at the national mean for this variable, the value of this interaction term is also zero. However, as the descriptive statistics are unweighted, and the unweighted values for 371 CZs implicitly put equal weight on all CZs regardless of size, both the mean and the median of this interaction term are less than zero, as many of the smaller CZs have college grad percents well below the national mean. Finally, to avoid confusion, in the actual regressions, a logarithmic change or level variable that is 2.3 percent in this table would be entered into the computer as 0.023.

5. REGRESSION ESTIMATES

The paper now presents regression estimates. I first consider effects of occupational demand shocks on everyone, then on different education and racial groups. For each of these groupings, I first consider regression estimates, before showing these estimates' implications for effects on employment rates, wages, and earnings in diverse commuting zones.

Everyone Ages 25–64: Basic Regression Estimates

Table 12 reports estimated effects of different occupation demand shocks on the three labor market outcomes for everyone, and how effects vary with CZ baseline characteristics.

These regression coefficients show the following.[14] First, at the means, demand shocks to mid occupations have significant positive effects on real wages and real earnings, whereas demand shocks to high and low occupations do not have significant effects at the means. This mid occupation demand shock effect is of appreciable magnitude: one percent extra growth in mid occupations, as a percent of total baseline employment, increases real earnings per person by 1.4 percent. A one standard deviation change in this mid-occupation variable is 3.2 percent, so a one-standard deviation improvement would boost real earnings per person by over 4 percent.

[14] In this and in subsequent tables, coefficients with a t-statistic whose absolute value exceeds 1.96 are bolded.

Table 12 Key Coefficients in Regressions for Changes in Labor Market Outcomes for Everyone Ages 25–64
Dependent variable: change from 2000 to 2015–2019 in log of three labor market outcomes, 371 CZs

Demand shock		Employment rate	Real wage	Real earnings
High-occ	By itself	−0.0698	−0.1718	−0.2004
		(0.0984)	(0.1836)	(0.3519)
	Interacted w/ ln(EmpRate index, 2000)	**−5.84**	−0.92	**−19.13**
		(2.23)	(2.68)	(7.44)
	Interacted w/ diff of ln(CollGradRate)	0.412	−0.039	0.854
	from U.S. mean	(0.268)	(0.375)	(0.908)
Mid-occ	By itself	0.158	**0.706**	**1.356**
		(0.159)	(0.216)	(0.426)
	Interacted w/ ln(EmpRate index, 2000)	2.19	−1.38	7.07
		(1.57)	(1.38)	(4.01)
	Interacted w/ diff of ln(CollGradRate)	−0.095	0.583	0.502
	from U.S. mean	(0.418)	(0.433)	(1.139)
Low-occ	By itself	0.022	−0.347	−0.291
		(0.217)	(0.333)	(0.675)
	Interacted w/ ln(EmpRate index, 2000)	1.77	1.17	**14.63**
		(2.07)	(1.78)	(6.49)
	Interacted w/ diff of ln(CollGradRate)	−0.776	−0.961	−2.971
	from U.S. mean	(0.597)	(0.693)	(1.801)

NOTE: Robust standard errors in parentheses below regression coefficients. Regression also includes interaction variables by themselves. Coefficients with t-statistics whose absolute value exceeds 1.96 are bolded.

Second, high occupation demand shocks have statistically significantly greater effects on the employment rate and real earnings per person if a CZ's employment rate is lower. In contrast, low occupation demand shocks have statistically significantly greater effects on real earnings per person if a CZ's employment rate is higher.

How to explain these high and low occupation results? High occupation shocks may have greater effects on in-migration, particularly if the baseline employment rate is high, which will drive up local prices. Unlike high jobs, low jobs may have less migration effects; unlike mid jobs, low jobs offer less "wage premia" benefits. Perhaps low job benefits depend more on significantly tightening the local labor market and thereby changing employers' wages and hiring practices, which will occur more when the baseline employment rate is higher.

Everyone Ages 25–64: Implications of Regressions for Effects of Different Shocks in Diverse CZs

Using the estimates in Table 12, Tables 13 through 15 then explore what these estimates mean for the effects of different labor demand shocks in diverse CZs. These demand shocks differ in composition by occupation group, and the diversity across CZs is for CZs with different baseline combinations of employment rates and college graduation rates. All of these estimates are for the adjusted labor market outcomes for everyone ages 25–64.

Each of these tables presents similar types of statistics. Panel A shows how effects vary with the CZ's baseline employment rate, holding constant the CZ's baseline college grad percent.[15] The first three sets of rows (by a "set of rows" I mean a coefficient with a standard error estimate in parentheses below) show effects of demand shocks to low occupations, mid occupations, and high occupations, at different percentiles of the baseline CZ employment rate. Each of these shocks holds the other two shocks constant. This expands upon the regression estimates by showing effects and standard errors at these percentiles.

But of course, usually demand shocks do not occur just to one occupation group. If an area has industries that are growing nationally, usually this industry growth will create jobs in all three occupation groups. In other words, the three occupation group demand shocks are strongly positively correlated, with correlations of over 0.7, as shown in Table 9.

Therefore, the next set of rows shows the effects of a combination of occupation group shocks that is "average." We can define an "average" demand shock by regressing each occupation group shock on the sum of all three demand shocks, where this sum is the "local share effect" or "Bartik instrument." The resulting regression coefficients must sum to one.

[15] The college grad percent is held constant at the 2000 baseline median for all CZs.

These coefficients suggest that the "average" demand shock is 29.6 percent in high occupations, 43.8 percent in mid occupations, and 26.6 percent in low occupations.[16]

Panel B does the same kind of analysis, but this time focused on how the effects of different demand shocks vary in CZs whose baseline percentage of residents with college degrees is different.[17]

Employment rate results for everyone

Turning first to the employment rate results (Table 13), the main significant findings of Panel A are that mid jobs have significant positive effects on employment rates for CZs whose baseline employment rate was in the top quartile, and that in this same top quartile, high occupation demand shocks have negative effects on employment rates.[18] If we look at an average shock, such shocks tend to have an effect of around 0.07 to 0.11. This is somewhat less than the research literature consensus of closer to 0.20, although some literature estimates are closer to 0.10 (Bartik 2020, Table 2). The lower effects may reflect that the dependent variable here adjusts the change in employment rate for demographic composition. Also, the time period considered here is 17 years, whereas many prior studies are considering periods of about a decade, and employment rate effects may depreciate. The estimated effect of an average demand shock tends to go up in CZs with lower baseline employment rates, for example increasing by 50 percent as we go from the 90th percentile of the baseline employment rate to the 10th percentile (1.50 = 0.1109 / 0.0741). This is consistent with some prior research (Bartik 2015), but less than

[16] The coefficients (robust standard errors) on the overall demand shock in the three regressions are: high occ regression, 0.29585 (0.01076); mid occ regression, 0.43832 (0.01076); low occ regression, 0.26583 (0.00901).

[17] The CZ's baseline employment rate is held constant at the overall sample median. Thus, the estimates at the median are the same in both Panels A and B.

[18] These differences at the top quartile of employment rates are statistically significant. The t-stat on the mid shock effect vs. the high shock effect at the 75th percentile (90th percentile) is 3.29 (3.54). For low shock vs. high shock, the t-stat at the 75th (90th) percentile is 2.56 (2.77). See Appendix Table A1 for more t-stats on the differences between different shock types.

in other studies (Bartik 2021a). But the differences with the baseline employment rate are not statistically significant.[19]

Table 13 How Effects of Labor Demand Shocks on Employment Rates of Everyone Vary with CZ Characteristics

Panel A: With CZ employment rate					
	Percentile				
	10th	25th	50th	75th	90th
High	0.2528	0.0474	−0.1577	**−0.3271**	**−0.4668**
	(0.2104)	(0.1481)	(0.1090)	(0.1132)	(0.1410)
Mid	0.0211	0.0981	0.1750	**0.2384**	**0.2907**
	(0.1595)	(0.1213)	(0.1004)	(0.1039)	(0.1204)
Low	0.1009	0.1631	0.2252	0.2765	0.3188
	(0.1849)	(0.1485)	(0.1433)	(0.1650)	(0.1955)
"Average" shock	0.1109	**0.1004**	**0.0899**	**0.0812**	0.0741
	(0.0593)	(0.0399)	(0.0280)	(0.0310)	(0.0410)
Panel B: With college grad rate					
	Percentile				
	10th	25th	50th	75th	90th
High	−0.3298	−0.2560	−0.1577	−0.0557	0.0134
	(0.1861)	(0.1477)	(0.1090)	(0.1010)	(0.1185)
Mid	0.2145	0.1975	0.1750	0.1515	0.1356
	(0.1893)	(0.1317)	(0.1004)	(0.1532)	(0.2114)
Low	0.5490	0.4100	0.2252	0.0332	−0.0969
	(0.2819)	(0.1975)	(0.1433)	(0.2100)	(0.2912)
"Average" shock	**0.1424**	**0.1199**	**0.0899**	0.0587	0.0377
	(0.0385)	(0.0288)	(0.0280)	(0.0418)	(0.0546)

NOTE: Estimates based on employment rate regression reported in Table 12, and its variance-covariance matrix. Standard errors in parentheses. Bolded estimates have t-stats whose absolute value exceeds 1.96.

What this breakdown by demand shock type reveals is that the tendency of "average" labor demand shocks to have larger effects when baseline employment rates are lower is totally due to high-occupation demand shocks. High occupation demand shocks have negative effects at higher employment rates, and are more likely to increase the employment of residents if there are plenty of available local workers. In contrast, mid and low demand shocks if anything seem to have greater effects in boosting employment rates if the baseline employment rate is higher.

[19] The t-statistic on effects of the average shock at higher employment rates versus lower employment rates is −0.44. The t-statistics on the differentials of each type of shock with baseline characteristics directly follows from looking at the interaction coefficients and standard errors in Table 12.

In Panel B, the effects of the occupational demand shocks on employment rates, at different percentiles of the baseline college grad percent, are generally imprecisely estimated. However, the effect of an average demand shock is more precisely estimated. The point estimates suggest large differentials with baseline college grad percentages, with effects being much larger in CZs with low baseline college grad percentages. For example, for an average shock, the estimated effect is 278 percent greater when the baseline college grad percent is at the 10th percentile than at the 90th percentile (3.78 = 0.1424 / 0.0377). However, these differentials by baseline college grad percentages are only suggestive (t-statistic of −1.37, two-tailed probability of around 17 percent). But only CZs at around the median college grad percent or lower have statistically significant effects of “average shocks” on employment rates.

The results suggest that the places in which demand shocks make the most difference are places with lower employment rates or lower college graduation percents. Place distress, identified by whether places have higher impacts of labor demand shocks on employment rates, may be due to more than low baseline employment rates. Low baseline college grad percents may also be associated with greater effects of demand shocks on local employment rates. These two baseline characteristics are correlated: the correlation between the baseline college variable and the baseline employment rate variable used in the regressions is 0.512. The correlation may be due in part to cause and effect linkages that go in both directions. Places with low employment rates may have lower in-migration and higher out-migration of college-educated persons; places with lower college grad percents may attract less job growth, thereby reducing local employment rates.

Wage results for everyone

Turning now to the wage results for everyone in Table 14, the most statistically significant and largest finding is that shocks to mid jobs have large positive effects on real wages, in CZs with a wide variety of baseline employment rates and college grad percents. These effects are often 0.5 or above—a 1 percent shock to mid jobs, as a percent of total base employment, will increase wages by over 0.5 percent. In contrast, high jobs or low jobs do not seem to have significant positive effects on overall local real wages.[20]

Table 14 How Effects of Labor Demand Shocks on Wages of Everyone Vary with CZ Characteristics

Panel A: With CZ employment rate					
	Percentile				
	10th	25th	50th	75th	90th
High	−0.0929	−0.1252	−0.1574	−0.1840	−0.2060
	(0.2888)	(0.2149)	(0.1633)	(0.1545)	(0.1750)
Mid	**0.6509**	**0.6022**	**0.5537**	**0.5136**	**0.4805**
	(0.1878)	(0.1581)	(0.1395)	(0.1358)	(0.1415)
Low	−0.1733	−0.1322	−0.0911	−0.0572	−0.0292
	(0.2365)	(0.2219)	(0.2244)	(0.2391)	(0.2585)
"Average" shock	**0.2117**	**0.1918**	**0.1719**	**0.1555**	**0.1419**
	(0.0569)	(0.0456)	(0.0419)	(0.0460)	(0.0533)
Panel B: With college grad rate					
	Percentile				
	10th	25th	50th	75th	90th
High	−0.1410	−0.1480	−0.1574	−0.1671	−0.1737
	(0.2308)	(0.1893)	(0.1633)	(0.1846)	(0.2211)
Mid	0.3103	**0.4148**	**0.5537**	**0.6981**	**0.7958**
	(0.1721)	(0.1313)	(0.1395)	(0.2104)	(0.2722)
Low	0.3097	0.1377	−0.0911	−0.3288	−0.4898
	(0.3063)	(0.2338)	(0.2244)	(0.3220)	(0.4162)
"Average" shock	**0.1766**	**0.1746**	**0.1719**	**0.1691**	**0.1672**
	(0.0476)	(0.0396)	(0.0419)	(0.0576)	(0.0718)

NOTE: Estimates based on wage regression reported in Table 12, and its variance-covariance matrix. Standard errors in parentheses. Bolded estimates have t-stats whose absolute value exceeds 1.96.

[20] Appendix Table A2 shows the t-statistics on the differential effects of different shock types at different baseline CZ characteristics. Mid shocks have statistically greater effects than high shocks at all employment rates and college grad percents from the 25th percentile up. Mid shocks have statistically significant greater effects than low shocks at all employment rates of 50th percentile down, and all college grad percents of 50th percentile and up.

For average demand shocks, wage rate effects do not differ dramatically with either baseline employment rates or college grad percentages. This is because of the importance of mid occupation shocks in average demand shocks, and the lack of variation in these effects.

Earnings results for everyone

Based on Table 15, mid shocks have statistically significant and large effects on real earnings per person for most CZs, including all CZs in the top 75 percentiles of baseline employment rates or grad percents. A 1 percent shock to mid jobs, as a percent of total jobs, increases earnings by 0.9 to 1.6 percent. Effects increase with higher baseline employment rates, and the differential is not quite statistically significantly (t-statistic = 1.76).

Table 15 How Effects of Labor Demand Shocks on Earnings of Everyone Vary with CZ Characteristics

Panel A: With CZ employment rate					
	Percentile				
	10th	25th	50th	75th	90th
High	0.9899	0.3176	−0.3537	**−0.9078**	**−1.3651**
	(0.7042)	(0.5188)	(0.4236)	(0.4562)	(0.5494)
Mid	0.6947	**0.9431**	**1.1912**	**1.3960**	**1.5650**
	(0.4265)	(0.3385)	(0.2950)	(0.3067)	(0.3467)
Low	−0.5727	−0.0587	0.4546	0.8782	1.2279
	(0.5630)	(0.4947)	(0.5256)	(0.6167)	(0.7207)
“Average” shock	**0.4451**	**0.4917**	**0.5383**	**0.5768**	**0.6085**
	(0.1622)	(0.1174)	(0.0989)	(0.1134)	(0.1406)
Panel B: With college grad rate					
	Percentile				
	10th	25th	50th	75th	90th
High	−0.7102	−0.5571	−0.3537	−0.1423	0.0008
	(0.7019)	(0.5684)	(0.4236)	(0.3594)	(0.3904)
Mid	0.9818	**1.0717**	**1.1912**	**1.3154**	**1.3995**
	(0.5567)	(0.3985)	(0.2950)	(0.4104)	(0.5602)
Low	1.6942	1.1620	0.4546	−0.2806	−0.7784
	(0.9589)	(0.7106)	(0.5256)	(0.6547)	(0.8703)
“Average” shock	**0.6706**	**0.6138**	**0.5383**	**0.4599**	**0.4067**
	(0.1237)	(0.1015)	(0.0989)	(0.1291)	(0.1600)

NOTE: Estimates based on earnings regression reported in Table 12, and its variance-covariance matrix. Standard errors in parentheses. Bolded estimates have t-stats whose absolute value exceeds 1.96.

High shocks have statistically significant negative effects on real earnings at high baseline employment rates. At the 90th percentile, a 1 percent shock to high employment, as a percent of total employment, reduces local earnings per person by over 1.3 percent.[21]

Average overall shocks have statistically significant and large effects on real earnings at many baseline employment rates and college grad percents. A 1 percent average shock typically increases earnings by 0.4 to 0.6 percent. Effects vary little with baseline CZ characteristics.

As with the wage results, these estimates raise questions for place-based policy. Earnings effects do not vary greatly with CZ characteristics, so reallocating jobs across CZs will not necessarily boost overall earnings.

Different Education Groups: Regression Estimates

Table 16 shows regression estimates for two education groups: persons ages 25–64 with less than a bachelor's degree, and persons in that age range with a bachelor's degree or more.

Focusing first on the results at the means, a high occupation demand shock is estimated to significantly reduce real wages for less-educated workers. This may reflect in-migration and resulting housing capitalization effects not reflected in wage adjustments for this group, that is less likely to access such jobs. Mid-occupation demand shocks increase real wages and real earnings, both for the less-educated group and the more-educated group. The effects are greater on real earnings for the less-educated group, which is less mobile. Low-occupation demand shocks depress real wages for the more-educated group. This result may also be due to in-

[21] As shown in Appendix Table A3, which does t-statistics on the differences across shock types in Table 15, mid shocks have statistically significant greater effects than high shocks at the 50th, 75th, and 90th percentiles of the employment rate distribution, and at the 25th, 50th and 75th percentiles of the college grad percent distribution, in each case holding the other baseline variable constant at the median.

migration and capitalization effects, and the irrelevance of these jobs to the more-educated group's job opportunities.

Table 16 Key Coefficients in Regressions for Changes in Labor Market Outcomes for Persons with Different Educational Attainment

Dependent variable: change from 2000 to 2015–2019 in log of following labor market outcome, 371 CZs

Demand shock		Results for persons with less than bachelor's degree			Results for bachelor's degree or more		
		Employment rate	Real wage	Real earnings	Employment rate	Real wage	Real earnings
High-occ	By itself	−0.1297	**−0.5410**	−0.8396	0.0817	−0.1778	−0.1523
		(0.1264)	(0.2098)	(0.5112)	(0.0934)	(0.2315)	(0.3215)
	Interacted w/ ln(EmpRate index, 2000)	**−6.32**	0.72	−17.65	−1.49	−1.57	−4.10
		(2.73)	(3.15)	(10.94)	(1.29)	(3.44)	(5.28)
	Interacted w/ diff of ln(CollGradRate) from U.S. mean	0.595	**−0.980**	0.572	−0.109	0.036	−0.060
		(0.337)	(0.432)	(1.319)	(0.232)	(0.545)	(0.798)
Mid-occ	By itself	0.240	**0.743**	**1.951**	−0.116	**0.940**	**0.728**
		(0.208)	(0.244)	(0.633)	(0.106)	(0.319)	(0.354)
	Interacted w/ ln(EmpRate index, 2000)	1.86	−2.22	4.06	**2.82**	−1.03	**6.80**
		(1.96)	(1.66)	(6.45)	(0.83)	(1.88)	(2.78)
	Interacted w/ diff of ln(CollGradRate) from U.S. mean	−0.133	0.765	1.327	−0.201	0.854	−0.648
		(0.533)	(0.520)	(1.656)	(0.248)	(0.584)	(0.709)
Low-occ	By itself	0.080	0.216	0.112	0.061	**−0.978**	−0.079
		(0.301)	(0.359)	(1.005)	(0.150)	(0.425)	(0.534)
	Interacted w/ ln(EmpRate index, 2000)	1.95	2.35	**26.33**	−1.79	−0.79	**−8.57**
		(2.61)	(2.22)	(9.20)	(1.12)	(3.29)	(3.67)
	Interacted w/ diff of ln(CollGradRate) from U.S. mean	−0.803	−0.556	**−4.966**	0.088	−0.812	1.619
		(0.794)	(0.841)	(2.567)	(0.395)	(0.884)	(1.195)

NOTE: Robust standard errors in parentheses below regression coefficients. Regression also includes interaction variables by themselves. Bolded coefficients have t-statistics whose absolute value exceeds 1.96.

For the employment rate interaction terms, a higher CZ employment rate at baseline will tend to:

- Lower a high occupation demand shock's effects on the less-educated group's employment rate;
- Boost a mid-occupation demand shock's effects on the more-educated group's employment rate and earnings;
- Boost a low-occupation demand shock's effect on the less educated group's real earnings.
- Lower a low occupation demand shock's effects on the more-educated group's real earnings.

These significant interaction effects can be explained by reasonable stories. Higher employment rates tend to increase in-migration and capitalization effects, but may reduce employment rate effects and increase real wage effects. For shocks that are poorly matched to a group (high occupation shocks for less-educated workers; low occupation shocks for high-education workers), the capitalization effects dominate. For other shocks, significantly tightening the local labor market may sometimes allow for direct labor market effects to dominate.

For the college graduation interaction terms, a higher local college grad percentage results in:

- Lower effects of a high-occupation demand shock on the less-educated group's real wages.
- Lower effects of a low-occupation demand shock on the less-educated group's real earnings.

These effects can be explained by telling a mismatch story. With more college grads, a high-occupation demand shock will not lead as much to employers upgrading less-educated persons to these jobs, as more college grads are available for these jobs. With more college grads, a low-occupation demand shock will lead to more in-migration, as fewer well-matched local workers are available, lowering effects on real earnings.[22]

[22] What about the statistical significance of the differences between the less- and more-educated groups? Appendix Table A4 examines this in one possible way, by using as a dependent variable the DIFFERENCE between the dependent variables for the less-educated group minus the more-educated group for the same labor market outcomes. This test conditions on the overall fixed effect. The differences that are "statistically significant," at standard levels (absolute t-stat exceeds 1.96) are the following. For mid shocks, the less-educated group's earnings are more affected by these shocks at the mean than for the more-educated group. For the low-shocks, the more-educated group's wages are more negatively affected than the less-educated group. In addition, for real earnings, the low-occupation shock varies more with either the baseline employment rate or the baseline college grad percent for the less-educated group.

Different Education Groups: Implications of Regressions for Effects of Different Shocks in Diverse CZs

Using the estimates in Table 16, Tables 17 through 19 show how different education groups have labor market outcomes affected by different labor demand shocks, and how this varies with CZ characteristics. Table 17 considers employment rates, Table 18 wage rates, and Table 19 earnings. The format of these three tables is similar to Tables 13 through 15, but these new tables present the estimates for the two education groups side-by-side.

Employment rate results for different education groups

As shown in Table 17, the main result for employment rate effects on different education groups is that effects are much larger for the less-educated group than the more-educated group. For an average demand shock, the effect on the employment rate of the less-education group ranges from 0.08 to 0.16, that is an average demand shock of 1 percent will boost employment rates in the less-educated group from 0.08 percent to 0.16 percent. The average shock's effects on employment rates of the more-educated group are much lower, and almost always statistically insignificant.

For this less-educated group, these average demand shock effects tend to be greater in CZs with lower baseline employment rates or college grad percentages. But these differences are not statistically significant.[23]

For the less-educated group, the effects of average demand shocks reflect diverse effects of the different occupational demand shocks. Mid-occupation shocks have positive effects on the less-educated group's employment rates, particularly at high baseline employment rates. High-

[23] The t-statistic on the average shock's difference with baseline employment rates is -0.65, and the differences with baseline college grad percentages is −0.80.

Table 17 How Effects of Labor Demand Shocks on Employment Rates of Non-College vs. College Grads Vary with CZ Characteristics

	Persons with less than a bachelor's degree					Persons with a bachelor's degree or more				
Panel A: With CZ employment rate										
	Percentile					Percentile				
	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
High	0.179	−0.043	**−0.265**	**−0.448**	**−0.600**	0.222	0.170	0.117	0.074	0.038
	(0.255)	(0.178)	(0.130)	(0.136)	(0.171)	(0.169)	(0.138)	(0.117)	(0.110)	(0.114)
Mid	0.138	0.203	**0.268**	**0.322**	**0.367**	**−0.272**	**−0.172**	−0.073	0.009	0.076
	(0.202)	(0.154)	(0.127)	(0.130)	(0.150)	(0.096)	(0.079)	(0.070)	(0.071)	(0.077)
Low	0.153	0.221	0.290	0.346	0.393	0.170	0.107	0.044	−0.008	−0.051
	(0.246)	(0.196)	(0.183)	(0.204)	(0.239)	(0.134)	(0.123)	(0.125)	(0.135)	(0.149)
"Average" shock	**0.1540**	**0.1351**	**0.1162**	**0.1007**	0.0878	−0.0081	0.0032	0.0144	0.0237	0.0313
	(0.0732)	(0.0494)	(0.0347)	(0.0380)	(0.0500)	(0.0351)	(0.0270)	(0.0221)	(0.0221)	(0.0250)
Panel B: With college grad rate										
	Percentile					Percentile				
	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
High	**−0.514**	**−0.407**	**−0.265**	−0.118	−0.018	0.163	0.143	0.117	0.090	0.072
	(0.221)	(0.174)	(0.130)	(0.129)	(0.156)	(0.189)	(0.155)	(0.117)	(0.096)	(0.101)
Mid	0.324	0.300	**0.268**	0.236	0.213	0.011	−0.025	−0.073	−0.123	−0.157
	(0.232)	(0.160)	(0.127)	(0.201)	(0.277)	(0.111)	(0.080)	(0.070)	(0.103)	(0.137)
Low	0.625	**0.481**	0.290	0.091	−0.044	0.007	0.023	0.044	0.066	0.081
	(0.350)	(0.239)	(0.183)	(0.290)	(0.403)	(0.222)	(0.167)	(0.125)	(0.146)	(0.190)
"Average" shock	**0.1562**	**0.1391**	**0.1162**	0.0925	0.0765	**0.0549**	0.0375	0.0144	−0.0096	−0.0259
	(0.0481)	(0.0350)	(0.0347)	(0.0540)	(0.0712)	(0.0268)	(0.0222)	(0.0221)	(0.0292)	(0.0362)

NOTE: Estimates based on employment rate regressions in Table 16, and their variance-covariance matrices. Standard errors in parentheses. Estimates whose t-stat exceeds 1.96 in absolute value are bolded.

occupation demand shocks have negative effects on the less-educated group's employment rates for some CZs, those with high baseline employment rates or low college grad rates.[24]

Wage results for different education groups

As shown in Table 18, average demand shocks increase real wage rates much more for less-educated groups, compared to more educated groups. For the less-educated group, a one percent average demand shock increases real wages by 0.2 to 0.3 percent, at a variety of baseline

[24] Appendix Table A5 presents evidence on the statistical significance of differentials in different shocks. Among other results, for the less-educated group, mid shocks have greater effect than high shocks at the 50th through 90th percentiles of the baseline employment rate, and at the 10th through the 50th percentile of the baseline college grad rate. Appendix Table A6 looks instead at regressions of the DIFFERENCE between the changes in employment rates of the less-educated minus the more-educated group. The less-educated group shows significantly higher effects of average shocks, particularly at lower baseline employment rates. This is largely due to significantly higher effects of mid shocks, particularly at lower employment rates. High shocks have significantly more negative effects on the employment rate of the less-educated group if the baseline employment rate is high or the baseline college grad percent is low.

employment rates and college grad percents. For the more-educated group, average demand shocks increase real wages by an amount generally less than 0.1 percent, and the effects are statistically insignificant. This pattern presumably in part reflects the greater mobility of the more-educated group.

Table 18 How Effects of Labor Demand Shocks on Wages of Non-College and College Grads Vary with CZ Characteristics

	Non-college graduates					College graduates				
Panel A: With CZ employment rate										
	Percentile					Percentile				
	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
High	−0.329	−0.303	−0.278	−0.257	−0.240	−0.071	−0.126	−0.181	−0.227	−0.264
	(0.334)	(0.249)	(0.192)	(0.185)	(0.212)	(0.371)	(0.296)	(0.258)	(0.266)	(0.299)
Mid	**0.701**	**0.623**	**0.545**	**0.481**	**0.428**	**0.785**	**0.748**	**0.712**	**0.682**	**0.658**
	(0.212)	(0.173)	(0.148)	(0.143)	(0.150)	(0.275)	(0.243)	(0.228)	(0.228)	(0.239)
Low	0.192	0.274	0.357	0.425	0.482	**−0.699**	**−0.727**	**−0.754**	**−0.777**	**−0.796**
	(0.264)	(0.245)	(0.249)	(0.271)	(0.298)	(0.345)	(0.308)	(0.313)	(0.347)	(0.390)
"Average" shock	**0.2609**	**0.2561**	**0.2514**	**0.2475**	**0.2443**	0.1372	0.0976	0.0581	0.0254	−0.0015
	(0.0632)	(0.0512)	(0.0478)	(0.0527)	(0.0609)	(0.0879)	(0.0708)	(0.0648)	(0.0704)	(0.0809)
Panel B: With college grad rate										
	Percentile					Percentile				
	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
High	0.131	−0.045	−0.278	**−0.521**	**−0.685**	−0.196	−0.190	−0.181	−0.172	−0.166
	(0.274)	(0.225)	(0.192)	(0.212)	(0.252)	(0.411)	(0.335)	(0.258)	(0.234)	(0.259)
Mid	0.226	**0.363**	**0.545**	**0.734**	**0.862**	0.356	**0.509**	**0.712**	**0.924**	**1.067**
	(0.197)	(0.142)	(0.148)	(0.237)	(0.314)	(0.268)	(0.220)	(0.228)	(0.310)	(0.387)
Low	0.589	0.489	0.357	0.219	0.126	−0.416	−0.561	**−0.754**	**−0.955**	**−1.091**
	(0.399)	(0.296)	(0.249)	(0.347)	(0.458)	(0.438)	(0.344)	(0.313)	(0.413)	(0.524)
"Average" shock	**0.2942**	**0.2758**	**0.2514**	**0.2261**	**0.2089**	−0.0126	0.0178	0.0581	0.0999	0.1283
	(0.0568)	(0.0473)	(0.0478)	(0.0628)	(0.0775)	(0.0721)	(0.0625)	(0.0648)	(0.0831)	(0.1008)

NOTE: Estimates based on wage regressions in Table 16, and their variance-covariance matrices. Standard errors in parentheses. Estimates whose t-stat exceeds 1.96 in absolute value are bolded.

For the less-educated group, the average shock's positive wage effects mostly reflect the positive effects of mid-occupation demand shocks. For CZs with a variety of baseline characteristics, mid-occupation demand shocks tend to have an effect in the range from 0.4 to 0.9—a 1 percent increase in demand to these types of jobs, compared to overall employment, increases wages by 0.4 to 0.9 percent. These mid-occupation effects offset some negative effects at high college graduation rates of high-occupation demand shocks. These negative effects may reflect mismatch between high-occupation shocks and this less-educated group, which may lower real wages due to in-migration and capitalization effects on local prices. .

For the more-educated group, the average shock's small effects reflect the countering influence of mid-occupation versus low-occupation demand shocks. For the more-educated group, mid-occupation demand shocks have large positive effects, while low-occupation demand shocks have large negative effects. For the mid-occupation shocks, the higher real wages for the more-educated group can be explained as the expected effect of such a labor demand boost. For the low-occupation shock, the lower real wage can plausibly be explained by economic reasoning as the result of in-migration and capitalization effects on local prices, and the absence of any direct labor market benefits for such a high-education group of a low shock.[25]

Earnings results for different education groups

As Table 19 shows, the average demand shocks also have much larger effects on the less-educated group, compared to the more-educated group. For the less-educated group, for a wide variety of CZ baseline characteristics, an average demand shock of 1 percent is estimated to increase real earnings per person by 0.5 to 1.0 percent. For the more-educated group, a 1 percent demand shock only increases real earnings per person by 0.1 to 0.3 percent.

For the less-educated group, the average shock's effects positive effects largely reflect positive effects of mid-occupation demand shocks. These effects are quite large: a 1 percent shock to mid-occupation demand, as a percent of total jobs, raises real earnings by 1.2 percent to

[25] Appendix Table A7 examines t-statistics on the DIFFERENCES between the shock effects shown in Table 18 at various baseline CZ characteristics. For the less-educated group, mid shocks have greater effects than high shocks at most baseline characteristics. For the more-educated group, mid shocks have greater effects than both low shocks and high shocks for most baseline characteristics. Appendix Table A8 estimates the statistical significance of the cross-group differences in Table 18, by regressing, on the same right hand side variables, the DIFFERENCE between the changes in wages of the less-educated group, minus the more-educated group. Average demand shocks have significantly larger effects on the less educated group at most baseline characteristics. The low demand shock has significantly more negative effects for the more-educated group at most baseline characteristics.

2.1 percent, under various CZ baseline conditions. At high baseline employment rates or low baseline college grad percents, less-educated workers are also helped by low-occupation demand shocks. In high employment rate CZs, less-educated groups' real earnings are negatively affected by high-occupation demand shocks, which may reflect migration and capitalization effects.

Table 19 How Effects of Labor Demand Shocks on Earnings of Non-College & College Grads Vary with CZ Characteristics

	Non-college graduates					College graduates				
Panel A: With CZ employment rate										
	Percentile					Percentile				
	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
High	0.317	−0.303	−0.923	**−1.434**	**−1.856**	0.168	0.025	−0.119	−0.238	−0.336
	(1.109)	(0.813)	(0.623)	(0.621)	(0.731)	(0.566)	(0.447)	(0.386)	(0.399)	(0.450)
Mid	1.289	**1.432**	**1.575**	**1.692**	**1.789**	0.399	**0.638**	**0.876**	**1.073**	**1.236**
	(0.676)	(0.518)	(0.427)	(0.435)	(0.497)	(0.339)	(0.280)	(0.247)	(0.247)	(0.266)
Low	−0.498	0.427	1.351	**2.114**	**2.744**	0.119	−0.182	−0.483	−0.731	**−0.936**
	(0.850)	(0.748)	(0.778)	(0.895)	(1.033)	(0.415)	(0.379)	(0.385)	(0.421)	(0.467)
"Average"	**0.5266**	**0.6517**	**0.7765**	**0.8795**	**0.9646**	**0.2564**	**0.2385**	**0.2206**	**0.2058**	**0.1936**
shock	(0.2643)	(0.1894)	(0.1528)	(0.1709)	(0.2122)	(0.1070)	(0.0782)	(0.0669)	(0.0770)	(0.0950)
Panel B: With college grad rate										
	Percentile					Percentile				
	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
High	−1.161	−1.059	−0.923	−0.781	−0.685	−0.094	−0.105	−0.119	−0.134	−0.144
	(1.027)	(0.833)	(0.623)	(0.529)	(0.572)	(0.630)	(0.513)	(0.386)	(0.327)	(0.350)
Mid	1.021	**1.259**	**1.575**	**1.903**	**2.125**	**1.147**	**1.031**	**0.876**	**0.716**	0.607
	(0.788)	(0.562)	(0.427)	(0.611)	(0.833)	(0.320)	(0.251)	(0.247)	(0.345)	(0.439)
Low	**3.424**	**2.534**	1.351	0.122	−0.710	**−1.158**	−0.868	−0.483	−0.082	0.189
	(1.359)	(1.017)	(0.778)	(0.976)	(1.283)	(0.585)	(0.445)	(0.385)	(0.518)	(0.670)
"Average"	**1.0140**	**0.9120**	**0.7765**	**0.6356**	**0.5403**	**0.1670**	**0.1900**	**0.2206**	**0.2524**	**0.2739**
shock	(0.1856)	(0.1518)	(0.1528)	(0.2060)	(0.2573)	(0.0820)	(0.0667)	(0.0669)	(0.0907)	(0.1136)

NOTE: Estimates based on earnings regressions in Table 16, and their variance-covariance matrices. Standard errors in parentheses. Estimates whose t-stat exceeds 1.96 in absolute value are bolded.

For the more-educated group, the average shock's positive but smaller effects on real earnings largely reflect positive but smaller effects of mid-occupation demand shocks. Compared to the less-educated group, a mid-occupation demand shock of 1 percent increases real earnings by perhaps 0.6 percent to 1.2 percent, or a little more than half of the estimated effects on the less-educated group. For the more-educated group, low-occupation or high-occupation demand shocks do not appear to have positive real earnings effects.[26]

Different Racial Groups: Regression Estimates and Selected Results for Diverse CZs

Table 20 shows regression estimates of how different demand shocks affect labor market outcomes for the Black group and the non-Hispanic group. As can be seen in the table, the estimates for the Black sample are quite imprecise for employment rates and wages, but more significant results occur for earnings. The white estimates are very similar to the overall estimates for everyone ages 25–64.[27]

Therefore, my discussion focuses on the real earnings results on the Black group, and contrast these results with the results for the white group, which are similar to the overall sample.

As shown in Tables 20 and 21, high-occupation shocks tend to have strong negative effects on Black earnings, compared to white earnings, although the differences are not statistically significant. High-occupation shocks may cause more adverse gentrification effects on Black real earnings.

For the Black group, mid shocks have strong positive effects on Black earnings, particularly in CZs with low or moderate employment rates, or CZs with moderate or high college grad percents. These effects are large: a 1 percent mid shock increases Black earnings in some CZs by 3 to 9 percent. This pattern of effects may reflect relative supply and demand:

---

[26] Appendix Table A9 shows that many of the different shock effects shown in Table 19 are statistically significantly different. Appendix Table A10 focuses instead on the differences in earnings effects between the two groups, and finds for many baseline CZ characteristics that both average earnings effects and the low shock effects are higher for the less-educated group.

[27] As appendix Table A11 shows, the Black employment rate and wage results are noisy enough that that are very few statistically significant differences between the Black vs. white employment rate and wage results. The earnings results show significantly higher Black effects of mid shocks at the means, and significantly lower Black effects of high shocks at the means. Black earnings effects also show more significant variation with baseline CZ characteristics.

Table 20 Key Coefficients in Regressions for Changes in Labor Market Outcomes for Persons from Two Different Racial Groups

		Results for Black persons			Results for white persons		
Dependent variable: change from 2000 to 2015–2019 in log of following labor market outcome, 371 CZs							
Demand shock		Employment rate	Real wage	Real earnings	Employment rate	Real wage	Real earnings
High-occ	By itself	−1.4167	−0.3509	**−5.1921**	−0.0922	−0.1742	−0.0483
		(1.2820)	(1.2742)	(2.5805)	(0.0916)	(0.1838)	(0.3470)
	Interacted w/ ln(EmpRate index, 2000)	22.28	−26.07	34.84	−6.77	0.30	**−19.67**
		(22.81)	(20.30)	(38.84)	(1.93)	(3.10)	(6.88)
	Interacted w/ diff of ln(CollGradRate) from U.S. mean	−4.281	3.903	−2.464	0.187	0.181	0.825
		(2.205)	(2.427)	(3.805)	(0.235)	(0.389)	(0.893)
Mid-occ	By itself	1.883	1.276	**7.139**	0.140	**0.573**	**1.231**
		(1.154)	(1.152)	(2.359)	(0.148)	(0.224)	(0.431)
	Interacted w/ ln(EmpRate index, 2000)	−16.78	−0.46	−34.67	**3.35**	−1.78	**8.11**
		(13.11)	(8.39)	(17.69)	(1.35)	(1.54)	(3.82)
	Interacted w/ diff of ln(CollGradRate) from U.S. mean	2.864	1.801	**12.554**	−0.146	0.314	−0.046
		(2.863)	(2.252)	(4.665)	(0.351)	(0.435)	(1.027)
Low-occ	By itself	−2.079	1.118	−1.902	0.094	−0.199	−0.434
		(1.415)	(1.548)	(2.639)	(0.206)	(0.302)	(0.646)
	Interacted w/ ln(EmpRate index, 2000)	−3.56	8.75	**66.80**	1.64	−0.12	**12.26**
		(16.39)	(14.22)	(23.79)	(1.60)	(2.03)	(5.35)
	Interacted w/ diff of ln(CollGradRate) from U.S. mean	−2.472	−2.961	**−18.130**	−0.447	−0.709	−1.930
		(3.654)	(3.358)	(6.423)	(0.520)	(0.598)	(1.659)

NOTE: Robust standard errors in parentheses below regression coefficients. Regression also includes interaction variables by themselves. Coefficients whose ratio to their standard error has an absolute value of 1.96 or above are bolded. Sample size for Black persons for earnings is 370 CZs, and for wages is 369 CZs.

when there are more college grads in the workforce, and the employment rate is low, more Black workers may be able to access these mid jobs.

Low-occupation demand shocks have strong positive effects on Black earnings in some CZs, those with high employment rates and low college grad percents. In these CZs, a 1 percent low shock increases earnings by 6 to 10 percent. With a tighter labor market, but with many non-college grads who are employed, employers may be motivated to seek out a wider variety of local non-college workers, including Black non-college workers.[28]

[28] Appendices Tables A12 and A13 examine the statistical significance of the shock differences for each racial group, and of the differences across racial groups. For the Black group, mid and low shocks tend to have significantly greater earnings effects than high shocks for many baseline characteristics. For cross-race differentials, effects on Black earnings minus white earnings are significantly greater for mid shocks when the baseline employment rate is low or the college grad rate is high. For low shocks, Black effects are significantly greater than

Table 21 How Effects of Labor Demand Shocks on Earnings of Two Racial Groups Vary with CZ Characteristics

	Results for Black Persons					Results for White Persons				
Panel A: With CZ employment rate										
	Percentile					Percentile				
	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
High	−7.114	−5.889	−4.666	−3.657	−2.824	1.190	0.499	−0.191	−0.761	**−1.231**
	(4.613)	(3.437)	(2.465)	(2.035)	(2.109)	(0.657)	(0.491)	(0.408)	(0.439)	(0.524)
Mid	**6.310**	**5.091**	**3.875**	2.870	2.042	0.641	**0.926**	**1.211**	**1.445**	**1.639**
	(2.297)	(1.873)	(1.586)	(1.509)	(1.573)	(0.422)	(0.339)	(0.297)	(0.305)	(0.340)
Low	−1.949	0.399	2.743	4.678	**6.275**	−0.822	−0.391	0.039	0.395	0.688
	(2.287)	(2.071)	(2.179)	(2.484)	(2.840)	(0.518)	(0.474)	(0.501)	(0.571)	(0.652)
"Average"	0.1429	0.5953	1.0470	**1.4198**	**1.7275**	**0.4146**	**0.4496**	**0.4844**	**0.5132**	**0.5370**
shock	(0.8473)	(0.6694)	(0.5618)	(0.5564)	(0.6122)	(0.1513)	(0.1113)	(0.0938)	(0.1048)	(0.1276)
Panel B: With college grad rate										
	Percentile					Percentile				
	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
High	−3.638	−4.080	−4.666	**−5.276**	−5.689	−0.535	−0.388	−0.191	0.013	0.151
	(2.911)	(2.613)	(2.465)	(2.653)	(2.949)	(0.676)	(0.546)	(0.408)	(0.354)	(0.390)
Mid	−1.364	0.885	**3.875**	**6.981**	**9.085**	**1.230**	**1.221**	**1.211**	**1.199**	**1.192**
	(1.958)	(1.530)	(1.586)	(2.305)	(2.954)	(0.485)	(0.357)	(0.297)	(0.417)	(0.553)
Low	**10.308**	**7.061**	2.743	−1.743	−4.781	0.844	0.499	0.039	−0.438	−0.762
	(3.618)	(2.784)	(2.179)	(2.566)	(3.270)	(0.881)	(0.658)	(0.501)	(0.627)	(0.825)
"Average"	1.0659	1.0578	1.0470	1.0358	1.0282	**0.6050**	**0.5533**	**0.4844**	**0.4129**	**0.3645**
shock	(0.6198)	(0.5461)	(0.5618)	(0.7022)	(0.8399)	(0.1177)	(0.0956)	(0.0938)	(0.1249)	(0.1561)

NOTE: Estimates based on earnings regressions in Table 20, and their variance-covariance matrices. Standard errors in parentheses. Estimates whose t-stat exceeds 1.96 in absolute value are bolded.

For an average composition demand shock, the effect on Black real earnings goes up with baseline employment rates by quite a bit, although this result falls short of statistical significance (t-statistic = 1.73). Effects do not vary much with the baseline college grad percent.

This pattern also raises questions for place-based policy. Average demand shocks in CZs that are "distressed" in that they have low employment rates yields little benefits for Black earnings, even though it increases white earnings. Only in CZs whose baseline employment rate is quite high does the average employment shock significantly increase Black earnings. This pattern fits into the stereotype that Black workers are the last hired for many higher paying jobs. For an average job shock to increase Black earnings, it takes a really hot local labor market.

white effects when the baseline employment rate is high or the college percent is low. For high shocks, effects on Black vs. white earnings are significantly lower when the college grad percent is high.

Reflections on Regression Results

Based on these results, the most important implication is that increases in mid jobs are likely to have higher economic and social benefits, at least at the local labor market level. Mid shocks tend to have the most consistent positive effects on employment rates, wages, and earnings for a wide variety of groups in a wide variety of commuting zones. Mid shocks tend to have stronger effects for more disadvantaged groups, such as less-educated groups and Blacks.

In contrast, high shocks may even have negative effects on labor market outcomes in some CZs, such as those that start out at a high baseline employment rate. These negative effects are particularly large for less-educated groups.

In CZs with high employment rates and low college grad percents, low-occupation demand shocks have large positive effects on earnings of less-educated and Black workers. But for more-educated groups, low-occupation demand shocks have negative effects on real wages.

Ex post, these patterns of effects can be "explained", by a model of labor demand and supply with capitalization. Mid shocks have wide benefits because they pay higher wages but are accessible to many groups. Low shocks and high shocks tend to have greater relative benefits for the group most likely to gain these jobs, less-educated workers for the low shocks, and more educated workers for the high shocks. The negative effects on the "mismatched" group that are sometimes observed may reflect in-migration effects that push up prices, without corresponding greater job availability for the mismatched group.

At the national level, the empirical estimates cannot be immediately quantitatively applied. The national effects of mid shocks, for example, would have to take these results, and combine them with migration estimates, and some assumptions about the spatial pattern of different shocks, to infer how some national pattern of mid shocks would affect national labor market outcomes. Local estimates are not enough for any quantitative estimates of national effects, without some general equilibrium model of how local estimates fit into a national economy with geographic labor mobility. But it does seem right to make some qualitative inferences at the national level: declines in mid jobs may hurt many workers' labor market outcomes, and particularly workers with less educational credentials, racial disadvantages, or other characteristics that affect their ability to access high-occupation jobs.

Of course, these results do not demonstrate that this particular job categorization, into Autor's low vs. mid vs. high jobs, is the optimal way to categorize jobs. Perhaps another grouping by occupation or industry would do better in predicting local labor market outcomes. But this grouping seems to "work" in that effects do differ significantly by these three job types.

At the local level, the results support the conventional wisdom that less-educated workers and disadvantaged races are more affected by local labor demand shocks. These greater effects may reflect that such workers are less geographically mobile than more-educated white groups.

For place-based policy, the results suggest that policymakers should consider this question: what are the relative social benefits of boosting local employment rates, versus boosting local earnings? If boosting local employment rates provide much higher social benefits, per dollar of earnings created, compared to boosting earnings through higher wages or work hours, then these results support the conventional wisdom that place-based policies should be targeted at places that are "distressed" in the sense of having low employment rates. The results suggest that such distressed places are even more in need of a labor demand boost if a higher percent of the local population lacks a college degree, which may reduce mobility. However, if what matters is the local real earnings boost from place-based policies, such geographic targeting does not have a clear rationale. Local demand shocks may boost earnings as much in CZs with higher baseline employment rates as those with lower baseline employment rates.

The results do show that more than the overall job creation matters. Job type also matters, and in particular local economic development policies in most local areas should consider how to target mid-occupation jobs, and whether high or low jobs better match the local labor supply.

To help in targeting, the next section provides information on benefits of different job types in different CZs, and on what job types are provided by different export-base industries.

6. DIVERSE CZ JOB NEEDS AND APPROPRIATE TARGET INDUSTRIES

Although most CZs will benefit most from demand increases for mid occupations, high and low job types may have stronger effects for some CZs. Furthermore, state and local policymakers, to bring about these occupation demand shocks, must identify appropriate target industries, for example industries to be targeted for economic development assistance.[29]

To identify which CZs most need which job type, calculations were based on the earnings regressions for the less-educated group. Why this choice? First, earnings are a more appropriate bottom line than employment rates or wages. Second, the less-educated group and the more-educated group have quite different earnings effects. Third, given trends towards increased inequality, it is sensible to target economic development to help the less-educated group.

For each CZ, the calculation is the estimated earnings effects on the less-educated group of each of the three demand shocks. As mentioned before, these demand shocks to a job type are due to the area's industry mix and national trends, and is calculated as a percentage of the area's base employment. The earnings effects are the change in the natural logarithm of the less-educated group's earnings per capita for 25–64-year-olds. Thus, the calculation is of a particular

[29] Policymakers could also try to encourage employers within an industry to change their relative job type mix, but this is likely to be more complex to design and harder to accomplish.

elasticity. Based on the interaction terms in the regression, these estimated elasticity effects will vary with the CZ's baseline employment rate, and percent of residents who are college graduates.

The calculations are based on the latest ACS data, from 2015–2019. This means that the calculations are up to date predictions for what would be the effect of demand shocks to different job types in each CZ, given the CZ's characteristics "today" (or rather 2015–2019).

Given the way the demand shocks are defined, these demand shocks reflect shocks to export base industries, as they affect each job type, as a percent of base employment. These export-base demand shocks will in turn have multiplier effects, on a variety of other industries. The estimates reflect the reduced form effects of both the initial change in job type demand, and what other types of multiplier effects this might have on other industries and the various job types. But these reduced form effects are appropriate for state and local economic development policy. Policymakers can target attracting location decisions or encouraging expansions of a particular export-base industry. But the resulting multiplier effects of other industries to a large extent occur naturally, without further policy intervention.

Appendix Table A14 shows the calculations for all 371 CZs. Table 22 reports selected results from the full sample for the most populous CZs, and for CZs that have unusually high effects for the high shock and the low shock.

From the full appendix Table A14, in 223 of the 371 CZs, the largest elasticity is for the mid-demand shock. But these 223 CZs tend to include the largest CZs, so 86 percent of the total population of these 371 CZs is in these 223 CZs.[30] Of the 371 CZs, 116 have their highest effect from the low demand shock, and 32 from the high demand shock. But because these 116 and 32 CZs are smaller, they comprise only 12 percent and 2 percent, respectively, of the 371 CZ total

[30] In turn, as previously mentioned, these 371 CZs are 96 percent of the U.S. population.

population. Most people live in CZs where mid shocks have greater earnings effects for persons with less than a four-year college degree.

As shown in Table 22, the largest CZs in most cases tend to have their largest elasticity of earnings for the mid demand shock. The smaller CZs that have the highest effects from high demand shocks tend to be CZs with very low employment rates and low college graduation rates.

Table 22 Results for Selected CZs for Predicted Effects on Earnings of Less-than-bachelors Group of Low, Mid, and High Demand Shocks

CZ number	CZ population in 2000	Most populous county in CZ, 2000	Emp rate index relative to nation, 2015–2019	College percent of population ages 25–64, 2015–2019 (%)	High effect	Mid effect	Low effect
Panel A: Results for 10 most populous CZs							
69	16,372,860	Los Angeles CA	0.993	31.7	−0.74	1.86	0.16
405	10,762,079	Kings NY	1.005	41.4	−0.80	2.26	−0.83
159	8,610,555	Cook IL	1.018	40.9	−1.03	2.30	−0.44
391	6,661,455	Bergen NJ	1.027	44.7	−1.14	2.45	−0.65
58	5,100,708	Alameda CA	1.023	48.3	−1.04	2.54	−1.12
296	5,077,106	Wayne MI	0.981	34.0	−0.49	1.90	−0.50
538	4,770,018	Harris TX	1.001	32.8	−0.86	1.93	0.20
281	4,751,998	Middlesex MA	1.031	50.0	−1.14	2.61	−1.10
92	4,435,552	Philadelphia PA	1.000	41.0	−0.73	2.23	−0.90
93	4,414,255	Fairfax VA	1.058	52.1	−1.59	2.78	−0.61
Panel B: Results for 5 CZs with highest high shock effects							
254	117,860	Harlan KY	0.681	12.8	5.38	−0.87	−5.24
252	241,910	Pike KY	0.682	13.1	5.37	−0.84	−5.32
248	144,876	Laurel KY	0.750	13.8	3.72	−0.39	−3.06
31	266,731	Navajo AZ	0.748	12.3	3.72	−0.55	−2.58
590	275,785	Mercer WV	0.762	15.2	3.52	−0.20	−3.16
Panel C: Results for 5 CZs with highest low shock effects							
316	106,811	McLeod MN	1.119	21.3	−3.08	1.81	5.30
205	212,843	Woodbury IA	1.116	23.4	−2.98	1.93	4.75
198	190,148	Cerro Gordo IA	1.108	23.7	−2.85	1.91	4.52
191	131,395	Grant WI	1.108	23.8	−2.85	1.92	4.50
618	195,484	Sheboygan WI	1.105	23.9	−2.79	1.92	4.38

NOTE: See appendix Table A14 notes for more detail on calculations. The predictions are based on coefficients from Table 16 for the less-educated group for earnings effects, and use the 2015–2019 value in the CZ of the employment rate index and the college grad percent.

For low demand shocks, the CZs with the greatest benefits tend to be CZs with high employment rates and below average college graduation rates. These patterns reflect the interaction coefficients in the earnings regression for less-educated workers from Table 16. High shocks pay off the most if a CZ's employment rate is low. Low shocks pay off the most if a CZ has a high employment rate and a low college grad percent.[31]

Suppose state and local policymakers want to bring about a demand shock to mid-occupation jobs, or (for a significant number of smaller CZs) to low-occupation jobs, or (for a very few smaller CZs) to high-occupation jobs. What industries should be targeted? First of all, policymakers will want to target "export-base" industries, which in turn employ above-average percentages of the types of jobs that are desired.

Export-base industries can be identified in a variety of ways. One way to do so is to look at how much an industry's share of total employment varies across different areas. Industries that sell mostly locally will tend to have a similar share of total area employment in most areas. For example, restaurants and bars will tend to have a similar share of total employment in most local economies, as people buy these goods and services locally. In contrast, motor vehicles manufacturing will comprise a widely varying share of employment in different local economies.

Using WholeData for 2016, the last year in the data, I calculated the "location quotient" for each of the 112 industries in WholeData, for each of the 371 CZs. The "location quotient" is the CZ's share of total employment in that industry, divided by the national share of employment in that industry. For each industry, the standard deviation of this location quotient was calculated across the 371 CZs. The 112 industries were then rank-ordered by this standard deviation, with the larger standard deviations representing industries more likely to be export-base, and the smaller standard deviations representing industries more likely to be locally-oriented.

[31] This is further confirmed by calculating the correlation between the high and low demand shock effects for a CZ and the CZ's baseline characteristics. The area's high effect has a negative correlation with the area's employment rate of −0.990. The area's low effect is correlated with the area's employment rate (college grad percent) by 0.598 (−0.264).

Across all 112 industries, the highest standard deviation of the CZ location quotient was for coal mining, followed by tire manufacturing. The lowest standard deviation of the CZ location quotient was for restaurants and bars, followed by personal services.

The full ranking of all 112 industries is shown in appendix Table A15. As a rough guide to thinking about possible export-base industries, I set a cutoff such that all industries were included that had a standard deviation of their location quotient that was equal to or higher than "software publishers." This cutoff included all manufacturing industries as export-base industries, along with various services industries and distribution industries, such as business support services and warehousing. Of the 112 industries, 59 industries were classified as export-base. However, these 59 industries only comprised 15 percent of total employment.

Table 23 provides an excerpt of appendix Table A15. The excerpt is limited to industries that are "export-base" according to my definition (based on the LQ standard deviation), and have 200,000 or more employees (in 2016, based on WholeData). These are 28 industries, which comprise 65 percent of total export-base employment, and about 10 percent of total employment.

For each of the 28 industries (in Table A15, for all 112 industries), I report the industry's employment size, the standard deviation of its location quotient, and the percent of employment that is in low-, mid-, and high-occupations. In addition, boldface on these percentages of industry employment in each occupation type are used for percentages that are "unusually" high, which is defined as at least one-standard deviation higher than the all-industry mean.

Of the 28 larger industries in Table 23, 11 are unusually high in their "mid" share. These comprise many but not all manufacturing industries, for example manufacturing industries such as motor vehicle manufacturing and fabricated metal products. But this list also includes business support services. These 11 industries comprise only 5 percent of total employment, and only 33 each opercent of total export-base employment. An area that wanted to focus on growing mid employment would focus on only a portion of the export-base sector.

Table 23: Occupational Group Shares of Larger, Export-base Industries

Industry group	Industry description	Industry employment, 2016	St. dev LQ	Low share (%)	Mid share (%)	High share (%)
3116	Animal slaughtering, processing, and seafood	421,202	4.37	28.0	**58.4**	13.6
337	Furniture and related products manufacturing	359,933	4.04	18.0	**62.8**	19.2
313-315	Fabric and textile mills & apparel	302,633	3.50	12.7	**66.3**	21.0
321	Miscellaneous wood product manufacturing	351,448	3.34	29.9	53.5	16.6
322	Paper and pulp mills and products	334,672	3.24	23.9	**54.6**	21.5
335	Electrical machinery and equipment manufacturing	333,844	2.92	12.3	52.6	35.0
3361-3363	Motor vehicles and motor vehicle equipment mfg	861,870	2.86	16.9	**56.1**	27.0
3391	Medical equipment and supplies	275,880	2.82	7.7	48.1	44.2
5111	Newspapers and book publishing	350,552	2.65	5.5	24.7	**69.8**
all other 325	Industrial and miscellaneous chemicals	225,219	2.38	16.1	41.3	42.6
3254	Pharmaceuticals and medicines	246,051	2.36	7.8	32.1	**60.2**
3364	Aircraft and aerospace manufacturing	395,524	2.23	11.6	34.2	54.2
all other 311	Dairy, animal foods specialty foods	668,250	1.69	30.0	47.9	22.2
all other 339	Miscellaneous manufacturing	252,227	1.66	18.8	**55.4**	25.8
3261	Plastics products	598,596	1.51	18.6	**59.6**	21.8
333	Machinery manufacturing	979,932	1.46	13.8	51.4	34.8
all other 334	Other electronic components and products.	736,040	1.44	6.5	34.1	**59.4**
all other 327	Cement, concrete, & other non-metallic mineral prod	245,001	1.36	37.1	40.3	22.6
3118	Bakeries	289,434	1.29	22.1	**64.4**	13.5
493	Warehousing and storage	812,620	1.19	**54.2**	36.6	9.3
332	Fabricated metal products manufacturing	1,367,201	1.17	15.5	**61.3**	23.2
488	Services incidental to transportation	677,864	1.16	**53.3**	25.7	21.1
323	Printing and related support activities	437,522	1.09	9.0	**64.8**	26.2
721	Traveler accommodations	1,971,617	1.07	**59.5**	20.5	20.0
5614	Business support services	751,639	1.04	5.5	**67.6**	26.9
562	Waste management and remediation services	375,310	0.87	**63.7**	19.3	17.0
22	Utilities	604,385	0.85	29.1	35.7	35.3
5112	Software publishers	516,621	0.85	1.0	18.4	**80.6**

NOTE: This table is excerpted from appendix Table A15. The industries selected are those whose standard deviation of the location quotient across CZs is equal or greater than software publishing, and which had 200,000 or more employees as of 2016. The bold percentages are percentages in low, mid, or high occupations that exceed a cutoff of 1 standard deviation above the unweighted mean share in that industry. These cutoffs are: low, 51.4%; mid, 54.5%; high, 57.1%.

Within this group of 28 larger industries, four are unusually focused in "low" occupations. This includes industries such as warehousing. These four industries comprise 3 percent of total employment, and 21 percent of total export-base employment.

Of the 28 larger industries, four are unusually concentrated in their "high" share. This includes software publishers, but also such manufacturing industries as pharmaceuticals, and other electronics components. These four industries are only 2 percent of total employment, and 10 percent of export employment.

The remaining 9 of the 28 larger export-base industries are not unusually high in any of the three occupational type shares, although obviously they all vary to some degree from the all-industry average.

In evaluation of an area's industry targeting—both past performance and future plans—state and local policymakers might find it useful to analyze the total effects by occupation group of the mix of industries actually attracted or grown, or that the area plans to attract or grow. If a CZ is one of the many CZs that might want to increase demand for mid-occupations, the CZ might want to consider how industry targets can be emphasized that will hire such occupations.

7. CONCLUSION

One conclusion from these results is the importance of job type. Different occupational demand shocks have different effects on different groups, sometimes of opposite sign, not just magnitude.

The results support the "polarization hypothesis" of David Autor in its broadest form: mid jobs matter. They particularly matter in many of the largest CZs, which are often at or above the national average in their employment rates and college grad percents. More mid jobs boost employment rates, wages and earnings, and the loss of such jobs depresses these outcomes.

Matching jobs to skills also matters. High-occupation demand shocks have greater relative benefits for the more-educated, low-occupation shocks for the less-educated.

From a policy perspective, the results suggest that policymakers should consider if there are cost-effective ways to create more mid job opportunities. Such jobs seem to offer broad benefits. For example, can policies such as manufacturing extension, or customized job training, help manufacturing firms that offer mid jobs to be more competitive, and expand? (Bartik 2010)

More broadly, if mid jobs offer large benefits because they pay wage premia, policymakers should consider how policy can encourage more firms to adopt a "good jobs" strategy. Wage standards can be pushed up through higher minimum wages and easier unionization (Autor, Mindell, and Reynolds 2020), or even more ambitiously, by government wage boards (Dube 2019). Policymakers can also consider how to facilitate upward mobility to mid jobs (Demaria, Fee, and Wardrip 2020).

Research should push beyond the limits of the current analysis, and consider alternative ways of categorizing job type, and categorizing local labor market characteristics. What is the best way to classify jobs by type if the goal is to estimate job type effects on labor market outcomes? What local labor market characteristics offer the most power in determining how job shocks will affect labor market outcomes? The research challenge is how to meaningfully summarize the complexity of labor markets, in a way that can guide both how we think about labor markets, and how we act to improve their functioning.

APPENDIX

More Details on Data Creation Procedures, and Supplemental Tables

Housing Price Calculations and Local Price Calculations

Local prices are constructed based on a rental price index for each CZ in both the 2000 time period, and the 2015–2019 period. For each time period and each CZ, we estimate mean rental prices for 2-bedroom apartments, and mean rental prices for 3-bedroom apartments. We do the same calculations for the entire United States. Also, for the nation, we calculate the shares of 2-bedroom apartments and 3-bedroom apartments. Using those shares, we calculate a weighted average for 2- and 3-bedroom apartments together, both for each CZ and the nation. The ratio of this weighted average for each CZ, to the same weighted average for the nation, is the CZ's rental price index.

We then subtract 1 from this relative housing price ratio to get each area's differential housing price, as a proportion of national housing prices in the nation. We multiply this ratio by 0.50, and then add back in the 1. The resulting ratio is the estimated local price differential.

The 0.50 weight on relative housing prices in overall local prices is derived based on Aten (2006). She calculates relative housing price differentials and relative overall local price differentials for 38 areas using BLS data. A regression of the relative overall local price differential on the local housing price differential yields a coefficient of 0.501 with a standard error of (0.029). This 0.50 coefficient is somewhat greater than the weight of 0.42 that overall housing has in BLS's Consumer Price Index.

Other researchers have used similar procedures. Moretti (2013) and McHenry and McInerny (2014) both used the simpler method of simply taking the ratio of average 2-bedroom and 3-bedroom rent in each local area to the nation, without calculating 2-bedroom and 3-

bedroom separately. As an alternative, we also did those simpler calculations, and found a correlation of 0.99 across 371 CZs with our more complex procedure. McHenry and McInerney used a weight of around 0.40, derived from the housing weight in the CPS. Moretti used a weight of 0.62, derived from a regression of changes in overall local prices on changes in local housing prices. McHenry and McInerny's procedure seems likely to underweight the housing influence on local prices, as it ignores spillover effects of local housing prices on other local prices. Moretti's approach may overstate the long-run influence of local housing prices on overall local prices, as demand shocks that increase local housing prices will also increase local real wages.

One note: it is possible that this procedure means that demand shocks that particularly increase real wages—for example, mid demand shocks in this current paper—may lead to higher increases in local prices than are derived from this estimation procedure. The rationale: if wages go up more, this puts more upward pressure on local prices. Therefore, the regression-estimated effects on real wages may be somewhat overstated. The problem is that really both wages and prices are simultaneously determined, and the fully correct procedure is to simultaneously estimate both of them. The challenge: we only have a limited number of CZs with price info, which restricts our ability to do such simultaneous estimation. However, given that not all of a wage increase will be translated into local price increases, the estimates given here should be right qualitatively in terms of what shocks increase real wages or real earnings the most.

Wage Calculations

Using Census and ACS data, wage rates are calculated as wage and salary earnings divided by annual hours worked. Observations are dropped if self-employment income is nonzero, as respondent reports of weeks worked and work hours could include self-employment. Annual hours worked are derived by multiplying usual hours worked per week by weeks worked. Weeks worked are derived as the midpoint of the weeks-worked interval reported in the Census or ACS. Individual observations are dropped if the number of weeks worked is less than 14 or the usual hours worked are fewer than 11. The dropping of usual hours worked if they are fewer than 11 is based on measurement error due to respondents misinterpreting the question as being asked about usual hours worked in a day rather than a week, as documented by Baum-Snow and Neal (2009). The midpoint assignment of weeks worked is similar to procedures used by Perry, Thomason, and Bernhardt (2016), who also provide evidence that this method yields similar results to using continuous weeks worked, except for the first interval, weeks worked less than 14, which is dropped in this analysis.

Allocated Observations and Sample Sizes

The calculations for employment rates, earnings, and wages exclude "allocated variables," that is cases where there was no response for the person to the Census or ACS question, and the Census Bureau filled in the answer based on similar persons. Because more people refuse to answer the earnings question, the sample size is smaller for earnings than for employment rates. Because wages are only defined for persons who work, and because (see above) wages are only calculated for persons with particular responses about self-employment income, weeks worked and hours worked per week, the sample size for estimating wages is even smaller than for earnings.

Both the 2000 Census and the 2015–2019 ACS are about a 5 percent sample. The minimum population size of the CZs in the sample is 100,000. Therefore, the sample size is generally good for most groups, with the exception of Black people in some CZs. At the extreme, 2 of the 371 CZs have no valid observations in the 2000 Census on Black wages, and must be excluded from the regressions. The median sample size among the 371 CZs for the

Black wage sample is 146 persons, and the 10th percentile is 6 persons, so there are some sample size issues here. Some experimentation with restricting the Black sample to CZs where there are at least 30 observations on earnings did not suggest results that were much different, and this restricted sample tended to blow up standard errors.

For the other groups, sample size is not a problem. The next smallest group is persons with a BA or more. The minimum BA plus sample size for the wage variable in the 2000 Census data is 154 persons, and the 10th percentile of this sample size distribution is 296 persons.

Occupational Classification

The occupational classification into three groups sought to approximate the three-group classification used by Autor (2019), which in turn is based on occupational classifications previously developed by Dorn (no date, downloaded November 1, 2021). However, we simplified this task by using the OCC1990 code reported in IPUMS.

Our classification using OCC1990 is as follows:

- High occupations are occupations 3 to 258 minus 175 (recreation workers) and plus 417 to 423 (fire and police) and 905 (military).
- Mid occupations are 274 to 389, plus occupations 628 through 799, and dropping occupations 748 (laundry workers) and 773 (motion picture projectionists)
- Low occupations are 405 to 617, and 803-889, plus 175, 748, and 773.

Supplemental Tables

Fifteen tables supply supplemental information to the estimates reported in the text tables. The tables fall into two groups, with two added tables that each stand on their own.

Group 1 are tables that provide t-tests of whether the effects of the different effects vary: what are the relative effects of low shocks versus high shocks, mid shocks versus high shocks, and low shocks versus mid shocks. To derive these t-tests, the difference between the two shock estimates was calculated, and then the relevant variance-covariance matrix from the underlying regression was used to calculate the standard error of this difference. Each of these appendix tables has a note describing what table they relate to. If a user wants to know the difference for which the t-test is performed, they can go back to the table and calculate the difference from the estimates presented. The standard error would then be the difference divided by the t-statistic; from the way the t-statistic is defined. These tables are Tables A1, A2, A3, A5, A7, A9, and A12.

Group 2 are tables that provide estimates and standard errors of the difference between the estimates for two different groups, either the less than four-year degree group versus the bachelor's group, or the Black group vs. the white non-Hispanic group. These estimates are derived by using the same right-hand side variables, but using as a dependent variable the change in a labor market outcome for one group MINUS the change for the other group. The resulting estimated coefficient for the education breakdown is simply equal to the less than 4-year college estimate minus the bachelor's plus estimate, in the text tables. But the standard error estimate is one type of statistical test for whether the two groups differ. In the case of Black minus white estimates, the estimates for the Black group by itself, and for the Black minus white differential, are only 370 CZ observations for earnings, and 369 for wages, so the estimates are not precisely the same as Black estimates minus white estimates, as the white estimates are based on 371 CZs. But this is still a test of whether the Black and white estimates differ for this slightly smaller sample. The appendix tables in this group are Tables A4, A6, A8, A10, A11, and A13.

Table A14 uses the coefficient estimates for the less-educated group for earnings changes, and the characteristics of each CZ in the 2015–2019 period, to predict the elasticity with respect to different types of occupation shocks for each of the 371 CZs.

Table A15 reports the standard deviation of the 2016 location quotient across 371 CZs for each of the 112 industries that are non-zero in WholeData. The table is sorted from highest to lowest standard deviation, which approximately sorts for the extent to which the industry is "export-base." The table also reports the percent of the industry's employment that, as of 2015–2019, was in low-, mid-, and high-occupations.

Some of the national analyses of industry and occupation data use seven additional industries that are identified in a way that can be reconciled over time in Census/ACS data, but are not in WholeData, because they are not in County Business Patterns. These include: Crop production (NAICS 111); Animal production (112); Rail transportation (482); Postal services (491); Household services (814); Government except for military (921-927); Military (928).

Table A1 t-stats on Shock Differentials in Employment Rate Effects at Different Percentiles of Distribution of Baseline Employment Rates and College Grad Percents

Panel A: With CZ employment rate					
	Percentile				
	10th	25th	50th	75th	90th
Low-high	−0.46	0.47	1.81	2.56	2.77
Mid-high	−0.74	0.23	2.03	3.29	3.54
Low-mid	0.30	0.29	0.23	0.16	0.10
Panel B: With college grad rate					
	Percentile				
	10th	25th	50th	75th	90th
Low-high	2.30	2.31	1.81	0.36	−0.35
Mid-high	1.83	2.05	2.03	1.02	0.45
Low-mid	0.76	0.70	0.23	−0.35	−0.49

NOTE: These t-stats correspond to testing whether shock effects vary at different percentiles in Table 13. For example, "Low-high" at 90th percentile of employment rate is t-test of low shock of 0.3188 in Table 13, minus high shock of −0.4668. This difference, divided by standard error of the difference, yields 2.77.

Table A2 t-stats on Shock Differentials in Wage Effects at Different Percentiles of Distribution of Baseline Employment Rates and College Grad Percents

Panel A: With CZ employment rate					
	Percentile				
	10th	25th	50th	75th	90th
Low-high	−0.19	−0.02	0.21	0.39	0.50
Mid-high	1.80	2.33	2.94	3.02	2.65
Low-mid	−2.29	−2.20	−1.97	−1.70	−1.45
Panel B: With college grad rate					
	Percentile				
	10th	25th	50th	75th	90th
Low-high	1.03	0.82	0.21	−0.39	−0.61
Mid-high	1.36	2.15	2.94	2.69	2.38
Low-mid	0.00	−0.84	−1.97	−2.14	−2.07

NOTE: These t-stats correspond to testing whether shock effects of different shock types (high, mid, low) vary at different percentiles in Table 14.

Table A3 t-stats on Shock Differentials in Earnings Effects at Different Percentiles of Distribution of Baseline Employment Rates and College Grad Percents

Panel A: With CZ employment rate					
	Percentile				
	10th	25th	50th	75th	90th
Low-high	−1.42	−0.44	1.01	1.98	2.42
Mid-high	−0.30	0.87	2.66	3.69	3.88
Low-mid	−1.70	−1.45	−1.02	−0.64	−0.37
Panel B: With college grad rate					
	Percentile				
	10th	25th	50th	75th	90th
Low-high	1.74	1.61	1.01	−0.17	−0.75
Mid-high	1.64	2.04	2.66	2.47	1.90
Low-mid	0.51	0.09	−1.02	−1.65	−1.65

NOTE: These t-stats correspond to testing whether shock effects of different shock types (high, mid, low) vary at different percentiles in Table 15.

Table A4 Effects of Key Variables on Difference of Change in Less-Educated Minus More-Educated Groups' Labor Market Outcomes

Dependent variables: Change from 2000 to 2015–2019 for less-educated group, minus change for more-educated group, for 3 labor market outcomes

Demand shock		Employment rate	Real wage	Real earnings
High-occ	By itself	−0.211	−0.363	−0.687
		(0.129)	(0.238)	(0.493)
	Interacted w/ ln(EmpRate index, 2000)	−4.83	2.29	−13.56
		(2.56)	(3.62)	(10.77)
	Interacted w/ diff of ln(CollGradRate) from	0.704	−1.016	0.632
	U.S. mean	(0.363)	(0.626)	(1.452)
Mid-occ	By itself	0.356	−0.196	**1.223**
		(0.212)	(0.306)	(0.591)
	Interacted w/ ln(EmpRate index, 2000)	−0.96	−1.19	−2.74
		(2.05)	(2.09)	(7.07)
	Interacted w/ diff of ln(CollGradRate) from	0.068	−0.089	1.975
	U.S. mean	(0.584)	(0.667)	(1.558)
Low-occ	By itself	0.019	**1.194**	0.191
		(0.315)	(0.408)	(0.890)
	Interacted w/ ln(EmpRate index, 2000)	3.74	3.15	**34.90**
		(2.74)	(4.33)	(8.00)
	Interacted w/ diff of ln(CollGradRate) from	−0.891	0.256	**−6.585**
	U.S. mean	(0.910)	(1.168)	(2.197)

NOTE: Robust standard errors in parentheses below regression coefficients. Regression also includes interaction variables by themselves. As expected, these coefficients exactly equal the difference in coefficients from Table 16. Coefficients whose ratio to their standard error exceed in absolute value 1.96 are bolded.

Table A5 t-statistics on Differences in Effects of Different Kinds of Shocks for Different Education Groups at Different Percentiles of Baseline CZ

	Persons with less than a bachelor's degree					Persons with a bachelor's degree or more				
Panel A: With CZ employment rate										
	Percentile					Percentile				
	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
Low-high	−0.06	0.86	2.14	2.78	2.88	−0.20	−0.27	−0.35	−0.39	−0.40
Mid-high	−0.11	0.90	2.65	3.67	3.69	−2.13	−1.85	−1.24	−0.45	0.24
Low-mid	0.04	0.06	0.08	0.08	0.08	2.53	1.72	0.70	−0.09	−0.64
Panel B: With college grad rate										
	Percentile					Percentile				
	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
Low-high	2.47	2.60	2.14	0.63	−0.06	−0.43	−0.42	−0.35	−0.12	0.04
Mid-high	2.33	2.67	2.65	1.33	0.65	−0.62	−0.86	−1.24	−1.33	−1.17
Low-mid	0.55	0.49	0.08	−0.32	−0.40	−0.01	0.22	0.70	0.84	0.79

NOTE: This Table presents t-statistics on the differences between the different shocks from Table 17.

Table A6 Differences in Effects of Shocks on Less-Educated Minus More-Educated Employment Rates, at Various CZ Characteristics

Panel A: With CZ employment rate					
	Percentile				
	10th	25th	50th	75th	90th
High	−0.043	−0.213	**−0.383**	**−0.522**	**−0.638**
	(0.256)	(0.188)	(0.148)	(0.151)	(0.179)
Mid	**0.409**	**0.375**	**0.342**	**0.314**	0.291
	(0.198)	(0.149)	(0.125)	(0.134)	(0.159)
Low	−0.017	0.114	0.246	0.354	0.443
	(0.258)	(0.210)	(0.200)	(0.225)	(0.262)
"Average" shock	**0.1621**	**0.1319**	**0.1019**	**0.0770**	0.0565
	(0.0716)	(0.0484)	(0.0343)	(0.0377)	(0.0496)

Panel B: With college grad rate					
	Percentile				
	10th	25th	50th	75th	90th
High	**−0.676**	**−0.550**	**−0.383**	−0.208	−0.090
	(0.257)	(0.204)	(0.148)	(0.132)	(0.153)
Mid	0.313	0.325	**0.342**	0.359	0.370
	(0.258)	(0.174)	(0.125)	(0.204)	(0.288)
Low	0.618	0.458	0.246	0.025	−0.124
	(0.425)	(0.291)	(0.200)	(0.304)	(0.431)
"Average" shock	**0.1013**	**0.1015**	**0.1019**	**0.1022**	0.1024
	(0.0498)	(0.0369)	(0.0343)	(0.0506)	(0.0664)

Table A7 t-statistics on Differences in Shock Effects on Wages for Different Education Groups at Different Percentiles of CZ Baseline

	Non-college graduates					College graduates				
Panel A: With CZ employment rate										
	Percentile					Percentile				
	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
Low-high	1.08	1.45	1.75	1.81	1.74	−1.06	−1.21	−1.24	−1.11	−0.96
Mid-high	2.14	2.60	3.05	2.88	2.29	1.60	2.03	2.35	2.32	2.11
Low-mid	−1.26	−0.95	−0.53	−0.15	0.14	−2.78	−2.97	−2.96	−2.80	−2.60
Panel B: With college grad rate										
	Percentile					Percentile				
	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
Low-high	0.82	1.23	1.75	1.65	1.42	−0.31	−0.66	−1.24	−1.50	−1.45
Mid-high	0.25	1.40	3.05	3.40	3.28	0.97	1.53	2.35	2.60	2.42
Low-mid	0.66	0.31	−0.53	−0.97	−1.05	−1.22	−2.11	−2.96	−2.81	−2.56

NOTE: This table corresponds to effects shown in Table 18. The t-statistics use variance-covariance matrix to test whether a shock of one type minus a shock of another type is significantly different.

Table A8 Differences in Effects of Shocks on Less-Educated Minus More-Educated Wages, at Various CZ Characteristics

Panel A: With CZ employment rate					
	Percentile				
	10th	25th	50th	75th	90th
High	−0.258	−0.177	−0.097	−0.031	0.024
	(0.370)	(0.309)	(0.294)	(0.322)	(0.366)
Mid	−0.084	−0.126	−0.167	−0.202	−0.230
	(0.258)	(0.226)	(0.217)	(0.227)	(0.247)
Low	**0.890**	**1.001**	**1.111**	**1.203**	**1.278**
	(0.363)	(0.313)	(0.333)	(0.395)	(0.466)
"Average" shock	0.1237	0.1586	**0.1934**	**0.2221**	**0.2459**
	(0.0939)	(0.0776)	(0.0740)	(0.0820)	(0.0943)

Panel B: With college grad rate					
	Percentile				
	10th	25th	50th	75th	90th
High	0.327	0.145	−0.097	−0.348	**−0.519**
	(0.493)	(0.399)	(0.294)	(0.241)	(0.258)
Mid	−0.130	−0.146	−0.167	−0.189	−0.204
	(0.317)	(0.242)	(0.217)	(0.297)	(0.384)
Low	1.005	**1.050**	**1.111**	**1.175**	**1.218**
	(0.642)	(0.474)	(0.333)	(0.396)	(0.531)
"Average" shock	**0.3067**	**0.2581**	**0.1934**	0.1262	0.0807
	(0.0921)	(0.0786)	(0.0740)	(0.0873)	(0.1036)

Table A9 t-statistics for Differential Shock Effects on Earnings for Different Education Groups at Different CZ Baseline Characteristics

	Non-college graduates					College graduates				
Panel A: With CZ employment rate										
	Percentile					Percentile				
	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
Low-high	−0.48	0.55	1.93	2.79	3.11	−0.06	−0.29	−0.55	−0.70	−0.76
Mid-high	0.62	1.54	2.94	3.66	3.56	0.29	0.98	1.86	2.39	2.55
Low-mid	−1.61	−0.98	−0.21	0.36	0.73	−0.46	−1.48	−2.51	−3.21	−3.64
Panel B: With college grad rate										
	Percentile					Percentile				
	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
Low-high	2.31	2.31	1.93	0.73	−0.02	−0.99	−0.90	−0.55	0.07	0.40
Mid-high	1.46	2.00	2.94	3.08	2.59	1.48	1.68	1.86	1.59	1.20
Low-mid	1.23	0.90	−0.21	−1.24	−1.46	−3.08	−3.35	−2.51	−1.02	−0.41

NOTE: These t-stats use the variance covariance matrices from the two regressions behind Table 19, and report the statistical significance of one shock minus another shock at different baseline characteristics.

Table A10 Differences in Effects of Shocks on Less-Educated Minus More-Educated Earnings, at Various CZ Characteristics

Panel A: With CZ employment rate					
	Percentile				
	10th	25th	50th	75th	90th
High	0.149	−0.328	−0.803	−1.196	**−1.520**
	(1.171)	(0.878)	(0.677)	(0.644)	(0.725)
Mid	0.890	0.794	0.698	0.619	0.554
	(0.707)	(0.518)	(0.400)	(0.404)	(0.479)
Low	−0.617	0.609	**1.834**	**2.845**	**3.679**
	(0.782)	(0.702)	(0.730)	(0.828)	(0.944)
"Average" shock	0.2703	**0.4132**	**0.5559**	**0.6737**	**0.7709**
	(0.2587)	(0.1797)	(0.1405)	(0.1610)	(0.2056)

Panel B: With college grad rate					
	Percentile				
	10th	25th	50th	75th	90th
High	−1.067	−0.954	−0.803	−0.647	−0.541
	(1.167)	(0.940)	(0.677)	(0.518)	(0.535)
Mid	−0.126	0.228	0.698	**1.187**	**1.518**
	(0.743)	(0.529)	(0.400)	(0.572)	(0.780)
Low	**4.582**	**3.402**	**1.834**	0.205	−0.899
	(1.226)	(0.939)	(0.730)	(0.867)	(1.111)
"Average" shock	**0.8470**	**0.7220**	**0.5559**	**0.3833**	0.2664
	(0.1742)	(0.1425)	(0.1405)	(0.1859)	(0.2314)

NOTE: This comes from regressing the DIFFERENCE in earnings changes of the less-educated minus the more-educated group on the right-hand side variables.

Table A11 Effects of Key Variables on Difference of Change in Black Minus White Labor Market Outcomes

Dependent variables: Change from 2000 to 2015–2019 for Black group, minus change for white group, for 3 labor market outcomes

Demand shock		Employment rate	Real wage	Real earnings
High-occ	By itself	−1.324	−0.180	**−5.171**
		(1.276)	(1.313)	(2.549)
	Interacted w/ ln(EmpRate index, 2000)	29.06	−26.36	54.49
		(22.83)	(21.48)	(39.02)
	Interacted w/ diff of ln(CollGradRate) from U.S. mean	**−4.469**	3.719	−3.337
		(2.129)	(2.489)	(3.856)
Mid-occ	By itself	1.743	0.707	**5.969**
		(1.117)	(1.166)	(2.359)
	Interacted w/ ln(EmpRate index, 2000)	−20.14	1.32	**−42.74**
		(12.76)	(8.88)	(17.54)
	Interacted w/ diff of ln(CollGradRate) from U.S. mean	3.010	1.494	**12.720**
		(2.732)	(2.281)	(4.541)
Low-occ	By itself	−2.173	1.311	−1.586
		(1.381)	(1.561)	(2.583)
	Interacted w/ ln(EmpRate index, 2000)	−5.21	8.87	**54.68**
		(15.78)	(15.23)	(22.15)
	Interacted w/ diff of ln(CollGradRate) from U.S. mean	−2.025	−2.262	**−16.398**
		(3.521)	(3.349)	(6.166)

NOTE: Robust standard errors in parentheses below regression coefficients. Regression also includes interaction variables by themselves. These coefficients equal the differences in Table 20 for the employment rate variable, but not wages and earnings, as the Black sample and differenced sample is 369 CZs and 370 CZs for wages and earnings, and it is 371 for the white sample. Coefficients whose ratio to their standard error exceed in absolute value 1.96 are bolded.

Table A12 t-statistics for Differentials in Different Shock Effects at Different Baseline CZ Characteristics

	Results for Black Persons					Results for White Persons				
Panel A: With CZ employment rate										
	Percentile					Percentile				
	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
Low-high	0.90	1.43	2.11	2.47	2.44	−1.98	−1.08	0.30	1.35	1.92
Mid-high	2.11	2.29	2.41	2.14	1.53	−0.59	0.62	2.49	3.67	3.99
Low-mid	−2.35	−1.45	−0.35	0.51	1.09	−2.02	−1.93	−1.66	−1.37	−1.13
Panel B: With college grad rate										
	Percentile					Percentile				
	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
Low-high	2.61	2.56	2.11	0.99	0.22	1.04	0.86	0.30	−0.55	−0.90
Mid-high	0.58	1.43	2.41	2.80	2.84	1.89	2.19	2.49	1.99	1.42
Low-mid	2.29	1.59	−0.35	−2.02	−2.48	−0.31	−0.79	−1.66	−1.74	−1.55

NOTE: These t-statistics test the differences between different shock types in Table 21.

Table A13 Differences in Effects of Shocks on Black Minus White Earnings, at Various CZ Characteristics

Panel A: With CZ employment rate					
	Percentile				
	10th	25th	50th	75th	90th
High	−8.317	−6.401	−4.489	−2.911	−1.608
	(4.595)	(3.428)	(2.481)	(2.088)	(2.191)
Mid	**5.695**	**4.193**	2.693	1.455	0.433
	(2.290)	(1.860)	(1.562)	(1.472)	(1.526)
Low	−1.201	0.720	2.639	**4.223**	**5.530**
	(2.205)	(1.977)	(2.041)	(2.300)	(2.615)
"Average" shock	−0.2834	0.1355	0.5538	0.8990	1.1840
	(0.8396)	(0.6650)	(0.5595)	(0.5538)	(0.6081)

Panel B: With college grad rate					
	Percentile				
	10th	25th	50th	75th	90th
High	−3.097	−3.694	−4.489	**−5.315**	**−5.874**
	(3.011)	(2.680)	(2.481)	(2.621)	(2.897)
Mid	−2.615	−0.336	2.693	**5.841**	**7.972**
	(1.821)	(1.435)	(1.562)	(2.305)	(2.948)
Low	**9.482**	**6.544**	2.639	−1.419	−4.166
	(3.337)	(2.554)	(2.041)	(2.508)	(3.220)
"Average" shock	0.4581	0.4992	0.5538	0.6106	0.6490
	(0.6253)	(0.5446)	(0.5595)	(0.7084)	(0.8538)

Table A14 Estimated Effect of Different Types of Job Shocks, Based on:

CZ number	CZ population in 2000	Most populous county in CZ, 2000	Emp rate index relative to nation, 2015–2019	College percent of population ages 25–64, 2015–2019 (%)	High effect	Mid effect	Low effect
69	16,372,860	Los Angeles CA	0.993	31.7	−0.74	1.86	0.16
405	10,762,079	Kings NY	1.005	41.4	−0.80	2.26	−0.83
159	8,610,555	Cook IL	1.018	40.9	−1.03	2.30	−0.44
391	6,661,455	Bergen NJ	1.027	44.7	−1.14	2.45	−0.65
58	5,100,708	Alameda CA	1.023	48.3	−1.04	2.54	−1.12
296	5,077,106	Wayne MI	0.981	34.0	−0.49	1.90	−0.50
538	4,770,018	Harris TX	1.001	32.8	−0.86	1.93	0.20
281	4,751,998	Middlesex MA	1.031	50.0	−1.14	2.61	−1.10
92	4,435,552	Philadelphia PA	1.000	41.0	−0.73	2.23	−0.90
93	4,414,255	Fairfax VA	1.058	52.1	−1.59	2.78	−0.61
98	3,955,878	Miami −Dade FL	1.021	32.3	−1.22	1.99	0.82
602	3,942,141	King WA	1.007	41.1	−0.84	2.26	−0.75
115	3,797,219	Fulton GA	1.028	40.5	−1.22	2.32	−0.12
34	3,469,660	Maricopa AZ	0.978	30.6	−0.50	1.75	−0.05
90	3,405,239	Fairfield CT	1.024	41.1	−1.15	2.33	−0.30
551	3,029,141	Dallas TX	1.034	35.8	−1.39	2.18	0.65
64	2,955,948	San Diego CA	0.988	37.8	−0.55	2.07	−0.84
301	2,945,557	Hennepin MN	1.073	43.9	−1.93	2.61	0.61
444	2,945,432	Cuyahoga OH	1.013	32.7	−1.09	1.98	0.57
74	2,880,863	Denver CO	1.032	45.4	−1.21	2.49	−0.60
275	2,665,798	Baltimore MD	1.038	41.6	−1.36	2.40	−0.02
456	2,603,382	Allegheny PA	0.999	37.7	−0.74	2.11	−0.54
109	2,395,806	Hillsborough FL	0.986	31.7	−0.62	1.83	0.00
70	2,392,984	Santa Clara CA	1.006	47.6	−0.74	2.45	−1.50
168	2,205,367	St. Louis MO	1.034	38.6	−1.35	2.28	0.28
411	2,178,976	Westchester NY	1.006	42.0	−0.82	2.28	−0.87
101	2,074,294	Orange FL	0.975	31.0	−0.44	1.75	−0.18
188	1,972,568	Hamilton OH	1.027	35.4	−1.27	2.14	0.51
475	1,927,729	Multnomah OR	1.010	40.5	−0.90	2.25	−0.60
616	1,906,527	Milwaukee WI	1.050	35.2	−1.66	2.22	1.11
424	1,871,337	Mecklenburg NC	1.022	36.3	−1.18	2.16	0.26
574	1,825,821	Salt Lake UT	1.012	35.5	−1.02	2.08	0.13
451	1,796,667	Franklin OH	1.018	37.7	−1.08	2.19	−0.04
564	1,785,464	Tarrant TX	1.028	30.4	−1.38	1.94	1.29
72	1,779,581	Sacramento CA	0.970	32.6	−0.32	1.80	−0.57
390	1,752,454	Camden NJ	1.013	33.1	−1.07	1.99	0.48
229	1,714,305	Jackson MO	1.046	39.1	−1.54	2.34	0.50
532	1,712,209	Bexar TX	0.979	28.1	−0.57	1.64	0.41
175	1,688,854	Marion IN	1.027	36.7	−1.25	2.18	0.33
62	1,651,466	Fresno CA	0.926	18.0	0.17	0.82	1.14
279	1,582,870	Providence RI	1.023	33.9	−1.23	2.06	0.62
488	1,572,797	Lancaster PA	1.057	29.6	−1.88	2.02	2.16
107	1,533,024	Palm Beach FL	1.001	31.8	−0.88	1.89	0.37
427	1,474,723	Wake NC	1.013	45.5	−0.90	2.42	−1.08
266	1,471,226	Orleans Parish LA	0.991	29.6	−0.75	1.76	0.46
386	1,413,162	Clark NV	0.996	23.7	−0.96	1.48	1.69
404	1,407,701	Erie NY	0.998	32.4	−0.82	1.91	0.20
285	1,342,643	Kent MI	1.023	30.0	−1.31	1.90	1.25
534	1,324,649	Travis TX	1.025	44.2	−1.11	2.43	−0.65

Table A14 (Continued)

CZ number	CZ population in 2000	Most populous county in CZ, 2000	Emp rate index relative to nation, 2015–2019	College percent of population ages 25–64, 2015–2019 (%)	High effect	Mid effect	Low effect
428	1,283,665	Guilford NC	1.005	28.5	−1.01	1.76	1.02
59	1,267,433	San Joaquin CA	0.972	24.2	−0.52	1.41	0.95
518	1,246,072	Davidson TN	1.038	39.4	−1.41	2.33	0.27
50	1,233,842	Shelby TN	1.008	28.4	−1.07	1.77	1.11
181	1,211,862	St. Joseph IN	1.022	27.0	−1.34	1.76	1.73
273	1,193,065	Hillsborough NH	1.065	38.2	−1.87	2.39	1.08
95	1,176,424	Duval FL	1.001	31.4	−0.90	1.88	0.45
403	1,171,476	Albany NY	1.012	35.1	−1.01	2.07	0.15
490	1,161,851	Berks PA	1.019	28.3	−1.26	1.81	1.42
66	1,158,838	Kern CA	0.888	15.1	0.81	0.42	0.90
448	1,133,119	Montgomery OH	1.011	27.1	−1.16	1.72	1.44
462	1,107,088	Oklahoma OK	1.001	31.3	−0.89	1.87	0.44
177	1,100,617	Jefferson KY	1.014	31.4	−1.11	1.93	0.77
413	1,095,723	Monroe NY	1.010	35.9	−0.97	2.09	−0.01
597	1,085,282	Virginia Beach city VA	1.034	32.4	−1.45	2.05	1.13
542	1,070,477	Hidalgo TX	0.936	18.3	−0.02	0.89	1.35
135	1,062,761	Honolulu HI	1.066	34.2	−1.95	2.25	1.66
584	1,039,784	Henrico VA	1.033	39.0	−1.33	2.29	0.20
407	1,031,931	Onondaga NY	0.988	30.8	−0.68	1.80	0.19
2	1,016,420	Mobile AL	0.943	23.8	0.00	1.27	0.25
32	999,679	Pima AZ	0.932	29.2	0.33	1.49	−1.10
4	981,196	Jefferson AL	0.971	32.7	−0.33	1.81	−0.58
292	955,504	Genesee MI	0.959	28.2	−0.19	1.56	−0.16
466	905,987	Tulsa OK	1.003	28.4	−0.98	1.75	0.98
496	894,148	Greenville SC	0.999	29.7	−0.88	1.79	0.65
299	892,144	Lucas OH	1.007	26.1	−1.10	1.65	1.52
397	870,732	El Paso TX	0.948	25.4	−0.06	1.37	0.07
474	851,251	Lane OR	0.971	27.5	−0.43	1.58	0.28
498	814,767	Richland SC	0.993	30.6	−0.76	1.81	0.34
450	809,696	Mahoning OH	0.972	22.7	−0.55	1.33	1.26
202	802,903	Douglas NE	1.068	37.5	−1.94	2.38	1.26
495	793,081	Luzerne PA	0.992	26.1	−0.84	1.60	1.12
184	786,022	Lake IN	0.978	23.7	−0.65	1.41	1.23
513	766,390	Knox TN	0.968	29.4	−0.34	1.65	−0.13
100	763,641	Sarasota FL	0.955	27.2	−0.14	1.49	−0.10
80	761,829	El Paso CO	0.955	34.9	0.00	1.83	−1.33
392	747,508	Bernalillo NM	0.945	31.3	0.13	1.64	−1.08
259	716,562	East Baton Rouge Parish LA	1.003	29.0	−0.97	1.78	0.88
447	700,722	Stark OH	1.034	21.6	−1.69	1.51	3.17
102	692,118	Lee FL	0.982	27.4	−0.63	1.62	0.61
610	683,260	Dane WI	1.079	43.9	−2.02	2.62	0.74
282	679,852	Hampden MA	0.996	34.0	−0.75	1.96	−0.10
269	656,666	Cumberland ME	1.012	34.4	−1.04	2.04	0.27
73	645,859	Santa Barbara CA	1.005	32.9	−0.93	1.95	0.29
48	630,691	Pulaski AR	0.997	31.2	−0.83	1.85	0.37
104	622,916	Escambia FL	0.951	27.8	−0.06	1.51	−0.30
500	620,303	Horry SC	0.961	21.8	−0.38	1.22	1.18
276	603,491	Frederick MD	1.028	29.5	−1.39	1.90	1.45
212	599,633	Sedgwick KS	1.019	31.2	−1.21	1.94	0.93
108	598,014	Polk FL	0.954	19.1	−0.32	1.02	1.64
124	596,431	Hamilton TN	0.987	25.8	−0.75	1.56	1.04

Table A14 (Continued)

CZ number	CZ population in 2000	Most populous county in CZ, 2000	Emp rate index relative to nation, 2015–2019	College percent of population ages 25–64, 2015–2019 (%)	High effect	Mid effect	Low effect
97	589,037	Brevard FL	0.932	29.8	0.33	1.52	−1.17
499	587,033	Charleston SC	1.016	36.1	−1.08	2.12	0.14
161	583,400	Peoria IL	0.997	34.1	−0.78	1.97	−0.08
421	582,849	Cumberland NC	0.924	21.4	0.30	1.04	0.24
323	566,443	Hinds MS	0.988	30.0	−0.69	1.76	0.32
105	563,452	Volusia FL	0.941	22.7	0.01	1.19	0.43
136	555,648	Ada ID	0.994	30.5	−0.78	1.81	0.39
408	554,731	Erie PA	0.971	26.0	−0.45	1.50	0.56
614	549,508	Outagamie WI	1.071	28.0	−2.15	2.00	2.78
172	548,338	Allen IN	1.051	25.4	−1.87	1.80	2.77
257	548,015	Lafayette Parish LA	0.973	22.1	−0.60	1.30	1.44
6	545,215	Muscogee GA	0.950	25.3	−0.10	1.38	0.15
519	542,758	Sullivan TN	0.899	22.9	0.83	1.02	−0.84
463	541,958	Denton TX	1.040	43.5	−1.38	2.46	−0.18
288	540,618	Saginaw MI	0.943	22.3	−0.03	1.18	0.56
123	534,047	Richmond GA	0.956	25.3	−0.20	1.40	0.30
151	533,502	Winnebago IL	1.016	22.0	−1.36	1.47	2.60
237	530,098	Fayette KY	1.000	34.9	−0.81	2.01	−0.13
142	526,455	Spokane WA	0.941	29.2	0.16	1.53	−0.83
14	519,190	Madison AL	0.962	33.9	−0.14	1.81	−1.00
334	514,398	Greene MO	0.975	25.2	−0.56	1.48	0.85
594	508,302	Newport News city VA	1.033	32.7	−1.43	2.06	1.06
189	507,334	Polk IA	1.068	39.3	−1.90	2.44	1.02
489	501,061	Cambria PA	0.963	20.3	−0.46	1.14	1.58
563	497,632	Jefferson TX	0.891	16.8	0.80	0.57	0.48
491	483,136	Lycoming PA	0.989	21.8	−0.88	1.34	1.91
529	471,113	Nueces TX	0.962	19.4	−0.46	1.08	1.77
60	467,580	Butte CA	0.907	21.9	0.65	0.99	−0.37
1	460,437	Montgomery AL	0.949	26.5	−0.04	1.43	−0.13
164	456,870	Scott IA	1.017	27.3	−1.25	1.75	1.56
194	456,560	Linn IA	1.071	37.0	−1.99	2.37	1.39
406	455,578	Broome NY	0.978	26.2	−0.58	1.54	0.72
91	438,892	Sussex DE	1.011	25.8	−1.18	1.66	1.67
429	434,942	Pitt NC	0.980	22.2	−0.72	1.33	1.61
263	434,500	Caddo Parish LA	0.959	23.1	−0.31	1.29	0.84
431	417,388	Spartanburg SC	0.971	22.1	−0.56	1.29	1.39
591	413,549	Loudoun VA	1.055	48.0	−1.57	2.65	−0.29
423	398,358	Buncombe NC	0.990	34.1	−0.66	1.94	−0.25
546	396,295	Gregg TX	0.955	17.6	−0.39	0.91	2.06
409	395,424	Steuben NY	0.961	31.8	−0.16	1.73	−0.71
121	391,393	Chatham GA	0.987	27.8	−0.72	1.66	0.67
118	389,162	Bibb GA	0.955	25.9	−0.17	1.43	0.15
114	386,437	Hall GA	1.006	34.8	−0.93	2.04	0.06
170	385,524	Tippecanoe IN	1.012	26.8	−1.18	1.71	1.51
41	383,916	Washington AR	1.013	31.9	−1.09	1.95	0.66
150	382,938	Madison IL	0.992	26.6	−0.83	1.62	1.01
154	382,019	Champaign IL	0.993	34.3	−0.70	1.96	−0.22
18	379,304	Anchorage Borough AK	0.972	31.1	−0.38	1.74	−0.29
389	361,286	Grafton NH	1.026	35.0	−1.26	2.12	0.54
606	360,394	Kanawha WV	0.884	22.7	1.11	0.94	−1.22
613	355,725	Brown WI	1.074	28.9	−2.19	2.05	2.70

Table A14 (Continued)

CZ number	CZ population in 2000	Most populous county in CZ, 2000	Emp rate index relative to nation, 2015–2019	College percent of population ages 25–64, 2015–2019 (%)	High effect	Mid effect	Low effect
535	354,892	Bell TX	0.941	23.0	0.03	1.21	0.35
380	351,913	Lancaster NE	1.080	37.5	−2.13	2.42	1.55
615	351,371	Marathon WI	1.060	25.6	−2.01	1.84	2.95
605	351,035	Monongalia WV	0.920	27.3	0.51	1.35	−1.08
415	341,794	Catawba NC	0.988	19.0	−0.94	1.15	2.58
99	340,223	Leon FL	0.932	35.9	0.45	1.76	−2.13
258	335,872	Calcasieu Parish LA	0.933	20.2	0.09	1.01	0.79
179	333,336	Monroe IN	1.009	26.8	−1.13	1.70	1.43
486	332,543	Benton WA	0.970	25.7	−0.45	1.48	0.61
49	329,285	Sebastian AR	0.932	17.7	0.04	0.83	1.39
333	328,067	Boone MO	1.016	36.9	−1.07	2.15	0.03
7	327,986	Etowah AL	0.919	18.4	0.32	0.82	0.84
443	326,042	Richland OH	0.982	17.6	−0.89	1.03	2.81
155	324,858	Sangamon IL	1.004	29.2	−0.98	1.79	0.87
222	324,444	Shawnee KS	1.040	37.2	−1.47	2.26	0.61
426	324,362	Onslow NC	0.955	23.6	−0.22	1.30	0.61
271	323,346	Penobscot ME	0.991	28.7	−0.77	1.72	0.63
580	321,422	Chittenden VT	1.060	42.4	−1.73	2.51	0.45
94	320,038	Alachua FL	0.920	33.9	0.63	1.64	−2.15
241	315,465	Cabell WV	0.819	19.7	2.39	0.44	−2.54
430	313,403	Nash NC	0.983	17.5	−0.92	1.03	2.88
320	305,162	Eau Claire WI	1.075	27.4	−2.23	1.99	2.98
549	300,223	Lubbock TX	1.019	28.1	−1.26	1.80	1.45
5	296,865	Calhoun AL	0.924	16.3	0.15	0.68	1.57
171	296,739	Vanderburgh IN	1.029	28.0	−1.44	1.83	1.73
262	295,634	Ouachita Parish LA	0.896	20.3	0.82	0.85	−0.32
547	294,452	Smith TX	0.921	21.2	0.36	1.01	0.19
306	291,642	St. Louis MN	1.004	26.3	−1.05	1.66	1.39
174	290,277	Delaware IN	0.959	19.0	−0.42	1.04	1.80
588	288,086	Roanoke city VA	1.006	28.6	−1.03	1.77	1.03
211	288,053	Jasper MO	0.997	21.3	−1.04	1.34	2.25
303	285,687	Stearns MN	1.094	27.4	−2.53	2.06	3.44
520	282,170	Madison TN	0.931	19.0	0.10	0.92	1.03
410	281,710	St. Lawrence NY	0.886	22.4	1.08	0.93	−1.12
537	281,566	McLennan TX	0.996	21.9	−1.02	1.38	2.11
149	278,775	Cape Girardeau MO	0.946	22.4	−0.09	1.20	0.63
590	275,785	Mercer WV	0.762	15.2	3.52	−0.20	−3.16
422	274,418	New Hanover NC	0.960	34.8	−0.10	1.84	−1.17
116	274,187	Floyd GA	0.982	18.2	−0.87	1.08	2.64
582	272,078	Albemarle VA	1.028	40.5	−1.22	2.32	−0.12
260	271,339	Terrebonne Parish LA	0.968	15.7	−0.70	0.82	2.99
138	269,408	Bonneville ID	0.962	27.5	−0.26	1.54	0.03
31	266,731	Navajo AZ	0.748	12.3	3.72	−0.55	−2.58
414	264,311	Alamance NC	1.013	21.7	−1.32	1.44	2.58
442	260,171	Allen OH	1.065	20.3	−2.23	1.55	4.23
531	257,818	Potter TX	1.012	22.8	−1.27	1.50	2.31
460	256,909	Grayson TX	0.957	20.3	−0.34	1.11	1.40
483	256,870	Jackson OR	0.927	23.2	0.29	1.17	−0.09
603	255,885	Yakima WA	0.983	17.0	−0.92	0.99	3.02
126	255,239	Clarke GA	0.970	33.0	−0.31	1.82	−0.65
302	252,249	Cass ND	1.089	34.2	−2.33	2.33	2.23

Table A14 (Continued)

CZ number	CZ population in 2000	Most populous county in CZ, 2000	Emp rate index relative to nation, 2015–2019	College percent of population ages 25–64, 2015–2019 (%)	High effect	Mid effect	Low effect
247	251,962	Montgomery TN	0.925	24.5	0.36	1.22	−0.41
319	251,516	Minnehaha SD	1.094	34.6	−2.41	2.37	2.30
493	250,544	Centre PA	0.973	35.5	−0.33	1.93	−0.91
586	248,296	Rockingham VA	1.028	27.1	−1.45	1.79	1.89
96	247,686	Bay FL	0.904	20.9	0.68	0.92	−0.23
252	241,910	Pike KY	0.682	13.1	5.37	−0.84	−5.32
452	241,710	Erie OH	1.057	20.9	−2.09	1.56	3.89
15	241,253	Lauderdale MS	0.937	17.1	−0.08	0.80	1.72
12	238,504	Cullman AL	0.896	13.8	0.60	0.33	1.61
528	237,997	Angelina TX	0.873	17.0	1.17	0.51	−0.12
494	233,377	Clearfield PA	0.935	18.4	0.00	0.89	1.29
560	232,651	Webb TX	0.953	18.4	−0.33	0.97	1.79
277	231,546	Barnstable MA	1.049	40.6	−1.58	2.41	0.40
454	230,802	Hancock OH	1.047	19.8	−1.95	1.45	3.92
309	228,758	Olmsted MN	1.079	40.1	−2.08	2.51	1.20
585	228,345	Lynchburg city VA	1.002	29.4	−0.94	1.79	0.78
522	227,689	Sevier TN	0.950	16.3	−0.34	0.80	2.31
117	226,817	Lowndes GA	0.938	19.6	−0.02	0.99	1.07
455	225,620	Scioto OH	0.882	15.8	0.95	0.45	0.50
178	224,109	Vigo IN	0.934	19.8	0.07	0.98	0.90
400	223,921	Santa Fe NM	0.918	32.7	0.65	1.58	−2.04
9	223,531	Houston AL	0.936	18.9	0.01	0.93	1.18
325	223,006	Lee MS	0.993	22.7	−0.94	1.41	1.85
195	222,077	Black Hawk IA	1.069	27.7	−2.12	1.98	2.79
339	221,652	Franklin MO	0.988	21.4	−0.89	1.32	2.00
539	221,360	Brazos TX	0.962	35.3	−0.13	1.87	−1.18
476	220,515	Cowlitz WA	0.909	17.3	0.47	0.69	0.86
13	212,843	Tuscaloosa AL	0.953	29.0	−0.07	1.57	−0.46
205	212,843	Woodbury IA	1.116	23.4	−2.98	1.93	4.75
261	211,281	Rapides Parish LA	0.888	16.6	0.85	0.55	0.45
167	210,624	McCracken KY	0.931	22.0	0.19	1.11	0.29
125	208,048	Cherokee GA	1.018	34.5	−1.14	2.07	0.42
300	207,795	Crow Wing MN	1.007	22.2	−1.19	1.44	2.30
196	207,298	Story IA	1.060	35.5	−1.82	2.27	1.32
166	200,248	Dubuque IA	1.083	25.8	−2.39	1.93	3.47
45	198,587	Craighead AR	0.953	21.4	−0.25	1.17	1.06
329	197,829	Forrest MS	0.907	25.1	0.71	1.18	−1.04
311	195,728	La Crosse WI	1.049	30.1	−1.74	2.01	1.87
446	195,508	Belmont OH	0.909	19.4	0.54	0.84	0.29
618	195,484	Sheboygan WI	1.105	23.9	−2.79	1.92	4.38
525	193,757	Maury TN	0.963	17.6	−0.54	0.95	2.29
39	192,233	Jefferson AR	0.866	15.6	1.28	0.36	0.07
198	190,148	Cerro Gordo IA	1.108	23.7	−2.85	1.91	4.52
356	189,594	Missoula MT	1.003	34.3	−0.88	2.00	0.06
471	187,887	Pottawatomie OK	0.926	21.1	0.25	1.03	0.36
305	187,822	Blue Earth MN	1.082	29.0	−2.30	2.09	2.87
556	185,746	Hunt TX	0.990	24.5	−0.85	1.50	1.40
544	183,854	Victoria TX	0.983	18.8	−0.87	1.12	2.50
112	181,725	Dougherty GA	0.944	19.5	−0.14	1.01	1.26
465	180,806	Comanche OK	0.922	19.4	0.28	0.90	0.68
176	178,501	Howard IN	1.006	19.2	−1.26	1.24	3.02

Table A14 (Continued)

CZ number	CZ population in 2000	Most populous county in CZ, 2000	Emp rate index relative to nation, 2015–2019	College percent of population ages 25–64, 2015–2019 (%)	High effect	Mid effect	Low effect
236	177,901	Warren KY	0.950	25.1	−0.10	1.37	0.19
183	176,902	Kosciusko IN	1.037	19.5	−1.78	1.39	3.72
44	176,651	Garland AR	0.925	18.5	0.21	0.85	0.97
245	176,541	Hardin KY	0.962	19.0	−0.47	1.05	1.88
457	174,834	Wood WV	0.897	19.6	0.78	0.80	−0.11
36	174,558	Mohave AZ	0.852	12.6	1.44	0.01	0.70
497	174,107	Beaufort SC	0.988	30.1	−0.68	1.77	0.28
10	174,099	Lauderdale AL	0.934	20.5	0.09	1.03	0.73
545	173,806	Taylor TX	0.989	22.2	−0.88	1.37	1.84
589	173,449	Halifax VA	0.915	17.0	0.34	0.70	1.12
417	173,375	Moore NC	0.953	27.1	−0.12	1.49	−0.12
527	172,780	Ector TX	0.991	15.4	−1.13	0.89	3.71
186	171,994	Daviess KY	0.993	20.8	−0.98	1.30	2.25
278	171,849	Berkshire MA	1.021	32.6	−1.23	2.01	0.78
76	168,053	San Juan NM	0.948	24.9	−0.07	1.35	0.16
156	167,269	Coles IL	0.985	20.9	−0.85	1.27	2.04
608	165,346	Raleigh WV	0.812	17.9	2.48	0.28	−2.30
593	165,054	Montgomery VA	0.978	37.8	−0.38	2.03	−1.10
144	164,083	Whitman WA	0.948	27.9	0.00	1.50	−0.41
517	164,054	Bradley TN	0.939	19.3	−0.04	0.97	1.18
349	163,878	Gallatin MT	1.041	40.2	−1.44	2.36	0.25
221	163,553	Buchanan MO	0.967	22.4	−0.48	1.29	1.20
173	163,229	Bartholomew IN	1.004	26.0	−1.04	1.64	1.43
286	163,210	Emmet MI	0.924	19.6	0.24	0.93	0.68
477	162,918	Douglas OR	0.915	16.7	0.33	0.67	1.22
37	159,908	Yuma AZ	0.908	16.2	0.46	0.60	1.14
54	159,075	Bowie TX	0.889	16.7	0.84	0.56	0.44
562	159,067	Midland TX	1.017	23.8	−1.34	1.58	2.23
327	158,975	Lowndes MS	0.947	26.8	0.01	1.44	−0.25
53	158,796	White AR	0.898	17.0	0.68	0.62	0.63
81	158,760	Mesa CO	0.984	29.3	−0.62	1.71	0.32
505	158,345	Pennington SD	1.047	29.9	−1.72	2.00	1.88
324	157,828	Washington MS	0.824	17.7	2.22	0.32	−1.85
501	157,221	Sumter SC	0.910	17.5	0.47	0.71	0.81
274	155,673	Allegany MD	0.912	20.2	0.51	0.91	0.17
310	155,646	Otter Tail MN	1.078	23.6	−2.36	1.80	3.80
530	155,587	Wichita TX	0.929	22.1	0.23	1.11	0.20
162	155,550	Williamson IL	0.906	22.5	0.67	1.03	−0.53
350	155,301	Yellowstone MT	1.056	31.5	−1.83	2.09	1.82
287	154,346	Grand Traverse MI	0.994	29.8	−0.79	1.77	0.51
478	153,464	Deschutes OR	0.989	33.2	−0.65	1.90	−0.15
153	153,077	La Salle IL	1.003	19.8	−1.19	1.27	2.78
255	152,917	Hopkins KY	0.909	15.3	0.39	0.53	1.49
418	152,862	Watauga NC	0.933	22.5	0.17	1.15	0.22
148	152,326	Adams IL	1.011	22.1	−1.27	1.45	2.44
458	152,229	Muskogee OK	0.879	17.0	1.05	0.53	0.07
68	151,209	Klamath OR	0.786	16.7	3.01	0.06	−2.79
103	149,525	Columbia FL	0.770	11.6	3.17	−0.51	−1.53
146	149,495	Cache UT	1.011	36.6	−0.98	2.12	−0.07
612	149,452	Barron WI	1.050	18.8	−2.04	1.39	4.25
134	148,644	Hawaii HI	0.957	27.7	−0.17	1.53	−0.12

Table A14 (Continued)

CZ number	CZ population in 2000	Most populous county in CZ, 2000	Emp rate index relative to nation, 2015–2019	College percent of population ages 25–64, 2015–2019 (%)	High effect	Mid effect	Low effect
600	145,850	Chelan WA	0.996	21.3	−1.03	1.34	2.24
248	144,876	Laurel KY	0.750	13.8	3.72	−0.39	−3.06
514	144,868	Coffee TN	0.992	20.2	−0.98	1.25	2.38
67	144,447	Mendocino CA	0.906	17.9	0.55	0.73	0.59
122	144,073	Bulloch GA	0.935	18.0	−0.01	0.86	1.39
217	143,164	Riley KS	1.027	33.8	−1.30	2.08	0.74
419	142,384	Beaufort NC	0.961	21.4	−0.38	1.20	1.26
200	142,360	Wapello IA	1.053	23.6	−1.95	1.70	3.18
445	142,266	Athens OH	0.875	23.3	1.30	0.93	−1.61
328	141,638	Lafayette MS	0.905	18.2	0.58	0.74	0.48
158	141,019	Marion IL	0.964	21.1	−0.45	1.20	1.41
214	139,631	Washington OK	0.988	21.3	−0.88	1.31	2.03
63	139,466	Humboldt CA	0.920	27.9	0.54	1.38	−1.21
412	138,652	Jefferson NY	0.951	22.0	−0.18	1.20	0.83
8	137,684	Dallas AL	0.803	14.5	2.57	−0.05	−1.54
550	137,553	Tom Green TX	0.980	22.1	−0.72	1.33	1.61
83	137,489	Garfield CO	1.068	41.1	−1.88	2.49	0.80
291	136,866	Isabella MI	0.875	22.6	1.29	0.90	−1.46
163	136,428	Des Moines IA	1.029	19.4	−1.66	1.35	3.55
335	136,343	Johnson MO	0.985	20.0	−0.86	1.21	2.26
165	135,141	Kankakee IL	0.983	19.7	−0.84	1.19	2.27
180	133,948	Dearborn IN	1.038	19.8	−1.79	1.41	3.66
140	131,573	Kootenai ID	0.993	24.9	−0.89	1.54	1.38
191	131,395	Grant WI	1.108	23.8	−2.85	1.92	4.50
571	130,054	Washington UT	0.955	25.0	−0.19	1.38	0.32
321	129,443	Alcorn MS	0.908	14.5	0.39	0.46	1.69
472	127,616	Payne OK	0.951	23.2	−0.16	1.26	0.60
437	125,502	Burleigh ND	1.099	33.3	−2.50	2.33	2.59
187	125,493	Hillsdale MI	1.014	17.0	−1.46	1.12	3.80
317	125,473	Grand Forks ND	1.077	30.7	−2.19	2.14	2.47
249	123,933	Pulaski KY	0.826	14.0	2.03	0.02	−0.60
340	123,068	St. Francois MO	0.888	16.1	0.85	0.50	0.59
33	122,151	Coconino AZ	0.969	35.0	−0.25	1.89	−0.97
284	121,831	Marquette MI	0.906	24.3	0.72	1.13	−0.92
587	121,346	Smyth VA	0.930	20.0	0.16	0.97	0.74
395	121,160	Curry NM	0.928	17.8	0.12	0.81	1.26
141	120,495	Twin Falls ID	1.045	19.9	−1.91	1.45	3.82
330	120,424	Jones MS	0.891	15.7	0.77	0.48	0.80
253	120,319	Dyer TN	0.926	17.0	0.14	0.75	1.41
297	119,990	Mecosta MI	0.953	18.6	−0.32	0.98	1.74
388	117,961	Cheshire NH	1.039	32.4	−1.53	2.07	1.26
254	117,860	Harlan KY	0.681	12.8	5.38	−0.87	−5.24
322	117,654	Pike MS	0.846	16.1	1.70	0.31	−0.70
71	116,372	Nevada CA	0.910	30.1	0.77	1.43	−1.86
251	116,214	Madison KY	0.887	24.0	1.10	1.02	−1.42
130	115,602	Spalding GA	0.928	15.6	0.04	0.65	1.91
294	114,358	Marinette WI	0.964	23.4	−0.40	1.33	0.91
203	113,403	Marshall IA	1.089	23.8	−2.54	1.85	4.03
111	113,084	Coffee GA	0.849	12.1	1.47	−0.06	0.84
394	112,980	Chaves NM	0.912	17.0	0.40	0.69	1.03
359	111,082	Flathead MT	0.986	29.5	−0.66	1.73	0.34

Table A14 (Continued)

CZ number	CZ population in 2000	Most populous county in CZ, 2000	Emp rate index relative to nation, 2015–2019	College percent of population ages 25–64, 2015–2019 (%)	High effect	Mid effect	Low effect
113	110,937	Baldwin GA	0.940	20.9	−0.01	1.08	0.80
526	110,310	Anderson TX	0.867	14.2	1.20	0.24	0.57
449	109,839	Highland OH	0.940	16.4	−0.15	0.76	2.01
318	109,838	Rice MN	1.092	28.2	−2.49	2.09	3.26
127	108,379	Thomas GA	0.953	16.5	−0.40	0.82	2.34
208	106,875	Leavenworth KS	1.008	29.2	−1.05	1.81	0.97
316	106,811	McLeod MN	1.119	21.3	−3.08	1.81	5.30
521	106,252	Putnam TN	0.948	22.1	−0.13	1.19	0.74
119	105,403	Laurens GA	0.866	13.9	1.21	0.20	0.67
55	105,137	Mississippi AR	0.945	14.3	−0.33	0.60	2.82
231	105,073	Reno KS	1.026	23.5	−1.49	1.59	2.52
492	105,050	Mc Kean PA	0.938	17.9	−0.07	0.87	1.53
516	104,128	Cumberland TN	0.902	13.5	0.47	0.33	1.87
35	103,867	Graham AZ	0.802	16.0	2.62	0.08	−2.03
416	100,657	Wilkes NC	0.958	19.0	−0.41	1.04	1.77
558	100,231	Maverick TX	0.916	15.9	0.29	0.61	1.47

NOTE: This table lists the 371 CZs in the sample by their year 2000 population. CZs are “named” by the county and state of their largest county. Table also reports the employment rate index for area, based on this study's methodology for controlling for demographics using 160 cells. An index of 1 would mean the adjusted employment rate for the area is just equal to the national average. The college grad percentage for persons ages 25–64-year-olds is also reported. Both employment rate index and college grad are based on 2015–2019 ACS. The predicted effects of low, middle, and high shocks are the predictions based on the regression estimates for real earnings effects for the less than 4-year college group in Table 16. These predictions calculated elasticities by combining these estimated coefficients with the 2015–2019 values in the CZ for the adjusted employment rate index, and the college grad percent. The employment rate variable in the predictions is the natural logarithm of the employment rate index. The college grad variable in the predictions is the natural logarithm of the college grad percentage, minus the natural logarithm of the national mean for 2015–2019, which is 33.3 .

Table A15 List of Industries Sorted by Standard Deviation of Location Quotient Across 371 CZs, with Data on Industry Employment, and Share of Employment in Low, Mid ,and High Occupations

Industry NAICS	Industry description	Industry employment, 2016	St. dev. LQ across 371 CZs, 2016 data	Low share	Mid share	High share	Cumulative employment share
2121	Coal mining	42,962	18.10	**76.6**	9.2	14.2	0.0
32621	Tires	49,712	13.65	21.8	**55.4**	22.9	0.1
all other 212	Other mining	97,166	11.70	**62.7**	17.5	19.8	0.2
3122	Tobacco	13,110	9.71	19.1	45.9	35.1	0.2
3365	Railroad rolling stock mfg	28,773	9.01	16.8	51.4	31.8	0.2
113	Forestry and logging	47,153	8.55	**65.7**	13.3	21.1	0.2
213	Support activities for mining	188,774	7.02	**51.5**	16.6	31.9	0.4
3366	Ship and boat bldg	135,576	6.92	28.4	43.7	27.9	0.5
3271	Pottery, ceramics, clay	31,888	6.34	20.1	**55.0**	24.9	0.5
483	Water transportation	63,261	6.25	**51.6**	22.3	26.1	0.6
211	Oil and gas extraction	93,083	6.04	29.8	16.6	53.6	0.7
3253	Ag. chemicals	27,434	5.96	23.1	37.5	39.4	0.7
3313	Aluminum prod. and processing	55,213	5.69	21.4	54.2	24.4	0.7
316	Footwear mfg + leather products mfg	24,271	5.42	10.0	**63.2**	26.8	0.8
3369	Other transportation equipment mfg	29,924	5.06	14.1	52.8	33.1	0.8
3311-3312	Iron and steel mills & steel products mfg	135,298	4.93	30.0	51.1	18.9	0.9
487	Scenic & sightseeing transportation	28,260	4.45	**59.6**	18.5	22.0	0.9
3272	Glass products	88,937	4.44	23.8	**55.4**	20.8	1.0
3116	Animal slaughtering, processing, and seafood	421,202	4.37	28.0	**58.4**	13.6	1.4
all other 326	Rubber products, except tires	73,637	4.29	15.8	**64.5**	19.7	1.4
115	Support activities for ag. and forestry	86,884	4.23	**76.1**	9.2	14.6	1.5
114	Fishing, hunting, and trapping	5,891	4.18	**79.2**	8.6	12.2	1.5
3315	Foundries	113,914	4.14	19.5	**59.5**	21.0	1.6
3341	Computer & peripheral equip mfg	42,546	4.11	6.2	27.9	**66.0**	1.6
337	Furniture and related products mfg	359,933	4.04	18.0	**62.8**	19.2	1.9
3252	Resin, synthetic rubber, and fibers and filaments	93,144	3.86	17.5	**59.1**	23.4	2.0
324	Petroleum refining & products	99,717	3.58	20.8	41.0	38.2	2.1

Table A15 (Continued)

Industry NAICS	Industry description	Industry employment, 2016	St. dev. LQ across 371 CZs, 2016 data	Low share	Mid share	High share	Cumulative employment share
3314	Nonferrous metal, except aluminum, production and processing	57,524	3.56	22.3	**56.2**	21.5	2.1
313-315	Fabric and textile mills & apparel	302,633	3.50	12.7	**66.3**	21.0	2.4
486	Pipeline transport.	46,610	3.46	42.1	24.3	33.6	2.4
321	Miscellaneous wood product mfg	351,448	3.34	29.9	53.5	16.6	2.7
322	Paper and pulp mills and products	334,672	3.24	23.9	**54.6**	21.5	3.0
335	Electrical machinery and equip mfg	333,844	2.92	12.3	52.6	35.0	3.3
3361-3363	Motor vehicles and motor vehicle equipment mfg	861,870	2.86	16.9	**56.1**	27.0	4.0
3391	Medical equipment and supplies	275,880	2.82	7.7	48.1	44.2	4.3
5111	Newspapers and book publishing	350,552	2.65	5.5	24.7	**69.8**	4.6
all other 325	Industrial and misc. chemicals	225,219	2.38	16.1	41.3	42.6	4.7
3254	Pharmaceuticals and medicines	246,051	2.36	7.8	32.1	**60.2**	5.0
3364	Aircraft and aerospace mfg	395,524	2.23	11.6	34.2	54.2	5.3
3121	Beverage	179,399	1.92	29.4	41.2	29.4	5.4
3255	Paint, coating, and adhesives	59,181	1.88	13.5	50.0	36.5	5.5
all other 311	Dairy, animal foods specialty foods	668,250	1.69	30.0	47.9	22.2	6.1
all other 339	Misc. mfg	252,227	1.66	18.8	**55.4**	25.8	6.3
3256	Soap, cleaning compound, and cosmetics	95,003	1.62	16.6	43.6	39.9	6.3
5122	Sound recording industries	22,428	1.55	2.0	11.3	**86.7**	6.4
3261	Plastics products	598,596	1.51	18.6	**59.6**	21.8	6.9
333	Machinery mfg	979,932	1.46	13.8	51.4	34.8	7.7
all other 334	Other electronic components and products	736,040	1.44	6.5	34.1	**59.4**	8.3
all other 327	Cement, concrete, & other non-metallic mineral products	245,001	1.36	37.1	40.3	22.6	8.5
3118	Bakeries	289,434	1.29	22.1	**64.4**	13.5	8.8
493	Warehousing and storage	812,620	1.19	**54.2**	36.6	9.3	9.5
332	Fabricated metal products mfg	1,367,201	1.17	15.5	**61.3**	23.2	10.6
488	Services incidental to transportation	677,864	1.16	**53.3**	25.7	21.1	11.2

Table A15 (Continued)

Industry NAICS	Industry description	Industry employment, 2016	St. dev. LQ across 371 CZs, 2016 data	Low share	Mid share	High share	Cumulative employment share
323	Printing and related support activities	437,522	1.09	9.0	**64.8**	26.2	11.6
721	Traveler accommodations	1,971,617	1.07	**59.5**	20.5	20.0	13.2
5614	Business support services	751,639	1.04	5.5	**67.6**	26.9	13.9
562	Waste management and remediation services	375,310	0.87	**63.7**	19.3	17.0	14.2
22	Utilities	604,385	0.85	29.1	35.7	35.3	14.7
5112	Software publishers	516,621	0.85	1.0	18.4	**80.6**	15.1
5615	Travel arrangements and reservation services	217,161	0.83	12.0	52.5	35.5	15.3
4512	Bookstores	89,874	0.82	6.8	**60.9**	32.3	15.4
all other 611	Colleges and universities, and other schools	2,604,422	0.81	10.4	14.7	**74.9**	17.6
5322-5399	Other rental	366,722	0.77	30.7	30.6	38.7	17.9
484	Truck transportation	1,384,898	0.77	**82.1**	11.0	6.9	19.1
447	Gasoline stations	876,304	0.77	22.6	**55.6**	21.7	19.8
6215,6219	Other health care services	566,175	0.76	22.3	17.5	**60.2**	20.3
481	Air transportation	462,493	0.76	40.5	26.3	33.2	20.7
6216	Home health care services	1,343,752	0.75	**65.3**	5.8	29.0	21.8
5415-5417	Computer services, scientific services, technical services, science R&D	3,606,914	0.72	2.9	13.1	**84.0**	24.8
485	Buses and taxis and other transit	494,081	0.69	**87.7**	6.2	6.1	25.3
713	Amusement ind.	1,616,887	0.68	62.2	14.1	23.8	26.6
5321	Auto rental	165,474	0.66	40.9	32.6	26.5	26.8
492	Couriers and messengers	595,168	0.63	**53.0**	36.1	10.9	27.3
6241-6243	Family & community svcs & voc. rehab	2,142,494	0.62	39.3	13.3	47.4	29.1
55	Mgt of companies and enterprises	3,343,621	0.60	7.2	26.4	**66.4**	31.9
5611,5612,5618,5619	Other administrative, and other support services	923,268	0.59	21.4	36.2	42.4	32.7
524	Insurance related	2,352,902	0.56	1.1	34.9	**64.0**	34.7
5413-5414	Architectural, engineering, and design and related services	1,497,759	0.56	3.3	13.1	**83.6**	35.9
711-712	Performing arts, sports, museums	648,175	0.54	24.5	12.0	**63.5**	36.5
454	Misc retail including mail order	612,485	0.52	15.3	52.3	32.5	37.0

Table A15 (Continued)

Industry NAICS	Industry description	Industry employment, 2016	St. dev. LQ across 371 CZs, 2016 data	Low share	Mid share	High share	Cumulative employment share
5121	Motion pictures and video industries	419,722	0.52	19.3	17.5	**63.2**	37.4
5616	Investigation and security services	920,776	0.51	**73.3**	12.1	14.6	38.1
4511	Sporting goods, hobby, toy, music	467,604	0.50	8.1	**59.3**	32.6	38.5
513,515	Radio and TV broad-casting and cable	258,321	0.49	15.1	16.9	**68.0**	38.7
6111	Elementary and secondary schools	1,004,293	0.48	14.8	6.3	**78.9**	39.6
5613	Employment services	2,413,971	0.45	27.3	30.1	42.6	41.6
5418	Advertising & public relations	468,620	0.45	2.7	19.8	**77.6**	42.0
623	Nursing and care facilities	3,362,720	0.44	**56.4**	6.4	37.2	44.9
514,516-519	Internet, telecommunications, info services, data processing services	1,783,760	0.43	14.8	29.5	55.8	46.4
531	Real estate	1,537,455	0.40	17.9	11.8	**70.3**	47.7
5617	Services to buildings and dwellings and landscaping	1,826,059	0.40	**90.6**	5.0	4.3	49.2
5419	Vet services & other prof. and scientific related svs	619,969	0.40	13.1	32.6	54.2	49.7
452	Dept stores, general merchandise, warehouse	2,813,353	0.38	12.7	**64.6**	22.7	52.1
622	Hospitals	5,646,817	0.37	17.7	15.1	**67.2**	56.9
444	Building supplies, hardware, lawn shops	1,271,677	0.36	17.9	**57.5**	24.7	58.0
448	Clothing stores, jewelry stores, shoe stores	1,713,636	0.35	5.3	**62.6**	32.1	59.4
443	Appliance and electronics stores	370,773	0.32	11.6	52.5	35.8	59.7
5411	Legal services	1,121,017	0.32	0.6	20.1	**79.4**	60.7
6244	Childcare	904,605	0.32	**50.5**	2.1	47.4	61.4
442	Furniture and furnishing stores	442,906	0.31	16.9	51.5	31.6	61.8
23	Construction	6,082,597	0.30	**73.2**	8.1	18.8	66.9
453	Florists, office supplies, gifts	760,898	0.29	11.1	52.4	36.5	67.6
521-523,525-529	Banking and financial services	3,658,032	0.28	1.1	30.3	**68.7**	70.7
5412	Accounting, tax prep., bookkeeping and payroll svcs	1,072,619	0.28	0.6	31.5	**67.9**	71.6
42	Wholesale trade	5,820,831	0.27	25.4	42.8	31.8	76.5

Table A15 (Continued)

Industry NAICS	Industry description	Industry employment, 2016	St. dev. LQ across 371 CZs, 2016 data	Low share	Mid share	High share	Cumulative employment share
813	Religious services and civic groups	2,712,148	0.27	16.6	20.0	**63.4**	78.8
811	Auto repair and other goods repair	1,222,930	0.26	**63.5**	21.3	15.2	79.8
441	Auto dealers and parts	1,904,863	0.25	33.2	42.3	24.4	81.4
445-446	Grocery stores, convenience stores, liquor stores, drug stores	4,107,676	0.25	18.1	**56.0**	25.9	84.9
6211-6214	Offices of health practitioners	5,117,033	0.23	18.2	24.7	**57.1**	89.2
812	Personal services	1,419,286	0.22	**80.2**	11.7	8.1	90.4
722	Restaurants and bars	11,336,501	0.20	**74.1**	12.6	13.4	100.0

NOTE: Industry employment data comes from WholeData, and is for 112 private industries with non-zero data in 2016. Data is sorted by standard deviation of the CZ location quotient for that industry across 371 CZs as of 2016. The low, mid, and high employment shares in each industry are based on 2015–2019 ACS data.

REFERENCES

Amior, Michael, and Alan Manning. 2018. "The Persistence of Local Joblessness." *American Economic Review* 108(7): 1942–70.

Aten, Bettina H. 2006. "Interarea Price Levels: An Experimental Methodology." *Monthly Labor Review* 129(2006): 47–62.

Austin, Benjamin, Edward Glaeser, and Lawrence H. Summers. 2018. "Saving the Heartland: Place-based Policies in 21st Century America." *Brookings Papers on Economic Activity* Spring (2018).

Autor, David. 2019. "Work of the Past, Work of the Future." *American Economic Association Papers and Proceedings* 2019, 109: 1–32 https://doi.org/10.1257/pandp.20191110

Autor, David, David Dorn, and Gordon Hanson. 2019. "When Work Disappears: Manufacturing Decline and the Falling Marriage Market Value of Young Men." *American Economic Review: Insights* 1(2): 161–178. DOI: 10.1257/aeri.20180010

Autor, David, David Mindell, and Elisabeth Reynolds. 2020. *The Work of the Future: Building Better Jobs in an Age of Intelligent Machines.* Report, MIT Work of the Future Project.

Bartik, Alexander W. 2018, "Moving Costs and Worker Adjustment to Changes in Labor Demand: Evidence from Longitudinal Census Data." *Manuscript, University of Illinois at Urbana-Champaign* (2018).

Bartik, Timothy J. 2021a. "How Long-Run Effects of Local Demand Shocks on Employment Rates Vary with Local Labor Market Distress." Upjohn Institute Working Paper 21-339. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research. https://doi.org/10.17848/wp21-339

Bartik, Timothy J. 2021b. "Measuring Local Job Distress." Upjohn Institute Working Paper 20-335. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research. https://doi.org/10.17848/wp20-335

Bartik, Timothy J. 2020. "Using Place-Based Jobs Policies to Help Distressed Communities." *Journal of Economic Perspectives* 34(3): 99–127. DOI: 10.1257/jep.34.3.99

Bartik, Timothy J. 2015. "How Effects of Local Labor Demand Shocks Vary with the Initial Local Unemployment Rate." *Growth and Change* 46(4): 529–557.

Bartik, Timothy J. 2010. "Bringing Jobs to People: How Federal Policy Can Target Job Creation for Economically Distressed Areas." Hamilton Project Discussion Paper. Washington, DC: Brookings Institution.

Bartik, Timothy J. 2001. *Jobs for the Poor: Can Labor Demand Policies Help?* New York: Russell Sage Foundation.

Bartik, Timothy J. 1996. “The Distributional Effects of Local Labor Demand and Industrial Mix: Estimates Using Individual Panel Data.” *Journal of Urban Economics* 40(2): 150–178.

Bartik, Timothy J. 1991. *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, MI: W.E. Upjohn Institute for Employment Research

Bastian, Jacob, and Katherine Michelmore. 2018. “The Long-Term Impact of the Earned Income Tax Credit on Children’s Education and Employment Outcomes.” *Journal of Labor Economics* 36(4): 1127–1163.

Baum-Snow, Nathaniel, and Derek Neal. 2009. “Mismeasurement of Usual Hours Worked in the Census and ACS.” *Economics Letters* 102(1): 39–41.

Bayer, Patrick, and Kerwin Kofi Charles. 2018. “Divergent Paths: A New Perspective on Earnings Differences between Black and White Men Since 1940.” *The Quarterly Journal of Economics* 133(3): 1459–1501.

Beaudry, Paul, David A. Green, and Benjamin M. Sand. 2014. “Spatial Equilibrium with Unemployment and Wage Bargaining: Theory and Estimation.” *Journal of Urban Economics* 79(1): 2–19.

Blakely, Tony A., Sunny C.D. Collings, and June Atkinson. 2003. “Unemployment and Suicide. Evidence for A Causal Association?” *Journal of Epidemiology & Community Health* 57(8): 594–600.

Carpenter, Craig Wesley, Anders Van Sandt, and Scott Loveridge. 2021. “Measurement Error in U.S. Regional Economic Data.” *Journal of Regional Science*. https://doi.org/10.1111/jors.12551

Charles, Kerwin Kofi, Erik Hurst, and Mariel Schwartz. 2018. “The Transformation of Manufacturing and the Decline in U.S. Employment.” *NBER Macroeconomics Annual* 33: 307–372.

Clark, Sandra Luckett, John Iceland, Thomas Palumbo, Kirby Posey, and Mai Weismantle. 2003. “Comparing Employment, Income, and Poverty: Census 2000 and the Current Population Survey.” Report, U.S. Census Bureau.

Demaria, Kyle, Kyle Fee, and Keith Wardrip. 2020. “Exploring a Skills-Based Approach to Occupational Mobility”. Report, Federal Reserve Banks of Cleveland and Philadelphia.

Diamond, Rebecca. 2016. "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980–2000." *American Economic Review* 106(3): 479–524. DOI: 10.1257/aer.20131706

Diette, Timothy M., Arthur H. Goldsmith, Darrick Hamilton, and William Darity. 2018. "Race, Unemployment, and Mental Health in the USA: What Can We Infer about the Psychological Cost of the Great Recession across Racial Groups?" *Journal of Economics, Race, and Policy* 1: 75–91.

Dorn, David. No date. "Occupation Codes." Available at https://www.ddorn.net/data.htm as of November 1, 2021.

Dube, Arindrajit. 2019. "Using Wage Boards to Raise Pay." Policy Brief 4, Economists for Inclusive Prosperity.

Fowler, Christopher S., and Leif Jensen. 2020. "Bridging the Gap between Geographic Concept and the Data We Have: The Case of Labor Markets in the USA." *Environment and Planning A: Economy and Space* 52(7): 1395–1414.

Gould, Elise. 2020. "State of Working America Wages 2019." Report, Economic Policy Institute.

Hoffmann, Florian, David S. Lee, and Thomas Lemieux. 2020. "Growing Income Inequality in the United States and Other Advanced Economies." *Journal of Economic Perspectives* 34(4): 52–78. DOI: 10.1257/jep.34.4.52

Isserman, Andrew M., and James Westervelt. 2006. "1.5 Million Missing Numbers: Overcoming Employment Suppression in County Business Patterns Data." *International Regional Science Review* 29(3): 311–335.

Kromer, Braedyn, and David Howard. 2011. "Comparison of ACS and CPS Data on Employment Status." Report, U.S. Census Bureau.

Macaluso, Claudia. 2019. "Skill Remoteness and Post-Layoff Labor Market Outcomes." Working paper. https://drive.google.com/file/d/11qYFzL6MmRU7vKUb-2qJ6B_KFBWJhsI8/view

McHenry, Peter, and Melissa McInerney. 2014. "The Importance of Cost of Living and Education in Estimates of the Conditional Wage Gap between Black and White Women." *Journal of Human Resources* 49(3): 695–722.

Moretti, Enrico. 2013. "Real Wage Inequality." *American Economic Journal: Applied Economics* 5(1): 65–103.

Perry, Ian, Sarah Thomason, and Annette Bernhardt. 2016. "Data and Methods for Estimating the Impact of Proposed Local Minimum Wage Laws." Data Brief, Center on Wage and Employment Dynamics, University of California-Berkeley.

Pierce, Justin R., and Peter K. Schott. 2020. "Trade Liberalization and Mortality: Evidence from U.S. Counties." *American Economic Review: Insights* 2(1): 47–64. DOI: 10.1257/aeri.20180396

Stuart, Bryan A. 2017. "Essays on the Economics of People and Places." Dissertation, University of Michigan Department of Economics.