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How Long-Run Effects of Local Demand Shocks on Employment Rates Vary with Local Labor Market Distress

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ABSTRACT

This paper estimates that long-run changes in a county's prime-age employment rate are significantly affected by labor demand shocks to both the county and its overlying commuting zone (CZ). The overall benefits of labor demand shocks are due more to CZ demand shocks than county demand shocks. A lower preexisting county employment rate increases the effects of CZ demand shocks. Simulations suggest that low prior employment rate CZs, versus higher-rate CZs, will have much larger employment rate effects from demand shocks. Targeting jobs at more distressed counties within a CZ has modest effects, much lower than the effects of targeting jobs at more distressed CZs.

JEL Classification Codes: R23

Key Words: Local labor markets; job creation benefits; local labor demand; regional distress

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This study estimates the long-run effects on local employment rates of local labor demand shocks. It also examines how such effects vary with an area's prior labor market distress.

Within the research literature, this study fills an important gap. Based on one group of papers, local labor demand shocks have large employment rate effects in the long run.[1] But this research does not examine how effects vary with preexisting labor market problems. Based on another group of papers, an increase in local labor demand increases employment rates by more if an area's preexisting labor market was more distressed. But this research has mostly focused on the short run.[2] The current study examines demand effects in the long run and how they vary with prior labor market conditions.

How long-run effects of local demand shocks vary in different local labor markets is a key issue in evaluating place-based policies, which may redistribute jobs among local labor markets. For such redistribution to have national benefits, the benefits of job growth must differ across local labor markets.

Another contribution of the paper is to help clarify what size of area constitutes a local labor market. The paper examines long-run changes in a county's prime-age employment rate, which are allowed to vary with demand shocks to both the county and the overlying commuting zone (CZ). Both types of geographic shocks matter. Which has larger effects, the CZ shock or the county shock? That depends on whether one considers just effects within the county, or what the estimates imply for effects over the entire CZ.

[1] See later discussion. These papers include Beaudry, Green, and Sand (2014) and Amior and Manning (2018). Bartik (2020a) provides a review.

[2] See later discussion. The relevant papers include Austin, Glaeser, and Summers (2018); Bartik (2015, 2020b).

The paper also clarifies that the main reason demand shocks have larger effects in more distressed local labor markets is because **commuting zone** demand shocks have greater effects in **more-distressed counties.** On average, the local labor market allocates more job opportunities to nonemployed groups, including residents in more distressed counties.

The paper uses as a dependent variable the change in a county's "prime-age employment rate" (employment to population ratio for 25- to 54-year-olds), with that change measured from the 2000 census to the average from the American Community Survey for the 2014–2018 period. The sample is all U.S. counties with populations of more than 65,000 that are in CZs with populations greater than 200,000. This sample is 609 counties in 225 CZs. These counties make up 79 percent of the U.S. population, and these CZs make up 88 percent of the U.S. population.

The right-hand-side variables of interest are demand shocks to the county and CZ. These demand shocks are the predicted change in employment for the county or CZ due to the year 2000 distribution of jobs by industry in each type of geographic area, and the national growth rate for each industry from 2000 to 2016. The industry data come from the Upjohn Institute's WholeData data series, which overcomes suppressions in County Business Patterns to yield estimates for over 1,000 industries for each U.S. county from 1998 to 2016.

Preexisting local labor market conditions are measured as the prime-age employment rate as of 2000 in both the county and the CZ. The empirical work allows both CZ and county demand shocks to have effects that vary by either county or CZ employment rates. As already alluded to, the only significant interaction effect is that CZ shocks have greater effects when the preexisting county employment rate is lower.

Using the empirical results, simulations show large differences (over 3-to-1) in employment rate effects of local demand shocks in distressed versus nondistressed CZs. The employment rate effects are mostly due to effects in more-distressed counties. Targeting more-distressed counties for demand shocks makes some difference, but the differences are substantively modest and statistically insignificant.

WHY DO WE CARE?

Local employment rates in the United States show large disparities. For example, as of 2018, the prime-age employment rate in different CZs was 75.5 percent at the population-weighted 10th percentile versus 84.5 percent at the 90th percentile, a 90–10 gap of 9 percentage points (Bartik 2020a).

Lower local employment rates contribute to many local problems. These problems include mental illness, substance abuse, and family breakups (Autor, Dorn, and Hanson 2019; Diette et al. 2018; Pierce and Schott 2017); and adverse effects on child development (Bastian and Michelmore 2018) and state and local government budgets (Charles, Hurst, and Schwartz 2018).

Local labor demand increases can benefit both the individual and society. The earnings benefits of the jobs exceed the individual worker's own opportunity cost of their time by at least 40 percent (Haveman and Weimer 2015; Mas and Pallais 2019). By reducing family and government problems, increasing local employment rates has social spillover benefits.

Why might the effects of local demand shocks on local employment rates persist in the long run? Because of effects on human capital. Job creation in the short run provides local residents with additional job skills and reduces their social problems, which may increase local residents' long-run employability. In addition, local job increases may improve local public services such as education, which may also boost local employment rates. Short-run shocks to local labor demand have effects on the quality of local labor supply in the long run.

If local labor demand shocks boost local employment rates by more in some local labor markets, the social benefits of such job creation are higher. Redistributing jobs to such areas may increase national employment rates by redistributing jobs to where labor supply is more elastic (Austin, Glaeser, and Summers 2018; Bartik 2020a).

Local labor market conditions will affect how local employment rates respond to local labor demand shocks. A percentage shock to local jobs must be divided between a percentage effect on the local employment rate and a percentage effect on the local population, because employment is the mathematical product of the employment rate and the population. Newly created jobs are taken up by three sources: 1) local residents who were already employed, 2) local residents who were nonemployed, and 3) in-migrants. When jobs are taken by local residents who were already employed, the resulting job vacancies are filled in the same three ways. These job vacancy chains are only terminated when all new jobs result in a combination of higher local employment rates and higher local population. Along these vacancy chains, employers' hiring decisions are influenced by the availability of local labor. If more local labor is available, due to a lower prior employment rate, local job growth will have a higher effect on the local employment rate.

The key empirical parameter that matters is the elasticity of the local employment rate with respect to some demand shock to local jobs. As shown in Bartik (2020b), the benefit-cost ratio of local job creation will be proportional to the elasticity of local job creation. In some CZ z, the elasticity of the local employment rate with respect to a job shock will be

$H_z = \partial\ln(E_z/P_z) / \partial\ln(E_z)$, where E_z and P_z are employment and population in CZ z. Suppose the benefit B of some increase in the employment rate in CZ z equals parameter b times the population P_z times $d(E_z/P_z)$. Suppose total costs C of increasing employment in z can be written as parameter c times (dE_z). Then the benefit-cost ratio of job creation policies in CZ z can be written as

$$(1) \qquad \frac{B}{C} = bP_z \frac{\mathrm{d}\frac{E_z}{P_z}}{c(\mathrm{d}E_z)} = \frac{b}{c} H_z$$

LITERATURE REVIEW

Two recent papers on demand shocks' long-run effects are by Beaudry, Green, and Sand (2014) and Amior and Manning (2018). Beaudry et al. consider decade-long effects of industry-mix predicted job growth on local employment rates for 142 primary metropolitan areas, 1970 to 2007 (with the 2000–2007 change being a short decade). The estimated elasticity is 0.24.

Amior and Manning use decade-long industry-mix predicted job growth as an instrument for actual job growth for 722 CZs, 1950 to 2010. The estimated effects are on population. The population effects imply an employment rate elasticity of 0.30.

As reviewed by Bartik (2020a), these significant long-run effects are consistent with most of the empirical literature.[3]

Two recent papers look at how short-run effects of demand shocks vary with preexisting local labor market conditions: Austin, Glaeser, and Summers (2018) and Bartik (2020b). Austin, Glaeser, and Summers estimate how the year-to-year change in the prime-age male employment

[3] Blanchard and Katz (1992) is a prominent exception. However, their finding of no long-run employment rate effects of local demand shocks is not robust to alternative estimation approaches (Bartik 1993; Rowthorn and Glyn 2006).

rate is affected by industry-mix predicted demand shocks and the preexisting prime-age male employment rate. The geographic unit used is either states or 1,063 "consistent Public Use Microdata Areas" (PUMAs).[4] PUMAs are areas of about 100,000 in population that are the smallest geographic unit with which individual households can be associated in various census surveys. "Consistent PUMAs" are PUMAs matched over different time periods. Austin, Glaeser, and Summers find that the preexisting prime-age male employment rate alters the effects of demand shocks on the prime-age male employment rate. Comparing the 10th and the 90th percentiles of the prime-age male employment rate, the elasticity is 46 percent (state estimates) or 44 percent (consistent PUMA estimates) greater in local areas with a lower prior prime-age male employment rate.[5]

Bartik (2020b) examines how the year-to-year change in the overall age 16 and up employment to population ratio is affected by industry-mix predicted demand shocks and the prior year's employment to population ratio. The geographic units are CZs exceeding 200,000 in population.[6] The estimates find effects of the prior year's employment rate on demand shock effects that are statistically significant and substantively important. Consider a CZ at the 10th percentile of the overall employment rate versus at the 90th percentile (52 percent employment rate versus 66 percent). The elasticity of the employment rate is 36 percent greater in the needier CZ.

To my knowledge, only one study both provides *long-run* estimates and looks at how demand shock effects on employment rates vary with prior local economic conditions. Bartik

[4] Austin, Glaeser, and Summers' (2018) state data run from 1977–1978 to 2015–2016, and their consistent PUMA data are from 2005–2006 to 2015–2016.

[5] These calculations use the distribution of the prime-age male employment rate across all 709 year-2000-defined CZs. The 10th percentile is an 80.0 percent prime-age male employment rate, and the 90th percentile is an 89.5 percent prime-age male employment rate.

[6] There are 240 such zones, comprising 89 percent of the U.S. population. The data run from 2005–2006 to 2015–2016.

(2015) does so in a lagged dependent variable model. Therefore, the estimates directly show only immediate effects and the lagged dependent variable's effects. The inferred long-run effects are conditional on the dynamic structure being correct. In the long run, demand shocks have 70 percent greater effects in a high-unemployment metro area.[7]

Most of the previous research simply assumes some local labor market definition: state, metro area, CZ, consistent PUMA. One exception is Bartik (2020b), which includes some analyses that looks at *short-run* effects on county employment rates of county demand shocks and CZ demand shocks. That research finds highly statistically significant effects on counties of CZ demand shocks, but no statistically significant effects of county demand shocks, holding CZ demand shocks constant. But that finding pertains to short-run effects; the present study considers long-run effects. If we want to affect long-run labor market outcomes through local labor demand policies, should we think of local labor markets as being CZs or counties?

MODEL

The paper's model can be written as

(2) ln(*prime-age labor market outcome in county average from 2014–2018 from ACS*) − ln(*prime-age labor market outcome in county in 2000 U.S. census*) =

B_0 + B_{dc} × (*county demand shock from 2000 to 2016*) + B_{dz} × (*CZ demand shock from 2000 to 2016*) +

B_c × ln(*prime-age employment rate in county in 2000 U.S. census*) + B_z × ln(*prime-age employment rate in CZ in 2000 U.S. census*) +

B_{cc} × [(ln(*prime-age employment rate in county in 2000 U.S. census*) × (*county demand shock from 2000 to 2016*)] + B_{zc} × [ln(*prime-age employment rate in CZ in 2000 U.S. census*) × (*county demand shock from 2000 to 2016*)] +

[7] The data used are 23 large metro areas, from 1979 to 2011.

B_{cz} × [(ln(*prime-age employment rate in county in 2000 U.S. census*) × (*CZ demand shock from 2000 to 2016*)] + B_{zz} × [ln(*prime-age employment rate in CZ in 2000 U.S. census*) × (*CZ demand shock from 2000 to 2016*)]

The dependent variable, the change in the natural log of the county's prime-age labor market outcomes from 2000 to the 2014–2018 period, varies across regressions among three dependent variables: the change in the natural log of 1) the employment to population ratio or employment rate, 2) the employment to labor force ratio, and 3) the labor force participation rate. Because the change in the log of the employment rate is the sum of the change in the log of the other two labor market outcomes, the estimated coefficients with the employment rate dependent variable will be the sum of the corresponding coefficients in the other two estimating equations.

I initially estimate the variant of the model without interaction terms and then add in interaction terms between the initial prime-age employment rates in the county and the CZ, and the county and CZ demand shocks.

What are the implications of these different elasticities? Consider the equation without interaction terms. As shown in Bartik (2020b), if we weight equally gains in the employment to population ratio in all parts of the CZ, the sum of the two elasticities (for county demand shocks and CZ demand shocks) will be proportional to the benefit-cost ratio for job creation in the CZ, regardless of where the jobs are created within the CZ.[8] A 1 percent CZ demand shock is more costly than a 1 percent county shock because it is more jobs, but the CZ demand shock also benefits more people.

Suppose instead we only count benefits for county residents. Then the benefit-cost ratio for job growth in the county, versus job growth in the CZ outside the county, will be proportional to the ratio [B_{dc} + B_{dz} × (*proportion of CZ employment in county*)] / [B_{dz} × (*proportion of CZ*

[8] This proposition is also shown in Appendix A to this study, based on Bartik (2020b).

employment in county]). For this sample, on average 33.7 percent of CZ employment is in the county being analyzed.

If we consider the interaction specification, matters are more complicated. After the main results are estimated, some illustrative simulations will be done to show how benefits vary with various job growth shocks to different counties in a CZ at different prior employment rates.

DATA

To estimate the model, data on prime-age labor market outcomes are taken from aggregated census data. The labor market outcomes are employment to population ratios (employment rates), employment to labor force ratios, and labor force participation rates. These data are available for all counties for both the year 2000 and for the five-year period from 2014–2018. The 2000 data are from the 2000 census, and the 2014–2018 data are from the American Community Survey. Appendix B provides further details on how these employment rates are derived from the available data.

The demand shocks are measured as the natural logarithm of (1 + *the predicted proportional demand shock to growth for the geographic unit, county, or CZ*). The (*predicted proportional demand shock to growth for the county or CZ*) takes national job growth for each industry from 2000 to 2016 and multiplies it for a particular county or CZ by the share of the county or CZ's jobs in each industry as of 2000. The industry job data for the nation and each county and CZ is taken from the Upjohn Institute's WholeData. This WholeData has estimates of jobs in over 1,000 six-digit NAICS industries for each county in the United States, and each year from 1998 to 2016. These data are derived by an algorithm that overcomes data suppressions in

County Business Patterns. This algorithm was originally developed by Isserman and Westervelt (2006).

As shown in Bartik (1991), this measure of predicted growth proxies for shocks to national demand for a geographic area's "export-base" or "tradable" industries; that is, industries that compete in the national or international market for goods or services. This particular demand shock measure has been critiqued in recent years; the argument is that in some cases this demand shock might be correlated with local labor supply shifters (Goldsmith-Pinkham, Sorkin, and Swift 2020). However, in the current model, with over 1,000 industries, there are diverse industries driving the demand shock measure in different areas. It is not obvious how this demand shock measure might be biased, in one way or another, by unobserved supply shifters.

Appendix C provides descriptive statistics.

RESULTS WITHOUT INTERACTION TERMS

Table 1 shows results without interaction terms: on average in this sample, how are long-run changes in a county's prime-age employment rate, and other labor market outcomes, affected by county versus CZ demand shocks?

As mentioned, the overall benefit-cost ratio over a CZ from job creation that increases employment rates will be proportional to the combined county plus CZ elasticity.[9] As shown in Table 1, this overall employment rate elasticity is due mostly to effects on labor force participation rates. In the long run, unemployment rates are only slightly affected.

[9] The model directly estimates the county coefficient and CZ coefficient. The sum of the coefficients and their standard error is computed using the estimated covariance matrix for the model's coefficients.

Compared to the prior literature, this study's estimated magnitude of the overall CZ plus county elasticity is similar. The estimated elasticity is 0.34. As already mentioned, previous studies find long-run elasticities that are close to 0.30.

But the present study also investigates whether the overall CZ elasticity matters more, or the distribution of jobs within the CZ. If "matters more" is interpreted as "statistical significance," the answer is clear. The elasticity of a county's employment rate, unemployment rate, or labor force participation rate with respect to a CZ demand shock is much more statistically significant—has a higher *t*-statistic—than the elasticity with respect to a county demand shock. With an employment rate dependent variable, the *t*-statistic on the CZ shock is 3.94 (= 0.2484 / 0.0630), considerably greater than the *t*-statistic on the county shock of 2.49 (= 0.0868 / 0.0348).

But if "what matters more" depends more on the substantive magnitude, the answer depends on the question being asked. In terms of the overall benefit-cost ratio for the CZ of job creation: the CZ elasticity is almost three times as large as the county elasticity. Therefore, job shocks to the CZ are more important than the within-CZ job allocation in determining the overall CZ benefit-cost ratio for job creation.

But from the perspective of a county's benefits, a job shock in the county will have about twice the effect on the county's employment rate as the same sized job shock in the rest of the CZ, once we take account of the CZ being bigger than the county. The ratio of effects on the county's employment rate of a within-county shock to an outside-county-within-CZ shock is 2.04.[10]

[10] 2.04 = [0.0868 + (0.337)(0.2484)] / [(0.337)(0.2484)].

RESULTS WITH INTERACTION TERMS

Table 2 shows results with interaction terms: the effects of both CZ demand shocks and county demand shocks are allowed to vary with both the CZ and county employment rates. Hence there are four interaction terms: the two demand shocks with the two prior employment rates.

Of these four interaction terms, the only term that is statistically significant is the CZ demand shock interacted with the prior county employment rate. A CZ demand shock has statistically significantly greater effects if the county's year 2000 prime-age employment rate was lower. This holds for all three dependent variables.

This interaction term is not only statistically significant, the interaction coefficient has a magnitude that is substantively important. Consider the interaction term when the dependent variable is the change in the natural log of the employment rate. In the data, the standard deviation of the natural log of the year 2000 prime-age employment rate in the county is 0.0716. A one standard-deviation reduction in a county's year 2000 ln(*prime-age employment rate*) will increase the elasticity of response of the employment rate to a CZ demand shock by 0.2717 (equals standard deviation of 0.0716 times interaction coefficient of −3.7944). As shown in Table 1, the average elasticity of the employment rate response to a CZ demand shock is 0.2484. Thus, a one standard deviation lower prior prime-age employment rate increases this CZ elasticity by more than double, by 109 percent (= 0.2717 / 0.2484).

What about the other interaction terms? County demand shocks also tend to have higher effects when the prior county prime-age employment rate is lower, but insignificantly so. As for the prior CZ employment rate, although the interaction effects are statistically insignificant, they have what might initially be perceived to be the "wrong sign": when the prior CZ employment rate is lower, the effects of CZ demand shocks or county demand shocks on a county's employment rate tends to be higher; that is, the interaction coefficient is positive, not negative.

Upon further reflection, such a positive interaction coefficient is plausible. Holding prior county employment rates constant, higher prior CZ employment rates imply that that labor market in the remainder of the CZ, outside the county, will be tighter. A tighter overall CZ labor market might mean that a demand shock to the CZ or county will tend to attract more in-migrants from outside the CZ. On the other hand, a tighter labor market outside the county may mean that any CZ or county demand shock may tend to allocate a greater share of jobs to county residents versus residents in the rest of the CZ. On net, it seems like the latter effect dominates. But the net effect is statistically insignificant.

SIMULATIONS USING INTERACTION ESTIMATES

To get a fuller sense of the implications of these interaction estimates, Tables 3 and 4 present some simulations of how various elasticities differ in CZs and counties with different prior employment rates. Table 3 shows elasticities in CZs where all counties have the same prior prime-age employment rate. Table 4 shows elasticities in CZs where counties have different prior prime-age employment rates.

In Table 3, the different rows show the overall elasticity of different labor market outcomes with respect to a demand shock, at different percentiles of the year 2000 prime-age employment rate. The percentiles are taken from the distribution of the CZ employment rate. All the counties in the CZ are assumed to have the same prime-age employment rate as the overall CZ average. The demand shock is assumed to be a uniform demand shock throughout the CZ.

However, given that the CZ is uniform, the average elasticity over the entire CZ will not vary with the distribution of the shock.

As shown in Table 3, at different prior employment rates, the elasticity of employment rate outcomes in response to a demand shock differs enormously. The overall employment rate elasticity in high employment rate CZs, at the 90th percentile, is 0.14. In a median prior employment rate CZ, this elasticity increases to 0.29, or double the high employment rate elasticity. In low prior employment rate CZ, at the 10th percentile, this elasticity further increases to 0.52. Overall, from the high employment rate CZs to the low employment rate CZs, the elasticity increases more than threefold, from 0.14 to 0.52.[11]

The employment rate elasticity differentials are greater between the 10th percentile CZ and the median CZ, compared to between the median CZ and the 90th percentile CZ. Part of the explanation is that the upper tail of the CZ prior employment rate differential is somewhat more compressed than the lower tail. For example, the year 2000 median prime-age employment rate is 77.5 percent. The 10th percentile CZ is almost 6 percentage points lower at 71.8 percent, but the 90th percentile is only about 4 percentage points higher at 81.4 percent. The upper tail's compression may reflect in part the infeasibility of pushing the employment rate upward beyond a certain point. To put it another way, distressed CZs differ more from the median than booming CZs differ from the median.

Compared to the previous research literature, this is a much greater contrast in employment rate effects. As mentioned, the prior research literature finds that low employment rate areas tend to show a greater demand shock elasticity, compared to high employment rate areas. But the differential was only perhaps a 30–50 percent greater effect, not a threefold

[11] As mentioned in the table notes, these differentials are also highly statistically significant.

increase. This is partially explained by the fact that here we are analyzing a long-run elasticity, and these past studies are analyzing short-run elasticities. The long-run elasticities on average tend to be lower, so differentials based on prior employment rates tend to be larger proportionately.[12] The lower long-run elasticities probably reflect that, in response to a labor demand shock, migration responses loom larger in the long run than in the short run. But this is particularly true for CZs with higher prior employment rates. So, in analyzing the benefits and costs of demand shocks in CZs with different prior employment rates, in the long run the benefits versus costs are far more favorable in CZs with lower prior employment rates.

Most of these differentials across different prior CZ employment rates are due to labor force participation rate effects, not unemployment rate effects. As shown in Table 3, the overall employment rate elasticity differential between the 10th and 90th percentile CZs is 0.381 (0.520 − 0.139). Of that 0.381 differential, 0.258 is due to labor force participation rate effects (0.409 − 0.151), and 0.123 is due to unemployment rate effects [0.111 – (−0.012)].

Table 4 reports results for simulations in which the CZ has diverse prior employment rate conditions across counties. I assume the CZ is divided between two counties of equal employment size. The county differential is set based on the distribution in this sample of the county minus the CZ employment rate. The 10th percentile of this difference is −3.26 percentage points. I assume this describes the needier county in these simulations.

Five different CZs are considered, at the same five CZ prior employment rates considered previously in Table 3, at the various percentiles of the overall CZ distribution: 10th, 25th,

[12] So, for example, in Austin, Glaeser, and Summers' (2018) "consistent PUMA" results, the estimated short-run elasticities at the 10th and 90th percentiles are 1.240 and 0.859, which is a percentage difference of 44 percent, but an absolute difference of 0.381. As it so happens, in the current paper in Table 3, the absolute difference between the 10th and 90th percentile is also 0.381 (0.520 − 0.139), but this corresponds to a threefold differential because long-run elasticities are much smaller.

median, 75th, and 90th. The same county differential is considered for each of these CZs. For example, the 10th percentile CZ has an overall employment rate of 71.8 percent. I assume that one county has an employment rate of 68.5 percent, the “needier” county in that CZ (= 71.8 percent − 3.3 percent). The other county in that CZ would then have an employment rate that is adjusted upward so that the two counties together have a CZ employment rate of 71.8 percent.[13] The 90th percentile CZ has an overall prime-age employment rate of 81.4 percent. The needier county in this CZ is assumed to have a prior prime-age employment rate of 78.1 percent (= 81.4 percent − 3.3 percent), with the less needy county being sufficiently higher that the overall CZ has an employment rate of 81.4 percent.

I consider two types of employment shocks in each of these five CZs. Both of these shocks are 1 percent to overall CZ employment. However, one shock is uniform in both counties. The other shock is all in the needier county, or 2 percent in the needier county.

For each of these two shocks in each of these five CZs, I report the elasticity of the employment rate in both the needier county and the nonneedy county. I also report the overall elasticity for the CZ as a whole, which is the average of the two. For a given percentage shock to overall CZ employment, this overall CZ elasticity would be proportional to the benefit-cost ratio for the job creation, assuming gains in employment rates are valued equally regardless of where they occur in the CZ.[14]

[13] Because it is the employment-weighted sum of the individual county elasticities that is related to the benefit-cost ratio for employment shocks to employment among counties in a CZ, and for simplicity, the employment to population ratio for the needy and nonneedy counties are adjusted by keeping employment equal in the two counties, and adjusting the population up or down in each so it sums to the original total.

[14] See Appendix A for more on the relationship between this employment-weighted overall elasticity and a job creation program’s benefit-cost ratio.

In addition, for comparison, I also report the overall CZ elasticities that were previously reported in Table 3, which show the elasticity of the CZ employment rate when the CZ has no differentials in prior employment rates in its component counties.

First, note that when we move to a world where counties in a CZ differ, the overall elasticity of the CZ employment rate is not much different for a uniform demand shock. For example, for a 10th percentile CZ, if the CZ is uniform, the overall elasticity is 0.5199, whereas if the counties within the CZ are different, the overall average elasticity is 0.5149.

However, with the divergent counties, it is clear that most of the overall CZ employment rate elasticity is due to effects on residents of the needier county. This differential grows when we consider CZs with higher overall prior employment rates. For example, in the 10th percentile CZ, over two-thirds of the overall CZ elasticity occurs because of employment rate effects in the needier county (0.7259 in the needy county vs. 0.3040 in the nonneedy county). In the 75th percentile or 90th percentile CZs, almost all the overall CZ effects are due to effects in the needier county (0.3860 vs. 0.0079 for the 75th percentile, 0.3206 vs. −0.0496 for the 90th percentile).[15]

What does this mean? One interpretation: CZ demand shocks tend to have benefits that spread to nonemployed groups, which includes counties with low prime-age employment rates. This is particularly true when the overall CZ is doing well.

What happens if we target the needier county for the demand growth? This helps the needier county but hurts the less-needy county. The overall CZ average tends to go up. However, the increase in the overall CZ response tends to be modest. For the 10th percentile CZ, targeting

[15] The needier county effect versus the less-needy county effect has a *t*-statistic of 3.68. This is the same for all such comparisons because it reflects the variance covariance matrix for only the interaction terms involving the county prime-age rate.

the needier county increases the overall CZ average elasticity from 0.5149 to 0.5452. For the 90th percentile CZ, targeting the needier CZ increases the overall CZ average elasticity from 0.1355 to 0.1621. If we're focused on overall CZ benefits, targeting has benefits but they are substantively small, as well as statistically insignificant.[16]

CONCLUSION

The main findings of this paper are threefold:

1) The overall local labor market effects of local demand shocks are due more to demand shocks to the CZ, not to counties within the CZ. However, the county demand shocks are important to how demand shock effects are distributed geographically,

2) Distressed CZs have far larger employment rate effects of demand shocks than nondistressed CZs, with differentials of over three to one. These effects are mainly due to effects on groups with low employment rates within the zone, including counties with particularly low employment rates.

3) Targeting distressed areas within a CZ for jobs may have aggregate benefits, but they are modest.

An important area for further research is other local factors that might affect the local employment rate effects of demand shocks. For example, it is plausible that if a county with a low employment rate has better transportation, information, or workforce links to the larger CZ labor market, then the employment rate effects of local demand shocks will be greater. But this plausible hypothesis needs to be tested with empirical research.

[16] The differential between the overall CZ elasticity for the targeting scenario versus uniform job growth has a *t*-statistic of 0.57. This is, not coincidentally, the *t*-statistic on the interaction term between the county demand shock and the county's prior employment rate.

Appendix A

Some Results from Bartik (2020b), Plus Some Additional Results

If we estimate elasticities of a county's employment rate with respect to both shocks to county employment and CZ employment, then total benefits depend on how one weights benefits to the county versus benefits elsewhere in the CZ, and also on whether the shock is to the county or elsewhere in the CZ. Suppose total benefits B are equal to benefit weight b_1 times the change in the county's employment rate times the county's population, plus some benefit weight b_2 times the product of the change in the employment rate and the population of the rest of the CZ, or

(3) $$B = b_1 \left(\mathrm{d}\frac{E_1}{P_1} \right) P_1 + b_2 \left(\mathrm{d}\frac{E_2}{P_2} \right) P_2$$

where E_1, P_1, E_2, and P_2 are employment and population in the county (Area 1) and elsewhere in the CZ (Area 2).

The employment rate in either Area 1 or Area 2 will change due to demand shocks to each area's employment and the CZ's employment. Suppose that we estimate an equation that shows elasticities of the county's employment rate with respect to both county employment and the CZ's employment, and these elasticities are G_{a1} and G_{z1}. Then the term $[\mathrm{d}(E_1/P_1)]\ P_1$ can be written as

(4) $$\left(\mathrm{d}\frac{E_1}{P_1} \right) P_1 = G_{a1}\mathrm{d}(E_1) + \left(\frac{E_1}{E_1+E_2} \right) G_{z1}(\mathrm{d}E_1 + \mathrm{d}E_2)$$

A similar equation can be written for Area 2:

(5) $$\left(\mathrm{d}\frac{E_2}{P_2} \right) P_2 = G_{a2}\mathrm{d}(E_2) + \left(\frac{E_2}{E_1+E_2} \right) G_{z2}(\mathrm{d}E_1 + \mathrm{d}E_2)$$

Costs of job creation are assumed to be the same everywhere:

(6) $$C = c(\mathrm{d}E_z) = c\ (\mathrm{d}E_1 + \mathrm{d}E_2)$$

The benefit-cost ratio can be calculated by plugging Equations (4) and (5) into Equation (3) and dividing by Equation (6). If we assume $b_1 = b_2 = b$, $G_{a1} = G_{a2}$, and $G_{z1} = G_{z2}$ and we assume that we weight gains in employment rates equally throughout the CZ, then regardless of where in the CZ the jobs are created, the benefit-cost ratio is proportional to the sum of the two elasticities, or

(7) $$\frac{B}{C} = \left(\frac{b}{c}\right)(G_a + G_z)$$

Suppose alternatively that we set $b_2 = 0$: we only value Area 1 (the city?), and not Area 2 (the suburbs?). Then the benefit-cost ratio depends upon where in the CZ the jobs are located if G_a is nonzero. If the jobs are created in Area 1, the benefit cost ratio is:

(8) $$\frac{B}{C} = \frac{b_1}{c}\left[G_a + \left(\frac{E_1}{E_1+E_2}\right)G_z\right]$$

But if $b_2 = 0$, and the jobs are created in Area 2, the benefit-cost ratio is:

(9) $$\frac{B}{C} = \frac{b_1}{c}\left[\left(\frac{E_1}{E_1+E_2}\right)G_z\right]$$

So, if we only value one part of the CZ, then demand shocks that occur elsewhere in the CZ are downweighted, as shown in Equation (9), by the proportion of employment in the one valued part of the CZ. But if the demand shock occurs in the valued part of the CZ, we add in differential effects of nearby jobs (Eq. 8).

Suppose instead that either G_{a1} does not equal G_{a2}, or G_{z1} does not equal G_{z2}. But suppose we return to weighting benefits equally everywhere in the CZ. Then note that if we divide Equation (4) by E_1, and Equation (5) by E_2, we get equations expressing the percentage change in the employment rate, as a function of the area's two elasticities (county and CZ) multiplied by the percentage shock to county and zone employment, respectively. These elasticities may vary with county and CZ characteristics, such as the preexisting prime-age employment rate. It is this county-level percentage change in the employment rate that is first calculated in the models reported in Table 4.

If we then weight each county's percentage change in the employment by its share of total CZ employment, and multiply by $\frac{b}{c(dE_Z)}$, we then get the benefit-cost ratio for local job creation as

$$(10) \qquad \frac{B}{C} = \frac{b}{c} \frac{\left[\left(\frac{E_1}{E_Z}\right)\left(\mathrm{d}\frac{E_1}{P_1}\right)\left(\frac{P_1}{E_1}\right) + \left(\frac{E_2}{E_Z}\right)\left(\mathrm{d}\frac{E_2}{P_2}\right)\left(\frac{P_2}{E_2}\right)\right]}{\left(\frac{\mathrm{d}E_Z}{E_Z}\right)} .$$

In other words, this employment share–related sum of each area's specific elasticity of the employment rate—divided by the percentage change in overall zone employment and multiplied by the ratio of benefits per job created for persons due to higher employment rates, over costs per job of creating jobs—will equal the benefit-cost ratio. When the zone employment change is set equal to 1 percent, for example, this percentage calculation times the ratio of benefits per job to costs per job will generate the benefit-cost ratio.

Appendix B

More Details on How Labor Market Outcomes Data Were Calculated and Defined

The labor market outcome data used in this study are based on aggregated statistics for counties reported by the U.S. census. The aggregated census data is used rather than microdata in part because this avoids imperfect matches between the Public Use Microdata Areas (PUMAs) used in the microdata, and the county's boundaries. In addition, the aggregated data are based on a 50 percent larger sample of the population than is true for the microdata.

One constraint is that to get complete county data after the American Community Survey was begun in 2005, we need to use the five-year average files, 2014–2018 in this case. Complete county data are required to accurately calculate the labor market outcomes for all CZs.

The county data are then mapped to the groups of counties called CZs using CZ definitions based on the 2010 census created by Penn State researchers (Fowler and Jensen 2020).

The calculations of civilian labor market outcomes require some algebra using the census data. The census reports four data items for prime-age persons:

1) Ratio of civilian employment E to the sum of civilian population C and military population (and employment) M, which I define as $e^{**} = E / (C + M)$;

2) Total population P, which $= C + M$;

3) labor force participation rate including military, which I write as l^*, and which equals civilian labor force L plus military employment M, divided by total population P;

4) the civilian unemployment rate, which I write as u, and which is the ratio of civilian unemployment U to civilian labor force L.

Using these four data items, it is possible to calculate the civilian employment rate, labor force participation rate, and employment to labor force ratio.

Appendix C

Descriptive Statistics

Table A1 reports descriptive statistics for the variables included in the regression: the dependent variable changes in the log of the three different labor market outcomes; the demand shocks at both the county and CZ level; and the preexisting level of the log of the prime-age employment rate in 2000, both for the county and CZ. I also report some unlogged versions of the prior prime-age employment rate.

The descriptive statistics are for the 609 county observations. Thus, for the CZ-level statistics (based on 225 CZs), often several counties will have the same CZ data.

There is considerable variation in all the variables. The prime-age employment rate improved in log percentage points by almost 5 points in counties at the 90th percentile and decreased by almost 4 percentage points in counties at the 10th percentile. The demand shock measures have a 90–10 percentile differential of 14 percentage (log) points predicted at the county level, and 11 percentage (log) points predicted growth at the CZ level. The year 2000 prime-age employment rate shows a near 10 percentage point differential at the CZ level (81 percent versus 72 percent), and a more than 12 percentage point differential at the county level (84 percent versus 71 percent).

In the prior prime-age employment rate statistics, there is some sign that the distribution is more compressed at the upper end. The differentials from the 75th percentile to the 90th percentile are smaller in absolute value than the differentials from the 25th percentile to the 10th percentile.

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Table 1 Effects of Commuting Zone (CZ) and County Demand Shocks on Changes in County Labor Market Outcomes from 2000 to 2014–2018 Period

	Dependent Variable: Change from 2000 to 2014–18 in ln of County's Prime-Age		
	Employment/population	Employment/labor force	Labor force/population
Demand shock measure for			
County	0.0868 (0.0348)	0.0024 (0.0129)	0.0844 (0.0271)
CZ	0.2484 (0.0630)	0.0481 (0.0222)	0.2003 (0.0486)
County + CZ	0.3352 (0.0541)	0.0505 (0.0190)	0.2847 (0.0423)

NOTE: Robust standard errors in parentheses. Dependent variable is change in log of labor market outcome for prime age (age 25–54) in a particular county from 2000 to the average for the 2014–2018 period. Sample is 609 counties in 225 CZs. The chosen counties are those of 65,000 population or more in CZs of 200,000 population or more. Standard errors correct for clustering at the CZ level. The right-hand-side variables are demand shocks to the county and CZ, based on year 2000 industrial mix in the county or CZ, and industry-specific growth rates from 2000 to 2016.

Table 2 Effects of County and Commuting Zone (CZ) Demand Shocks on Changes from 2000 to 2014–2018 Period in Prime-Age Labor Market Outcomes: Variation with Preexisting County and CZ Employment Rates

	Dependent Variable: Change from 2000 to 2014–18 in ln of County's Prime-Age		
	Employment/ population	Employment/ labor force	Labor force/ population
RHS variable			
County demand shock	0.2241 (0.2155)	0.0721 (0.0870)	0.1520 (0.1512)
CZ demand shock	−0.7115 (0.2575)	−0.2868 (0.1134)	−0.4247 (0.1815)
County demand shock interacted with county's 2000 employment rate	−0.6354 (1.1196)	0.1205 (0.3210)	−0.7559 (0.9142)
CZ demand shock interacted with county's 2000 employment rate	−3.7944 (1.4206)	−0.9475 (0.4157)	−2.8469 (1.2720)
County demand shock interacted with CZ's 2000 employment rate	1.1594 (1.1924)	0.1434 (0.4094)	1.0160 (0.9590)
CZ demand shock interacted with CZ's 2000 employment rate	0.2255 (1.8133)	−0.3008 (0.5612)	0.5263 (1.5666)

NOTE: Standard errors in parentheses. In addition to right-hand-side variables noted, regression also includes the initial county and CZ employment rate variables by themselves. County and CZ demand shocks are predicted logarithmic growth in county or CZ employment predicted by the area's year 2000 employment by industry, and by national job growth by industry from 2000 to 2016. The interaction with county and CZ year 2000 employment rate are with the natural log of the prime-age employment to population ratio for the county or CZ. Sample is 609 counties in 225 CZs. Standard errors are adjusted for clustering at CZ level.

Table 3 Effects of Uniform Demand Shocks to Uniform Commuting Zone (CZ) on Changes in Logged Labor Market Outcomes, 2000 to 2014–2018 Period, and How It Varies with CZ's Preexisting Employment Rates

Percentile in 2000	2000 Prime-Age Employment Rate (%)	Elasticity of Employment/ Population Ratio	Elasticity of Employment/ LF Ratio	Elasticity of LF-to-Population Ratio
10	71.8	0.5199 (0.0770)	0.1109 (0.0267)	0.4090 (0.0603)
25	75.2	0.3821 (0.0617)	0.0664 (0.0222)	0.3157 (0.0473)
50	77.5	0.2879 (0.0598)	0.0359 (0.0242)	0.2520 (0.0432)
75	79.8	0.2010 (0.0650)	0.0078 (0.0291)	0.1931 (0.0441)
90	81.4	0.1394 (0.0720)	−0.0121 (0.0336)	0.1515 (0.0473)

NOTE: Standard errors in parentheses. These estimates are derived from the interaction specification in Table 2, and simply calculate different linear combinations of those coefficients to get elasticities at different preexisting levels of the prime-age employment rate. These estimates all assume that the prior prime-age employment rate is identical in both the county and the CZ. This prior employment rate is set to various percentiles of the distribution of the prime-age employment rate across CZs. The differential across different prime-age employment rates is always statistically significant, with absolute values of *t*-statistics of 4.25 for the employment rate equation, 3.06 for the employment to labor force equation, and 4.15 for the labor force participation rate equation.

Table 4 Effects of Demand Shocks under Various Assumptions about Distribution of Shock across Diverse Counties in CZ

Overall CZ percentile of employment rate distribution	CZ's baseline employment rate (%)	Uniform shock in uniform CZ	Uniform shock in needy county	Uniform shock in nonneedy county	Average for CZ of uniform shock	Shock only in needy county, effect in that county	Shock only in needy county, effect in nonneedy county	CZ average of targeted shock
10	71.8	0.5199 (0.0770)	0.7259 (0.1124)	0.3040 (0.0749)	0.5149 (0.0764)	0.8061 (0.1860)	0.2843 (0.0950)	0.5452 (0.1022)
25	75.2	0.3821 (0.0617)	0.5787 (0.1001)	0.1764 (0.0584)	0.3776 (0.0611)	0.6813 (0.1439)	0.1315 (0.0701)	0.4064 (0.0830)
50	77.5	0.2879 (0.0598)	0.4784 (0.0973)	0.0889 (0.0560)	0.2837 (0.0592)	0.5964 (0.1239)	0.0268 (0.0646)	0.3116 (0.0758)
75	79.8	0.2010 (0.0650)	0.3860 (0.0992)	0.0079 (0.0613)	0.1969 (0.0645)	0.5181 (0.1157)	−0.0700 (0.0706)	0.2240 (0.0749)
90	81.4	0.1394 (0.0720)	0.3206 (0.1030)	−0.0496 (0.0686)	0.1355 (0.0716)	0.4628 (0.1171)	−0.1386 (0.0801)	0.1621 (0.0778)

NOTE: Standard errors in parentheses. All estimates derived from interaction specification presented in Table 2. The first column of results reproduce the estimates in Table 3 for a uniform CZ at different percentiles of the CZ year 2000 prime-age employment rate distribution. The remaining scenarios consider effects in a hypothetical CZ divided into two equally sized counties, one needy and one nonneedy. The needier county is 3.26 percentage points below the CZ average prime-age employment rate, and the nonneedy county employment rate is adjusted upward so that the two counties add up to the overall CZ average. Employment in each county is kept equal to the same figure, and population figures adjusted to get the appropriate county and CZ employment rates. We consider two shock scenarios. The next three columns of results consider again a uniform shock of 1% to employment in both counties. But the shock effect is broken down for effects in both the needier and nonneedier counties, as well as the average of the two counties, which is the average CZ effect. The last three columns consider a targeted scenario. The overall shock to the CZ's employment is still 1%, but now that shock is not 1% in each county, but rather 2% in the needier county and zero in the other county. These last three columns show the effects of this in the needier and nonneedier county, and the overall CZ effect, which is the average of the two counties. The differential between the needy and nonneedy county is highly significant, with a *t*-statistic of 3.68 in the needy county elasticity minus the nonneedy county elasticity. The differential between the targeted employment shock versus the untargeted is statistically insignificant, with a *t*-statistic of 0.57.

Table A1 Descriptive Statistics for Variables in Regression

	Mean	sd	Min	p10	p25	p50	p75	p90	Max
Change in ln(prime Emp/Pop) from 2000 to 2014–2018	0.0054	0.0412	−0.1462	−0.0378	−0.0162	0.0036	0.0222	0.0485	0.2221
Change in ln(prime Emp/LF) from 2000 to 2014–2018	−0.0099	0.0135	−0.0667	−0.0258	−0.0177	−0.0100	−0.0030	0.0041	0.0592
Change in ln(prime LF/Pop) from 2000 to 2014–2018	0.0154	0.0347	−0.1197	−0.0222	−0.0035	0.0140	0.0311	0.0544	0.1900
Demand shock to county, 2000 to 2016	0.1048	0.0631	−0.1939	0.0321	0.0727	0.1103	0.1424	0.1731	0.2866
Demand shock to CZ, 2000 to 2016	0.1078	0.0459	−0.1663	0.0443	0.0832	0.1127	0.1365	0.1545	0.2532
ln(prime-age Emp/Pop) in county in 2000	−0.2566	0.0716	−0.7141	−0.3399	−0.2879	−0.2456	−0.2098	−0.1803	−0.1329
ln(prime-age Emp/Pop) in CZ in 2000	−0.2628	0.0580	−0.5775	−0.3309	−0.2856	−0.2547	−0.2261	−0.2059	−0.1302
Prime-age E/Pop in county in 2000 (%)	77.4		49.0	71.2	75.0	78.2	81.1	83.5	87.6
Prime-age E/Pop in CZ in 2000 (%)	76.9		56.1	71.8	75.2	77.5	79.8	81.4	87.8

NOTE: Descriptive statistics for variables in the regression. Note that because the census changed its method of asking labor force questions to more closely match BLS results, the prime-age employment rate tended to increase over time for measurement reasons.