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# Place Distress and Job Growth: Are Recent Job Growth Trends Significantly More Favorable for Distressed Counties?

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**Abstract:** This paper examines whether recent job growth trends have become more favorable toward counties with greater baseline economic distress. Job growth trends are "competitive job growth," which is defined as growth that exceeds what would be expected based on how a county's industries are growing nationally. Baseline county distress is measured by the county's "prime-age employment rate," the employment to population ratio for 25–54-year-olds. The core findings are fourfold. First, for the most distressed counties, job growth trends have become more favorable since 2019, compared to the 2001–2007 and 2007–2019 periods. The timing of this recent improvement is consistent with a possible influence of recent federal policies. Second, for the least distressed counties, job growth trends have become less favorable in post-2019 growth and 2007–2019 growth compared to the 2001–2007 period. The timing suggests these trends are probably due not to recent federal policies but rather to other economic forces such as rising costs in some less distressed counties. Third, similar trends are also evident for industry groups such as manufacturing and high-tech, again industries which recently have been targeted by federal policies. Fourth, these recent trends toward greater job growth in more distressed counties are modest in size, in the sense that they are insufficient to significantly lower employment rate gaps between more distressed counties and the national average.

**JEL Classification Codes:** R12, R28

**Key Words:** Place-based policies; Regional growth trends; Local growth trends; High-tech growth trends

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This paper provides a preliminary economic analysis of whether job growth trends since 2019 have shifted away from the most booming places and toward distressed places. Both the Trump administration and Biden administration have had rhetoric about helping distressed places, and both adopted some policies that are relevant to distressed places. Can we see any job growth trends that might reflect effects of this rhetoric and policies? Can we see any job growth trends that might plausibly be due to economic forces, such as rising housing prices in some booming places, that might help redistribute jobs to the most jobs-short places?

Over the past year, several reports have looked at recent business investment trends during the post-2020 recovery period in particular industrial sectors in different counties. These reports found some evidence that these recent trends have favored distressed counties. The current paper's analysis also looks at county trends, but it complements these other recent reports with a methodology that differs in the following ways:

- This paper looks at county job growth trends, not investment trends.
- This paper focuses where possible on trends from business cycle peak to peak, not just during the post 2020 recovery period.
- This paper's main focus is on overall job growth trends, whereas other reports have focused more narrowly on particular industrial sectors.
- This paper includes an explicit statistical comparison between the recent period and earlier periods.
- This paper focuses on "competitive job growth"; that is, on a county's job growth after controlling for the county's industrial mix and national industry growth trends.

More specifically, this report examines average annual county job growth rates over three time periods: 2001–2007; 2007–2019; and 2019–2022/2023 (the last half of 2022 and the first half of 2023), which is currently the last period available with the data we use on detailed industries. We examine how a county's average annual job growth rate is related to its "prime-age employment rate" (employment to population ratio for 25–54-year-olds) during the baseline period; that is, at the beginning of each time period. Our analysis controls for predicted county job growth if each industry in the county just grew at the industry's national growth rate over the time period.

Examining overall job growth focuses on an economic trend that is more directly related to county labor market outcomes than is true of private investment trends, particularly private investment in one particular industrial sector. Peak-to-peak growth is more likely to reflect long-term trends, whereas good local performance during a recovery could reflect more temporary factors, such as recovery from a particularly severe downturn. Controlling for a county's industry mix is more likely to reveal trends due to either policy or economic events that make a county more competitive for growing and attracting jobs.

The results show statistically significant differences in the most recent time period, from the 2019 business cycle peak to the present, in "competitive job growth trends" for counties at the extremes in baseline prime-age employment rates. By "competitive job growth trends," we mean annual county job growth after controlling for predicted county job growth due to its industry mix. For counties at baseline in the top quintile of employment rates, relative competitive job growth rates, compared to the all-county average, declined in the most recent period, compared to trends in the prior two periods. For counties at baseline in the bottom quintile of employment rates, relative competitive job growth rates compared to the all-county average increased in the most recent period compared to trends in the prior two periods.

The declining relative job growth trend shifts for the most booming quintiles started when comparing 2007–2019 to 2001–2007, but then went further in the most recent 2019 to the present period. This time pattern is consistent with the hypothesis that these changing relative trends are related to some fundamental economic trends, not recent federal policies. For example, perhaps higher housing costs and other costs in some booming counties have over time increasingly outweighed agglomeration economies in these booming counties. This is backed by the finding that these overall job growth trends for the "better-off" counties also occur for high-tech job growth.

The increasing relative job growth trends for the most distressed quintile occur only in the most recent time period. This could be considered to be consistent with the hypothesis that something is different about policy in the most recent period.

The magnitude of these changes is larger for the most booming quintile. Average annual competitive job growth rates in these booming quintiles shifted from 0.2 percent above average in the 2001–2007 period to 0.3 percent below average in the 2019–2022/23 period. For the most distressed quintiles, average annual competitive job growth rates shifted from 0.2 percent below average in the 2001–2007 period to 0.1 percent above average (but not statistically significantly above average) in the 2019–2022/23 period.

Are these differences "large"? If they continued for at least 10 years, these relative competitive job growth trends might make some difference for the more distressed counties. However, the difference for these counties is that rather than falling further behind, the more recent trends are on average close to neutral for distressed counties. The county trends in 2001–2007 imply that after 10 years, these counties would have cumulative job growth about 2.3 percent below the average. Based on other research, this cumulative job growth deficit might reduce employment rates in this distressed quintile of county by about 0.8 percentage points. These distressed counties are on average below the overall average prime-age employment rate by about 9 percentage points. So, the further deterioration in the most distressed counties is not trivial, but it is less than 10 percent of the overall 9 percentage point gap. In contrast, the county trends in 2019–2022/23 imply that cumulative competitive job growth in these counties after 10 years would be about 0.8 percentage points greater than the average county. This estimated differential for the most distressed quintile would raise their employment rate by only 0.3 percentage points, which is very small relative to the 9 percentage point gap. The bottom line: if we are to help distressed counties through boosting their employment growth, we need to see much stronger relative trends for distressed counties. But at least we are not seeing trends that leave these distressed counties further behind.

## BACKGROUND: MOTIVATION FOR THIS PAPER'S FOCUS ON JOB GROWTH IN DISTRESSED PLACES, AND PAST RESEARCH

### Past Trends and Their Consequences

From 1900 until 1990 or so, American geographic disparities seemed to be a problem that was being solved, due to market forces and the regular workings of governments, and without special "place-based" policies (Austin, Glaeser, and Summers 2018). Regional incomes were converging, as businesses moved from the relatively well-off North to Southern states.

But over the last 30 or 40 years, geographic disparities have persisted or in some cases worsened. For example, during this time period, prime-age employment rates (employment to population ratios for persons aged 25–54) at the local labor market level show large disparities that are highly persistent. The differential between a local labor market at the 10th percentile, and one at the 90th percentile, is about 10 percentage points (Bartik 2022). The correlation over a decade or two is often 0.8 or above (Bartik 2020a,b; Austin, Glaeser, and Summers 2018).

Some research suggests that prime-age employment rates have even diverged over time, in that places that initially had lower prime-age employment rates tend to show worse trends than more booming places (Austin, Glaeser, and Summers 2018). Furthermore, median income growth in different places over the past 30 or 40 years shows no tendency to converge across places (Austin, Glaeser, and Summers 2018).

Places with low employment rates and low real earnings rates have more residents with social problems such as substance abuse and crime, and tend to have more family break-ups (Autor, Dorn, and Hanson 2019; Diette et al. 2018; Pierce and Schott 2017). The problems associated with low employment rates, and low employment rates in good jobs, have long-term consequences. Residents who are unemployed or underemployed lose valuable labor market experience, as well as self-confidence. These problems, as well as problems with substance abuse and crime, will reduce their long-run earnings (Bartik 2020a). In addition, these problems with low earnings will reduce local tax revenue and hence the ability of local governments to deliver important public services such as education. All of these problems will tend to be reflected in lower long-term earnings for the next generation—children brought up in fragile families, with fewer employed adult role models, amid higher rates of neighborhood crime, and in lower-quality schools will have more difficulty in achieving upward income mobility (Freedman 2017). All these local problems will tend to lead to continued weak local labor demand, further reducing future adult earnings (Garin and Rothbaum 2024); that is, local economic conditions often tend to be reinforcing over time, resulting in a vicious cycle of decline from initial distress.

These problems due to place distress help lead to an interest in boosting job growth in distressed places. A skeptic might say, why bring “jobs to people” when you can bring “people to jobs”—that is, move them out of distressed places? But a “people to jobs” policy is too costly to do at scale and is likely to hurt those left behind. People have high attachments to a familiar place and so are reluctant to move. Even a large subsidy for out-migration of $10,000—which probably exceeds what is politically feasible—would only increase out-migration rates by 2 percentage points (A. Bartik and Rinz 2018; Kennan and Walker 2011). Furthermore, when people leave a low-employment-rate labor market, their departure does not help boost the employment rate for those left behind. Research suggests that if a distressed place has a population loss of x percent, its employment will decline by at least x percent, and the distressed place’s employment rate will remain low (see Bartik [2019] for a review of the research literature). Population loss directly reduces demand for local goods and services, lowers property values and local wealth and tax revenues, and tends to remove younger and more-educated workers from the local workforce, all of which discourage local job growth.

In contrast, higher job growth in distressed places can significantly increase local employment rates. Empirical estimates suggest that in a distressed place, a 1 percent boost to local job growth will raise the local employment rate by up to one-half of 1 percent (Bartik 2024). In other words, when jobs are created in distressed places, about half of those jobs end up being reflected in local residents getting a job when they otherwise would not have one, and the other half end up boosting in-migration. These employment rate effects are persistent, lasting at least 15 or 20 years—labor market experience and its beneficial effects in reducing social problems pay off in higher long-run employment and earnings.

**The Rise of Rhetoric (and Reality?) of Support for Place-Based Policies, and the Role of Market Forces**

Both the Trump and Biden administrations have had rhetoric about helping disadvantaged communities. For example, in 2018 President Trump argued that the United States had developed "a geographic disparity—a very big one, in many cases—where some cities have thrived, while others have suffered chronic economic and social hardship" (White House 2018). As a result, President Trump advocated that "the resources of the whole federal government [should] be leveraged to rebuild low-income and impoverished neighborhoods that have been ignored by Washington in years past" (White House 2018). President Biden has stated that "too many communities across America have faced a loss of wealth, prosperity, and possibilities that still reverberate today." Therefore, the federal government should "reconnect . . . disadvantaged communities and neighborhoods to new opportunities for future prosperity" (White House 2024).

But it is unclear the extent to which this rhetoric has been matched by explicit place-based policies that would significantly spur job growth in distressed counties or larger local labor market areas. The largest Trump-era "place-based policy" was the bipartisan-adopted Opportunity Zones program, which provided favorable capital gains treatment for investment in state-designated distressed census tracts and has estimated 10-year costs that range up to $103 billion (Congressional Budget Office 2022). But most of the research on Opportunity Zones does not suggest large effects on jobs, particularly if we focus on net job growth in a county or local labor market, as opposed to perhaps simply subsidizing investments that would have occurred anyway in an already-gentrifying neighborhood (Bartik 2021).

During the Biden administration, most of the explicit place-based programs to spur job growth in distressed places have been relatively small-scale pilot programs. The total dollar allocation for place-based programs such as the Build Back Better Regional Challenge, Tech

Hubs, Regional Economic Engines, the Recompete Pilot Program, and the Reconnecting Communities Pilot program—all of which explicitly target distressed communities for various types of economic development assistance—have received total funding so far of around $3 billion, which is small relative to the size of the job gap in distressed counties or local labor markets (Coy 2023; Hourihan, Muro, and Chapman 2023).

It is possible that larger job growth boosts for distressed counties or local labor markets might occur due to place-oriented features of more general programs. For example, the Coronavirus State and Local Fiscal Recovery Fund, adopted in early 2021, provided $350 billion in aid to state and local government, with the funding formulas for this aid including some adjustments for need (Council of State Governments 2021).[1] These funds could be used for the following purposes: replacing revenue lost due to the pandemic; premium pay for essential workers; dealing with increased public health or other public services needs at least somewhat related to the pandemic; child care services; infrastructure investments in water, sewer, and broadband; surface transportation projects; and community development program services that principally benefit low and moderate income persons (Treasury Department 2024). The Bipartisan Infrastructure Bill, adopted in late 2021, provided $1.2 trillion in infrastructure spending over 10 years and $550 billion over the next five years (McKinsey and Company 2021). This infrastructure bill included several specific provisions that might help distressed communities: providing $65 billion to expand broadband, including to many distressed rural communities; $21 billion to help with environmental remediation at abandoned mines, Superfund

[1] State government aid under SLFRF was based in part on relative state unemployment, and an allowable state use was to aid local governments with fiscal problems. The metropolitan city portion of SLFRF followed the Community Development Block Grant funding formula, which is related to city need. Other SLFRF aid is based more on equal per capita allocations, but even this allocation might be more significant for more distressed local areas.

sites, and brownfield sites; and an inclusion of the Infrastructure Bill in the Biden administration's Justice40 initiative, under which agencies are supposed to make sure that designated programs devote 40 percent of their funding to communities that in some sense are disadvantaged (White House 2021, 2022, 2023a). The Inflation Reduction Act, adopted in mid-2022, included many tax credits for clean energy projects (possibly to exceed $500 billion over 10 years), with extra tax credits provided for communities dependent on coal or other fossil fuels (Cato Institute 2023; White House 2023b).

Another possibility is that all this federal interest, and some funding, for help to more distressed communities may be signaling to private investors that future support for these communities will be forthcoming. As a result, private businesses may be more inclined to add jobs in distressed communities.

Private investors may also change job growth plans in response to increased costs in some booming places and the rise of remote work. With higher housing prices and other costs in places such as Silicon Valley, these areas are less attractive for job-generating investments. The rise of remote work after the pandemic may make it more obvious that diversifying industries outside existing high-tech agglomerations is more economically feasible.

**Prior Reports on Trends**

Four reports have looked at how recent investments in various industrial sectors have been geographically distributed. The focus of these reports has generally been on announced investments in some of the sectors targeted by recent federal industrial policies—such as clean energy and semiconductors—and on the period since 2021 or since the passage of industrial policy-related legislation, such as the Inflation Reduction Act.

The bottom-line summary from these reports is that there is evidence that some investments in these industry sectors have been flowing at above average rates to communities that are relatively more distressed. But there is less evidence that there has been a significant shift in overall investment toward the most distressed communities.

Among the findings:

- From 2021 to May 2023, announced private investment in semiconductors and electronics, clean energy, and a few other advanced industries has been allocated to the highest quartile of employment rate counties at considerably less than their current share of U.S. gross domestic product. The main beneficiaries are counties in the two middle quartiles of their baseline employment rate distribution. The lowest quartile of counties has a share of these investments that is similar to its current share of U.S. GDP (Haskins and Parilla 2023).
- From the August 2022 passage of the Inflation Reduction Act, which provided credits for clean energy investments, until June 2022, announced investment in "Energy Communities"—communities adjudged to be distressed due for example to a coal mine closure, and eligible for extra tax credits—has been relatively greater compared to the period from 2018 until July 2022. In addition, 70–86 percent of post-IRA clean energy investments have been in counties that are "above average" in distress, with the percentage fluctuating on various county distress measures. There is some evidence that this percentage is somewhat greater from August 2022 until June 2023 than it was in the

2018 to July 2022 period: the percentage of announced investment going to low-income counties rose from 68 to 78 percent (Van Nostrand and Ashenfarb 2023).[2]

- Jobs in digital high-tech industries (e.g., software development, computer systems design) in the 2010–2018 period were very concentrated in typical high-tech cities such as San Francisco and Seattle. From 2020 to 2022, job growth in these industries was more spread out to places such as Miami and Denver (Muro and You 2023).
- In the 2021–2022 period, announced and actual investment in "strategic sectors"—clean energy, semiconductors, biomanufacturing, other advanced industries—has occurred at an above average rate in the most distressed counties. These counties, which have employment rates at least 5 percentage points below the national average, comprise 13 percent of the U.S. population but have received 16 percent of announced strategic sector investments. However, these distressed counties received only 7 percent of overall non-residential private investment in 2021–2022, a percentage that was virtually the same as what they received during the 2010–2020 period (Parilla et al. 2024).

These reports' focus, which tends to be on announced investment in strategic sectors since 2021, has both advantages and disadvantages:

- Focusing on announced investments perhaps allows some forecast of what overall economic trends will eventually occur. But investment is less directly related to improving local labor market outcomes than is overall job growth.
- Focusing on strategic sectors that have been targeted by recent federal policy is an understandable focus, given widespread interest across the nation in these industrial

[2] An updated analysis that extends the post-IRA period, adding in data from July to December 2023, is generally consistent with the prior analysis (Van Nostrand and Ashenfarb 2024). Some of the shift toward distressed counties is slightly lower. For example, the percentage of announced investment in low-income counties in the post-IRA period is now 75 percent of total investment, whereas it was 78 percent using the earlier data.

policies and their geographic impact. But again, an important issue is whether such strategic investment improves the overall economy in distressed regions, including overall job growth.

- Focusing on the period since 2021, or since a particular bill was passed, is also understandable. However, the 2021–2022 period is an economic recovery period. Some of the patterns of investment may reflect economic recovery from an extremely distressed economy. Long-run economic development trends for different places may be more related to economic trends from business cycle peak to business cycle peak.
- Finally, an important issue in judging the most recent pattern of economic growth in different counties or other places is how it compares with prior time periods. These prior reports include a few comparisons with the past, but these comparisons are limited and no statistical tests are done to determine whether the recent period is significantly different in its pattern.

As will be explained in the next section, the current paper tries to provide a complementary analysis to these prior reports in a number of ways, including by focusing more on total job growth from business cycle peak to peak, and by explicitly comparing the current period with past periods.

## OUTLINE OF THIS PAPER'S NEW EMPIRICAL ANALYSIS

This paper's main model relates a county's average annual job growth rate to its baseline employment rate. The dependent variable, the average annual job growth rate, is calculated for each of the 3,000 plus counties in the contiguous United States, for each of three time periods—that is, over 9,000 observations are in the regression. The baseline employment rate is measured as the prime-age employment rate of the county around the beginning of each time period. The regression controls for national time period effects as well as effects on county job growth due to the county's industrial mix.

More specifically, we estimate the following equation:

(1) $100 * [\ln(J_{ctk2}) - \ln(J_{ctk1})]/(t_{k2} - t_{k1}) = B_k + \sum_k [B_{q1k} * D_{q1ck} + B_{q2k} * D_{q2ck} + B_{q3k} * D_{q3ck} + B_{q4k} * D_{q4ck} + B_{q5k} * D_{q5ck} + B_{imixk} * IMIX_{ctk}] + \varepsilon_{ck}$

Here,

- $J_{ctk1}$ is the number of jobs in county $c$ in the year $t1$ that is the beginning of time period $k$;
- $J_{ctl2}$ is jobs in the year $t2$ that is the end point of time period $k$;
- Three time periods are included in the estimation;
- Dividing by the years between period 1 and 2 $(t_{k2} - t_{k1})$ converts this to average annual job growth in log percentage terms;
- Multiplying by 100 means that a log growth rate of 0.5 percent per year will be represented as 0.5, not 0.005;
- $B_k$ is a dummy for the time period $k$:
- $D_{q1ck}$ through $D_{q5ck}$ are dummies for five quintiles of the prime-age employment rate at the beginning of time period $k$;
- The summation over the three time periods *k* means that we include 15 dummies for these quintiles, five for each of the three time periods;
- $IMIX_{ctk}$ is a prediction of the average annual log job growth in county $c$ in time period $k$, based on industrial mix, which is multiplied by 100 to match the dependent variable;
- $\varepsilon_{ck}$ is the disturbance term for a particular county $c$ and time period $k$.

- As the coefficients indicate, in addition to the time period dummy varying across the three time periods, so do the coefficients on the quintile dummies and the coefficients on the industrial mix variable.

More on each of these variables and the estimation follows.

**Job measures**. Job measures are from Lightcast and are based primarily on the U.S. Bureau of Labor Statistics' survey, the Quarterly Census of Employment and Wages.[3] The time periods considered are from 2001–2007, 2007–2019, and 2019 to the average of the last two quarters of 2022 and the first two quarters of 2023. The endpoints of 2001 and 2022/23 are dictated by the current availability of these data. The years 2007 and 2019 are business cycle peaks. Fortunately, 2001 is close to the business cycle peak of 2000, and 2022/23, while not a peak, is not close to the trough of the recession. The job growth rate is calculated as close to peak to peak as possible on the grounds that this will represent long-run growth trends in the county better than measuring from trough to trough or from different points of the business cycle. The dependent variable is multiplied by 100 so that an average annual job growth rate of 0.2 percent, for example, would be represented by 0.2, not 0.002.

**Employment rate**. The employment rate is measured as the "prime-age employment rate"; that is, the employment to population ratio for 25–54-year-olds. The prime-age rate is chosen because this partially controls for age mix of the population, and because this age range is generally expected to work. The rate is measured as close to the baseline as possible for all counties: the 2000 Census for the 2001–2007 period, the 2005–2009 period for the 2007–2019 period, and the 2015–2019 period for the 2019–2022/23 period. To get data on all counties, the 2000 Census must be used, and five-year averages from the American Community Survey, which

[3] Appendix B provides more detail on the Lightcast data.

started in 2005. (For single years, data are only available for counties exceeding 65,000 in population.) For each time period, the sample of counties is divided into weighted quintiles, where the weights are prime-age population of each county. Quintiles are used, rather than simply using the prime-age employment rate as a regressor, to allow us to explore how job growth varies from the most distressed quintile (quintile 1) to the least distressed or most booming quintile (quintile 5).[4]

**Industrial mix variable**. The industrial mix variable is a version of the so-called "share" component of a shift-share analysis of county job growth, sometimes called the Bartik instrument (Bartik 1991). Specifically, we calculate what the number of jobs in county $c$ would be if each industry in the county grew at its national average from year $t1$ to year $t2$. This is then added to baseline employment, the log is taken, and we subtract out the logarithm of baseline employment. We then divide by the number of years in the time period interval to convert to expected annual job growth, and then multiply by 100 to convert to log percentage units, similar to the dependent variable.

More specifically, the industrial mix variables can be written as

(2) $$IMIX_{ck} = 100 * [\ln(J_{ctk1} + predicted\ job\ growth\ from\ t1\ to\ t2\ in\ period\ k) - \ln(J_{ctk1})]/(t_{k2} - t_{k1})$$

Predicted job growth is given by Equation (3):

(3) $$\sum_i J_{ckt1i} * \left(\frac{J_{nkt2i}}{J_{nkt1i}}\right) - J_{ckt1}$$

[4] The quintile specification is strongly preferred by the Akaike Information Criterion to the specification that just puts baseline values of the natural log of the baseline prime-age employment rate on the right-hand side.

Here, $i$ indexes industry, $J_{ckt1i}$ is jobs in industry $i$ in county $c$ in year $t1$ at the beginning of time period $k$, $J_{nkt2i}$ is jobs in the nation in industry $i$ in year $t2$ at the end of time period $k$, and $J_{nkt1i}$ is jobs in the nation in industry $i$ in year $t1$ at the beginning of time period $k$.

The purpose of this industrial mix variable is to control for county job growth that is solely due to whether the county has an industrial mix that happens to do well nationally, which increases national demand for the county's specialized export-base industries. Including this industrial mix variable in the regression has at least two good rationales. First, a job growth measure that controls for industrial mix will provide a better measure of the county's competitiveness for job growth, which is what policy can most readily affect. The county's fortunes due to its industrial mix are not readily alterable by policy. Second, the competitive job growth, after controlling for industrial mix, is likely to be the main determinant of long-run growth. Counties that can sustain competitive job growth, whether through public policies or other economic influences, are likely to be the best performers in the long run. The short-run advantages or disadvantages of industrial mix eventually fade, as industry location is more malleable in the long run than the short run. In the short run, national demand influences on an area's specialized industries are the main drivers of local employment growth, but such demand-side influences are less important for long-term job growth, which is dominated more by supply-side influences: whether natural economic forces or public policies are making this particular place a more productive and thus competitive place in which to add jobs.[5]

[5] This contention is somewhat separate from the issue of whether the short-run share effect or the short-run shift effect is a better predictor of long-term growth. In general, as we go to the longer term, although the current share effect predicts the future share effect, and the current shift effect predicts the future shift effect, these correlations become weaker as we extend the future time period (Lahr and Ferreira 2020). In other words, even though in the long run it is the magnitude of the competitive shift effect that drives long-run job growth, it is not necessarily the case that short-run competitive shift effects will be a great predictor of long-run success. The places that are able to have sustained competitive shift effects will be the most successful in the long term, but these are not necessarily the places that in the short run have a strong positive competitive shift effect.

**Estimation**. This model is estimated with pooled panel data, with three time period observations for each county.[6] But, as shown above, the model allows all the coefficients to vary for each time period. The quintile dummies for each time period sum to the time period dummy, so the model cannot be estimated without a linear constraint. In the reported results, we impose the constraint that the sum of the quintile coefficients in each time period sum to zero. This defines the quintile effects as being the difference of the annual job growth rate effects for counties in that quintile from the all-county average.

The model is estimated using base period employment weights. This minimizes noise due to job growth trends in small counties and puts an appropriately greater weight on larger counties' job growth trends.

The model's standard errors allow for clustering by county. This allows appropriately for the disturbance term to be correlated by county. An alternative would be to estimate the equation separately for each time period. But then determining the statistical significance for the differences between coefficients on the quintile dummies across time periods would require making some assumption about the covariance of a particular quintile's estimated coefficient across different time periods. Allowing for the within county correlation, and estimating the pooled regression, allows a given quintile's coefficient estimate to be appropriately compared across time periods, as it allows the covariance of the quintile estimates across time period to be calculated.[7]

[6] There is one newly defined county in Colorado (Broomfield County) that only has two observations for the two latter time periods. Loving County, Texas is missing from the 2000 Census data and also only has two observations.

[7] An alternative would be to go back to an older econometric technique of doing "seemingly unrelated regressions," and explicitly incorporating the within-county correlation into the estimation. However, this imposes more modeling assumptions on the resulting estimates. Simply allowing for the within county correlation and pooling the three time periods into one regression seems more likely to be robust to misspecification.

**Additional industry models estimated**. Although the main focus is on overall job growth, we also do estimates that focus on particular industry types of job growth. Specifically, we do estimates that focus on job growth due to manufacturing, high-tech industries, clean energy industries, and semiconductors. The appendix explains the specific industries included in each industry grouping.

For the industry group regressions, the dependent variable is redefined as the contribution to overall annual county job growth rates of that particular industry grouping. That is, the dependent variable is given by Equation (4):

(4) $$100 * \{\frac{\left[\ln\left(J_{ctk1}+\left(J_{ctkg2}-J_{ctkg1}\right)\right)-\ln(J_{ctk1})\right]}{t_{k2}-t_{k1}}\}$$

Here, $J_{ctkg2}$ and $J_{ctkg1}$ are the total employment at the end year ($t2$) and beginning year ($t1$) of time period $k$ in industry group $g$.

Why this formulation? We are interested in how counties at different baseline prime-age employment rates are faring with respect to overall job growth. We are interested in how different industries contribute to that overall job growth. If an area has very fast job growth rates in some industry group but the group is initially a miniscule component of the area's economy, the area's overall growth will be little affected by that one industry group's growth.

On the right-hand side, the industrial mix variable is redefined so it simply measures the predicted effect on overall job growth if all the specific industries within industry group $g$ simply grew at their national average from time period $t1$ to $t2$ within time period $k$. That is, the industrial mix effect is Equation (5):

(5) $$100 * \{[\ln [J_{ctk1} + \sum_{Iing}(J_{ctkgi1} * \left(\frac{J_{ntkgi2}}{J_{ntkgil}}\right) - J_{ctkg1})] - \ln (J_{ctk1})\}/(t_{k2} - t_{k1})$$

Here, the industrial mix prediction is constructed by predicting what would have happened to overall county job growth rates in time period $k$ if only the industries in industry group $g$ in county $c$ were blown up by national growth trends over that time period.

Therefore, the regression controls for the initial share of the industry group $g$ in each county's industrial mix, as well as the initial concentration of each industry within that group, and the performance of all these individual industries in that grouping over that time period in the nation.

## EMPIRICAL RESULTS

### Main Results

This paper's main empirical results are shown in Table 1. This table reports the estimated "effects" during each time period of a county being in different quintiles of the prime-age employment rate during the time period's baseline. The estimated effects are on annual logarithmic job growth rates of a county in that baseline quintile group, relative to the average for all counties. As mentioned above, the regression also includes industrial mix predictions of growth, which are not reported in the table.[8] Thus, these are measures of "competitive" job growth—that is, job growth that is greater than or less than job growth expected based on the county's specialized industries and how they are faring nationally.

[8] The coefficients on this industry mix prediction are 1.205 (standard error equals 0.124) for the 2001–2007 period, 1.075 (0.238) for 2007–2019 period, and 0.902 (0.133) for 2019–2022/23 period. These coefficients are similar to what we would expect due to prior research on county multipliers (Bartik and Sotherland 2019).

**Table 1 “Effects” of Baseline Quintile of Prime-Age Employment Rate on Average Annual Competitive Shift Job Growth for Counties, Three Time Periods**

| Baseline average prime-age employment rate | | 2001–2007 | 2007–2019 | 2019–2022/23 |
|---|---|---|---|---|
| 70.3 | Q1 diff | −0.2277 | −0.2905 | 0.0757 |
| | | (0.1705) | (0.0907) | (0.1034) |
| 77.1 | Q2 diff | −0.0898 | −0.0384 | 0.1705 |
| | | (0.1529) | (0.0840) | (0.1523) |
| 79.2 | Q3 diff | 0.0854 | 0.0954 | 0.2513 |
| | | (0.1497) | (0.0765) | (0.1479) |
| 81.3 | Q4 diff | −0.0153 | 0.1447 | −0.2203 |
| | | (0.1206) | (0.0732) | (0.1581) |
| 84.5 | Q5 diff | 0.2473 | 0.0888 | −0.2773 |
| | | (0.1193) | (0.0778) | (0.1346) |

NOTE: This reports one regression. The regression estimates “effects” on annual average county job growth rates of initial base period prime-age employment, controlling for national time period effects, and predicted job growth due to industry mix. Standard errors are in parentheses before estimated coefficients. Dependent variable is average annual ln percentage growth in total jobs in a county over each of three time periods. This ln percentage is multiplied by 100 so that a change of 0.02 in the log is two. The quintile variables assign each county to a quintile based on its prime-age employment rate in the baseline period (2000, or 2005–2009, or 2015–2019). The quintiles are defined based on prime-age population weights by county in each baseline period. Mean quintile prime-age employment rates as of 2015–2019 baseline are shown. Quintile means are weighted by regression weight, which is 2019 employment. The estimated quintile effects here are deviations from overall mean over all quintiles. Hence, effect of 0.10 means that quintile is estimated to have 0.1 percent greater average job growth in that time period than the overall average for all counties, controlling for predictions based on the county’s industrial mix and national industry growth trends. The regression has three time periods for almost all counties (a few counties have two due to county redefinitions), which ends up with 9,322 total observations for county by three time periods. Regressions are weighted by base period (2000, 2007, 2019) employment.
SOURCE: Authors’ estimates.

As shown in the table, the quintile with the lowest baseline prime-age employment rate, quintile 1, has average annual “competitive” job growth that is significantly less (by about 0.3 percent per year) than the all-county average during the second time period, 2007–2019, but not the other two time periods.[9] The quintile of counties with the highest baseline prime-age employment rate, quintile 5, has an annual average competitive job growth rate significantly greater (at between 0.2 and 0.3 percent) than the all-county average during the first time period, 2001–2007, and significantly below the all-county average (by about 0.3 percent per year) during the third time period, 2019–2202/23.[10] Finally, the counties in the next to highest baseline

[9] The t-statistic is −3.20 for the second time period.
[10] t-statistics for the first and third time period are 2.07 and −2.06.

employment rate quintile, quintile 4, are significantly above the all-county average in annual average competitive job growth during the second time period, 2007–2019.[11]

However, what is most relevant is change over time, and in particular, whether the most recent time period shows differences from past time periods. Counties in the most distressed baseline employment rate quintile, quintile 1, show a more favorable competitive job growth in the most recent period compared to the first two time periods.[12] The counties in the top employment rate quintile, quintile 5, show an annual average competitive job growth rate in the most recent period that is statistically significantly lower than either of the prior two time periods.[13] Finally, for the next to highest quintile, the most recent period shows lower competitive job growth rates compared to the 2007–2019 period.[14]

Qualitatively, there is some sign that the reduction in quintile 5's competitive job growth advantage over other counties began in the 2007–2019 period, although this reduction is not statistically significant.[15] During this time period, the next highest employment rate quintile did better. Later on, during the most recent time period, the most distressed baseline employment rate quintile, quintile 1, did better than the all-county average.

But are these effects "large" in some sense? Suppose we translate these average annual job growth effects into what would occur in overall percentage job growth if these average annual effects persisted for 10 years. For the counties in the highest employment rate quintile at baseline, the coefficients in Table 1 imply that such counties, if they followed the period 1 average annual job growth trends, would have competitive job growth that would cumulate to a

[11] t-statistic is 1.98.

[12] The t-statistic for the quintile 1 differential in the most recent period versus the past two time periods are 2.25 and 3.35.

[13] The t-statistic for this quintile's most recent time period, compared to the first and second time periods, are −3.56 and −3.07.

[14] The t-statistic is −2.29.

[15] The t-statistic on the quintile 5 effect in 2007–2019, versus 2001–2007, is −1.31.

job gain of 2.7 percent above the average county after a 10-year period.[16] In contrast, during the most recent period, the coefficients in Table 1 imply that if the most recent trends persisted for 10 years, the counties in the top employment rate job growth would have cumulative job growth of 2.9 percent below the average county. The difference is 5.6 percent in jobs, which does not seem a trivial difference.

For the most distressed quintile, the time period 1 (2001–2007) estimated relative trend, if continued for 10 years, would imply cumulative competitive job growth of 2.4 percent below average. The most recent time period (2019–2022/23) competitive growth effect for quintile 1, if continued for 10 years, would imply competitive job growth after 10 years of 0.8 percent above average. The difference of 3.2 percent is not trivial. However, it should be noted that the most recent trend is barely above average, and that the difference of the most distressed quintile from the overall county average is not statistically significant. But at least the most distressed counties are not losing ground in terms of job growth.

How much would the changes in job growth in the most distressed counties affect their distress? Empirical estimates suggest that for distressed counties, about half of extra jobs created would increase the local employment rate. If we apply these calculations to the most distressed quintile, the 10-year cumulative jobs growth deficit following the first time period's estimates of 2.4 percent below average would end up reducing the average prime-age employment rate in this quintile by 0.8 percentage points.[17] On the other hand, if the third time period's time trend continued for 10 years, resulting in cumulative extra job growth of 0.8 percent above average, the prime-age employment rate in this quintile would be increased by 0.3 percentage points.[18] As

[16] This calculation converts to actual percentages, not log percentages.
[17] $0.8 = exp\big(ln(0.703) + 0.5 * (-0.02277)\big) - 0.703.$
[18] $0.3 = exp(ln(0.703) + 0.5 * (0.00757)) - 0.703.$

shown in Table 1, the counties in this quintile have a baseline employment rate of 70.3 percent. This is almost 9 percentage points below the overall sample average of 79.0 percent. So, these changing job growth rates at least mean that the gap with other quintiles would not increase by 0.8 percentage points, which is not trivial but is less than a tenth of the overall gap of the bottom quintile from the mean. And the boost from the latest trends would not have much effect on lowering the gap. Much more job growth or other policies would be needed to lower these gaps by even one-third.

**Breaking Down Main Results**

These effects are average differentials for each quintile. To explore these trends more, we look at growth trends within quintile 1 and quintile 5. Do the average trends in different periods in competitive job growth for these two quintiles reflect some extreme outliers, or do they reflect more general trends for counties in these quintiles?

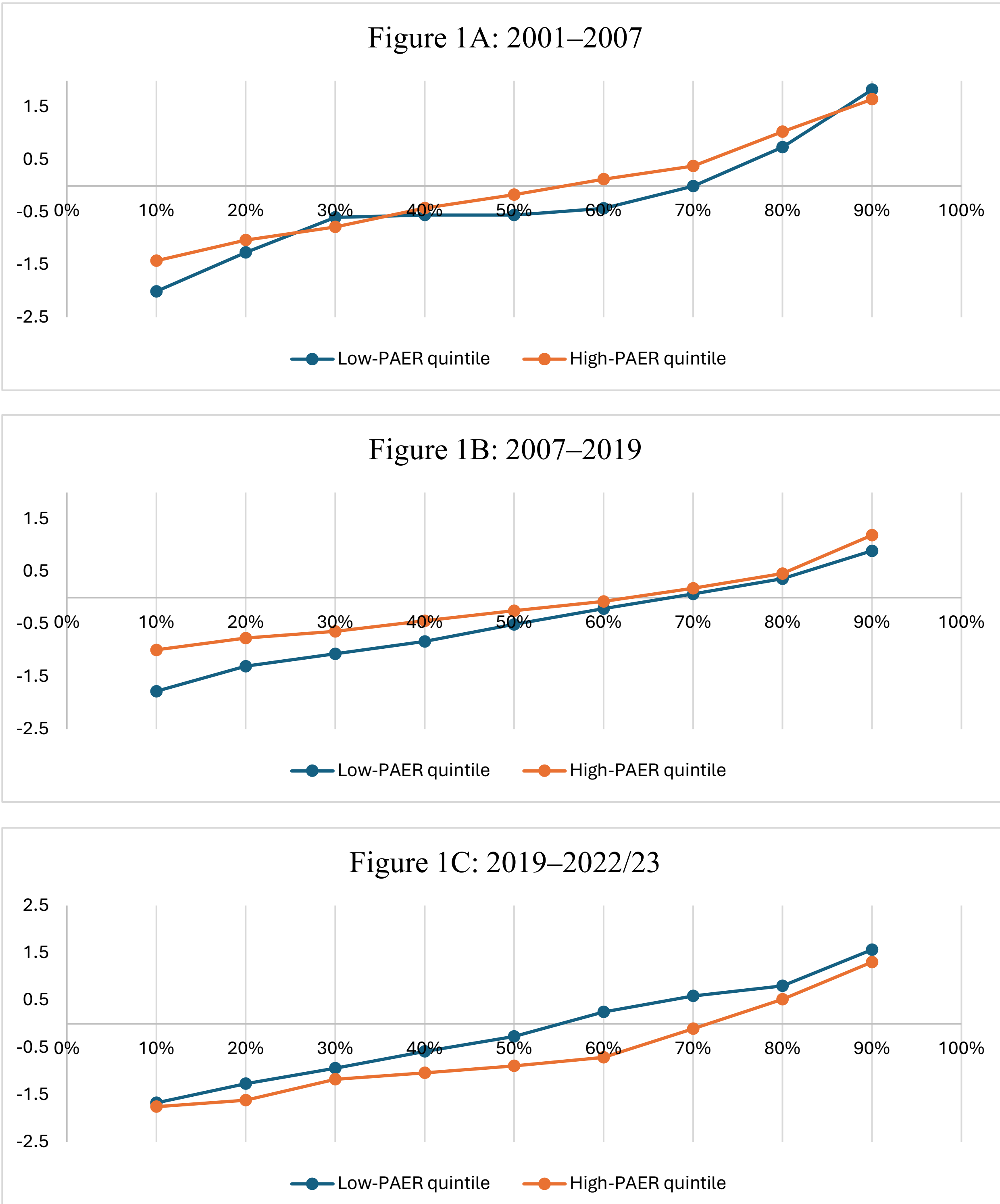
Table 2 and Figures 1A, 1B, and 1C look at the trends at different percentiles within quintile 1 and quintile 5. That is, we first calculate competitive job growth for each county in these two quintiles by subtracting out the job growth due to local industrial mix. We then rank each county in a quintile by its annual average percent competitive job growth during the time period. We then calculate weighted percentiles of that job growth. The weights used are baseline employment. Thus, the 10th percentile of quintile 1's competitive employment growth is the annual competitive job growth rate such that 10 percent of the baseline employment in that quintile is at that job growth rate or below. The 50th percentile is the median job growth rate of that quintile—that is, half the baseline employment is in counties whose annual competitive job growth rate is below that cutoff and half is above.

**Table 2 Comparison of Counties in "Low-PAER" Quintile and Those in "High-PAER" Quintile in Competitive Average Annual Job Growth Differential, Three Time Periods**

| | 2001–2007 | | 2007–2019 | | 2019–2022/23 | |
|---|---|---|---|---|---|---|
| Percentile of quintile (%) | Low-PAER quintile | High-PAER quintile | Low-PAER quintile | High-PAER quintile | Low-PAER quintile | High-PAER quintile |
| 10 | −2.01 | −1.42 | −1.78 | −0.99 | −1.67 | −1.75 |
| 20 | −1.27 | −1.03 | −1.30 | −0.77 | −1.26 | −1.61 |
| 30 | −0.60 | −0.78 | −1.06 | −0.64 | −0.94 | −1.17 |
| 40 | −0.55 | −0.42 | −0.83 | −0.44 | −0.58 | −1.04 |
| 50 | −0.55 | −0.17 | −0.51 | −0.25 | −0.27 | −0.89 |
| 60 | −0.43 | 0.13 | −0.21 | −0.07 | 0.25 | −0.71 |
| 70 | 0.00 | 0.38 | 0.07 | 0.18 | 0.59 | −0.11 |
| 80 | 0.74 | 1.03 | 0.36 | 0.46 | 0.80 | 0.52 |
| 90 | 1.83 | 1.65 | 0.89 | 1.19 | 1.57 | 1.30 |

NOTE: These figures are for average annual growth rates, in log percentage terms (e.g., annual change in log multiplied by 100), for counties in different quintiles of the distribution of prime-age employment rates. Quintiles of prime-age employment rates are in weighted terms, using baseline prime-age population as weights. Growth rates are differentials of annual job growth after subtracting out part predicted based on industrial mix, as estimated in regression including the Bartik instrument. Percentiles are percentiles of the distribution of counties weighted by baseline employment. Percentiles are within each quintile.
SOURCE: Authors' estimates.

**Figure 1 Competitive Annual Job Growth Rates, Counties with Low vs. High Baseline Employment Rate, Different Percentiles of Quintile Competitive Job Growth**




SOURCE: Table 2.

NOTE: Competitive annual job growth rates shows average annual job growth rates, in percentage terms, after controlling for industry mix, relative to national average.

In the first time period, the relatively poor performance of the most distressed baseline counties versus the least distressed baseline counties is for counties at the 40th to 80th percentiles, and for those at the 10th percentile or below. In the second time period, the lower job growth of the most distressed baseline counties is concentrated in counties below the median. Finally, in the last period, the stronger performance of the most distressed baseline counties versus the least distressed counties is for counties in the middle, from the 40th to the 70th percentiles.

Generally, the finding is that these trends in the different quintiles reflect broad trends for many counties in each quintile, not a few outliers. Also interesting is that the very best performing counties, those at the 90th percentile or above, tend to have similar competitive job growth performance for both quintiles in all three time periods. A county is not doomed to poor competitive job growth rates simply because it has high baseline distress. The top counties in the most distressed quintile have annual competitive job growth rates exceeding 1 percent.

**Different Industries**

This paper also looks at a county's average annual percentage competitive job growth trends due to growth in different industry groups, and how these vary with baseline county employment rates during each of these three time periods. We report the effects for counties in each quintile of baseline prime-age employment rates, and the regressions look at job growth effects after controlling for the mix of industries in that group in the county, as well as national growth rate trends for specific industries during the time period.

We look at four industry groups: manufacturing, high-tech, clean energy, and semiconductors. Industry definitions are discussed more in Appendix B.

Table 3 reports results for both manufacturing and high-tech industries. The clean energy and semiconductor results are quite imprecise, and not much can be gleaned from them; therefore, they are reported in Appendix A.

**Table 3 How Competitive Job Growth for Different Industry Groups Varied by Baseline Prime-Age Employment Rate of County, Three Time Periods**

| Panel A: Manufacturing | 2001–2007 | 2007–2019 | 2019–2022/23 |
|---|---|---|---|
| Quintile 1 Differential | −0.04432 | −0.03217 | 0.00903 |
| | (0.02188) | (0.00991) | (0.01246) |
| Quintile 2 Differential | −0.00161 | −0.01158 | −0.00095 |
| | (0.01908) | (0.01807) | (0.01663) |
| Quintile 3 Differential | −0.01861 | −0.00314 | 0.00710 |
| | (0.01798) | (0.00946) | (0.01619) |
| Quintile 4 Differential | 0.00121 | 0.01737 | −0.00425 |
| | (0.01832) | (0.01111) | (0.01361) |
| Quintile 5 Differential | 0.06333 | 0.02953 | −0.01093 |
| | (0.01754) | (0.00940) | (0.01552) |
| **Panel B: High-Tech** | **2001–2007** | **2007–2019** | **2019–2022/23** |
| Quintile 1 Differential | −0.03802 | −0.05144 | 0.02535 |
| | (0.03065) | (0.01556) | (0.02147) |
| Quintile 2 Differential | −0.01941 | −0.01725 | −0.01382 |
| | (0.02895) | (0.01788) | (0.02496) |
| Quintile 3 Differential | −0.02203 | 0.04960 | 0.00935 |
| | (0.02727) | (0.02222) | (0.03366) |
| Quintile 4 Differential | −0.02572 | 0.01347 | −0.03129 |
| | (0.03124) | (0.02635) | (0.03553) |
| Quintile 5 Differential | 0.10518 | 0.00562 | 0.01040 |
| | (0.02858) | (0.02440) | (0.04846) |

NOTE: Each panel reports one regression. Dependent variable is county's average annual job growth rate due solely to growth in that industry group. Dependent variable multiplies 100 times annual average change in ln(jobs) due to that industry, so 0.05 is 5 one-hundredths of 1 percent. Regressions control for predicted overall job growth if each industry within an industry group in a county grew at national job growth rate over that time period. Regressions are weighted by baseline employment. Standard errors (in parentheses) adjust for clustering by county.
SOURCE: Authors' estimates.

For manufacturing, Table 3 shows that the most distressed quintile did significantly better in job growth due to manufacturing in the most recent time period (2019–2022/23), compared to either of the prior time periods.[19] For the least distressed quintile, counties in this group did significantly worse in competitive job growth due to manufacturing during the most recent time

[19] The t-statistics on the difference of the most recent quintile 1 differential effect, from the first and second period, are 2.16 and 2.65.

period compared to either of the two prior time periods.[20] Furthermore, the lower growth for quintile 5 due to manufacturing in the second time period, 2007–2019, compared to the first time period, 2001–2007, is almost statistically significant.[21]

How large are these manufacturing competitive job growth effects? Large enough to plausibly explain about one-quarter to one-third of the overall job growth trends described in Table 1. If these trends continued for 10 years, the quintile 1 differential effects in the first time period imply a job growth effect due to manufacturing of about −0.5 percent versus +0.1 percent during the latest time period.[22] Thus, the direct effect of faster manufacturing job growth for this quintile was sufficient to improve cumulative 10-year job growth by 0.6 percent. If we assume a plausible multiplier of about 2 or so for manufacturing, this is sufficient to cause overall job growth to show a more favorable trend of 1.2 percent in the most recent period compared to the 2001–2007 period. As discussed above, the total differential job growth trend for quintile 1, if extrapolated over 10 years, was 3.2 percent in jobs.

For the least distressed quintile, the coefficients in Table 3 imply that if these competitive job growth trends due to manufacturing persisted for 10 years, the first time period's effects imply cumulative job effects of 0.7 percent above average. The most recent period's coefficients imply cumulative manufacturing job growth of 0.1 percent below average. The 0.8 percent differential, with a multiplier of 2, would imply effects on overall job growth of about 1.6 percent. This is a little more than one-quarter of the overall cumulative 10-year effect projected of about 5.6 percent. So, manufacturing job growth trends help explain both quintile 1 and 5 results, but they are slightly more important in explaining quintile 1's changing trends.

[20] The relevant t-statistics are −3.32 and −2.46.
[21] The t-statistic is −1.92.
[22] Again, all these calculations convert log percentages to actual percentages.

For high-tech, the trends for quintile 1 show effects for the more recent period that are significantly better than the second time period, and almost significantly greater than the first time period.[23] For quintile 5, the second time period is significantly different from the first time period, and the third time period is almost significantly different from the first time period.[24]

Thus, for high-tech, there is some sign that whatever is affecting the least distressed counties is a trend that started in the 2007–2019 period. The high-tech trends are unlikely to be mostly explained by post 2019 policies.

How large are these high-tech effects? Large enough that with multipliers, we might explain up to half of the overall job growth trends by county distress. Considering quintile 1, the time period 1 effects, if continued for 10 years, would lower overall job growth by 0.4 percent. The period 3 effects would cumulate over 10 years to increase relative job growth by 0.3 percent. The differential has a direct effect on boosting overall job growth due to trends in high-tech job growth of 0.7 percent. Multipliers of 3 or more have been estimated for high-tech (Bartik and Sotherland 2019). Therefore, with multipliers, overall job growth might be boosted by a little over 2 percent. This is over half of the total differential job growth trend of 3.2 percent.

Similarly, for quintile 5, the first period's high-tech trends, if continued for 10 years, might directly increase job growth by about 1.1 percent. The last period's trends might increase overall job growth by 0.1 percent. The differential is a reduction in the high-tech direct contribution to growth of 1.0 percent. With a high-tech multiplier of up to 3, the effect on overall job growth rates might be 3.0 percent. This is over half of overall job growth effects of 5.6 percent, as discussed above.

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[23] The relevant t-statistics are 3.02 versus the second time period, 1.87 versus the first time period.
[24] The second versus first time period has a t-statistic of −2.57; third versus first, t-statistic of −1.83.

We should note here that it is not appropriate to add together what manufacturing explains out of total job growth trends, and what high-tech explains, to get a total explained by high-tech and manufacturing. Some industries in manufacturing are also in high-tech, so adding the two together would involve some double counting.

## CONCLUSION

The bottom-line conclusion is that there is some sign in the most recent time period, since 2019, that job growth trends have become more favorable for the most distressed counties and less favorable for the least distressed counties. These trends seem to occur in part due to trends in manufacturing industries, and particularly in high-tech industries.

The pattern suggests that something occurred in the 2007–2019 period to lower high-tech growth, and perhaps other growth, in the least distressed counties. A plausible hypothesis is that this may be due to problems caused by rising housing prices and other higher local costs in such counties. These rising costs may now be outweighing agglomeration economies in some high-tech business location decisions, as well as perhaps affecting other firms.

The most recent period is different for the more distressed counties, which are doing relatively better than past trends in overall job growth, as well as in job growth due to manufacturing and high-tech.

Are these recent trends due to public policy? That is a possibility, but at this stage it must be viewed as more of a plausible hypothesis than anything that is proven. Proving causation would have to look at specific policies and how they affected particular counties.

An additional caveat is that these positive trends for distressed counties only  keep them from falling further behind other counties,. The more positive trends for more distressed counties are clearly insufficient at present to significantly lower the employment rate gap between distressed counties and the national average, let alone the gap versus the least distressed counties. Much bigger job growth boosts for distressed counties, or other policy changes, would be needed to significantly lower employment rate gaps between these counties and the nation.

Another limitation is that we do not know at present whether these 3.5-year trends for distressed counties, from 2019–2022/23, will persist in the future. Optimistically, these trends could continue to strengthen. Perhaps the various policies discussed above will have stronger effects as we fully implement various industrial policies—for example, to promote manufacturing, high-tech, and clean energy. On the other hand, if these recent positive trends for the most distressed counties are due more to the transitory state and local government fiscal assistance, then these positive trends may also prove to be transitory. We plan to repeat these analyses as economic trends unfold during the current economic recovery.

## Appendix A

## Additional Regression Results

For robustness checks, we also estimated the model without including the Bartik instrumental variables. For reasons mentioned in the text, we believe "competitive" job growth is a better indication of long-term local job growth trends, which might be due to various policies. But the model without the Bartik instruments shows the pure growth differentials without these controls. Table A1 reports these alternative estimates.

**Table A1 Effects of Baseline Quintile of Prime-Age Employment Rate on Average Annual Job Growth for Counties, Three Time Periods, Controls Only for Time Period Effects**

| | 2001–2007 | 2007–2019 | 2019–2022/23 |
|---|---|---|---|
| Q1 diff | −0.1715 | −0.3444 | −0.0970 |
| | (0.1835) | (0.1001) | (0.1118) |
| Q2 diff | −0.0742 | −0.0657 | 0.0566 |
| | (0.1662) | (0.0876) | (0.1355) |
| Q3 diff | 0.1033 | 0.1172 | 0.2634 |
| | (0.1648) | (0.0743) | (0.1546) |
| Q4 diff | −0.0550 | 0.1469 | −0.1009 |
| | (0.1226) | (0.0753) | (0.1549) |
| Q5 diff | 0.1974 | 0.1461 | −0.1222 |
| | (0.1194) | (0.0767) | (0.1336) |

NOTE: This table reports data for only one regression. The regression estimates "effects" on county average annual job growth rates, during each of three time periods, as a function of national time dummies, and dummies for what quintile of the baseline prime-age employment rate the county was in. Dependent variable is average annual ln percentage growth in total jobs in a county over that time period. This ln percentage is multiplied by 100 so that a change of 0.02 in the log is 2. The quintile variables assign each county to a quintile based on its prime-age employment rate in the baseline period (2000, or 2005–2009, or 2015–2019). The quintiles are defined based on prime-age population weights by county in each baseline period. Quintile effects are estimated effects minus overall mean for that time period. Given how dependent variable is measured, coefficient of 0.1 for a quintile means that the quintile's' average annual job growth rate is 0.1 percent greater than overall average. The regression has three time periods for almost all counties (a few counties have two due to county redefinitions), which ends up with 9,322 total observations for county by three time periods. Regressions are weighted by base period (2000, 2007, 2019) employment. Standard errors adjust for clustering at county level.
SOURCE: Authors' estimates.

Comparing Table A1 with the main paper's Table 1, the results are qualitatively similar. The most recent time period shows less favorable trends for the least distressed quintile of counties, and more favorable trends for the most distressed quintile of counties. The magnitude of the differences is reduced in Table A1. In addition, the differences are not quite as statistically significant. In the case of quintile 5, the least distressed quintile, the most recent period's differences from the first two time periods have t-statistics of −2.18 and −2.29., respectively.[25] For the most distressed quintile, quintile 1, the most recent period, compared to the 2007−2019 period, has a t-statistic of 1.94. The quintile 1 recent period difference from the 2001−2007 period has a t-statistic of 0.48.

As another robustness test, we also added to the specification of Table 1 by including not only the Bartik instrumental variables but also dummy variables for each of the nine census regions for each time period. This is intended to address the following question: Are these trends favoring more distressed counties, and not less distressed counties, simply due to broad regional trends? For example, many Southern counties have low baseline employment rates, and so a trend toward the South would tend to favor distressed counties.

Why does our baseline specification in Table 1 of the paper not include the regional dummies? Because, in our view, if public policy or economic events are favoring distressed counties, we would expect to see that reflected in regional trends. Therefore, in our view, including dummies for the nine census regions overly controls for part of what we are trying to measure. Nonetheless, it is of interest whether the trends by county distress are only due to trends by region, or also reflect trends within the nine census regions.

[25] That is, the t-statistic for 2019–2022/23 versus 2001–2007 is −2.18, and versus 2007–2019 is −2.29.

**Table A2  Effects on Annual Job Growth Rates, Controlling for Industrial Mix and Region Effects**

| | 2001–2007 | 2007–2019 | 2019–2022/23 |
|---|---|---|---|
| Quintile 1 differential | −0.4223 | −0.3742 | −0.0964 |
| | (0.1591) | (0.0911) | (0.1044) |
| Quintile 2 | −0.1901 | −0.1546 | 0.0589 |
| | (0.1152) | (0.0737) | (0.1249) |
| Quintile 3 | −0.0539 | 0.0219 | 0.1951 |
| | (0.1173) | (0.0563) | (0.0936) |
| Quintile 4 | 0.0850 | 0.2358 | −0.0395 |
| | (0.1012) | (0.0624) | (0.1075) |
| Quintile 5 | 0.5814 | 0.2710 | −0.1181 |
| | (0.1190) | (0.0774) | (0.1240) |

NOTE: This table reports data for only one regression. The regression estimates "effects" on county average annual job growth rates, during each of three time periods, as a function of national time dummies, the Bartik instrument predicting county job growth due to baseline industrial mix and national economic trends, 9 region dummies, and dummies for what quintile of the baseline prime-age employment rate the county was in. Dependent variable is average annual ln percentage growth in total jobs in a county over that time period. This ln percentage is multiplied by 100 so that a change of 0.02 in the log is 2. The quintile variables assign each county to a quintile based on its prime-age employment rate in the baseline period (2000, or 2005–2009, or 2015–2019). The quintiles are defined based on prime-age population weights by county in each baseline period. Quintile effects are estimated effects minus overall mean for that time period. Given how dependent variable is measured, coefficient of 0.1 for a quintile means that the quintile's average annual job growth rate is 0.1 percent greater than overall average. The 9 region dummies are for the standard census regions. The regression has three time periods for almost all counties (a few counties have two due to county redefinitions), which ends up with 9,322 total observations for county by three time periods. Regressions are weighted by base period (2000, 2007, 2019) employment. Standard errors adjust for clustering at county level.
SOURCE: Authors' estimates.

Comparing Table A2 with the main paper's Table 1, the results are again qualitatively similar: the recent time period shows less favorable trends for quintile 5, the least distressed counties, and more favorable trends for quintile 1, the most distressed counties. The magnitude of the changes over time are not dissimilar. The differences of the most recent time period with the first two time periods are clearly statistically significant. For quintile 5, the t-statistics are −3.56 and −3.07, respectively. For quintile 1, the t-statistics for the most recent time period, compared to the two prior time periods, are 2.25 and 3.35, respectively.

Overall, the bottom line seems to be that these trends that disfavor the least distressed counties and favor the more distressed counties are occurring within regions. These county patterns do not simply reflect regional trends.

Finally, this appendix also reports results for estimating the paper's main model, with Bartik instrument controls, for clean energy industries and semiconductor industries.

**Table A3 Differential Annual Competitive Job Growth by Quintile, Clean Energy Industries and Semiconductors**

| Panel A: Clean Energy | 2001–2007 | 2007–2019 | 2019–2022/23 |
|---|---|---|---|
| Quintile 1 Differential | 0.01061 | −0.01449 | 0.01443 |
| | (0.01667) | (0.00780) | (0.01456) |
| Quintile 2 Differential | 0.00663 | −0.00227 | −0.00078 |
| | (0.01493) | (0.00809) | (0.01477) |
| Quintile 3 Differential | 0.01310 | −0.00183 | 0.01426 |
| | (0.01471) | (0.00816) | (0.01829) |
| Quintile 4 Differential | −0.01596 | 0.00898 | −0.01878 |
| | (0.01556) | (0.00747) | (0.01390) |
| Quintile 5 Differential | −0.01438 | 0.00961 | −0.00913 |
| | (0.01409) | (0.00652) | (0.01219) |
| **Panel B: Semiconductors** | **2001–2007** | **2007–2019** | **2019–2022/23** |
| Quintile 1 Differential | −0.00132 | −0.00197 | −0.00017 |
| | (0.00220) | (0.00108) | (0.00131) |
| Quintile 2 Differential | −0.00093 | 0.00019 | −0.00215 |
| | (0.00306) | (0.00089) | (0.00146) |
| Quintile 3 Differential | 0.00172 | −0.00144 | 0.00291 |
| | (0.00358) | (0.00217) | (0.00245) |
| Quintile 4 Differential | −0.00333 | 0.00172 | −0.00066 |
| | (0.00408) | (0.00219) | (0.00253) |
| Quintile 5 Differential | 0.00387 | 0.00150 | 0.00008 |
| | (0.00384) | (0.00191) | (0.00195) |

NOTE: Panels A and B each report data for one regression. Paper provides details on specification. Regression controls for industry mix and how it affects job growth due to the industry.

Perusing Table A3, it is clear that the estimates are extremely imprecise. Essentially there are few if any quintile effects that are significantly different from zero. Furthermore, analysis of differences over time does not reveal any statistically significant effects. The estimates are simply too noisy. These industry sectors are smaller, and therefore it is harder to detect their effects on overall county job growth, which is this paper's focus.

## Appendix B

## Data Source and Industry Group Classifications

### LIGHTCAST

Lightcast employment counts at the six-digit NAICS industry level are used to measure employment growth in this analysis. The data include 947 industries. It should be noted that Lightcast modifies the industry categories to use consistent NAICS codes and county definitions from 2001 to the present.

The Lightcast industry employment counts are primarily based on QCEW data, which according to Lightcast cover 95 percent of the U.S. workforce. Sources including the ACS and BEA are used to cover the remaining 5 percent of the workforce, including self-employed workers and workers in industries not covered by the QCEW. The ACS is the main source Lightcast uses to produce counts of self-employed workers. ACS five-year county estimates for 2000 and 2007 do not exist so cannot be used by Lightcast to estimate self-employed workers for all counties during those periods. To ensure our samples are as comparable as possible across time, we excluded self-employed workers from the sample. The Lightcast sample used in the analysis does incorporate some non-QCEW data to cover other sources of employment not covered by the QCEW, such as employment in certain government and nonprofit sectors. Counts of these workers are estimated using sources including the BEA's State Personal Income and Employment and Local Area Personal Income and Employment datasets.

It should be noted that 60 percent of QCEW industry datapoints at the county level are suppressed. Any county-level employment dataset based on QCEW data will be subject to this limitation. Lightcast imputes the missing datapoints using the Census's County Business Patterns dataset.

## INDUSTRY SECTORS

### Manufacturing

All six-digit industries classified as manufacturing according to the NAICS system are included in this sector.

### High-Tech

To create a list of high-tech industries, we apply the same methodology used in Bartik and Sotherland (2019). We use the 2019 five-year ACS to estimate the percentage of jobs in each ACS NAICS industry sector with a share of total employment in BLS defined technical occupations (Hecker 2005) greater than twice the national average. Because ACS NAICS industries are classified at the four-digit level or lower, we count any six-digit industry in the Lightcast data that falls under one of these higher aggregate sectors as high-tech. We then crosswalk the 2017 NAICS used in the 2015–2019 ACS to 2022 NAICS before applying the list to the Lightcast data.

**Table B1: High-Tech Industry List**

| Industry name | NAICS code | Tech emp. share (%) | Jobs |
|---|---|---|---|
| Custom Computer Programming Services | 541511 | 61.0 | 1,132,853 |
| Computer Systems Design Services | 541512 | 61.0 | 1,161,791 |
| Computer Facilities Management Services | 541513 | 61.0 | 79,999 |
| Other Computer Related Services | 541519 | 61.0 | 137,537 |
| Research and Development in Nanotechnology | 541713 | 51.9 | 25,621 |
| Research and Development in Biotechnology (except Nanobiotechnology) | 541714 | 51.9 | 289,881 |
| Research and Development in the Physical, Engineering, and Life Sciences (except Nanotechnology and Biotechnology) | 541715 | 51.9 | 531,844 |
| Research and Development in the Social Sciences and Humanities | 541720 | 51.9 | 67,387 |
| Architectural Services | 541310 | 45.8 | 203,422 |
| Landscape Architectural Services | 541320 | 45.8 | 35,176 |
| Engineering Services | 541330 | 45.8 | 1,111,510 |
| Drafting Services | 541340 | 45.8 | 9,555 |
| Building Inspection Services | 541350 | 45.8 | 26,646 |
| Geophysical Surveying and Mapping Services | 541360 | 45.8 | 13,925 |
| Surveying and Mapping (except Geophysical) Services | 541370 | 45.8 | 54,910 |
| Testing Laboratories and Services | 541380 | 45.8 | 177,269 |
| Guided Missile and Space Vehicle Manufacturing | 336414 | 43.6 | 77,275 |
| Guided Missile and Space Vehicle Propulsion Unit and Propulsion Unit Parts Manufacturing | 336415 | 43.6 | 16,897 |
| Other Guided Missile and Space Vehicle Parts and Auxiliary Equipment Manufacturing | 336419 | 43.6 | 8,433 |
| Software Publishers | 513210 | 42.9 | 648,524 |
| Electronic Computer Manufacturing | 334111 | 39.0 | 115,567 |
| Computer Storage Device Manufacturing | 334112 | 39.0 | 14,606 |
| Computer Terminal and Other Computer Peripheral Equipment Manufacturing | 334118 | 39.0 | 32,505 |
| Bare Printed Circuit Board Manufacturing | 334412 | 37.9 | 26,564 |
| Semiconductor and Related Device Manufacturing | 334413 | 37.9 | 203,789 |
| Capacitor, Resistor, Coil, Transformer, and Other Inductor Manufacturing | 334416 | 37.9 | 17,502 |
| Electronic Connector Manufacturing | 334417 | 37.9 | 23,217 |
| Printed Circuit Assembly (Electronic Assembly) Manufacturing | 334418 | 37.9 | 58,964 |
| Other Electronic Component Manufacturing | 334419 | 37.9 | 63,716 |
| Manufacturing and Reproducing Magnetic and Optical Media | 334610 | 37.9 | 11,839 |
| Computing Infrastructure Providers, Data Processing, Web Hosting, and Related Services | 518210 | 37.5 | 481,329 |
| Web Search Portals and All Other Information Services | 519290 | 37.0 | 156,966 |
| Telephone Apparatus Manufacturing | 334210 | 32.9 | 15,557 |
| Radio and Television Broadcasting and Wireless Communications Equipment Manufacturing | 334220 | 32.9 | 51,839 |
| Other Communications Equipment Manufacturing | 334290 | 32.9 | 18,480 |
| Audio and Video Equipment Manufacturing | 334310 | 32.9 | 19,124 |
| Aircraft Manufacturing | 336411 | 32.7 | 231,670 |
| Aircraft Engine and Engine Parts Manufacturing | 336412 | 32.7 | 83,338 |
| Other Aircraft Parts and Auxiliary Equipment Manufacturing | 336413 | 32.7 | 98,987 |
| Electromedical and Electrotherapeutic Apparatus Manufacturing | 334510 | 32.0 | 75,814 |
| Search, Detection, Navigation, Guidance, Aeronautical, and Nautical System and Instrument Manufacturing | 334511 | 32.0 | 131,325 |
| Automatic Environmental Control Manufacturing for Residential, Commercial, and Appliance Use | 334512 | 32.0 | 13,366 |
| Instruments and Related Products Manufacturing for Measuring, Displaying, and Controlling Industrial Process Variables | 334513 | 32.0 | 56,973 |

**Table B1 (Continued)**

| Industry name | NAICS code | Tech emp. share (%) | Jobs |
|---|---|---|---|
| Totalizing Fluid Meter and Counting Device Manufacturing | 334514 | 32.0 | 8,683 |
| Instrument Manufacturing for Measuring and Testing Electricity and Electrical Signals | 334515 | 32.0 | 38,206 |
| Analytical Laboratory Instrument Manufacturing | 334516 | 32.0 | 48,022 |
| Irradiation Apparatus Manufacturing | 334517 | 32.0 | 14,193 |
| Other Measuring and Controlling Device Manufacturing | 334519 | 32.0 | 41,481 |
| Medicinal and Botanical Manufacturing | 325411 | 27.8 | 41,515 |
| Pharmaceutical Preparation Manufacturing | 325412 | 27.8 | 227,233 |
| In-Vitro Diagnostic Substance Manufacturing | 325413 | 27.8 | 32,094 |
| Biological Product (except Diagnostic) Manufacturing | 325414 | 27.8 | 44,781 |
| Timber Tract Operations | 113110 | 26.9 | 3,088 |
| Forest Nurseries and Gathering of Forest Products | 113210 | 26.9 | 2,108 |
| Agents for Wireless Telecommunications Services | 517122 | 24.9 | |
| Satellite Telecommunications | 517410 | 24.9 | 9,413 |
| All Other Telecommunications | 517810 | 24.9 | 45,742 |
| Wireless Telecommunications Carriers (except Satellite) | 517112 | 24.9 | 90,979 |
| Telecommunications Resellers | 517121 | 24.9 | 42,753 |
| Crude Petroleum Extraction | 211120 | 23.6 | 82,936 |
| Natural Gas Extraction | 211130 | 23.6 | 31,269 |
| Wired Telecommunications Carriers | 517111 | 22.5 | 481,167 |
| Turbine and Turbine Generator Set Units Manufacturing | 333611 | 21.7 | 17,509 |
| Speed Changer, Industrial High-Speed Drive, and Gear Manufacturing | 333612 | 21.7 | 11,460 |
| Mechanical Power Transmission Equipment Manufacturing | 333613 | 21.7 | 13,500 |
| Other Engine Equipment Manufacturing | 333618 | 21.7 | 49,244 |
| Petrochemical Manufacturing | 325110 | 20.8 | 25,397 |
| Industrial Gas Manufacturing | 325120 | 20.8 | 20,112 |
| Synthetic Dye and Pigment Manufacturing | 325130 | 20.8 | 10,769 |
| Other Basic Inorganic Chemical Manufacturing | 325180 | 20.8 | 40,777 |
| Ethyl Alcohol Manufacturing | 325193 | 20.8 | 10,104 |
| Cyclic Crude, Intermediate, and Gum and Wood Chemical Manufacturing | 325194 | 20.8 | 4,102 |
| All Other Basic Organic Chemical Manufacturing | 325199 | 20.8 | 42,465 |
| Printing Ink Manufacturing | 325910 | 20.8 | 7,501 |
| Explosives Manufacturing | 325920 | 20.8 | 7,299 |
| Custom Compounding of Purchased Resins | 325991 | 20.8 | 17,339 |
| Photographic Film, Paper, Plate, Chemical, and Copy Toner Manufacturing | 325992 | 20.8 | 6,713 |
| All Other Miscellaneous Chemical Product and Preparation Manufacturing | 325998 | 20.8 | 43,265 |
| Book Publishers | 513130 | 20.7 | 55,759 |
| Periodical Publishers | 513120 | 20.7 | 70,901 |
| All Other Publishers | 513199 | 20.7 | 50,734 |
| Greeting Card Publishers | 513191 | 20.7 | 2,910 |
| Directory and Mailing List Publishers | 513140 | 20.7 | 17,859 |
| Newspaper Publishers | 513110 | 19.3 | 100,669 |
| Surgical and Medical Instrument Manufacturing | 339112 | 19.3 | 143,716 |
| Surgical Appliance and Supplies Manufacturing | 339113 | 19.3 | 107,026 |
| Dental Equipment and Supplies Manufacturing | 339114 | 19.3 | 16,618 |
| Ophthalmic Goods Manufacturing | 339115 | 19.3 | 24,016 |
| Dental Laboratories | 339116 | 19.3 | 44,540 |
| Petroleum Refineries | 324110 | 19.3 | 61,440 |
| Hydroelectric Power Generation | 221111 | 17.9 | 7,777 |
| Fossil Fuel Electric Power Generation | 221112 | 17.9 | 74,758 |
| Nuclear Electric Power Generation | 221113 | 17.9 | 37,368 |
| Solar Electric Power Generation | 221114 | 17.9 | 11,789 |

**Table B1 (Continued)**

| Industry name | NAICS code | Tech emp. share (%) | Jobs |
|---|---|---|---|
| Wind Electric Power Generation | 221115 | 17.9 | 9,018 |
| Geothermal Electric Power Generation | 221116 | 17.9 | 1,251 |
| Biomass Electric Power Generation | 221117 | 17.9 | 2,178 |
| Other Electric Power Generation | 221118 | 17.9 | 3,851 |
| Electric Bulk Power Transmission and Control | 221121 | 17.9 | 25,962 |
| Electric Power Distribution | 221122 | 17.9 | 220,272 |
| Electric Lamp Bulb and Other Lighting Equipment Manufacturing | 335139 | 17.2 | 12,128 |
| Residential Electric Lighting Fixture Manufacturing | 335131 | 17.2 | 7,422 |
| Commercial, Industrial, and Institutional Electric Lighting Fixture Manufacturing | 335132 | 17.2 | 20,037 |
| Power, Distribution, and Specialty Transformer Manufacturing | 335311 | 17.2 | 29,533 |
| Motor and Generator Manufacturing | 335312 | 17.2 | 37,428 |
| Switchgear and Switchboard Apparatus Manufacturing | 335313 | 17.2 | 37,434 |
| Relay and Industrial Control Manufacturing | 335314 | 17.2 | 42,615 |
| Battery Manufacturing | 335910 | 17.2 | 49,377 |
| Fiber Optic Cable Manufacturing | 335921 | 17.2 | 13,243 |
| Other Communication and Energy Wire Manufacturing | 335929 | 17.2 | 13,175 |
| Current-Carrying Wiring Device Manufacturing | 335931 | 17.2 | 29,537 |
| Noncurrent-Carrying Wiring Device Manufacturing | 335932 | 17.2 | 11,085 |
| Carbon and Graphite Product Manufacturing | 335991 | 17.2 | 10,012 |
| All Other Miscellaneous Electrical Equipment and Component Manufacturing | 335999 | 17.2 | 35,440 |
| Commercial and Service Industry Machinery Manufacturing | 333310 | 17.1 | 91,117 |
| Construction Machinery Manufacturing | 333120 | 16.3 | 73,686 |
| Mining Machinery and Equipment Manufacturing | 333131 | 16.3 | 9,226 |
| Oil and Gas Field Machinery and Equipment Manufacturing | 333132 | 16.3 | 47,066 |
| Offices of Bank Holding Companies | 551111 | 15.7 | 8,923 |
| Offices of Other Holding Companies | 551112 | 15.7 | 85,703 |
| Corporate, Subsidiary, and Regional Managing Offices | 551114 | 15.7 | 2,447,169 |
| Railroad Rolling Stock Manufacturing | 336510 | 15.0 | 21,111 |
| Food Product Machinery Manufacturing | 333241 | 14.8 | 20,976 |
| Semiconductor Machinery Manufacturing | 333242 | 14.8 | 30,023 |
| Sawmill, Woodworking, and Paper Machinery Manufacturing | 333243 | 14.8 | 13,031 |
| All Other Industrial Machinery Manufacturing | 333248 | 14.8 | 69,516 |
| Industrial and Commercial Fan and Blower and Air Purification Equipment Manufacturing | 333413 | 14.8 | 31,683 |
| Heating Equipment (except Warm Air Furnaces) Manufacturing | 333414 | 14.8 | 16,257 |
| Air-Conditioning and Warm Air Heating Equipment and Commercial and Industrial Refrigeration Equipment Manufacturing | 333415 | 14.8 | 97,208 |
| Air and Gas Compressor Manufacturing | 333912 | 14.8 | 19,257 |
| Measuring, Dispensing, and Other Pumping Equipment Manufacturing | 333914 | 14.8 | 27,653 |
| Elevator and Moving Stairway Manufacturing | 333921 | 14.8 | 10,927 |
| Conveyor and Conveying Equipment Manufacturing | 333922 | 14.8 | 36,943 |
| Overhead Traveling Crane, Hoist, and Monorail System Manufacturing | 333923 | 14.8 | 14,674 |
| Industrial Truck, Tractor, Trailer, and Stacker Machinery Manufacturing | 333924 | 14.8 | 30,370 |
| Power-Driven Handtool Manufacturing | 333991 | 14.8 | 13,909 |
| Welding and Soldering Equipment Manufacturing | 333992 | 14.8 | 15,285 |
| Packaging Machinery Manufacturing | 333993 | 14.8 | 24,402 |
| Industrial Process Furnace and Oven Manufacturing | 333994 | 14.8 | 9,314 |
| Fluid Power Cylinder and Actuator Manufacturing | 333995 | 14.8 | 16,026 |
| Fluid Power Pump and Motor Manufacturing | 333996 | 14.8 | 18,630 |
| All Other Miscellaneous General Purpose Machinery Manufacturing | 333998 | 14.8 | 46,614 |
| Natural Gas Distribution | 221210 | 14.8 | 113,105 |

**Table B1 (Continued)**

| Industry name | NAICS code | Tech emp. share (%) | Jobs |
|---|---|---|---|
| Media Streaming Distribution Services, Social Networks, and Other Media Networks and Content Providers | 516210 | 14.6 | 239,232 |
| Iron Ore Mining | 212210 | 14.6 | 5,031 |
| Gold Ore and Silver Ore Mining | 212220 | 14.6 | 16,464 |
| Copper, Nickel, Lead, and Zinc Mining | 212230 | 14.6 | 18,620 |
| Other Metal Ore Mining | 212290 | 14.6 | 4,594 |
| Paint and Coating Manufacturing | 325510 | 14.5 | 42,667 |
| Adhesive Manufacturing | 325520 | 14.5 | 24,035 |
| Nitrogenous Fertilizer Manufacturing | 325311 | 14.5 | 8,928 |
| Phosphatic Fertilizer Manufacturing | 325312 | 14.5 | 5,850 |
| Fertilizer (Mixing Only) Manufacturing | 325314 | 14.5 | 7,320 |
| Pesticide and Other Agricultural Chemical Manufacturing | 325320 | 14.5 | 14,821 |
| Compost Manufacturing | 325315 | 14.5 | 1,031 |
| Automobile and Light Duty Motor Vehicle Manufacturing | 336110 | 14.0 | 250,623 |
| Heavy Duty Truck Manufacturing | 336120 | 14.0 | 38,743 |
| Motor Vehicle Body Manufacturing | 336211 | 14.0 | 57,297 |
| Truck Trailer Manufacturing | 336212 | 14.0 | 43,611 |
| Motor Home Manufacturing | 336213 | 14.0 | 20,853 |
| Travel Trailer and Camper Manufacturing | 336214 | 14.0 | 49,171 |
| Motor Vehicle Gasoline Engine and Engine Parts Manufacturing | 336310 | 14.0 | 58,325 |
| Motor Vehicle Electrical and Electronic Equipment Manufacturing | 336320 | 14.0 | 61,141 |
| Motor Vehicle Steering and Suspension Components (except Spring) Manufacturing | 336330 | 14.0 | 33,903 |
| Motor Vehicle Brake System Manufacturing | 336340 | 14.0 | 21,481 |
| Motor Vehicle Transmission and Power Train Parts Manufacturing | 336350 | 14.0 | 80,674 |
| Motor Vehicle Seating and Interior Trim Manufacturing | 336360 | 14.0 | 74,857 |
| Motor Vehicle Metal Stamping | 336370 | 14.0 | 83,920 |
| Other Motor Vehicle Parts Manufacturing | 336390 | 14.0 | 154,539 |
| Ship Building and Repairing | 336611 | 13.8 | 101,824 |
| Boat Building | 336612 | 13.8 | 51,167 |
| Administrative Management and General Management Consulting Services | 541611 | 13.8 | 837,727 |
| Human Resources Consulting Services | 541612 | 13.8 | 97,901 |
| Marketing Consulting Services | 541613 | 13.8 | 326,044 |
| Process, Physical Distribution, and Logistics Consulting Services | 541614 | 13.8 | 163,992 |
| Other Management Consulting Services | 541618 | 13.8 | 122,847 |
| Environmental Consulting Services | 541620 | 13.8 | 98,070 |
| Other Scientific and Technical Consulting Services | 541690 | 13.8 | 215,295 |
| Pipeline Transportation of Crude Oil | 486110 | 13.4 | 11,485 |
| Pipeline Transportation of Natural Gas | 486210 | 13.4 | 32,224 |
| Pipeline Transportation of Refined Petroleum Products | 486910 | 13.4 | 7,398 |
| All Other Pipeline Transportation | 486990 | 13.4 | 1,051 |
| Soap and Other Detergent Manufacturing | 325611 | 13.0 | 28,091 |
| Polish and Other Sanitation Good Manufacturing | 325612 | 13.0 | 24,761 |
| Surface Active Agent Manufacturing | 325613 | 13.0 | 4,702 |
| Toilet Preparation Manufacturing | 325620 | 13.0 | 58,537 |
| Farm Machinery and Equipment Manufacturing | 333111 | 13.0 | 68,328 |
| Lawn and Garden Tractor and Home Lawn and Garden Equipment Manufacturing | 333112 | 13.0 | 19,531 |
| Drilling Oil and Gas Wells | 213111 | 12.8 | 49,587 |
| Support Activities for Oil and Gas Operations | 213112 | 12.8 | 214,944 |
| Support Activities for Coal Mining | 213113 | 12.8 | 4,843 |
| Support Activities for Metal Mining | 213114 | 12.8 | 4,970 |
| Support Activities for Nonmetallic Minerals (except Fuels) Mining | 213115 | 12.8 | 3,267 |

**Table B1 (Continued)**

| Industry name | NAICS code | Tech emp. share (%) | Jobs |
|---|---|---|---|
| Small Electrical Appliance Manufacturing | 335210 | 12.6 | 12,161 |
| Major Household Appliance Manufacturing | 335220 | 12.6 | 54,111 |

NOTE: Some 2022 six-digit NAICS industries are associated with more than one 2017 six-digit NAICS industry. For example, many industries, such as directory and mailing list publishers, were previously separated into two different internet-based and non-internet-based industry sectors. The internet sectors were combined with the non-internet specific sector in the 2022 NAICS system. In cases such as these, a tech-concentration share average is calculated for the new 2022 NAICS industry sector, weighted by total employment in the two or more 2017 NAICS industry sectors that previously comprised the new sector. This average is used to determine whether the new industry meets the twice the national average threshold. In other cases, 2017 NAICS were separated into two industry categories in the 2022 NAICS, in which case the employment concentration based on the 2017 definition must be applied to both industries.

### Clean Energy

We use a list of clean energy industries at the six-digit NAICS level created by Brookings Metro for a 2019 report on clean energy jobs to define clean energy industries for this analysis. Our list is essentially the same, except we crosswalk the NAICS in the Brookings list, which are based on 2017 definitions, to 2022 NAICS.

### Semiconductors

We define semiconductor industries narrowly. The only companies likely to receive substantial semiconductor incentives through the CHIPS Act, and the only ones that have so far are companies with dedicated high-tech semiconductor manufacturing operations classified under a small subset of semiconductor-related NAICS codes. We expect these dedicated semiconductor industries are most likely to shift their investment patterns as a direct result of recent policies, so we focus on this small group of industries. The list includes all six-digit NAICS industries falling under semiconductor and other electronic component manufacturing (NAICS code 3344), as well as semiconductor machinery manufacturing (NAICS code 333242).

## Appendix C

## Descriptive Statistics

**Panel A: 2001–2007**

| 2001–2007 | Overall annual growth (%) | Clean energy annual growth (%) | High-tech annual growth (%) | Manufacturing annual growth (%) | Semiconductor annual growth (%) | Bartik instrument (overall) (%) |
|---|---|---|---|---|---|---|
| Mean | 0.60 | 0.00 | −0.13 | −0.34 | −0.03 | 0.63 |
| Std. dev. | 1.56 | 0.30 | 0.43 | 0.46 | 0.09 | 0.40 |
| Minimum | −24.89 | −5.00 | −5.37 | −5.78 | −3.75 | −3.61 |
| Maximum | 15.78 | 5.94 | 11.92 | 4.53 | 1.66 | 3.22 |
| 10% | −0.93 | −0.23 | −0.58 | −0.79 | −0.08 | 0.22 |
| 25% | −0.36 | −0.10 | −0.29 | −0.51 | −0.03 | 0.52 |
| 50% | 0.40 | 0.00 | −0.12 | −0.26 | 0.00 | 0.67 |
| 75% | 1.30 | 0.11 | 0.08 | −0.12 | 0.00 | 0.83 |
| 90% | 2.46 | 0.26 | 0.27 | 0.05 | 0.01 | 1.00 |

| 2001–2007 | PAER in Q1 (%) | PAER in Q2 (%) | PAER in Q3 (%) | PAER in Q4 (%) | PAER in Q5 (%) |
|---|---|---|---|---|---|
| Mean | 67.00 | 73.68 | 77.03 | 79.54 | 83.09 |
| Std. dev. | 4.12 | 1.10 | 0.77 | 0.78 | 1.79 |
| Minimum | 33.73 | 71.67 | 75.60 | 78.25 | 80.95 |
| Maximum | 71.66 | 75.59 | 78.24 | 80.93 | 94.67 |
| 10% | 61.99 | 72.25 | 75.98 | 78.46 | 81.19 |
| 25% | 65.96 | 72.64 | 76.36 | 78.88 | 81.66 |
| 50% | 67.80 | 73.90 | 77.05 | 79.55 | 82.56 |
| 75% | 69.43 | 74.57 | 77.76 | 80.33 | 84.17 |
| 90% | 70.87 | 75.09 | 78.08 | 80.56 | 85.67 |

NOTE: All descriptive statistics are weighted by county total jobs in the base period. Overall annual average growth = $100 * [\ln(J_{ctk2}) - \ln(J_{ctk1})]/(t_{k2} - t_{k1})$ where $J_{ctk}$= county total jobs, $t_{k2}$ = last time period, $t_{k1}$ = base time period. Note that for the 2019–2022/23 period, we divide by 3.5. Industry sector specific annual average growth = $100 * \{\frac{[\ln(J_{ctk1}+(J_{ctkgi2}-J_{ctkgi1}))-\ln(J_{ctk1})]}{tk2-tk1}\}$ where $J_{ctgi}$ = county total jobs in specific industry. Bartik instrument predicted growth rate = $100 * [\ln(J_{ctk1} + predicted\ jobs) - \ln(J_{ctk1})]/(t1 - t0)$ where predicted jobs = sum over all industries I of $J_{ctk1i} * (\frac{J_{nkt2i}}{J_{nkt1i}})$ $J_{ctk1}$ where $J_{nkti}$ = national employment in industry $i$. Prime-age employment rates are calculated using the 2005–2009 ACS.
SOURCE: Authors' estimates.

**Panel B: 2007–2019**

| 2007–2019 | Overall annual growth (%) | Clean energy annual growth (%) | High-tech annual growth (%) | Manufacturing annual growth (%) | Semiconductor annual growth (%) | Bartik instrument (overall) (%) |
|---|---|---|---|---|---|---|
| Mean | 0.63 | 0.00 | 0.07 | −0.07 | 0.00 | 0.73 |
| Std. dev. | 0.94 | 0.15 | 0.28 | 0.21 | 0.03 | 0.24 |
| Minimum | −5.95 | −2.31 | −2.78 | −3.33 | −1.09 | −1.20 |
| Maximum | 15.29 | 12.72 | 12.89 | 13.13 | 0.81 | 2.67 |
| 10% | −0.39 | −0.10 | −0.17 | −0.23 | −0.02 | 0.49 |
| 25% | 0.09 | −0.05 | −0.06 | −0.15 | −0.01 | 0.61 |
| 50% | 0.59 | 0.00 | 0.04 | −0.06 | 0.00 | 0.72 |
| 75% | 1.11 | 0.05 | 0.14 | 0.00 | 0.00 | 0.84 |
| 90% | 1.65 | 0.12 | 0.35 | 0.10 | 0.00 | 0.99 |

| | PAER in Q1 (%) | PAER in Q2 (%) | PAER in Q3 (%) | PAER in Q4 (%) | PAER in Q5 (%) |
|---|---|---|---|---|---|
| Mean | 69.52 | 75.39 | 77.39 | 79.20 | 82.74 |
| Std. dev. | 4.67 | 0.70 | 0.52 | 0.64 | 1.99 |
| Minimum | 31.39 | 73.96 | 76.60 | 78.20 | 80.41 |
| Maximum | 73.94 | 76.60 | 78.20 | 80.40 | 97.50 |
| 10% | 65.09 | 74.31 | 76.69 | 78.34 | 80.75 |
| 25% | 68.20 | 75.02 | 76.91 | 78.63 | 81.08 |
| 50% | 70.82 | 75.22 | 77.42 | 79.20 | 82.37 |
| 75% | 72.72 | 75.90 | 77.83 | 79.66 | 83.84 |
| 90% | 73.42 | 76.44 | 78.13 | 80.17 | 85.54 |

NOTE: All descriptive statistics are weighted by county total jobs in the base period. Overall annual average growth = $100 * [\ln(J_{ctk2}) - \ln(J_{ctk1})]/(t_{k2} - t_{k1})$ where $J_{ctk}$= county total jobs, $t_{k2}$ = last time period, $t_{k1}$ = base time period. Note that for the 2019–2022/23 period, we divide by 3.5. Industry sector specific annual average growth = $100 * \{\frac{[\ln(J_{ctk1}+(J_{ctkgi2}-J_{ctkgi1}))-\ln(J_{ctk1})]}{tk2-tk1}\}$ where $J_{ctgi}$ = county total jobs in specific industry. Bartik instrument predicted growth rate = $100 * [\ln(J_{ctk1} + predicted\ jobs) - \ln(J_{ctk1})]/(t1 - t0)$ where predicted jobs = sum over all industries I of $J_{ctk1i} * (\frac{J_{nkt2i}}{J_{nkt1i}})$ $J_{ctk1}$ where $J_{nkti}$ = national employment in industry $i$. Prime-age employment rates are calculated using the 2005–2009 ACS.
SOURCE: Authors' estimates.

**Panel C: 2019–2022/23**

| | Overall annual growth (%) | Clean energy annual growth (%) | High-tech annual growth (%) | Manufacturing annual growth (%) | Semiconductor annual growth (%) | Bartik instrument (overall) (%) |
|---|---|---|---|---|---|---|
| Mean | 0.25 | 0.08 | 0.15 | 0.01 | 0.00 | 0.57 |
| Std. dev. | 1.42 | 0.30 | 0.43 | 0.32 | 0.04 | 0.42 |
| Minimum | −30.91 | −18.58 | −18.04 | −12.30 | −1.28 | −3.66 |
| Maximum | 31.15 | 16.36 | 7.77 | 7.66 | 0.96 | 8.20 |
| 10% | −1.17 | −0.07 | −0.19 | −0.21 | −0.01 | 0.09 |
| 25% | −0.64 | 0.00 | −0.04 | −0.09 | 0.00 | 0.35 |
| 50% | 0.07 | 0.07 | 0.08 | 0.00 | 0.00 | 0.57 |
| 75% | 1.06 | 0.16 | 0.31 | 0.09 | 0.00 | 0.79 |
| 90% | 1.88 | 0.30 | 0.52 | 0.24 | 0.02 | 1.05 |

| | PAER in Q1 (%) | PAER in Q2 (%) | PAER in Q3 (%) | PAER in Q4 (%) | PAER in Q5 (%) |
|---|---|---|---|---|---|
| Mean | 70.33 | 77.15 | 79.17 | 81.28 | 84.49 |
| Std. dev. | 5.20 | 0.77 | 0.55 | 0.68 | 1.71 |
| Minimum | 14.16 | 75.45 | 78.11 | 80.08 | 82.49 |
| Maximum | 75.44 | 78.09 | 80.08 | 82.48 | 95.89 |
| 10% | 64.64 | 75.94 | 78.41 | 80.33 | 82.78 |
| 25% | 69.02 | 76.47 | 78.67 | 80.71 | 83.12 |
| 50% | 71.68 | 77.32 | 79.15 | 81.33 | 83.98 |
| 75% | 73.64 | 77.84 | 79.63 | 81.91 | 85.35 |
| 90% | 74.55 | 77.88 | 79.99 | 82.09 | 86.96 |

NOTE: All descriptive statistics are weighted by county total jobs in the base period. Overall annual average growth = $100 * [\ln(J_{ctk2}) - \ln(J_{ctk1})]/(t_{k2} - t_{k1})$ where $J_{ctk}$= county total jobs, $t_{k2}$ = last time period, $t_{k1}$ = base time period. Note that for the 2019–2022/23 period, we divide by 3.5. Industry sector specific annual average growth = $100 * \{\frac{[\ln(J_{ctk1}+(J_{ctkgi2}-J_{ctkgi1}))-\ln(J_{ctk1})]}{tk2-tk1}\}$ where $J_{ctgi}$ = county total jobs in specific industry. Bartik instrument predicted growth rate = $100 * [\ln(J_{ctk1} + predicted\ jobs) - \ln(J_{ctk1})]/(t1 - t0)$ where predicted jobs = sum over all industries I of $J_{ctk1i} * (\frac{J_{nkt2i}}{J_{nkt1i}}) J_{ctk1}$ where $J_{nkti}$ = national employment in industry $i$. Prime-age employment rates are calculated using the 2005–2009 ACS.
SOURCE: Authors' estimates.

Mean annual county employment growth, weighted by county total jobs, was similar in both 2001–2007 and 2007–2019, with employment growing at a rate of around 0.6 percent annually in the former period and 0.63 percent in the latter. As a result of the pandemic, annual average employment growth fell to 0.25 percent in the 2019–2022/23 period. Although we observe a shift toward greater relative growth in lower prime-age employment rate quintiles in our analysis, this shift has occurred over a generally low employment growth period. As QCEW data from more recent quarters are released, the average annual growth rate from 2019 will likely increase as well.

Although overall employment growth has slowed, we see noticeable increases in weighted mean annual growth rates in the high-tech, clean energy, and manufacturing sectors during the 2019–2022/23 period compared to the previous two periods. Recall that these industry growth variables are defined so that they measure the contribution of these industry groups to overall job growth rates; hence, these particular sector contributions tend to be lower in magnitude than overall job growth. The increasing growth trend in manufacturing and high-tech employment were already occurring from 2001–2007 to 2007–2019. However, it seems plausible that federal policies aimed at combatting climate change could be a factor in the increasing growth in clean energy employment relative to the previous two periods.

The weighted mean prime-age employment rate increased by over 3 percentage points between the first and last period in quintiles 1 and 2. The prime-age employment rate in quintile 5, in contrast, increased by a little under 1.5 percentage points and decreased from 2001–2007 to 2007–2019.

Part of these prime-age employment rate trends are due to measurement changes. Census Bureau measures of employment rates in the 2000 Census, and in the American Community Survey (ACS) prior to 2008, tended to be lower than in the Current Population Survey (CPS). This lower employment rate is due in part to the Census and ACS probing less for whether those surveyed had any employment. The ACS survey questions were modified, starting in 2008, in a manner that tended to increase employment rates to be more consistent with the CPS (Kromer and Howard 2011). These changing ACS employment rate measures is another good reason that this analysis uses quintiles of the employment rate to measure economic distress.

Mean annual county employment growth is relatively similar to the average Bartik instrument prediction of overall employment growth during the first two periods but diverges significantly in the final period. This is because Lightcast's modified QCEW employment data include counts by industry and state for employment that cannot be assigned to a specific county for technical reasons. Industry growth in employment not associated with a specific county is incorporated into the calculation of the Bartik instrument variables but is not factored into the overall growth rates of the individual counties. From 2019 to 2023, the number of unassigned jobs in the Lightcast data increased from a national total of approximately 3,280,000 to 5,070,000.

The increase in the number of unassigned jobs is most likely the result of an increase in the prevalence of remote work. This growth in the number of unassigned remote workers may bias our results in an unknown way. It could be that the remote worker trend is higher in less distressed counties, which would bias the results toward showing less favorable results in the recent time period for less distressed counties. On the other hand, perhaps the increasing number of remote workers are relocating to lower-cost counties, which would tend to be more economically distressed counties. This would bias the results toward showing less favorable recent trends for more distressed counties. Further research is needed on where remote workers are locating, which would allow better measurement of job growth trends including such workers.

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