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Abstract
Economists typically celebrate productivity growth as the chief way to improve living standards. They also advocate that particular cities and regions strive to be as productive as possible to attract business and increase employment. However, while productivity growth may reduce costs, improve quality, or lead to innovation and new products, if demand is insufficiently elastic, labor demand may decrease, reducing employment in that location. In other words, places experiencing the most productivity growth may face some unintended consequences, such as weakening of local labor markets. In this paper, we study county-level effects of productivity growth and productivity levels in the computer and electronic product manufacturing industry (NAICS334), the goods sector (excluding NAICS334) and in the services sector on total employment growth, employment growth in major sectors, income and earnings growth. The results suggest that productivity growth generally suppresses job growth but has boosting effects on earnings and, to a lesser degree, on per-capita income, although there is considerable variation across geographies and specific outcomes.

Key words: local productivity growth, local productivity level, employment growth, income growth, earnings growth, instrumental variable estimation, computer and electronic product manufacturing

I. Introduction

Economists typically celebrate productivity growth as central to improving living standards and developing new products for the general population. Elementary economics textbooks describe that while productivity has increased remarkably since the 19th century, so have total employment and living standards (Case *et al*., 2012). The neoclassical economic theory predicts that there should be a comparable increase in wages as productivity grows. It is unsurprising, then, that at the local and regional levels improved productivity and innovation are viewed as a prerequisite for future growth and development that is needed for regional competitiveness (e.g., Combes *et al*., 2004).

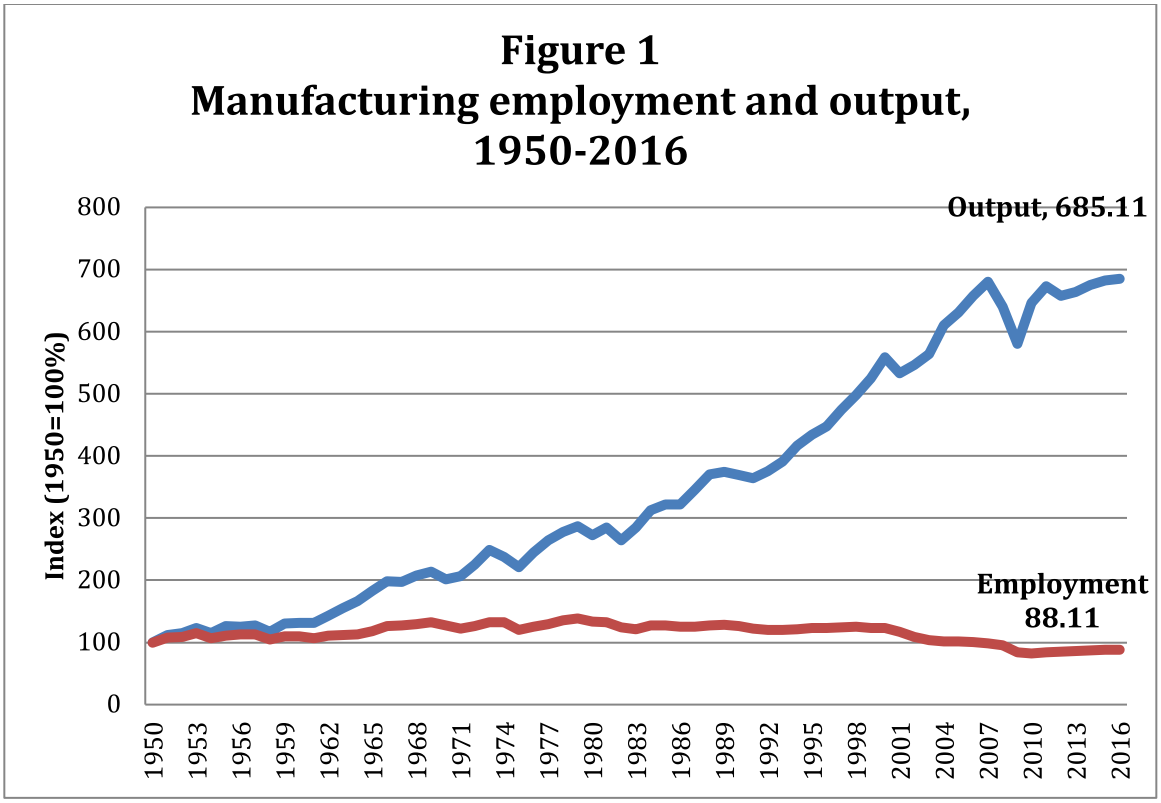
Recent research, however, increasingly shifts to explore and document both the positive and negative effects of productivity growth and automation. There is no question that consumers benefit from better and less expensive products that are due to improved productivity. It is highly probable that the global benefits of productivity growth exceed its global costs. Yet, even if aggregate jobs are created on net as a result of productivity growth, there still could be net job losses that are locally concentrated in the very places where the production occurs as the economy reorganizes. Autor and Salomons (2017), for instance, show that productivity growth boosts *country-level* employment, but productivity gains within an industry lead to contraction of that industry.

Given the tendency for many industries to be spatially concentrated, negative effects of productivity growth are likely to be felt more strongly in localities where productive industries locate. In other words, the costs and benefits of productivity growth are not uniformly distributed across space. Places where the productivity growth is taking place may suffer on balance if productivity growth leads to job losses and/or the profits are extricated elsewhere (e.g., to a firm's global shareholders)—i.e., the benefits are globally dispersed to consumers and owners elsewhere, while the costs are concentrated in place of production. Indeed, there are growing concerns that the sanguine story about productivity growth is less applicable in the current environment as "losing" regions are not compensated to offset their losses.

The argument that productivity growth and innovation may kill jobs is by no means new. Ricardo voiced his concerns about the end of work long time ago (Ricardo, 1821). Neisser (1942) discussed the tradeoffs of productivity growth in what was then commonly labeled as increases in technological unemployment. These concerns gained traction against the backdrop of sluggish job growth after 2000 and the post-Great Recession's weak recovery for a number of reasons. New-economy firms such as Apple, Google, and Facebook create immense wealth while creating far fewer jobs than the old manufacturing industries of decades past. The changing relationship between wages and productivity may further suggest a new economic order. Since the 1970s, median U.S. wages have greatly lagged productivity growth, a break from the well-established link between productivity and wages in the early part of the 20th century (Krugman, 2015; Mishel and Gee, 2012).

Similarly, U.S. manufacturing productivity growth has long been associated with a declining workforce, even well before the introduction of digital technologies and expansion of trade with low-wage nations. To illustrate, Figure 1 shows the time trend of US manufacturing output and manufacturing employment over the 1950-2016 period. It shows that during this time, production rose nearly seven-fold while employment fell by 12%, implying a 778% increase in average labor productivity. Since 2000, these data suggest a 171% increase in average labor productivity but also a decline in employment.

Recent evidence suggests that higher-order computer technologies allow for automation of many abstract tasks (Brynjolfsson and McAfee, 2012; Krugman, 2012; Smith, 2013; Ford, 2015; Tufekci, 2015; Council of Economic Advisors, 2016) and these technologies apply across a wide range of goods- and service-producing industries. For example, Frey and Osborne (2013) contend that 47% of jobs are at risk of being displaced by new technologies in the next decade or two. Acemoglu and Restrepo (2017) argue that displacement effects can potentially be large. They find that between 1990-2007, one more industrial robot per-thousand workers reduces the local employment/population ratio by 0.18-0.34 percentage points and lowers wages by 0.25-0.5 percent. While such estimates seem quite high, even if overestamated, they may herald possible dire effects.



Sources: U.S. Bureau of Labor Statistics, Output in Manufacturing in the United States (DISCONTINUED) [USAOTPT], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/USAOTPT; U.S. Bureau of Labor Statistics, Manufacturing Sector: Real Output [OUTMS], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/OUTMS; U.S. Bureau of Labor Statistics, All Employees: Manufacturing [MANEMP], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/MANEMP

In addition, other factors are creating pressures on low- and middle-skilled workers. For example, in addition to skill-biased technological change that has generally favored high-skilled workers since the 1970s, labor market polarization puts those in routine occupations at risk of being replaced by technology (e.g., Autor and Dorn, 2013; Autor *et al*., 2015; Autor *et al*., 2003; Beaudry *et al*., 2010), leading to an increase in income inequality. In fact, Hershbein and Kahn (2016) find that this polarization accelerated during the Great Recession due to a combination of labor hoarding and an opportunity to upgrade technology during the downturn. Beaudry *et al*., (2010) and Beaudry *et al*., (2016) find that since 2000, the demand for high-skilled (cognitive tasked) workers has declined, pushing them down the occupational chain, creating even more pressure for middle-skilled workers.

Despite the long-brewing debate, there is no consensus on the relationship between productivity and job growth at the national level (Sabadash, 2013), let alone the local level, which is the purpose of our research. There has been significant research on how productivity and technological change affect aggregate employment (or unemployment), wages, and income distribution. For example, utilizing the argument that agglomeration economies increase productivity, Cingano and Schivardi (2004) show that larger cities have higher wages stemming from higher productivity, but not necessarily more job growth. Yet, research on the impact of total productivity growth on *local* labor markets (as opposed to national labor markets) is scarce. A number of studies looked at the local effects of particular technological innovations, such as computerization or robots, but none on overall productivity growth, which can vary for a host of reasons including capital deepening or simple learning-by-doing. From the viewpoint of a worker who loses her job to productivity growth, it is unlikely that the exact reason (robots or simple production changes, for example) matters much. In this respect, an examination of overall productivity growth is useful so that findings from subsets of productivity growth drivers (e.g., robots) are not used to overgeneralize aggregate productivity growth effects.

In contrast to the existing literature, we more directly examine how *overall* productivity levels and productivity growth affect regional labor markets; what are the relative contributions of productivity growth and productivity levels in computer and electronic manufacturing industries, goods and services and whether having a mix of high-productivity industries is beneficial. As opposed to narrower studies of the effects of (say) robots or computerization, we are among the first to directly assess the relation between *local-level overall* productivity and a range of outcomes including jobs, earnings, and income growth. The exception is Hornbeck and Moretti (2018) (hereafter HM), though there are key differences between their study and ours. First, our model directs us to use average labor productivity (ALP), while HM use total factor productivity (TFP). Second, HM are more interested in individual distributional outcomes, while we are more interested in the relative effects on local labor markets, especially differing productivity effects across sectors and how productivity growth in different sectors may have different effects[1]. Third, our focus is counties versus MSAs. A county focus allows us to consider rural areas, which have drawn more attention after President Trump's election. Fourth, there are key specification differences. Namely, we first difference the variables in our specification in order to eliminate omitted county fixed effects; we emphasize three-year shocks versus HM's focus on long-term 10-year shocks; and our post-2000 analysis versus their analysis of pre-2000 data.

In addition to studying the relationship between productivity and more traditional economic outcomes, such as total employment and income, we expand the focus of our analysis to include employment in high-tech vs. low-tech industries and in goods-producing industries vs. services. We measure overall productivity growth and initial 1998 productivity at a county level and perform individual analyses for rural, small metropolitan, and large metropolitan counties over the 2000 – 2015 period to account for differing agglomeration effects by city size.

We then repeat the analyses using separate measures of productivity for computer and electronic product manufacturing (NAICS334), goods (agriculture, mining, manufacturing, construction) and services instead of total productivity measures. To the best of our knowledge, we are the first to appraise the effects of *local* productivity growth in computer and electronic product manufacturing on local employment, income, and earnings.

II. Conceptual model

Following Blien and Ludewig (2014) and Blien and Sanner's (2014) use of the Appelbaum and Schettkat's (1999) model, the following shows the tradeoffs of the

[1] HM only consider manufacturing productivity.

substitution and compensation effects in the relationship between productivity growth and employment assuming Hicks neutral technological progress. Firm j's average labor productivity π with employment N and output Q equals

$$\pi = Q/N \tag{1}$$

where $Q=f(P,y)$, $f_P<0$ and $f_y<0$; y is income and P is price (subscript j is dropped for convenience). The price markup z implies that

$$P = zW/\pi \tag{2}$$

Taking logs and differentiating (1) and (2) with respect to time and assuming the markup z is fixed in the short-run we arrive at (3) and (4).

$$\dot{N} = \dot{Q} - \dot{\pi} \tag{3}$$

$$\dot{P} = \dot{W} - \dot{\pi} \tag{4}$$

The total derivative of Q from the equation (1) is:

$$dQ = f_P P + f_y dy \tag{5}$$

After some algebraic manipulations and dividing both sides by Q we get:

$$\dot{Q} = -e_{PQ}\dot{P} + \eta\dot{Y} \tag{6}$$

where $e_{PQ}$is the own price elasticity and η is the income elasticity. In the last step, substitute (6) into (3) and substitute $\dot{P}$ in (4) to derive the following:

$$\dot{N} = \left(e_{PQ} - 1\right)\dot{\pi} - e_{PQ}\dot{W} + \eta\dot{Y} \tag{7}$$

Assuming all j firms in industry i and region a are identical, we can write:

$$\dot{N}_{ai} = \left(e_{PQ} - 1\right)\dot{\pi} - e_{PQ}\dot{W}_{ai} + \eta\dot{Y}_{ai} \tag{8}$$

Several insights follow from equation (8). Firstly, employment growth is positive if demand is elastic. This holds for monopolies and in a Dixit-Stiglitz framework, but it is not necessarily the case in other settings (Blien and Sanner, 2014). Secondly, if wage growth equals productivity growth as suggested by the neoclassical economic theory, employment growth is expected to fall at the rate of productivity growth net of income growth. Rapid income growth in the economy should offset these productivity effects especially for superior goods. For nearly the last five decades, however, U.S. wage growth has lagged behind productivity growth, meaning employment growth should increase.

The model has been extended to include the following scenarios to show that demand must be elastic to ensure employment does not decline in response to productivity growth: 1) If labor supply is perfectly elastic in a regional setting (e.g. in a spatial equilibrium model), the results are not affected. Combes *et al*. (2004) show that even in the case of inelastically supplied labor, the results still hold, although the magnitude of the effect is reduced. 2) Introducing a wage curve structure produces similar dampening effects but the main conclusion holds. Blien and Sanner (2014) generalize the results to account for cross-price elasticities in other industries. 3) Assuming $\dot{\pi}$ is equal across all industries to simplify things, $\dot{N} = \dot{\pi}(\eta - 1)$ or employment only rises if output produced in the region is superior. Since η equals one on average, employment must fall in some industries in some regions.

When examining the regional dimension of productivity empirically, it is important to keep in mind that local effects are *unlikely* to be identical to the effects at the national level. For instance, labor market effects are more concentrated when considering the fact that the place of production or industries in a region may have more elastic demand because regions have a smaller share of a given industry's production. Another example would be a case when productivity growth reduces total industry employment across the nation but remaining employment may still concentrate in more productive regions. Expectations about changes in future productivity may affect contemporaneous migration patterns. Finally, if the capital owners benefit the most as a result of recent trends in productivity, while rents and dividends flow out of highly productive regions to the owners of capital (e.g., especially equity owners or absentee owners), the local benefits of productivity and innovation would be less pronounced.

Our conceptual model follows a long literature that examines regional economic outcomes pioneered by Glaeser and co-authors (Glaeser *et al*., 1991; Glaeser *et al*., 2001;

Glaeser *et al*., 1995), which has been extended by many others including Betz *et al*. (2015) and Tsvetkova and Partridge (2016). A key underlying feature of our research is a spatial equilibrium framework (SEM) where indirect utility V in area a and firm profits are equalized across space in equilibrium, i.e. $V_a(.) = V^N(.)$ with positive net migration into a if $V_a(.) > V^N(.)$ and $\pi_a(.) = \pi^N(.)$ with positive movements of firms and capital into a if $\pi_a(.) > \pi^N(.)$. In this setup, V and π are both functions of site-specific factors including amenities, socioeconomic and demographic characteristics of a locality that affect household wellbeing and firm productivity (see HM for a more elaborate SEM framework).

III. Empirical approach

In operationalizing our conceptual model described above for empirical testing, the main difference of our estimation approach from past regional research is that, while using important determinants described in the literature as control variables, we augment the model with measures of productivity level and productivity growth.

Productivity. Starting in the mid-1990s, the U.S. economy enjoyed a surge in productivity growth led by information technology advances (Jorgenson *et al*., 2008; Ortega-Argilés, 2012; Van Ark *et al*., 2008). Yet, this productivity surge subsided shortly after 2000, increasing concerns that living standards will stagnate even as others increasingly worry about robots and ongoing automation. As noted above, however, productivity *growth* may have both positive and negative consequences for regional economic performance. Besides its ability to contribute to regional competitiveness, increased regional productivity may contribute to job loss and income inequality (Autor *et al*., 2015; Autor *et al*., 2008; Blien and Ludewig, 2014; Blien and Sanner, 2014; Mortensen and Pissarides, 1998; Vivarelli *et al*., 1996). By contrast, the *level* of productivity appears to have neutral or positive effects on regional outcomes, as it indicates a more competitive region that attracts firms and increases wages, though it could indicate industries that are in the process of shedding workers (HM do not consider productivity level effects).

Existing research uses various measures of productivity, such as total factor productivity, labor productivity, or exposure to computerization among others (Autor *et al*., 2015; Del Gatto *et al*., 2011; Van Beveren, 2012). In this paper, we use two basic measures of county-level labor productivity, the imputed value-added-per-worker in the beginning of a period and imputed growth of value added per worker in a county. We employ average labor productivity because (1) it is what our theoretical model suggests and (2) it is the most appropriate measure for the analysis of labor productivity effects on local outcomes. We use the U.S. Bureau of Economic Analysis (BEA) state-level data and divide value added by U.S. industry sectors by each sector's employment to derive the state-level average value added per worker in each industry. Using data provided by the Upjohn Institute (Bartik, Biddle, Hershbein and Sotherland, 2018), we then use each county's sectoral employment composition from County Business Patterns with suppressed values filled in using linear programming algorithm developed by Isserman and Westervelt (2006) to impute the initial level of productivity in a county and productivity growth over time.

The formulas for the two measures are given below. Equation (1) shows how growth in value added per hour is calculated.

$$VApW_{cst} = \sum_i S_{icst-1} VApW_{ist-1,t} \qquad (9)$$

where S_{icst-1} is employment share of sector *i* in county *c* (state *s*) in the previous year, and $VApW_{ist-1,t}$ is the growth rate of value added per worker in state *s*'s sector *i* between years *t-1* and *t*. We first-difference the productivity growth variable before inclusion in the models. The measure is essentially the expected growth in local productivity if productivity of all the county's sectors grows at the corresponding state-level productivity growth rates. The *VApW* measure has the advantage of using state productivity growth to proxy for local productivity growth, which could be endogenous. Yet, as long as there is no labor supply response to the lagged industry structure *after* conditioning on the other control variables that *also control for local labor supply*, the growth of value added per worker should be exogenous.[2]

The main potential disadvantage of this measure is that it is a proxy based on more general (aggregated) data, which we hope is mitigated by using state-level value added measures as opposed to the national ones. Still, if the state-level productivity measures are substantially different from county measures, they will introduce measurement error that can bias the coefficient to zero. If such a bias is present, our results would be conservative estimates.[3]

A measure of productivity level in a county is given by equation (2)

$$VApW_{cst} = \sum_i S_{icst} logVApW_{ist} \quad (10)$$

where $VApW_{cst}$ is the calculated added value per worker in county c (state s) in year t, S_{icst} is identical to the above, and $logVApW_{ist}$ is the logarithmic transformation of the state-level value added per worker in sector i in year t. This measure is the county's expected (logarithmically transformed) productivity level if all of its industries are as productive as their state-level counterparts (same caveats apply as in the case of the productivity growth proxy discussed in the previous paragraph). The interpretation of the productivity change coefficients is simply the impact of a one-percent productivity shock. The descriptive statistics show the means of the productivity change variables are quite small (0.1% or less), but at the tails, the size of the shocks are quite large.

Both productivity measures are calculated using data for 39 sectors as reported by the BEA (the finest disaggregation available), which *exclude* government (NAICS92, Public Administration).[4] Because these variables are based on the state-level trends, they can be considered exogenous in the analysis of productivity and its effects on economic outcomes at a county level.

We include both productivity growth and productivity level (lagged by one year) in

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[2] A key difference with HM is that we directly incorporate the productivity shock term in our model while they use a similarly constructed measure as an exogenous instrument for TFP.

[3] HM use firm-level data to construct a measure of local TFP from the Census of Manufacturers to obtain a local measure, in which estimating firm-level TFP introduces its own measurement error

[4] http://www.bls.gov/jlt/jltnaics.htm.

our models to explore potential variations in their effects on employment, earnings and income. The productivity growth variable is of the primary interest since it is consistent with the notion that the public is concerned about *rising* automation and outsourcing, which are affecting employment and wages. At the same time, a county's lagged level of productivity can also play an additional role, though one that is of less interest in our case.

The literature suggests that productivity growth is not uniform across industries (Ngai and Samaniego, 2011). Arguably, the most significant advances are taking place in computer and electronic product manufacturing (Houseman, Bartik and Sturgeon, 2015) and the goods sector (agriculture, mining, manufacturing and construction) in general, though some service sectors that are relatively more reliant on information technologies may enjoy significant productivity growth as well. To account for such heterogeneity, we perform additional analyses using separate productivity measures calculated for (1) computer and electronic product manufacturing, (2) goods sector excluding NAICS334, and (3) nongoods, or services, sector.

Economic performance measures (dependent variables). Our models explain growth in employment, earnings and income, which are important indicators of local economic health, as a function of productivity, industrial composition and a set of other regional characteristics. More specifically, our main analysis focuses on total employment growth. Given the evidence, we expect unequal employment responses to changes in productivity across industries and so we also examine the following measures: employment growth in goods and services (separately); employment growth in high-tech and low-tech sectors (separately); per capita personal income growth (PCPI); average wage per job growth (AWPJ); and median household income growth.

The high-tech/low-tech distinction follows Fallah *et al*. (2014) with agriculture, mining, construction, and manufacturing comprising the goods sector and all other sectors (except government) comprising services. Appendix Table A1 lists industries included in the high-tech category. We use an "unsuppressed" version of the County Business Patterns dataset to calculate employment growth measures. In this version (provided by the W. E. Upjohn Institute for Employment research), a linear programming algorithm developed by Isserman and Westervelt (2006) was applied to fill in values suppressed because of confidentiality requirements. AWPJ and PCPI measures were created using form CA4 from the U.S. Bureau of Economic Analysis. Median household income data come from the U.S. Census Bureau's Small Area Income and Poverty Estimates program. All dependent and main explanatory variables (except for productivity levels) are first-differenced to account for county-level invariant characteristics that can plausibly drive the outcomes. Our analysis covers the 2000-2015 period.

We start our analysis with employment because it has been a focus of intensive policy and scholarly debates, which are of significant interest to the public. Job growth is also a key determinant of other wellbeing indicators (Kofi, Hurst and Schwartz 2018). Employment can be linked to productivity growth via two offsetting effects (Sabadash, 2013). On the one hand, new technologies and machinery may substitute for workers, increasing unemployment and/or dampening job growth (substitution effect). This may happen if, for example, productivity growth favors capital and is neutral for workers. For skill-based technological change (SBTC) at given input prices, this leads to substitution of high-skilled for low-skilled workers, in which the net employment effects can be negative.

Technology-led productivity growth is also expected to increase unemployment if there are high costs of updating production technologies and those existing firms lay off workers (Mortensen and Pissarides, 1998). Indeed, while it is possible that the new or dynamic firms in a highly productive industry are expanding, it is also possible that older, less dynamic firms in that industry may suffer, which would also be true for the locality where the latter companies are based—i.e., some of the positive gains could be offset elsewhere even if the industry is expanding overall. The so-called "end of work" argument brings this situation to extreme implying that technology will replace the need for most labor. Likewise, some of the substitution is across new and dying industries (a situation reminiscent of replacement of horses by automobiles a century ago). As the old industries contract, structural unemployment for displaced workers increases.

On the other hand, growing productivity may lead to a greater employment growth via compensation effects that economists typically regard as dominant. If new technologies sufficiently reduce production costs and prices, the demand surge should stimulate employment when product demand is elastic—i.e., the increase in demand has to be more than sufficient to offset the decrease in labor needed to produce a given level of output (Blien and Ludewig, 2014; Blien and Sanner, 2014). The invention of new goods and creation of new markets should also expand employment. Thus, the productivity growth-employment relation on the net is an empirical question.

The empirical evidence, indeed, finds divergent effects of productivity growth on employment, though most of the evidence is at the national/international level. For example, Autor and Salomon (2017) analyze the link between productivity growth and job creation in 19 countries at the national and industry levels and conclude that greater productivity leads to higher employment in national analyses, whereas productivity-enhancing industries tend to shrink. In Germany, a positive relationship is observed in industries that face elastic demand and a negative one in industries with inelastic demand, in line with theoretical predictions (Blien and Ludewig, 2014). For the U.S., Cavelaars (2005) finds a positive relationship between labor productivity growth and job growth after 1980, whereas Nordhaus (2005) finds a positive relation between productivity growth and employment in U.S. manufacturing.

For Italy, Vivarelli and co-authors (Vivarelli *et al*., 1996) report increased employment in knowledge-based and capital goods-producing industries as a result of technological progress, while the relationship in other industries is the opposite. Several studies present evidence of a negative relationship (Dew-Becker and Gordon, 2008; Marquis and Trehan, 2010). Gallegati and co-authors attempt to reconcile divergent findings in the literature by arguing that productivity increases tend to displace jobs in the short and medium runs and create long-run employment (Gallegati *et al*., 2014; Gallegati *et al*., 2015). Overall, the nature of an industry and its production processes determine if labor-saving or new product-creating consequences of a new technology and innovation dominate (Bogliacino and Pianta, 2010).

We then turn our attention to another central measure of regional economic performance, namely income growth. In neoclassical economic theory, wage equals (the value of) marginal productivity of labor and we expect an approximately one-to-one increase in labor compensation as productivity rises. Whereas a post-war increase in productivity is well documented (Jorgenson *et al*., 2014; Ortega-Argilés, 2012), growth in real hourly median wage has lagged far behind (Mishel and Gee, 2012). We use three measures, namely growth in PCPI, AWPJ and median household income as dependent variables in addition to our employment growth measures.

Estimation strategy. In our model, economic outcomes in county c, state s, during time period τ are a function of the following vectors of variables: annual productivity growth (between years *t-1* and *t*), lagged productivity levels in *t-1*, economic conditions which are measured by variables either lagged by one year (employment shares) or calculated annually (industry mix term), geography, demographics, and natural amenities.

$$\Delta OUTCOME_{c\tau} = \alpha + \boldsymbol{\beta}\Delta \boldsymbol{PRODGR}_{c\tau} + \boldsymbol{\psi PROD}_{ct-1} + \boldsymbol{\delta ECON}_{c\dagger} + \boldsymbol{\phi GEOG}_{c} + \boldsymbol{\theta DEMOG}_{c1990} + \boldsymbol{\gamma AMENITY}_{c} + \sigma_s + \varepsilon_{c\tau} \quad (11)$$

where $\beta, \psi, \delta, \phi, \theta$ and γ are coefficients or coefficient vectors; σ_s are state fixed effects (coefficients reflect average county variation within states); $\varepsilon_{c\tau}$ is the residual clustered within BEA Economic Areas (173 total for nonmetro counties, 135 for counties in small MSAs and 65 for counties in large MSAs) to account for spatial autocorrelation. The next subsection gives more details on the control variables.

We estimate equation (11) using OLS regression (an instrumental variable approach is also used as a sensitivity check below). The sample consists of 3,048 continental U.S.

counties. To avoid aggregation bias and to account for differing agglomeration effects, in line with the previous literature, we conduct the analyses separately for the following three groups: 2,231 nonmetropolitan counties, 382 counties that belong to metropolitan statistical areas (MSAs) with a 1990 population of up to 500,000 (referred to as small-metro counties), and 435 remaining counties (referred to as large metro counties) using the June 1999 delineation[5] (Partridge *et al*., 2008; Partridge *et al*., 2009). We first include total productivity growth and a lagged total productivity level as explanatory variables and then replace them with more disaggregated-sectoral productivity measures to explore potential differences in the effects of productivity in different parts of local economies.

Control variables. The vector of variables that account for county economic conditions consists of three measures. First, we need to control for demand shocks to separate the effects of productivity growth from the effects that demand shocks would have on the local economy – i.e., we ask does productivity growth have additional effects beyond the effects of basic demand shocks? The industry mix term is the predicted growth rate of a county's employment if all of its industries grow at their corresponding national rates. The industry mix variable is exogenous because it is based on *national* growth rates and lagged local industry employment shares. The industry mix term is also referred to as the Bartik (1991) instrument and is widely used in regional and urban research (Betz and Partridge, 2013; Partridge and Rickman, 1999; Tsvetkova and Partridge, 2016; Tsvetkova *et al*., 2017). The variable is calculated as follows:

$$IndMix_{ct} = \sum_i S_{cit-1} NG_{it-1,t} \qquad (12)$$

where S_{cit-1} stands for the share of industry i in county c in period t-1 and $NG_{it-1,t}$ is the national growth rate of industry i between years t-1 and t. A first-difference of the industry mix variable is included in the model. The variable is calculated using employment data at the four-digit North American Industry Classification System (NAICS) code using the

[5] The three samples are referred to as S1, S2 and S3, respectively, in the tables of results below.

“unsuppressed” CBP data from the Upjohn Institute.

The coefficient on the industry mix term can be interpreted as the average multiplier across all industries—i.e., if one job is created exogenously, the coefficient shows how many jobs are created on net after all spillovers including input-output links are accounted for. In our models that include the industry mix term, the estimated coefficients on the productivity variables specify their productivity effects after accounting for the local growth effects of having a mix of fast or slow growing industries. It is important to control for the demand conditions (by the industry mix term in our case) because they can be correlated with productivity growth and, if the industry mix term is omitted, our estimates could suffer from an omitted variable bias.

In addition to the industry mix term, the effects of industrial composition are accounted for by the inclusion of the share of high-tech employment in a county in year 2000 and the labor-intensive manufacturing share in 1990. These variables are important predictors of economic fortunes of a location with the former related to high-paying jobs, while the latter captures the effects of local exposure to low-cost international competition, primarily from China. The variables should account for any correlation between import competition and productivity growth—e.g., fierce foreign competition may spur domestic productivity growth, potentially leading to a spurious correlation between productivity growth and industry conditions. Lagging these variables also mitigates any endogeneity. Appendix Table A2 lists the NAICS codes for the low-wage manufacturing sector.

In order to separate productivity effects on county performance from the net-productivity effects of (or access to) agglomeration, we include the 1990 population size, land area, and distance to larger urban centers, which constitute the geography vector in our models. For counties outside of metropolitan areas, each model includes a measure of county population. For metro counties, the models include the county own population and population of its metropolitan area. All population counts are in logs. The U.S. Census Bureau is the data source for this variable.

The effects of urban hierarchy and access to urban services are captured by variables that measure distance to the nearest metro area for rural counties and a distance to the center of urban core for metro counties supplemented with measures of incremental distance to the nearest MSA with population of at least 250,000; incremental distance to the nearest MSA with population of at least 500,000 and to the nearest MSA with population of at least 1.5 million measured in 1990 (see Partridge et al., 2008 for a discussion of these variables). The final geography variable is land area to account for density effects. The variables are derived from the U.S. Census Bureau data and calculated (when necessary) using the ArcGIS software.

Average educational attainment influences socioeconomic outcomes including productivity levels. In addition, industry productivity growth could be strongly correlated with concentrations of highly educated people, especially in high-tech industries. Thus, we include three educational controls, percent of adults with high school diploma only, percent of adults with Bachelor's degree, and percent of adults with graduate or professional degree. The effects of racial and ethnic composition are captured by the shares of African-American, American Native, Asian and other races, as well as the percent of residents of Hispanic origin. The data for these variables are from the 1990 U.S. Decennial Census to mitigate any endogeneity effects.

Lastly, the amenity vector consists of the U.S. Department of Agriculture Economic Research Service (USDA ERS) natural amenity scale (with category one being the reference group) and three indicators for being within 50 miles to the Great Lakes, the Atlantic Ocean and the Pacific Ocean. In addition to these variables, each model includes a set of state dummies to factor out state-invariant characteristics, such as tax and regulatory environment and year fixed effects to account for common national trends that affect all counties similarly. Appendix Table B1 reports summary statistics for the dependent and main independent variables.

In interpreting the time-invariant level variables (e.g., lagged productivity level), an insignificant coefficient does not mean that the variable is economically unimportant because the variable may have persistent effects captured in the county fixed effect. With the county fixed effects (first) differenced out, these coefficients reflect any additional "disequilibrium" effects that these variables have on economic growth after their cross-sectional long-term effects are differenced out in the county fixed effect.

IV. Estimation results and discussion

Base Employment Results. Each table in this section reports estimates for a set of dependent variables with results for all subsamples reported next to each other for easy comparison. Table 1 shows results for the base model that includes total productivity growth and initial total productivity level, followed by the models that split productivity measures by sector. The models include a full set of controls and dummy/fixed effects variables, but for brevity the tables show estimation coefficients for the productivity variables and the industry mix term only. Appendix Table C1 shows all estimation results for models reported in Table 1.[6]

The upper panel of Table 1 reveals a negative impact of productivity level and (generally) no impact of productivity growth on total employment growth, as well as on job growth in the goods sector. The effects are generally insignificant in the service sectors except in large cities.

A more detailed analysis reported in the lower panel shows a nuanced picture. First, productivity growth in the computer and electronic product manufacturing (NAICS334) industry (Comp) is associated with decreased total and goods sector job growth in both metro samples, but not in the rural samples, which could be due to a different composition of computer manufacturing in rural areas. Other productivity growth variables are insignificant except for the negative effects of productivity growth in services on goods employment growth in large MSA counties. Counties with higher productivity *levels* tend

[6] Full estimation results are available upon request.

to have lower job growth. In particular, the NAICS334 productivity level is negatively related to services employment growth, but positively related to goods employment growth—suggesting that any negative net employment effects tend to be more concentrated in computer and electronic manufacturing. This result is noteworthy because the NAICS334 sector accounts for a vast share of measured productivity growth in the economy (Houseman et al., 2015).

Service productivity levels appear to decrease total and goods employment growth in all samples. Goods productivity level (excluding computer and electronic product manufacturing) has a negative relation with total and service-sector employment in metro samples. Hence, high productivity levels in the goods or services sectors is associated with depressed employment in the other sector, indicating that any employment gains in one sector crowds out employment in the other sector (probably to reestablish spatial equilibrium). Overall, our analysis shows that local effects of productivity (both growth and level) have generally negative or zero effects on total employment and employment by major sector. The only positive coefficient on the lagged productivity level in nonmetro models for service employment disappears in the sectoral analysis in the lower panel.

Table 1. OLS estimation results for first-differenced employment growth (% Δ), total and for goods and services separately

	Total employment			Goods employment			Services employment		
	S1	S2	S3	S1	S2	S3	S1	S2	S3
Base model									
ΔProductivity growth	-.031	-.022	-.1	-.058	-.22*	-.16	.046	.084	-.1*
	(-1.23)	(-0.36)	(-1.51)	(-0.48)	(-1.96)	(-1.65)	(1.05)	(1.43)	(-1.71)
Productivity level (lag)	-2.7***	-3.4**	-3.4**	-33**	-12***	-9.6***	1.7***	-.094	-.37
	(-3.56)	(-2.37)	(-2.14)	(-2.17)	(-3.98)	(-3.78)	(2.65)	(-0.08)	(-0.29)
ΔIndustry mix	.48***	1.2***	1.2***	1.3**	2.4***	1.8***	.12	.78***	.7***
	(4.28)	(4.92)	(6.02)	(2.30)	(3.98)	(5.00)	(1.01)	(2.79)	(3.41)
Productivity variables for NAICS334, goods (no NAICS334) and services separately									
ΔComp productivity growth	3.6e-03	-.52**	-.38***	-.2	-1.5***	-.84***	.29	.11	-.25
	(0.06)	(-2.61)	(-3.57)	(-0.69)	(-2.97)	(-2.93)	(1.61)	(1.10)	(-1.61)
ΔGoods productivity growth (no comp)	-.038	5.9e-03	-.044	-.091	-.13	.014	.038	.069	-.09
	(-1.43)	(0.09)	(-0.51)	(-0.88)	(-1.37)	(0.13)	(0.91)	(1.02)	(-1.09)
ΔServices productivity growth	.049	.066	-.16	.81	.058	-.33**	-.07	.11	-.12
	(0.51)	(0.60)	(-1.57)	(1.41)	(0.42)	(-2.06)	(-0.71)	(0.85)	(-1.12)
Comp productivity level	-.76	2.6	-1.2	-7.8	21	8.8**	-2.9**	-4.7***	-3.2**
	(-0.64)	(0.67)	(-0.58)	(-0.61)	(1.48)	(2.51)	(-2.37)	(-3.12)	(-2.17)

Goods productivity level (no comp)	-.036 (-0.04)	-4.6** (-2.01)	-4.9** (-2.04)	-2.5 (-0.16)	1.9 (0.53)	4 (1.64)	-3.9*** (-3.70)	-7.4*** (-3.00)	-7.3*** (-3.39)
Services productivity level	-2** (-2.50)	-4.2** (-2.49)	-4** (-2.17)	-24 (-1.61)	-10*** (-3.46)	-6.3*** (-2.76)	.24 (0.31)	-2.1 (-1.39)	-2.5 (-1.53)
ΔIndustry mix	.47*** (4.21)	1.2*** (4.74)	1.1*** (5.99)	1.1** (2.04)	2.2*** (3.82)	1.8*** (4.92)	.15 (1.19)	.81*** (2.87)	.7*** (3.50)

*** - 0.01% significance; ** - 0.05% significance; * - 0.1% significance;
Standard errors adjusted for clusters within the 177 BEA economic areas for S1, 135 BEA economic areas for S2 and 66 BEA economic areas for S3; t-stat in parentheses; number of observations is 2,237 for S1, 382 for S2 and 435 for S3.
Sample 1 (S1) includes nonmetro counties; sample 2 (S2) includes counties in MSAs with population under 500 thousand; sample 3 (S3) includes all other counties. 1990 U.S. Census Bureau population data are used for grouping counties into samples. In addition to the control variables reported in Table C1, all models include state and year fixed effects, USDA amenity levels and location within 50 kms from Great Lakes, Atlantic Ocean, and Pacific Ocean. See the text for further details.

In line with the literature, we also estimate the effects of productivity growth and productivity level on the unemployment rate (not shown for brevity). The results suggest that productivity growth *decreases* unemployment growth, while lagged productivity levels are associated with *higher* unemployment growth, in which especially the latter effect is consistent with the employment results. The detailed productivity analysis by sector suggests that the unemployment reducing effects of productivity growth stems entirely from the goods sector (excluding NAICS334), while productivity levels in all sectors have positive and statistically significant effects on unemployment growth.

We tried some alternative specifications to assess the robustness of these results (not shown due to brevity). First, we omitted the industry mix (Bartik) demand shifter to assess whether including the local-based demand shock measure is affecting our productivity results, finding that the conclusions are essentially unchanged. Second, we omitted the other control variables except for the state fixed effects, finding that the main patterns were not greatly affected, giving us further confidence that the results are robust.

High-tech/Low-tech Employment Results. We now further refine our analysis by examining the productivity effects on job growth in high-tech and low-tech industries separately. The estimation results for the "detailed" models are presented in Table 2. In line with our expectations, the NAICS334 computer productivity *growth* suppresses job growth mostly in high-tech industries (there is also a significant negative effect on low-tech job growth in large metro counties). Again illustrating substitution across industries, productivity *level* in computer and electronic manufacturing is positively related to high-tech job growth but has a suppressing effect on low-tech employment in the nonmetro and small metro samples, illustrating that at the *local level*, what may be good for one sector can often displace employment in other sectors.

Increased goods- (excluding NAICS334) and service-productivity levels are also associated with less high-tech job growth, further suggesting workers do move to higher productivity-level industries, while migration could change the skilled composition. It appears that large-metro high-tech employment is negatively affected by all productivity-*growth* and productivity-*level* measures (with the exception of NAICS334). Low-tech job growth in nonmetro counties is positively related to productivity growth in NAICS334, which may link to higher local wages and local demand. (Table 3 will show a positive link between productivity growth in the NAICS334 industry and average wage growth in nonmetro counties). Likewise, goods productivity level (excluding NAICS334) is positively related to low-tech job growth in nonmetro counties, while greater computer productivity level is negatively related to this outcome in the S1 and S2 subsamples. Overall in terms of statistical significance, high-tech employment is more affected by the productivity measures.

Table 2. OLS estimation results for first-differenced employment growth (mid-point formula), high-tech and low-tech

	High-tech employment			Low-tech employment		
	S1	S2	S3	S1	S2	S3
ΔComp productivity growth	-1.3** (-2.60)	-2.4** (-2.59)	-.76* (-1.86)	.35*** (3.28)	.058 (0.56)	-.29* (-1.96)
ΔGoods productivity growth (no comp)	-.085 (-0.57)	-.034 (-0.27)	-.57** (-2.27)	-.027 (-0.87)	.018 (0.25)	.019 (0.26)
ΔServices productivity growth	.36 (1.27)	.28 (0.97)	-.51** (-2.24)	.061 (0.91)	.025 (0.26)	-.079 (-0.72)
Comp productivity level	30*** (3.40)	31* (1.78)	19** (2.51)	-3.9*** (-3.31)	-2.7** (-2.02)	-2.4 (-1.52)
Goods productivity level (no comp)	-14*** (-6.82)	-22*** (-2.97)	-19*** (-3.26)	2.4*** (3.67)	-.77 (-0.39)	-.91 (-0.47)
	-10***	-17***	-13**	-.087	-1.4	-.77

Services productivity level	(-6.31)	(-2.77)	(-2.08)	(-0.15)	(-0.95)	(-0.48)
	2.4e-03	.43	1*	.53***	1.1***	1***
ΔIndustry mix	(0.01)	(0.51)	(1.88)	(5.42)	(4.68)	(5.28)

*** - 0.01% significance; ** - 0.05% significance; * - 0.1% significance;
Standard errors adjusted for clusters within the 177 BEA economic areas for S1, 135 BEA economic areas for S2 and 66 BEA economic areas for S3; t-stat in parentheses; # of observations is 2,237 for S1, 382 for S2 and 435 for S3.

Sample 1 (S1) includes nonmetro counties; sample 2 (S2) includes counties in MSAs with 1990 population under 500 thousand; sample 3 (S3) includes all other counties. 1990 U.S. Census Bureau population data are used for grouping counties into samples. See Table 1's notes for a list of other control variables. Full results are available on request from the authors. See the text for further details.

Wages and Income. Table 3 presents results for annual growth in personal per-capita income, in average wage per job, and median-household income. In contrast to the employment results, where the statistically significant productivity measures tend to have mostly negative effects, productivity *growth* generally is associated with enhanced per-capita personal income and average wage per job growth rates, while productivity *levels* are negatively associated with income and earnings growth. One cause could be productivity growth is associated with upskilling but high productivity levels could be associated with substitution towards capital (in the cumulative sense). In particular, productivity growth in both goods (without NAICS334) and services has a strong positive effect on PCPI and AWPJ regardless of the sample (with the exception of small cities sample in the PCPI equations, where goods productivity growth is insignificant).

Productivity growth in NAICS334 is positively related to average wage per job growth in nonmetro counties, whereas computer manufacturing productivity level has the same effects on PCPI and AWPJ growth in small-metro counties. Yet, the computer manufacturing productivity results suggest that the sector is associated with less employment and little offsetting gains in incomes. These results imply that a high-tech strategy related to this industry should be very cautiously undertaken at the local level.

On the other hand, nonmetro and small metro counties that are more productive in producing goods other than computer and electronic products lag in PCPI growth, in AWPJ growth (in all metro counties) and in median household income growth in nonmetro counties. Counties enjoying a greater productivity level in services experience lower growth in per-capita personal income and in average wage per job (in all samples) and in median household income. In terms of statistical significance, median household income is less affected than the income and wage growth measures, which could mean that productivity's local income effects are more concentrated at the tails of the distribution.[7]

Table 3. OLS estimation results for first-differenced earnings and income growth (% Δ) variables

	PCPI			AWPJ			Median HH income		
	S1	S2	S3	S1	S2	S3	S1	S2	S3
ΔComp productivity growth	-.03 (-0.70)	-.026 (-0.29)	.14 (0.80)	.056*** (3.41)	.073 (1.30)	.25 (1.45)	-.049* (-1.75)	.043 (0.98)	.066 (1.11)
ΔGoods productivity growth (no comp)	.091*** (4.14)	.031 (1.43)	.063* (1.79)	.053*** (5.84)	.066*** (2.78)	.096*** (3.52)	-.011 (-0.89)	.028 (0.77)	9.6e-03 (0.17)
ΔServices productivity growth	.42*** (3.30)	.24*** (4.20)	.5*** (4.22)	.14*** (4.01)	.12*** (2.74)	.26*** (4.51)	-.021 (-0.51)	.022 (0.36)	.13* (1.88)
Comp productivity level	-.65 (-1.50)	1.4*** (2.84)	-.67 (-0.79)	-.26 (-0.70)	1.2*** (3.04)	1.1 (0.91)	-.26 (-1.02)	-.048 (-0.08)	-.19 (-0.30)
Goods productivity level (no comp)	-.34** (-2.16)	-.87** (-2.24)	-1.6 (-1.48)	-.19 (-1.43)	-.9** (-2.12)	-.84** (-2.29)	-.26* (-1.96)	-.49 (-1.01)	-.47 (-1.02)
Services productivity level	-.66*** (-4.59)	-1.2*** (-3.82)	-1.9 (-1.51)	-.47*** (-4.11)	-1*** (-3.43)	-.84** (-2.17)	-.19** (-2.19)	-.45 (-1.25)	-.63* (-1.94)
ΔIndustry mix	-.12** (-1.99)	-.062 (-0.77)	-.081 (-1.23)	.021 (0.93)	-2.1e-03 (-0.03)	-.032 (-0.54)	.096*** (3.16)	.11 (0.93)	.12 (1.33)

*** - 0.01% significance; ** - 0.05% significance; * - 0.1% significance;
Standard errors adjusted for clusters within the 177 BEA economic areas for S1, 135 BEA economic areas for S2 and 66 BEA economic areas for S3; t-stat in parentheses; number of observations is 2,237 for S1, 382 for S2 and 435 for S3.

Sample 1 (S1) includes nonmetro counties; sample 2 (S2) includes counties in MSAs with 1990 population under 500 thousand; sample 3 (S3) includes all other counties. 1990 U.S. Census Bureau population data are used for grouping counties into samples. See Table 1's notes for a list of other control variables. Full results are available on request from the authors. See the text for further details.

V. Sensitivity analysis

We now conduct a series of sensitivity analyses by first estimating the base models using instrumental variables (IV) because of the possibility of both reverse causality and omitted variables related to the explanatory variables in our models that might introduce a bias into the estimates (to be sure, HM use a similar variable as an exogenous instrument). Just as important, given that we use a proxy for productivity growth calculated, in part, from state-level data, the use of an IV approach should mitigate problems of potential

[7]While the main purpose of our study is not to assess inequality, using the county's Gini coefficient, we found relatively little statistical link between productivity and inequality, somewhat consistent with HM's findings due to offsetting effects at the top and bottom of the distribution.

measurement error.

Following Partridge et al. (2017), we utilize a novel way to construct two instruments for the productivity variables. Using the STATA psmatch2 procedure (Leuven & Sianesi, 2003), we identify the first and the second matches for each county determined by minimizing the Mahalanobis distance on a series of observable characteristics that include the industry mix variable, shares of routine (Autor, Dorn and Hanson, 2015), and high-tech employment (Fallah, Partridge and Rickman, 2014), as well as employment in manufacturing and agriculture, log of population, share of adults with graduate degree, distance to the nearest MSA, 1998 productivity level (the earliest year for which the detailed industry-level employment data are available) and productivity growth for 1998-2001; for metropolitan areas we also use the log of metropolitan area population. These characteristics are generally key observable features associated with local productivity structures. All characteristics for matching are measured in year 2000 (except for productivity growth for 1998-2001 and the industry mix term for which we use the average value over the study period).

Counties were exactly matched on their metro/nonmetro status. All matches lie *at least* 125 miles away from the county being matched to ensure that spillovers are inconsequential and to limit any correlation of omitted variables due to spatial proximity. Additionally, every matching county is selected from a *different* state than the county being matched to avoid the confounding influence of common factors, such as tax regime, business climate, or culture. After we identify two matching counties for every county, we calculate productivity measures (growth rates and levels) using employment data for the matching counties and *value added data* for the state of the county being matched (the BEA value-added data at the industry/sector level are available by state) to derive value-added per worker and employment shares used in calculating county-level productivity. We then use productivity measures of the *matching* counties as the instruments for productivity measures of the counties being matched. The advantage of having two instruments is that we can conduct an overidentification test in addition to conventional tests for instrument strength and the presence of endogeneity. Tables 4 and 5 and show the IV results.

Before we describe the IV estimation results, it is important to note that possible endogeneity (or measurement error) is detected in 11 of the 18 models in Tables 4 and 5 as suggested by the Durbin P-value at the 5% level of significance. The endogeneity is more likely to be a problem in the employment equations compared to the income and earnings models. While some instruments are weak (mostly those measuring productivity in NAICS334 industry, plausibly due to relatively few counties having its presence), all models are identified.

Table 4. IV estimation results for first-differenced employment growth (% Δ), total and for goods and services separately

	Total employment			Goods employment			Services employment		
	S1	S2	S3	S1	S2	S3	S1	S2	S3
ΔComp productivity growth (v1)	0.166 (0.133)	-0.263** (0.130)	-0.142 (0.188)	1.483* (0.852)	-0.765** (0.299)	-1.146*** (0.384)	0.376*** (0.140)	0.055 (0.119)	0.028 (0.210)
ΔGoods productivity growth (no comp) (v2)	0.019 (0.071)	-0.009 (0.166)	-0.143 (0.107)	-0.099 (0.747)	-0.276 (0.198)	-0.191 (0.187)	0.110 (0.077)	0.309 (0.215)	-0.101 (0.126)
ΔServices productivity growth (v3)	0.028 (0.066)	0.050 (0.070)	-0.160* (0.083)	-0.944 (0.787)	0.009 (0.126)	-0.353*** (0.133)	0.011 (0.071)	0.079 (0.077)	-0.072 (0.097)
Comp productivity level v(4)	0.075 (4.827)	-1.546 (4.603)	2.915 (7.307)	5.604 (24.427)	0.133 (8.265)	0.545 (14.686)	-1.274 (5.458)	-2.663 (5.186)	2.892 (7.750)
Goods productivity level (no comp) v(5)	0.148 (1.694)	-2.893 (7.871)	-3.893 (7.645)	-8.218 (26.355)	-7.763 (9.969)	-4.120 (13.146)	0.478 (1.874)	-1.212 (13.259)	-2.974 (8.654)
Services productivity level v(6)	-0.433 (1.286)	-2.459 (6.390)	-1.859 (4.676)	-8.227 (23.713)	-7.211 (7.393)	-2.674 (9.018)	0.050 (1.387)	-0.779 (11.064)	-1.446 (5.244)
ΔIndustry mix	0.466*** (0.153)	1.219*** (0.203)	1.171*** (0.173)	1.202** (0.528)	2.364*** (0.512)	1.826*** (0.264)	0.127 (0.147)	0.760*** (0.224)	0.713*** (0.206)
1st stage F-stat v(1)	2.184	16.97	7.167	2.024	16.94	7.308	2.184	16.97	7.167
1st stage F-stat v(2)	5.723	5.657	22.39	9.913	5.086	18.11	5.723	5.657	22.39
1st stage F-stat v(3)	368.3	265.3	294.1	373.9	249.4	290.2	368.3	265.3	294.1
1st stage F-stat v(4)	4.635	4.397	6.730	3.014	3.871	6.259	4.635	4.397	6.730
1st stage F-stat v(5)	121.8	31.69	18.40	100.7	28.59	17.53	121.8	31.69	18.40
1st stage F-stat v(6)	121.7	26.85	28.23	103.7	23.95	28.77	121.7	26.85	28.23
Endogeneity test p-val	0.000	0.503	0.623	0.000	0.000	0.000	0.000	0.001	0.000
Over-ID test p-val	0.334	0.290	0.725	0.387	0.389	0.854	0.070	0.402	0.866

*** - 0.01% significance; ** - 0.05% significance; * - 0.1% significance;
Standard errors adjusted for clusters within the 177 BEA economic areas for S1, 135 BEA economic areas for S2 and 66 BEA economic areas for S3; t-stat in parentheses; number of observations is 2,237 for S1, 382 for S2 and 435 for S3.

Sample 1 (S1) includes nonmetro counties; sample 2 (S2) includes counties in MSAs with 1990 population under 500 thousand; sample 3 (S3) includes all other counties. 1990 U.S. Census Bureau population data are used for grouping counties into samples. See Table 1's notes for a list of other control variables. Full results are available on request from the authors. See the text for further details.

Table 4's results continue to generally support the weak negative link between computer productivity growth and job growth (3 of the 5 significant coefficients are negative), but most of the other employment-productivity results are insignificant. The two cases where the NAICS334 productivity growth term is positive are for nonmetro goods and services employment—while corresponding OLS results are insignificant. Thus, we should caution that our previous negative findings from OLS estimation may be overstated, but the positive effects only apply in rural goods (without NAICS334) and services employment, meaning only a small part of the economy may have a positive productivity growth-employment growth relationship, with the general pattern being that greater local productivity growth is not associated with *faster* job growth.

Results in Table 5 generally show a positive relation between productivity growth and per-capita personal income and average wage growth, supporting the OLS results. A notable difference is that productivity growth in the NAICS334 industry considerably boosts AWPJ growth in all county types (it was mostly insignificant in the OLS results), while a significant effect of productivity level variables disappears in the models that exhibit evidence of endogeneity. Also there is a general lack of significance for all productivity measures in the median household income models, supporting the OLS results.

Table 5. IV estimation results for first-differenced earnings and income growth (% Δ) variables

	PCPI			AWPJ			Median HH income		
	S1	S2	S3	S1	S2	S3	S1	S2	S3
ΔComp productivity growth (v1)	0.025 (0.070)	0.204** (0.104)	0.212 (0.179)	0.135** (0.065)	0.232** (0.110)	0.457*** (0.170)	-0.061 (0.038)	-0.047 (0.074)	-0.072 (0.139)
ΔGoods productivity growth (no comp) (v2)	0.241*** (0.034)	0.148** (0.071)	0.067 (0.055)	0.069*** (0.023)	0.087** (0.043)	0.052 (0.050)	0.034 (0.033)	0.006 (0.077)	-0.094 (0.081)
ΔServices productivity growth (v3)	0.508*** (0.053)	0.295*** (0.045)	0.555*** (0.082)	0.199*** (0.026)	0.185*** (0.037)	0.345*** (0.049)	0.002 (0.032)	0.004 (0.053)	0.127* (0.065)
Comp productivity level v(4)	-1.732 (3.448)	1.037 (2.328)	2.033 (4.904)	-0.352 (1.802)	0.429 (1.924)	3.372 (4.021)	0.293 (1.839)	-1.469 (2.488)	1.877 (4.154)
Goods productivity level (no comp) v(5)	-1.043 (0.940)	-1.882 (1.872)	-1.972 (3.830)	-0.099 (0.499)	-1.994 (1.785)	-1.548 (3.150)	-0.356 (0.664)	-1.161 (2.519)	-1.479 (3.873)
Services productivity level v(6)	-1.087 (0.691)	-1.602 (1.458)	-1.571 (2.351)	-0.229 (0.381)	-1.738 (1.338)	-0.766 (1.980)	-0.213 (0.514)	-1.141 (1.949)	-1.205 (2.523)
	-0.120***	-0.057	-0.070	0.018	0.008	-0.031	0.088***	0.103	0.122*

ΔIndustry mix	(0.042)	(0.096)	(0.070)	(0.019)	(0.047)	(0.058)	(0.025)	(0.078)	(0.070)
1st stage F-stat v(1)	2.184	16.97	7.167	2.184	16.97	7.167	2.184	16.97	7.167
1st stage F-stat v(2)	5.723	5.657	22.39	5.723	5.657	22.39	5.723	5.657	22.39
1st stage F-stat v(3)	368.3	265.3	294.1	368.3	265.3	294.1	368.3	265.3	294.1
1st stage F-stat v(4)	4.635	4.397	6.730	4.635	4.397	6.730	4.635	4.397	6.730
1st stage F-stat v(5)	121.8	31.69	18.40	121.8	31.69	18.40	121.8	31.69	18.40
1st stage F-stat v(6)	121.7	26.85	28.23	121.7	26.85	28.23	121.7	26.85	28.23
Endogeneity test p-val	0.094	0.012	0.373	0.004	0.004	0.021	0.790	0.348	0.643
Over-ID test p-val	0.692	0.993	0.818	0.470	0.816	0.563	0.901	0.298	0.900

*** - 0.01% significance; ** - 0.05% significance; * - 0.1% significance;
Standard errors adjusted for clusters within the 177 BEA economic areas for S1, 135 BEA economic areas for S2 and 66 BEA economic areas for S3; t-stat in parentheses; number of observations is 2,237 for S1, 382 for S2 and 435 for S3.

Sample 1 (S1) includes nonmetro counties; sample 2 (S2) includes counties in MSAs with 1990 population under 500 thousand; sample 3 (S3) includes all other counties. 1990 U.S. Census Bureau population data are used for grouping counties into samples. See Table 1's notes for a list of other control variables. Full results are available on request from the authors. See the text for further details.

In the next step we conduct a series of analyses to probe into the mechanisms of the productivity/outcome linkages. Beaudry *et al*. (2010) argue that information and communication technology (ICT) is more quickly adopted in areas with better educated populations, whereas Autor and Dorn (2013) find that ICT is linked to greater declines in routine tasks. Thus, we assess whether interaction between productivity and share of university graduates increases job losses because the productivity adoption accelerates the loss of low-skilled workers. We then repeat the analysis using the share of routine-task employment instead of the share of university graduates in the interaction models. The results are reported in Appendix Tables D1 and D2 for total employment growth and average wage per job growth, respectively. Overall, there seems to be very few statistically significant interactions, especially with education. In the total job growth models, only one interaction term (goods productivity growth excluding NAICS334 interacted with the share of adults with BA degree or higher in the S3 sample) attains statistical significance at the 5% level. While the interaction is negative, the main effects are insignificant. This complicates interpretation, but it does weakly suggest that productivity growth associated with more educated workers displaces lower-skilled workers.

In the AWPJ models, the negative relationship to NAICS334 productivity level is mitigated by a greater share of college graduates. As follows from Table D2, the share of routine employment in a county is more likely to be an intervening factor in the relationship between productivity measures and average wage growth than for job growth. In the nonmetro sample, counties with greater routine employment enjoy smaller stimulating effects of NAICS334 productivity growth, suggesting that the growth in computer manufacturing productivity is displacing routine workers. However, a greater share of routine workers is associated with a more simulative (less negative) wage effect from service productivity growth. Lastly, in large MSA counties, the negative effect of goods productivity growth (excluding computer and electronic manufacturing) is alleviated by a greater share of routine employment, which is somewhat surprising given that these technologies are thought to displace routine workers. However, as noted above, these results should be taken with caution.

VI. Conclusion

In this paper, we test a common perception that productivity and productivity growth are universally beneficial to the local economies. From a theoretical perspective, the compensation and substitution effects of productivity growth are at work and should, on balance, determine the relationship between productivity and employment. There are several reasons to expect local labor markets to be differentially affected compared to the aggregate case. For instance, the productivity effects can be spatially distinct from the positive consumption effects that are derived from greater productivity or migration might play a role in offsetting differential shocks to help restore spatial equilibrium.

We construct novel measures of county-level productivity that utilize state-level value added data by industry/sector and corresponding industry/sector employment shares by county. We separate productivity measures into those pertaining to the NAICS334 computer and electronic product manufacturing industry, goods sector (excluding NAICS334) and services to discern varying effects within local economies and to account for the out-sized influence of computer manufacturing. The outcomes of interest are employment, earnings, and income growth variables, which we supplement with detailed analyses of employment by sector. The analyses are performed separately for nonmetro counties, counties within small MSAs with populations under 500,000 in 1990 and in large MSA counties (all remaining counties) to explore the heterogeneity along the rural-urban continuum.

OLS and IV results generally suggest that NAICS334 productivity growth is associated with decreased local job growth in metro counties (total and goods employment), though the IV results suggest a possible positive employment response in service industries of rural counties. Productivity growth is generally positively associated with per-capita personal income growth and average wage growth, though there are variations across model specifications and geographies.

Focusing on the IV results, productivity growth in the computer manufacturing industry emerges as a consistent suppressing factor in the goods jobs growth in all metro samples and in total job growth in counties in small MSAs. While generally negatively related to job growth (with stronger effects detected in the high-tech sector), NAICS334 productivity growth consistently stimulates average wage per job growth in all types of counties. One other feature of the results is that high-productivity growth in one sector can crowd out growth in other sectors (perhaps due to higher wages and attracting high-skilled workers).

In sum, the relatively weak negative effects of productivity growth (except in computer and electronic products) are offset by positive productivity level effects, along with the general income-increasing effects of productivity growth. This suggests that a local development strategy of having a concentration of industries with high productivity growth (except for computer manufacturing) may be a good one (though HM caution that wage gains will also be capitalized into housing prices). This is especially true since such an industry composition is less likely to be insulated from larger negative shocks. Yet, we warn that one should not extrapolate and suggest these findings represent national effects, in which many authors are guilty of interpreting regional results that way. Namely, in our empirical analysis, the time fixed effects capture common national trends that include productivity effects that could overwhelm our direct results. Finally, our findings in this paper are remarkably in line with those of HM. This is despite examining different periods, vastly different empirical specification, their use of MSAs and TFP compared to counties and average labor productivity. This adds confidence in both papers' findings.

Overall, productivity growth emerges as a positive driver of AWPJ and PCPI growth with a few exceptions, where only two productivity growth variables (out of three) are significant. Productivity level, on the other hand, is generally not statistically linked to earnings and income variables in our analysis. There is also practically no evidence of any effects of productivity on median household income. This fact, combined with the strong positive effects detected in the PCPI and AWPJ models, may indirectly point to the increasing income gap during the study period. An exploratory analysis of the intervening role potentially played by two factors highlighted in the literature on the effects of productivity and automation growth, namely educational attainment and the share of routine employment, produced mixed results. There seems to be some limited evidence of possible intervening impact of the routine employment share in the AWPJ models but the estimates are largely inconclusive.

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Appendix A

Table A1. List of high-technology industries

NAICS code	Industry
1131	Timber Tract Operations
1132	Forest Nurseries and Gathering of Forest Products
2111	Oil and Gas Extraction
3241	Petroleum and Coal Products Manufacturing
3251	Basic Chemical Manufacturing
3252	Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing
3253	Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing
3254	Pharmaceutical and Medicine Manufacturing
3255	Paint, Coating, and Adhesive Manufacturing
3259	Other Chemical Product and Preparation Manufacturing
3332	Industrial Machinery Manufacturing
3333	Commercial and Service Industry Machinery Manufacturing
3336	Engine, Turbine, and Power Transmission Equipment Manufacturing
3339	Other General Purpose Machinery Manufacturing
3341	Computer and Peripheral Equipment Manufacturing
3342	Communications Equipment Manufacturing
3343	Audio and Video Equipment Manufacturing
3344	Semiconductor and Other Electronic Component Manufacturing
3345	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing
3346	Manufacturing and Reproducing Magnetic and Optical Media
3353	Electrical Equipment Manufacturing
3364	Aerospace Product and Parts Manufacturing
3369	Other Transportation Equipment Manufacturing
4234	Professional and Commercial Equipment and Supplies Merchant Wholesalers
4861	Pipeline Transportation of Crude Oil
4862	Pipeline Transportation of Natural Gas
4869	Other Pipeline Transportation
5112	Software Publishers
5171	Wired Telecommunications Carriers
5172	Wireless Telecommunications Carriers (except Satellite)
5174	Satellite Telecommunications
5179	Other Telecommunications
5182	Data Processing, Hosting, and Related Services
5191	Other Information Services
5211	Monetary Authorities-Central Bank
5232	Securities and Commodity Exchanges
5413	Architectural, Engineering, and Related Services
5415	Computer Systems Design and Related Services
5416	Management, Scientific, and Technical Consulting Services
5417	Scientific Research and Development Services
5511	Management of Companies and Enterprises
5612	Facilities Support Services
8112	Electronic and Precision Equipment Repair and Maintenance

Table A2. List of labor-intensive manufacturing industries

NAICS code	Industry
3131	Fiber, Yarn, and Thread Mills
3132	Fabric Mill
3133	Textile and Fabric Finishing and Fabric Coating Mills
3141	Textile Furnishings Mills
3149	Other Textile Product Mills
3151	Apparel Knitting Mills
3152	Cut and Sew Apparel Manufacturin
3159	Apparel Accessories and Other Apparel Manufacturing
3161	Leather and Hide Tanning and Finishing
3162	Footwear Manufacturing
3169	Other Leather and Allied Product Manufacturing
3371	Household and Institutional Furniture and Kitchen Cabinet Manufacturing
3372	Office Furniture (including Fixtures) Manufacturing
3379	Other Furniture Related Product Manufacturing
3399	Other Miscellaneous Manufacturing

Appendix B

Table B1. Summary statistics for main variables used in estimation by sample

Variable	Nonmetro (S1)				Small metro (S2)				Large metro (S3)			
	Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max	Mean	St.Dev	Min	Max
Dependent variables												
ΔTotal employment growth	0.01	15.62	-579.51	579.12	-0.02	8.11	-116.72	115.22	-0.05	7.27	-126.53	90.98
ΔGoods employment growth	0.11	99.32	-10,532.94	10,387.92	0.07	16.67	-486.61	394.71	0.11	12.58	-203.21	218.33
ΔServices employment growth	-0.04	16.85	-728.19	729.73	-0.06	9.52	-228.93	225.77	-0.10	7.86	-121.17	112.20
ΔHigh-tech employment growth	-1.39	62.30	-400.00	400.00	-0.07	31.67	-270.84	233.33	-0.11	26.94	-234.51	294.23
ΔLow-tech employment growth	0.02	13.09	-211.31	251.03	-0.02	7.49	-78.05	84.27	-0.05	6.90	-108.05	102.23
ΔPer capita personal income growth	-0.08	10.47	-160.66	191.77	0.00	4.96	-74.82	51.08	0.00	5.85	-174.64	186.48
ΔAverage wage per job growth	-0.08	4.95	-114.61	70.06	-0.05	3.02	-34.68	17.69	-0.07	3.57	-67.86	78.22
ΔMedian household income growth	0.07	7.76	-63.67	61.50	0.14	6.90	-32.50	30.21	0.08	6.27	-28.49	38.43
Independent variables												
ΔVA per worker growth	-0.14	4.77	-85.04	98.99	-0.12	4.24	-45.31	62.14	-0.12	3.12	-23.22	31.75
log VA per worker initial level (lagged)	-2.82	0.20	-3.67	-0.94	-2.81	0.14	-3.23	-1.77	-2.76	0.15	-3.53	-1.97
ΔNAICS334 VA per worker growth	-0.01	0.94	-85.65	76.06	-0.02	0.92	-24.76	26.77	-0.02	0.70	-14.94	18.15
ΔGoods (no NAICS334) VA per worker growth	-0.06	4.17	-77.75	97.72	-0.05	3.39	-43.22	59.85	-0.05	2.16	-24.34	28.59
ΔServices VA per worker growth	-0.07	1.86	-27.43	27.61	-0.05	1.95	-15.98	17.68	-0.05	1.76	-7.87	9.16
log NAICS334 VA per worker initial level (lagged)	-0.01	0.04	-1.88	0.00	-0.02	0.05	-1.64	0.02	-0.02	0.04	-0.50	0.01
log Goods (no NAICS334) VA per worker initial level (lagged)	-0.64	0.34	-2.45	0.00	-0.53	0.25	-1.86	-0.03	-0.49	0.23	-1.73	-0.04
log Services VA per worker initial level (lagged)	-2.17	0.43	-3.67	-0.17	-2.26	0.31	-3.10	-0.96	-2.25	0.26	-3.42	-1.10
ΔIndustry mix	0.04	2.83	-106.36	108.59	0.01	2.52	-17.28	20.37	-0.01	2.52	-12.03	13.30
High-tech employment share in 2000	5.32	6.16	0.00	66.98	8.13	5.32	0.31	33.72	10.20	6.85	0.06	46.39
Low wage manufacturing share in 1990	3.94	6.20	0.04	44.15	2.52	4.56	0.10	38.69	2.52	4.13	0.07	28.83
Log Population in 1990	9.60	0.96	6.12	12.07	11.39	0.88	8.55	13.09	11.87	1.29	8.58	16.00

Log MSA Population in 1990 (metro samples only)	0.00	0.00	0.00	0.00	12.25	0.54	10.95	13.10	14.24	0.69	13.14	16.00
% high school diploma only	35.07	5.91	13.54	52.56	32.66	6.29	15.60	49.09	32.34	6.12	14.77	49.42
% BA degree	7.94	3.34	1.82	40.32	11.02	4.11	3.03	25.71	12.41	5.32	3.18	28.90
% Professional and graduate degree	3.76	1.88	0.34	23.48	6.05	3.38	1.73	29.67	6.49	3.49	1.27	23.97
% African-American	8.13	15.12	0.00	86.24	9.41	11.77	0.02	57.66	9.82	11.47	0.02	63.18
% Native American	1.65	6.19	0.00	82.41	0.71	1.97	0.04	29.23	0.63	1.73	0.02	19.73
% Asian	0.33	0.44	0.00	5.47	1.12	1.53	0.02	12.76	1.51	2.47	0.04	29.13
% Other race	1.79	4.79	0.00	44.43	2.01	4.35	0.01	29.08	1.93	3.65	0.04	22.19
% Non-Hispanic origin	95.59	11.66	2.78	100.00	95.19	10.93	6.13	99.85	95.38	8.18	30.42	99.87
Distance to nearest MSA	90.31	58.73	0.00	408.19	12.45	14.78	0.00	110.34	29.83	19.94	0.00	145.83
Incr distance to metro >250k	67.24	106.43	0.00	621.43	64.74	96.65	0.00	621.56	2.37	9.64	0.00	78.10
Incr distance to metro>500k	43.16	67.37	0.00	490.15	71.23	78.73	0.00	490.54	1.62	7.15	0.00	60.96
Incr distance to metro>1500k	90.79	114.44	0.00	597.11	76.36	108.16	0.00	530.77	96.48	143.24	0.00	599.21

Note: Δ = change; WPJ = wage per job; HH = household
Number of observations is 3,048 except for ln(MSApop) where the number is determined by corresponding MSA definition (1,054 during the 1990-2000 period and 1,063 during the 2010-2013 period)

Appendix C

Table C1. Full OLS estimation results for total employment growth variables

	1990-2000			2000-2010			2010-2013		
	S1	S2	S3	S1	S2	S3	S1	S2	S3
ΔComp productivity growth	3.6e-03 (0.06)	-.52** (-2.61)	-.38*** (-3.57)	-.2 (-0.69)	-1.5*** (-2.97)	-.84*** (-2.93)	.29 (1.61)	.11 (1.10)	-.25 (-1.61)
ΔGoods productivity growth (no comp)	-.038 (-1.43)	5.9e-03 (0.09)	-.044 (-0.51)	-.091 (-0.88)	-.13 (-1.37)	.014 (0.13)	.038 (0.91)	.069 (1.02)	-.09 (-1.09)
ΔServices productivity growth	.049 (0.51)	.066 (0.60)	-.16 (-1.57)	.81 (1.41)	.058 (0.42)	-.33** (-2.06)	-.07 (-0.71)	.11 (0.85)	-.12 (-1.12)
Comp productivity level	-.76 (-0.64)	2.6 (0.67)	-1.2 (-0.58)	-7.8 (-0.61)	21 (1.48)	8.8** (2.51)	-2.9** (-2.37)	-4.7*** (-3.12)	-3.2** (-2.17)
Goods productivity level (no comp)	-.036 (-0.04)	-4.6** (-2.01)	-4.9** (-2.04)	-2.5 (-0.16)	1.9 (0.53)	4 (1.64)	-3.9*** (-3.70)	-7.4*** (-3.00)	-7.3*** (-3.39)
Services productivity level	-2** (-2.50)	-4.2** (-2.49)	-4** (-2.17)	-24 (-1.61)	-10*** (-3.46)	-6.3*** (-2.76)	.24 (0.31)	-2.1 (-1.39)	-2.5 (-1.53)
ΔIndustry mix	.47*** (4.21)	1.2*** (4.74)	1.1*** (5.99)	1.1** (2.04)	2.2*** (3.82)	1.8*** (4.92)	.15 (1.19)	.81*** (2.87)	.7*** (3.50)
HT emp share, 2000	.013* (1.76)	.053** (2.33)	.047*** (2.77)	.21** (1.98)	.14** (2.04)	.069** (2.06)	-.011 (-1.55)	.021 (1.13)	.029 (1.52)
Low-wage manuf share, 1990	.027*** (3.30)	4.3e-04 (0.02)	-.019 (-1.21)	.25*** (3.63)	.25*** (4.22)	.22*** (4.76)	-.058*** (-6.11)	-.1*** (-3.87)	-.11*** (-4.57)
lnPop, 1990	.025 (0.61)	.035 (0.44)	.051 (0.67)	-.35 (-1.19)	-1.2*** (-3.30)	-.65*** (-4.26)	-.018 (-0.33)	.4*** (2.92)	.23** (2.60)
lnPop (MSA), 1990	0 (.)	-7.1e-03 (-0.09)	-.052 (-1.07)	0 (.)	.8* (1.92)	.32** (2.22)	0 (.)	-.33** (-2.39)	-.15** (-2.36)
% HS only, 1990	.017** (2.36)	6.6e-03 (0.36)	-.019 (-1.22)	.22*** (2.77)	.2** (2.47)	.036 (0.65)	-.028*** (-2.91)	-.057** (-2.51)	-.04** (-2.04)
% BA, 1990	.019 (1.17)	8.9e-03 (0.46)	-3.8e-03 (-0.30)	-.12 (-1.17)	.017 (0.19)	-.021 (-0.45)	.065*** (2.93)	.039 (1.48)	.012 (0.54)
% grad&prof, 1990	-.079*** (-3.23)	-.023 (-1.10)	-.045** (-2.27)	-.82*** (-3.20)	-.058 (-0.56)	-.14** (-2.55)	.06** (2.21)	-.034 (-1.27)	-.014 (-0.52)
% Black, 1990	2.1e-03 (0.75)	9.3e-03* (1.77)	7.1e-03** (2.05)	.013 (0.55)	.022 (1.11)	-6.0e-03 (-0.57)	1.8e-03 (0.47)	8.7e-03 (1.58)	.01* (1.97)
% Native, 1990	-.016*** (-2.81)	.013 (1.40)	-.028 (-1.14)	-.11** (-2.24)	-.016 (-0.38)	.11 (1.43)	.011* (1.79)	.036** (2.59)	-.076 (-1.59)
% Asian, 1990	-.08 (-1.27)	-.031 (-1.23)	.026*** (2.77)	.75 (1.25)	-.073 (-0.52)	5.0e-03 (0.12)	-.15* (-1.79)	6.9e-03 (0.17)	.045*** (3.22)
% Other, 1990	.022** (2.19)	.019 (1.11)	-.015 (-0.91)	.16* (1.90)	.25*** (2.96)	.17** (2.30)	-.026** (-2.03)	-.056** (-2.14)	-.073** (-2.57)
% Non-hisp, 1990	3.9e-03 (0.79)	4.9e-03 (0.86)	-.014* (-1.82)	.072* (1.87)	.067** (2.06)	.051** (2.13)	-.02*** (-3.79)	-.019* (-1.89)	-.035*** (-3.31)
Near MSA, km	-2.0e-03*** (-3.09)	1.1e-03 (0.54)	9.0e-04 (0.41)	-.021*** (-3.56)	-.015 (-1.12)	-9.5e-03 (-1.34)	3.5e-03*** (4.65)	5.8e-03 (1.26)	2.7e-03 (0.81)
IncrDist to 250k+	3.9e-04 (0.79)	4.9e-05 (0.08)	6.7e-03* (1.84)	-2.3e-04 (-0.06)	-4.8e-03* (-1.67)	-9.8e-03 (-1.01)	1.2e-03*** (2.84)	1.8e-03** (2.38)	9.1e-03* (1.88)
IncrDist to 500k+	1.9e-04 (0.48)	-6.7e-04* (-1.67)	3.0e-03 (1.06)	5.8e-03 (1.56)	-2.8e-03 (-1.33)	1.7e-03 (0.15)	-1.2e-04 (-0.25)	5.7e-04 (0.80)	3.8e-03 (0.67)

IncrDist to 1.5m+	-4.8e-04 (-1.49)	-5.0e-04 (-1.36)	-3.9e-04 (-0.82)	1.4e-03 (0.46)	-3.8e-04 (-0.19)	-1.5e-04 (-0.10)	9.7e-05 (0.26)	-4.2e-04 (-0.88)	-8.3e-04 (-1.22)
Constant	-4.4* (-1.68)	-14*** (-2.70)	-10 (-1.55)	-55 (-1.18)	-31*** (-3.13)	-14* (-1.69)	-.45 (-0.15)	-7.8 (-1.36)	-5.8 (-1.11)
N	35,696	6,112	6,960	30,661	5,984	6,864	35,696	6,112	6,960
R-sq	0.022	0.103	0.120	0.009	0.110	0.153	0.012	0.047	0.062

*** - 0.01% significance; ** - 0.05% significance; * - 0.1% significance;
Standard errors adjusted for clusters within the 177 BEA economic areas for S1, 135 BEA economic areas for S2 and 66 BEA economic areas for S3; t-stat in parentheses; number of observations is 2,238 for S1, 382 for S2 and 435 for S3.

Sample 1 (S1) includes nonmetro counties; sample 2 (S2) includes counties in MSAs with 1990 population under 500 thousand; sample 3 (S3) includes all other counties. 1990 U.S. Census Bureau population data are used for grouping counties into samples. In addition to the control variables reported in Table C1, all models include fixed effects for USDA amenity levels, location within 50 kms from Great Lakes, Atlantic Ocean, and Pacific Ocean, as well as state and year fixed effects. Full results are available on request from the authors. See the text for further details.

Appendix D

Table D1. OLS estimation results for total employment growth (interaction models)

	Interacting variable: *% College Graduates*			Interacting variable: *% Routine Employment*		
	S1	S2	S3	S1	S2	S3
ΔComp productivity growth	-.32 (-1.52)	-.97** (-2.22)	-.52* (-1.73)	.32 (0.47)	-2.8 (-1.20)	1.1 (0.69)
ΔGoods productivity growth (no comp)	-.036 (-0.52)	.29 (1.25)	.3 (1.43)	-.07 (-0.37)	.14 (0.34)	-.74 (-1.34)
ΔServices productivity growth	.29** (2.05)	.26 (0.90)	-.18 (-0.76)	.45 (0.67)	-1.5** (-2.04)	.82 (1.10)
Comp productivity level	1.8 (0.76)	12 (1.46)	-.97 (-0.23)	-4.6 (-0.74)	57* (1.71)	-7.7 (-0.35)
Goods productivity level (no comp)	.79 (0.65)	-4.8 (-0.98)	-3.5 (-1.26)	6.6 (1.46)	-7.6 (-0.45)	-3.1 (-0.63)
Services productivity level	-1.5 (-1.48)	-3.4 (-0.92)	-3.2 (-1.23)	1 (0.30)	-2.3 (-0.18)	.34 (0.07)
Interacting variable	-.16 (-0.46)	-.15 (-0.26)	-.14 (-0.67)	-35 (-0.96)	-10 (-0.10)	-23 (-0.65)
ΔComp productivity growth X Interacting variable	.025* (1.88)	.023 (1.51)	7.4e-03 (0.60)	-1 (-0.57)	6.7 (1.00)	-4.8 (-1.03)
ΔGoods productivity growth (no comp) X Interacting variable	-3.6e-04 (-0.05)	-.022 (-1.47)	-.026** (-2.19)	.11 (0.22)	-.4 (-0.37)	1.9 (1.27)
ΔServices productivity growth X Interacting variable	-.019* (-1.66)	-.011 (-0.78)	1.2e-03 (0.16)	-1.4 (-0.59)	4.7** (2.10)	-3 (-1.40)
Comp productivity level X Interacting variable	-.24 (-1.10)	-.5* (-1.74)	2.1e-03 (0.02)	14 (0.69)	-162* (-1.77)	23 (0.38)
Goods productivity level (no comp) X Interacting variable	-.078 (-0.50)	.015 (0.06)	-.082 (-1.19)	-22 (-1.34)	6.6 (0.15)	-2.7 (-0.21)
Services productivity level X Interacting variable	-.042 (-0.39)	-.058 (-0.27)	-.036 (-0.48)	-12 (-1.00)	-8.2 (-0.24)	-12 (-0.90)
ΔIndustry mix	.47*** (4.21)	1.2*** (4.78)	1.1*** (6.01)	.45*** (3.89)	1.2*** (4.47)	1.1*** (5.70)

** - 0.01% significance; ** - 0.05% significance; * - 0.1% significance;
Standard errors adjusted for clusters within the 177 BEA economic areas for S1, 135 BEA economic areas for S2 and 66 BEA economic areas for S3; t-stat in parentheses; number of observations is 2,238 for S1, 382 for S2 and 435 for S3.

Sample 1 (S1) includes nonmetro counties; sample 2 (S2) includes counties in MSAs with 1990 population under 500 thousand; sample 3 (S3) includes all other counties. 1990 U.S. Census Bureau population data are used for grouping counties into samples. In addition to the control variables reported in Table C1, all models also include fixed effects for states, USDA amenity levels and location within 50 kms from Great Lakes, Atlantic Ocean, and Pacific Ocean. Full results are available on request from the authors. See the text for further details.

Table D2. OLS estimation results for average wage per job growth (interaction models)

	Interacting variable: *% College Graduates*			Interacting variable: *% Routine Employment*		
	S1	S2	S3	S1	S2	S3
ΔComp productivity growth	-.026 (-0.32)	-.057 (-0.30)	-.82 (-1.56)	.31*** (2.83)	-.78 (-1.16)	2.4 (1.66)
ΔGoods productivity growth (no comp)	.029 (1.16)	.087 (1.59)	.028 (0.41)	.033 (0.74)	.068 (0.55)	-.7*** (-3.26)
ΔServices productivity growth	.15** (2.40)	.076 (0.84)	.38*** (2.83)	-.29*** (-2.71)	-.17 (-0.90)	.18 (0.47)
Comp productivity level	-.95* (-1.68)	.76 (0.86)	-3.7** (-2.21)	-2.2 (-1.38)	12* (1.97)	3.2 (0.21)
Goods productivity level (no comp)	-.1 (-0.43)	-1.3* (-1.93)	-1.3*** (-2.68)	.34 (0.73)	3.4 (1.54)	-1 (-0.49)
Services productivity level	-.28 (-1.35)	-1.2** (-2.44)	-1.2* (-1.93)	-.38 (-0.81)	2.9* (1.79)	-1.8 (-0.80)
Interacting variable (college grad% or routine%)	-.049 (-1.05)	.031 (0.57)	.051 (1.04)	-1.5 (-0.40)	-30** (-2.14)	4.9 (0.27)
ΔComp productivity growth X Interacting variable	6.4e-03 (1.12)	6.4e-03 (0.63)	.048 (1.62)	-.69** (-2.13)	2.6 (1.23)	-6.1 (-1.52)
ΔGoods productivity growth (no comp) X Interacting variable	2.4e-03 (1.07)	-1.6e-03 (-0.40)	5.1e-03 (1.12)	.039 (0.36)	-.016 (-0.05)	2.3*** (3.67)
ΔServices productivity growth X Interacting variable	-1.2e-03 (-0.29)	2.2e-03 (0.53)	-6.3e-03 (-1.37)	1.5*** (4.05)	.82 (1.47)	.18 (0.17)
Comp productivity level X Interacting variable	.063 (1.24)	.024 (0.69)	.2** (2.19)	5.8 (0.96)	-33* (-1.86)	-2.3 (-0.05)
Goods productivity level (no comp) X Interacting variable	-5.6e-03 (-0.31)	.027 (1.16)	.027* (1.85)	-2.2 (-1.57)	-12* (-1.92)	-1.3 (-0.21)
Services productivity level X Interacting variable	-.017 (-1.04)	8.8e-03 (0.46)	.018 (0.92)	-.16 (-0.11)	-11** (-2.22)	1.5 (0.22)
ΔIndustry mix	.021 (0.93)	7.7e-04 (0.01)	-.026 (-0.41)	-6.2e-03 (-0.24)	-.031 (-0.49)	-.041 (-0.63)

*** - 0.01% significance; ** - 0.05% significance; * - 0.1% significance;
Standard errors adjusted for clusters within the 177 BEA economic areas for S1, 135 BEA economic areas for S2 and 66 BEA economic areas for S3; t-stat in parentheses; number of observations is 2,238 for S1, 382 for S2 and 435 for S3.

Sample 1 (S1) includes nonmetro counties; sample 2 (S2) includes counties in MSAs with 1990 population under 500 thousand; sample 3 (S3) includes all other counties. 1990 U.S. Census Bureau population data are used for grouping counties into samples. In addition to the control variables reported in Table C1, all models also include fixed effects for states, USDA amenity levels and location within 50 kms from Great Lakes, Atlantic Ocean, and Pacific Ocean. Full results are available on request from the authors. See the text for further details.