Urban-Rural Productivity Spillovers: Theory and Evidence from Colorado

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Abstract

I investigate how growth in total factor productivity (TFP) in an urban core associates with future employment growth in its rural periphery. I develop a two-location spatial general equilibrium model that highlights the interactions between a city and rural town in its hinterland, which hypothesises a negative association between TFP growth in the former and employment growth in the latter. I test the implications of the model by evaluating confidential establishment-level data on a core-periphery system in the state of Colorado from 2001 to 2017. I find TFP growth in an urban core correlates with lower future employment growth in its rural periphery.

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1 Introduction

To further understanding of urban-rural linkages, I study how total factor productivity (TFP) growth in an urban core relates to employment growth in its rural periphery. Using confidential establishment-level data from the Quarterly Census of Employment and Wages (QCEW), I estimate how TFP growth among a cluster of highly integrated Metropolitan Statistical Areas (MSAs), known as the Front Range Urban Corridor (FRUC) in the US state of Colorado, associates with future employment in the cluster's hinterland. This paper evaluates the implications of urban TFP growth for local core–periphery systems, adding further context to the relationship between an urban centre and its hinterland. Consistent with theoretical predictions, I find revenue TFP growth in an urban core correlates with lower future employment growth in its rural periphery.

To guide the empirical analysis, I develop a two-location spatial general equilibrium trade framework that highlights economic interactions between a city and a rural town

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located in its hinterland. Following recent quantitative spatial economic models, this theoretical framework synthesises the gravity structure international trade theory and a (homogeneous and) perfectly mobile labour supply to study the allocation of economic activity over space. There are ex-ante production differences between the city and rural town that promote clustering within the former. Micro-founded input-output linkages in the city give rise to agglomeration economies and aggregate increasing returns to scale production technology, while firms in the rural town produce using constant returns technology. Differences in housing markets translate to location-specific expenditure shares and fixed housing supply generates dispersion forces. The system produces a unique and point-wise stable equilibrium. When calibrated with empirically guided parameter values, the urban-rural labour allocation in the model is consistent with evidence from the US. As a result of exogenous growth shocks to urban TFP, the model predicts that (1) TFP growth in the city associates with negative employment growth in the rural town, (2) local TFP growth in the rural town can mitigate negative effects of a positive urban TFP shock, and (3) the negative employment growth response in the rural town is less severe the larger is the TFP gap (in levels) between the city and rural town.

The model informs a reduced form specification I take to data to test the theoretical hypothesis of a negative association between urban revenue TFP growth and rural employment growth. Leveraging the detailed data on twenty differentiated sectors for the whole of Colorado, I estimate a composite measure of annual urban revenue TFP and segment the data on establishments in the FRUC's rural hinterland into smaller census designated regions known as ZIP Code Tabulation Areas (ZCTAs). The modelled data generation process defines employment growth in a rural ZCTA, in part, as a function of past TFP growth in a weighted average of the MSAs that comprise the FRUC. I uniquely relate TFP growth in each MSA to individual ZCTAs using structural gravity inspired spatial connectivity weights derived from the theoretical model.

Since the revenue TFP estimates are likely to contain substantial measurement error, I construct Bartik style shift-share instruments and estimate the empirical model using the feasible two-step generalised methods of moments (GMM) estimator. The main result finds that a one standard deviation increase in the aggregate FRUC's three-year revenue TFP growth rate (which amounts to 3.4 percentage points) correlates with an average 1.34 percentage point lower ZCTA employment growth rate over the following three-year period. The sign and significance of this result are robust to a wide variety of alternative empirical specifications.

Previous research analysing the local implications of revenue TFP growth has been restricted to particular sectors, namely manufacturing, as well as city-to-city spillovers. Likewise, past studies analysing peer effects between urban and rural areas have focused primarily on evidence related to associations between population growth rates in core and periphery systems. I complement the existing literature by offering further evidence on sub-national revenue TFP and its local associations. Additionally, I build upon preceding findings related to urban-rural spillovers, moving away from exclusively considering population growth comovements and instead, by studying correlations related to urban revenue TFP growth, I evaluate other potential avenues of influence.

2 Related Literature

This study is an intersection of two streams of the urban and spatial economic literature. The first related set of research is that analysing sub-national total factor productivity (TFP). Much of the work concerned with investigating disparities in TFP levels and the effects of its growth over time has focused on between country analysis. However, there are a growing number of studies turning their attention to local TFP, which have curated some stylised facts about sub-national TFP patterns.

Though TFP is challenging to measure, studies that have estimated local TFP find evidence of the existence of large within-country TFP disparities, which explains some of the nominal wage variation across space (Moretti, 2011). Moretti (2011) finds that counties in the right tail of the distribution have a TFP estimate 2.9 times higher than those in the left tail. Such spatial heterogeneity is not unique to the US. Ciani, Locatelli, and Pagnini (2019) find sub-national manufacturing TFP estimates in the North of Italy are between 12% and 30% higher than estimates from the, comparatively rural, South of Italy.

This literature identifies strong evidence in favour of TFP persistence over time (Moretti, 2011), implying persistent disparities in the level of TFP. Further, TFP growth between regions is found to vary as much as TFP levels. In estimating manufacturing TFP growth in the US among urban areas from 1980 to 1990, Hornbeck and Moretti (2020) find locations at the 10^{th} percentile experienced -2.2% TFP growth and those in the 90^{th} percentile experienced 13.7% growth, while the median growth rate was 4.5%.

There are many proposed reasons as to why these subnational differences exist. They may reflect local infrastructure disparities or heterogeneous location-specific policy related to production (Albanese, de Blasio, and Locatelli, 2019; Hornbeck and Moretti, 2020). Given insights from the urban economics literature studying agglomeration economies, there is evidence of firm clustering promoting productivity spillovers and growth over time. For example, areas with larger industrial clusters seem to experience higher productivity levels and growth rates (Greenstone, Hornbeck, and Moretti, 2010; Moretti, 2011; Hornbeck and Moretti, 2020). Some authors argue supply-side influences, including location or industry-specific technological innovation, spur TFP growth in some regions (Syverson, 2004; Albanese, de Blasio, and Locatelli, 2019; Hornbeck and Moretti, 2020). Syverson (2004) also proposes that demand-side forces, particularly "spatial substitutibility," can increase production efficiency. If producers are clustered and consumers have access to sufficiently substitutable alternatives, this may stimulate competition in the local market thereby introducing a Melitz (2003)-flavoured truncation of the local productivity distribution, pushing less efficient producers out of the market and increasing average local productivity.

Considering the evidence on local TFP disparities, Hornbeck and Moretti (2020) investigate how city-level growth in manufacturing revenue TFP impact the residents of cities that experience TFP growth (which they call the "direct effects") as well as residents of other cities where TFP growth does not occur via changes to the spatial equilibrium (the "indirect effects"). They find local TFP growth increases local earnings, house prices/rents, and employment (mainly due to in-migration), although the benefit experienced by individuals varies based upon their level of education and their position in the housing market (home owner versus renter). They also find that the migration stimulated by TFP growth elsewhere causes other cities to experience wage increases and house price decreases in response to out-migration to the booming city. However the magnitude of these effects are too associated with individual skill levels. On net, they find the average US worker benefits substantially from revenue TFP growth in manufacturing.

This paper joins a second strand of literature studying urban growth shadows (or the lack thereof). The economic history of the US has been characterised by periods of regional divergence and convergence. Kemeny and Storper (2020) find evidence for interregional income convergence during the mid to late 20^{th} century, but periods of divergence during the mid 19^{th} to early 20^{th} centuries and since the 1980s. Notably, there is an increasing divide between the success of particular urban areas and rural areas/declining urban areas, and part of this regional asymmetry story appears to stem from how neighbouring regions, including urban and rural neighbours, help or hurt each other's economic growth prospects.

A central prediction of the New Economic Geography class of models is that the centripetal forces that give rise to urban cores facilitate "agglomeration shadows," otherwise known as urban growth shadows, that prevent proximal urban areas to form (Partridge et al., 2009). Indeed, Cuberes, Desmet, and Rappaport (2019) find proximity to large urban areas was negatively correlated to local population growth from 1840-1920 in the US. However, they also find that since the 1920s, areas close to densely populated urban cores experience faster population growth, hinting at the absence of the previous growth shadows and instead favouring evidence of urban growth spillovers. Evidence from Partridge et al. (2009) using US data from 1990-2006 and Rauch (2014) using US data from 2000 find similar positive correlations between large urban centres and the population size of their hinterlands. However, Cuberes, Desmet, and Rappaport (2019) find that this positive correlation seems to be weakening during the 21^{st} century. While there is evidence that comovements in population growth between urbanised areas and more sparsely populated areas have changed with time, the exact mechanisms that define the urban-rural relationship are not entirely clear.

To rationalise their findings of urban growth spillovers in the later 20^{th} century, Cuberes, Desmet, and Rappaport (2019) propose that innovations to transport technology, which have reduced commuting costs, have encouraged commuting. As such, they argue that suburban and rural areas adjacent to large metropolitan areas have grown due to people choosing to live in those communities but work in the urban core. However, when considering some of the local growth multipliers Moretti (2010) describes that stem from *local* (tradable-sector) employment growth, it is not necessarily the case that the observed population growth can be linked to meaningful economic growth if residents are working elsewhere. That is to say, it is difficult to assess the extent of urban growth spillovers (or reject the existence of growth shadows) in the late 20^{th} and early 21^{st} centuries exclusively from associations in population growth trends.

In this paper, I complement the existing literature by adapting the questions and methodology of Hornbeck and Moretti (2020) from an urban-to-urban spillover analysis to an urban-to-rural spillover analysis, thereby offering further insights as to the associations between sub-national (estimated) revenue TFP and labour market outcomes, namely employment growth. Furthermore, I provide additional context to the urban and rural relationship, moving away from studying associations between population growth to instead considering other urban forces (i.e. urban revenue TFP growth) which may covary with observables in nearby rural places.

3 Theoretical Framework: The Urban-Rural General Equilibrium

To guide my empirical analysis, I develop a general equilibrium model that illustrates the underlying link between exogenous growth in urban total factor productivity (TFP) and rural employment growth. I consider a region comprised of two locations, a city c and rural town r, with ex-ante differences in production technology and consumer expenditure shares that are connected by intra-regional trade and a mobile homogeneous labour supply. The model clarifies urban TFP's relationship to the equilibrium distribution of activity across space and offers useful qualitative predictions concerning co-movements between urban TFP growth and employment growth in rural areas located in the core's hinterland.

3.1 Production

Both the city and rural town produce a unique final good that is consumed locally and in the other location. The urban and rural goods are differentiated according to their point of origin (i.e. the Armington assumption from international trade) and by the processes in which they are produced. Similar to Michaels, Rauch, and Redding (2012), who differentiate production technology by sector, I differentiate production technology by location. The city features increasing returns to factor inputs external to firms while the rural town produces using constant returns to scale technology, implying the city exhibits agglomeration economies while the rural town has no centripetal forces that promote clustering.

Urban Production In an approach following Krugman and Venables (1995) and Duranton and Puga (2004), I micro-found aggregate urban agglomeration economies via input-output linkages. In the city, there is a single production sector composed of two sub-sectors. A sub-sector of perfectly competitive final good producing firms ("final firms" henceforth) utilises a bundle of input varieties produced by the other sub-sector comprised of a mass M of monopolistically competitive firms ("intermediate firms" henceforth) that use labour as their only input. Put differently, there is a single urban production sector that uses labour and some fraction of output to produce final output.

The perfectly competitive final firms produce according to a Dixit and Stiglitz (1977)-style constant elasticity of substitution (CES) production technology

$$Y_c = A_c^F \left[\int_0^M z(\kappa)^{\frac{1}{1+\varepsilon}} d\kappa \right]^{1+\varepsilon} \tag{3.1}$$

where Y_c is the total supply of the final good produced in the city, A_c^F is the city-specific final firm TFP, and $z(\kappa)$ is the input produced by intermediate firm indexed κ. Each intermediate input enters the final good production technology with a constant elasticity of input substitution, denoted $\frac{1+\varepsilon}{\varepsilon}$, where I assume $\varepsilon > 0$. This CES production specification implies final firms possess a "taste for diversity" for input varieties in the production of Y_c such that the final firms prefer to use all the inputs available in the city, utilising relatively cheaper inputs more intensively in their production process at a rate dictated by the elasticity of input substitution. As ε approaches zero, intermediate inputs become perfect substitutes in final good production while as ε approaches infinity, the equation (3.1) becomes the Cobb-Douglas production function, in which case inputs enter at a fixed proportion independent of final good output or the relative prices of input varieties.

Monopolistically competitive intermediate firms are single product firms where each firm κ produces one variety $z(\kappa)$ using a single factor of production, labour $\ell(\kappa)$, and so the available alternatives equals the number of firms. Each intermediate firm utilises the following production technology:

$$z(\kappa) = A^L \ell^D(\kappa) - f \tag{3.2}$$

where $\ell^D(\kappa)$ is firm κ's labour demand, A^L is the (constant) marginal product of labour, and f are the fixed costs associated with the production of input variety $z(\kappa)$, a formulation following Ethier (1982). Intermediate goods providers are assumed homogeneous and therefore face identical A^L and f.

Final firms in the city choose inputs $z(\kappa)$, priced $g(\kappa)$ per unit, and face total input costs $\int_0^M g(\kappa)z(\kappa)d\kappa$. They seek to minimise their production costs subject to their production technology

$$\min_{\{z(\kappa)\}_{\kappa=0}^M} \quad \int_0^M g(\kappa)z(\kappa)d\kappa \quad \text{s.t.} \quad A_c^F \left[\int_0^M z(\kappa)^{\frac{1}{1+\varepsilon}} d\kappa \right]^{1+\varepsilon} \geq Y_c$$

which yields final firms' demand for input variety κ of the form

$$z(\kappa) = \left[\frac{g(\kappa)}{G} \right]^{-\left(\frac{1+\varepsilon}{\varepsilon}\right)} \frac{A_c^F Y_c}{G} \tag{3.3}$$

where $G \equiv \frac{[\int_0^M g(\kappa)^{-\frac{1}{\varepsilon}}]^{-\varepsilon}}{A_c^F}$ is a price index measuring the "true" cost of urban final good production. G is decreasing in M and A_c^F, implying that final firms find production cheaper when there are more varieties for them to choose from and when they are more productive in transforming input varieties into the final output.

The market equilibrium for input varieties (which, considering said market is nested within a city where employment and wages are endogenously determined in general equilibrium of the region, is necessarily a partial equilibrium) is characterised by three conditions. The first condition is the intermediate firm profit maximisation condition, where the marginal revenue for each firm κ (MR_κ) equals the marginal costs faced by firm κ (MC_κ). The set of points for which $MR_\kappa = MC_\kappa$ holds is referred to as the intermediate firm equilibrium locus. The second condition is that free entry and exit in the monopolistically competitive market pressures equilibrium profits to zero, at which point the price of variety κ, $g(\kappa)$, is equal to the average costs faced by firm κ (AC_κ). The set of points for which $g(\kappa) = AC_\kappa$ holds is called the intermediate firm sub-sector equilibrium locus. Third, given that intermediate firms utilise labour as their sole input, the equilibrium depends in part upon the urban labour market clearing equilibrium, L_c, where the urban labour supply equals the urban labour demand (which is in turn endogenously determined in the general equilibrium).

The intermediate firm locus is identified by solving the firm's profit maximisation problem. Given intermediate firms are monopolistically competitive, they display no strategic behaviour towards one another (i.e. they ignore their interdependence in making pricing decisions) and therefore take G as given. Furthermore, intermediate firms take the output decision of final firms Y_c, final firms' TFP A_c^F, and wages paid to workers in the city w_c as given as well. Thus, facing final firm demands in equation (3.3), intermediate firm κ chooses $g(\kappa)$ to maximise profits $\Pi(\kappa)$ subject to labour input costs:

$$\max_{g(\kappa)} \quad \Pi(\kappa) = g(\kappa)z(\kappa) - w_c \ell^D(\kappa) = g(\kappa)z(\kappa) - w_c\left(\frac{z(\kappa)+f}{A^L}\right)$$

where the substitution for $\ell^D(\kappa)$ follows from solving equation (3.2) for $\ell^D(\kappa)$. Profit maximising behaviour implies the optimal price set by firm κ is $g(\kappa) = \left(\frac{1+\varepsilon}{A^L}\right)w_c$, meaning the optimal price is a mark-up $\frac{1+\varepsilon}{A^L}$ over marginal labour costs w_c faced by the firm. This mark-up is decreasing as labour becomes more productive on the margin (i.e. decreasing in A^L) and increasing as inputs become less fungible (i.e. increasing in ε). Note that the optimal price for firm κ is independent of the index κ, meaning this price is the optimal price set by *all* intermediate firms in equilibrium.That is,

$$g(\kappa) = g = \left(\frac{1+\varepsilon}{A^L}\right)w_c \quad \forall\kappa \tag{3.4}$$

For the firm's second order sufficient condition to be satisfied, and thus for equation (3.4) to be the true profit maximising price set by intermediate firms, it must be that $\varepsilon > 0$, which motivates the initial assumption made on ε.

Equation (3.4) characterises the intermediate firm equilibrium locus, defining the set of points for which $MC = MR$ given w_c, which is endogenously determined in the general equilibrium. The optimal price set by all intermediate firms implies perfect cost pass-through from intermediate firms to final firms. Furthermore, equation (3.4) indicates that the price-cost margin, $\frac{g}{w_c} = \frac{1+\varepsilon}{A^L}$, is a constant ratio determined by exogenous model parameters.

Setting total profits earned by intermediate firms to zero (i.e. imposing the zero-profit condition) and solving for price reveals

$$g = \frac{w_c \ell^D(\kappa)}{z(\kappa)} = \left(1 + \frac{f}{z(\kappa)}\right)\frac{w_c}{A^L} \tag{3.5}$$

which is a rectangular hyperbola. The set of points in equation (3.5) defines the intermediate firm sub-sector equilibrium locus, containing all the points at which $g = AC$. Notice that the functional form of average costs implies that prices are decreasing in output $z(\kappa)$ as a result of overhead costs f being spread across a greater quantity of output, meaning intermediate firms move down their average cost curve as production expands. As such, the production technology of the monopolistically competitive intermediate firms displays firm-level increasing returns.

The point of intersection between the firm and sector equilibrium loci, equations (3.4) and (3.5) respectively, defines the equilibrium supply of input varieties. Substituting the firm equilibrium locus into the sub-sector equilibrium locus and solving for firm κ's output $z(\kappa)$ gives

$$z(\kappa) = z = \frac{f}{\varepsilon} \quad \forall \kappa \tag{3.6}$$

and so in equilibrium each intermediate producer supplies an identical amount of output. This means, under the assumption of final good CES production technology, the intensive production margin of intermediate firms (i.e. how *much* each intermediate goods firm produces in equilibrium) depends on fixed production costs scaled by the degree of substitutability between inputs. As fixed production costs grow, each intermediate supplier produces less in equilibrium while as the substitutability of inputs increases, intermediate suppliers produce more in equilibrium. Like pricing decisions, intermediate goods producers' output choices are independent of final firm demands.

Substituting equation (3.6) into intermediate firm labour demands $\ell^D(\kappa)$ shows that in equilibrium, each intermediate firm demands $\ell^D = \frac{f(1+\varepsilon)}{A^L \varepsilon}$. Since in equilibrium all M intermediate firms are identical, total labour demand in the city is $L_c^D = n\ell^D = M\frac{f(1+\varepsilon)}{A^L \varepsilon}$. Assuming the urban labour market equilibrium condition holds (i.e. $L_c^S = L_c^D = L_c$, where L_c is endogenously determined in the spatial equilibrium) and subsequently solving for M yields

$$M = \left(\frac{w_c}{gz}\right) L_c = \left[\frac{\varepsilon A^L}{f(1+\varepsilon)}\right] L_c \tag{3.7}$$

Therefore, the extensive intermediate goods production margin (i.e. how *many* intermediate firms are operating in equilibrium) is determined endogenously by the urban labour market equilibrium, L_c, which is scaled by the inverse of the product of equilibrium output z and the price cost ratio $\frac{g}{w_c}$, which in turn is determined by the parameters ε, f, and A^L. Thus, the equilibrium intermediate goods extensive production margin becomes more sensitive to changes in the (endogenously determined) urban labour market equilibrium as the substitutability of inputs declines, fixed production costs decline, and/or the marginal product of labour increases.

Equation (3.6) holds regardless of final good producers' input demands in equilibrium. Substituting the equilibrium output of all M homogeneous intermediate firms into the final good production technology equation (3.1), it follows that

$$
\begin{aligned}
Y_c &= A_c^F \left[\int_0^n \frac{f}{\varepsilon}^{\frac{1}{1+\varepsilon}} di \right]^{1+\varepsilon} \\
&= A_c^F M^{1+\varepsilon} \frac{f}{\varepsilon}
\end{aligned}
$$

which, given equation (3.7), implies equilibrium final good production in the city can be expressed as

$$Y_c = A_c L_c^{1+\varepsilon} \tag{3.8}$$

where $A_c \equiv A_c^F \left(\frac{\varepsilon}{f}\right)^{\varepsilon} \left(\frac{A^L}{1+\varepsilon}\right)^{1+\varepsilon}$ is an endogenously determined variable that measures the composite TFP level in the city, which is a function of the parameters that determine the firm-level productivity of both the intermediate and final good production processes. Therefore, the aggregate productivity of the city A_c is comprised of the productivity of all urban firm types.

In analysing the impact of urban TFP growth within this model, since worker-consumers are assumed identical across the region (meaning workers in both the city and rural town have identical marginal product of labour, A^L) and the degree of input substitutability ε is fixed, all sources of urban TFP innovation in this model are assumed to come from exogenous shocks to A_c^F or f and not innovations to the marginal product of labour. Crucially, this model is not exploring changes in the production capacity of labour; rather it is exploring the effects related to more general gains in the production capacity of factor inputs. However, I remain agnostic as to the exact source of innovation and, for simplicity express such perturbations as growth in the composite productivity A_c.

Taking logarithmic transformations of the right- and left-hand sides of equation (3.8) and totally differentiating reveals

$$\widehat{y_c} = \widehat{a_c} + (1+\varepsilon)\widehat{l_c}$$

where $\widehat{x_c} \equiv \frac{dX_c}{X_c}$ for $X_c \in \{Y_c, A_c, L_c\}$ denotes a proportional change. This reveals that a unit change in the urban labour market equilibrium level of workers corresponds to a greater than one-unit response in output of the final good in the city since $\varepsilon > 0$, so while individual final good producing firms face constant returns to scale production technology in the form of equation (3.1), in aggregate the city features increasing returns to labour due to input-output linkages. This implies external economies to scale in urban final good production. Thus, through the productive advantages of final good producers clustering in the city and, therefore, sharing in a wider variety of intermediate inputs provided by a monopolistically competitive intermediate goods producing sector, the city features agglomeration economies.

The intensity of the agglomeration economies in the city is dictated by the size of $\varepsilon > 0$. Recall that input varieties become less fungible in final good production as ε increases.

Thus, agglomeration economies grow as final good producers require a larger variety of inputs in their production process. The underlying mechanism is the slope of final firm demands. Under monopolistic competition, final firm demand curves (i.e. equation 3.3) slope downward, with their gradient determined by ε. Demands under ε large correspond to steeper final firm demand curves for each input variety produced, which translates to larger consumer surplus going to final firms in the production of another variety. Put differently, the agglomeration externality in the city grows as intermediate firms capture less of the benefit of introducing an additional variety on account of higher values of ε.

In micro-founding agglomeration economies, it is important to note that this model results in some strong and implausible (partial) equilibrium outcomes. In particular, the price cost margin is constant and results in perfect pass-through, intermediate firm output choices are independent of final firm demands, and the intermediate firm production intensive and extensive margins are independent in equilibrium. These results are consequences of the assumption that final firms utilise the special case, but mechanically useful, CES production specification. While alternative final firm input demand specifications exist with more appealing monopolistically competitive firm equilibrium outcomes, such as pricing that is linked to input demand (e.g. the "well-behaved" demand systems Mrázová and Neary (2017) classify as subconvex), for the purposes of agglomeration micro-foundations, this is an admissible simplifying assumption.

Perfect competition, and the accompanying free entry and exit condition, among final firms drives equilibrium profits to zero. Using equation (3.8), zero profits implies the urban equilibrium wage can be written

$$w_c = p_c A_c L_c^{\varepsilon} \tag{3.9}$$

where p_c is the mill price (i.e. "factory gate price") of the final good produced in the city.

Rural Production Unlike in the city, rural final good producing firms use labour, not intermediate input varieties, as their sole factor input, and so there are no economies of scale external to the firm. Instead, perfectly competitive final firms in the rural town produce according to constant returns to scale technology

$$Y_r = A_r L_r \tag{3.10}$$

where Y_r is the aggregate supply of the final good produced in the rural town, A_r is the rural town-specific composite TFP level, and L_r is the rural labour market equilibrium quantity of worker-consumers, which (like L_c) is endogenously determined in the general equilibrium. Similar to composite TFP in the city, composite TFP in the rural town can be decomposed such that $A_r \equiv A_r^F A^L$, where A_r^F is the TFP of final firms in the rural town and A^L is the marginal product of labour common to workers in either location. In equilibrium, the rural wage is such that the zero-profit condition holds

$$w_r = p_r A_r \tag{3.11}$$

where p_r is the mill price of the final good produced in the rural town.

3.2 Consumption

The region's economy is populated by $\overline{L}$ identical, intra-regionally mobile worker-consumers. Workers possess the common marginal product of labour A^L described in Section 3.1 and supply one unit of labour inelastically in the location (either c or r) they choose to live, earning the wage specific to that location. Workers derive utility from goods consumption, housing consumption, and location-specific amenities. Housing expenditure in each location $i \in \{c, r\}$ is reallocated as a lump sum to workers living in that location, as in Helpman (1998) and Redding (2016), implying that worker income I_i is the sum of wages earned through labour and rents earned from housing expenditures.

Similar to Redding (2016), workers living in location i have Cobb-Douglas preferences defined over goods consumption Q_i and housing consumption h_i which are subject to an exogenous, location-specific amenity parameter Θ_i

$$U_i = \Theta_i \left(\frac{Q_i}{\delta_i}\right)^{\delta_i} \left(\frac{h_i}{1-\delta_i}\right)^{1-\delta_i} \tag{3.12}$$

where $\delta_i \in (0,1)$ is the location-specific share of total income spent on goods consumption. Given this preference specification and the lump sum redistribution of housing rents to residents, income in i can be rewritten as

$$I_i = \frac{w_i}{\delta_i} \tag{3.13}$$

The goods consumption index Q_i is a CES aggregator defined over workers in location i's consumption of the good produced in i, denoted $q_{i,i}$, and the good produced in the other location $i' \neq i$, denoted $q_{i',i}$:

$$Q_i = \left[q_{i,i}^{\frac{\sigma-1}{\sigma}} + q_{j,i}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{3.14}$$

where $\sigma > 1$ is the elasticity of substitution between the two goods varieties, which is common to locations.[1] To simplify the model, I assume that workers inelastically consume a unit of housing (i.e. impose $h_i = 1$), choosing Q_i to maximise their utility subject to their budget constraint, solving

$$\max_{Q_i} \quad U_i = \Theta_i \left(\frac{Q_i}{\delta_i}\right)^{\delta_i} \left(\frac{1}{1-\delta_i}\right)^{1-\delta_i} \quad \text{s.t.} \quad e_i + r_i \leq I_i$$

where e_i is total goods expenditure by workers in i and r_i is the rental price of a unit of housing in i. To choose their optimal goods consumption bundle Q_i, workers in i must

[1] Like Allen and Arkolakis (2014), I restrict my attention to $\sigma > 1$ so that trade flows between the city and rural town are decreasing in transport costs. See Section (3.3).

also solve

$$\max_{q_{i,i},q_{j,i}} \quad Q_i = \left[q_{i,i}^{\frac{\sigma-1}{\sigma}} + q_{i',i}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \quad \text{s.t.} \quad p_{i,i}q_{i,i} + p_{i',i}q_{i',i} \leq e_i = \delta_i I_i = w_i$$

where $p_{i,i}$ is the price of good i paid by workers in i, $p_{i',i}$ is the price of good i' paid by workers in i, and $\delta_i I_i = w_i$ is the share of total income spent on goods by workers living in i. This implies Marshallian demands

$$\begin{aligned} q_{i,i} &= \left(\frac{p_{i,i}}{P_i}\right)^{-\sigma} \frac{w_i}{P_i} \\ q_{i',i} &= \left(\frac{p_{i',i}}{P_i}\right)^{-\sigma} \frac{w_i}{P_i} \end{aligned} \tag{3.15}$$

where $P_i \equiv \left[(p_{i,i})^{1-\sigma} + (p_{i',i})^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$ is an index that measures the "true" cost of living in location i and functions identically to G, but in a demand-side context. Substituting these demands into the expression for Q_i reveals the optimal goods consumption bundle for workers residing in i can be expressed

$$Q_i = \frac{w_i}{P_i} \tag{3.16}$$

Given the worker's Cobb-Douglas preference specification and the definition of δ_i, the ratio $\frac{1}{1-\delta_i}$ can be re-expressed as $\frac{I_i}{r_i}$, that is the ratio of total income to housing expenditure. Furthermore, assuming i has a fixed housing supply H_i, the housing market clearing implies that the total value of housing in i, $r_i H_i$, must equal total housing expenditure by workers in i, $(1-\delta_i)I_i L_i$, where L_i is the endogenously determined equilibrium quantity of workers in i. Solving for r_i from the housing market clearing condition and substituting it into the income to housing expenditure ratio, it follows that

$$\frac{1}{1-\delta_i} = \frac{I_i}{r_i} = \frac{H_i}{(1-\delta_i)L_i} \tag{3.17}$$

Letting $h_i = 1$ and substituting equations (3.16) and (3.17) into equation (3.12), the worker living in i has indirect utility

$$U_i = \Theta_i \left(\frac{w_i}{\delta_i P_i}\right)^{\delta_i} \left(\frac{H_i}{(1-\delta_i)L_i}\right)^{1-\delta_i}$$

Choosing units such that $\Theta_i = \frac{\delta_i^{\delta_i}(1-\delta_i)^{1-\delta_i}}{H_i}$, indirect utility can be expressed

$$U_i = L_i^{\delta_i - 1} \left(\frac{w_i}{P_i}\right)^{\delta_i} \tag{3.18}$$

implying that the utility of living in i is increasing in the wage w_i, decreasing in the price index P_i, and decreasing in the population L_i. The result that utility is decreasing in the size of the local population implies that the fixed housing supply operates as a dispersion force that works in opposition to clustering forces in i. The sensitivity of indirect utility to changes in the endogenous variables $\{w_i, P_i, L_i\}$ is exogenously determined by the size of δ_i.

In deciding where to live and supply her labour, a worker-consumer chooses to locate where her utility is maximised. Assuming no uncertainty, she observes the set of values $\{w_c, w_r, P_c, P_r, L_c, L_r\}$ and chooses to live in the city whenever indirect utility in the city is such that $U_c > U_r$ and the rural town whenever indirect utility there is such that $U_c < U_r$. She is indifferent between living in the city and rural town in the event that $U_c = U_r$.

3.3 Intra-Regional Trade, Total Demands, and Gravity

I assume intra-regional trade is costly, with trade costs taking the Samuelson (1954) iceberg form, implying that in order for a unit of a good produced in i' to arrive in i, $\tau_{i',i} > 1$ units must be shipped because $\tau_{i',i} - 1$ units of good i' "melts" in transit to i. To factor trade costs into goods pricing, I express the price of good i' paid by workers in i as $p_{i',i} = \tau_{i',i} p_{i'}$, where $p_{i',i}$ is a mark-up of factor $\tau_{i',i}$ over the mill price $p_{i'}$. Given there are no frictions associated with local trade, the price for good i in i is the mill price, i.e. $p_{i,i} = p_i$. Under these trade cost assumptions, the local price index for location i can be re-expressed as $P_i \equiv \left[p_i^{1-\sigma} + (\tau p_{i'})^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$.

Due to costly trade, the total demand for goods produced in each location is intimately linked with transport costs. Assuming bilaterally symmetric trade costs between the city and rural town (i.e. $\tau_{c,r} = \tau_{r,c} = \tau$) it follows that for $q_{r,c}$ units of the rural good to arrive in the city, $x_{r,c} = \tau q_{r,c}$ must be shipped. Similar logic follows for the quantity of the urban good $x_{c,r}$ that must be shipped to meet rural demand $q_{c,r}$. Letting $x_{c,c} = q_{c,c}$ and $x_{r,r} = q_{r,r}$ (since, again, there are no local trade frictions), the total regional demands for the urban good X_c and rural good X_r are

$$
\begin{aligned}
X_c &= x_{c,c} L_c + x_{c,r} L_r = p_c^{-\sigma}\left[P_c^{\sigma-1} w_c L_c + P_r^{\sigma-1} w_r L_r \tau^{1-\sigma}\right] \\
X_r &= x_{r,c} L_c + x_{r,r} L_r = p_r^{-\sigma}\left[P_c^{\sigma-1} w_c L_c \tau^{1-\sigma} + P_r^{\sigma-1} w_r L_r\right]
\end{aligned}
\tag{3.19}
$$

where $\{L_c, L_r\}$ is the (endogenously determined) allocation of total labour $\overline{L}$ between the two locations. Since workers are assumed identical, demands are common to all workers. As such, total demands are the individual demands of workers in location i multiplied by the number of workers located in i.

The CES demand specification for worker preferences over goods allow the value of intra-regional trade to be expressed as an Anderson (1979)/Anderson and van Wincoop (2003)-style gravity relationship. Denote the value of trade originating in the city and delivered to the rural town as $V_{c,r} = p_c x_{c,r}$ and the value of trade originating in the rural town and delivered to the city as $V_{r,c} = p_r x_{r,c}$. Given the functional specification of $x_{r,c}$ and $x_{c,r}$ as well as Marshallian demands $q_{r,c}$ and $q_{c,r}$, equilibrium intra-regional trade values are

$$V_{r,c} = \left(\frac{p_r}{P_c}\right)^{1-\sigma} w_c L_c \tau^{1-\sigma}$$
$$V_{c,r} = \left(\frac{p_c}{P_r}\right)^{1-\sigma} w_r L_r \tau^{1-\sigma}$$

Since $\sigma > 1$, as trade costs τ grow, the value (i.e. quality adjusted volume) of trade between the city and the rural town decreases.

Algebraic manipulation (as I show in Appendix A.1) reveals the above can be re-expressed as so-called "structural gravity" equations

$$\begin{aligned} V_{r,c} &= \left(\frac{\tau}{\Lambda_r P_c}\right)^{1-\sigma} \frac{w_r L_r w_c L_c}{wL} \\ V_{c,r} &= \left(\frac{\tau}{\Lambda_c P_r}\right)^{1-\sigma} \frac{w_c L_c w_r L_r}{wL} \end{aligned} \tag{3.20}$$

where $\Lambda_i \equiv \left[P_i^{\sigma-1}\theta_i + P_{i'}^{\sigma-1}\tau^{1-\sigma}\theta_{i'}\right]^{\frac{1}{1-\sigma}}$ for $i \in \{c,r\}$ is a θ-weighted average of the transport costs relative to local prices $p_{i'}$ faced by location i and $\theta_i = \frac{w_i L_i}{wL}$ is the share of total regional income earned in i. As such, while P_i measures how costly it is to consume in i, Λ_i measures how costly it is to export from i to i'. The structural gravity equations (3.20) state that bilateral trade flows between the city and rural town depend log-linearly on exporter and importer size (as measured by labour costs) and negatively on bilateral trade costs. Anderson and van Wincoop (2003) call Λ_i and $P_{i'}$ multilateral resistance terms, as increases in either reduce trade volume between the city and rural town. The term $\frac{w_c L_c w_r L_r}{wL}$ reflects "frictionless trade," which depends only on the relative size of trading parties.

3.4 Equilibrium

Given optimal producer and consumer behaviour as well as intra-regional trade dynamics described in the preceding sections, the model can be summarised by the following set of simultaneous equations:

$$\begin{aligned} Y_c &= A_c L_c^{1+\varepsilon} & Y_r &= A_r L_r \\ w_c &= p_c A_c L_c^{\varepsilon} & w_r &= p_r A_r \\ X_c &= p_c^{-\sigma}\left[P_c^{\sigma-1} w_c L_c + P_r^{\sigma-1} w_r L_r \tau^{1-\sigma}\right] & X_r &= p_r^{-\sigma}\left[P_c^{\sigma-1} w_c L_c \tau^{1-\sigma} + P_r^{\sigma-1} w_r L_r\right] \\ P_c &= \left[p_c^{1-\sigma} + (\tau p_r)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} & P_r &= \left[(\tau p_c)^{1-\sigma} + p_r^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \\ U_c &= L_c^{\delta_c - 1}\left(\frac{w_c}{P_c}\right)^{\delta_c} & U_r &= L_r^{\delta_r - 1}\left(\frac{w_r}{P_r}\right)^{\delta_r} \end{aligned} \tag{3.21}$$

These equations determine the instantaneous equilibrium, which is characterised by five conditions that map to those specified in Allen and Arkolakis (2014), but in a two-location environment.

First, goods markets must clear, meaning the total supply of both the rural good Y_r

and the urban good Y_c must satisfy total demands in both the city and the rural town for both goods, i.e. X_r and X_c.[2] Second, the regional labour market must feature full employment. That is to say, not only must local labour markets clear (e.g. $L_r^D = L_r^S = L_c$), but so too must the equilibrium distribution of labour between the city and rural town sum to $\overline{L}$, the region's total labour force. Third, both locations must be inhabited, meaning not all workers can live in the city while none live in the rural town, and vice versa. Forth, utilities must equalise over space, meaning the utility of living in the city must match that of living in the rural town so that the marginal worker is indifferent between living in the city or the rural town. The final condition is that the equilibrium must be feature point-wise stability, meaning that no small number of workers can increase their utility by moving to the other location i.e. no spatial utility arbitrage is possible. The equilibrium criterion can therefore be summarised as follows:

1. Goods markets clear: $Y_r + Y_c = X_r + X_c$
2. Full regional employment: $L_r + L_c = \overline{L}$
3. Both locations are inhabited: $\{L_c, L_r\} \in \mathbb{R}_{++}$
4. Utility equalisation over space: $U_r = U_c$
5. Point-wise stability (no spatial arbitrage): $\frac{dU_i}{dL_i} < 0$ for $i \in \{c, r\}$

Given its non-linearities, I solve the model numerically. Using the system of equations (3.21), I numerically evaluate the system at different distributions of the total factor endowment $\overline{L}$ between the city and rural town such that goods markets clear [3] Computing U_r and U_c at these points and finding where they equalise, I identify candidate equilibria that satisfy requirements one through five above.

With the exception of the elasticity of substitution, iceberg transport costs, and urban agglomeration economies (which were chosen to match common values used in the literature), the exogenous parameters in the model were calibrated to reflect empirical realities concerning differences between urban and rural areas, especially those located in the FRUC and its hinterland. In particular, care was taken to calibrate exogenous location-specific TFP, A_c and A_r, according to estimates from this paper performed in Section 4.3 and to choose location-specific expenditure shares, δ_c and δ_r, that match to empirical estimates for urban and rural spending. The baseline values and sources for model parameters are given in Table (3.1) and the resulting dynamics are shown in Figure (3.1).

Figure (3.1) plots the (log of) utility in the city (blue) and rural town (red) against the share of the region's total labour force $\overline{L}$ (normalised to unity) working and living in the city, L_c. Along each curve, both goods markets clear. Labour allocations (L_c, L_r) to the left of the point E_0 imply higher utility in the city relative to the rural town, while

[2] An implication of this equilibrium requirement is that not only must the zero profit condition hold for final firms in the city and rural town, but so too must the intermediate firm profit maximising condition and intermediate firm sub-sector zero profit condition.

[3] i.e. given factors allocation $\{L_c, L_r\}$ where $L_r + L_c = \overline{L}$, I numerically identified the set $\{p_c, p_r, w_c, w_r, P_c, P_r\}$ at which point $Y_r + Y_c = X_r + X_c$.

Table 3.1: Baseline Theoretical Model Parameter Values

Parameter	Source	Value	Comments
Elasticity of substitution: σ	Allen and Arkolakis (2014)	$\sigma = 4$	Equilibrium becomes more sensitive to changes in σ as its value decreases, though the main qualitative implications are robust to parameterisation.
Iceberg trade costs: τ	Fujita, Krugman, and Venables (1999)	$\tau = 1.7$	This value corresponds to the "intermediate transport costs" in Fujita, Krugman, and Venables (1999). As in Allen and Arkolakis (2014), higher transport costs encourage clustering in the city. Main qualitative results are robust parameterisations.
Urban agglomeration economies: ε	Allen and Arkolakis (2014)	$\varepsilon = 0.1$	Parameterisation consistent with empirical agglomeration evidence from Rosenthal and Strange (2004).
Urban TFP: A_c	Author's estimates	$A_c = 0.94$	Averaged estimated TFP for Front Range urban corridor. See Section 4.3 for estimation details and Appendix Table (B.10) for estimate source.
Rural TFP: A_r	Author's estimates	$A_r = 0.73$	Averaged estimated TFP for rural Colorado ZCTAs located within the FRUC rural periphery. See Section 4.3 for estimation details and Appendix Table (B.9) for estimation source.
Urban goods expenditure share: δ_c	Author's calculation using Hawk (2013)	$\delta_c = 0.77$	Average total non-housing expenditure (total expenditure net shelter, house furnishings and equipment, and household operation spending) for urban households in 2011 was 74%, while just non-shelter expenditure was 79%. Taking the average between the two expenditure measures (like Allen and Arkolakis, 2014) for urban households implied value of roughly 77%
Rural goods expenditure share: δ_r	Author's calculation using Hawk (2013)	$\delta_c = 0.85$	Average total non-housing expenditure for rural households in 2011 was 82%, while just non-shelter expenditure was 87%. Taking the average expenditure share implied a value roughly 85%.

allocations to the right of E_0 imply higher utility in the rural town relative to the city. In both scenarios, workers located in the place with lower utility can make profitable utility gains moving to the other location (i.e. perform spatial arbitrage). Utility differences stimulate intra-regional migration, the direction of which is indicated by the arrows along each curve, with workers moving to either the city or rural town depending on where said utility gains can be made.

This process continues until point E_0, which is the unique and point-wise stable equilibrium of the model comprised of the set of values $\{L_i^*, p_i^*, w_i^*, w_i^*, U_i^*, M^*, g^*\}$ for $i \in \{c, r\}$.

At E_0, both goods markets clear, the region features full employment, both locations have positive populations, the curves cross so utilities equalise over space and, finally, since $\frac{dU_c}{dL_c} < 0$ and $\frac{dU_r}{d(1-L_c)} < 0$, E_0 is point-wise stable. Under this parameterisation, E_0 is the only crossing point of U_r and U_c for $L_c \in (0,1)$ and is thus unique.

However, while utilities are equal at E_0, other components of the equilibrium are not. Wages in the city are higher than wages in the rural town (i.e. there is a rural-urban earnings gap) and the urban good is cheaper than the rural good (due to increasing returns). As a direct result of equilibrium pricing and the costs associated with intra-regional trade, the price index in the city is lower than that in the rural town. Finally, the equilibrium factor endowments are not symmetric. As in classic urban models, the model's equilibrium city size is the result of the fundamental trade-off of urban economics, i.e. the competing agglomeration economies and diseconomies associated with population size. The equilibrium value of L_c is the point at which the marginal benefit of an additional worker in urban final good production is equal to the marginal cost she introduces moving to the city via increased housing costs.

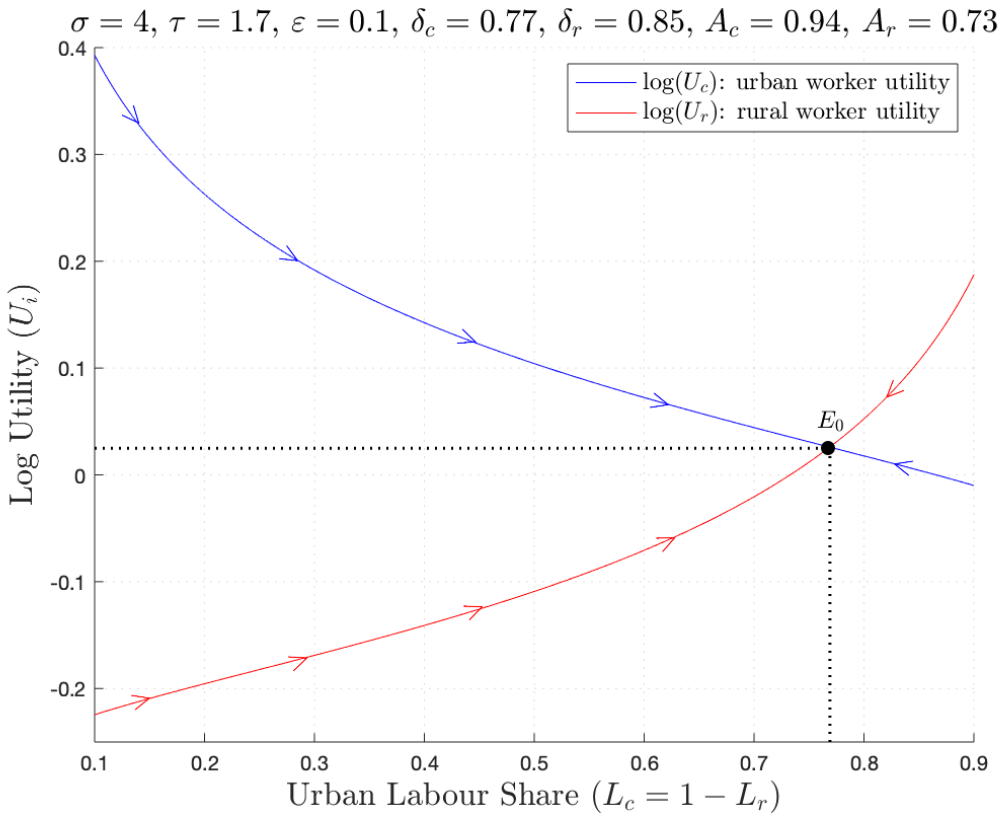
The equilibrium labour allocation asymmetry at E_0 is akin to the core-periphery class of models pioneered by Krugman (1991a), Krugman (1991b), and Fujita, Krugman, and Venables (1999).[4] This model predicts workers will cluster in the location that exhibits increasing returns, with about 78% of the region's total worker population residing in the city. This urban-rural population divide is close to the actual rural-urban population spread in the US, where in 2010 approximately 80% of the population lived in cities while 20% live in rural communities (US Census Bureau, 2016).

However, since this model borrows extensively from the menu of assumptions common among quantitative spatial models developed in the past decade, the underlying mechanisms driving the rural-urban asymmetry differ from core-periphery models. Namely, the centripetal forces promoting urban clustering here result from input-output linkages within urban production, not due to the re-enforcing agglomeration cycle powered by the home market effect and price effect. Additionally, the centrifugal forces in this model are not transport costs between locations, but rather dispersion forces introduced via a fixed housing stock.[5] Finally, this model abstracts from the "flat earth" assumption common to the core-periphery model and other new economic geography models, where all regions are ex-ante identical. The fact that the city and rural town have different technology, productivity, and preferences (in the form of budget shares) ex-ante powers the ex-post uneven equilibrium factor allocation. Moreover, by relaxing assumptions of symmetry among locations, the differences between the city and rural town results in a unique equilibrium, unlike the multiplicity of equilibria that are possible for certain transport cost levels in new economic geography models.

[4] Specifically, Fujita, Krugman, and Venables (1999) find the core-periphery pattern arises (and is point-wise stable) for "low" and "intermediate" transport costs. For transport costs above the core-periphery sustain point, they find that the only stable equilibrium, which is also unique, is a symmetric equilibrium where both locations have half of all workers in the sector with increasing returns.

[5] In fact, I show in Appendix Figure (A.2) that increasing intra-regional transport costs stimulates further clustering in the city, just as in the framework developed by Allen and Arkolakis (2014).

Figure 3.1: Baseline Model Dynamics



Notes: This figure demonstrates the underlying model dynamics towards a unique and point-wise stable spatial equilibrium between the city and rural town, denoted E_0. I plot utility in each region as a function of the region's share of labour living and working in the city. Along each curve, both goods markets clear. For labour allocations below E_0, utility in the city (blue) is greater than utility in the rural town (red), stimulating migration of workers from the rural periphery to the urban core. The converse is true to the right of E_0, where utility gains can be made moving from the city to the rural town. The arrows along the curves depict these transition dynamics. Given the technology and expenditure asymmetries, which operate as centripetal and centrifugal forces, respectively, between the city and the rural town, the resulting equilibrium E_0 implies a larger share of labour locating in the city.

3.5 Effect of Urban TFP Growth on Rural Employment Growth

I now explore how the unique, point-wise stable equilibrium outlined in the preceding section responds first to exogenous growth in urban TFP A_c in isolation, then to simultaneous growth in urban and rural TFP. Suppose the region is initially located at the equilibrium point, E_0, where $A_c = 0.94$. Suppose further that A_c exogenously increases by 3.4% to $A_c = 0.97$ while rural TFP A_r remains unchanged.[6] Figure (3.2a) plots utility in both the city and rural town against the rural employment share L_r and documents the change from the initial equilibrium to the new equilibrium, denoted E_1.

The TFP growth in the city shifts utility in the city *and* the rural town upwards; however the utility gains in the city at the original equilibrium are considerably larger. For instance, the 3.4% increase in urban TFP facilitates an approximately 2.3% utility gain

[6] I experiment with this particular growth value, as this is a one standard deviation in the explanatory variable of interest in the empirical analysis and the 3.4 percentage point value is used to interpret the benchmark parameter estimates.

in the city but only a 0.1% utility gain in the rural town for any given labour allocation in the neighbourhood of E_0. As such, the shift in urban utility dominates, prompting the new point-wise stable spatial equilibrium E_1 to exhibit a lower share of workers living in the rural town, but a higher level of equilibrium regional utility. Specifically, moving from E_0 to E_1, the rural labour force declines by about 8% while the utility of workers living in either location increases by roughly 1.9%. Workers are unambiguously better off regardless in both places, but there is out-migration from the rural town on account of urban TFP growth.

Consider now a situation in which instead of isolated exogenous urban TFP growth, rural TFP grows as well, but at a slower rate. Suppose that A_c still grows 3.4%, but also A_r experiences half as large growth (i.e. 1.7%), thereby increasing to 0.74. Figure (3.2b) plots utility in both the city and rural town against the rural employment share L_r and documents the change from the initial equilibrium to the new equilibrium, denoted E_1'. The urban TFP shock's impact on utility in the city is effectively unchanged, however, the growth in rural TFP increases rural utility at E_0 by 1.1%. The new equilibrium E_1' sports a utility level 2.1% larger than that at E_0 and the rural share of total regional employment declines by 4.3%.

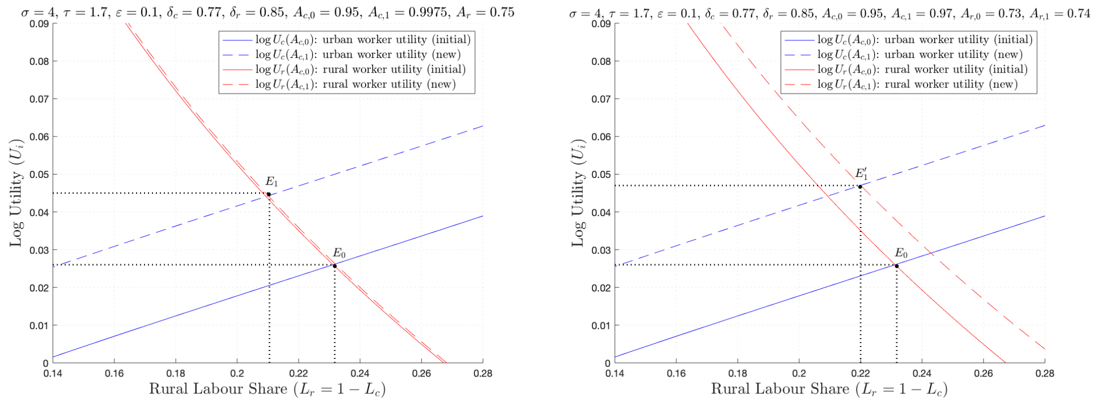
These shocks reveal that urban TFP growth has negative implications for growth in rural employment, however the negative effects can be mitigated by local innovations to rural TFP. The model conveys that the regional economy's adjustment to exogenous urban TFP shocks operates through TFP's relationship with final good pricing, wages, and utility equalisation requirements in equilibrium. Perfect competition among final good firms implies that the price of the final good produced in i is equal to the marginal cost of producing said good in i. Furthermore, in this market structure, factors of production are paid their marginal product. An increase in A_c stimulates a decrease in p_c and an increase in w_c via decreasing marginal costs faced by final firms in the city through increased productivity by the marginal worker.

The requirement that utilities equalise over space puts upward pressure on rural wages to maintain the labour force necessary to meet total regional demands for the rural good. In the case of an isolated urban TFP shock, since rural TFP remains unchanged, this upward pressure on rural wages increases the marginal cost of production, thereby increasing the market clearing price of the rural good. The decrease in p_c and increase in p_r, in turn, adjust the location-specific price indices, notably with P_r growing substantially more than P_c on account of changes to p_r being more influential in the determination of the rural price index.[7] Urban TFP growth, then, stimulates growth in wages and price indices in both locations. However, wages in the city grow more than wages in the rural town while the rural price index grows more than the urban price index. Given the functional specification of (indirect) utility, these differences originating from increases in A_c result in spatial arbitrage from the rural town to the city until dispersion forces in the city prohibit further utility gains through migration.

Figure (3.3a) shows the relationship between equilibrium rural labour share L_r^* and

[7] Mechanically, this is due to the influence of rural price increases being discounted by τ in P_c's functional specification.

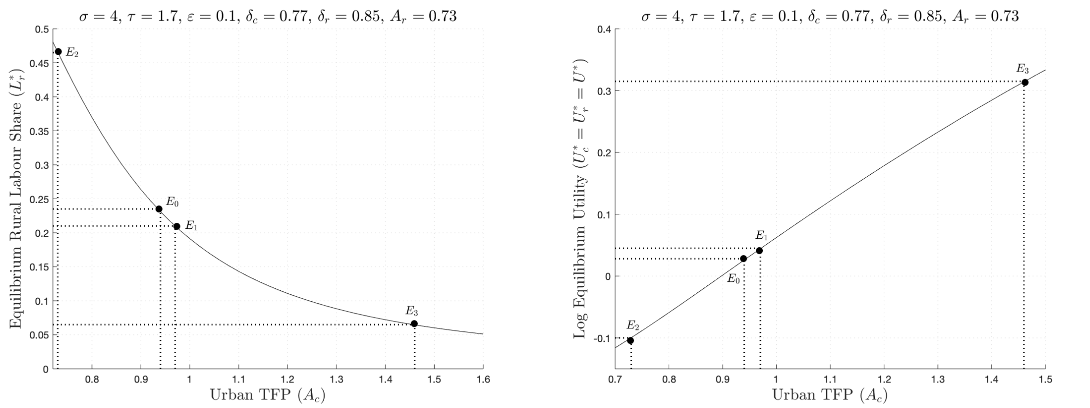
Figure 3.2: TFP Growth Shocks and the Rural Labour Share



(a) Isolated positive urban TFP growth **(b)** Positive urban and rural TFP growth

Notes: The figure details the model's response to exogenous changes in urban TFP A_c. Panel (a) evaluates the comparative statics of urban utility (blue) and rural utility (red) associated with increasing A_c by 3.4% in (L_r, U) space, which moves the system from initial equilibrium E_0 to new equilibrium E_1. While regional utility is higher in the new equilibrium, the share of labour living in the rural town is lower. Panel (b) evaluates the comparative statics of urban utility and rural utility associated with increasing A_c by 3.4% *and* increasing A_r by 1.7% in (L_r, U) space, which moves the system from initial equilibrium E_0 to new equilibrium E_1', which is to the right of E_1 given the innovations to rural TFP blunt the effects of an urban TFP increase.

Figure 3.3: Urban TFP and the Rural Labour Share



(a) Equilibrium L_r as a function of urban TFP **(b)** Equilibrium U as a function of urban TFP

Notes: The figure details the equilibrium's response to exogenous changes in urban TFP A_c. Panel (a) plots the equilibrium level of rural employment L_r^* against A_c, revealing a "rural flight" associated with high levels of A_c. Panel (b) plots the equilibrium (log) utility level U^* against A_c, implying that innovations to TFP in the urban core unambiguously leaves workers living in either location better off. Thus, the model's main qualitative finding is that urban TFP growth is associated with employment growth declines in the rural town, but aggregate well-being is higher across both locations.

urban TFP A_c. The growth of A_c prompts "rural flight" to the city, facilitating an emptying of the rural town. However, the effect of sequential urban TFP growth is blunted as A_c grows in levels. As the absolute level of the city's TFP increases, the subsequent rate of rural out-migration due to future urban TFP gains decreases. For example, if A_c is relatively low (e.g. 0.8), a 1% increase in urban TFP would have a much larger negative effect on rural labour levels compared to 1% growth in urban TFP if it is initially large (e.g. 1.4). As such, the model predicts regions with a large ex-ante urban-rural TFP gap will not experience large ex-post rural flight due to urban TFP growth. Instead, regions with small initial urban-rural TFP gaps will see the largest geographic population shifts. This has interesting implications for regions with emerging cities that do not have a large TFP edge over their rural periphery, as the model suggests they will experience much faster rates of urbanisation after an exogenous TFP shock.

The equilibria previously discussed, E_0 and E_1, are shown in figure (3.3a) alongside two additional equilibria. E_2 is the unique, point-wise stable equilibrium when there is no regional asymmetry in TFP levels ($A_c = A_r$). The ex-ante technology differences between the two regions ensure that even when TFP in levels are equal (which is empirically not the case, and cities are found to be more productive), there is an asymmetric equilibrium with (slight) clustering in the city. E_3 is the equilibrium when the city has a TFP in levels twice that of the rural town. In this case, a little over 5% of the region's population lives in the rural town (high degree of regional urbanisation). From a welfare perspective, this model predicts that urban TFP growth leaves the region's inhabitants unambiguously better off. Figure (3.3b) plots the (log) of equilibrium utility against urban TFP levels, demonstrating a near log-linear relationship between welfare and urban TFP.

The simplistic two-region set-up of this model in combination with its lack of dynamic processes are unrealistic simplifying assumptions. However, there are there are three key qualitative insights this model provides to guide the empirical analysis. First, it predicts that urban TFP growth corresponds to negative rural employment growth. Second, local TFP growth in the rural town can, to some extent, counteract out-migration facilitated by urban TFP growth. Finally, the decline in rural employment due to urban TFP gains is decreasing in urban TFP levels and so TFP growth in highly productive cities will not prompt large rural out-migration. Motivated by the implications of the model, in the empirical analysis to follow, I test the suggested relationship between TFP growth in an urban core and employment growth within rural communities located in that urban core's hinterland.

4 Data Construction

To empirically test the associations between growth in rural employment and urban total factor productivity (TFP) implied by the theoretical model, I use data on ZCTAs located in the FRUC and its rural hinterland in US state of Colorado from 2001 to 2017. I combine confidential establishment-level employment and labour cost data with estimates of TFP growth for 361 ZCTAs, 245 of which are located in a parent county considered urban and the remaining 116 located in a parent county considered rural. Data on urban ZCTAs are aggregated according to their parent MSA. The empirical analysis explores how employment growth in the average rural ZCTA covaries with growth in a spatial connectivity weight sum of FRUC TFP.

In the discussion to follow, all monetary units are adjusted for inflation and are in terms of 2001 USD, consistent with the Bureau of Labor Statistic (BLS) Consumer Price Index (CPI) for the Denver-Aurora-Lakewood MSA (the Denver MSA henceforth). While the Denver CPI only measures price dynamics for a bundle of goods purchased by urban consumers living in Denver, there are observable differences between the evolution of the Denver CPI against the aggregate US CPI as well as the Western US CPI (see Appendix B.1). As such, deflating according to the Denver CPI seems most appropriate for constructing constant price data for spatial units in the state of Colorado compared to the other trans-state alternatives.

4.1 Geography and Spatial Units of Analysis

Before discussing the data in detail, I briefly discuss Colorado's geography and the spatial units studied in the empirical analysis. Colorado is a state located in the Western US with a total estimated population of 5.7 million residents as of 2018 (Colorado State Demography Office, 2019) and is home to a diverse geography consisting of mountains, plains, and deserts. For administrative purposes, Colorado is subdivided into 64 counties, 17 of which are considered 'urban' by the US Department of Agriculture's Rural Urban Continuum Codes (RUCC), with the remaining 47 considered 'rural.'[8]

The state's urban counties are grouped into larger geographic units by the US Office of Management and Budget (OMB) called Metropolitan Statistical Areas (MSAs), with each of these MSAs having at least one urbanised area of 50,000 or more inhabitants.[9] Colorado has seven MSAs: Boulder, Colorado Springs, Denver (which contains the state's capital and is the largest MSA), Fort Collins, Grand Junction, Greeley, and Pueblo. With the exception of Grand Junction, all of Colorado's urban counties are located along the eastern edge of the Rocky Mountains in an urban cluster referred to as the Front Range Urban Corridor (FRUC). In 2018, the FRUC was estimated to be home to approximately 4.8 million people, which accounts for 85% of the state's population. Given the definition of MSAs as spatial units oriented around a core urbanised area, the FRUC is are the empirical mapping of the city from the theoretical model.

Just as some of Colorado's counties are the elements of larger geographic units (i.e. MSAs), counties are comprised of smaller geographic units. The US Census Bureau subdivides Colorado's 64 counties into 526 census designated regions known as ZIP Code Tabulation Areas (ZCTAs), so-called due to the fact that they more or less map to the boundaries of the US Postal Service's Zone Improvement Plan (ZIP) codes, which organise regional mail delivery throughout the US. ZCTAs are small geographic units, and those located in sparsely populated areas tend to be associated with a town or unincorporated areas with a post office. As such, ZCTAs located within rural counties, rural ZCTAs henceforth, roughly serve as the empirical analogue to the rural town from the theoretical model.

[8] The RUCC is a classification scheme that distinguishes densely populated metropolitan counties from more sparsely populated rural counties based on the population of the largest urban cluster in a particular county. Counties with an urban cluster of fewer than 50,000 residents are considered nonmetropolitan. 'Rural' in this study is adopted as a term to refer to these nonmetropolitan areas that are sparsely populated.

[9] See https://www.census.gov/programs-surveys/metro-micro/about.html for classification details.

Excluding Grand Junction, Colorado displays a quintessential core and periphery geographic rural-urban divide, with a centralised urban core surrounded by a rural periphery. To empirically test the theoretical model's implications in regard to TFP growth in the city being negatively associated with employment growth in the rural town, I isolate Colorado's amenable urban-rural geography, restricting my analysis to the FRUC and its hinterland. As such, in this paper I exclude Grand Junction and its hinterland (which includes 79 ZCTAs), instead considering the six MSAs that comprise the FRUC and the ZCTAs located in its hinterland. I define the FRUC hinterland as the group of rural ZCTAs for which the closest MSA by road in kilometres (estimation details on this are described below) is either Boulder, Colorado Springs, Denver, Fort Collins, Greeley, or Pueblo. I further reduce the sample of rural ZCTAs by restricting attention to ZCTAs that have at least one reporting establishment each year during the sampling interval (2001 to 2017) and more than 10 employees working locally in any given year. The exact details concerning these selection criteria are given below, but it results in a sample of 116 rural ZCTAs.

In Figure (4.1), I map the locations of the spatial units discussed above in the state of Colorado. Each polygon in the map is the boundaries of a ZCTA. Polygons shaded white are ZCTAs either not within the FRUC/its hinterland or excluded due to insufficient data, blue ZCTAs are located within the FRUC, and red ZCTAs are part of the rural periphery. The different shades of blue among the FRUC ZCTAs differentiate the six MSAs that make up the FRUC. In the empirical analysis to follow, I investigate how TFP growth in the collective blue region associates with employment growth in each individual the red regions.

4.2 Employment and Labour Cost

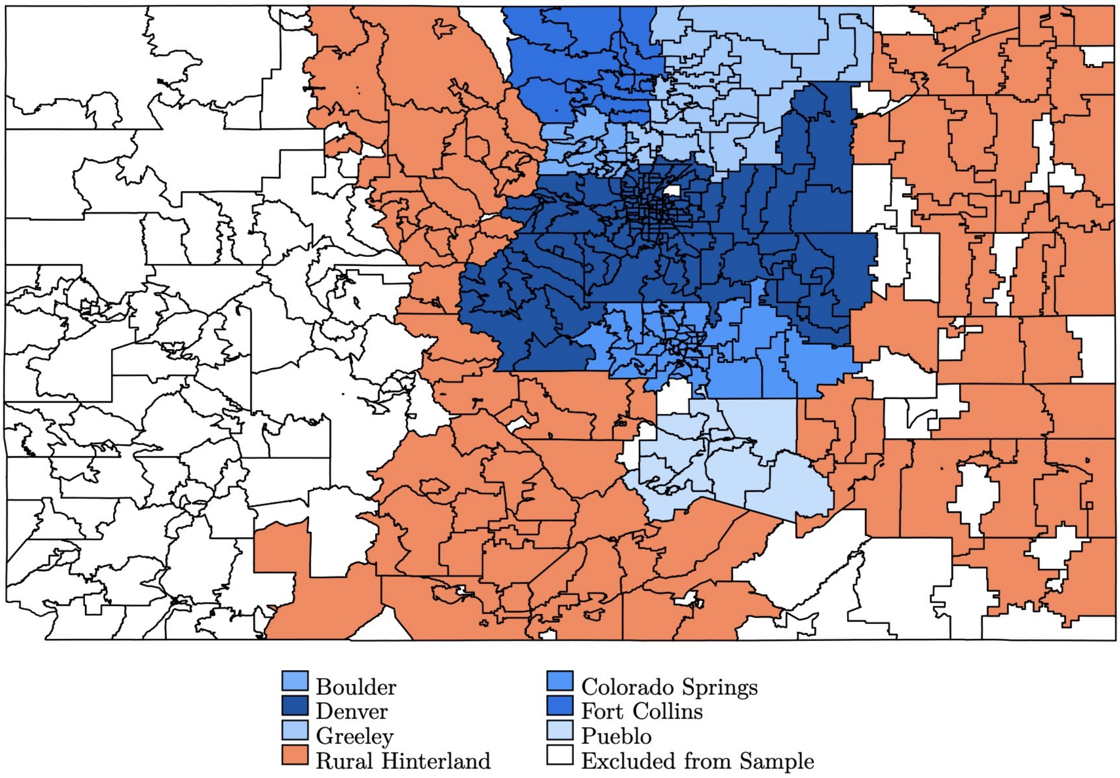
I measure ZCTA employment and labour cost among privately owned business establishments by two-digit NAICS sectors from 2001 to 2017.[10] These data are confidential establishment-level data from the Quarterly Census of Employment and Wages (QCEW) provided by the Colorado Department of Labor and Employment (CDLE).[11] These data offer detailed accounts on the geographic location and sectoral classification of individual business establishments, as well as records concerning their monthly employment levels and quarterly wage expenditures. I use these data to estimate the average number of workers employed within a ZCTA in a given year and the total costs for labour paid by all establishments in a ZCTA over the course of a year for each sector in each sample ZCTA.

Denote $e \in \{1, 2, \ldots, E\}$ as the set of all reporting business establishments in the Colorado

[10] The North American Industrial Classification System (NAICS) is a sector classification system that groups establishments into sectors based on the similarity of their production processes OMB (2017). The NAICS divides the economy into 20 sectors, which are numerically identified by a two-digit code.

[11] The CDLE is the Colorado state-level counterpart of the Bureau of Labor Statistics (BLS). The QCEW is a nationally coordinated survey by BLS that tabulates the employment and wages of establishments, specifically those that employ workers other than the proprietor and report to the US Unemployment Insurance (UI) programme. Approximately 97% of employers in the US report to the QCEW. These data do not include statistics on non-employing (e.g. "gig economy") establishments.

Figure 4.1: Front Range Urban Corridor MSAs and Rural Hinterland



Notes: This figure maps the spatial units of interest in reference to the entire state of Colorado. Each polygon represents a different ZCTA located in the state of Colorado. ZCTAs in white are excluded from the sample (either due to not belonging to the Front Range Urban Corridor (FRUC) urban-rural system or insufficient data), blue ZCTAs are part of MSAs that belong to the FRUC, and red ZCTAs make up the FRUC's rural periphery. Different shades of blue denote different MSAs.

QCEW.[12] For each establishment e reporting in year $t \in \{1, 2, \ldots, T\}$, I average the monthly employment count to estimate the annual employment level of e, $L_{e,t}$. I aggregate the reported (before tax) total wage bill paid by e for each quarter in t to estimate total labour costs paid by establishment e during t, $W_{e,t}L_{e,t}$.[13] Let $e^{i,h}$ be a subset of the set of total business establishments that include establishments reporting to be located in ZCTA $i \in \{1, 2, \ldots, N\}$ and operating in sector $h \in \{1, 2, \ldots, H\}$.[14] I then estimate average employment in ZCTA i's sector h as

$$L_{i,h,t} = \sum_{e \in e^{i,h}}^{E} L_{e,t}$$

$$W_{i,h,t}L_{i,h,t} = \sum_{e \in e^{i,h}}^{E} W_{e,t}L_{e,t}$$

Total employment and labour costs in ZCTA i are estimated as the sum of $L_{i,h,t}$ and

[12] In any given year, there were around 170,000 reporting establishments in the state of Colorado.

[13] I use before tax labour costs, as these data are likely to better reflect the total value of the labour being purchased for production purposes.

[14] It need not be the case $H = 20$. Some ZCTAs, particularly those in the hinterland, do not have establishments operating in all 20 NAICS two-digit sectors.

$W_{i,h,t}L_{i,h,t}$ across sectors h, respectively, i.e.

$$L_{i,t} = \sum_{h=1}^{H} L_{i,h,t}$$
$$W_{i,t}L_{i,t} = \sum_{h=1}^{H} W_{i,h,t}L_{i,h,t}$$

which are equivalent to aggregating $L_{e,t}$ and $W_{e,t}L_{e,t}$ across $e \in e^i$, where e^i is the set of business establishments located in ZCTA i. Note then that $e^{i,h} \in e^i$. To be clear, ZCTA employment (sectoral and total) in this study is the sum of the average level of employment among establishments belonging to the relevant parent set of interest (i.e. either $e^{i,h}$ or e^i). In other words, it represents the average count of employees working in a ZCTA over the course of a year. This process allocates employees to the ZCTA in which they work (strictly speaking, where their employer reports to be located), not necessarily where these employees live. The ZCTA total wage bill is the sum of (pre-tax) compensation paid to workers by establishments belonging to the relevant parent set of interest and is therefore not an average.

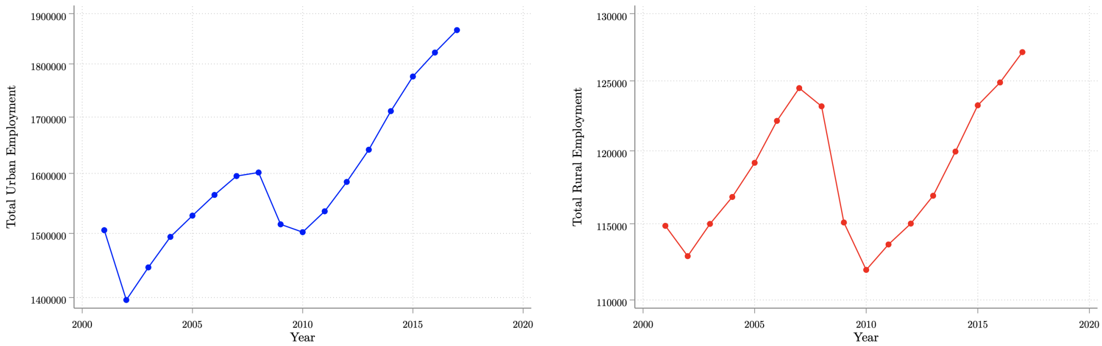
I exclude any ZCTAs for which $L_{i,t}$ is below 10 for any t from the sample used in the empirical analysis, the motivation being their size restricts meaningful inference. I also exclude ZCTAs with inconsistent reporting over the years of observation, retaining those that reported every year from 2001 to 2017. These selection criteria exclude 50 ZCTAs located in the FRUC hinterland.[15] These excluded ZCTAs are not necessarily devoid of economic activity. It reflects that the businesses operating in these ZCTAs do not fit the criteria that requires them to report to the QCEW. Considering many of the excluded rural ZCTAs are located in agriculturally intensive areas, it is likely that the businesses operating within their borders do not employ extra-familial workers. Many of these businesses are probably classified as sole-proprietorship establishments (e.g. family farms, community stores, etc.).[16] I present summary statistics concerning these data, accompanied by sectoral analysis and time series behaviour commentary, for the sample in Appendix B.2.

The data articulate a sizable urban-rural employment gap, with the average urban ZCTA having an employment count on the order of six times that of the average rural ZCTA. In fact, these data suggest that during the observation period, on average 93% of employees were working in an urban ZCTA in any given year. I also find this rural-urban employment gap extends from levels to rates of growth, with above average annual employment growth concentrated among urban ZCTAs. In Figure (4.2), I plot the evolution of (aggregated) urban and rural employment in the sample over time. Both series demonstrate cyclicality consistent with the business cycle. Rural and urban Colorado experienced employment declines during the 2001 and 2007-2009 recessions, but the effect of and recovery from these shocks differed. Following the Dotcom bust in 2001,

[15] These stipulations also eliminated 22 FRUC ZCTAs out of 267, as evidenced by the white gaps in the FRUC of Figure (4.1).

[16] The same intuition holds for any excluded urban ZCTAs.

Figure 4.2: Colorado Employment Dynamics, 2001-2017



(a) Urban Colorado Employment

(b) Rural Colorado Employment

Notes: Panel (a) plots total urban employment in the sample over time and Panel (b) plots total rural employment.

urban Colorado experienced a 7.5% employment decline, while during the 2007-2009 Great Recession, urban employment dropped by 6.4%. Conversely, the reaction of rural employment to the 2001 recession was milder relative to the Great Recession, with rural employment declining by 1.77% during the former and 10.6% during the latter. Furthermore, urban recovery from the Great Recession was swifter, surpassing peak employment levels in 2008 by 2012, while rural employment did not return to 2008 levels until 2015. The differences in urban and rural employment trends mainly stem from differences in regional industrial composition. The 2001 recession hit urban Colorado particularly hard due to its concentration in technology and telecommunication sectors, which were at the centre of the Dotcom bust (Kacher and Weiler, 2017). Given the influence of the business cycle on rural employment dynamics, I control for time fixed effects in the empirical analysis.

4.3 Total Factor Productivity

I use the confidential QCEW data on ZCTAs employment and labour cost in tandem with publicly available county-level and national data on two-digit NAICS sector private Gross Domestic Product (GDP) and value of capital stock to estimate ZCTA equivalents annually from 2001 to 2017. I then use the estimated GDP and capital stock value by sector series to measure ZCTA revenue TFP. The revenue TFP estimates of urban ZCTAs are aggregated to measure MSA revenue TFP.

ZCTA Gross Domestic Product Estimation I estimate GDP for Colorado ZCTAs using recently released county GDP data from the Bureau of Economic Analysis (BEA) (BEA, 2019a). These data offer a comprehensive economic profile of US counties, providing dollar estimates of total output as well as output for each two-digit NAICS sector from 2001 to 2017. Using the data described in Section (4.2), I allocate county $b \in \{1,2,\ldots,B\}$ GDP in sector h to all ZCTAs i within its borders proportional to each ZCTA's share of b's sector h total wage bill. Due to disclosure concerns, county GDP data for certain sectors are suppressed for around 20% of sector-county observations, with approximately 90% of these suppressed observations within rural counties. I impute these missing data using a process described in Appendix B.3.1.[17]

Given data on two-digit NAICS sector-level GDP for each county in Colorado over the period of interest, I estimate ZCTA GDP for each sector using the assumption that the share of county b's sector h total wage bill paid by the sector h establishments active in ZCTA $i \in i^b$, where i^b is the subset of ZCTAs i located in county b, is equal to i's share of county b's h output value.[18] Specifically, I divide the year t total wage bill for sector h in ZCTA $i \in i^b$, $W_{i,h,t}L_{i,h,t}$, by the year t total wage bill for h in county b, $W_{b,h,t}L_{b,h,t}$, to calculate ZCTA i's sector h labour cost share, which I denote as $\psi_{i\in i^b,h,t} = \frac{W_{i,h,t}L_{i,h,t}}{W_{b,h,t}L_{b,h,t}}$. Multiplying $\psi_{i\in i^b,h,t}$ by year t county b sector h GDP, $Y_{b,h,t}$, I estimate ZCTA $i \in i^b$'s sector h GDP in year t as

$$Y_{i,h,t} = \psi_{i\in i^b,h,t} Y_{b,h,t}$$

with i's total GDP expressed as

$$Y_{i,t} = \sum_{h=1}^{H} \psi_{i\in i^b,h,t} Y_{b,h,t}$$

This estimation procedure yields sector level and aggregate GDP estimates for all ZCTAs i in the state of Colorado over the observable period. Summary statistics concerning these estimated series are presented in Appendix B.3.2 for ZCTAs located in the FRUC and its rural periphery alongside an applied example of the procedure.

A more direct way of estimating ZCTA GDP using a wage bill share approach is to allocate ZCTA $i \in i^b$ a share of b's total GDP equal to i's share of b's aggregate total wage bill, and then allocate the estimate for i's total GDP to each sector h at a rate equal to h's share of i's aggregate total wage bill. As I show in Appendix B.3.3, while this "alternative" method produces similar total GDP estimates for ZCTAs on average compared to the "primary" method described above, it results in noticeable differences at the sector level, implying a nontrivial choice in estimation procedure.

Using total wage bill shares to allocate GDP implies a risk of introducing a systematic bias in sector-level GDP estimation. There is the possibility of rewarding sectors that are labour intensive or use high skilled (and presumably higher paid) labour more GDP than sectors that are capital intensive or use low-skill labour, biasing the ZCTA GDP estimates. Assuming within sector labour–capital utilisation rates and skill distributions are more or less constant across establishments in a county, by allocating county GDP shares *within*

[17] Since a county's total output is never withheld, I exploit this property and estimate suppressed observations using the unsuppressed QCEW data from Section (4.2). I allocate a share of each county's GDP that is unaccounted for among the unsuppressed sectors to the suppressed sectors at a rate proportional to that sector's share of the county's total wage bill, which operates under the assumption that larger labour costs are likely to have a larger share of GDP. Given that suppression arises in connection to sectors with relatively little output, noise introduced by this approach is minimal.

[18] It is important to note that while I do not use all ZCTAs in the empirical analysis, I estimate GDP for *all* ZCTAs in the state of Colorado, so as to not over-allocate county GDP to ZCTAs. For instance, if county b has three ZCTAs, but one is excluded from the sample due to the criteria described above, by not allocating GDP to all possible ZCTAs, I risk overestimating the GDP in the two ZCTAs that are in the sample.

sectors to ZCTA-level counterparts, the primary method mitigates the extent of such a bias. However, in relying upon *between* sector total wage bill shares, the alternative method is more susceptible to this bias, thereby motivating the use of the primary method.

ZCTA Capital Stock Value Estimation The BEA provide annual data concerning the value of the net stock of private fixed assets by sector for the aggregate US (BEA, 2019c), but subnational analogues are not yet publicly available. As such, I estimate local capital stock value in an approach exploiting the annual local data described above on ZCTA labour costs and GDP alongside national wage bill data from the BLS (BLS, 2019) as well as national GDP and capital stock value data from the BEA (BEA, 2020). The method borrows from estimation procedures in the literature measuring market power, where a common practice is to infer 'normal' profits by applying an estimated or assumed capital return rate to a measure of the stock of capital. I effectively back engineer this strategy, estimating capital stock by applying a capital return rate to a measure of profits.

Following standard accounting decomposition, GDP in ZCTA i for sector h in year t, denoted $Y_{i,h,t}$, is equal to the sum of total wages paid to employees (i.e. the total wage bill), denoted $W_{i,h,t}L_{i,h,t}$, and total profits earned by the firm/capital owners, denoted $\Pi_{i,h,t}$, i.e. $Y_{i,h,t} = W_{i,h,t}L_{i,h,t} + \Pi_{i,h,t}$. Algebraic manipulation reveals $\Pi_{i,h,t} = Y_{i,h,t} - W_{i,h,t}L_{i,h,t}$. Simultaneously, total profits are equal to the product of the capital return rate $c_{i,h,t}$ (i.e. the per-unit cost of capital use paid to the owner of capital) and the value of net capital stock, $RK_{i,h,t}$, where R is the price of capital and K is capital stock, i.e. $\Pi_{i,h,t} = c_{i,h,t}RK_{i,h,t}$.

Equating the two profit decompositions and solving for the value of capital stock in ZCTA i for sector h in year t, it follows that

$$RK_{i,h,t} = \frac{Y_{i,h,t} - W_{i,h,t}L_{i,h,t}}{c_{i,h,t}} \tag{4.1}$$

Given appropriate data on $W_{i,h,t}L_{i,h,t}$, $Y_{i,h,t}$, and $c_{i,h,t}$, this equation specifies an estimation procedure for the value of sector-specific capital stock at the ZCTA-level across the years of observation.

The data on $W_{i,h,t}L_{i,h,t}$ and $Y_{i,h,t}$ detailed above can be used to estimate the numerator in equation (4.1), which necessitates that $\Pi_{i,h,t} = Y_{i,h,t} - W_{i,h,t}L_{i,h,t} > 0$. There is a small subset of observations in the sample (< 5%) for which this does not hold, likely due to imprecision introduced by the utilisation of GDP estimates.[19] In the event $\Pi_{i,h,t} < 0$, estimates are replaced with data-motivated alternatives, as detailed in Appendix B.4.1.

To estimate $c_{i,h,t}$, I use the national accounts on aggregate GDP Y_t and the value of capital stock RK_t, both sourced from the BEA, alongside aggregate labour cost W_tL_t from the national QCEW. Substituting these data into $RK_t = \frac{Y_t - W_tL_t}{c_t}$ and solving for c_t results in a national time varying estimate for the capital return rate. In estimating capital

[19] Out of 108,787 observations, there are 4,471 for which the GDP net the total wage bill is less than zero. Although each of the 18 NAICS two-digit sectors had some observations violating the assumption $\Pi_{i,h,t} < 0$, most came from (1) Agriculture, Forestry, Fishing, and Hunting, (2) Management of Companies and Enterprises, and (3) Professional, Scientific, and Technical Services, all of which are by definition labour intensive sectors, potentially explaining their large wage bills.

stock value, I use c_t as a proxy for $c_{i,h,t}$, which was on average 0.23 from 2001 to 2017.[20] Sector-specific, time varying capital return rates, denoted $c_{h,t}$, can be calculated using an analogous approach, the results of which I present in Appendix B.4.2. However, these estimates for certain sectors yield implausibly large $c_{h,t}$. This likely reflects unobservable inter-sector capital ownership patterns. For instance, sector h may rent, instead of own, capital from other sectors, which would bias the estimated capital return rate for h upwards. These concerns motivate the use of c_t over $c_{h,t}$ in my estimation of capital stock values.

Combining the total wage bill data, local GDP estimates, and the estimates of c_t, I estimate the value of capital stock in ZCTA i used by sector h during year t as

$$RK_{i,h,t} = \frac{Y_{i,h,t} - W_{i,h,t}L_{i,h,t}}{c_t} = \left[\frac{Y_{i,h,t} - W_{i,h,t}L_{i,h,t}}{Y_t - W_tL_t}\right]RK_t \tag{4.2}$$

Detailed summary statistics concerning the estimated capital stock series among all ZCTAs, urban ZCTAs, and rural ZCTAs in the sample are provided in Appendix B.4.3.

The term in square brackets in equation (4.2) is (an estimate of) sector h in ZCTA i's share of aggregate US profits ($Y_t - W_tL_t$). Therefore, this capital stock estimation procedure allocates to sector h in ZCTA i an equivalent share of aggregate capital (RK_t). This formulation immediately follows from my assumption that the rate of return (c_t) is the same for all sectors and locations.

This approach resembles the procedure introduced in Garofalo and Yamarik (2002), who use the same national-level GDP and capital stock value series discussed above to estimate the value of state-level capital stocks. They apportion the national capital stock value for sector h in year t to that of each state o using the ratio of state GDP in h to total GDP in h

$$RK_{o,h,t} = \left[\frac{Y_{o,h,t}}{Y_{h,t}}\right]RK_{h,t} \tag{4.3}$$

They then estimate total state-level capital stock as $RK_{o,t} = \sum_{h=1}^{H} RK_{o,h,t}$. The similarities between equations (4.2) and (4.3) lend credibility to the estimates obtained via (4.2). Furthermore, although equation (4.2) omits national-level industrial heterogeneity and attempts to estimate capital stock for a smaller geographical unit, it builds upon the Garofalo and Yamarik (2002) procedure by exploiting data more relevant to the value of capital stock (i.e. the capital income component of GDP, as opposed to total GDP).

Although it ignores sectoral variation in capital return rates, this estimation procedure imposes few restrictions on the data aside from the assumed functional specification of $cRK = Y - WL$. For robustness, I estimate ZCTA sector-level capital stock series using an alternative specification of the capital return rate which relies on more rigid assumptions. Specifically, given the equilibrium capital return rate (or user cost of capital) can be expressed $c_{i,h,t} = \delta_{i,h,t} + r_{i,h,t} + \upsilon_{i,h,t}$ where $\delta_{i,h,t}$ is the capital depreciation rate, $r_{i,h,t}$ is the rate of interest, and $\upsilon_{i,h,t}$ is a risk premium, I estimate capital depreciation by sector over

[20] This series was highly persistent over the sampling period, with little if any deviation from 0.23. See Appendix Figure (B.8).

time using relevant BEA data (BEA, 2019b) and make assumptions on the values of r and v. I present the results of this robustness inquiry in Appendix B.4.4, alongside a detailed comparison of said results against those estimated using the "primary" method described above.

As I show in the Appendix, the alternative approach results in smaller, relatively static capital return rate estimates compared to the primary estimation strategy. This in turn leads to larger capital stock estimates in levels relative to those from the primary approach. However, when plotted against the (log of the) average ZCTA total capital stock estimate from the primary approach, as I do in Appendix Figure (B.9), the series estimated via the alternative method yields similar dynamics. Thus, there are nontrivial differences between estimation strategies in levels, but not in rates of change. This is unsurprising considering both methods use the same GDP and labour cost estimates. Unlike the alternative approach, which requires making inflexible assumptions on the interest rate and risk premium (both of which are likely to display large inter-sector and regional heterogeneity), the primary approach is agnostic with respect to the values of δ, r, and v and resembles other capital stock estimation strategies in the literature.

ZCTA TFP Estimation Combining the data on ZCTA labour cost from the QCEW with the estimated GDP and capital stock value series, I follow in the tradition of Griliches and Ringstad (1971) by employing a cost-share approach to estimate ZCTA TFP, using estimates of the share of output going to labour and capital to measure the output elasticities. Where the data allow, I follow the TFP measurement strategies utilised by Hornbeck and Moretti (2020).

I assume that in each ZCTA i, sector h during year t uses the following constant returns to scale Cobb-Douglas production technology:

$$Y_{i,h,t} = A_{i,h,t}(W_{i,h,t}L_{i,h,t})^{\alpha_{i,h,t}}(RK_{i,h,t})^{1-\alpha_{i,h,t}} \tag{4.4}$$

where $Y_{i,h,t}$ is GDP, $W_{i,h,t}L_{i,h,t}$ are labour inputs measured in terms of the total wage bill, $RK_{i,h,t}$ is the value of capital inputs, $\alpha_{i,h,t} < 1$ is the labour input elasticity, and $A_{i,h,t}$ is Hicks neutral TFP. Note that here I use $W_{i,h,t}L_{i,h,t}$ and $RK_{i,h,t}$ as qualty-adjusted measures of labour and capital inputs. Equation (4.4) implies a log-linear relationship between TFP, the factors of production, and factor output elasticities of the form

$$\log(A_{i,h,t}) = \log(Y_{i,h,t}) - \alpha_{i,h,t}\log(W_{i,h,t}L_{i,h,t}) - (1-\alpha_{i,h,t})\log(R_{i,h,t}K_{i,h,t}) \tag{4.5}$$

Interpreting $\alpha_{i,h,t}$ as labour's share of GDP, for each ZCTA-sector-year observation, I estimate $\alpha_{i,h,t}$ according to

$$\alpha_{i,h,t} = \frac{W_{i,h,t}L_{i,h,t}}{Y_{i,h,t}}$$

The resulting estimates contain a small subset (< 5%) for which $\alpha_{i,h,t} > 1$, violating the CRS assumption in equation (4.4). Since capital's share of GDP can be written as the profit share of GDP, as $1 - \alpha_{i,h,t} = 1 - \frac{W_{i,h,t}L_{i,h,t}}{Y_{i,h,t}} = \frac{Y_{i,h,t}-W_{i,h,t}L_{i,h,t}}{Y_{i,h,t}} = \frac{\Pi_{i,h,t}}{Y_{i,h,t}}$, $\alpha_{i,h,t}$ may in turn be written as $\alpha_{i,h,t} = 1 - \frac{\Pi_{i,h,t}}{Y_{i,h,t}}$, meaning $\alpha_{i,h,t} > 1$ if and only if $\frac{\Pi_{i,h,t}}{Y_{i,h,t}} < 0$. Thus, observations for which $\alpha_{i,h,t} > 1$ are the same observations where $\Pi_{i,h,t} < 0$ from when I estimate capital stock. I replace these estimates of $Y_{i,h,t}$ and $W_{i,h,t}L_{i,h,t}$ that lead to $\alpha_{i,h,t} < 1$ with the identical estimates that ensure $\Pi > 0$ from the capital stock estimation process, which in turn ensures $\alpha < 1$.[21]

Substituting data on $Y_{i,h,t}$, $W_{i,h,t}L_{i,h,t}$, $RK_{i,h,t}$, and $\alpha_{i,h,t}$ into equation (4.5), I estimate sector h TFP in each ZCTA i. Note that, as in Hornbeck and Moretti (2020), this resulting measure of TFP is a measure of "revenue productivity," meaning $A_{i,h,t}$ may reflect market power as well as physical productivity. Therefore, growth in this measure over time has a broad meaning, reflecting increases in the value of output for reported levels of sector h input expenditures. This measure is broad in the sense that there are many components contributing to revenue TFP changes within this measure, including changes in physical productivity (i.e. increases in output for given levels of capital and labour inputs) as well as increases in the real price of output. As Hornbeck and Moretti (2020) note, revenue TFP is the correct measure for the purposes of evaluating how TFP growth influences regional labour markets due to the fact that both sources of variation (i.e. physical productivity and price changes) influence labour markets in equivalent ways via stimulating firm labour demand.

To estimate ZCTA i's average TFP in year t, I exponentiate estimates of $\log(A_{i,h,t})$ and weight $A_{i,h,t}$ by h's year t employment share in i, denoted $\xi_{i,h,t} = \frac{L_{i,h,t}}{L_{i,t}}$.[22] Summing $\xi_{i,h,t}A_{i,h,t}$ over all active sectors h, I estimate average (composite) revenue TFP in i as

$$A_{i,t} = \sum_{h} \xi_{i,h,t} A_{i,h,t}$$

I provide summary statistics concerning estimates of $A_{i,h,t}$ and $A_{i,t}$ in Appendix B.5.1. The average urban and rural estimates for $A_{i,t}$ presented in the Appendix are used to calibrate the initial urban core and rural town TFP levels in the theoretical model from Section 3.4.

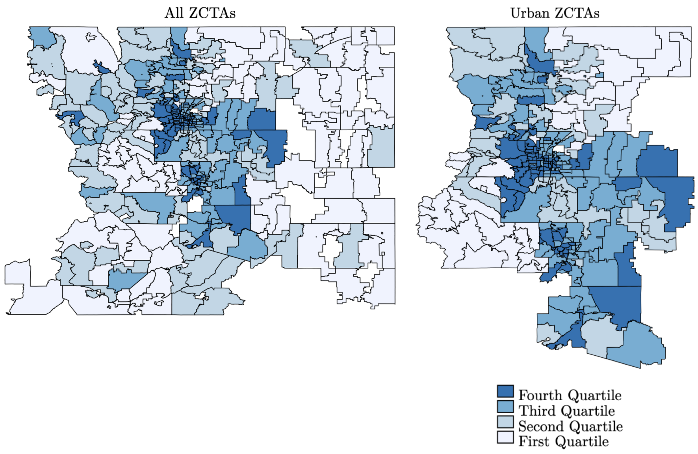
Figure (4.3) maps the spatial distribution of TFP among ZCTAs in the sample. Panel (a) presents the average aggregate TFP in levels for each ZCTA from 2001 to 2017 (i.e. $\frac{1}{T}\sum_{t=1}^{T} A_{i,t}$ where $T = 16$), with darker shades of blue implying a higher average level of TFP over the sampling period. Panel (b) shows the compound annual TFP growth rate in each ZCTA from 2001 to 2017, with green indicating above average change, red below average change, and darker colours representing a change of more than one standard deviation from the mean. The resulting TFP estimates imply regional heterogeneity not only in levels, but also in rates of change, consistent with other evidence of (estimated) TFP differences over space (Syverson, 2004; Greenstone, Hornbeck, and Moretti, 2010; Moretti, 2011; Ciani, Locatelli, and Pagnini, 2019; Hornbeck and Moretti, 2020).

Figure (4.3a) shows there exists a gap in weighted-average TFP estimates between urban and rural ZCTAs, suggestive of between group variation. The data indicate that

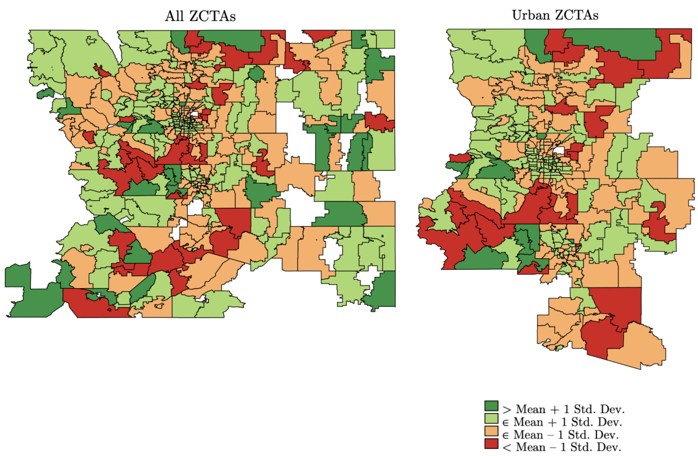
[21] See Appendix B.4.1 for replacement details.

[22] Naïvely averaging across sectors, and therefore applying equal weight to each active sector, risks over weighting sectors that are not particularly representative of a given ZCTA while under weighting those that are.

Figure 4.3: Spatial Distribution of Total Factor Productivity, 2001 to 2017



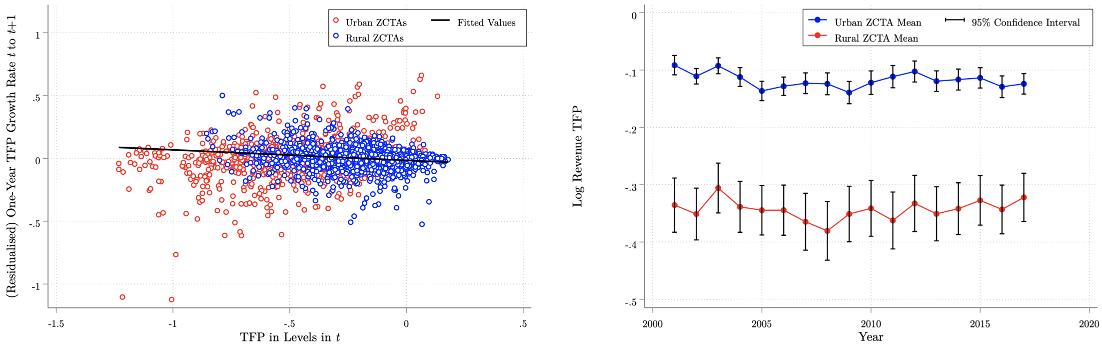
(a) Average TFP Level



(b) TFP Average Annual Growth Rate

Notes: Panel (a) maps the spatial distribution of TFP in levels. The leftmost map in Panel (a) shows the average total factor productivity (TFP) from 2001 to 2017 for the 379 sample ZCTAs, with the two other maps showing the same but for the 263 sample urban ZCTAs (centre) and 116 rural ZCTAs (right). To interpret the relative magnitude of TFP in a given ZCTAs, darker shades of blue reflect ZCTAs in higher percentiles of the set of all ZCTAs, with the darkest reflecting observations above the 75^{th} percentile. Panel (b) maps the spatial distribution of the annual change in TFP from 2001 to 2017. Similar to Panel (a), the three maps in panel (b) show annual TFP change in all (left), urban (centre), and rural (right) ZCTAs, respectively. The mean annual growth rate in the sample is -0.1% with one standard deviation of 1%. Observations above the mean are shaded green, while observations below are shaded red, with darker shading indicating the observation is more than one standard deviation from the mean.

Figure 4.4: Estimated TFP Series Behaviour by ZCTA Classification



(a) Average TFP levels vs. future annual growth **(b)** TFP change over time

Notes: Panel (a) shows correlations between year t TFP in levels for ZCTA i and the residuals from regressing ZCTA TFP growth from t to $t+1$ on time effects with cluster-robust standard errors at the county level, differentiating between urban ZCTAs (blue) and rural ZCTAs (red). Panel (b) plots the average TFP estimates among rural (red) and urban (blue) ZCTAs over time, with bars at each annual observation measuring the 95% confidence interval for the mean.

urban ZCTAs enjoy a productivity premium over rural peers, with the mean urban estimate of $A_{i,t}$ being 23% larger than that among rural ZCTAs. This gap is close to other estimates of the urban-rural productivity gap from OECD (2019), which find the average level of urban TFP is about 22% larger than the rural average among OECD countries from 2000 to 2015.

Figure (4.3b), however, suggests a Girbrat's Law-type relationship between the data in levels and differences, showing variation in annual growth across regional classifications that appears independent of the magnitude of TFP in levels.[23] ZCTAs with larger average TFP are not necessarily the ZCTAs that experience higher average annual TFP growth. Local TFP annual growth rates appear to be orthogonal to average TFP levels and the estimates imply a degree of within group variation in differences. To evaluate the prevalence of this apparent lack of association in the data, I regress the annual change in TFP from t to $t+1$ for $t \in \{2001, \ldots, 2016\}$ on time dummy variables clustering standard errors at the county level. In Figure (4.4a) I scatter plot the residuals from this regression against TFP in levels in t. The scatter plot of residualised ZCTA annual TFP growth against TFP in levels suggests a lack of strong association between TFP in levels and annual growth rates.

In Figure (4.4b), I plot the (unweighted) average level of ZCTA TFP over time for both urban and rural ZCTAs.[24] The urban-rural TFP divide is apparent in the gap between the plots. Furthermore, the wider confidence bands show that there is more between variation in the level of TFP between the rural ZCTAs than between the urban ZCTAs. However, despite these differences, the means of both series display a fair degree of persistence over time and change little from one year to the next, consistent with TFP persistence evidence from Moretti (2011).

[23] Gibrat's Law for cities states that future growth of a city is independent from its population density (i.e. rates of growth are not correlated with levels).

[24] The average is unweighted. For instance, the plotted year t average for $i \in i^u$, where i^u is the subset ZCTAs located in urban counties, is given by $\frac{1}{N}\sum_{i \in i^u}^{N} A_{i,t}$.

MSA TFP Estimates Estimates of urban ZCTA TFP suggest variation between and within the MSAs that comprise the FRUC. Appendix Figure (B.10) maps the spatial distribution of urban TFP among ZCTAs located in each of these MSAs in average levels and average annual growth rates from 2001 to 2017. Like in Figure (4.3), high average TFP in levels does not necessarily map to faster annual TFP growth. That said, comparing high performing MSAs such as Fort Collins or Boulder to a low performing MSA like Greeley reveals noticeable TFP disparities. The geographically (and demographically) larger MSAs, Denver and Colorado Springs, have a greater diversity of ZCTA TFP performance and growth over time.

There are many potential sources for variations in TFP levels and growth within and between MSAs. For instance, differences in connectivity to regional, national, and international markets facilitated by infrastructure, worker skill distributions, and industrial composition all may foster urban TFP asymmetries. In particular, diversity in industrial composition gives rise to differences in TFP over space due to the fact that certain sectors may feature stronger agglomeration spillovers, utilise technology that has undergone productivity-boosting innovations, or experience increases in real output prices. Given the method employed to estimate average TFP by ZCTA in this paper, the likely source of variation between ZCTAs is diversity in industrial composition. There are noticeable differences between sectors and depending on the labour allocation in a particular ZCTA, the weighted average may favour lower or higher TFP sectors.

Taking into consideration within variation among urban TFP estimates, in order to secure estimates for broader urban TFP measures with which to evaluate against employment dynamics in rural ZCTAs, I compute a weighted average TFP measure for each MSA within the FRUC using the urban ZCTA TFP estimates. The weighting procedure is similar to that used to estimate the sector average for each ZCTA. TFP observations on ZCTAs i within MSA c, with the subset of such ZCTAs denoted i^c, are weighted by the share of employees working in $i \in i^c$ out of the total labour force in c during year t, denoted $\zeta_{i,t} = \frac{L_{i,t}}{L_{c,t}}$. Summing the product $\zeta_{i,t} A_{i,t}$ over all ZCTAs in the set i^c, I estimate the TFP for MSA c during year t as

$$A_{c,t} = \sum_{i \in i^c}^{N} \zeta_{i,t} A_{i,t} \tag{4.6}$$

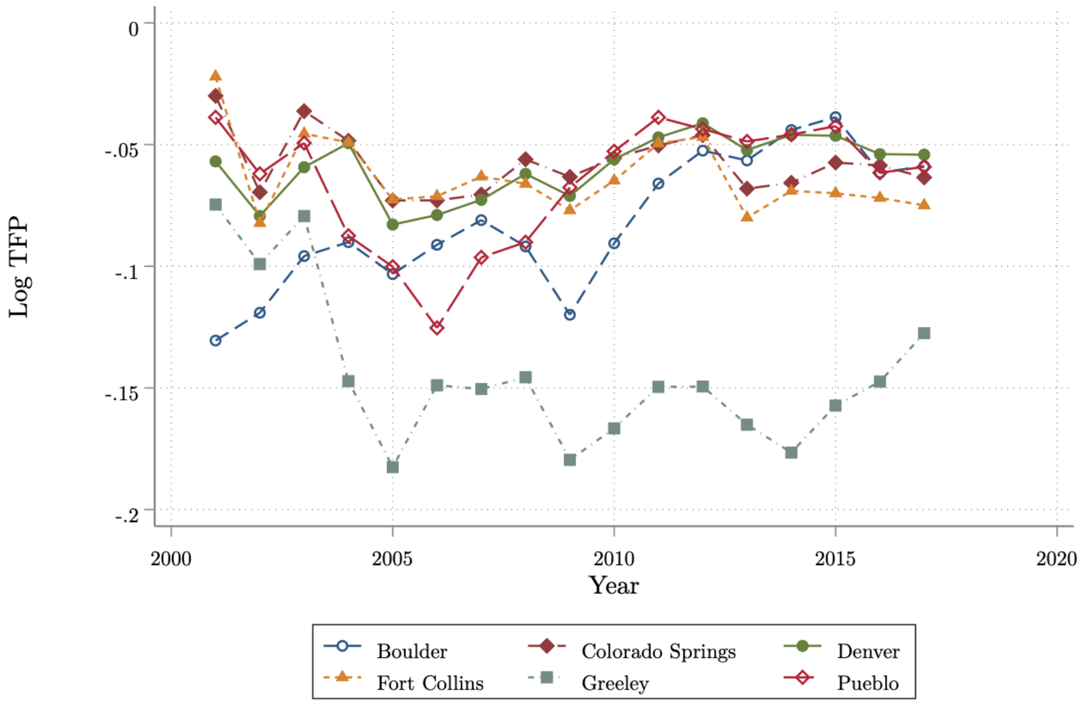
I present summary statistics on MSA-level aggregate TFP estimates in Appendix Table B.10.[25]

Figure (4.5) plots the evolution of the weighted average TFP in each MSA estimated via equation (4.6) from 2001 to 2017. The average (absolute) annual change in TFP among MSAs is 1.44% and the largest is 6.78%. With the exception of Greeley, the other the MSAs of the FRUC follow a broadly similar trend.[26] I exploit the variation in FRUC MSA

[25]In Appendix Table B.10, alongside estimates of $A_{c,t}$, I also present estimates of weighted TFP averages by sector for each MSA $A_{c,h,t}$.

[26]From 2003 to 2006, the employment weighted average of manufacturing TFP estimates among urban ZCTAs saw sharp decline (see Appendix Figure (B.11)). Manufacturing is Greeley's largest employment sector, with roughly 14% of reported employees working in the sector, and unlike other MSAs with a large

Figure 4.5: Estimated TFP Series Dynamics by MSA



Notes: This figure plots the log of the TFP measure for each of the six MSAs that comprise the Front Range Urban Corridor.

measures of TFP to evaluate how such movements associate with rural ZCTA employment growth.

Considerations and Limitations of TFP Estimates The revenue TFP estimation procedure follows Hornbeck and Moretti (2020) in assuming a similar production function specification (CRS Cobb-Douglas technology)[27], labour inputs (total labour costs)[28], and produces a similar TFP measure (revenue TFP). However, in comparing the TFP estimates above, especially those in MSAs, to the estimates in Hornbeck and Moretti (2020), there

manufacturing presence (e.g. Fort Collins or Boulder), Greeley is not diversified in high-TFP sectors, like professional services. As such, the TFP plunge in manufacturing disproportionately affected the weighted average ZCTA TFP in Greeley. This decline in manufacturing TFP in the early 21^{st} century is consistent with evidence from Syverson (2016), who reports manufacturing TFP went from growing 2.2% per year over 1995–2004 to 0.4% during 2005–2013.

[27] There are subtle differences in the production function specification, namely concerning the level of aggregation at which the Cobb-Douglas form is assumed to hold. Having data on plants, Hornbeck and Moretti (2020) assume it holds at the plant level, while I assume it holds at the ZCTA level. It is important to note that there is no compelling reason to believe a Cobb-Douglas production function specification holds better at the plant level than the ZCTA level or vice versa.

[28] In estimating plant-level productivity Hornbeck and Moretti (2020) define and measure labour input in plant p at time t as the weighted sum of hours worked by production workers, $H^{P}_{p,t}$, and non-production workers $H^{NP}_{p,t}$, weighted by their relative hourly wage. Denoting $L^{HM}_{p,t}$ as the Hornbeck-Moretti labour input measure, it follows that $L^{HM}_{p,t} = H^{P}_{p,t} + \left(\frac{w^{NP}_{p,t}}{w^{P}_{p,t}}\right)H^{P}_{p,t}$. Multiplying both sides of the equation by $w^{P}_{p,t}$ gives the total wage bill on the right hand side. Thus, the Hornbeck-Moretti measure of labour input is equivalent to expressing the total wage bill in constant prices, using a wage index for production workers.

are some distinctions to make.

The first difference is that the estimates above are not residuals from regressing output on inputs, though Hornbeck and Moretti (2020) state their parameter estimates for the elasticity of output with respect to labour (i.e. α) are similar to those produced via cost-share estimation, suggesting potential parallels between these cost-share estimates and OLS estimates. Second, I estimate TFP for a broad scope of sectors relative to Hornbeck and Moretti (2020), who measure only manufacturing TFP. They justify this decision by arguing that their years of observation (1980-2010) include manufacturing's peak employment in the US (providing a third of US private employment), manufacturing accounted for the majority of employment in the tradable goods sector, and manufacturing experienced large gains in TFP relative to other sectors. The confidential QCEW data on employment allocations in Colorado do not suggest such concentrations in manufacturing. From 2001 to 2017, on average about 7.9% of private sector employment in the sample was in manufacturing for any given year. The percent of rural private sector employment in manufacturing was smaller still, with an average share of 5.9% of total rural employees. In fact, over the sampling period, on average less than 20% of employment in the FRUC and its rural periphery is in NAICS sectors BLS considers "goods producing," with the remaining shares of employment in "service providing" sectors. Although measuring TFP growth in service sectors is less common in the literature, considering the employment shares in the data, restricting the sample to manufacturing is likely to misrepresent the influence of revenue TFP growth on rural labour dynamics given its small share of employment. Finally, given the limitations in their data, Hornbeck and Moretti (2020) estimate TFP at select ten year intervals from the late twentieth century to early twenty-first century in MSAs across the US, while the data used in this study allow for annual TFP estimates at the ZCTA level, though only for the state of Colorado.

TFP estimation introduces a number of issues and no single approach delivers overly desirable results. These estimates are no exception, and there is reason to suspect substantial measurement error in revenue TFP at the ZCTA level, which aggregates to the MSA level and threatens to bias any parameter estimates computed via OLS. Furthermore, reliance on estimated input-output data (i.e. capital stock value and GDP) worsens measurement error.

However, concerns associated with measurement error in the empirical analysis are mitigated using instrumental variables (which are discussed in Section 5.1). Furthermore, this approach to estimating revenue TFP has some attractive properties that are worth noting. First, this method applies as few assumptions on the data as possible. By assuming a standard Cobb-Douglas production function, as opposed to alternative functional specification (e.g. the transcendental logarithmic production function), it minimises the number assumptions that must be made on function parameters, requiring only the estimation of a single factor's output elasticity, α. Second, at the ZCTA level, it seeks to preserve time-varying elements of the data and does not assume TFP homogeneity among sectors by permitting between-sector TFP differences and weighting them accordingly. Third, it allows for within-city regional productivity heterogeneity when estimating urban

TFP via a weighted sum of the ZCTAs that make up the MSA. Finally, by computing a weighted average of TFP in each MSA according to employment shares, this method identifies TFP relevant to employees and so emphasises TFP signals that might stimulate rural to urban migration of workers, as described in the theoretical model in Section 3.5. In applying more weight to the TFP estimates of ZCTAs with higher employment, this method identifies the parts of MSAs that, if experiencing TFP growth, would be the most likely to demand more labour and draw workers in from the hinterland.

4.4 Spatial Connectivity and Gravity

To characterise the spatial dependence between the sample of rural ZCTAs and observations on urban TFP changes, I model exogenous spatial dependence drawing on the structural gravity equations defining trade flows between the rural town and city in the theoretical model from Section 3.3 and the empirical gravity literature.

Recall in Section 3.3, I show that trade value, and therefore quality adjusted volume, between the rural town and city can be expressed as

$$\begin{aligned} V_{r,c} &= \left(\frac{\tau}{\Lambda_r P_c}\right)^{1-\sigma} \frac{w_r L_r w_c L_c}{wL} \\ V_{c,r} &= \left(\frac{\tau}{\Lambda_c P_r}\right)^{1-\sigma} \frac{w_c L_c w_r L_r}{wL} \end{aligned} \tag{4.7}$$

where $\frac{\tau}{\Lambda_i P_{i'}}$ for $i, i' \in \{r, c\}$ measures bilaterally symmetric trade costs adjusted by the product of the relative costs firms in i face selling in both markets (measured by the index Λ_i) and the relative costs consumers in i' face consuming goods produced in both locations (measured by the index $P_{i'}$), $w_i L_i$ is labour income in i, and wL is the total labour income earned in the rural town and city (what I call the region in the model). In adjusting nominal trade costs τ, $\frac{\tau}{\Lambda_i P_{i'}}$ measures "true" trade costs. The term $V_{r,c}$ measures the quality adjusted trade volume travelling from the rural town to the city and $V_{c,r}$ the reverse. By equation (4.7), trade volume between i and i' is decreasing in the real cost of trade and increasing in the relative labour income of trading parties.

Empirically, trade volumes are well explained by simple gravity models like those in equation (4.7), which relate bilateral trade interactions log-linearly to the relative size of and distance between trading parties, with distance serving as a proxy for trade costs. Evaluating 2,508 estimates from 159 papers, Head and Mayer (2014) find regressing trade volume on distance and origin/destination GDP, alongside other controls such as contiguity of trading partners, colonial links, and country fixed effects, results (on average) in a distance parameter estimate of -0.93, exporter GDP parameter of 0.97, and an importer GDP parameter of 0.85. Thus, empirical evaluation of gravity-type models finds a 1% increase in distance is roughly associated with a 1% decrease in trade volumes, while increases in importer/exporter GDP is correlated with a 1% increase in trade volumes. Furthermore, Anderson and van Wincoop (2003) show these associations hold for intra-national trade between US states.

In the discussion of the empirical strategy to follow, I take log differences in the MSA

TFP series above to estimate TFP growth over time. I use these log differences to evaluate how urban TFP growth associations with rural employment growth. Given the insights from the theoretical model as well as the literature analysing the gravity relationship in trade, I introduce exogenous variation to MSA TFP changes using labour-income scaled inverse distance weights. In particular, I weight growth in MSA c TFP over a specified time period by the product of the (time invariant and bilaterally symmetric) inverse distance between rural ZCTA i and MSA c, which serves as a proxy for regional trade costs, denoted $d_{i,c}$, and a frictionless trade coefficient estimated as the product of the average total wage bill in ZCTA i and the average total wage bill in MSA c divided by the average aggregated wage bill of the entire FRUC and its hinterland. Thus, the spatial connectivity between i and c, $\omega_{i,c}$, is defined as

$$\omega_{i,c} = \frac{1}{d_{i,c}} \frac{(\overline{W}_i \overline{L}_i)(\overline{W}_c \overline{L}_c)}{\overline{WL}} \tag{4.8}$$

where $\overline{W}_i \overline{L}_i = \frac{1}{T}\sum_{t=1}^{T} W_{i,t}L_{i,t}$, $\overline{W}_c \overline{L}_c = \frac{1}{T}\sum_{t=1}^{T} W_{c,t}L_{c,t}$, and $\overline{WL} = \frac{1}{T}\sum_{t=1}^{T} W_t L_t$. Total labour costs are averaged over time due to the fact that these series display little variation over time. Note that whenever these spatial connectivity weights are applied to data, I scale the observations to ensure that the sample mean of the spatial connectivity weighted explanatory variable (e.g. the growth in TFP in Denver from 2003 to 2006) is equal to the sample mean of the non-spatially weighted sample mean of the explanatory variable to ease interpretation of parameter estimates.

Consistent with empirical evidence on trade and distance, the connectivity measure in equation (4.8) imposes a distance gravity parameter of -1 by assuming that $\omega_{i,c}$ is in part a function of inverse distance. This is equivalent to assuming $\sigma = 2$ in equation (4.7). Furthermore, as in structural and empirical gravity models, the intensity of connectivity depends on the relative size of the trading parties, as measured by relative labour costs. Equation (4.8) effectively weights urban TFP observations by an estimated measure of trade quality adjusted volumes. Larger values of $\omega_{i,c}$ imply greater spatial connectivity in terms of intra-regional trade, while $\omega_{i,c}$ small implies less spatial connectivity.

The introduction of exogenous spatial dependence between ZCTAs and MSAs plays two important roles. First, by weighting observations on MSA TFP growth by $\omega_{i,c}$, I mechanically introduce variation across rural ZCTAs in the primary explanatory variable. Unlike in past studies evaluating urban growth shadows, such as Cuberes, Desmet, and Rappaport (2019) or Partridge et al. (2009), who analyse urban-rural interaction using observations on multiple core-periphery systems across the US, my sample is restricted to a single urban core (the FRUC) and its hinterland. By assuming unique (albeit, time-invariant) forms of spatial dependence between each MSA c and ZCTA i, a change in urban TFP will have a varied effect across different ZCTAs, permitting econometric analysis. Second, by exogenously assuming a proxy for intra-regional trade gravity relationships between MSAs and rural ZCTAs, the spatial dependence measure $\omega_{i,c}$ links the empirical specification to the theoretical model.

However, note that equation (4.8) is a rather rigid assumption on the form of intra-regional spatial dependence, imposing structural parameterisations on how trade volumes react to distance between trading parties and trading party size. Furthermore, distance is an imperfect proxy for trade costs and assuming trade costs are symmetric may be an oversimplification of regional trade dynamics in the FRUC and its hinterland. That said, the use of real labour costs and the small scope (and, therefore, likely small pricing regime gaps) of the region being analysed accounts for/mitigates influence of the missing terms Λ_i and P_i. Likewise, the confidential data used to measure relative sizes offers some precision in quantifying the economic ties that size facilitates in trading relationships and is likely a better approximation of spatial dependence relative to the more conventional approach to measure dependence by inverse distance alone. Finally, care is taken to measure distances between locations as realistically as possible.

I measure the distance between ZCTA i and MSA c, $d_{i,c}$, in terms of Euclidean distances, minimum distance by road, and minimum travel time by road using an automobile. All physical distances are measured in kilometres (km) and travel time is measured in hours. The US Census Bureau assigns a name to each ZCTA, which I match to the appropriate decimal degree latitude and longitude to four decimal places. For MSAs, I did the same for the city which lends its name to the MSA, with the assumption that distance from the MSA should be measured in terms of distance from the economic hub of that MSA. In geo-referencing locations in this manner, I avoid problems that are potentially introduced by using geographic centroids.[29] To measure the Euclidean distance between ZCTA i and MSA c coordinates, I use a method from Picard (2010). To estimate distances by road and travel time between the same pairs of coordinates I follow the method outlined in Weber and Péclat (2017). The main specification utilises distances by road to construct the spatial connectivity measures $\omega_{i,c}$, with Euclidean and travel time distance measures used for robustness.

5 Empirical Model, Identification, and Estimation

In the notation to follow, for any variable in levels $X_{i,t}$ denote $x_{i,t} = \ln(X_{i,t})$ and let $\Delta x_{i,t,t+s} = x_{i,t+s} - x_{i,t} = \ln(X_{i,t-s}) - \ln(X_{i,t})$ represent variable X percent growth (to a first-order Taylor approximation) in location i from time t to $t+s$. To test the theoretical model's implications and empirically analyse the associations between growth in an urban core's TFP and employment growth dynamics in its hinterland, I model the rural ZCTA employment change data generation process as

$$\begin{gathered}\Delta l_{i,t,t+s} = \beta_0 + \beta_1 \sum_{c=1}^{C} \omega_{i,c} \Delta a_{c,t-k,t} + \delta_{t,t+s} + \Delta \nu_{i,t,t+s} \\ \text{for } i \in \{1,2,...,N\},\ c \in \{1,2,...,C\},\ t \in \{1,2,...,T\},\ k,s \in \{\mathbb{N} : k < s\}\end{gathered} \tag{5.1}$$

[29] A centroid is the geometric centre of a polygon. Shapefiles store data as n-degree polynomials and statistical software is available to calculate the coordinates that are associated with the geometric centre of said polygons. Given this geography of Colorado and my interest in rural ZCTAs this introduces the potential for problems. For rural ZCTAs, the geographic centre of the polygon could be on the top of a mountain or in an area inaccessible by roads, rendering measurement by road distance futile. Likewise, if economic activity of a ZCTA is clustered in a town on the edge of a ZCTA, measuring from the centre is a mismeasurement.

where $\Delta l_{i,t,t+s}$ is the growth in rural ZCTA i employment from year t to $t+s$, $\sum_{c=1}^{C} \omega_{i,c} \Delta a_{c,t-k,t}$ spatial connectivity-weighted sum of all MSA TFP growth within the FRUC from year $t-k$ to t, $\delta_{t,t+s}$ is a time indicator variable which equals unity for employment changes measured from t and $t+s$ and zero otherwise, and $\Delta \nu_{i,t,t+s}$ is an error term.

In the baseline empirical model, I pool observations on rural employment growth from year t to $t+s$ among 116 ZCTAs in the hinterland of the FRUC, with k,s fixed. I then evaluate these observations of rural employment growth against past realisations of the sum of (spatial connectivity weighted) MSA TFP growth in the FRUC from $t-k$ to t alongside an intercept term and time dummy variables. The explanatory variable of interest, β_1, can be interpreted as a coefficient (which is assumed common to the MSAs located in the FRUC) that measures the correlation between TFP growth in MSA c and future rural employment growth in ZCTA i after controlling for potential heterogeneous associations between c and i via the spatial connectivity weights $\omega_{i,c}$.

In regard to parameter identification, I make two assumptions on the data. First, since there are no compelling reasons to suspect that growth in the rural ZCTA employment disturbance term would be correlated with past urban TFP growth, I assume that $\mathbb{E}[\Delta a_{c,t-k,t} \Delta \nu_{i,t,t+s}] = 0 \;\; \forall i,c,t,k,s$. Second, to the extent that the spatial connectivity weights $\omega_{i,c}$ are time-invariant, it seems more likely that they would be correlated with time-invariant 'fixed' effects in local employment than with transient shocks to local employment growth captured in the error term of equation (5.1). In taking (log) differences of rural employment, these unobserved time-invariant effects with which $\omega_{i,c}$ may covary will be eliminated, and so here I also assume $\mathbb{E}[\omega_{i,c} \Delta \nu_{i',t,t+s}] = 0 \;\; \forall i,i',c,t,s$. While these assumptions are admissible, there remain outstanding concerns related to parameter identification and inference when estimating the empirical model specified by equation (5.1).

With respect to identification, as previously mentioned, the MSA TFP estimates are likely to contain substantial measurement error, leading to inconsistent parameter estimates were I to estimate equation (5.1) via pooled OLS.[30] With respect to inference, in estimating the variance-covariance matrix (and hence the standard errors of parameter estimates), any serial correlation in the error terms would prevent meaningful inference with parameter estimates, even if they are consistently estimated. Estimating standard errors to be robust to heteroskedasticity of White (1980) presumably results in biased standard error estimates due to serial correlation.[31] Furthermore, given the data are spatial, there is always the potential for spatial correlation in the error terms to bias heteroskedasticity-robust standard error estimates as well. Though clustering at the ZCTA-level can alleviate some concerns with respect to serial correlation, the same ap-

[30] Moreover, assuming the measurement error is serially uncorrelated and additive, it is exacerbated by taking differences, as I do in equation (5.1).

[31] There are three likely sources of serial correlation. The first is any transient shock to the (log) level of employment, which through the process of differencing would be transformed into moving average errors. The second is any persistent local business cycle shock to employment in levels and (log) differences. Finally, given I am pooling data, serial correlation in the error terms may extend from this use of overlapping data, since errors for ZCTA i in overlapping intervals t to $t+s$ are likely to be correlated. For example, if $s = 3$, the observed employment growth in ZCTA i from 2001 to 2004 is likely to be correlated with growth from 2002 to 2005.

proach does not necessarily hold for spatial dependence and depends largely on the form of such dependence in the data.

Below, I develop an estimation strategy to address each of these concerns in turn. To account for measurement error in the primary explanatory variable, I construct Bartik style shift-share instruments and utilise instrumental variable techniques to circumnavigate OLS inconsistency in the results section. I then test for spatial dependence in the dependent variable among rural ZCTAs to evaluate underlying spatial dependence threats to consistent standard error estimation, ultimately opting for a cluster-robust estimator which is robust to (particular forms of within-cluster) serial and spatial correlation in the disturbance terms. Finally, I describe a consistent and efficient estimation procedure in order to estimate the baseline model.

5.1 Instrumental Variables

Motivation Since revenue TFP is estimated as a residual from a production function, it will inherently reflect any measurement error in inputs and output (Hornbeck and Moretti, 2020). In this study, capital stock value and GDP are both estimates, implying good reasons to suspect a degree of error in both the input and output data described in Section 4.3. Moreover, differencing the (log of the) data will exacerbate the error in the event said measurement error is not permanent (and therefore would be eliminated by differencing). To circumnavigate this threat to identification that measurement error poses, I instrument the estimated the weighted aggregate FRUC TFP growth from $t-k$ to t with Bartik style shift-share instruments.

Shift-Share Instrument The "canonical" Bartik style shift-share instrument, proposed in Bartik (1991) and popularised by Blanchard and Katz (1992), is used to estimate labour supply elasticity by instrumenting local employment growth with local employment shares and national employment growth rates, with the underlying assumption that local growth can be decomposed into a location-specific component and a (location-exogenous) national component (Goldsmith-Pinkham et al., 2020). The application of this approach to instrument TFP measured with error is adapted from Hornbeck and Moretti (2020).

For expositional simplicity, suppose the measurement error in estimated TFP takes on an additive form.[32] That is, assume that the measurement error enters linearly into the estimated growth in MSA c TFP from year $t-k$ to t

$$\Delta\widetilde{a}_{c,t-k,t} = \Delta a_{c,t-k,t} + \Delta e_{c,t-k,t} \tag{5.2}$$

where $\Delta\widetilde{a}_{c,t-k,t}$ is the (log) differenced estimate from Section 4.3, $\Delta a_{c,t-k,t}$ is the "true" growth in c TFP from $t-k$ to t, and $\Delta e_{c,t-k,t}$ is the change in unobserved and time-varying measurement error. Furthermore, assume $\Delta e_{c,t-k,t}$ is mean zero (i.e. $\mathbb{E}[\Delta e_{c,t-k,t}] = 0 \forall c,t,k$), independent of TFP growth in c or any other MSA c' (i.e. $\mathbb{E}[A_{c,t} e_{c',t'}] = 0 \;\; \forall c,c',t$), and

[32]This need not be the true form of the measurement error, as the inconsistency of OLS when using mismeasured data is quite general. However, it eases exposition of the problem and its instrumental variable solution, which too is quite generalisable.

independent of innovations in the rural employment disturbance (i.e. $\mathbb{E}[\Delta e_{c,t-k,t}\Delta\nu_{i,t,t+s}] = 0 \;\forall i,c,t,k,s$).[33] When $\Delta\widetilde{a}_{c,t-k,t}$ is summed over c, as is done in the baseline specification, the data on the explanatory variable of interest, $\sum_{c=1}^{C}\omega_{i,c}\Delta a_{c,t-k,t}$, is then also measured with error.

Given the TFP measurement error is zero in expectation, the aggregate of the estimated TFP growth data will tend toward its true value as the sample size grows. As such, for a sufficiently large sample, aggregate TFP growth estimates $\sum_{c=1}^{C}\omega_{i,c}\Delta a_{c,t-k,t}$ will not feature measurement error, and therefore will not lead to inconsistent estimates. Drawing on the classic shift-share assumption that local growth trends are correlated with aggregate growth trends, I instrument spatial-connectivity weighted aggregate TFP growth in the FRUC from $t-k$ to t measured with error, $\sum_{c=1}^{C}\omega_{i,c}\Delta\widetilde{a}_{c,t-k,t}$, with a vector of shift-share instruments

$$\boldsymbol{B}_{i,t-k,t} = \begin{bmatrix} \omega_{i,1}B_{1,t-k,t} & \omega_{i,2}B_{2,t-k,t} & \dots & \omega_{i,C^r}B_{C^r,t-k,t} \end{bmatrix}$$

where $c \in \{1,2,\dots,C^r\}$ is a subset of the total set of MSAs $c \in \{1,2,\dots,C\}$ which have relevant shift-share instruments for $\sum_{c=1}^{C}\omega_{i,c}\Delta a_{c,t-k,t}$. Each element of $\boldsymbol{B}_{i,t-k,t}$ for MSAs $c \in \{1,2,\dots,C^r\}$ is

$$\omega_{i,c}B_{c,t-k,t} = \omega_{i,c}\sum_{h=1}^{H}\lambda_{c,h,t-k}g_{h,t-k,t} \tag{5.3}$$

where $\omega_{i,c}$ is the spatial connectivity weight between i and c (from Section), $\lambda_{c,h,t-k} = \frac{Y_{c,h,t}}{Y_{c,t}}$ is the output share expressed as the ratio of GDP in sector h to total GDP, and $g_{h,t-k,t}$ is an aggregate TFP growth rate for sector h across the entire urban (continental) US from $t-k$ to t.

Under the following assumptions, the elements of the vector $\boldsymbol{B}_{i,t-k,t}$ are informative and valid instrumental variables for $\sum_{c=1}^{C}\omega_{i,c}\Delta a_{c,t-k,t}$:

Assumption 1. *Urban TFP growth in MSA c from $t-k$ to t, $\Delta a_{c,t-k,t}$, can be decomposed into the sum of the (MSA-specific) inner product of the output share of sector h in year $t-k$ and MSA-specific TFP growth in sector h from $t-k$ to t, denoted $g_{c,h,t-k,t}$, across all industries h:*

$$\Delta a_{c,t-k,t} = \sum_{h=1}^{H}\lambda_{c,h,t-k}g_{c,h,t-k,t}$$

Assumption 2. *Local growth in sector h TFP, $g_{c,h,t-k,t}$, can be decomposed into a national growth component, $g_{h,t-k,t}$, and an idiosyncratic local component, $\ddot{g}_{c,h,t-k,t}$*

$$g_{c,h,t-k,t} = g_{h,t-k,t} + \ddot{g}_{c,h,t-k,t}$$

where $\ddot{g}_{c,h,t-k,t}$ is mean zero across cities (i.e. $\mathbb{E}[\ddot{g}_{c,h,t-k,t}] = 0$) and independent of local sector shares in $t-k$ (i.e. $\mathbb{E}[\lambda_{c,h,t-k}\ddot{g}_{c,h,t-k,t}] = 0$).

[33] The latter two assumptions follow from the fact that there is no compelling reason to suspect any correlation between the true TFP growth in c (or any other MSA) and the measurement error growth in estimated c TFP growth nor between growth in the rural employment error term and $\Delta e_{c,t-k,t}$.

Assumption 3. $\mathbb{E}[\lambda_{c,h,t-k}\Delta\nu_{i,t,t+s}] = 0 \ \forall i,c,t,k,s,h$: *Sector h output shares in MSA c at time $t-k$ are independent with respect to dynamic innovations to the rural ZCTA employment disturbance in i from t to $t+s$.*

Assumption 4. $\mathbb{E}[g_{h,t',t''}\nu_{i,t}] = 0 \quad \forall i \in \{1,2,\ldots,N\},\ h \in \{1,2,\ldots,H\},\ t,t',t'' \in \{1,2,...,T\}$: *Aggregate changes to sector h TFP among US cities are strictly exogenous with respect to the rural ZCTA employment disturbance.*

Assumptions 1 and 2 are the specifications Hornbeck and Moretti (2020) use to construct their shift-share instruments and both ensure informativeness.[34] Assumptions 3 and 4 ensure instrument validity.

Combining assumptions 1 and 2, $\Delta a_{c,t-k,t}$ can be written

$$\Delta a_{c,t-k,t} = \sum_{h=1}^{H} \lambda_{c,h,t-k}(g_{h,t-k,t} + \ddot{g}_{c,h,t-k,t}) = \sum_{h=1}^{H} \lambda_{c,h,t-k} g_{h,t-k,t} + \sum_{h=1}^{H} \lambda_{c,h,t-k} \ddot{g}_{c,h,t-k,t}$$

Thus, spatial connectivity weighted TFP for MSA c measured with (serially uncorrelated and additive) error can be expressed as

$$\begin{aligned}
\omega_{i,c}\Delta\widetilde{a}_{c,t-k,t} &= \omega_{i,c}\Delta a_{c,t-k,t} + \omega_{i,c}\Delta e_{c,t-k,t} \\
&= \omega_{i,c}\sum_{h=1}^{H} \lambda_{c,h,t-k} g_{h,t-k,t} + \omega_{i,c}\sum_{h=1}^{H} \lambda_{c,h,t-k}\ddot{g}_{c,h,t-k,t} + \omega_{i,c}\Delta e_{c,t-k,t} \\
&= \omega_{i,c}B_{c,t-k,t} + \omega_{i,c}\sum_{h=1}^{H} \lambda_{c,h,t-k}\ddot{g}_{c,h,t-k,t} + \omega_{i,c}\Delta e_{c,t-k,t}
\end{aligned}$$

It follows then that by assumptions 1 and 2, the covariance between $\omega_{i,c}B_{c,t-k,t}$ for any $c \in \{1,2,\ldots,C^r\}$ and $\sum_{c=1}^{C}\omega_{i,c}\Delta\widetilde{a}_{c,t-k,t}$ is non-zero, i.e.

$$\mathbb{E}\left[\left(\sum_{c=1}^{C}\omega_{i,c}\Delta\widetilde{a}_{c,t-k,t}\right)\omega_{i,c}B_{c,t-k,t}\right] \neq 0$$

given $\sum_{c=1}^{C}\omega_{i,c}\Delta\widetilde{a}_{c,t-k,t}$ is comprised of elements that define $\omega_{i,c}B_{c,t-k,t}$ (e.g. $\omega_{i,c}$, $\lambda_{c,h,t-k}$, and $g_{h,t-k,t}$) and so $\omega_{i,c}B_{c,t-k,t}$ is informative. By assumptions 3 and 4

$$\mathbb{E}[\Delta\nu_{i,t,t+s}\omega_{i,c}B_{c,t-k,t}] = \mathbb{E}[\Delta\nu_{i,t,t+s}]\,\mathbb{E}[\omega_{i,c}B_{c,t-k,t}] = 0$$

implying $\omega_{i,c}B_{c,t-k,t}$ satisfies the exclusion restriction and is therefore valid. Note that since there are more instruments than mismeasured variables, overidentifying conditions can be used to test satisfaction of the exclusion restriction.

Not only is the instrument vector $\boldsymbol{B}_{i,t-k,t}$ a valid and informative set of instruments for the primary explanatory variable in the baseline model, so too is it valid and informative for any of the components that make up $\sum_{c=1}^{C}\omega_{i,c}\Delta\widetilde{a}_{c,t-k,t}$. That is to say, $\boldsymbol{B}_{i,t-k,t}$ is a vector of valid and informative instruments for TFP growth in any individual MSA in

[34] While it is a more common practice in the context of Bartik-type instruments to use shares λ from some fixed initial time period, this follows the procedure in Hornbeck and Moretti (2020).

the FRUC. The shift-share instruments are weighted averages of the same sector specific national (urban) TFP growth rates, $g_{h,t-k,t}$, differing from each other only to the extent that the MSA-specific weights, $\lambda_{c,h,t-k}$, are different. For instance, consider (mismeasured) TFP growth from $t-k$ to t in MSA c (i.e. $\omega_{i,c}\Delta\widetilde{a}_{c,t-k,t}$) and the shift-share instrument for MSA c' over the same sampling period (i.e. $\omega_{i,c}B_{c',t-k,t}$). The two variables covary since they both are composed of $g_{h,t-k,t}$, meaning $\omega_{i,c}B_{c',t-k,t}$ is informative of $\omega_{i,c}\Delta\widetilde{a}_{c,t-k,t}$, and given assumptions 3 and 4, $\omega_{i,c}B_{c',t-k,t}$ is a valid instrument for $\omega_{i,c}\Delta\widetilde{a}_{c,t-k,t}$. I exploit this versatility in the results section, experimenting with a variety of alternative models to the baseline equation (5.1).

In addition to the standard shift-share instrument I present above, Hornbeck and Moretti (2020) test alternative instruments that are constructed similarly but rely on different identifying assumptions. Specifically, they construct a "technological shock" instrument, "export shock" instrument, and "stock price" instrument, all of which use different sources of growth other than aggregate estimated TFP to instrument local TFP changes. The technological shock instrument measures technological shocks using patenting activities, with the underlying assumption that urban TFP and patent activity are closely related. The export shock instrument uses the intuition that increased industry exposure to export markets would lead to higher innovation and therefore be correlated with a city's TFP change, and instruments urban TFP changes with industry level changes in exports. Finally, the stock price instrument assumes that stock price valuations capture a number of factors, including improvements to TFP. Therefore, they instrument urban TFP changes with industry-specific stock market return changes.

Hornbeck and Moretti (2020) are able to construct these alternative instruments due to the fact that they restrict their study to manufacturing industries and these alternative instruments are well suited to instrument goods-producing industries. It is less clear how informative patent activity, export exposure, or stock-market returns would be in explaining variation over time in TFP for service-providing industries. Despite limitations in urban TFP instrument options in this study, Hornbeck and Moretti (2020) find the standard Bartik style shift-share instruments results in similar parameter estimates to the other instruments, motivating its use in this paper.

Instrument Construction To construct the Bartik-style shift-share instruments for each MSA in the FRUC, I use the GDP data (aggregated to the MSA level) from Section 4.3 to estimate $\lambda_{c,h,t-k}$ and publicly available county data on two-digit NAICS sectors in urban counties to estimate $g_{h,t-k,t}$. For consistency with the TFP estimates from Section 4.3, all monetary data are adjusted for inflation using the Denver MSA CPI and are in 2001 USD.

In estimating $\lambda_{c,h,t-k}$, I measure MSA c's sector h output in year $t-k$, denoted $Y_{c,h,t-k}$, using county-level GDP data from BEA (2019a) with suppressed values estimated following the procedure outlined in Appendix B.3.1. Summing across industries h active in c during $t-k$ to measure total output in c, I estimate $\lambda_{c,h,t-k} = \frac{Y_{c,h,t-k}}{\sum_h Y_{c,h,t-k}}$.

Estimation of $g_{h,t-k,t}$ draws on the TFP estimation strategy from Section 4 using county-level GDP data from BEA (2019a), national capital stock data from BEA (2019c), and county-level QCEW data (i.e. annual employment and labour expenditures) from BLS

(2019). I estimate annual TFP in each sector h from 2001 to 2017 for a sample of 1,116 counties classified as urban using the method described in Section 4.3 (see Appendix C.1 for details), construct a weighted average for annual urban TFP in sector h (with weights determined by employment shares of counties in the sample), and estimate $g_{h,t-k,t}$ as the change in this average over time.[35] As before, a small sample of county GDP data feature suppression due to disclosure concerns.[36] Similar suppression is featured among a small subset of county-level QCEW data.[37] Previously, I used the unsuppressed total wage bill data from the Colorado QCEW to allocated unaccounted GDP; however given the QCEW data are suppressed here, missing values are estimated using imputed County Business Patterns (CBP) employment data from Eckert et al. (2020). See Appendix C.2 for imputation details.

After estimating TFP (in levels) $A_{b,h,t}$ for each county $b \in b^u$, where b^u is the set 1,116 US counties classified as urban, I calculate the share of sector h employees working in b out of total urban h employment in the sample during year t, denoted $\vartheta_{b,h,t} = \frac{L_{b,h,t}}{L_{h,t}}$, which I use to weight each observation $A_{b,h,t}$. Following Hornbeck and Moretti (2020), in order to avoid instrument cross-contamination (e.g. the instrument correlating with measurement error in the TFP estimate) when constructing the instrument for each FRUC MSA c, I drop observations $\vartheta_{b,h,t}A_{b,h,t}$ for counties $b \in c$ and estimate $A_{-c,h,t} = \sum_{b \notin c}^{B} \vartheta_{b \notin c,h,t}A_{b,h,t}$, where $A_{-c,h,t}$ is (the weighted) aggregate urban TFP from sector h among observations not belonging to MSA c. Note that $A_{-c,h,t}$ is not a weighted average, considering some observations are dropped. However, most weights $\vartheta_{b^u,h,t}$ are exceedingly small, with an average of 0.0009454, meaning the difference from the weighted average is negligible. The aggregate sector h urban TFP growth rate is estimated as $g_{-c,h,t-k,t} = \ln(A_{-c,h,t}) - \ln(A_{-c,h,t-k})$. Summing the product $\lambda_{c,h,t-k}g_{-c,h,t-k,t}$ over all industries h, the Bartik shift-share instrument for MSA c is constructed as

$$B_{c,t-k,t} = \sum_{h=1}^{H} \lambda_{c,h,t-k}g_{-c,h,t-k,t}$$

However, these instruments are not a panacea: not all MSA shift-share instruments are relevant and therefore should be/are used in estimation. Moreover, while these shift-share instruments prove useful in an environment instrumenting to account for urban TFP mismeasurement, the same cannot be said for instrumenting for mismeasurement in rural TFP estimates. I tested a variety of shift-share instruments for TFP growth in the rural ZCTAs, but with none achieving sufficient relevance, likely due to the small size (economically and geographically) of rural ZCTAs. As such, in alternative specifications of equation (5.1) where I control for local TFP innovations in the data generation process, I account for local TFP measurement error using alternative strategies to test the robustness

[35] The RUCC classifies 1,167 counties in the US as urban. From this total I drop non-contiguous counties, i.e. those in the states of Alaska and Hawaii. I also drop observations on urban counties in Virginia due to the fact that the states' so-called independent cities lead to problematic inconsistencies in data reporting.

[36] Missing industries accounted for a small portion of observations. Among counties classified as urban, the suppression rate was less than 12% of sector GDP observations.

[37] In the QCEW, the suppression rate was higher, at around 24% of observations.

of the urban TFP main result.

5.2 Testing for Spatial Dependence

As previously stated, given the spatial nature of these data, there are immediate concerns of spatial dependence within the sample. Such dependence, which arises frequently in geo-referenced data, occurs when local characteristics in proximal locations are positively or negatively correlated with observations in a particular place. Growth in unobservable and/or observable covariates in ZCTA i may depend on growth in covariates within another ZCTA i', and vice versa. While clustering standard errors at the ZCTA-level can alleviate concerns related to serial correlation in the disturbance, solutions to spatial correlation prove slightly less obvious and depend on the underlying form of spatial dependence in the sample.

Failure to properly account for spatial dependence will lead to biased standard error estimates. Consider the following alteration to equation (5.1) which incorporates spatial dependence in the error term

$$\begin{aligned} \Delta l_{i,t,t+s} =& \beta_0 + \beta_1 \sum_{c=1}^{C} \omega_{i,c} \Delta a_{c,t-k,t} + \delta_{t,t+s} + \Delta \nu_{i,t,t+s} \\ \Delta \nu_{i,t,t+s} =& \gamma \sum_{i' \neq i}^{N} \omega_{i,i'} \Delta \nu_{i',t,t+s} + \Delta \epsilon_{i',t,t+s} \end{aligned} \tag{5.4}$$

where $\Delta\nu_{i',t,t+s}$ is the error term in ZCTA $i' \in \{1,...,N\}$, $\omega_{i,i'}$ is an element of an (exogenously specified) N x N spatial connectivity matrix $\boldsymbol{W}$ that determines how ZCTA i's disturbance depends on the ZCTA $i' \neq i$ disturbance term, γ measures the magnitude of spatial dependence in the error term, and $\Delta\epsilon_{i',t,t+s}$ is an idiosyncratic error term component unique to i. If $\gamma \neq 0$, the estimated residual for ZCTA i (computed using some consistent estimates on the parameters in the baseline model) will be correlated with that of i' via the neglected correlation between $\Delta l_{i,t,t+s}$ and $\Delta l_{i',t,t+s}$, which in turn will bias Huber-White standard error estimates.[38] As such, a natural starting point to assess the threat of spatial dependence, and determine if there is a need to actively model spatial dependence in the baseline specification to consistently estimate the standard errors, is to evaluate if any spatial correlation is present in the data on $\Delta l_{i,t,t+s}$.

To rigorously test for the presence of spatial correlation in the employment data series among rural ZCTAs in the sample, I use a panel-data variation of Moran's I-Statistic (Moran, 1950) that adapts a testing procedure discussed in Beenstock and Felsenstein (2019). Although the Beenstock and Felsenstein (2019) panel test is intended to test for

[38] Since the explanatory variable of interest (i.e. aggregated spatial connectivity weighted FRUC TFP) is measured at a higher level of spatial aggregation than the rural employment data, I assume MSA-level TFP growth $\Delta a_{c,t-k,t}$ is uncorrelated with the sum of (future) local shocks to employment growth in several ZCTAs $\sum_{i' \neq i}^{N} \omega_{i,i'} \Delta\nu_{i',t,t+s}$ (i.e. the spatial lag term in the disturbance in the above equation), which follows from the previous assumption that (correctly measured) MSA-level TFP growth is uncorrelated with (later) local shocks to employment growth in ZCTA i. As such, there is no compelling reason to suspect the observed covariate of interest would be a source of spatial dependence in the residual and therefore I do not test for spatial dependence in the primary explanatory variable data here, instead focusing on evaluating evidence for or against spatial correlation in the dependent variable.

the presence of spatial dependence in estimated residuals (which I do in the Section 6), here instead of testing residuals, I test the degree to which demeaned data on employment in levels and (log) differences spatially covary.

Recall that in equation (5.4), spatial correlation (if present) depends in part on the elements $\omega_{i,i'}$ that comprise an exogenously specified N x N spatial connectivity matrix $\boldsymbol{W}$. The intuition of how these weights operate is similar to modelling spatial dependence between MSAs and ZCTAs in Section 4.4, in that the $\omega_{i,i'}$ weights mathematically describe how one place might influence outcomes in a different place. Note it is always the case that $\omega_{i,i} = 0$ (i.e. how i spatially depends on itself is assumed to be zero), so the diagonal of $\boldsymbol{W}$ is all zeros. However, unlike in the MSA to ZCTA environment, where the relationship studied is one-sided (i.e. I do not evaluate how a particular rural ZCTA i influences outcomes in MSA c, mainly due to the fact that the geographic/economic size differentials likely make the i to c effect negligibly small), here ZCTAs i and i' can influence each other.

The computation of the Moran's I-Statistic relies on a chosen specification for spatial dependence. That is, the econometrician is required to make an assumption on the form of spatial dependence in the sample via her choice of spatial weights $\omega_{i,i'}$. As such, the values the I-Statistic can take depend quite heavily on the chosen form of $\omega_{i,i'}$ and it is unlikely the results from Moran's I tests using only one variation of $\omega_{i,i'}$ will completely convey the realities of spatial dependence in a given sample. In testing ZCTA to ZCTA spatial dependence in the rural ZCTA employment data, I construct Moran's I-Statistics using six spatial weighting matrices, which are summarised in Table (5.1).

The (queen) contiguity matrix $\boldsymbol{W}_C$, inverse-distance matrix $\boldsymbol{W}_D$, and (queen) contiguity-inverse distance matrix $\boldsymbol{W}_{CD}$ are commonly used specifications to model spatial dependence. The two "Bester" matrices combine the contiguity/contiguity-inverse distance flavour of spatial dependence, but instead of grouping ZCTAs that are (first and second-order) neighbours, they instead allow for spatial connectivity to take place between ZCTAs that are located in the same 10,000-square-km grid square. Bester, Conley, and Hansen (2011) present a cluster-robust inference approach for dependent data in time series, spatial, and panel data environments, allowing for correlation within fixed clusters. A common response to potential spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) biasing standard error estimates in the applied spatial economic literature is to group spatial units on an arbitrary grid and perform cluster-robust inference. This method is used by a number of authors including Michaels, Rauch, and Redding (2012), Bleakley and Lin (2012), Michaels and Rauch (2018), and Bakker et al. (2020). For instance, Bleakley and Lin (2012) cluster errors related to their spatial units of interest in 60-square-mile grid squares. Here, I group ZCTAs into 10,000-square-kilometre "Bester" grid squares $j \in \{1, 2, \ldots, J\}$.[39] The final spatial connectivity matrix specification, the Gravity matrix $\boldsymbol{W}_G$, allows for spatial connectivity identical to that used to define the connectivity between ZCTAs and MSAs built upon the structural gravity foundations.[40]

[39] To group ZCTAs into grid clusters, I round the decimal latitude and longitude used to compute the spatial connectivity weights to the nearest whole number, given each whole degree amounts to about 100km at the equator, slightly less so moving North. I allocate ZCTA i and i' to grid square j if they share the same ones-place-rounded latitude and longitude.

[40] Although a common practice, note that I do not row normalise any of these matrices. My primary motivation

Table 5.1: ZCTA to ZCTA Spatial Connectivity Matrix Specifications

Specification	Matrix Elements	Description
(Queen) Contiguity ($\boldsymbol{W}_C$)	$\omega_{i,i'} = \begin{cases} 1 & \text{if } i,i' \text{ are neighbours} \\ 0 & \text{if otherwise} \end{cases}$	Spatial association between ZCTA i' and ZCTA i occurs if i and i' are first or second-order neighbours.
Bester Contiguity ($\boldsymbol{W}_B$)	$\omega_{i,i'} = \begin{cases} 1 & \text{if } i,i' \in j \\ 0 & \text{if otherwise} \end{cases}$	Spatial association between ZCTA i' and ZCTA i occurs if i and i' are in the same (Bester, Conley, and Hansen (2011)-inspired) 100-square-km grid square j.
Inverse Distance ($\boldsymbol{W}_D$)	$\omega_{i,i'} = \frac{1}{d_{i,i'}}$	Spatial associations between ZCTA i' on ZCTA i are discounted according to the inverse of the distance by road (in km) between i' and i (denoted $d_{i,i'}$).
(Queen) Contiguity-Inverse Distance ($\boldsymbol{W}_{CD}$)	$\omega_{i,i'} = \begin{cases} \frac{1}{d_{i,i'}} & \text{if } i,i' \text{ are neighbours} \\ 0 & \text{if otherwise} \end{cases}$	Spatial associations between ZCTA i' on ZCTA i are discounted according to the inverse of the distance by road (in km) between i' and i if i and i' are first or second-order neighbours.
Bester Contiguity-Inverse Distance ($\boldsymbol{W}_{BD}$)	$\omega_{i,i'} = \begin{cases} \frac{1}{d_{i,i'}} & \text{if } i,i' \in j \\ 0 & \text{if otherwise} \end{cases}$	Spatial associations between ZCTA i' on ZCTA i are discounted according to the inverse of the distance by road (in km) between i' and i if i and i' are in the same (Bester, Conley, and Hansen (2011)-inspired) 10,000-square-km grid square j.
Gravity ($\boldsymbol{W}_G$)	$\omega_{i,i'} = \frac{1}{d_{i,i'}} \frac{(\overline{W}_i \overline{L}_i)(\overline{W}_{i'} \overline{L}_{i'})}{\overline{WL}}$	Spatial connectivity measured in a gravity framework identically to weights between ZCTAs and MSAs from Section 4.4.

Notes: This table presents ZCTA to ZCTA spatial connectivity matrices used in this study. ZCTAs i and i' are said to be first-order neighbours if they share a border or vertex (the so-called "Queen" contiguity specification). ZCTA i' is a second-order neighbour of i if i' shares a border or vertex with a first-order neighbour of i. ZCTA to ZCTA distances by road are calculated using the method proposed by Weber and Péclat (2017), as before in Section 4.4.

Using each of the specifications for spatial dependence $\omega_{i,i'}$, I compute the Moran's I test statistic of $l_{i,t}$ in levels for all $t \in \{1, 2, \ldots, T\}$ as

$$I_t = \frac{1}{\sum_i \sum_{i'} \omega_{i,i'}} \frac{\sum_i \sum_{i'} \omega_{i,i'} (L_{i,t} - \overline{L}_t)(L_{i',t} - \overline{L}_t)}{\frac{1}{N} \sum_i (L_{i,t} - \overline{L}_t)^2} \tag{5.5}$$

where $\overline{L}_t$ is the average employment level among the rural ZCTAs in the sample in year t. I repeat this process using the growth data $\Delta l_{i,t,t+s}$ for all $t \in \{1, 2, \ldots, T\}$ and $s \in \{1, 2, \ldots, S\}$,

for not doing so is that row normalisation obscures the role of distance.

constructing the test statistic for (log) difference as

$$I_{t,t+s} = \frac{1}{\sum_i \sum_{i'} \omega_{i,i'}} \frac{\sum_i \sum_{i'} \omega_{i,i'}(\Delta l_{i,t,t+s} - \Delta \bar{l}_{t,t+s})(\Delta l_{i',t,t+s} - \Delta \bar{l}_{t,t+s})}{\frac{1}{N}\sum_i (\Delta l_{i,t,t+s} - \Delta \bar{l}_{t,t+s})^2} \tag{5.6}$$

where $\Delta \bar{l}_{t,t+s}$ is the averaged observed change from t to $t+s$. I compute the panel average for data in levels over the observed time period as $\bar{I} = \frac{1}{T}\sum_{t=1}^{T} I_t$.

The data on (log) differences can be aggregated and averaged in two distinct ways. The first considers all available data that are of the form t to $t+s$, implying data overlap. The second averages *sequential* data of the form t to $t+s$, implying no data overlap.[41] Using overlapping data or non-overlapping data in constructing the panel average may have different implications. For instance, it may be the case that sequential data do not feature spatial dependence, while pooling all data do, and so I test for dependence in both potential sample forms. I compute the panel average for data in differences where data overlap is allowed as $\bar{I}_s = \frac{1}{T_s}\sum_{t,t+s} I_{t,t+s \in t_s}$ where t_s is the set of all overlapping periods t to $t+s$ evaluated and T_s is the number of distinct periods over which the data can be averaged. I compute the panel average using non-overlapping data as $\bar{I}_s^* = \frac{1}{T_s^*}\sum_{t,t+s \in t_s} I_{t,t+s}$, where t_s^* is the set of all non-overlapping periods t to $t+s$ evaluated and T_s^* is the number of periods of non-overlapping data. According to Beenstock and Felsenstein (2019), when $\widetilde{\bar{I}} \in \{\bar{I}, \bar{I}_s, \bar{I}_s^*\}$ is divided by

$$\widetilde{V} = (\widetilde{V}^2)^{\frac{1}{2}} = \left[\frac{N^2 \sum_i \sum_{i'} \omega_{i,i'}^2 + 3\left(\sum_i \sum_{i'} \omega_{i,i'}\right)^2 - N\sum_i \left(\sum_{i'} \omega_{i,i'}\right)^2}{\widetilde{T}(N^2-1)\left(\sum_i \sum_{i'} \omega_{i,i'}\right)^2}\right]^{\frac{1}{2}}$$

where $\widetilde{T} \in \{T, T_k, T_k^*\}$, the resulting standardised panel average is distributed standard normal under the null hypothesis that there is no spatial dependence, i.e. $\frac{\widetilde{\bar{I}}}{\widetilde{V}} \sim N(0,1)$. The presence of spatial correlation can then be determined by comparing the standardised panel average Moran's I value to standard normal critical values. In Table (5.2), I report the P-values of the corresponding test statistics for all data tested and all spatial weighting matrices used.

While the data in levels robustly rejects the null hypothesis of no spatial correlation across spatial connectivity specifications, the data in (log) differences offer no compelling evidence in favour of spatial dependence in rural employment growth. Since this study is concerned with rural ZCTA employment growth rather than employment levels, these results give no immediate indication of a need to actively account for spatial dependence via inclusion of additional terms, such as a spatial lag, in the empirical model. As such, in the baseline estimation strategy, I estimate equation (5.1) and employ a "passive" response to spatial correlation using cluster-robust standard errors conventional in the applied

[41] For example, consider a two year change in rural employment, i.e. $s = 2$. The sample spans from 2001 – 2017, so the total set of two year changes in employment is {2001 – 2003, 2002 – 2004, 2003 – 2005, …, 2014 – 2016, 2015 – 2017}, which features temporal overlap. Considering two year changes in employment with no overlap, the set becomes {2001 – 2003, 2003 – 2005, 2005 – 2007, …, 2013 – 2015, 2015 – 2017}. Since the time dimension is shorter, the number of periods over which the non-overlapping data are averaged is smaller than the number for overlapping data.

Table 5.2: Standardised Panel Average Moran's I-Statistic P-Values

$\boldsymbol{W}$	Data-Form	Levels	$\Delta_{t,t+1}$	$\Delta_{t,t+2}$	$\Delta_{t,t+3}$	$\Delta_{t,t+4}$	$\Delta_{t,t+5}$	$\Delta_{t,t+6}$
$\boldsymbol{W}_C$	Non-Overlapping	0.00	0.30	0.80	0.93	0.37	0.36	0.85
	Overlapping			0.63	0.64	0.46	0.45	0.55
$\boldsymbol{W}_B$	Non-Overlapping	0.00	0.11	0.54	0.61	0.35	0.47	0.62
	Overlapping			0.42	0.54	0.45	0.41	0.49
$\boldsymbol{W}_D$	Non-Overlapping	0.00	0.42	0.77	0.59	0.50	0.41	0.58
	Overlapping			0.60	0.56	0.48	0.44	0.50
$\boldsymbol{W}_{CD}$	Non-Overlapping	0.00	0.06	0.66	0.50	0.39	0.32	0.59
	Overlapping			0.36	0.37	0.34	0.34	0.42
$\boldsymbol{W}_{BD}$	Non-Overlapping	0.00	0.08	0.63	0.43	0.44	0.36	0.53
	Overlapping			0.37	0.39	0.37	0.36	0.43
$\boldsymbol{W}_G$	Non-Overlapping	0.00	0.30	0.46	0.52	0.48	0.48	0.52
	Overlapping			0.43	0.48	0.47	0.46	0.47
N	116 Rural ZCTAs							

Notes: This table presents the P-values of the standardised panel average of Moran's I-Statistics for employment data in levels and (log) differences within the sample 116 rural ZCTAs using a variety of spatial connectivity matrices. Under the null hypothesis, there is no spatial correlation.

spatial economic literature in the event there is spatial correlation in the data the tests above fail to reveal.

5.3 Estimation Strategy

I estimate parameters in equation (5.1) using a two-step feasible generalised method of moments (GMM) estimator. Let $\boldsymbol{\Delta l}_i$ be a $(T-1-k)$ x 1 vector of employment change observations for ZCTA i, $\boldsymbol{X}_i$ a $(T-1-k)$ x $(T-k)$ matrix of explanatory variables, $\boldsymbol{Z}_i$ a $(T-1-k)$ x $(T-1-k+C^r)$ matrix of instruments (where C^r is the number of informative instruments, implying the system is just-identified if $C^r = 1$ and overidentified if $C^r > 1$), $\boldsymbol{\Delta \nu}_i$ a $(T-1-k)$ x 1 vector of error terms, and $\boldsymbol{\beta}$ a $(T-k)$ x 1 parameter vector, i.e.

$$\boldsymbol{\Delta l}_i = \begin{bmatrix} \Delta l_{i,1+k,1+k+s} \\ \vdots \\ \Delta l_{i,t,t+s} \\ \vdots \\ \Delta l_{i,T,T+s} \end{bmatrix} \qquad \boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \delta_{2+k,2+k+s} \\ \vdots \\ \delta_{t,t+s} \\ \vdots \\ \delta_{T,T+s} \end{bmatrix} \qquad \boldsymbol{\Delta \nu}_i = \begin{bmatrix} \Delta \nu_{i,1+k,1+k+s} \\ \vdots \\ \Delta \nu_{i,t,t+s} \\ \vdots \\ \Delta \nu_{i,T,T+s} \end{bmatrix}$$

$$
\boldsymbol{X}_i = \begin{bmatrix} 1 & \sum_{c=1}^{C} \omega_{i,c} \Delta a_{c,1,1+k} & 0 & \cdots & 0 & \cdots & 0 \\ 1 & \sum_{c=1}^{C} \omega_{i,c} \Delta a_{c,2,2+k} & 1 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 1 & \sum_{c=1}^{C} \omega_{i,c} \Delta a_{c,t-k,t} & 0 & \cdots & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 1 & \sum_{c=1}^{C} \omega_{i,c} \Delta a_{c,T-k,T} & 0 & \cdots & 0 & \cdots & 1 \end{bmatrix} \quad \boldsymbol{Z}_i = \begin{bmatrix} 1 & 0 & \cdots & 0 & \cdots & 0 & \boldsymbol{B}_{i,1,1+k} \\ 1 & 1 & \cdots & 0 & \cdots & 0 & \boldsymbol{B}_{i,2,2+k} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots \\ 1 & 0 & \cdots & 1 & \cdots & 0 & \boldsymbol{B}_{i,t-k,t} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots \\ 1 & 0 & \cdots & 0 & \cdots & 1 & \boldsymbol{B}_{i,T-k,T} \end{bmatrix}
$$

where $\boldsymbol{B}_{i,t-k,t}$ is a 1 x C^r row vector of relevant (spatial connectivity weighted) shift-share instruments. The baseline model can then be re-expressed as

$$
\boldsymbol{\Delta l}_i = \boldsymbol{X}_i \boldsymbol{\beta} + \boldsymbol{\Delta \nu}_i \tag{5.7}
$$

with linear moment conditions $g(\boldsymbol{\Delta l}_i, \boldsymbol{X}_i, \boldsymbol{Z}_i, \boldsymbol{\beta})$ of the form

$$
\mathbb{E}[g(\boldsymbol{\Delta l}_i, \boldsymbol{X}_i, \boldsymbol{Z}_i, \boldsymbol{\beta})] = \mathbb{E}[\boldsymbol{Z}_i^{\boldsymbol{T}} \boldsymbol{\Delta \nu}_i(\boldsymbol{\beta})] = \mathbb{E}[\boldsymbol{Z}_i^{\boldsymbol{T}} (\Delta \boldsymbol{l}_i - \boldsymbol{X}_i \boldsymbol{\beta})] = 0 \tag{5.8}
$$

and sample analogue

$$
g_N(\boldsymbol{\Delta L}_i, \boldsymbol{X}_i, \boldsymbol{Z}_i, \boldsymbol{\beta}) = \frac{1}{N} \sum_{i=1}^{N} g_i(\boldsymbol{\Delta L}_i, \boldsymbol{X}_i, \boldsymbol{Z}_i, \boldsymbol{\beta}) = \frac{1}{N} \sum_{i=1}^{N} \boldsymbol{Z}_i^{\boldsymbol{T}} (\Delta \boldsymbol{L}_i - \boldsymbol{X}_i \boldsymbol{\beta}) \approx 0 \tag{5.9}
$$

I compute $\widehat{\boldsymbol{\beta}}_{GMM}$ as the minimiser of the criterion function

$$
\widehat{\boldsymbol{\beta}}_{GMM} = \arg\min_{\boldsymbol{\beta}} \quad g_N(\boldsymbol{\Delta L}_i, \boldsymbol{X}_i, \boldsymbol{Z}_i, \boldsymbol{\beta})^{\boldsymbol{T}} \widehat{\boldsymbol{S}}_J^{-1} g_N(\boldsymbol{\Delta L}_i, \boldsymbol{X}_i, \boldsymbol{Z}_i, \boldsymbol{\beta}) \tag{5.10}
$$

where

$$
\widehat{\boldsymbol{S}}_J^{-1} = \frac{1}{J} \sum_{j=1}^{J} g_j(\boldsymbol{\Delta L}_j, \boldsymbol{X}_j, \boldsymbol{Z}_j, \widehat{\boldsymbol{\beta}}) g_j(\boldsymbol{\Delta L}_j, \boldsymbol{X}_j, \boldsymbol{Z}_j, \widehat{\boldsymbol{\beta}})^{\boldsymbol{T}} - g_J(\boldsymbol{\Delta L}_j, \boldsymbol{X}_j, \boldsymbol{Z}_j, \widehat{\boldsymbol{\beta}}) g_J(\boldsymbol{\Delta L}_j, \boldsymbol{X}_j, \boldsymbol{Z}_j, \widehat{\boldsymbol{\beta}})^{\boldsymbol{T}} \tag{5.11}
$$

$$
g_J(\boldsymbol{\Delta L}_j, \boldsymbol{X}_j, \boldsymbol{Z}_j, \widehat{\boldsymbol{\beta}}) = \frac{1}{J} \sum_{j=1}^{J} g_j(\boldsymbol{\Delta L}_j, \boldsymbol{X}_j, \boldsymbol{Z}_j, \widehat{\boldsymbol{\beta}}) = \frac{1}{J} \sum_{i=j}^{J} \boldsymbol{Z}_j^{\boldsymbol{T}} (\Delta \boldsymbol{L}_j - \boldsymbol{X}_j \widehat{\boldsymbol{\beta}})
$$

is the asymptotically efficient weighting matrix constructed using a consistent estimator of $\boldsymbol{\beta}$, $\widehat{\boldsymbol{\beta}}$, which allows the error terms $\boldsymbol{\Delta \nu}_i$ to be dependent (temporally and spatially) within J clusters. Since evidence from the previous section gives no strong indications of spatial correlation in the dependent variable, I adopt the "passive" response to account for potential spatial correlation in the residuals, using the "Bester" 10,000-square-kilometre grids as the baseline cluster specification. As the efficient GMM weight matrix, $\widehat{\boldsymbol{S}}_J^{-1}$ is robust to heteroskedasticity. Furthermore, since error terms can correlate within clusters, $\widehat{\boldsymbol{S}}_J^{-1}$ is robust to serial correlation (since a given ZCTA is located in the same cluster j across time) and spatial correlation of Bester, Conley, and Hansen (2011), provided spatial dependence takes place only among ZCTAs within the same cluster j, but not across clusters. In the event correlation takes place across clusters and following insights from

Kelly (2019), who performs simulations showing that persistence regressions using spatial data with spatial dependence can lead to spurious correlations, I perform tests in the results section to evaluate the presence of any spatial correlation in the residuals of $\widehat{\beta}_{GMM}$ from each estimated model, constructing panel standardised Moran's I-Statistics using all of the ZCTA to ZCTA spatial connectivity matrices from Table (5.1).

Provided $\widehat{S}_J^{-1}$ is positive semidefinite and asymptotically positive definite, β is an interior solution to the criterion function, the moment conditions are continuously differentiable, and the Jacobian of the moment conditions with respect to the parameter vector is of full rank, i.e. $\text{rank}\left(D_\beta \, \mathbb{E}[g(\boldsymbol{\Delta L}_i, \boldsymbol{X}_i, \boldsymbol{Z}_i, \beta)]\right) = T - k$, then $\widehat{\beta}_{GMM}$ is a consistent estimator for β and distributed asymptotically normal. Furthermore, given the system is overidentified (for $C^r > 1$), I test satisfaction of exclusion restrictions via Hansen's J test.

Considering recent debate and controversy surrounding the use of Bartik style shift-share instruments, some clarifying remarks concerning the moment conditions must be addressed. Goldsmith-Pinkham et al. (2020) show that the two-stage least squares (2SLS) estimator with the Bartik shift-share instrument is numerically equivalent to a GMM estimator with the local sector shares as instruments and a weight matrix constructed from the regionally exogenous growth rates. They argue this numerical equivalence implies that the exogeneity condition must be interpreted in terms of the "shares." That is, while the "shifts", the $g_{-c,h,t-k,t}$'s, influence relevance of the instruments, it is the shares, the $\lambda_{c,h,t-k}$'s, that determine satisfaction of the exclusion restriction. In light of this result, by testing overidentifying restrictions, I am in fact testing if Assumption 3 holds, since $g_{-c,h,t-k,t}$ is exogenous by construction.

6 Results

Higher Total factor productivity (TFP) growth in an urban core is hypothesised to be associated with lower employment growth in the core's rural periphery. This is precisely what I find. Following the estimation procedure discussed in Section 5 and setting $k = 3$ and $s = 3$ in equation (5.1), a one standard deviation increase in the aggregate TFP growth rate of the FRUC, which amounts to an additional 3.4 percentage points in TFP growth over a three-year period, is associated with a 1.34 percentage point lower average employment growth rate in ZCTAs located in the FRUC's rural periphery. I first investigate the robustness of the statistical significance of this result to alternative ways of estimating the variance-covariance matrix (and hence, the standard errors used to conduct inference on parameter estimates). Then, I evaluate the robustness of the result to alternative specifications of the baseline model, incorporating spatial lags and controlling for TFP. Furthermore, I evaluate the success of the spatial connectivity weights $\omega_{i,c}$ in capturing underlying heterogeneities in the associations between particular MSA c and ZCTA i by testing if the parameter β_1 is indeed common. Finally, I compare the results for $k = s = 3$ against other potential lag specifications and test for contemporaneous correlations between the primary explanatory variable and the dependent variable.

For each set of estimates, in addition to providing details concerning the sample size, R^2, t-ratio P-value for the explanatory variable of interest, and conducting relevant post-estimation tests for the class of instrumental variable estimators (where applicable), the residuals for each estimated model in the results below are tested for evidence of spatial dependence using the panel standardised Moran's I-Statistics discussed in Section 5.2. I replace the demeaned variable in equation (5.6) with the estimated residuals for the sample.[42] I construct six panel standardised Moran's I-Statistics using each of the ZCTA to ZCTA spatial connectivity matrices in Table (5.1) and report the P-value associated with each standardised I-Statistic when compared to a standard normal distribution. Recall that under the null hypothesis, there is no spatial correlation. Across parameter estimators, standard error estimators, and model specifications, I do not find robust evidence for spatial correlation in the disturbance term.

The (queen) contiguity matrix and Bester contiguity matrix frequently reject the null of no spatial dependence, however the other four specifications consistently fail to detect such dependence. There are two reasons why rejection of the null hypothesis of no spatial dependence under the contiguity-style spatial weighting matrices poses limited threat to consistent standard error estimates. The first is that, at least when clustering standard errors in the 10,000-square-km "Bester" grid squares, the standard error estimates are robust to this exact type of spatial dependence. Given $\boldsymbol{W}_C$ and $\boldsymbol{W}_B$ share a fair degree of overlap (i.e. most neighbours are located in the same 10,000-square-km cluster j), when clustering on the grid squares, the the robustness of errors to dependence within the j clusters likely extends to spatial dependence across neighbours. Second, assumption of spatial dependence implied by $\boldsymbol{W}_C$ and $\boldsymbol{W}_B$ is rather strong. If two ZCTAs are neighbours or located in the same cluster j, their comovements are given a weight of unity, assuming no effect of distance in the relationship, which unrealistically abstracts from how ZCTAs near and far likely influence one another. The other forms of weighting matrices, which factor in more realistic frictions (i.e. distance, relative size of trading parties, etc.) to correlation between two locations are likely less strict assumptions on how outcomes in various places associate with each other.

Benchmark Results Using data described above on the observed 116 rural ZCTAs in the hinterland of the FRUC, in Table (6.1) I present the parameter estimates resulting from regressing three-year growth in rural ZCTA employment from t to $t+3$ (i.e. $\Delta l_{i,t,t+3}$) on the sum of spatial connectivity weighted three-year growth in TFP from $t-3$ to t in the six MSAs that comprise the FRUC (i.e. $\sum_c \omega_{i,c}\Delta a_{c,t-3,t}$) and Intercept/Time Dummies

[42] That is, I construct the Moran's I-Statistic for estimated residuals (following Beenstock and Felsenstein (2019)) as

$$I_{t,t+s} = \frac{1}{\sum_i \sum_{i'} \omega_{i,i'}} \frac{\sum_i \sum_{i'} \omega_{i,i'} \widehat{\Delta v}_{i,t,t+s} \widehat{\Delta v}_{i',t,t+s}}{\frac{1}{N}\sum_i (\widehat{\Delta v}_{i,t,t+s})^2}$$

where $\widehat{\Delta v}_{i,t,t+s} = \Delta l_{i,t,t+s} - \widehat{\beta}_0 + \widehat{\beta}_1 \sum_{c=1}^{C} \omega_{i,c} \Delta a_{c,t-k,t} - \widehat{\delta}_{t,t+s}$ and "hatted"-parameters are consistent estimates.

($\delta_{t,t+3}$). That is, I estimate

$$\Delta l_{i,t,t+3} = \beta_0 + \beta_1 \sum_{c=1}^{C} \omega_{i,c} \Delta a_{c,t-3,t} + \delta_{t,t+3} + \Delta \nu_{i,t,t+3} \tag{6.1}$$

where $t \in \{2004, 2005, \ldots, 2014\}$. In columns (1) through (4), I use dependent (i.e. overlapping) temporal observations, while in columns (5) and (6) I use non-dependent (i.e. non-overlapping) temporal observations. The reference time regime (i.e. omitted time dummy variable) is 2004-2007 for columns (1) through (5) and 2005-2008 for column (6). Cluster-robust standard errors are reported beneath parameter estimates in parenthesis and are clustered in 10,000-square-km grid squares, robust to heteroskedasticity, serial correlation, and spatial correlation of the form considered by Bester, Conley, and Hansen (2011) within each cluster.

In column (1), I present results estimating the parameters in equation (6.1) via OLS. The first row gives the estimate for the explanatory variable of interest and the second row reports the estimated constant, which coincides with the parameter estimate for the omitted time dummy. The parameter estimates in rows 3-12 evaluate how each included temporal regime dummy $\delta_{t,t+3}$ compares to the omitted time dummy (i.e. $\delta_{2004,2007}$). Wald tests evaluating the joint significance of the time dummy variables rejects the null hypothesis they are jointly equal to zero, thereby justifying their inclusion. In fact, the behaviour of these estimates is consistent with evidence presented in Section 4.2 of rural employment growth trends. Pre-Great Recession three-year rural employment growth from 2004-2007 (the reference temporal regime) was positive, whereas intervals that span the crisis (e.g. 2005-2008, 2006-2009, etc.) had lower estimated average employment growth relative to the pre-crisis baseline. Finally, tests for spatial correlation in the residuals fail to detect robust evidence in favour of spatial dependence to which the estimated standard errors are not themselves robust.

There are underlying business cycle effects that explain variation over time in rural ZCTA employment growth rates in the sample. However, using OLS, there is no evidence of association between urban TFP growth and rural employment growth, as the t-ratio test fails to reject the null hypothesis that β_1 is statistically different from zero. Moreover, statistical insignificance aside, the OLS estimate suggests a negligible economic effect. The OLS parameter implies a one standard deviation increase in FRUC TFP growth over a three-year period of 3.4 percentage points is associated with a 0.19 percentage point decline in rural ZCTA employment growth in the following three-year period. However, there is a concern about the reliability of these OLS estimates likely due to aforementioned measurement error in urban TFP estimates, particularly when leveraged against results produced via instrumental variable approaches.

Columns (2), (3), and (4) utilise the Bartik-style shift share instruments discussed in Section 5.1 and estimate equation (6.1) via instrumental variable (IV) methods. Column (2) uses the two-stage least squares (2SLS) estimator, column (3) the continuously updating GMM estimator (CUE) of Hansen, Heaton, and Yaron (1996), and column (4) the feasible two-step generalised method of moments (GMM) estimator. In each IV regression, I instru-

Table 6.1: Benchmark Results

	(1)	(2)	(3)	(4)	(5)	(6)
	Overlapping Data				Non-Overlapping Data	
	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$
$\sum_c \omega_{i,c}\Delta a_{c,t-3,t}$	-0.063	-0.467**	-0.388***	-0.403***	-0.884***	-0.625***
	(0.114)	(0.182)	(0.127)	(0.153)	(0.319)	(0.207)
$\delta_{2005,2008}$	-0.076**	-0.078***	-0.048***	-0.060***		
	(0.029)	(0.028)	(0.014)	(0.019)		
$\delta_{2006,2009}$	-0.144***	-0.154***	-0.124***	-0.121***		
	(0.033)	(0.036)	(0.024)	(0.023)		
$\delta_{2007,2010}$	-0.208***	-0.217***	-0.172***	-0.172***	-0.216***	
	(0.039)	(0.040)	(0.032)	(0.029)	(0.039)	
$\delta_{2008,2011}$	-0.132***	-0.126***	-0.094***	-0.091***		-0.074**
	(0.035)	(0.034)	(0.032)	(0.027)		(0.032)
$\delta_{2009,2012}$	-0.039	-0.038	-0.006	-0.008		
	(0.030)	(0.029)	(0.022)	(0.020)		
$\delta_{2010,2013}$	0.011	0.015	0.043*	0.032	0.036*	
	(0.036)	(0.034)	(0.024)	(0.025)	(0.018)	
$\delta_{2011,2014}$	0.003	0.008	0.035*	0.025		0.069***
	(0.033)	(0.031)	(0.020)	(0.020)		(0.018)
$\delta_{2012,2015}$	-0.029	-0.017	0.011	-0.001		
	(0.039)	(0.036)	(0.022)	(0.021)		
$\delta_{2013,2016}$	-0.033	-0.032	-0.005	-0.012	-0.026	
	(0.025)	(0.025)	(0.018)	(0.017)	(0.018)	
$\delta_{2014,2017}$	-0.015	-0.017	0.013	0.006		0.024
	(0.024)	(0.024)	(0.018)	(0.018)		(0.024)
Constant	0.073***	0.073***	0.039***	0.050***	0.066***	0.020
	(0.019)	(0.019)	(0.010)	(0.012)	(0.008)	(0.015)
N	1276	1276	1276	1276	464	464
R^2	0.07	0.07	0.07	0.07	0.10	0.05
$\widehat{\beta_1}$ t-Ratio P-value	0.58	0.01	0.00	0.01	0.01	0.00
Estimator	OLS	2SLS	CUE	GMM	GMM	GMM
Weak ID F-Test	–	2471.52	2471.52	2471.52	65.58	4042.32
Weak IV-robust P-value	–	0.00	0.00	0.00	0.04	0.02
Hansen's J-Test P-value	–	0.59	0.55	0.59	0.98	0.21
C-Test P-value	–	0.02	0.02	0.02	0.06	0.12
Moran's I-Test P-value ($\boldsymbol{W_C}$)	0.10	0.02	0.36	0.00	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W_B}$)	0.00	0.00	0.01	0.00	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W_D}$)	0.40	0.41	0.44	0.41	0.77	0.44
Moran's I-Test P-value ($\boldsymbol{W_{CD}}$)	0.44	0.45	0.46	0.44	0.50	0.46
Moran's I-Test P-value ($\boldsymbol{W_{BD}}$)	0.45	0.46	0.46	0.45	0.48	0.48
Moran's I-Test P-value ($\boldsymbol{W_G}$)	0.55	0.59	0.64	0.57	0.64	0.50

Notes: This table displays estimates of equation (6.1). Columns (1)-(4) presents estimates using "dependent (i.e. overlapping) temporal observations and various estimators: column (1) ordinary least squares estimator, column (2) two-state least squares estimator, column (3) the continuously updating GMM estimator, and column (4) (the "benchmark" results) feasible two-step generalised method of moment estimator. Columns (5) and (6) estimate (6.1) using non-dependent (i.e. non-overlapping) temporal observations, with estimates computed using the GMM estimator. The excluded time dummy for columns (1)-(3) is that for 2004-2007; the excluded time dummy for columns (5)-6 is for 2005-2008. Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. The $\widehat{\beta_1}$ t-Ratio evaluates if $\widehat{\beta_1}$ is significantly different from zero; under the null hypothesis $\beta_1 = 0$. The excluded instruments used for $\sum_c \omega_{i,c}\Delta a_{c,t-3,t}$ are the Bartik-style shift share instruments from $t-3$ to t for all FRUC MSAs excluding Greeley. First stage results are presented in Appendix Table (D.1). The weak instrument F-test is the Kleibergen-Paap Wald rank F statistic; under the null the rank test fails. The weak IV-robust P-value is for the Stock-Wright S-statistic; under the null, β_1 is zero. Hansen's J-Test of overidentifying restrictions evaluates the orthogonality of the instruments to the residuals in overidentified models; under the null the instruments are exogenous. The C-Test evaluates if $\widehat{\beta}_{1,IV}$ for $IV \in \{2SLS, GMM, CUE\}$ is statistically distinguishable from $\widehat{\beta}_{1,OLS}$; under the null, the estimators produce the same estimates. The Moran's I-Test evaluates the presence of spatial dependence in the residuals of each estimated model using the standardised panel average of the global Moran's I, here constructed in six different ways using a variety of ZCTA to ZCTA spatial connectivity matrices (see Table (5.1) for details); under the null hypothesis, there is no spatial correlation among residuals.

ment $\sum_{c=1}^{C} \omega_{i,c} \Delta a_{c,t-3,t}$ with the shift-share instruments $\omega_{i,c} B_{c,t-3,t}$ for MSAs c including Boulder (BCO), Colorado Springs (COS), Denver (DEN), Fort Collins (FCO), and Pueblo (PUB). I do not use the shift-share instrument for Greeley (GXY) given it is not informative for $\sum_{c=1}^{C} \omega_{i,c} \Delta a_{c,t-3,t}$ when used alongside the other MSA instruments, as evidenced by Figure (4.5). I present the first-stage results in Appendix Table (D.1). In Appendix Table (D.2) I present GMM estimates of (6.1) produced using other instrument specifications, testing the sensitivity of the main results when all MSA shift-share instruments are included (i.e. Greeley is not dropped), when only one or two MSA shift-share instruments are used, and finally when sums and weighted averages of the shift-share instruments are used. The results are broadly similar (i.e. the main result is statically significant and negative), though significance of the main result is lost when the instruments are summed together/averaged due larger standard error estimates and smaller parameter estimates.

Inspection of the first stage regressions and instrument diagnostic tests suggest the set of Bartik style shift-share instruments are informative. Using the Kleibergen-Paap Wald rank F-statistic (Kleibergen and Paap, 2006) to test instrument strength, under the null hypothesis of which the rank test fails, the test statistic is 2,471.52, comfortably rejecting the null. Furthermore, the weak IV-robust P-value from the Stock-Wright S-Test (Stock and Wright, 2000), which is the GMM-analogue to the Anderson-Rubin Test, rejects the null that the coefficient on the instrumented explanatory variable (β_1) is zero, offering further confidence in the shift-share instruments' strength. Additionally, given the system is overidentified, I test satisfaction of the exclusion restriction using Hansen's J-statistic (Hansen, 1982), where under the (joint) null hypothesis the overidentifying restrictions are valid. The Hansen's J-Test P-values for 2SLS/GMM and CUE are all above 0.5 and I do not reject the null hypothesis, suggesting the instruments are orthogonal to the disturbance term.

Quick comparison of the OLS parameter estimate for $\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$ against those produced by 2SLS, GMM, and CUE ($\widehat{\beta}_{1,OLS}$, $\widehat{\beta}_{1,2SLS}$, $\widehat{\beta}_{1,GMM}$, and $\widehat{\beta}_{1,CUE}$, respectively henceforth) hint at underlying measurement error rendering OLS inconsistent and biased toward zero. I test if each IV parameter estimate differs (statistically) significantly from $\widehat{\beta}_{1,OLS}$ using a C-statistic, otherwise known as a Difference-in-Hansen test. Under the null, $\widehat{\beta}_{1,IV} = \widehat{\beta}_{1,OLS}$ for $IV \in \{2SLS, GMM, CUE\}$. The C-statistic P-value rejects the null, lending credibility to concerns of measurement error contamination in OLS estimation as emphasised in a closely related context by Hornbeck and Moretti (2020) and discussed in Section 5.1. Given the evidence in favour of the informativeness and validity of the shift-share instruments alongside that suggesting biased OLS estimates, I limit subsequent discussion to parameters estimated using the class of IV estimators. Moreover, comparing parameter estimates between IV estimators, while the CUE estimates appear to be the most efficient, they do not differ substantially from the feasible two-step GMM estimator. Given GMM is less computationally intensive and using it does not sacrifice substantive efficiency gains, I restrict subsequent analysis to the GMM estimates, defining the results in column (4) as the "benchmark results."

The GMM results in column (4) convey a similar story as OLS concerning the effects of business cycle dynamics on rural employment growth. However, there is a clear distinction in their implication of the relationship between urban TFP growth and rural employment growth, with the GMM results reporting a statistically significant negative comovement between the explanatory variable of interest and the dependent variable. Moreover, these results carry economic meaning, suggesting that a one standard deviation increase in FRUC TFP growth over three years, i.e. 3.4 percentage points, is associated on average with a 1.37 percentage point decline in the rural ZCTA employment growth rate over the following three years. During the period of observation, the average ZCTA three-year employment growth rate was 1.7%, which implies that a one standard deviation increase in the FRUC TFP growth rate covaries with an slowdown in rural employment growth, as the net three-year growth rate drops to 0.33%. While quantitatively different from the rural employment growth decrease associated with a 3.4% increase in urban TFP implied by the theoretical model ($\approx 8\%$), there are qualitative parallels, as the sign of the association matches the directional intuition of the model. Given the model's insights, the smaller comovement could in part be related to the particular rural-urban TFP levels disparities in the FRUC core-periphery system, thought it is likely there are more factors at play.

The use of overlapping temporal data in columns (1) through (4), while increasing the sample size, likely results in serial dependence in the error term. The use of cluster-robust standard errors to allow for serial (and spatial) dependence to occur within specified clusters, while justified asymptotically, may inflate the statistical significance of reported findings given the small number of clusters. However, this does not seem to be the case. In columns (5) and (6), I report GMM estimates of model (6.1) using non-overlapping data. The parameters in column (5) are estimated using data from 2004-2007, 2007-2010, 2010-2013, and 2013-2016. Column (6) results are estimated using data from 2005-2008, 2008-2011, 2011-2014, and 2014-2017. Relative to the benchmark results in column (4), statistical significance of the main result is preserved. Furthermore, results for the non-overlapping data imply a stronger association between FRUC TFP growth and rural employment growth, with a 3.4 percentage point increase in the three-year FRUC TFP growth rate correlating with between a 2.13 and 3.0 percentage point decline in the average future three-year employment growth rate among rural ZCTAs.

I show in Appendix Table (D.3) that this result is robust to the spatial connectivity distance measurement used in the construction of the gravity-style ZCTA-MSA weights $\omega_{i,c}$. Results from measuring distance by travel time (in hours by automobile) imply a 3.4 percentage point increase in FRUC TFP growth from $t-3$ to t is associated with 1.23 percentage point decreases in rural employment growth from t to $t+3$, while the Euclidean distance (in km) results suggest a 1.55 percentage point decrease, both of which are similar to the benchmark. Thus, I find the choice of different distance measure does not noticeably alter estimated cluster-robust standard errors, the instruments performance, nor conclusions regarding the presence of spatial correlation in the residuals.

Alternative Variance-Covariance Matrix Estimation I evaluate the robustness of the benchmark results to alternative estimators of the standard errors. Given I am working within the GMM environment, the choice of variance-covariance matrix estimator has direct relevance to the manifestation of the efficient GMM weighting matrix, which in turn influences parameter and standard error estimates. As noted, the benchmark results are estimated using cluster-robust standard errors where ZCTAs are grouped into 10,000-square-km grid squares. The resulting standard errors are then robust to heteroskedasticity, serial correlation, and spatial correlation of the specified form described by Bester, Conley, and Hansen (2011), provided these potential forms of dependence do not exist between the specified clusters.

In Table (6.2), I reproduce the benchmark results in column (4) and compare them to efficiet GMM estimates of equation (6.1) using Huber-White standard errors in column (1) and different clusters for cluster-robust inference in columns (2) and (3). In column (2), I cluster standard errors by ZCTA, implying these results are (asymptotically) robust to serial correlation and heteroskedasticity. In (3), I cluster standard errors by county (i.e. ZCTAs located in the same parent county are permitted to covary across time and space) and so these results are (asymptotically) robust to serial correlation, spatial correlation within-counties, and heteroskedasticity. Qualitatively, the various variance-covariance matrix estimators and corresponding GMM weight matrices yield similar results in terms of parameter and standard error estimates, though the benchmark standard errors clustered on the grid squares (the "Bester" clusters) appear to be the smallest. Moreover, the Moran's I-Test results are roughly consistent across variance-covariance estimators, with the exception that the test fails to reject the null of no spatial dependence between neighbouring ZCTAs using Huber-White robust standard errors or clustering errors on ZCTA. Given the similar results, I restrict subsequent variance-covariance estimation to the estimation specification in column (4).

Spatial Lag Model Although the evidence given by the panel standardised global Moran's I-Test for each regression thus far has failed to detect spatial correlation to which the standard error specification (i.e. the cluster-robust estimator using 10,000-square-km clusters) is not robust, to test for any unmodelled spatial dependence, I adapt (6.1) into a spatial lag model, which incorporates a spatial lag term of the dependent variable to the right hand side and uses one of the six ZCTA-ZCTA spatial connectivity matrices from Table 5.1. I estimate

$$\Delta l_{i,t,t+3} = \beta_0 + \beta_1 \sum_{c=1}^{C} \omega_{i,c} \Delta a_{c,t-3,t} + \beta_2 \sum_{i' \neq i}^{N} \omega_{i,i'} \Delta l_{i',t,t+3} + \delta_{t,t+3} + \Delta \nu_{i,t,t+3} \tag{6.2}$$

where $\sum_{i' \neq i}^{N} \omega_{i,i'} \Delta l_{i',t,t+3}$ is the spatial lag term and $\omega_{i,i'} \in \{\boldsymbol{W}_C, \boldsymbol{W}_B, \boldsymbol{W}_D, \boldsymbol{W}_{CD}, \boldsymbol{W}_{BD}, \boldsymbol{W}_G\}$. Note that the data on $\sum_{i' \neq i}^{N} \omega_{i,i'} \Delta l_{i',t,t+3}$ where $\omega_{i,i'} \in \boldsymbol{W}_G$ are scaled like the weighted urban TFP growth data such that the weighted mean equals the unweighted mean.

Table (6.3) presents the benchmark results for β_1 in column (1) against those resulting from estimates of equation (6.2) in columns (2) through (7), with the particular ZCTA-ZCTA spatial connectivity matrix used in estimation specified in the column header. These results are consistent with the benchmark estimates, with sign and statistical

Table 6.2: Alternative Variance-Covariance Matrix Estimation

	(1)	(2)	(3)	(4)
	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$
Var-Cov Matrix Estimator	Huber-White	Cluster-Robust		
Cluster	N/A	ZCTA	County	Bester
$\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$	-0.477***	-0.545***	-0.490***	-0.403***
	(0.182)	(0.206)	(0.177)	(0.153)
N	1276	1276	1276	1276
R^2	0.06	0.06	0.06	0.07
$\widehat{\beta}_1$ t-Ratio P-value	0.01	0.01	0.01	0.01
Intercept/Time Dummies	Yes	Yes	Yes	Yes
Estimator	GMM	GMM	GMM	GMM
Weak ID F-Test	23.44	493.74	356.84	2471.52
Weak IV-robust P-value	0.00	0.00	0.00	0.00
Hansen's J-Test P-value	0.61	0.73	0.79	0.59
C-Test P-value	0.00	0.00	0.01	0.02
Moran's I-Test P-value ($\boldsymbol{W}_C$)	0.37	0.13	0.03	0.00
Moran's I-Test P-value ($\boldsymbol{W}_B$)	0.00	0.00	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W}_D$)	0.44	0.44	0.43	0.41
Moran's I-Test P-value ($\boldsymbol{W}_{CD}$)	0.46	0.46	0.45	0.44
Moran's I-Test P-value ($\boldsymbol{W}_{BD}$)	0.46	0.46	0.46	0.45
Moran's I-Test P-value ($\boldsymbol{W}_G$)	0.64	0.66	0.62	0.57

Notes: This table displays estimates of equation (6.1) estimated using the two-step feasible generalised method of moments (GMM) estimator. Each column presents estimates using a different estimator for the standard errors: column (1) the Huber-White estimator robust to heteroskedasticity of White (1980), column (2) errors clustered on ZCTA codes implying robustness to heteroskedasticity and serial correlation within the cluster, column (3) errors clustered on county FIPS codes implying robustness to heteroskedasticity, serial correlation, and spatial correlation within the cluster, and column (4) the benchmark results estimating errors clustered in 10,000-square-km grid squares and are robust to spatial correlation of Bester, Conley, and Hansen (2011) alongside robustness to heteroskedasticity and serial correlation within the cluster, where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. The intercept term and time dummy variables were included in each specification (with the time dummy for 2004-2007 omitted). Instruments used in estimation and the post-estimation tests performed are identical to Table (6.1).

significant as well as absolute magnitude of parameter and standard error estimates virtually unchanged across $\boldsymbol{W}$, mitigating concerns of spatial correlation in the dependent variable contaminating standard error estimates. The estimated β_2 coefficients on the spatial lag terms are insignificantly different from zero and the Moran's I-Test P-values are relatively the same across specifications.

The notable exception is when the (queen) contiguity-weighted or Bester contiguity-weighted spatial lag is introduced, the Moran's I test does not reject the null of spatial dependence when residuals are weighted using $\boldsymbol{W}_C$. Given the standard error estimates on $\widehat{\beta}_1$ differ only by 0.005 between the benchmark and the $\boldsymbol{W}_C/\boldsymbol{W}_B$ spatial lag models, it does not seem that the inclusion of the spatial lag influences standard error estimates. As such, this gives some evidence in favour of the idea that the Moran's I-Test's rejection of the null under at least the $\boldsymbol{W}_C$ weighting scheme is a result of the strong assumptions

Table 6.3: Local Employment Growth Spatial Lag

	(1) $\Delta l_{i,t,t+3}$	(2) $\Delta l_{i,t,t+3}$	(3) $\Delta l_{i,t,t+3}$	(4) $\Delta l_{i,t,t+3}$	(5) $\Delta l_{i,t,t+3}$	(6) $\Delta l_{i,t,t+3}$	(7) $\Delta l_{i,t,t+3}$
Spatial Lag Connectivity Matrix	N/A	$\boldsymbol{W}_C$	$\boldsymbol{W}_B$	$\boldsymbol{W}_D$	$\boldsymbol{W}_{CD}$	$\boldsymbol{W}_{BD}$	$\boldsymbol{W}_G$
$\sum_c \omega_{i,c}\Delta a_{c,t-3,t}$	-0.403***	-0.384**	-0.395**	-0.384**	-0.389**	-0.402**	-0.397***
	(0.153)	(0.158)	(0.158)	(0.159)	(0.158)	(0.158)	(0.153)
$\sum_{i'\neq i} \omega_{i,i'}\Delta l_{i',t,t+3}$		0.009	0.213	0.354	0.014	0.108	-0.007
		(0.007)	(0.284)	(0.292)	(0.013)	(0.434)	(0.007)
N	1276	1276	1276	1276	1276	1276	1276
R^2	0.07	0.07	0.07	0.07	0.07	0.07	0.07
$\widehat{\beta}_1$ t-Ratio P-value	0.01	0.02	0.01	0.02	0.01	0.01	0.01
Intercept/Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	GMM	GMM	GMM	GMM	GMM	GMM	GMM
Weak ID F-Test	2471.52	1457.87	2284.83	2205.61	547.80	1332.94	408.51
Weak IV-robust P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen's J-Test P-value	0.59	0.61	0.58	0.58	0.59	0.58	0.59
C-Test P-value	0.02	0.01	0.01	0.01	0.01	0.01	0.01
Moran's I-Test P-value ($\boldsymbol{W}_C$)	0.00	0.42	0.12	0.08	0.50	0.01	0.00
Moran's I-Test P-value ($\boldsymbol{W}_B$)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W}_D$)	0.41	0.42	0.41	0.42	0.42	0.41	0.41
Moran's I-Test P-value ($\boldsymbol{W}_{CD}$)	0.44	0.45	0.45	0.45	0.45	0.44	0.44
Moran's I-Test P-value ($\boldsymbol{W}_{BD}$)	0.45	0.46	0.45	0.46	0.46	0.45	0.45
Moran's I-Test P-value ($\boldsymbol{W}_G$)	0.57	0.59	0.58	0.58	0.58	0.57	0.57

Notes: This table displays estimates of equation (6.1) in column (1) and equation (6.2) in columns (2) through (7)using different spatial connectivity matrices. Estimates are computed using the feasible two-step generalised methods of moments estimator (GMM). The intercept term and time dummy variables were included in each specification (with the time dummy for 2004-2007 omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. Instruments used in estimation and the post-estimation tests performed are identical to Table (6.1).

of spatial dependence this matrix specification implies rather than a reflection of spatial dependence in the residuals.

Accounting for Local TFP The theoretical model in Section 3.5 describes a positive auxiliary role for local TFP in the determination of the rural employment level that works against the negative local employment growth effects related to TFP growth in the urban core. Measurement error in rural TFP estimates coupled with the inability to construct informative Bartik-style shift-share instruments for said estimates (on account of the small size of individual rural ZCTAs hindering adequate correlation with national trends) thwarts identification and meaningful inference. However, here I test the implications of controlling for local rural ZCTA TFP growth on the β_1 parameter estimate in the benchmark specification.

In Table (6.4), I present the benchmark results in column (1) against different adaptations of equation (6.1) that incorporate local TFP. Column (2) reports parameter estimates for a model that adds a measure contemporaneous ZCTA TFP growth from t to $t+3$ into the baseline specification

$$\Delta l_{i,t,t+3} = \beta_0 + \beta_1 \sum_{c=1}^{C} \omega_{i,c}\Delta a_{c,t-3,t} + \beta_2 \Delta a_{i,t,t+3} + \delta_{t,t+3} + \Delta \nu_{i,t,t+3} \tag{6.3}$$

Column (3) presents results of estimating a model that includes lagged local TFP growth that coincides with the timing of urban TFP growth, i.e. year $t-3$ to t

$$\Delta l_{i,t,t+3} = \beta_0 + \beta_1 \sum_{c=1}^{C} \omega_{i,c} \Delta a_{c,t-3,t} + \beta_2 \Delta a_{i,t-3,t} + \delta_{t,t+3} + \Delta \nu_{i,t,t+3} \tag{6.4}$$

In column (4), I combine equations (6.3) and (6.4), estimating a model that includes both contemporaneous and lagged three-year local TFP growth

$$\Delta l_{i,t,t+3} = \beta_0 + \beta_1 \sum_{c=1}^{C} \omega_{i,c} \Delta a_{c,t-3,t} + \beta_2 \Delta a_{i,t,t+3} + \beta_3 \Delta a_{i,t-3,t} + \delta_{t,t+3} + \Delta \nu_{i,t,t+3} \tag{6.5}$$

The parameter estimates $\widehat{\beta_1}$ in columns (2) through (4) are broadly similar to the benchmark estimates in column (1). So too are the standard error estimates and Moran's I-Tests results. The estimated parameter for contemporaneous TFP growth is positive and weakly significant in both columns (2) and (4), while the lagged TFP growth parameter becomes insignificant when included alongside the contemporaneous growth in local TFP. This offers some evidence in favour of contemporaneous TFP growth plausibly playing a more important role in local employment growth relative to lagged local TFP innovations.

Table 6.4: Controlling for Local TFP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$
	No Local TFP Spatial Lag				Local TFP Spatial Lag					
Spatial Connectivity Matrix	N/A				$\boldsymbol{W}_C$	$\boldsymbol{W}_B$	$\boldsymbol{W}_D$	$\boldsymbol{W}_{CD}$	$\boldsymbol{W}_{BD}$	$\boldsymbol{W}_G$
$\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$	-0.403***	-0.371***	-0.437***	-0.390***	-0.391***	-0.413***	-0.444***	-0.435***	-0.389***	-0.367***
	(0.153)	(0.121)	(0.139)	(0.118)	(0.121)	(0.117)	(0.121)	(0.123)	(0.122)	(0.123)
$\Delta a_{i,t,t+3}$		0.164*		0.138*	0.171*	0.182**	0.177*	0.178*	0.167*	0.169*
		(0.089)		(0.082)	(0.090)	(0.089)	(0.091)	(0.092)	(0.091)	(0.089)
$\Delta a_{i,t-3,t}$			-0.134**	-0.064						
			(0.068)	(0.056)						
$\sum_{i' \neq i} \omega_{i,i'} \Delta a_{i',t,t+3}$					-0.005	-0.480	-0.500	-0.015	-0.081	0.0003***
					(0.010)	(0.318)	(0.346)	(0.015)	(0.434)	(0.00004)
N	1276	1276	1276	1276	1276	1276	1276	1276	1276	1276
R^2	0.07	0.09	0.08	0.09	0.09	0.09	0.09	0.09	0.09	0.09
$\widehat{\beta_1}$ t-Ratio P-value	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Intercept/Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM
Weak ID F-Test	2471.52	2225.99	2161.57	2058.13	2100.60	2265.72	2126.66	1502.64	1665.98	1309.04
Weak IV-robust P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen's J-Test P-value	0.59	0.51	0.56	0.51	0.51	0.54	0.51	0.52	0.50	0.54
C-Test P-value	0.02	0.07	0.04	0.10	0.09	0.08	0.08	0.07	0.08	0.06
Moran's I-Test P-value ($\boldsymbol{W}_C$)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W}_B$)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W}_D$)	0.41	0.41	0.41	0.41	0.41	0.41	0.42	0.42	0.41	0.41
Moran's I-Test P-value ($\boldsymbol{W}_{CD}$)	0.44	0.44	0.44	0.44	0.44	0.44	0.45	0.45	0.44	0.44
Moran's I-Test P-value ($\boldsymbol{W}_{BD}$)	0.45	0.46	0.45	0.45	0.46	0.46	0.46	0.46	0.46	0.46
Moran's I-Test P-value ($\boldsymbol{W}_G$)	0.57	0.57	0.61	0.59	0.57	0.57	0.58	0.58	0.57	0.57

Notes: This table displays estimates of equation (6.1) in column (1) against the estimates of equations (6.4) in column (2), (6.5) in column (3), (6.6) in column (4), and (6.7) in columns (5) through (8). Columns (5)-(8) report estimates for various specifications of the ZCTA to ZCTA spatial connectivity matrix (see Table 5.1 for details on the different ZCTA-ZCTA spatial connectivity matrices). All models are estimated using the feasible two-step generalised method of moments (GMM) estimator. The intercept term and time dummy variables were included in each specification (with the time dummy for 2004-2007 omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. Instruments used in estimation and the post-estimation tests performed are identical to Table (6.1).

In Appendix Table (D.4), I present the results of testing local TFP data for spatial dependence as I did in Section 5.2 for the local employment data. I find evidence for the presence of spatial correlation in the local TFP data in levels and (log) differences across spatial connectivity specifications. This is unsurprising given the process through which ZCTA GDP was estimated likely introduced some form of spatial dependence (i.e. allocating shares of a parent county's GDP to each ZCTA by industry). By including local TFP growth (which seems to be highly correlated with TFP growth in nearby ZCTAs), I risk contaminating the estimated residuals and introducing spatial dependence. To account for this, I incorporate a local TFP growth spatial lag, sometimes referred to in the literature as a "spatial Durbin" term (Beenstock and Felsenstein, 2019), into equation (6.3)

$$\Delta l_{i,t,t+3} = \beta_0 + \beta_1 \sum_{c=1}^{C} \omega_{i,c} \Delta a_{c,t-3,t} + \beta_2 \Delta a_{i,t,t+3} + \beta_3 \sum_{i' \neq i}^{N} \omega_{i,i'} \Delta a_{i',t,t+3} + \delta_{t,t+3} + \Delta \nu_{i,t,t+3} \quad (6.6)$$

and estimate equation (6.6) using each of the six ZCTA-ZCTA spatial connectivity matrices. I present the estimation results in columns (5) through (10) of Table (6.4). Again, the $\widehat{\beta_1}$'s do not differ substantially from the benchmark results and nor do the parameter estimates for the contemporaneous local TFP growth term differ noticeably from that in column (2) without the spatial lag. Considering the limited influence of the lagged local TFP growth from $t-k$ to t and the spatial lag term alongside the relative consistency of $\widehat{\beta_2}$ across specifications, there is evidence of some positive correlation between contemporaneous local TFP growth and local employment growth, which coincides with findings in the theoretical model. However, the β_2 estimates do not seem to influence β_1 estimates.

That said, considering local TFP is likely measured with error, $\widehat{\beta_2}$ may be biased towards zero, thus implying the "true" β_2 is potentially larger. This might cause local TFP growth to have a more substantial effect on the estimated value of β_1. To evaluate the sensitivity of estimates of β_1 to imposing larger values of β_2, I estimate

$$\Delta l^*_{i,t,t+3}(\varphi) = \Delta l_{i,t,t+3} - (\widehat{\beta_2} + \varphi \widehat{\sigma}_{\beta_2}) \Delta a_{i,t,t+3} = \beta_0 + \beta_1 \sum_{c=1}^{C} \omega_{i,c} \Delta a_{c,t-3,t} + \delta_{t,t+3} + \Delta \nu_{i,t,t+3} \quad (6.7)$$

where $\widehat{\beta_2} = 0.164$ is the estimated parameter on the contemporaneous growth in local TFP growth from column (2) in Table (6.4), $\widehat{\sigma}_{\beta_2} = 0.089$ is the corresponding estimated standard error, and φ is a multiplier term on the estimated standard error that increases the estimated effect of $\Delta a_{i,t,t+3}$ on local employment growth from t to $t+s$. This model transforms data on the dependent variable to reflect larger effects of local contemporaneous TFP to account for measurement error. I report the results of estimating equation (6.7) imposing different values of the parameter in Table (6.5). The sign, magnitude, and statistical significance of the main result prove resilient to the increasing influence of local contemporaneous TFP growth. The specification results in columns (2)-(5) estimate slightly smaller $\widehat{\beta_1}$ and standard errors relative to the benchmark.

Table 6.5: Controlling for Local TFP and Adjusting for Measurement Error

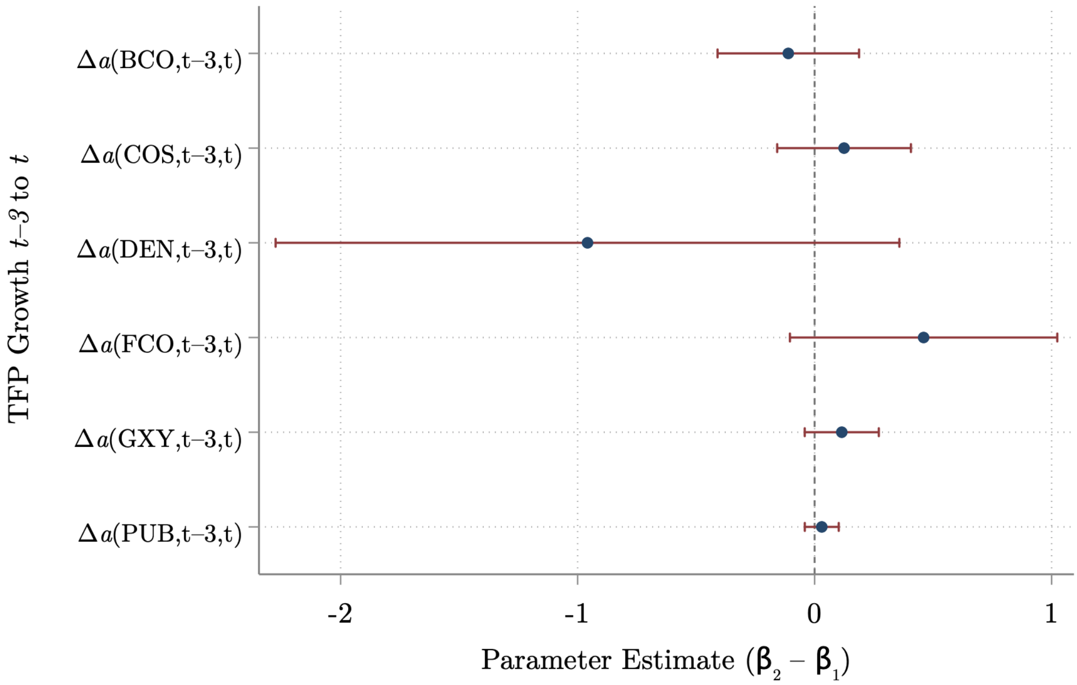
	(1) $\Delta l_{i,t,t+3}(\varphi)$	(2) $\Delta l^{*}_{i,t,t+3}(\varphi)$	(3) $\Delta l^{*}_{i,t,t+3}(\varphi)$	(4) $\Delta l^{*}_{i,t,t+3}(\varphi)$	(5) $\Delta l^{*}_{i,t,t+3}(\varphi)$
Standard Deviation Multiplier	N/A	$\varphi = 1$	$\varphi = 2$	$\varphi = 3$	$\varphi = 4$
$\sum_c \omega_{i,c}\Delta a_{c,t-3,t}$	-0.403***	-0.368***	-0.353***	-0.337***	-0.319**
	(0.153)	(0.126)	(0.122)	(0.122)	(0.125)
N	1276	1276	1276	1276	1276
R^2	0.07	0.07	0.07	0.07	0.07
$\widehat{\beta_1}$ t-Ratio P-value	0.01	0.00	0.01	0.01	
Intercept/Time Dummies	Yes	Yes	Yes	Yes	Yes
Estimator	GMM	GMM	GMM	GMM	GMM
Weak ID F-Test	2471.52	2471.52	2471.52	2471.52	2471.52
Weak IV-robust P-value	0.00	0.00	0.00	0.00	0.00
Hansen's J-Test P-value	0.59	0.46	0.42	0.40	0.38
C-Test P-value	0.02	0.10	0.13	0.15	0.17
Moran's I-Test P-value ($\boldsymbol{W}_C$)	0.00	0.00	0.00	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W}_B$)	0.00	0.00	0.00	0.01	0.04
Moran's I-Test P-value ($\boldsymbol{W}_D$)	0.41	0.41	0.42	0.42	0.43
Moran's I-Test P-value ($\boldsymbol{W}_{CD}$)	0.44	0.44	0.45	0.45	0.46
Moran's I-Test P-value ($\boldsymbol{W}_{BD}$)	0.45	0.46	0.46	0.46	0.47
Moran's I-Test P-value ($\boldsymbol{W}_G$)	0.57	0.57	0.57	0.57	0.56

Notes: This table displays estimates of equation (6.1) in column (1) against the estimates of equation (6.8) for various values of φ (number of standard deviations applied to account for measurement error in the local TFP parameter estimate in column (2) of table (6.4) in columns (2)-(5). All models are estimated using the feasible two-step generalised method of moments (GMM) estimator. The intercept term and time dummy variables were included in each specification (with the time dummy for 2004-2007 omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. Instruments used in estimation and the post-estimation tests performed are identical to Table (6.1).

Spatial Weights and Heterogeneous Associations In adapting the structural gravity result from the theoretical model to inform the spatial dependence between each ZCTA i and MSA c, the spatial connectivity weights $\omega_{i,c}$ allow the correlation between TFP growth in c and employment growth in i to vary both with the relative size of i and c as well as with the distance between i and c. As such, the $\omega_{i,c}$'s are designed to capture the potential heterogeneous associations between certain MSAs and ZCTAs. By controlling for heterogeneous correlation via the spatial weights, the parameter that measures the magnitude of association should be common to all the (spatial connectivity weighted) MSAs, which is assumed in equation (6.1) given β_1 is common to all (weighted) MSA TFP growth observations. Thus, in testing if the estimated β_1 coefficient is common among MSAs, I am implicitly testing if the spatial connectivity weights are appropriately capturing heterogeneity.

To test the null hypothesis that β_1 is common against the alternative hypothesis that at least one MSA c has a different parameter value, consider the following. Under the alternative hypothesis where one MSA has a distinct parameter, denoted β_2, the model

Figure 6.1: Urban TFP Growth by MSA and Future Rural ZCTA Employment Growth



Notes: This figure plots parameter estimates of $\beta_2 - \beta_1$ from equation (6.8) for MSA $c \in$ {Boulder (BCO), Colorado Springs (COS), Denver (DEN), Fort Collins (FCO), Greeley (GXY), Pueblo (PUB)}. Each point presents the parameter estimate using the two-step feasible GMM estimator, with red spikes representing the 95% confidence interval for the parameter estimate. In estimating equation (6.8) for various c, the excluded instruments used for $\omega_{i,c}\Delta a_{c,t-k,t}$ include the shift-share instrument for the MSA c being instrumented and an MSA $c' \neq c$. The excluded instruments for $\sum_{c' \neq c}^{C} \omega_{i,c'}\Delta a_{c',t-k,t}$ are two MSA shift share instruments unused in instrumenting $\omega_{i,c}\Delta a_{c,t-k,t}$. The intercept term and time dummy variables were included in each specification (with the time dummy for 2004-2007 omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011). Full results are presented in Appendix Table (D.5).

from equation (6.1) becomes

$$\Delta l_{i,t,t+3} = \beta_0 + \beta_1 \sum_{c' \neq c}^{C} \omega_{i,c'}\Delta a_{c',t-3,t} + \beta_2 \omega_{i,c}\Delta a_{c,t-3,t} + \delta_{t,t+3} + \Delta \nu_{i,t,t+3}$$

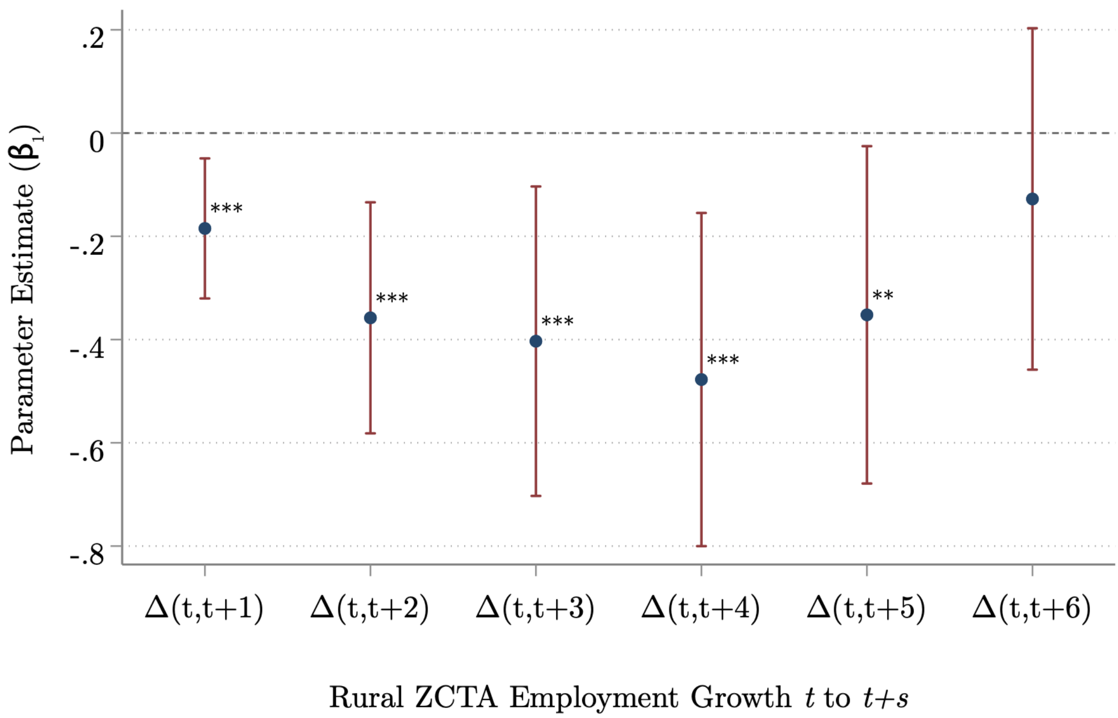
Adding and subtracting $\beta_1 \omega_{i,c}\Delta a_{c,t-3,t}$ to the right hand side, it follows that

$$\begin{aligned} \Delta l_{i,t,t+3} &= \beta_0 + \beta_1 \sum_{c' \neq c}^{C} \omega_{i,c'}\Delta a_{c',t-3,t} + \beta_2 \omega_{i,c}\Delta a_{c,t-3,t} + \delta_{t,t+3} + \Delta \nu_{i,t,t+3} \pm \beta_1 \omega_{i,c}\Delta a_{c,t-3,t} \\ &= \beta_0 + \beta_1 \sum_{c=1}^{C} \omega_{i,c}\Delta a_{c,t-3,t} + (\beta_2 - \beta_1)\omega_{i,c}\Delta a_{c,t-3,t} + \delta_{t,t+3} + \Delta \nu_{i,t,t+3} \end{aligned} \tag{6.8}$$

Under the null hypothesis $\beta_2 = \beta_1$, and so equation (6.8) reduces to equation (6.1).

In Figure (6.1), I plot the estimated coefficients $\beta_2 - \beta_1$ from estimating equation (6.8) separately for each of the FRUC MSAs. That is to say, I estimate six renditions of the

Figure 6.2: Three-Year FRUC TFP Growth and Future Rural ZCTA Employment Growth

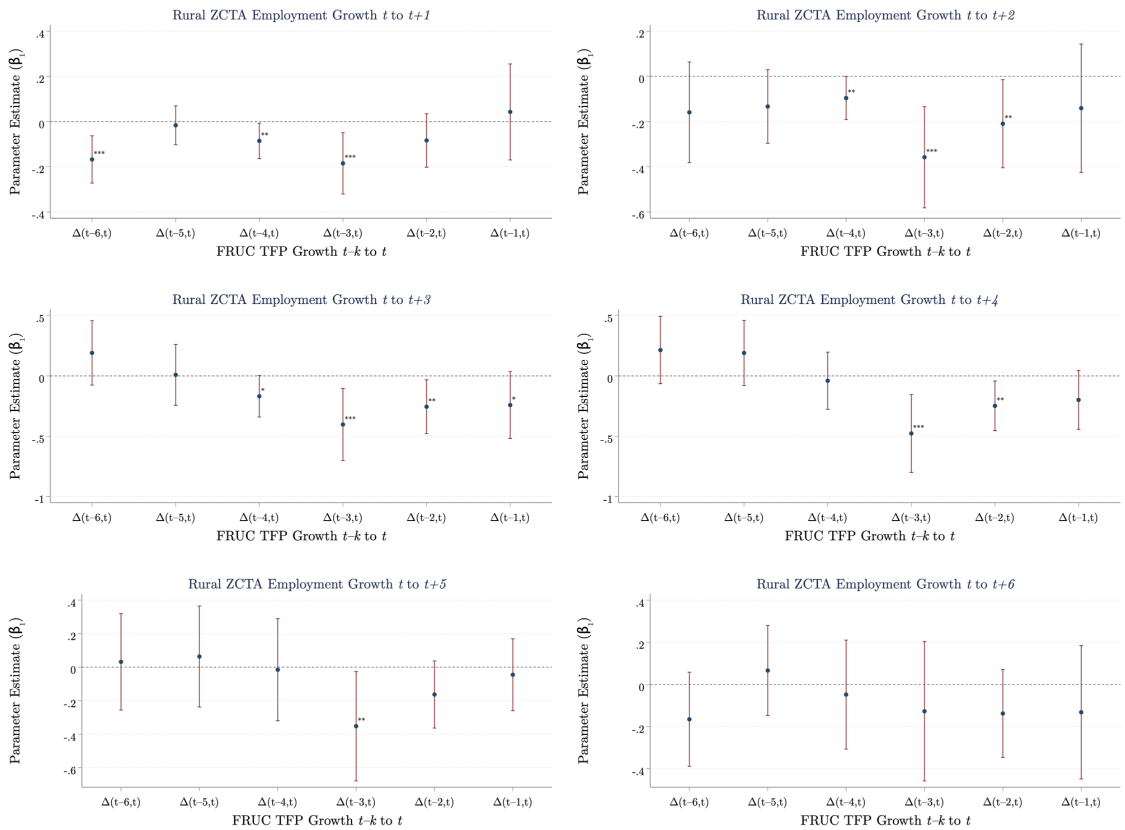


Notes: This figure plots estimates of equation (5.1) for $k = 3$ and for various $s \in \{1, 2, \ldots, 6\}$ in the text. Each point presents the parameter estimate for β_1 using the two-step feasible GMM estimator, with red spikes representing the 95% confidence interval for the parameter estimate. The x-axis gives various dependent variables for different s, where $\Delta(t, t + s)$ is the growth in rural ZCTA employment from year t to $t + s$. Moving from left to right along the x-axis implies larger intervals of time. The excluded instruments used for $\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$ include the following Bartik-Style Shift Share Instruments: $\omega_{i,BCO} B_{BCO,t-3,t}$, $\omega_{i,COS} B_{COS,t-3,t}$, $\omega_{i,DEN} B_{DEN,t-3,t}$, $\omega_{i,FCO} B_{FCO,t-3,t}$, and $\omega_{i,PUB} B_{PUB,t-3,t}$. The intercept term and time dummy variables were included in each specification (with the time dummy for the earliest possible period omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$ using a two-tailed test. Full results are presented in Appendix D, Table (D.6).

model above, specifying c to be a different MSA in each variation, testing if that particular c (e.g. Fort Collins) has a distinct coefficient $\widehat{\beta_2}$ on the weighted TFP growth term. The x-axis details the parameter value and the y-axis gives the MSA specified to be c in (6.8). The red spikes represent the 95% confidence interval for the parameter estimate. Full results are presented in Appendix D, Table (D.5). For all MSAs c, where c includes Boulder (BCO), Colorado Springs (COS), Denver (DEN), Fort Collins (FCO), Greeley (GXY), and Pueblo (PUB), the results do not reject the null that there is a common coefficient among MSAs, thereby offering evidence that the gravity-style weights $\omega_{i,c}$ are appropriately the capturing heterogeneous association between TFP growth in MSA c and employment growth in i.

Alternative Dynamic Time Specifications Thus far, I have restricted analysis to a particular time specification of the baseline model equation (5.1). Specifically, I have presented results where $k = s = 3$. The negative associations between TFP growth in the FRUC and rural employment growth prove to hold for other values of k and s. For instance, in

Figure 6.3: Three-Year FRUC TFP Growth and Future Rural ZCTA Employment Growth



Notes: This figure displays plots for estimates of equation (5.1) for various $k, s \in \{1, 2, \dots, 6\}$. Each point represents the parameter estimate for β_1 using the two-step feasible GMM estimator, with red spikes representing the 95% confidence interval for the parameter estimate. Each individual panel evaluates the model for a particular value of s. The x-axis is the period of lagged urban TFP growth (i.e. represents the value of k) on which the period of rural ZCTA employment growth is t to $t+s$ is regressed. The y-axis denotes the estimated parameter value. The excluded instruments used for $\sum_c \omega_{i,c} \Delta a_{c,t-k,t}$ include the following Bartik-Style Shift Share Instruments: $\omega_{i,BCO} B_{BCO,t-k,t}$, $\omega_{i,COS} B_{COS,t-k,t}$, $\omega_{i,DEN} B_{DEN,t-k,t}$, $\omega_{i,FCO} B_{FCO,t-k,t}$, and $\omega_{i,PUB} B_{PUB,t-k,t}$. The intercept term and time dummy variables were included in each specification (with the time dummy for the earliest possible period omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. Full results are presented in Appendix D, tables (D.7) – (D.12).

Figure (6.2) I plot the GMM parameter estimates for β_1 where $k = 3$ and $s \in \{1, 2, \dots, 6\}$. The x-axis is the period of employment growth being regressed on lagged three-year urban TFP growth (i.e. represents the value of s) and the y-axis gives the estimate for β_1. The red spikes denote the parameter estimate's 95% confidence interval. The negative and statistically significant $\widehat{\beta_1}$ holds for $s \in \{1, 2, \dots, 5\}$. In fact, it appears to increase over time, with the largest (in terms of absolute magnitude) estimated coefficient occurring four years after the conclusion of the urban TFP growth interval in year t, though the size of the association seems to lose its bite after the peak at four years, becoming statistically indistinguishable from zero after a six year growth period.

In Figure (6.3), I present β_1 estimates from models with all 36 possible combinations of $k \in \{1, 2, \dots, 6\}$ and $s \in \{1, 2, \dots, 6\}$. Each panel plots coefficients relating to different values of s. The layout of the plots is identical to that of figure (6.2), with the exception that the x-axis is the period of lagged urban TFP growth (i.e. represents the value of k) to which the period of rural ZCTA employment growth is t to $t + s$ is related. These collective results reinforce the findings in Figure (6.2) that the association is time sensitive. However, a key finding is that when the correlation between FRUC TFP growth and future rural ZCTA employment growth is significantly different from zero, it is negative. Across plots for various s, a general pattern seems to emerge, with the coefficient tending to increase (in absolute value) from $k = 6$ to $k = 3$ and returning to zero for $k < 2$, implying a robust association between FRUC TFP growth over a three-year period and future rural employment growth.

In addition to testing various lag structures for rural employment growth and urban TFP growth, I also test for the presence the contemporaneous correlations. That is, I evaluate how rural ZCTA employment growth from t to $t + 3$ associates with FRUC TFP growth over the same period of time, though the results do not prove to be statistically significant, suggesting the negative urban TFP and rural employment growth associations occur with some form of a lag. The results are provided in Appendix Table (D.13). This evidence is consistent with that of Hornbeck and Moretti (2020), who argue that the effects of growth in urban TFP that perturb the spatial equilibrium depend in part with how quickly agents respond to the shock. Agents' reaction may take time as workers and firms encounter frictions (e.g. housing/commercial lot availability, local infrastructure, etc.) that slow their migration or ability to commute across locations, influencing the speed of adjustment to the new equilibrium.

7 Conclusion

My analysis has two primary contributions. First, despite estimating revenue TFP as a composite of sectors, my estimates of ZIP Code Tabulation Area (ZCTA) and Metropolitan Statistical Area (MSA)-level revenue TFP follow established patterns in subnational manufacturing revenue TFP. I find estimated (composite) revenue TFP in levels is higher in urban ZCTAs relative to rural ZCTAs, indicating regional TFP asymmetries and potential productivity advantages stemming from urban agglomeration economies. I find average ZCTA revenue TFP to be highly persistent over time. My estimates imply that neighbouring MSAs follow similar trends in levels and rates of growth. Second, I find that during the first two decades of the 21^{st} century, in the Front Range Urban Corridor (FRUC) revenue TFP growth was correlated wtih lower future employment growth in its rural periphery.

These findings suggest that urban revenue TFP growth not only has direct and indirect implications for systems of cities, as shown by Hornbeck and Moretti (2020), but also for urban and rural linkages. Further, although the existing literature no robust findings for the presence of urban *population* growth shadows, the evidence given here seems to imply there may be urban growth shadows. operating through other mechanisms such as revenue TFP growth, that relate to different observables such as employment. While proximity to a large urban cluster, such as the FRUC, might encourage population growth in neighbouring non-metropolitan regions (Partridge et al., 2009; Cuberes, Desmet, and Rappaport, 2019), this spillover-induced growth may be accompanied by negative growth implications that population data do not detect. While on net rural areas may indeed benefit from proximity to large urban centres, the negative associations found in this study between TFP growth and future rural employment growth possibly suggest the benefits of closeness may be smaller in absolute magnitude.

There are notable limitations to this study. The first is that the findings relate only to a particular core and periphery system in the US (i.e. the FRUC and its hinterland), which limits the generalisability of these findings. The confidential establishment-level data used are limited to labour inputs, but lack detailed records on establishment capital stocks and output, which I must estimate in order to estimate revenue TFP. Considering revenue TFP is a problematic measure in its own right, particularly for service-oriented sectors, the likely mismeasured inputs and outputs used to estimate TFP in this study only exacerbate the issue.

That said, the FRUC core and periphery system offers an almost textbook amenable geography to study rural and urban relationships. Moreover, the main results fit the intuition of the more general theoretical model, implying these results might plausibly generalise to other core and periphery systems, at least in the Western US. Finally, the use of the shift-share instruments can alleviate some threats to identification posed by evaluating urban revenue TFP measured with error.

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Appendix A Model Appendix

A.1 Structural Gravity Derivation

Equating sales in $i \in \{i, i'\}$, $p_i X_{i,i} + p_i X_{i,i'}$, to total labour income in i, $w_i L_i$,

$$\begin{aligned} w_i L_i &= p_i X_{i,i} + p_i X_{i,i'} \\ &= p_i^{1-\sigma} \left[P_i^{\sigma-1} w_i L_i + P_{i'}^{\sigma-1} w_{i'} L_{i'} \tau^{1-\sigma} \right] \end{aligned}$$

and then solving for $p_i^{1-\sigma}$ reveals

$$p_i^{1-\sigma} = \frac{w_i L_i}{\left[P_i^{\sigma-1} w_i L_i + P_{i'}^{\sigma-1} w_{i'} L_{i'} \tau^{1-\sigma} \right]} \tag{A.1}$$

Recalling that trade value between i and i' are

$$V_{i,i'} = \left(\frac{p_i}{P_{i'}} \right)^{1-\sigma} w_{i'} L_{i'} \tau^{1-\sigma}$$

substituting equation (A.1) for $p_i^{1-\sigma}$ gives

$$\begin{aligned} V_{i,i'} &= \frac{P_i^{\sigma-1} w_i L_i w_{i'} L_{i'} \tau^{1-\sigma}}{\left[P_i^{\sigma-1} w_i L_i + P_{i'}^{\sigma-1} w_{i'} L_{i'} \tau^{1-\sigma} \right]} \\ &= \frac{P_i^{\sigma-1} w_i L_i w_{i'} L_{i'} \tau^{1-\sigma}}{\left[P_i^{\sigma-1} \frac{w_i L_i}{wL} wL + P_{i'}^{\sigma-1} \frac{w_{i'} L_{i'}}{wL} wL \tau^{1-\sigma} \right]} \\ &= \frac{P_i^{\sigma-1} \tau^{1-\sigma}}{\left[P_i^{\sigma-1} \theta_i + P_{i'}^{\sigma-1} \tau^{1-\sigma} \theta_{i'} \right]} \frac{w_i L_i w_{i'} L_{i'}}{wL} \end{aligned} \tag{A.2}$$

where $wL = w_c L_c + w_r L_r$ is the total regional labour income and $\theta_i = \frac{w_i L_i}{wL}$ is the share of total regional income earned in i. Letting $\Lambda_i^{1-\sigma} \equiv \left[P_i^{\sigma-1} \theta_i + P_{i'}^{\sigma-1} \tau^{1-\sigma} \theta_{i'} \right]$, equation (A.2) can be written as

$$V_{i,i'} = \left(\frac{\tau}{\Lambda_i P_i} \right)^{1-\sigma} \frac{w_i L_i w_{i'} L_{i'}}{wL} \tag{A.3}$$

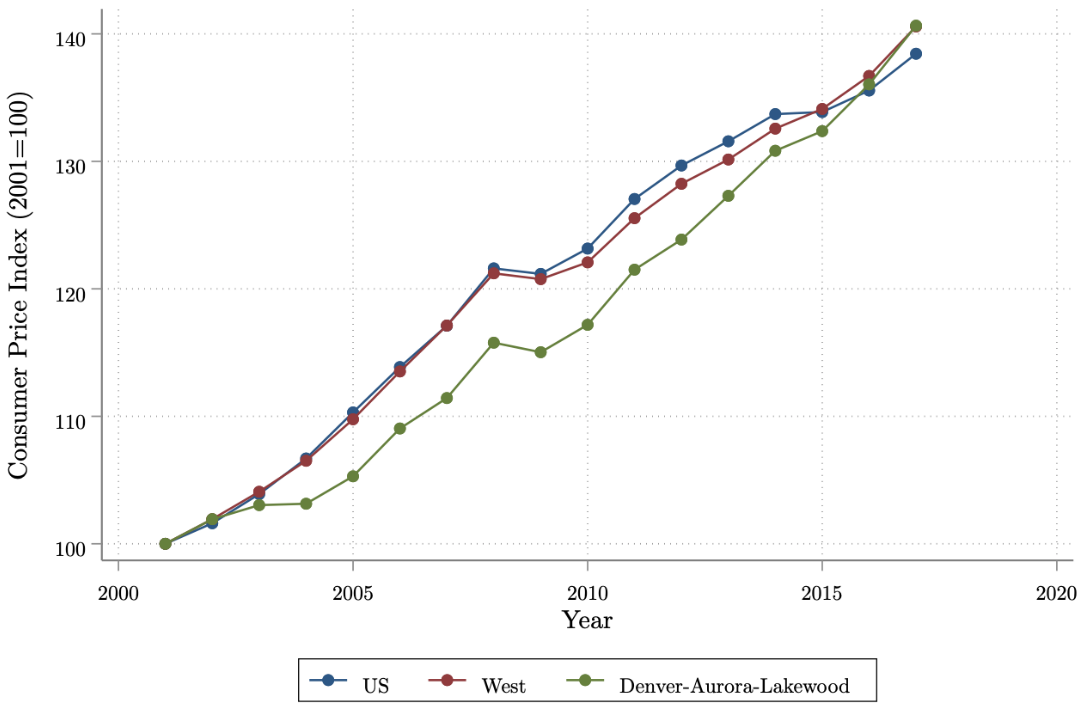
which captures the so-called structural gravity between i and i' á la Anderson and van Wincoop (2003).

Appendix B Data Appendix

B.1 Consumer Price Index

All monetary values in this paper are adjusted for inflation, with amounts given in 2001 USD according to the Denver-Aurora-Lakewood MSA (referred to as the Denver MSA in the paper) Consumer Price Index (CPI). The Consumer Price Index (CPI) is a measure of the average change over time in the prices paid by urban consumers living in the Denver-Aurora-Lakewood MSA for a market basket of consumer goods and services released by the BLS. Appendix Figure (B.1) plots the relative change in the US, Western US, and Denver-Aurora-Lakewood MSA CPI from 2001 to 2017.

Figure B.1: Consumer Price Index by Region, 2001-2017



Notes: This figure plots the Bureau of Labor Statistic's Consumer Price Index (prices paid by consumers in urban areas for a designated basked of goods) for consumers across the US (blue), consumers living in cities in the western US (red), and consumers living in the Denver-Aurora-Lakewood MSA (green). The index base year is 2001 and differences from 100 reflect a growth in prices faced by consumers on the specified consumption basket.

There are noticeable differences between the Denver-Aurora-Lakewood CPI and the other two CPI series, with the former trending beneath the latter two for most of the observed period. This motivates care in selection of the appropriate inflation adjustment measure for the monetary data. Although the CPI measuring the urban price evolution in Denver is likely different from price evolution in the hinterland, the Denver-Aurora-Lakewood CPI is the most appropriate way to deflate regional prices relative to other options to evaluate real changes over time, as it likely better reflects inflation trends in Colorado relative to the two other potential adjustment factors.

Table B.1: Employment Shares and ZCTA Average Annual Employment by Sector

	All			Urban			Rural		
	Emp Share (%)	ZCTA Employment		Emp Share (%)	ZCTA Employment		Emp Share (%)	ZCTA Employment	
	Mean	Mean	Std. Dev.	Mean	Mean	Std. Dev.	Mean		Std. Dev.
Total	100	4,543.80	8,272.53	100	6,110.28	9,458.09	100	1,022.41	1,810.26
Agriculture (11)	0.75	54.61	108.92	0.45	49.76	96.21	4.75	62.32	126.19
Natural Resource Extraction (21)	0.89	81.60	370.88	0.83	93.50	420.87	1.61	42.96	84.45
Utilities (22)	0.35	43.53	106.42	0.31	53.22	127.00	0.87	23.23	25.74
Construction (23)	7.44	363.49	696.62	7.38	472.07	792.69	8.22	96.50	182.45
Manufacturing (31-33)	7.79	351.55	951.16	7.98	483.78	1,105.77	5.31	54.29	249.63
Wholesale Trade (42)	5.01	279.90	766.20	5.13	366.52	881.00	3.29	47.01	66.16
Retail Trade (44-45)	13.01	589.83	1,056.22	12.83	782.38	1,206.42	15.36	156.97	284.86
Transportation (48-49)	3.3	149.96	799.52	3.4	207.36	955.09	2.05	20.94	41.27
Information (51)	4.15	281.05	912.35	4.35	358.71	1,031.07	1.46	29.25	39.83
Finance and Insurance (52)	5.53	333.38	1,137.49	5.7	434.54	1,310.84	3.26	51.60	64.52
Real Estate (53)	2.34	142.47	242.67	2.24	168.01	263.93	3.68	63.68	132.20
Professional Services (54)	9.18	487.00	1,443.74	9.62	641.94	1,649.07	3.16	44.53	83.42
Management (55)	1.58	143.26	477.37	1.67	166.41	514.39	0.3	12.51	22.45
Administrative (56)	7.54	426.34	806.90	7.82	548.08	897.03	3.8	59.90	100.41
Education (61)	1.35	109.39	203.89	1.41	126.26	217.44	0.49	17.71	24.96
Health Care (62)	12.04	732.76	1,157.85	12.06	921.41	1,275.27	11.77	191.27	354.35
Entertainment/Recreation (71)	2.32	154.89	325.63	2	162.92	306.76	6.7	129.40	378.48
Accommodation/Food Services (72)	11.83	620.99	1,033.56	11.16	775.35	1,149.10	20.79	254.62	528.47
Other (81)	3.62	201.00	311.01	3.66	260.08	343.54	3.13	44.01	79.13
N		97,607			70,972			26,635	

Notes: This table presents summary statistics concerning the employment data sourced from the Colorado QCEW for the sample. Employment shares measure the share of *total* employment in a particular sector for the specified region. For instance, under the All columns, the employment share refers to the share of all sample employees (rural or urban) working in each sector. The ZCTA Employment columns offer mean levels of sectoral employment within the specified subset of sample ZCTAs. Numbers next to sector titles reflect the two-digit NAICS code for that sector.

B.2 Employment and Labour Cost

Summary statistics concerning average ZCTA employment by sector are presented in Appendix Table (B.1). Employment shares are for the all employment, all urban employment, and all rural employment (i.e. they do not reflect an average by ZCTA), respectively. With the exception of agriculture, urban ZCTAs have higher average employment in all sectors and average total employment almost six times that among rural ZCTAs. Furthermore, there are distinct differences in employment allocation across sectors between rural and urban ZCTAs in the sample. For instance, the share of rural employment in accommodation and food service is twice that of the share of urban employment in the same sector, with a fifth of the rural labour force employed by an accommodation or food service establishment. On the other hand, almost 10% of urban employees work at an establishment classified under professional services, whereas only about 3% of rural labour is employed by such establishments.

To better compare total wage bill estimates among ZCTAs, I divide $W_{i,t}L_{i,t}$ by $L_{i,t}$ to estimate labour costs per worker. Summary statistics on these estimates are presented by sector in Appendix Table (B.2). There is a clear per employee labour cost gap between rural and urban ZCTAs, with differentials across all sectors favouring urban workers, with the exception of agriculture. There is a lengthy literature that accounts for the urban wage premium, which is reflected in these normalised labour cost estimates, attributing most of the gap to higher housing and non-durable consumption costs associated with living and working in a city. In Appendix Figure (B.2), I plot the average per employee expenditure for urban and rural ZCTAs across all sectors over time. The average urban ZCTAs experienced a modest decline following the 2001 recession and plateau during the Great Recession, but otherwise saw steady growth. Rural ZCTAs, on average, experienced real labour cost growth per employee until the Great Recession, narrowing the gap with the urban ZCTA gap. However, growth stalled during recovery.

Table B.2: ZCTA Wage Expenditure per Employee by sector

	All ZCTAs		Urban ZCTAs		Rural ZCTAs	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Total	31,471.79	12,116.10	34,181.42	12,764.76	25,380.60	7,546.43
Agriculture (11)	25,084.55	14,206.66	24,775.21	15,496.33	25,568.96	11,898.56
Natural Resource Extraction (21)	66,687.53	67,568.12	73,421.78	73,690.27	44,599.20	33,090.03
Utilities (22)	58,174.83	48,637.23	62,021.02	57,388.56	50,278.69	19,227.30
Construction (23)	34,344.31	13,297.24	36,558.76	13,593.41	28,859.93	10,721.08
Manufacturing (31-33)	35,240.20	23,285.42	39,081.27	25,351.34	24,621.48	10,538.20
Wholesale Trade (42)	53,426.00	29,881.12	58,612.73	26,370.92	39,384.26	34,031.42
Retail Trade (44-45)	20,620.39	8,549.47	21,835.75	8,947.04	17,681.44	6,640.38
Transportation (48-49)	32,538.88	35,211.23	33,540.11	30,198.08	29,790.17	46,164.28
Information (51)	46,676.06	29,152.63	51,918.82	29,813.38	29,602.50	18,503.03
Finance and Insurance (52)	45,264.61	30,785.04	48,770.16	33,439.76	35,510.50	18,557.58
Real Estate (53)	31,980.74	25,383.72	33,967.57	26,968.70	25,735.41	18,233.56
Professional Services (54)	48,296.88	24,896.69	52,824.08	23,383.25	35,250.39	24,525.89
Management (55)	81,678.58	82,224.31	82,338.29	83,869.44	77,861.71	71,934.77
Administrative (56)	26,316.79	12,704.13	27,546.17	12,479.08	22,543.92	12,650.62
Education (61)	28,031.22	18,545.21	28,604.83	17,806.69	24,800.62	21,993.18
Health Care (62)	29,317.38	16,434.84	31,532.11	17,357.75	22,922.48	11,185.76
Entertainment/Recreation (71)	18,776.86	18,127.23	19,627.39	19,807.94	16,058.47	10,737.46
Accommodation/Food Services (72)	12,587.98	5,814.24	13,029.73	6,028.46	11,538.49	5,121.57
Other (81)	24,434.28	17,264.36	26,184.81	19,069.67	19,711.50	9,520.00
N	92,346		67,844		24,502	

Notes: This table presents summary statistics concerning the employment-normalised wage bill by sector among ZCTAs. That is, the wage bill for sector h in ZCTA i during year t, $W_{i,h,t}L_{i,h,t}$, was divided by the number of employees $L_{i,h,t}$. Amounts above are in USD. Numbers next to sector titles reflect the two-digit NAICS code for that sector.

B.3 Real GDP

B.3.1 Suppressed County Level GDP Imputation

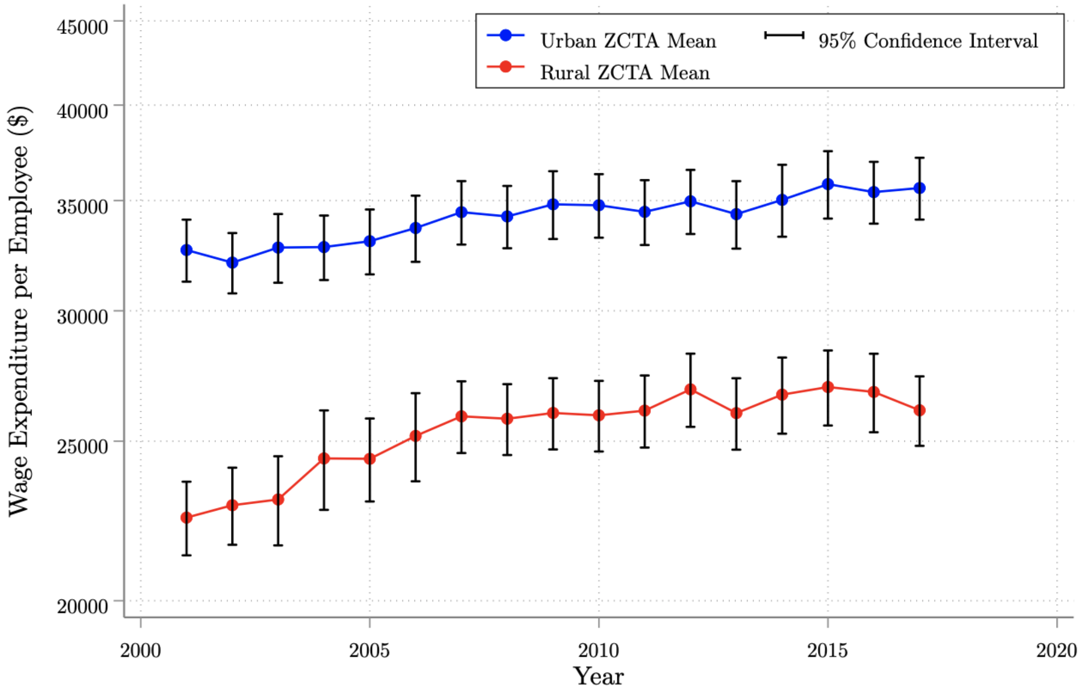
For any given year t, in order to impute county-level GDP values for suppressed sectors $h \in h''$ (where h'' is the set of suppressed sectors) in county b, I sum GDP across all non-suppressed sectors $h \in h'$ (where h' is the set of non-suppressed sectors) in b and estimate the value of total suppressed sector-level GDP as the residual $\widehat{u}_{b,t}$ when non-missing sector GDP $\sum_{h\in h'}^{H} Y_{b,h',t}$ is subtracted from the county total $Y_{b,t}$. That is

$$\widehat{u}_{b,t} = Y_{b,t} - \sum_{h\in h'}^{H} Y_{b,h',t}$$

I then aggregate ZCTA-level total wage bill data from Section 4.2 by sector h to the county-level and obtain an annual county-level estimate for the total wage bill by sector

$$W_{b,h,t}L_{b,h,t} = \sum_{i\in i^b}^{N} W_{i,h,t}L_{i,h,t}$$

Figure B.2: Total Labour Cost per Employee, 2001-2017



Notes: This figure plots time series of the mean urban ZCTA total wage bill divided by the number of employees (blue) against the rural ZCTA analogue (red). Each point is an annual mean and the vertical lines extending from each point along both series reflect the 95% confidence interval associated with that mean.

where i^b is the subset of ZCTAs $i \in \{1,2,\ldots,N\}$ located within parent county b. Note that since total wage bill data are unsuppressed, h is an element of the set composed of suppressed and non-suppressed sectors in the GDP data, i.e. $h \in \{h', h''\}$. Summing across each sector h's estimated total wage bill in b to obtain county total wage bill measure, $W_{b,t}L_{b,t} = \sum_{h=1}^{H} W_{b,h,t}L_{b,h,t}$, and then dividing each sector's total wage bill by the wage bill aggregation yields sector h's total wage bill share

$$\mu_{b,h,t} = \frac{W_{b,h,t}L_{b,h,t}}{W_{b,t}L_{b,t}}$$

Finally, multiplying the total wage bill share $\mu_{b,h,t}$ for each suppressed sector $h \in h''$ by the residual GDP $\widehat{u}_{b,t}$ results in an estimate for GDP of the form

$$Y_{b,h,t} = \mu_{b,h,t}\widehat{u}_{b,t}$$

for sector $h \in h''$.

To give a tangible example of this process, consider a hypothetical county b. Suppose the BEA estimate a total nominal GDP of \$1,500,000,000 for year t in b. Estimates for three sectors are suppressed, including (1) agriculture, (2) utilities, and (3) wholesale trade, with \$20,000,000 in output unaccounted for in the unsuppressed sectors' aggregated GDP data (i.e. $\widehat{u}_{b,t} = \$20m$). Furthermore, suppose that the unsuppressed QCEW data indicate

Table B.3: Estimated ZCTA Real GDP by Sector

	All ZCTAs		Urban ZCTAs		Rural ZCTAs	
Two-Digit NAICS Sector	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Total GDP	45,991.12	104,006.74	61,885.96	121,177.33	10,259.99	16,821.78
Agriculture (11)	766.29	1,988.26	436.76	1,346.73	1,290.32	2,628.92
Natural Resource Extraction (21)	2,380.36	9,263.27	2,598.25	10,346.80	1,673.06	4,028.81
Utilities (22)	1,545.43	3,639.15	1,910.97	4,174.72	779.72	1,902.97
Construction (23)	2,851.45	5,652.34	3,664.04	6,420.99	854.29	1,880.50
Manufacturing (31-33)	4,310.91	13,903.86	5,951.06	16,268.28	447.34	2,011.12
Wholesale Trade (42)	3,814.98	10,793.42	5,056.84	12,407.80	478.08	776.59
Retail Trade (44-45)	2,959.85	5,385.85	3,936.65	6,156.88	765.01	1,433.22
Transportation (48-49)	1,573.95	10,852.78	2,111.39	12,951.37	335.72	718.11
Information (51)	6,130.45	22,436.05	7,902.89	25,402.76	385.48	561.73
Finance (52)	4,134.61	15,830.63	5,388.18	18,289.59	644.91	749.08
Real Estate (53)	9,995.65	18,216.03	11,977.44	20,285.64	3,885.44	6,066.39
Professional Services (54)	5,690.59	19,693.28	7,523.06	22,594.11	459.91	903.00
Management (55)	1,856.42	6,775.20	2,124.04	7,316.95	345.73	371.03
Administrative (56)	2,095.18	4,344.10	2,670.15	4,867.35	364.90	617.85
Education (61)	810.28	1,571.64	936.79	1,677.85	123.14	192.92
Health Care (62)	4,205.06	7,521.46	5,297.02	8,378.21	1,072.47	2,067.53
Entertainment/Recreation (71)	959.02	3,641.20	1,046.63	3,930.07	680.69	2,493.17
Accommodation/Food Services (72)	1,891.25	3,697.64	2,286.50	4,047.09	953.41	2,450.71
Other (81)	1,526.07	2,457.46	1,956.06	2,738.31	384.22	608.67
N	97,385		70,906		26,479	

Notes: This table presents summary statistics concerning the estimates of aggregate and sector-level private establishment GDP for ZCTAs within the FRUC and its hinterland in tens of thousands of USD. Numbers next to sector titles reflect the two-digit NAICS code for that sector.

that in year t, the nominal total wage bill in b is measured to be \$400,000,000, \$7,000,000 of which went to employees working for establishments categorised in one of the three suppressed sectors. 20% went to agriculture employees, 10% to utilities employees, and 70% went to wholesale trade employees (these are the μs). By the procedure sketched above, the \$20,000,000 in unaccounted GDP in b is allocated according to these wage bill shares, with \$4,000,000 going to agriculture, \$2,000,000 to utilities, and \$14,000,000 to wholesale trade.

B.3.2 ZCTA GDP Summary Statistics

In the main text, I estimate GDP in ZCTA i located in county b (i.e. i belongs to the ZCTA subset i^b) by sector h as

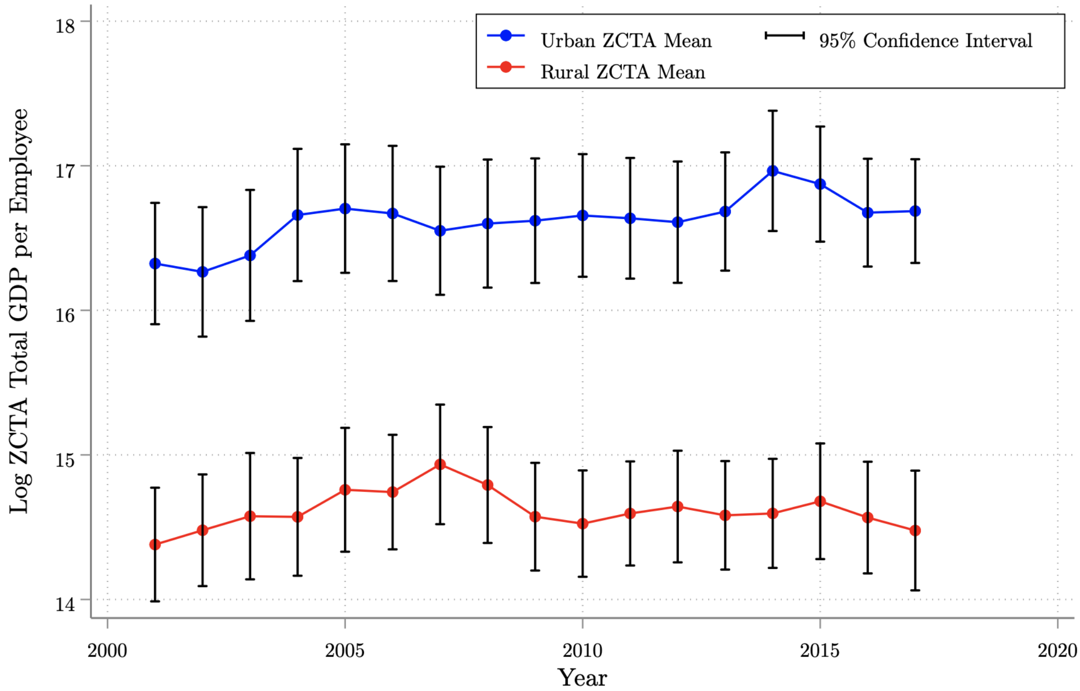
$$Y_{i,h,t} = \psi_{i,h,t} Y_{b,h,t}$$

where $\psi_{i,h,t}$ is the share of wages paid to sector h employees in b going paid to h employees in $i \in i^b$. Total GDP for ZCTA $i \in i^b$ is then the sum across sectors h.

$$Y_{i,t} = \sum_{h=1}^{H} \psi_{i,h,t} Y_{b,h,t}$$

To demonstrate this procedure in an example, suppose that county b has four reporting ZCTAs, one of which is ZCTA $i \in i^b$. Furthermore, assume b has an estimated wholesale trade GDP of \$14,000,000. In year t, QCEW data reports that wholesale trade firms located in the i accounted for 40% of b's wholesale trade total wage bill (i.e. $\psi_{i,h,t} = 0.4$).

Figure B.3: Average Urban and Rural ZCTA GDP Series Dynamics



Notes: This figure plots time series of the log mean urban ZCTA GDP per employee (blue) against the rural ZCTA analogue (red). Each point is an annual mean and the vertical lines extending from each point along both series reflect the 95% confidence interval associated with that mean.

As such, of b's estimated \$14,000,000 in Wholesale Trade GDP, \$5,600,000 (i.e. 40%) is allocated to i. Repeating this process for each two-digit NAICS sector and summing across all sectors h yields the year t total GDP estimate for $i \in i^b$. I present summary statistics of the results from this estimation procedure in Appendix Table (B.3).

This estimation strategy yields intuitive results. sectors such as agriculture, education, and entertainment/recreation are feature low relative output on average, while sectors like real estate, information, manufacturing, and professional services generate relatively high levels of output. Regional heterogeneity is also as expected: urban ZCTAs have substantially larger average estimated total output relative to their rural peers and have output dominance in comparatively "urban" sectors, such as professional services, manufacturing, and information, while rural ZCTAs have an edge in agriculture output.

In Appendix Figure (B.3), I plot the evolution of the (log of) urban ZCTA average total output per employee (blue) against the rural ZCTA analogue (red). Urban ZCTAs saw relatively stable output per worker over the sampling period, with noticeable stagnation during the Global Financial Crisis. Rural ZCTAs experienced sustained output per worker growth from 2001 to 2007, but a clear decline during the Crisis.

B.3.3 Alternative GDP Estimation Strategy and Methodological Comparison

For robustness, I estimate alternative sector-level ZCTA GDP series (Y^*) alongside the primary estimates (Y) generated using the process described in Section 4.3. The

Table B.4: Estimated ZCTA Real GDP Method Comparison by Sector

	Primary Method ($Y_{i,h,t}$) All ZCTAs		Alternative Method ($Y^*_{i,h,t}$) All ZCTAs		Difference ($Y_{i,h,t} - Y^*_{i,h,t}$) All ZCTAs	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Total GDP	45,991.12	104,006.74	46,045.79	106,116.39	−54.67	11,267.09
Agriculture (11)	766.29	1,988.26	509.33	1,109.14	256.96	1,147.07
Natural Resource Extraction (21)	2,380.36	9,263.27	1,925.88	10,926.18	454.48	5,827.91
Utilities (22)	1,545.43	3,639.15	843.36	2,318.47	702.07	2,374.55
Construction (23)	2,851.45	5,652.34	3,847.03	7,506.78	−995.58	2,444.81
Manufacturing (31-33)	4,310.91	13,903.86	4,519.48	13,818.60	−300.76	4,050.02
Wholesale Trade (42)	3,814.98	10,793.42	3,912.27	10,160.84	−97.29	1,639.02
Retail Trade (44-45)	2,959.85	5,385.85	3,573.82	6,386.30	−613.97	1,991.63
Transportation (48-49)	1,573.95	10,852.78	1,389.14	8,084.94	170.34	3,979.82
Information (51)	6,130.45	22,436.05	4,647.94	17,584.47	1,482.51	8,277.09
Finance (52)	4,134.61	15,830.63	5,006.68	19,287.28	−872.07	3,793.37
Real Estate (53)	9,995.65	18,216.03	1,373.92	3,138.78	8,621.73	15,312.51
Professional Services (54)	5,690.59	19,693.28	7,921.94	26,304.58	−2,231.35	7,213.54
Management (55)	1,856.42	6,775.20	3,308.38	13,570.77	−1,451.96	8,058.69
Administrative (56)	2,095.18	4,344.10	2,958.83	6,187.85	−863.65	2,183.54
Education (61)	810.28	1,571.64	778.50	1,595.86	31.77	859.59
Health Care (62)	4,205.06	7,521.46	6,785.52	11,716.85	−2,580.47	4,644.66
Entertainment/Recreation (71)	959.02	3,641.20	1,095.13	3,905.86	−136.11	1,062.94
Accommodation/Food Services (72)	1,891.25	3,697.64	2,395.42	4,506.01	−504.16	1,304.67
Other (81)	1,526.07	2,457.46	1,405.87	2,319.66	120.19	741.36
N	97,385		97,385		97,385	

Notes: This table presents summary statistics estimates for GDP in ZCTAs within the FRUC and its hinterland produced using different estimation procedures, in tens of thousands of USD. Numbers next to sector titles reflect the two-digit NAICS code for that sector. The primary method estimates are denoted Y, while the alternative method estimates are denoted Y^*.

alternative approach first estimates total GDP in ZCTA i located in county b, i.e. $i \in i^b$, as

$$Y^*_{i,t} = \chi_{i,t} Y_{b,t}$$

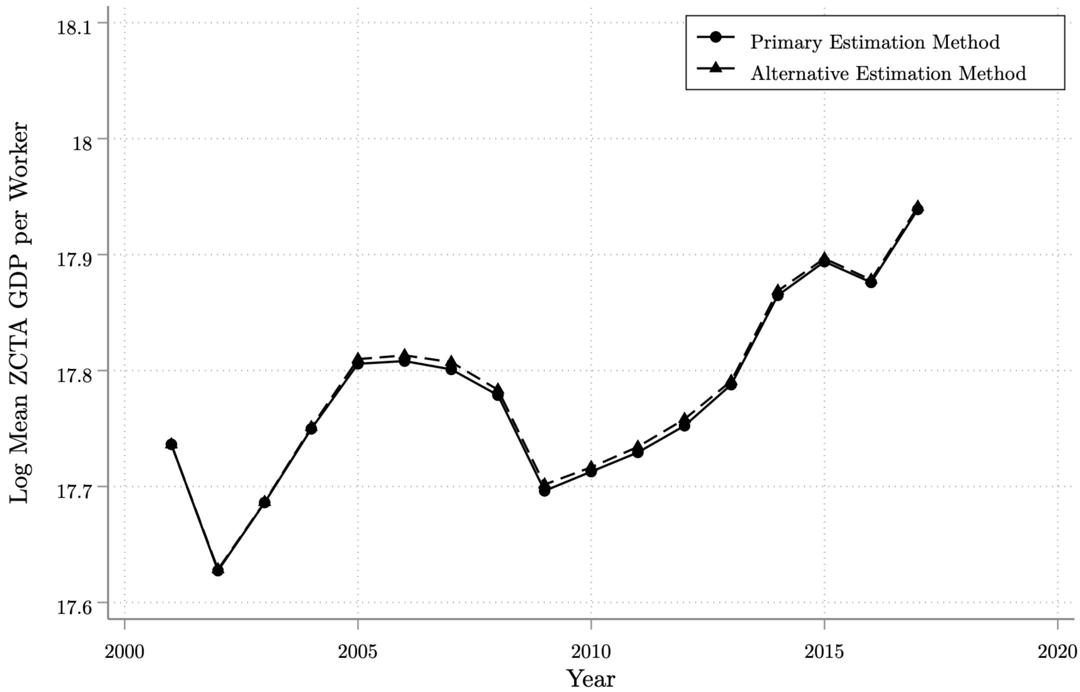
where $\chi_{i,t} = \frac{W_{i,t}L_{i,t}}{W_{b,t}L_{b,t}}$ is $i \in i^b$'s share of b's total payments to employees in t. Then, sector h GDP in $i \in i^b$ is estimated as

$$Y^*_{i,h,t} = \phi_{i,h,t} Y^*_{i,t}$$

where $\phi_{i,h,t} = \frac{W_{i,h,t}L_{i,h,t}}{W_{i,t}L_{i,t}}$ is the share of wages paid to sector h employees in $i \in i^b$ out of i's total labour cost. Summary statistics comparing estimates produced via the primary method and alternative methods are presented in Appendix Table (B.4).

While the resulting *total* GDP estimates are very similar between both methods, as demonstrated by the comparative plots of the (log of) ZCTA average GDP per worker in Appendix Figure (B.4), there are differences at the sector level. For instance, the alternative method allocates substantially more GDP to sectors such as professional services, health care, and management and substantially less to sectors including real estate and information. As I note in the text, this might stem from the fact that the alternative method possibly introduces a labour-intensive or skill-intensive bias.

Figure B.4: Average Estimated ZCTA GDP per Worker Series Dynamics



Notes: In this figure, the (log of the) average ZCTA GDP per worker estimated via the primary (solid) method is plotted against the alternative method (dashed).

B.4 Capital Stock

B.4.1 Profit Share of GDP Replacement

To ensure observations satisfy $Y_{i,h,t} - W_{i,h,t}L_{i,h,t} = \Pi_{i,h,t} > 0$, $\Pi_{i,h,t}$ is replaced with alternative estimates motivated by the data. These replacements are determined using a tiered approach, with the region/time level of replacement increasing in each stage.

On average, estimates for $\Pi_{i,h,t}$ varied little over time, so the first tier replaces $\Pi_{i,h,t} < 0$ with $\Pi_{i,h} = \frac{1}{T}\sum_t \Pi_{i,h,t}$, i.e. the profit share of sector h GDP in ZCTA i was averaged over all years t, and $\Pi_{i,h,t}$ was replaced by that average. This was appropriate for 18% of observations with $\Pi_{i,h,t} < 0$. If both $\Pi_{i,h,t} < 0$ and $\Pi_{i,h} < 0$, $\Pi_{i,h,t}$ was replaced with $\Pi_{r,h,t} = \frac{1}{R}\sum_{i^r} \Pi_{i^r,h,t}$, where r is the RUCC grouping for ZCTA i^r. That is, $\Pi_{r,h,t}$ gives an average labour share of GDP in sector h at time t for all ZCTAs within the same RUCC classification. This estimate was most appropriate to replace 56% of observations with $\Pi_{i,h,t} < 0$. If $\Pi_{i,h,t} < 0$, $\Pi_{i,h} < 0$, and $\Pi_{r,h,t} < 0$, I estimate profit share of GDP in t for sector h at time t as $\Pi_{r,h} = \frac{1}{RT}\sum_r\sum_t \Pi_{i,h,t}$, which was suitable for 9% of observations with $\Pi_{i,h,t} < 0$. If still $\Pi_{i,h,t}$, $\Pi_{i,h}$, $\Pi_{r,h,t}$, and $\Pi_{r,h,t}$ are all less than zero, I estimate $\Pi_{h,t} = \frac{1}{I}\sum_i \Pi_{i,h,t}$, which averages labour share over all ZCTAs at time t in sector h. This replaces $\Pi_{i,h,t}$ for 8% of observations with $\Pi_{i,h,t} < 0$. A final estimation strategy was to use $\Pi_h = \frac{1}{IT}\sum_i\sum_t \Pi_{i,h,t}$, which estimates average profit share of GDP across time and space and was applied to 1% of observations with $\Pi_{i,h,t} < 0$.

For the remaining 8% of observations with $\Pi_{i,h,t} < 0$, the labour share was imposed to

Table B.5: Estimated National Capital Return Rate by Sector, 2001-2017

Two-Digit NAICS Sector	Mean	Std. Dev.	Min	Max
Aggregate US	0.23	0.01	0.22	0.23
Agriculture (11)	0.24	0.04	0.19	0.31
Natural Resource Extraction (21)	0.14	0.03	0.07	0.20
Utilities (22)	0.12	0.01	0.10	0.13
Construction (23)	1.16	0.20	0.91	1.51
Manufacturing (31-33)	0.35	0.01	0.32	0.38
Wholesale Trade (42)	1.07	0.09	0.95	1.21
Retail Trade (44-45)	0.44	0.05	0.38	0.53
Transportation (48-49)	0.23	0.02	0.18	0.25
Information (51)	0.30	0.02	0.23	0.33
Finance (52)	0.51	0.07	0.31	0.61
Real Estate (53)	0.11	0.01	0.09	0.11
Professional Services (54)	0.86	0.03	0.82	0.91
Management (55)	0.22	0.01	0.20	0.24
Administration (56)	0.73	0.03	0.66	0.78
Education (61)	0.18	0.01	0.15	0.20
Health Care (62)	0.31	0.02	0.28	0.33
Entertainment/Recreation (71)	0.31	0.02	0.27	0.34
Accommodation/Food Services (72)	0.42	0.03	0.37	0.45
Other (81)	0.39	0.04	0.34	0.47
Inter-Sector Composite	0.42	0.31	.07	1.51
N	17			

Notes: This table presents summary statistics concerning the estimated capital return rate series for data on the aggregate US (which is used as the capital return rate when estimating the capital stock value series), each two-digit NAICS sector, and series on the inter-sector average. These series were estimated via the approach described in Section 4.1.

be 0.99. The observations for which 0.99 was imposed were all classified as urban and in the Agriculture, Forestry, Fishing, and Wildlife sector. Given that this sector accounts for roughly 0.5% of urban employment within any given year, this imposition has little effect on TFP estimation.

B.4.2 Capital Return Rate Estimation

In the main text, I show that the capital return rate c is equal to $\frac{Y-WL}{RK}$. Given this equivalence, I use annual data on the aggregate real value of fixed assets in the US RK_t from BEA (2019c) , the total real wage bill in the US W_tL_t from BLS (2019), and total US real GDP Y_t from BEA (2019a) to estimate an annual series on c_t. I repeat this process for each two-digit NAICS sector using the sector level analogues to these data to estimate an annual series $c_{h,t}$ for each sector h. I present summary statistics for each estimated series in Appendix Table (B.5).

Aggregate US refers to the estimated c_t series. National aggregate data suggest that capital in the US features a capital return rate of 23%, which changes little with time. The sector level data imply a high degree of inter-sector heterogeneity. sectors such as construction, wholesale trade, and professional services feature a high capital return rate and comparatively large variation over time, while sectors such as real estate, utilities, and education feature low capital return rates that are not volatile. Furthermore, this estimation procedure results in average capital return rates greater than 100% in the construction and wholesale trade sectors, which seems implausible.

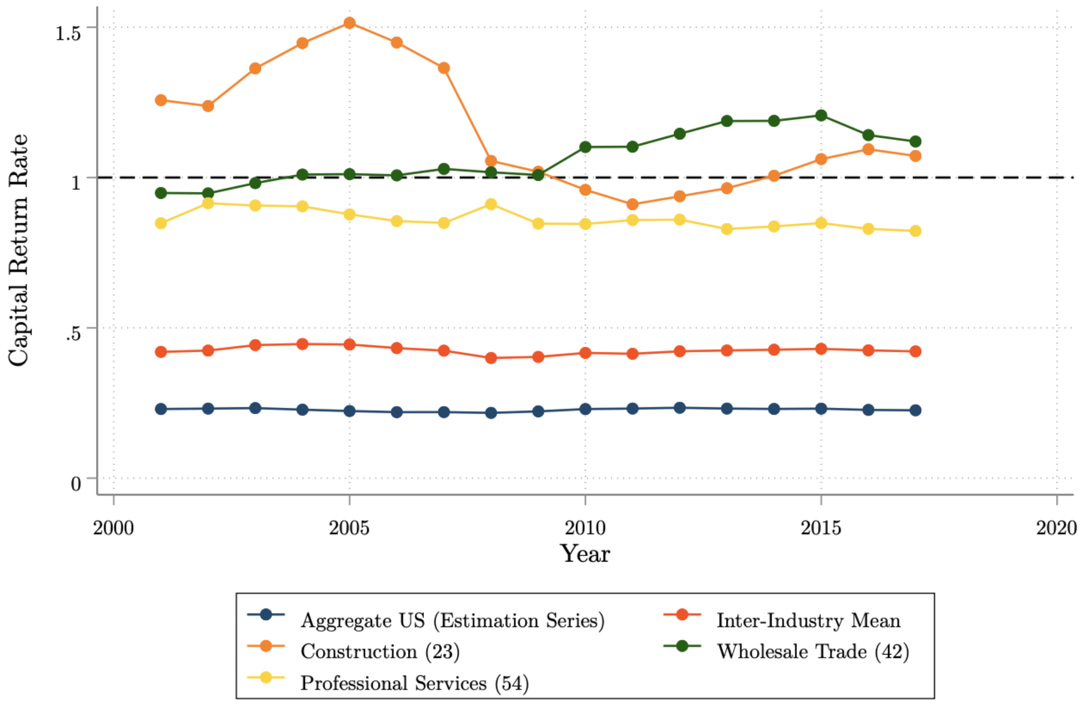
Capital return rate heterogeneity between sectors can be explained in part by the varying composition of capital portfolios. For instance, the capital holdings of the goods-producing sectors like manufacturing, which may include machinery and equipment used in goods production, would differ substantially from service-oriented sectors like education, which require less physical capital in their "production" process. These compositional differences would lead to differences in the value of rents earned by capital ownership. Likewise, the durability of capital used is likely to vary across sectors, which thereby influences capital return rate differences via variable rates of depreciation. Real estate is by definition composed of highly durable capital holdings, such as housing and commercial buildings, while construction features capital machinery that depreciates at a much faster rate due to the nature its use (drilling, clearing, building, etc.). Finally, sector-specific risk factors are also likely to influence differences in capital return rates through differences in risk premia. Firms in the finance sector may engage in riskier capital activities due to variations in financial product risks relative to the risks associated with capital in the health care sector, for example.

As I note in the text, the estimated capital return rates in certain sectors that exceed 100% on average are points of concern. Appendix Table B.5) shows that this concern stems from the construction and wholesale trade sectors. Again, this is likely stemming from unobserved inter-sector capital ownership patterns that bias certain sectors capital return rates up and others down. For instance, it may be the case that both the construction and wholesale trade sectors rent a large share of their capital from other sectors and therefore, the estimation method compensates for this discrepancy in the data by applying a large capital return rate to the limited amount of capital these sectors actually own. The professional services sector, too, features a rather high capital return rate, which given the smörgåsbord composition of the sector and close ties with other sectors, may also reflect extra-sector capital ownership patterns.[43]

In Appendix Figure (B.5), I plot the evolution of the aggregate US capital return rate series from 2001 to 2017 (blue) alongside the annual inter-sector average that excludes the aggregate US (red). The three sectors plotted above the aggregate US series and inter-sector average series, which are the only sectors to fall outside one standard deviation of the inter-sector average, are construction (orange), wholesale trade (green), and professional services (yellow). Note that the construction and wholesale trade series cross the unity

[43] Specifically, according to the NAICS manual, establishments classified as professional services "require a high degree of expertise and training" and that "the establishments in this sector specialize according to expertise and provide these services to clients in a variety of sectors" (OMB, 2017).

Figure B.5: National Capital Return Rate Series Dynamics



Notes: This figure plots select time series data from Appendix Table (B.5). The aggregate US series (blue) and series on the inter-sector average (red) lie beneath the three sectors that are, on average, more than one standard deviation from the inter-sector mean capital return rate: construction (orange), wholesale trade (green), and professional services (yellow). The aggregate US series was used to estimate ZCTA capital stock by sector.

threshold at a number of points over the interval of observation. The aggregated and sector average series display limited variability, while the plotted sectors, especially construction, features relatively large changes in value over time. With construction in particular, these changes align with the shock of and recovery from the Great Recession, with the capital return rate taking a noticeable drop in 2008 and steadily recovering from 2011. This might, in part, reflect the housing boom and bust that fuelled the crisis via the intimate link between construction and residential housing development. That is to say, the crisis altered returns to housing and therefore may have altered the returns to construction capital ownership.

The potential, unobserved inter-sector capital ownership patterns that might explain the implausible capital return rates in certain sectors cause reasonable concern against the use of the sector level series to estimate the capital stock value. Likewise, it is not immediately clear that taking a weighted or unweighted average of sector level-capital return rates eliminates this concern. However, the rate implied by the aggregated US data avoids inter-sector capital ownership concerns, motivating its use in estimation of the capital stock value series in this paper.

Table B.6: Estimated Real Value of Capital Stock by Sector

	All ZCTAs		Urban ZCTAs		Rural ZCTAs	
Two-Digit NAICS Sector	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Total	121,787.84	263,897.15	161,297.32	307,187.09	32,971.65	51,801.40
Agriculture (11)	2,838.62	7,896.94	1,468.08	4,981.37	5,018.11	10,695.05
Natural Resource Extraction (21)	7,299.30	26,932.00	7,548.04	29,409.31	6,479.95	16,286.42
Utilities (22)	5,427.75	13,078.73	6,643.96	14,785.86	2,864.84	7,827.59
Construction (23)	5,962.55	11,448.83	7,503.48	12,878.51	2,175.28	5,044.76
Manufacturing (31-33)	14,239.58	46,257.60	18,806.26	53,203.50	1,776.40	6,531.03
Wholesale Trade (42)	9,802.92	28,132.64	12,934.89	32,365.62	1,387.27	2,517.85
Retail Trade (44-45)	8,109.12	13,570.65	10,493.25	15,312.54	2,316.97	3,823.01
Transportation (48-49)	5,628.17	37,134.69	7,074.49	43,322.28	1,709.15	3,062.94
Information (51)	18,452.33	68,889.19	23,747.46	78,039.77	1,289.36	1,940.84
Finance (52)	9,071.97	32,205.90	11,644.13	37,191.13	1,911.57	2,172.67
Real Estate (53)	41,513.34	74,437.31	49,733.59	82,851.32	16,168.73	24,728.62
Professional Services (54)	10,812.53	37,322.67	14,185.35	42,844.06	1,185.03	2,159.86
Management (55)	2,699.10	12,294.01	2,969.35	13,310.08	1,173.64	1,268.11
Administrative (56)	3,906.15	7,768.60	4,887.07	8,688.64	954.22	1,786.20
Education (61)	2,210.27	4,586.46	2,555.02	4,907.90	337.79	560.43
Health Care (62)	6,599.47	11,837.54	8,145.30	13,159.90	2,164.85	4,338.08
Entertainment/Recreation (71)	2,366.05	9,248.22	2,570.47	9,960.45	1,715.34	6,440.33
Accommodation/Food Services (72)	4,298.00	8,444.92	5,139.60	9,222.28	2,301.07	5,752.31
Other (81)	4,242.44	6,789.96	5,372.61	7,582.37	1,241.26	1,863.35
N	379		263		116	

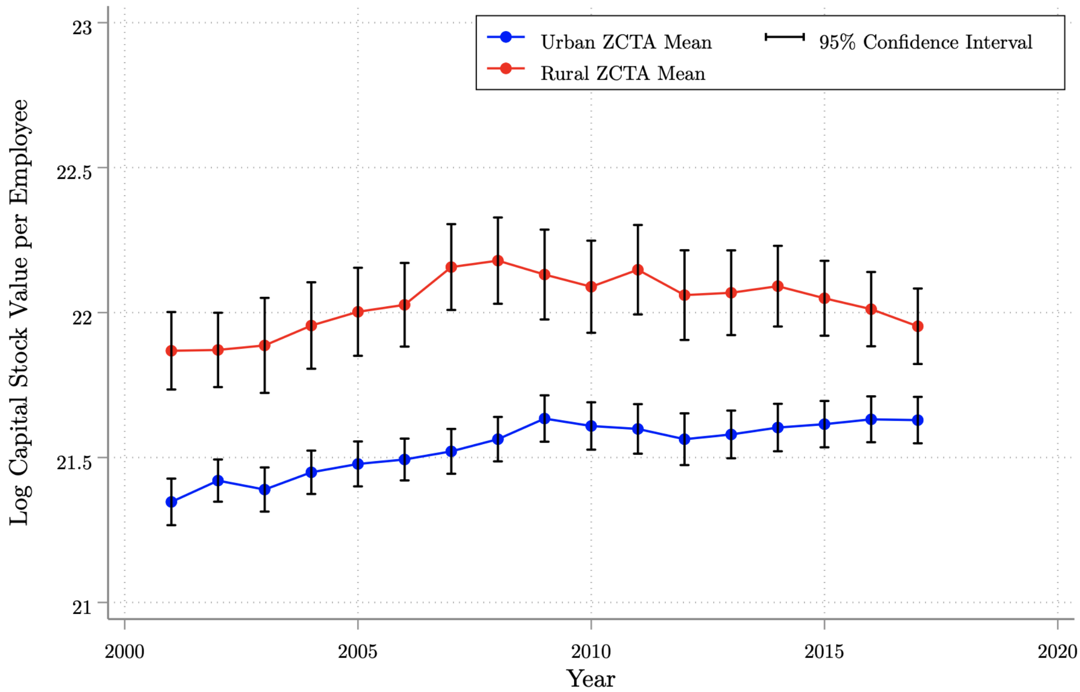
Notes: This table documents the mean and standard deviation of the real value of capital stock estimates (in tens of thousands USD) in Colorado ZCTAs by sector from 2001-2017, estimated via equation (4.4). The sector titles are shortened to conserve space; however the number in parenthesis next to each sector title corresponds to the indented NAICS sector (two-digit) classification that title represents.

B.4.3 Capital Stock Value Series Summary Statistics

Summary statistics concerning the estimated capital stock value series described in Section 4.1 are located in Appendix Table (B.6). This process seems to produce intuitive estimated data. Among all ZCTAs, capital intensive sectors like manufacturing, information, and real estate are estimated to have large holdings compared to labour intensive sectors such as education, management, or construction. Urban ZCTAs, on average, have greater total capital stock holdings relative to rural ZCTAs and sector-level differences align with standard assumptions on rural versus urban industrial composition and activity. For instance, rural ZCTAs have more agricultural capital holdings than urban ZCTAs, while the opposite is true for manufacturing capital allocation.

Turning to the dynamics of the estimated series, Appendix Figure (B.6) plots the evolution of the (log of the) average total value of capital stock per worker among urban ZCTAs (blue) against that in rural ZCTAs (red) from 2001 to 2017. Points along each line represent the annual mean of the series and the black spikes extending from each point reflect the 95% confidence interval associated with that estimated mean. These plots suggest that, while urban ZCTAs are estimated to have larger total capital value holdings, production in rural ZCTAs appears to be more capital intensive given the larger capital to labour ratio in Appendix Figure (B.6). Considering the distribution of skill/labour intensive sectors in urban versus rural areas, it seems plausible that urban

Figure B.6: Urban and Rural ZCTA Real Capital Stock Value Series Dynamics



Notes: This figure plots time series of the log mean urban ZCTA value capital stock per employee (blue) against the rural ZCTA analogue (red). Each point is an annual mean and the vertical lines extending from each point along both series reflect the 95% confidence interval associated with that mean.

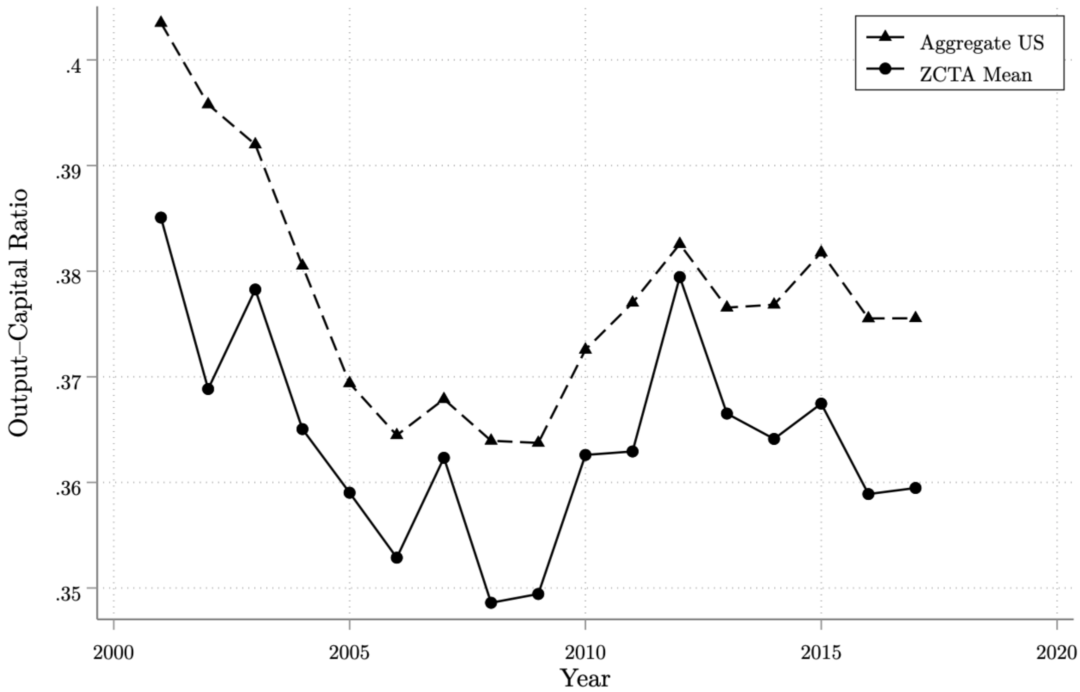
establishments rely more on labour inputs than capital inputs compared to the labour scarce rural ZCTAs. Moreover, it seems that while capital stock per employee saw constant growth in urban ZCTAs (with the exception of a decline from 2009 to 2012, likely related to capital investment declines during the crisis), rural ZCTAs have seen a relatively steady decline since 2008. Considering Figure (4.2b) shows increasing employment in rural ZCTAs for (most) of this period, this may be indicative of capital investment growth being outpaced by employment growth.

Dividing the total output estimates by ZCTA $Y_{i,t}$ from Section 4.3 by the total capital stock value series $RK_{i,t}$ for each ZCTA yields the Output-Capital Ratio, $\frac{Y_{i,t}}{RK_{i,t}}$. Plotting the mean value for the output-capital ratio by ZCTA against the US aggregate analogue, as is done in Appendix Figure (B.7) reveals that the GDP/capital estimates bear close resemblance on average to US trends, indicating this estimation process resulted in plausible estimates of capital stock value.

B.4.4 Alternative Capital Stock Estimation Strategy and Methodological Comparison

The alternative capital stock estimation method is identical to the primary method aside from the estimated series on the capital return rate. As I note in the text, by expressing the capital return rate as $c = \delta + r + v$, I can assume values for r and v common in the literature and estimate sector-level series on δ using data on sector-level capital

Figure B.7: Urban and Rural ZCTA Output-Capital Ratio



Notes: This figure plots the evolution of the US output-capital ratio computed using data from BEA (2019b) and BEA (2020) (dashed line) against the ZCTA average of that computed using the capital stock value and GDP value series estimated in this paper (solid line).

depreciation from BEA (2019b) and fixed-assets by sector data from BEA (2019c).

I estimate $\delta_{h,t}$ by dividing the real capital depreciation value in year t by the real capital stock value in year $t-1$ for data on sector h. Assuming a standard per-year interest rate of 2% and a risk premium of 6% as suggested by literature on the Equity Premium Puzzle, e.g. Mehra and Prescot (1985) and Kocherlakota (1996), I construct an alternative estimate of the capital return rate according to $c^*_{h,t} = \delta_{h,t} + 0.02 + 0.06$, where * indicates this is an alternative estimated series from the primary series described in the main text. I present relevant summary statistics for these series in Appendix Table (B.7).

The alternative estimation strategy yields a degree of variation between sectors; however, these series are relatively constant over time, with little change from year to year. All between and within group variation in these estimates come from the estimated depreciation rate series, given $r_{i,h,t} = r = 0.2$ and $v_{i,h,t} = v = 0.6$ are assumed common to all sectors and overall years. The estimates suggest, then, that the rate of capital depreciation within a given sector (and so the difference in capital depreciation between sectors) is relatively constant over time.

I plot select time series in Appendix Figure (B.8). Series which appear in Appendix Figure (B.5) retain their previous colourings. New series include utilities (grey), real estate (purple), and administration (emerald). These sectors, alongside professional services and construction, lie (on average) one standard deviation from the inter-sector average (red). While different in levels, these series display temporal consistency observed in the

Table B.7: Alternative Estimated National Capital Return Rate by Sector, 2001-2017

Two-Digit NAICS Sector	Mean	Std. Dev.	Min	Max
Aggregate US	0.14	0.00	0.13	0.14
Agriculture (11)	0.16	0.00	0.15	0.16
Natural Resource Extraction (21)	0.16	0.00	0.15	0.17
Utilities (22)	0.12	0.00	0.12	0.12
Construction (23)	0.21	0.00	0.20	0.22
Manufacturing (31-33)	0.19	0.00	0.19	0.20
Wholesale Trade (42)	0.20	0.01	0.19	0.21
Retail Trade (44-45)	0.15	0.00	0.14	0.15
Transportation (48-49)	0.14	0.00	0.14	0.15
Information (51)	0.19	0.01	0.18	0.20
Finance (52)	0.20	0.01	0.19	0.21
Real Estate (53)	0.11	0.00	0.11	0.11
Professional Services (54)	0.26	0.01	0.25	0.27
Management (55)	0.16	0.01	0.15	0.18
Administration (56)	0.21	0.01	0.19	0.23
Education (61)	0.13	0.00	0.12	0.13
Health Care (62)	0.15	0.00	0.14	0.15
Entertainment/Recreation (71)	0.16	0.01	0.15	0.17
Accommodation/Food Services (72)	0.14	0.00	0.13	0.14
Other (81)	0.13	0.00	0.13	0.13
Inter-Sector Composite	0.17	0 .04	0.11	0.27
Observations	17			

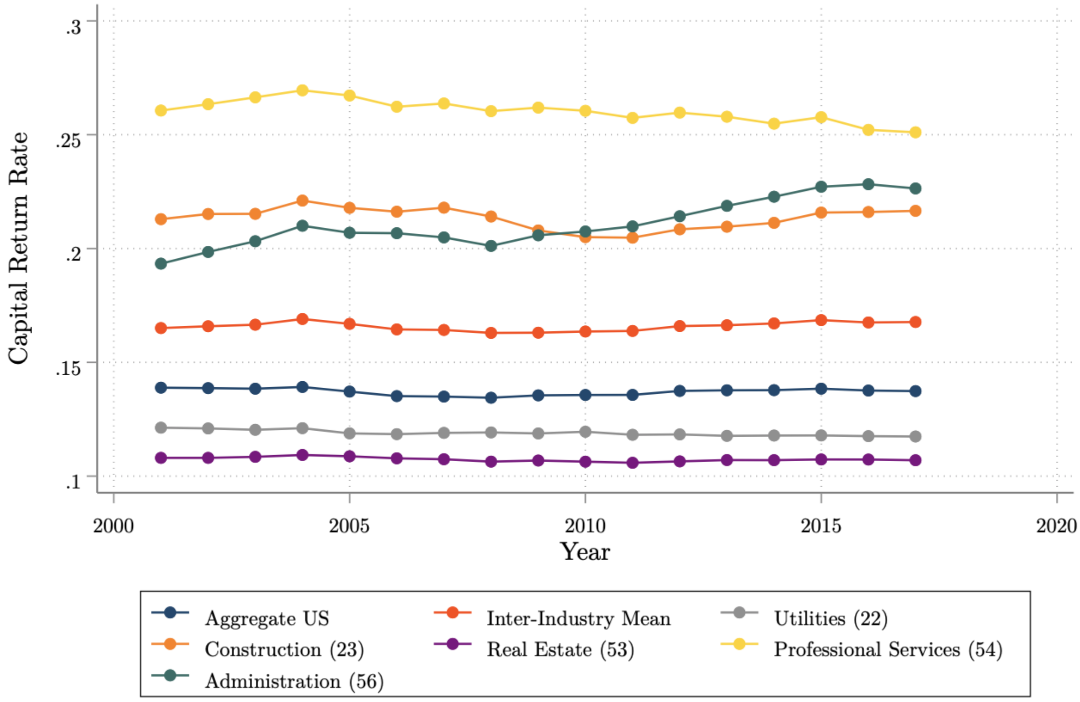
Notes: This table presents summary statistics concerning the estimated capital return rate series for data on the aggregate US, each two-digit NAICS sector, and series on the inter-sector average. These series were estimated via the alternative approach described in the main text and in Appendix B.4.4.

summary statistics.

Contrasting the estimated capital return rate series generated using to the method (c) against the estimates from the alternative estimation method (c^*), with the exception of natural resource extraction, the primary method estimates a higher capital return rate relative to the alternative method. Though sectors that are outliers in the primary estimation approach, such as construction and professional services, remain outliers, the degree to which they are different from other sectors is much smaller in the alternative approach. As such, it may be the case the inter-sector capital ownership patterns do not influence depreciation rates to a large extent. Furthermore, the alternative approach does not produce estimated series with annual capital return rates greater than 100%.

In Appendix Table (B.8) I compare estimates of capital stock from the primary and alternative methods (in tens of thousands USD). For a more natural comparison with the series estimated using the primary method, despite the fact that there are no sector-level capital return rates under the alternative method that exceed unity, the alternative method

Figure B.8: National Capital Return Rate Series Dynamics (Alternative Estimates)



Notes: This figure plots select time series data from Appendix Table (B.7). The aggregate US series (blue) and series on the inter-sector average (red) lie beneath the three sectors that are, on average, more than one standard deviation from the inter-sector mean capital return rate, which include construction (orange), administration (emerald), and professional services (yellow), and above the two series that are on average less than one standard deviation from the inter-sector mean, which include utilities (grey) and real estate (purple).

capital stock series are estimated via the aggregate US capital return rate from Appendix Table (B.7).

Given the smaller capital return rates, the alternative method produces larger capital stock value estimates relative to the primary method. In terms of sector-level differences, there are large gaps between sectors such as information and real estate capital stock estimates while there are smaller gaps for sectors like agriculture and education, implying sector heterogeneity implications in method selection. However, when plotting the average ZCTA capital stock value per employee series estimated from both methods, as in Appendix Figure (B.9), the underlying dynamics remain consistent regardless of capital return rate specification. Both series utilise the same capital share of GDP estimates, so by construction they are likely to have similar dynamics, but this does alleviate concerns of method selection influencing results given this study is interested in associations between rates of change and not between levels.

Table B.8: Estimated ZCTA Real Value of Capital Stock Comparison by Sector

	Primary Method ($\widehat{RK_{i,h,t}}$)		Alternative Method ($\widehat{RK^*_{i,h,t}}$)		Estimation Difference ($\widehat{RK_{i,h,t} - RK^*_{i,h,t}}$)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Total	121,787.84	263,897.15	202,008.66	437,684.64	−80,220.82	173,896.94
Agriculture (11)	2,838.62	7,896.94	4,710.86	13,096.19	−1,872.24	5,202.67
Natural Resource Extraction (21)	7,299.30	26,932.00	12,115.70	44,782.55	−4,816.41	17,860.42
Utilities (22)	5,427.75	13,078.73	9,004.28	21,703.94	−3,576.53	8,630.98
Construction (23)	5,962.55	11,448.83	9,867.83	18,910.47	−3,905.28	7,465.24
Manufacturing (31-33)	14,239.58	46,257.60	23,620.50	77,085.88	−9,380.92	30,846.84
Wholesale Trade (42)	9,802.92	28,132.64	16,263.33	46,682.95	−6,460.41	18,560.58
Retail Trade (44-45)	8,109.12	13,570.65	13,447.01	22,487.91	−5,337.90	8,923.58
Transportation (48-49)	5,628.17	37,134.69	9,338.80	61,750.49	−3,710.64	24,624.37
Information (51)	18,452.33	68,889.19	30,586.82	114,069.65	−12,134.49	45,206.32
Finance and Insurance (52)	9,071.97	32,205.90	15,051.82	53,427.14	−5,979.85	21,232.64
Real Estate (53)	41,513.34	74,437.31	68,868.01	123,439.14	−27,354.67	49,032.98
Professional Services (54)	10,812.53	37,322.67	17,945.46	61,949.19	−7,132.92	24,641.12
Management (55)	2,699.10	12,294.01	4,483.39	20,478.81	−1,784.29	8,189.53
Administrative (56)	3,906.15	7,768.60	6,474.19	12,860.92	−2,568.04	5,095.70
Education (61)	2,210.27	4,586.46	3,670.06	7,624.22	−1,459.80	3,039.79
Health Care (62)	6,599.47	11,837.54	10,953.28	19,647.13	−4,353.81	7,814.96
Entertainment/Recreation (71)	2,366.05	9,248.22	3,928.31	15,348.69	−1,562.26	6,102.52
Accommodation/Food Services (72)	4,298.00	8,444.92	7,126.77	13,993.23	−2,828.77	5,552.15
Other (81)	4,242.44	6,789.96	7,033.49	11,251.46	−2,791.06	4,464.75
N	379		379		379	

Notes: This table documents the mean and standard deviation of the real value of capital stock estimates (in tens of thousands USD) using both the primary and alternative estimation methods in Colorado ZCTAs by sector from 2001-2017 alongside moments concerning the difference between the estimates.

B.5 Total Factor Productivity

B.5.1 Total Factor Productivity Series Summary Statistics

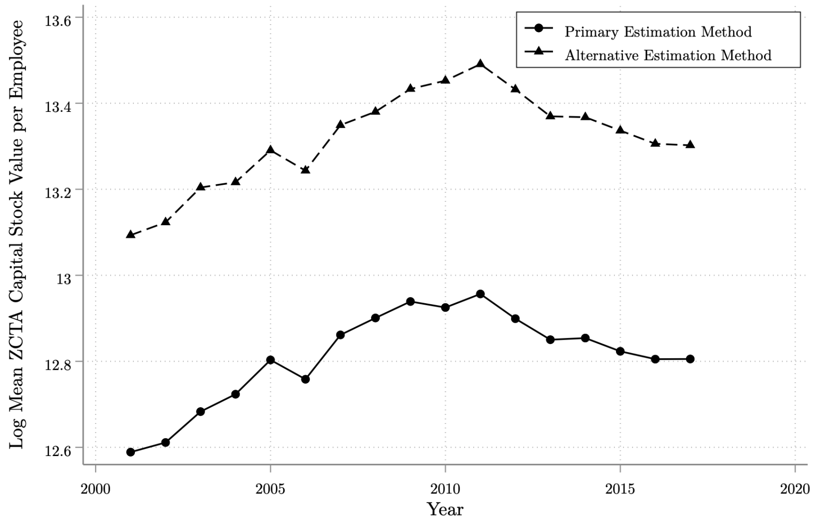
In Appendix Table (B.9), I present summary statistics on ZCTA sector-level and (weighted) average TFP estimates for the sample of all ZCTAs, urban ZCTAs and rural ZCTAs. These data reveal between sector differences in estimated TFP, with sectors such as health care, professional services, and management having higher average TFP relative to real estate, agriculture, and information. Furthermore, there is within industry average TFP variation based on location. For instance, the manufacturing sector has an average TFP level of 0.84 in urban ZCTAs, but an average of 0.77 in rural ZCTAs.

In Appendix Table (B.10), I present the weighted average TFP estimate by sector for each of the MSAs in the Front Range Urban Corridor (FRUC) and the FRUC overall. The weighted sector average is the average of the estimates from equation (4.6) from 2001 to 2017. For each MSA c, the sector h weighted average, $\overline{A}_{c,h}$, was estimated as

$$\overline{A}_{c,h} = \frac{1}{T} \sum_{t=1}^{T} \sum_{i \in i^c}^{N} \zeta_{i,h,t} A_{i,h,t}$$

where $i \in i^c$ is the set of ZCTAs located in c, $\zeta_{i,h,t} = \frac{L_{i,h,t}}{L_{c,h,t}}$ is the share of total sector h employment in c located in $i \in i^c$. The averages for the FRUC are the employment share

Figure B.9: Average Estimated ZCTA Total Capital Stock Value Series Dynamics



Notes: In this figure, the (log of the) average ZCTA estimated capital stock value per worker using the primary estimation method is plotted against the alternative method. Though there is a clear gap in levels, both methods yield similar dynamics concerning the average evolution of local capital stock holdings over time.

weighted averages of each of the MSAs averaged from 2001 to 2017. That is, the weighted sector average for the FRUC is

$$\overline{A}_{FRUC} = \frac{1}{T}\sum_{t=1}^{T}\sum_{c=1}^{C}\zeta_{c,t}A_{c,t}$$

where $\zeta_{c,t} = \frac{L_{c,t}}{L_{FRUC,t}}$ is the share of workers in c out of the entire FRUC. Similarly, the sector specific FRUC average is

$$\overline{A}_{FRUC,h} = \frac{1}{T}\sum_{t=1}^{T}\sum_{c=1}^{C}\zeta_{c,h,t}A_{c,h,t}$$

where $\zeta_{c,h,t} = \frac{L_{c,h,t}}{L_{FRUC,h,t}}$ and $A_{c,h,t} = \sum_{i\in i^c}^{N}\zeta_{i,h,t}A_{i,h,t}$. Again, this table reveals between sector variation and within sector variation between MSAs.

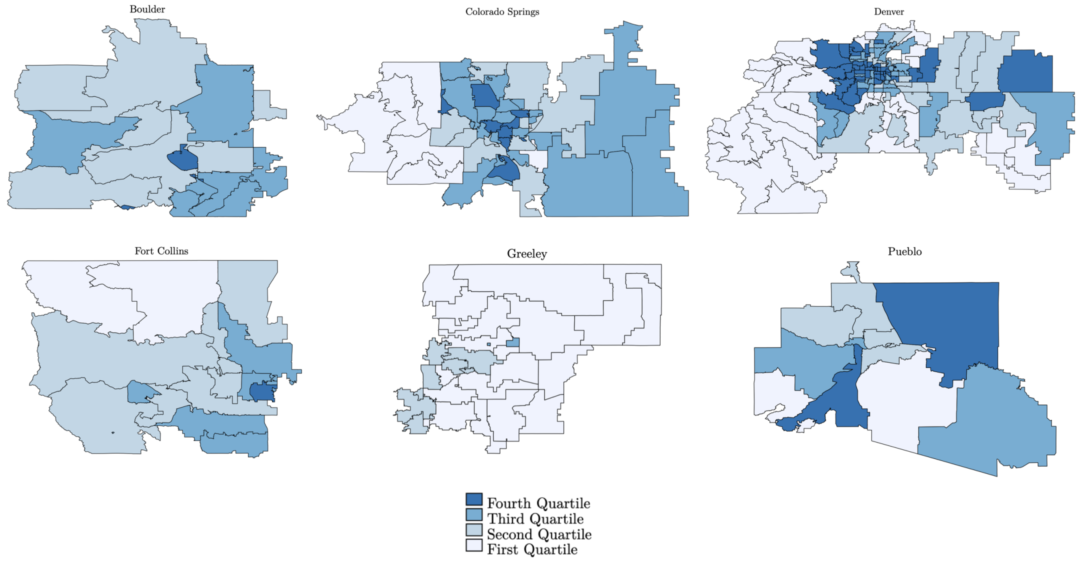
Note that the Rural ZCTA average from Appendix Table (B.9), 0.73, is used to calibrate the rural town initial TFP level in the theoretical model from Section 3.4. The FRUC average from Appendix Table (B.10), 0.94, is used to calibrate the city's initial TFP level.

B.5.2 Urban Manufacturing TFP Dynamics

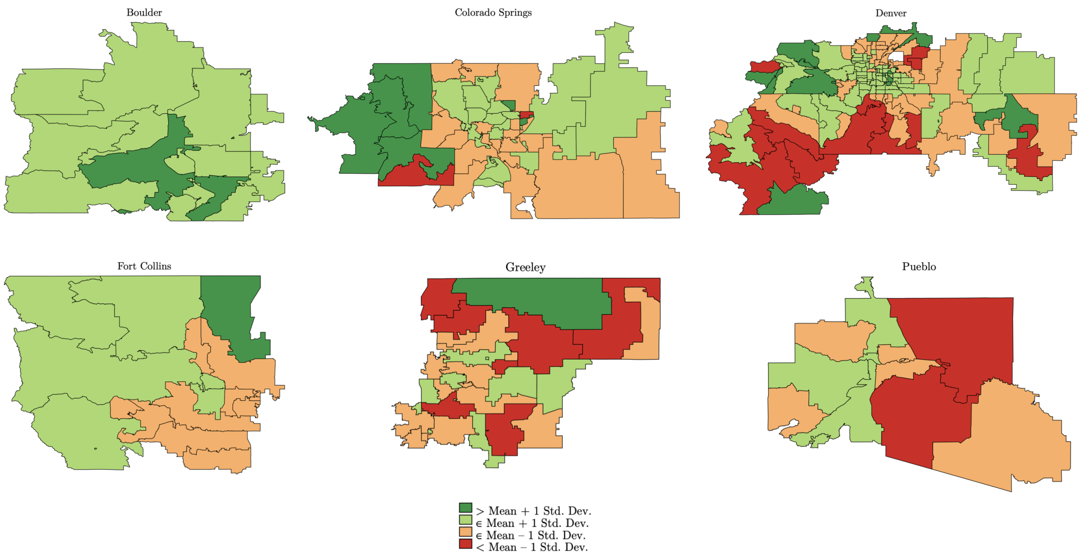
In Appendix Figure (B.11), I plot the weighted average of urban manufacturing TFP against the weighted average of all urban TFP from 2001 to 2017. For h = manufacturing, the urban average for year t is computed as

$$A_{h,t} = \sum_{i\in i^u}^{N}\zeta_{i,h,t}A_{i,h,t}$$

Figure B.10: Spatial Distribution of Urban TFP, 2001 to 2017



(a) TFP Levels



(b) TFP Annual Growth Rate

Notes: Panel (a) maps the spatial distribution of average TFP in levels among the six MSAs located in the Front Range Urban Corridor in Colorado from 2001 to 20017. Similar to Figure (4.4a), to interpret the relative magnitude of TFP in a given ZCTA, darker shades of blue reflect ZCTAs in higher percentiles of the set of urban ZCTAs, with the darkest reflecting observations above the 75^{th} percentile. Panel (b) maps the spatial distribution of the annual change in TFP from 2001 to 2017 among MSAs. The mean annual growth rate in the sample of urban ZCTAs is -0.2% with one standard deviation being 0.8%. Observations above the mean are shaded green, while observations below are shaded red, with darker shading indicating the observation is more than one standard deviation from the mean.

Table B.9: Estimated ZCTA TFP by Sector

	All ZCTAs		Urban ZCTAs		Rural ZCTAs	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
(Weighted) Sector Average	0.85	0.15	0.90	0.12	0.73	0.16
Agriculture (11)	0.62	0.29	0.66	0.30	0.55	0.27
Natural Resource Extraction (21)	0.72	0.30	0.78	0.30	0.53	0.23
Utilities (22)	0.69	0.33	0.62	0.30	0.85	0.35
Construction (23)	0.90	0.20	0.95	0.15	0.78	0.25
Manufacturing (31-33)	0.82	0.19	0.84	0.16	0.77	0.23
Wholesale Trade (42)	0.81	0.15	0.84	0.12	0.74	0.18
Retail Trade (44-45)	0.88	0.11	0.89	0.10	0.83	0.12
Transportation (48-49)	0.73	0.21	0.78	0.18	0.58	0.20
Information (51)	0.68	0.20	0.70	0.21	0.58	0.15
Finance and Insurance (52)	0.84	0.19	0.90	0.15	0.68	0.21
Real Estate (53)	0.30	0.08	0.30	0.08	0.31	0.08
Professional Services (54)	0.91	0.23	0.97	0.19	0.73	0.21
Management (55)	0.90	0.32	0.96	0.29	0.55	0.23
Administrative (56)	0.94	0.22	1.01	0.17	0.75	0.25
Education (61)	0.81	0.19	0.82	0.18	0.78	0.23
Health Care (62)	1.06	0.19	1.10	0.13	0.93	0.25
Entertainment/Recreation (71)	0.85	0.18	0.87	0.16	0.78	0.21
Accomodation/Food Service (72)	0.90	0.15	0.94	0.08	0.81	0.23
Other (81)	0.67	0.18	0.72	0.17	0.54	0.16
N	93,686		68,736		24,950	

Notes: This table presents summary statistics concerning the TFP series by sector estimated in Section 4.3 for the entire sample of ZCTAs as well as the urban and rural subsets. data sourced from the Colorado QCEW for the sample. Numbers next to sector titles reflect the two-digit NAICS code for that sector.

where i^u is the set of all urban ZCTAs and $\zeta_{i,h,t} = \frac{L_{i,h,t}}{L^u_{h,t}}$ is the share of total urban h employment in year t working in ZCTA i. The inter-sector average is computed as

$$A_t = \sum_{i \in i^u}^{N} \zeta_{i,t} A_{i,t}$$

where $\zeta_{i,t} = \frac{L_{i,t}}{L^u_t}$ and $A_{i,t}$ is the weighted average from the main text.

Table B.10: Estimated MSA TFP by Sector

	FRUC Mean	Boulder Mean	Colorado Springs Mean	Denver Mean	Fort Collins Mean	Greeley Mean	Pueblo Mean
(Weighted) Sector Average	0.94	0.92	0.94	0.94	0.94	0.87	0.94
Agriculture (11)	0.60	0.78	0.79	0.67	0.71	0.48	0.73
Natural Resource Extraction (21)	0.88	0.71	0.66	1.07	0.61	0.37	0.45
Utilities (22)	0.70	0.47	0.52	0.83	0.36	0.29	0.36
Construction (23)	1.01	0.81	0.96	1.04	0.99	0.93	1.03
Manufacturing (31-33)	0.87	0.82	0.87	0.86	1.01	0.78	0.88
Wholesale Trade (42)	0.85	0.84	0.89	0.85	0.78	0.91	0.89
Retail Trade (44-45)	0.90	0.92	0.89	0.90	0.90	0.89	0.93
Transportation (48-49)	0.83	0.88	0.85	0.84	0.90	0.73	0.60
Information (51)	0.74	0.67	0.65	0.78	0.66	0.58	0.63
Finance and Insurance (52)	0.96	1.00	0.93	0.98	0.86	0.82	0.82
Real Estate (53)	0.31	0.29	0.28	0.33	0.29	0.28	0.26
Professional Services (54)	1.04	1.07	1.07	1.03	1.01	1.00	0.84
Management (55)	1.02	1.15	1.16	1.00	1.11	1.21	0.83
Administrative (56)	1.07	0.98	1.08	1.08	1.04	1.04	0.92
Education (61)	0.81	0.83	0.95	0.77	0.85	0.88	0.79
Health Care (62)	1.13	1.11	1.12	1.13	1.11	1.15	1.14
Entertainment/Recreation (71)	0.87	0.78	0.88	0.89	0.78	0.97	0.88
Accommodation/Food Services (72)	0.94	0.95	0.92	0.94	0.93	0.96	0.96
Other (81)	0.79	0.74	0.93	0.80	0.65	0.54	0.59
N	17	17	17	17	17	17	17

Notes: This table presents summary statistics concerning the TFP series by sector estimated in Section 4.3 for each MSA in the FRUC and a weighted average for the Front Range Urban Corridor. Numbers next to sector titles reflect the two-digit NAICS code for that sector.

Appendix C Empirical Specification Appendix

C.1 Estimating Urban US County TFP

Given data on sector-level GDP $Y_{b,h,t}$ for counties $b \in b^u$, where b^u is the subset of US counties classified as urban by the RUCC, and labour costs $W_{b,h,t}L_{b,h,t}$ for each urban county in year t, I estimate the value of capital stock $RK_{b,h,t}$ via the cost-share approach described in detail in Section 4.3

$$RK_{b^u,h,t} = \frac{Y_{b,h,t} - W_{b,h,t}L_{b,h,t}}{c_t} = \left[\frac{Y_{b,h,t} - W_{b,h,t}L_{b,h,t}}{Y_t - W_t L_t}\right] RK_t$$

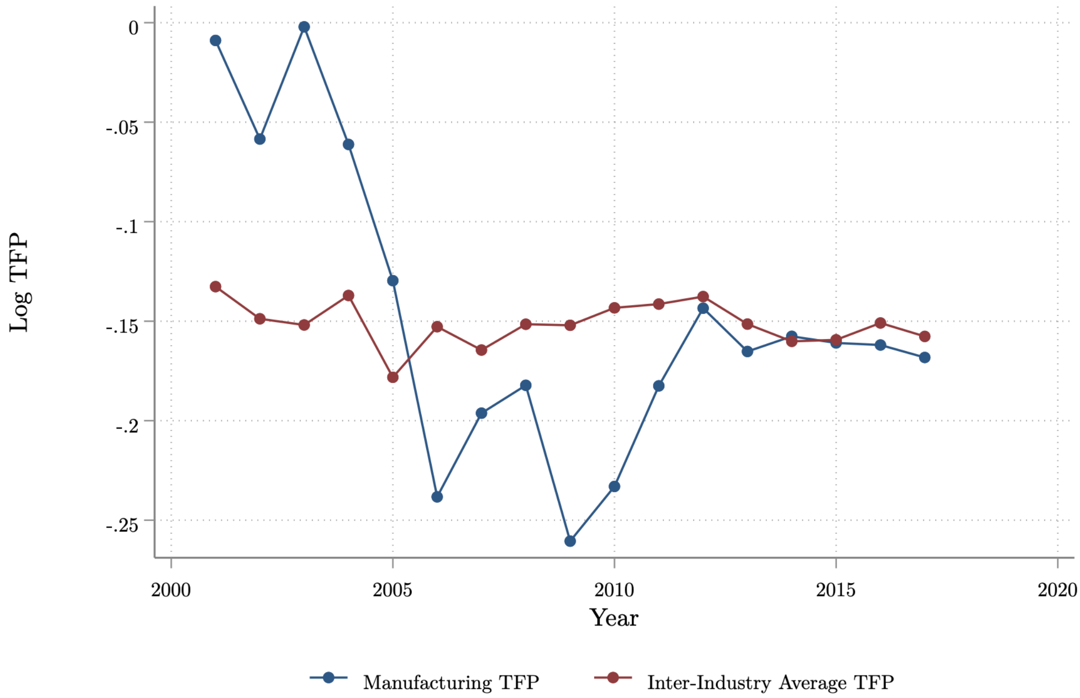
where Y_t, W_tL_t, and RK_t are the national valuations of total GDP, labour costs, and capital stock in year t. I then estimate county b sector h TFP as the residual

$$\log(A_{b,h,t}) = \log(Y_{b,h,t}) - \alpha_{b,h,t}\log(W_{b,h,t}L_{b,h,t}) - (1-\alpha_{b,h,t})\log(RK_{b,h,t})$$

where the output elasticity of labour is estimated as $\alpha_{b,h,t} = \frac{W_{b,h,t}L_{b,h,t}}{Y_{b,h,t}}$.[44]

[44]Data for which $\alpha_{b,h,t} > 1$ were replaced following the same procedure discussed in Section 4.3.

Figure B.11: Urban Manufacturing TFP Series Dynamics



Notes: This figure plots the employment (weighted) urban ZCTA average of manufacturing TFP (blue) over time relative to the inter-sector average (red).

C.2 Estimating Suppressed County-Level Data for Urban US Counties

The County Business Patterns (CBP) is an annual county-level data series provided by the US Census Bureau that offers subnational economic data by sector. These data include the number of establishments, employment during the week of 12 March, first quarter payroll, and annual payroll. However, as Isserman and Westervelt (2006) note, two out of every three employment statistics are suppressed to protect the rights of employers to confidentiality. For 2002, Isserman and Westervelt (2006) calculate that the U.S. Census Bureau has not disclosed the number of employees in 1.5 million cases. Eckert et al. (2020) develop a linear programming method that exploits the large set of adding-up constraints implicit in the hierarchical arrangement of the data to impute missing employment for all counties in the US, offering a comprehensive database on county-level employment by sector. They publicly provide these imputed data.

I estimate suppressed data (GDP, employment, and total wage bill) in an approach nearly identical to that in Appendix B.3.1. For county b in year t, the unsuppressed data for each sector h are aggregated and subtracted from the reported county total to deliver an estimate for the value of the suppressed data. Employment for each missing sector h in county b during year t according to Eckert et al. (2020) was then divided by the total employment count for all the missing industries in b to produce a missing sector employment share. The product of this share and the total value of the missing data were allocated as the estimate for county b's year t real GDP, real total wage bill value, or annual

QCEW employment total for sector h.[45] The underlying intuition for this methodology is that employment levels are correlated with output and wage shares. Of course, this is an imperfect assumption and likely to introduce some degree of error in the estimation, but it mitigates measurement error introduced by other, less informed approaches, such as ignoring missing industries, despite them being small, or dividing the missing data evenly among suppressed industries. Note that I also impute missing QCEW employment data with CBP employment data. This is in an effort to ensure consistent employment measurement across all aspects of the study. Clearly, CBP employment measures will be highly informative about suppressed QCEW employment measures.

Appendix D Results Appendix

[45]Given that the GDP and wage data came from two different data sources compiled by different US governmental data authorities, it is not necessarily the case that county b was missing both sector h's GDP data *and* total wage bill data/employment.

Table D.1: Baseline First Stage Results

	Overlapping Data	Non-Overlapping Data	
	(1)	(2)	(3)
	$\sum_c \omega_{i,c}\Delta a_{c,t-3,t}$	$\sum_c \omega_{i,c}\Delta a_{c,t-3,t}$	$\sum_c \omega_{i,c}\Delta a_{c,t-3,t}$
$\omega_{i,BCO}B_{BCO,t-3,t}$	-0.0014***	-0.0041***	-0.0019***
	(0.0001)	(0.0005)	(0.0001)
$\omega_{i,COS}B_{COS,t-3,t}$	-0.0004**	-0.0013***	0.0015**
	(0.0001)	(0.0003)	(0.0006)
$\omega_{i,DEN}B_{DEN,t-3,t}$	0.0002***	0.0006***	0.0001***
	(0.0000)	(0.0001)	(0.0000)
$\omega_{i,FCO}B_{FCO,t-3,t}$	0.0013***	0.0011*	0.0009***
	(0.0003)	(0.0005)	(0.0002)
$\omega_{i,PUB}B_{PUB,t-3,t}$	0.0027***	0.0076***	-0.0066**
	(0.0007)	(0.0021)	(0.0026)
$\delta_{2005,2008}$	0.0082***		
	(0.0022)		
$\delta_{2006,2009}$	-0.0097***		
	(0.0029)		
$\delta_{2007,2010}$	-0.0211***	-0.0122***	
	(0.0057)	(0.0035)	
$\delta_{2008,2011}$	0.0040**		0.0051***
	(0.0019)		(0.0016)
$\delta_{2009,2012}$	-0.0101***		
	(0.0029)		
$\delta_{2010,2013}$	0.0009	0.0009	
	(0.0013)	(0.0017)	
$\delta_{2011,2014}$	0.0011		0.0105***
	(0.0015)		(0.0027)
$\delta_{2012,2015}$	0.0138***		
	(0.0042)		
$\delta_{2013,2016}$	-0.0048***	0.0011	
	(0.0014)	(0.0014)	
$\delta_{2014,2017}$	-0.0035***		0.0055***
	(0.0010)		(0.0018)
Constant	0.0081***	0.0043**	0.0005
	(0.0023)	(0.0017)	(0.0012)
N	1276	464	464
R^2	0.53	0.57	0.63
Estimator	OLS	OLS	OLS

Notes: This table displays the first stage estimates for the benchmark results in Table (6.1) estimated using the ordinary least squares (OLS) estimator. The intercept term and time dummy variables were included in each specification (with the time dummy for 2004-2007 omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. In addition to Intercept/Time Dummies (which are included in the second stage), the excluded instruments are the spatial connectivity weighted shift-share instrument for each MSA c, $\omega_{i,c}B_{c,t-3,t}$, where the set of informative MSAs c include Boulder (BCO), Colorado Springs (COS), Denver (DEN), Fort Collins (FCO), and Pueblo (PUB). Greeley (GXY) is not informative when included with the other MSAs and so is not used in estimation. The excluded time dummy for columns (2) and (3) is that for 2004-2007; the excluded time dummy for column (4) is for 2005-2008.

Table D.2: Alternative Instrumental Variables Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$
Instrument Set	Benchmark	$\sum_c \omega_{i,c} B_{c,t-3,t}$	$\sum_c \lambda_{c,t} \omega_{i,c} B_{c,t-3,t}$	$\omega_{i,GXY} B_{GXY,t-3,t}$	$\omega_{i,BCO} B_{BCO,t-3,t}$ $\omega_{i,DEN} B_{DEN,t-3,t}$	$\omega_{i,GXY} B_{GXY,t-3,t}$ $\omega_{i,PUB} B_{PUB,t-3,t}$	$\omega_{i,BCO} B_{BCO,t-3,t}$ $\omega_{i,FCO} B_{FCO,t-3,t}$	All Cities
$\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$	-0.403***	-0.215	-0.204	-0.382**	-0.368**	-0.385**	-0.440***	-0.434***
	(0.153)	(0.210)	(0.212)	(0.170)	(0.161)	(0.168)	(0.151)	(0.148)
N	1276	1276	1276	1276	1276	1276	1276	1276
R^2	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.06
$\widehat{\beta}_1$ t-Ratio P-value	0.01	0.31	0.34	0.02	0.02	0.02	0.00	0.00
Intercept/Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM
Weak ID F-Test	2471.52	1300.12	723.22	23.22	392.26	39.07	15.61	1711.02
Weak IV-robust P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Hansen's J-Test P-value	0.59	–	–	–	0.36	0.92	0.25	0.65
C-Test P-value	0.02	0.42	0.46	0.04	0.20	0.04	0.03	0.02
Moran's I-Test P-value ($\boldsymbol{W}_C$)	0.00	0.06	0.07	0.03	0.06	0.03	0.20	0.00
Moran's I-Test P-value ($\boldsymbol{W}_B$)	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.00
Moran's I-Test P-value ($\boldsymbol{W}_D$)	0.41	0.40	0.40	0.41	0.41	0.41	0.44	0.41
Moran's I-Test P-value ($\boldsymbol{W}_{CD}$)	0.44	0.44	0.44	0.44	0.44	0.44	0.45	0.44
Moran's I-Test P-value ($\boldsymbol{W}_{BD}$)	0.45	0.45	0.45	0.45	0.45	0.45	0.46	0.45
Moran's I-Test P-value ($\boldsymbol{W}_G$)	0.57	0.56	0.56	0.58	0.59	0.58	0.65	0.56

Notes: This table displays estimates of equation (6.1) estimated using the two-step feasible generalised method of moments (GMM) estimator. Each column presents estimates using different combinations of shift-share instruments for the explanatory variable of interest. The instruments used to procure the estimates in a particular column are listed in the column header. The intercept term and time dummy variables were included in each specification (with the time dummy for 2004-2007 omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. Instruments used in estimation and the post-estimation tests performed are identical to Table (6.1).

Table D.3: Alternative Urban-Rural Spatial Connectivity Distance Specifications

	(1)	(2)	(3)
	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$	$\Delta l_{i,t,t+3}$
Distance Measure	Road (km)	Travel Time (hr)	Euclidean (km)
$\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$	-0.403***	-0.362**	-0.456***
	(0.153)	(0.151)	(0.144)
N	1276	1276	1276
R^2	0.07	0.07	0.07
$\widehat{\beta_1}$ t-Ratio P-value	0.01	0.02	0.00
Intercept/Time Dummies	Yes	Yes	Yes
Estimator	GMM	GMM	GMM
Weak ID F-Test	2471.52	1245.01	21.63
Weak IV-robust P-value	0.00	0.00	0.00
Hansen's J-Test P-value	0.59	0.64	0.52
C-Test P-value	0.02	0.04	0.00
Moran's I-Test P-value ($\boldsymbol{W}_C$)	0.00	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W}_B$)	0.00	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W}_D$)	0.41	0.40	0.42
Moran's I-Test P-value ($\boldsymbol{W}_{CD}$)	0.44	0.44	0.45
Moran's I-Test P-value ($\boldsymbol{W}_{BD}$)	0.45	0.45	0.46
Moran's I-Test P-value ($\boldsymbol{W}_G$)	0.57	0.56	0.59

Notes: This table displays estimates of equation (6.1) estimated using the two-step feasible generalised method of moments (GMM) estimator. Each column presents estimates using a different measurement of distance used in the construction of the gravity weights between ZCTAs and MSAs. Column (1) presents the benchmark results, where distance is defined in terms of distance by road in kilometres. Column (2) presents distance is in terms of travel time, measured in hours of travel by automobile. Finally, column (3) presents estimates with Euclidean distances in kilometres. The intercept term and time dummy variables were included in each specification (with the time dummy for 2004-2007 omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. Instruments used in estimation and the post-estimation tests performed are identical to Table (6.1).

Table D.4: Local TFP Standardised Panel Average Moran's I-Statistic P-Values

$\boldsymbol{W}$	Data-Form	Levels	$\Delta_{t,t+1}$	$\Delta_{t,t+2}$	$\Delta_{t,t+3}$	$\Delta_{t,t+4}$	$\Delta_{t,t+5}$	$\Delta_{t,t+6}$
$\boldsymbol{W}_C$	Non-Overlapping	0.00	0.00	0.00	0.00	0.00	0.04	0.00
	Overlapping			0.00	0.00	0.00	0.00	0.00
$\boldsymbol{W}_B$	Non-Overlapping	0.00	0.00	0.00	0.00	0.01	0.09	0.08
	Overlapping			0.00	0.00	0.00	0.00	0.00
$\boldsymbol{W}_D$	Non-Overlapping	0.00	0.00	0.00	0.00	0.01	0.00	0.10
	Overlapping			0.00	0.00	0.00	0.00	0.00
$\boldsymbol{W}_{CD}$	Non-Overlapping	0.00	0.00	0.00	0.00	0.00	0.01	0.06
	Overlapping			0.00	0.00	0.00	0.00	0.00
$\boldsymbol{W}_{BD}$	Non-Overlapping	0.00	0.00	0.00	0.00	0.01	0.05	0.14
	Overlapping			0.00	0.00	0.00	0.00	0.00
$\boldsymbol{W}_G$	Non-Overlapping	0.00	0.01	0.02	0.18	0.25	0.28	0.36
	Overlapping			0.01	0.11	0.15	0.13	0.17
N	116 Rural ZCTAs							

Notes: This table presents the P-values of the standardised panel average of Moran's I-Statistics for local TFP data in levels and (log) differences within the sample 116 rural ZCTAs using a variety of spatial connectivity matrices. Under the null hypothesis, there is no spatial correlation.

Table D.5: Results for Figure 6.1 (MSA TFP Change Parameter Heterogeneity)

	(1) $\Delta l_{i,t,t+3}$	(2) $\Delta l_{i,t,t+3}$	(3) $\Delta l_{i,t,t+3}$	(4) $\Delta l_{i,t,t+3}$	(5) $\Delta l_{i,t,t+3}$	(6) $\Delta l_{i,t,t+3}$
$\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$	-0.424***	-0.548**	0.508	-0.862**	-0.875**	-0.486**
	(0.159)	(0.239)	(0.656)	(0.342)	(0.351)	(0.193)
$\omega_{i,BCO} \Delta a_{BCO,t-3,t}$	-0.111					
	(0.152)					
$\omega_{i,COS} \Delta a_{COS,t-3,t}$		0.124				
		(0.144)				
$\omega_{i,DEN} \Delta a_{DEN,t-3,t}$			-0.958			
			(0.671)			
$\omega_{i,FCO} \Delta a_{FCO,t-3,t}$				0.460		
				(0.288)		
$\omega_{i,GXY} \Delta a_{GXY,t-3,t}$					0.115	
					(0.080)	
$\omega_{i,PUB} \Delta a_{PUB,t-3,t}$						0.030
						(0.037)
N	1276	1276	1276	1276	1276	1276
R^2	0.06	0.07	0.07	0.06	0.06	0.07
$(\widehat{\beta_2} - \widehat{\beta_1})$ t-Ratio P-value	0.47	0.39	0.15	0.11	0.15	0.41
Intercept/Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	GMM	GMM	GMM	GMM	GMM	GMM
Weak ID F-Test	12.81	29.02	34.45	89.13	365.36	49.81
Weak IV-robust P-value	0.00	0.00	0.00	0.00	0.00	0.00
Hansen's J-Test P-value	0.47	0.53	0.64	0.69	0.51	0.51
C-Test P-value	0.18	0.05	0.06	0.02	0.11	0.06
Moran's I-Test P-value ($\boldsymbol{W}_C$)	0.02	0.02	0.01	0.10	0.00	0.01
Moran's I-Test P-value ($\boldsymbol{W}_B$)	0.00	0.00	0.02	0.03 0.00	0.00	
Moran's I-Test P-value ($\boldsymbol{W}_D$)	0.40	0.41	0.44	0.41	0.43	0.42
Moran's I-Test P-value ($\boldsymbol{W}_{CD}$)	0.44	0.44	0.45	0.44	0.45	0.45
Moran's I-Test P-value ($\boldsymbol{W}_{BD}$)	0.45	0.45	0.46	0.46	0.46	0.46
Moran's I-Test P-value ($\boldsymbol{W}_G$)	0.56	0.58	0.63	0.59	0.59	0.60

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This presents results for the coefficient plots in figure (6.1). All models estimated using the feasible two-step generalised method of moments (GMM) estimator. BCO refers to the Boulder MSA, COS to the Colorado Springs MSA, DEN to Denver MSA, FCO to Fort Collins MSA, GXY to Greeley MSA, and PUB to Pueblo MSA. The intercept term and time dummy variables were included in each specification (with the time dummy for 2004-2007 omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. Instruments used in estimation and the post-estimation tests performed are identical to Table (6.1).

Table D.6: Results for Figure 6.2 (Three-Year Urban TFP Growth and Rural ZCTA Employment Growth over Time)

	(1) $\Delta l_{i,t,t+1}$	(2) $\Delta l_{i,t,t+2}$	(3) $\Delta l_{i,t,t+3}$	(4) $\Delta l_{i,t,t+4}$	(5) $\Delta l_{i,t,t+5}$	(6) $\Delta l_{i,t,t+6}$
$\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$	-0.185***					
	(0.069)					
$\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$		-0.358***				
		(0.114)				
$\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$			-0.403***			
			(0.153)			
$\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$				-0.477***		
				(0.165)		
$\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$					-0.352**	
					(0.167)	
$\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$						-0.128
						(0.169)
N	1508	1392	1276	1160	1044	928
R^2	0.04	0.06	0.07	0.06	0.06	0.06
$\widehat{\beta_1}$ t-Ratio P-value	0.01	0.00	0.01	0.00	0.03	0.45
Intercept/Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	GMM	GMM	GMM	GMM	GMM	GMM
Weak ID F-Test	2518.81	2641.74	2471.52	1477.03	1378.46	2190.23
Weak IV-robust P-value	0.00	0.00	0.00	0.03	0.05	0.04
Hansen's J-Test P-value	0.54	0.61	0.59	0.70	0.65	0.41
C-Test P-value	0.36	0.01	0.02	0.01	0.21	0.99
Moran's I-Test P-value ($\boldsymbol{W}_C$)	0.00	0.97	0.00	0.00	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W}_B$)	0.00	0.01	0.00	0.00	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W}_D$)	0.47	0.75	0.52	0.48	0.59	0.50
Moran's I-Test P-value ($\boldsymbol{W}_{CD}$)	0.50	0.61	0.50	0.43	0.48	0.46
Moran's I-Test P-value ($\boldsymbol{W}_{BD}$)	0.50	0.59	0.48	0.41	0.46	0.45
Moran's I-Test P-value ($\boldsymbol{W}_G$)	0.34	0.50	0.3	0.27	0.57	0.44

Notes: This presents results for the coefficient plots in figure (6.2). All models estimated using the feasible two-step generalised method of moments (GMM) estimator. The intercept term and time dummy variables were included in each specification (with the time dummy for the earliest possible period omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. Instruments used in estimation and the post-estimation tests performed are identical to Table (6.1).

Table D.7: Results for Figure 6.3 (Urban TFP Growth over Time and Rural Employment Growth t to $t+1$)

	(1) $\Delta l_{i,t,t+1}$	(2) $\Delta l_{i,t,t+1}$	(3) $\Delta l_{i,t,t+1}$	(4) $\Delta l_{i,t,t+1}$	(5) $\Delta l_{i,t,t+1}$	(6) $\Delta l_{i,t,t+1}$
$\sum_c \omega_{i,c} \Delta a_{c,t-1,t}$	0.043 (0.108)					
$\sum_c \omega_{i,c} \Delta a_{c,t-2,t}$		-0.084 (0.060)				
$\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$			-0.185*** (0.069)			
$\sum_c \omega_{i,c} \Delta a_{c,t-4,t}$				-0.086** (0.040)		
$\sum_c \omega_{i,c} \Delta a_{c,t-5,t}$					-0.016 (0.044)	
$\sum_c \omega_{i,c} \Delta a_{c,t-6,t}$						-0.168*** (0.053)
N	1740	1624	1508	1392	1276	1160
R^2	0.03	0.03	0.04	0.04	0.04	0.05
$\widehat{\beta_1}$ t-Ratio P-value	0.69	0.17	0.01	0.03	0.71	0.00
Intercept/Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	GMM	GMM	GMM	GMM	GMM	GMM
Weak ID F-Test	16433.70	9352.53	2518.81	253.18	419.73	460.85
Weak IV-robust P-value	0.05	0.01	0.00	0.00	0.04	0.04
Hansen's J-Test P-value	0.34	0.42	0.54	0.77	0.18	0.61
C-Test P-value	0.25	0.57	0.36	0.85	0.55	0.03
Moran's I-Test P-value ($\mathbf{W}_C$)	0.00	0.00	0.00	0.00	0.00	0.00
Moran's I-Test P-value ($\mathbf{W}_B$)	0.00	0.59	0.00	0.07	0.00	0.00
Moran's I-Test P-value ($\mathbf{W}_D$)	0.59	0.36	0.58	0.36	0.49	0.46
Moran's I-Test P-value ($\mathbf{W}_{CD}$)	0.54	0.43	0.55	0.44	0.49	0.47
Moran's I-Test P-value ($\mathbf{W}_{BD}$)	0.57	0.45	0.53	0.44	0.50	0.54
Moran's I-Test P-value ($\mathbf{W}_G$)	0.48	0.50	0.52	0.44	0.60	0.19

Notes: This presents results for the coefficient plot concerning rural employment growth from t to $t+1$ in figure (6.3). All models estimated using the feasible two-step generalised method of moments (GMM) estimator. The intercept term and time dummy variables were included in each specification (with the time dummy for the earliest possible period omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. The excluded instruments used for $\sum_c \omega_{i,c} \Delta a_{c,t-k,t}$ for $k \in \{1, 2, \ldots, 6\}$ are the Bartik-style shift share instruments for Boulder (BCO), Colorado Springs (COS), Denver (DEN), Fort Collins (FCO), and Pueblo (PUB): $\omega_{i,BCO} B_{BCO,t-k,t}$, $\omega_{i,COS} B_{COS,t-k,t}$, $\omega_{i,DEN} B_{DEN,t-k,t}$, $\omega_{i,FCO} B_{FCO,t-k,t}$, and $\omega_{i,PUB} B_{PUB,t-k,t}$. Post-estimation tests are identical to those performed in Table (6.1).

Table D.8: Results for Figure 6.3 (Urban TFP Growth over Time and Rural Employment Growth t to $t+2$)

	(1) $\Delta l_{i,t,t+2}$	(2) $\Delta l_{i,t,t+2}$	(3) $\Delta l_{i,t,t+2}$	(4) $\Delta l_{i,t,t+2}$	(5) $\Delta l_{i,t,t+2}$	(6) $\Delta l_{i,t,t+2}$
$\sum_c \omega_{i,c} \Delta a_{c,t-1,t}$	-0.141					
	(0.145)					
$\sum_c \omega_{i,c} \Delta a_{c,t-2,t}$		-0.210**				
		(0.100)				
$\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$			-0.358***			
			(0.114)			
$\sum_c \omega_{i,c} \Delta a_{c,t-4,t}$				-0.096**		
				(0.049)		
$\sum_c \omega_{i,c} \Delta a_{c,t-5,t}$					-0.133	
					(0.083)	
$\sum_c \omega_{i,c} \Delta a_{c,t-6,t}$						-0.159
						(0.114)
N	1624	1508	1392	1276	1160	1044
R^2	0.05	0.06	0.06	0.07	0.07	0.08
$\widehat{\beta_1}$ t-Ratio P-value	0.33	0.04	0.00	0.05	0.11	0.16
Intercept/Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	GMM	GMM	GMM	GMM	GMM	GMM
Weak ID F-Test	15235.11	9002.71	2641.74	172.10	335.03	481.10
Weak IV-robust P-value	0.00	0.00	0.00	0.00	0.07	0.03
Hansen's J-Test P-value	0.13	0.22	0.61	0.27	0.20	0.46
C-Test P-value	0.85	0.14	0.01	0.72	0.65	0.28
Moran's I-Test P-value ($\mathbf{W}_C$)	0.00	0.00	0.42	0.53	0.00	0.00
Moran's I-Test P-value ($\mathbf{W}_B$)	0.00	0.00	0.00	0.08 0.00	0.00	
Moran's I-Test P-value ($\mathbf{W}_D$)	0.48	0.43	0.31	0.48	0.64	0.81
Moran's I-Test P-value ($\mathbf{W}_{CD}$)	0.48	0.48	0.40	0.47	0.57	0.65
Moran's I-Test P-value ($\mathbf{W}_{BD}$)	0.52	0.50	0.39	0.48	0.57	0.66
Moran's I-Test P-value ($\mathbf{W}_G$)	0.53	0.37	0.45	0.60	0.35	0.42

Notes: This presents results for the coefficient plot concerning rural employment growth from t to $t+2$ in figure (6.3). All models estimated using the feasible two-step generalised method of moments (GMM) estimator. The intercept term and time dummy variables were included in each specification (with the time dummy for the earliest possible period omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. The excluded instruments used for $\sum_c \omega_{i,c} \Delta a_{c,t-k,t}$ for $k \in \{1, 2, \ldots, 6\}$ are the Bartik-style shift share instruments for Boulder (BCO), Colorado Springs (COS), Denver (DEN), Fort Collins (FCO), and Pueblo (PUB): $\omega_{i,BCO} B_{BCO,t-k,t}$, $\omega_{i,COS} B_{COS,t-k,t}$, $\omega_{i,DEN} B_{DEN,t-k,t}$, $\omega_{i,FCO} B_{FCO,t-k,t}$, and $\omega_{i,PUB} B_{PUB,t-k,t}$. Post-estimation tests are identical to those performed in Table (6.1).

Table D.9: Results for Figure 6.3 (Urban TFP Growth over Time and Rural Employment Growth t to $t+3$)

	(1) $\Delta l_{i,t,t+3}$	(2) $\Delta l_{i,t,t+3}$	(3) $\Delta l_{i,t,t+3}$	(4) $\Delta l_{i,t,t+3}$	(5) $\Delta l_{i,t,t+3}$	(6) $\Delta l_{i,t,t+3}$
$\sum_c \omega_{i,c}\Delta a_{c,t-1,t}$	-0.242*					
	(0.142)					
$\sum_c \omega_{i,c}\Delta a_{c,t-2,t}$		-0.256**				
		(0.114)				
$\sum_c \omega_{i,c}\Delta a_{c,t-3,t}$			-0.403***			
			(0.153)			
$\sum_c \omega_{i,c}\Delta a_{c,t-4,t}$				-0.169*		
				(0.088)		
$\sum_c \omega_{i,c}\Delta a_{c,t-5,t}$					0.009	
					(0.129)	
$\sum_c \omega_{i,c}\Delta a_{c,t-6,t}$						0.191
						(0.136)
N	1508	1392	1276	1160	1044	928
R^2	0.06	0.06	0.07	0.07	0.08	0.09
$\widehat{\beta_1}$ t-Ratio P-value	0.09	0.02	0.01	0.05	0.95	0.16
Intercept/Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	GMM	GMM	GMM	GMM	GMM	GMM
Weak ID F-Test	13713.72	8704.40	2471.52	148.13	380.00	536.19
Weak IV-robust P-value	0.00	0.00	0.00	0.03	0.10	0.06
Hansen's J-Test P-value	0.22	0.41	0.59	0.37	0.31	0.37
C-Test P-value	0.53	0.14	0.02	0.42	0.78	0.32
Moran's I-Test P-value ($\boldsymbol{W}_C$)	0.00	0.00	0.00	0.00	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W}_B$)	0.00	0.00	0.00	0.00	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W}_D$)	0.46	0.21	0.41	0.51	0.91	0.14
Moran's I-Test P-value ($\boldsymbol{W}_{CD}$)	0.50	0.34	0.44	0.51	0.75	0.25
Moran's I-Test P-value ($\boldsymbol{W}_{BD}$)	0.54	0.37	0.45	0.49	0.73	0.31
Moran's I-Test P-value ($\boldsymbol{W}_G$)	0.28	0.39	0.57	0.41	0.70	0.28

Notes: This presents results for the coefficient plot concerning rural employment growth from t to $t+3$ in figure (6.3). All models estimated using the feasible two-step generalised method of moments (GMM) estimator. The intercept term and time dummy variables were included in each specification (with the time dummy for the earliest possible period omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. The excluded instruments used for $\sum_c \omega_{i,c}\Delta a_{c,t-k,t}$ are the Bartik-style shift share instruments for Boulder (BCO), Colorado Springs (COS), Denver (DEN), Fort Collins (FCO), and Pueblo (PUB): $\omega_{i,BCO}B_{BCO,t-k,t}$, $\omega_{i,COS}B_{COS,t-k,t}$, $\omega_{i,DEN}B_{DEN,t-k,t}$, $\omega_{i,FCO}B_{FCO,t-k,t}$, and $\omega_{i,PUB}B_{PUB,t-k,t}$. Post-estimation tests are identical to those performed in Table (6.1).

Table D.10: Results for Figure 6.3 (Urban TFP Growth over Time and Rural Employment Growth t to $t+4$)

	(1) $\Delta l_{i,t,t+4}$	(2) $\Delta l_{i,t,t+4}$	(3) $\Delta l_{i,t,t+4}$	(4) $\Delta l_{i,t,t+4}$	(5) $\Delta l_{i,t,t+4}$	(6) $\Delta l_{i,t,t+4}$
$\sum_c \omega_{i,c}\Delta a_{c,t-1,t}$	-0.199					
	(0.124)					
$\sum_c \omega_{i,c}\Delta a_{c,t-2,t}$		-0.248**				
		(0.105)				
$\sum_c \omega_{i,c}\Delta a_{c,t-3,t}$			-0.477***			
			(0.165)			
$\sum_c \omega_{i,c}\Delta a_{c,t-4,t}$				-0.040		
				(0.121)		
$\sum_c \omega_{i,c}\Delta a_{c,t-5,t}$					0.191	
					(0.138)	
$\sum_c \omega_{i,c}\Delta a_{c,t-6,t}$						0.214
						(0.142)
N	1392	1276	1160	1044	928	812
R^2	0.06	0.06	0.06	0.07	0.08	0.07
$\widehat{\beta_1}$ t-Ratio P-value	0.11	0.02	0.00	0.74	0.17	0.13
Intercept/Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	GMM	GMM	GMM	GMM	GMM	GMM
Weak ID F-Test	899.30	9065.58	1477.03	289.86	1419.63	3340.02
Weak IV-robust P-value	0.00	0.01	0.03	0.19	0.11	0.06
Hansen's J-Test P-value	0.37	0.46	0.70	0.52	0.56	0.19
C-Test P-value	0.41	0.11	0.01	0.38	0.81	0.12
Moran's I-Test P-value ($\mathbf{W}_C$)	0.00	0.00	0.00	0.00	0.00	0.02
Moran's I-Test P-value ($\mathbf{W}_B$)	0.00	0.00	0.00	0.00	0.94	0.00
Moran's I-Test P-value ($\mathbf{W}_D$)	0.29	0.32	0.62	0.97	0.30	0.47
Moran's I-Test P-value ($\mathbf{W}_{CD}$)	0.37	0.38	0.56	0.82	0.32	0.44
Moran's I-Test P-value ($\mathbf{W}_{BD}$)	0.41	0.42	0.52	0.78	0.36	0.48
Moran's I-Test P-value ($\mathbf{W}_G$)	0.34	0.22	0.68	0.83	0.72	0.47

Notes: This presents results for the coefficient plot concerning rural employment growth from t to $t+4$ in figure (6.3). All models estimated using the feasible two-step generalised method of moments (GMM) estimator. The intercept term and time dummy variables were included in each specification (with the time dummy for the earliest possible period omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. The excluded instruments used for $\sum_c \omega_{i,c}\Delta a_{c,t-k,t}$ are the Bartik-style shift share instruments for Boulder (BCO), Colorado Springs (COS), Denver (DEN), Fort Collins (FCO), and Pueblo (PUB): $\omega_{i,BCO}B_{BCO,t-k,t}$, $\omega_{i,COS}B_{COS,t-k,t}$, $\omega_{i,DEN}B_{DEN,t-k,t}$, $\omega_{i,FCO}B_{FCO,t-k,t}$, and $\omega_{i,PUB}B_{PUB,t-k,t}$. Post-estimation tests are identical to those performed in Table (6.1).

Table D.11: Results for Figure 6.3 (Urban TFP Growth over Time and Rural Employment Growth t to $t+5$)

	(1) $\Delta l_{i,t,t+5}$	(2) $\Delta l_{i,t,t+5}$	(3) $\Delta l_{i,t,t+5}$	(4) $\Delta l_{i,t,t+5}$	(5) $\Delta l_{i,t,t+5}$	(6) $\Delta l_{i,t,t+5}$
$\sum_c \omega_{i,c} \Delta a_{c,t-1,t}$	-0.045					
	(0.110)					
$\sum_c \omega_{i,c} \Delta a_{c,t-2,t}$		-0.163				
		(0.102)				
$\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$			-0.352**			
			(0.167)			
$\sum_c \omega_{i,c} \Delta a_{c,t-4,t}$				-0.015		
				(0.156)		
$\sum_c \omega_{i,c} \Delta a_{c,t-5,t}$					0.063	
					(0.154)	
$\sum_c \omega_{i,c} \Delta a_{c,t-6,t}$						0.032
						(0.147)
N	1276	1160	1044	928	812	696
R^2	0.06	0.05	0.06	0.07	0.07	0.06
$\widehat{\beta_1}$ t-Ratio P-value	0.68	0.11	0.03	0.92	0.68	0.83
Intercept/Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	GMM	GMM	GMM	GMM	GMM	GMM
Weak ID F-Test	588.65	9705.26	1378.46	1177.62	1115.25	2292.18
Weak IV-robust P-value	0.03	0.01	0.05	0.07	0.26	0.18
Hansen's J-Test P-value	0.36	0.22	0.65	0.52	0.76	0.34
C-Test P-value	0.53	0.53	0.21	0.67	0.80	0.31
Moran's I-Test P-value ($\mathbf{W}_C$)	0.00	0.00	0.00	0.00	0.04	0.00
Moran's I-Test P-value ($\mathbf{W}_B$)	0.88	0.00	0.00	0.00	0.00	0.00
Moran's I-Test P-value ($\mathbf{W}_D$)	0.27	0.61	0.98	0.57	0.56	0.94
Moran's I-Test P-value ($\mathbf{W}_{CD}$)	0.40	0.58	0.84	0.46	0.46	0.76
Moran's I-Test P-value ($\mathbf{W}_{BD}$)	0.45	0.56	0.78	0.46	0.50 .67	
Moran's I-Test P-value ($\mathbf{W}_G$)	0.12	0.45	0.95	0.77	0.36	0.98

Notes: This presents results for the coefficient plot concerning rural employment growth from t to $t+5$ in figure (6.3). All models estimated using the feasible two-step generalised method of moments (GMM) estimator. The intercept term and time dummy variables were included in each specification (with the time dummy for the earliest possible period omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. The excluded instruments used for $\sum_c \omega_{i,c} \Delta a_{c,t-k,t}$ are the Bartik-style shift share instruments for Boulder (BCO), Colorado Springs (COS), Denver (DEN), Fort Collins (FCO), and Pueblo (PUB): $\omega_{i,BCO} B_{BCO,t-k,t}$, $\omega_{i,COS} B_{COS,t-k,t}$, $\omega_{i,DEN} B_{DEN,t-k,t}$, $\omega_{i,FCO} B_{FCO,t-k,t}$, and $\omega_{i,PUB} B_{PUB,t-k,t}$. Post-estimation tests are identical to those performed in Table (6.1).

Table D.12: Results for Figure 6.3 (Urban TFP Growth over Time and Rural Employment Growth t to $t+6$)

	(1) $\Delta l_{i,t,t+6}$	(2) $\Delta l_{i,t,t+6}$	(3) $\Delta l_{i,t,t+6}$	(4) $\Delta l_{i,t,t+6}$	(5) $\Delta l_{i,t,t+6}$	(6) $\Delta l_{i,t,t+6}$
$\sum_c \omega_{i,c}\Delta a_{c,t-1,t}$	-0.132					
	(0.162)					
$\sum_c \omega_{i,c}\Delta a_{c,t-2,t}$		-0.138				
		(0.107)				
$\sum_c \omega_{i,c}\Delta a_{c,t-3,t}$			-0.128			
			(0.169)			
$\sum_c \omega_{i,c}\Delta a_{c,t-4,t}$				-0.048		
				(0.132)		
$\sum_c \omega_{i,c}\Delta a_{c,t-5,t}$					0.066	
					(0.109)	
$\sum_c \omega_{i,c}\Delta a_{c,t-6,t}$						-0.166
						(0.114)
N	1160	1044	928	812	696	580
R^2	0.05	0.05	0.06	0.06	0.05	0.06
$\widehat{\beta_1}$ t-Ratio P-value	0.41	0.19	0.45	0.71	0.55	0.15
Intercept/Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	GMM	GMM	GMM	GMM	GMM	GMM
Weak ID F-Test	459.44	8135.55	2190.23	17309.93	1680.60	3416.56
Weak IV-robust P-value	0.01	0.03	0.04	0.02	0.12	0.09
Hansen's J-Test P-value	0.20	0.20	0.41	0.38	0.42	0.38
C-Test P-value	0.19	0.79	0.99	0.91	0.51	0.52
Moran's I-Test P-value ($\boldsymbol{W}_C$)	0.07	0.00	0.00	0.00	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W}_B$)	0.00	0.00	0.00	0.00	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W}_D$)	0.57	0.96	0.80	0.60	0.92	0.10
Moran's I-Test P-value ($\boldsymbol{W}_{CD}$)	0.54	0.81	0.59	0.48	0.75	0.26
Moran's I-Test P-value ($\boldsymbol{W}_{BD}$)	0.56	0.75	0.57	0.51	0.65	0.31
Moran's I-Test P-value ($\boldsymbol{W}_G$)	0.32	0.88	0.81	0.25	0.95	0.81

Notes: This presents results for the coefficient plot concerning rural employment growth from t to t+6 in figure (6.3). All models estimated using the feasible two-step generalised method of moments (GMM) estimator. The intercept term and time dummy variables were included in each specification (with the time dummy for the earliest possible period omitted). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. The excluded instruments used for $\sum_c \omega_{i,c}\Delta a_{c,t-k,t}$ for $k \in \{1, 2, \ldots, 6\}$ are the Bartik-style shift share instruments for Boulder (BCO), Colorado Springs (COS), Denver (DEN), Fort Collins (FCO), and Pueblo (PUB): $\omega_{i,BCO}B_{BCO,t-k,t}$, $\omega_{i,COS}B_{COS,t-k,t}$, $\omega_{i,DEN}B_{DEN,t-k,t}$, $\omega_{i,FCO}B_{FCO,t-k,t}$, and $\omega_{i,PUB}B_{PUB,t-k,t}$. Post-estimation tests are identical to those performed in Table (6.1).

Table D.13: Lagged and Contemporaneous Urban TFP Growth

	(1) $\Delta l_{i,t,t+3}$	(2) $\Delta l_{i,t,t+3}$
$\sum_c \omega_{i,c} \Delta a_{c,t-3,t}$	-0.403***	
	(0.153)	
$\sum_c \omega_{i,c} \Delta a_{c,t,t+3}$		0.177
		(0.270)
N	1276	1624
R^2	0.07	0.05
$\widehat{\beta}_1$ t-Ratio P-value	0.01	0.51
Intercept/Time Dummies	Yes	Yes
Estimator	GMM	GMM
Weak ID F-Test	2471.52	209.10
Weak IV-robust P-value	0.00	0.00
Hansen's J-Test P-value	0.59	0.25
C-Test P-value	0.02	0.29
Moran's I-Test P-value ($\boldsymbol{W}_C$)	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W}_B$)	0.00	0.00
Moran's I-Test P-value ($\boldsymbol{W}_D$)	0.52	0.27
Moran's I-Test P-value ($\boldsymbol{W}_{CD}$)	0.50	0.38
Moran's I-Test P-value ($\boldsymbol{W}_{BD}$)	0.48	0.36
Moran's I-Test P-value ($\boldsymbol{W}_G$)	0.30	0.18

Notes: This table displays estimates of equation (6.1) in column (1) alongside estimates of a model in which growth in urban TFP occurs contemporaneously with growth in employment (i.e. from t to $t+3$) in column (2), both models being estimated using the two-step feasible generalised method of moments (GMM) estimator. The intercept term and time dummy variables were included in each specification (with the time dummy for 2004-2007 omitted in column (1) and 2001-2004 for column (2)). Standard errors are clustered in 10,000-square-km grid squares and are robust to heteroskedasticity, serial correlation, and spatial correlation of the form discussed in Bester, Conley, and Hansen (2011) where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ using a two-tailed test. Instruments used in estimation and the post-estimation tests performed are identical to Table (6.1).