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Local Labor Markets Should Be Redefined: New Definitions Based on Estimated Demand-Shock Spillovers

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Local Labor Markets Should Be Redefined: New Definitions Based on Estimated Demand-Shock Spillovers

Researching the causes and consequences of unemployment

Upjohn Institute Working Paper 24-407

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ABSTRACT

This paper provides estimates that lead to better U.S. labor market definitions. Current U.S. labor market definitions—for example, metropolitan areas and commuting zones—are unsatisfactory because they are ad hoc and usually do not correspond to commonly used local planning areas. This paper proposes basing U.S. labor market definitions on how a job shock to a county affects nearby counties' employment rates. New estimates of county spillovers are presented. Using these estimated spillovers, new multicounty labor market definitions are based on maximizing a weighted sum of total spillovers captured, versus taking the average size of within-market effects. These new "spillover-defined local labor markets" (SLMs) correspond more closely to commonly used local planning areas, and they better capture spillovers and commuting flows without becoming excessively large.

JEL codes: R10, R12, R23

Key words: Local labor markets, commuting zones, metropolitan areas

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Upjohn Institute working papers are meant to stimulate discussion and criticism among the policy research community. Content and opinions are the sole responsibility of the author.

This paper proposes a new empirical approach to defining local labor markets in the United States. This new approach is based on the estimated size of demand-shock spillover effects, from one county to another, on county employment rates. Counties are grouped into local labor markets based on an algorithm that considers grouping to involve a trade-off: combining more counties into a local labor market area increases the spillovers that are captured, but it reduces the average within-area spillover.

As outlined in the next section, the motivation for this paper is that current local labor market definitions often do not match intuitively plausible local labor market planning areas. Many local labor market definitions are "too large," combining counties that are not closely connected. In fewer cases—although involving many people and jobs—local labor market definitions are "too small," separating areas that are sufficiently connected that they should be grouped together. These problems occur in part because current procedures for defining local labor markets are ad hoc and hence arbitrary and inconsistent.

Current local labor market definitions are problematic for both research and policy. For research, too-large or too-small local labor market definitions may result in estimates of labor market effects of local labor demand shocks or supply shocks that are incorrect. For policy, mistaken local labor market definitions may make it more difficult for policymakers to target, design, or implement appropriate local labor market policies. For example, if state or federal policymakers are aiming to target "distressed local labor markets," mistaken definitions may incorrectly identify what places to target. For local policymakers, if you only have data for the wrong local labor market area, you will have an incorrect understanding of the local area's mix of industries and job skills, which may lead to poorly designed economic and workforce development policies. For local politics, different sub-areas within a labor market area will have

to perceive large spillover effects of job creation across the entire area to be willing to implement cooperative area-wide job creation policies.

This paper pilots a new approach to local labor market definitions, an approach based on empirical estimates. In this new approach, the first task is to estimate how a county's employment rate is affected by demand shocks in nearby counties. This demand shock spillover is allowed to depend on the extent of cross-county commuting. Compared to existing local labor market definitions, what is different about this new approach is that empirical estimation tells us how important commuting is at different magnitudes for individual counties, rather than making arbitrary assumptions about what commuting thresholds to use for groups of counties.

Using these empirical estimates of spillover effects, the second task of the approach is to come up with a practical algorithm for grouping counties into local labor market areas. Adding one more county to an adjacent tentative labor market area would usually increase the total size of spillover effects captured, if any of the counties in the grouping have any spillover effects on the county in question, or vice versa. But adding one more county may reduce the average size of such spillovers, in that a randomly chosen employment shock may have lower average effects on the employment rates of the diverse counties in the proposed local labor market. An algorithm can put different weights on these two criteria—total spillovers captured; average size of spillovers—and examine how local labor market definitions vary with such relative weights.

This paper is a pilot that reports one set of estimates and one way of weighing total spillovers captured versus average size of spillovers in defining local labor markets. The pilot aspect of this is that there are many ways such estimation and labor market definitions could be done. Future research will explore a variety of approaches.

But this pilot estimation already illustrates this new approach's potential. Compared to current local labor market definitions, the new definition better conforms to some local labor market planning regions. In addition, the new definition does better at capturing more commuting and more spillover effects without making many local labor markets unduly large.

I label the resulting labor market definitions as "spillover-based local labor markets," or SLMs. The acronym captures one feature of these new definitions: the resulting SLMs are often "slimmer" or smaller in geographic area than is true of the current widely used definitions of local labor markets. Some of the methods used in constructing currently used local labor market areas do too much ad hoc aggregation, which results in many local labor market areas absorbing too many nearby areas. Within currently used local labor market areas, the spillover effects between many sub-areas within a defined local labor market area are too small for the aggregation to make sense. Basing local labor market definitions explicitly on spillovers helps to avoid this excess aggregation. The pilot SLMs proposed here are but one version of spilloverbased local labor markets. However, other versions would similarly seek to make sure that average spillover effects within local labor markets are sufficiently great. Our defined local labor markets should ensure that sub-areas within the local labor market area have strong common interests in cooperative area-wide local labor market policies.

In the current pilot paper, I first motivate this paper by explaining what we might hope to accomplish with local labor market definitions. Then, I discuss the challenges that exist with current local labor market definitions. Following that, I outline how I estimate labor demand spillover effects across counties. I then explain specifically how I use these estimates to define local labor markets. The resulting local labor market definitions are then compared with current official local labor market definitions. A conclusion outlines possible next steps.

LOCAL LABOR MARKET DEFINITIONS AND THEIR USES

A local labor market may be defined as an area within which there is "sufficient commuting" that changes in job creation or labor supply in one portion of the local labor market are relatively quickly transmitted to affect labor market outcomes throughout the local labor market. Commuting has such transmission effects because of chains of job vacancies. For example, if a job is created in a particular suburb—call it Suburb A—this may affect job availability in the central city. Some of this effect is from workers in the central city commuting to jobs in Suburb A. But there may be effects even for central city residents who do not have a car or transit option to commute to Suburb A. For example, suppose some suburban workers who currently commute to a central city job end up accepting the new suburban job. This opens up job vacancies for central city workers, including central city workers who do not have a car or other transit options for taking the new job in Suburb A. Therefore, we expect the new suburban job to affect employment rates and wages of all central city workers, not just those central city workers who can access the new job.

Three points should be noted about this definition of local labor markets. First, local labor markets may not be the same as local economies. Labor demand shocks that affect job creation in one community may have multiplier effects on jobs in other communities, by way of not just consumer purchases (which might have similar geographic reach to commuting) but also from supplier linkages (which may have somewhat larger geographic reach than commuting). Defining the spatial area within which demand shocks may most readily spread to affect job creation—a "local economy definition"—may be somewhat different from defining the spatial area within which the actual realized job creation has quick effects on labor market outcomes through commuting—a "local labor market definition."

Second, commuting is not the only way to transmit local shocks to job creation or labor supply. In addition, shocks to local job creation and labor supply can be spatially transmitted by migration of either households or firms. A labor demand shock or supply shock in one area that affects that area's wages and employment rates will affect the area's attractiveness to firms and households. The area's changes in wages and employment rates will affect the decisions of firms about locating or expanding in the area, and will also affect the decisions of households to migrate to or from the area. These changes in the location decisions of firms and households will consequently affect whether firms locate or expand in other areas, and how many households there are in other areas. Because of these job-growth and migration effects on other areas, these other areas will experience some alteration in their labor market outcomes—for example, these other areas will experience some alteration in wages and employment rates.

However, these "migration" transmission mechanisms are generally thought to be slower acting than commuting effects. Furthermore, if a local job-creation or labor-supply shock creates short-run effects, through commuting, on the employment experiences of local residents, this changed employment experience may have long-run effects, even after migration more fully adjusts (Bartik 1991, 2020). If a local worker gets a job who otherwise would be nonemployed— or gets a better job who otherwise would have a worse job—this improved employment experience in the short run increases job skills and self-confidence, reduces involvement in substance abuse and crime, and reduces family breakups. All of these effects may increase the local worker's long-run employment rates and wages, and may also spill over to improve the future prospects of the worker's children.¹

¹ As argued in recent research by Chetty et al. (2024), improved employment rates of the parents in a child's peer group may also have social spillover benefits that improve the child's adult earnings.

A third point is that there is no perfect way to define local labor market areas to avoid *some* spillover effects across local labor markets, once one allows for all the effects of commuting chains. A job shock in Manhattan is indirectly linked to what happens in San Francisco by commuting chains that go county by county across the United States. On the one hand, the effects of a job shock in New York City on labor market conditions in San Francisco, through chains of commutes, is likely to be small: some of the commuting probabilities across counties are small, and as we pile one such commuting link on another, the resulting interlinked transmission strength will tend to weaken. On the other hand, the total transmission of job shocks to Manhattan on all faraway places, not just San Francisco, may be quite large in aggregate.²

What is a definition of local labor markets trying to achieve? The ideal definition would achieve two goals. First, out of all intercounty spillovers, the defined local labor markets should internally contain a large share. Second, within each local labor market, the average internal effects of shocks should be large. However, no definition will perfectly optimize both of these goals. Local labor market definitions will have to balance a trade-off between, on the one hand, capturing a larger proportion of spillover effects and, on the other, maximizing the internal interconnectedness of the local areas. For example, if we tweak our local labor market definitions to make the average local labor market larger, the resulting tweaked definitions will include more spillovers, but an average shock within any area will have smaller effects on the average person within the area.

How areas are defined is important for two purposes: 1) research and 2) policy. First, for researchers, a better definition of local labor markets—one in which more spillovers are captured

² This point has been made in recent research by Manning and Petrongolo (2017), Mansfield (2021), and Mansfield (2024).

and internal labor market conditions are more closely tied within an area—allows a researcher to more precisely estimate the effects of labor supply shocks or job creation shocks on labor market conditions. Of course, a researcher can still get estimates of the effects of job creation shocks or labor supply shocks when labor markets are defined inappropriately. For example, one can estimate a model in which a local labor market is defined as a "state." States as local labor markets are implausible—Pennsylvania is clearly not one local labor market. But when defining local labor markets too broadly, one is essentially averaging effects across multiple local labor markets from average job creation or supply shocks in those multiple markets. This is likely to increase the imprecision of estimates, and also bias the estimated effects of shocks toward zero. On the other hand, if local labor markets are defined too narrowly, then the estimates are likely to underestimate the effects of shocks by omitting important spillovers.³ Furthermore, the resulting underdefined local labor markets will tend to have heavy spillovers and correlations across adjacent areas, which may create spatial correlation problems with accurately estimating the standard errors.

For policymakers, local labor market definitions help define the area within which local policies that affect job creation or labor supply should be planned, coordinated, and financed to both capture a large proportion of spillovers and legitimately ask for financial support. For example, if a local economic development organization is planning an industrial park, one might ask, "What local communities are sufficiently affected that these local communities would be willing to provide financial support?" If average spillovers are sufficiently attenuated, pleas for financial support are likely to be unheeded. Cooperative policies for a local labor market area are

³ Appendix A argues for underestimation of demand shock effects on local labor markets due to either overdefining or underdefining local labor markets.

more politically viable if average spillovers are high enough that different sub-areas perceive common interests in increasing jobs anywhere in the local labor market.

CHALLENGES WITH CURRENT LOCAL LABOR MARKET DEFINITIONS USED IN THE UNITED STATES⁴

All commonly used local labor market areas in the United States rely on aggregating counties into local labor markets. The most commonly used official definition of local labor markets in the United States is that of "core-based statistical areas" (e.g., metropolitan areas and micropolitan areas). However, at the outset we will briefly mention two other alternative U.S. local labor market definitions: 1) BEA economic areas and 2) commuting zones. In recent years, commuting zones in particular have frequently been used in economic research.⁵

BEA Economic Areas

The Bureau of Economic Analysis (BEA) at the U.S. Department of Commerce delineated "BEA economic areas" in 1977, 1995, and most recently in 2004.⁶ This definition on the one hand seeks to define local labor markets, and on the other hand seeks to define local markets for products and local markets for information. The BEA's definition does not seem to consider that these different regional markets might be of different sizes:

"These economic areas represent the relevant regional markets for labor, products, and information. They are mainly determined by labor commuting patterns that delineate local labor markets and that also serve as proxies for local markets where businesses in the areas sell their

⁴ Prior critiques of current local labor market definitions are in Goetz, Partridge, and Stevens (2018), and in private communication from Mark Partridge with the author.

⁵ The trend toward using commuting zones in economics research seems to have begun with Autor and Dorn (2013), who remark that "We are not aware of prior economic research that makes use of this geographic construct [of CZs]."

⁶ See Johnson and Kort (2004). It does not seem that there are any plans to update BEA economic areas, or at least I have not found any reference to such plans.

products. In less populous parts of the county, newspaper readership data are also used to measure the relevant regional markets."⁷

BEA started with metropolitan areas and some micropolitan areas. It then sought to add all remaining counties to these starting "nodes," largely based on commuting data. BEA then further combined the resulting areas to achieve some minimum size for each BEA economic area, and to minimize rates of out-commuting or in-commuting:

"To limit labor market interdependence, the maximum rate of total out-commuting for an economic area was set at 8 percent, and the maximum rate of commuting from one economic area to any other economic area was set at 4 percent."

The resulting BEA economic areas are quite large. The entire United States is divided into 179 BEA economic areas.

Given the goals of minimizing out-commuting and ensuring minimum-sized thresholds, the resulting BEA economic areas place an almost total emphasis on the goal of encompassing all possible labor market spillovers, and almost no emphasis on maximizing the average size of spillovers within such BEA economic areas. Any informed local observer is going to look at most of these areas and say, "This is too big: many counties within this area have little to do with each other."

For example, the BEA economic area that includes Kalamazoo extends all the way up west Michigan to encompass both Grand Rapids and Big Rapids (see Map 1). No one in Big Rapids or in Kalamazoo thinks of these two communities as being in the same local labor market.

⁷ As the use of newspaper readership data suggests, these definitions were conceived in another era.

Map 1 West Michigan BEA Economic Area



SOURCE: Author's compilation.

To illustrate this, the estimate from the U.S. Census Bureau is that of the 17,891 workers living in Mecosta County, only 0.1 percent work in Kalamazoo County.⁸ This reflects that the commuting distance from Big Rapids to Kalamazoo is 108 miles, with an estimated rush hour commuting time of one and a half hours to two hours and 10 minutes.⁹ Of course, there may be sufficient "indirect" commuting ties between Big Rapids and Kalamazoo to have labor market spillovers—for example, both Mecosta County and Kalamazoo County have commuters to Kent

⁸ All of these commuting rates are based on American Community Survey (ACS) data from 2016 to 2020. I use these data because they are currently used to generate core-based statistical areas. However, I have also looked at the Census-Bureau reported percentages from the 2006–2010 ACS data used in the empirical estimation reported later in the paper, and the commuting flow percentages are quite similar.

⁹ Data from Google Maps predictions of commuting time to arrive by 9:00 a.m. in Kalamazoo on a weekday.

County (6.9 percent and 1.5 percent, respectively, out of each county's resident workers). However, on the whole, strong labor market spillovers between Big Rapids and Kalamazoo seem implausible.

Commuting Zones

With support from the Economic Research Service of the U.S. Department of Agriculture, researchers developed "commuting zones" (CZs) starting in the late 1980s (Tolbert and Killian 1987). Versions supported by USDA funding were created using census data from 1980, 1990, and 2000. More recently, independent researchers at Penn State have updated commuting-zone definitions using a very similar methodology based on 2006–2010 commuting data from the American Community Survey (ACS) (Fowler, Rhubart, and Jensen 2016; Fowler and Jensen 2020).

The purpose of designating commuting zones seems to have been to include rural areas in labor market areas, but to not require that the resulting labor market areas necessarily be based around urban centers—unlike the BEA economic areas, which are based on CBSAs. As the original 1987 paper on CZs states, researchers were concerned that "large-scale urban trends can obscure important trends in less populated areas" (Tolbert and Killian 1987). As a result, they wanted to adopt a method that "applies consistent grouping criteria to recent commuting data and does not require a group of counties to have an urban center."

In the latest version of commuting zones, based on the most recent commuting data, all U.S. counties are grouped into one of 625 commuting zones. Previous versions had commuting zone numbers that diminished from 765 (1980) to 741 (1990) to 709 (2000).

When one examines the resulting CZs, they frequently appear to be too large to be plausible local labor market areas. For example, consider the commuting zone that encompasses

my home community of Kalamazoo. This includes six counties in Michigan and three counties in Indiana, including St. Joseph County (Ind.), which includes the city of South Bend (see Map 2).

Map 2 Kalamazoo/South Bend Commuting Zone



SOURCE: Author's compilation.

To any resident of southwest Michigan, putting Kalamazoo and South Bend into the same labor market seems a stretch. Based on Google Maps, the commuting distance from South Bend to Kalamazoo is 73 miles. At rush hour, this commute is estimated to take from 1 hour 15 minutes up to 1 hour 50 minutes.

Looking at commuting data, of the 129,112 resident workers in Kalamazoo County, only 0.01 percent work in St. Joseph County, Indiana. Going in the other direction, of the 127,286 resident workers in St. Joseph County, Indiana, only 0.03 percent work in Kalamazoo County.

Therefore, Kalamazoo and South Bend seem to have almost zero direct commuting interaction. Of course, they may have some indirect interaction via counties that are geographically in-between. But is this enough to make them part of the same local labor market?

What is going on here? Commuting zones are created by first counting the sum of the number of commuters between any two counties, divided by the resident workers in the smaller of the two counties. This statistic is then maxed out at 0.99 and subtracted from 1:

(1) CZ grouping statistic between counties k and $s = 1 - (C_{ks} + C_{sk}) / Min(E_k, E_s)$,

where C_{ks} is commuting from county k to county s, C_{sk} from s to k, and E_k and E_s are employment by place of residence in counties k and s.

To create commuting zones, we initially treat each county as its own local labor market. The statistic described in Equation (1) is calculated for all county pairs. One then clusters together the two counties for which this statistic is lowest to create a new tentative list of local labor markets. The statistic is then recalculated with this two-county pair included as a local labor market for which this equation is calculated with all other counties. One then picks the lowest pair of two local labor markets on this statistic, out of all possible pairs, and combines that lowest pair into a new local labor market. We then once again recalculate the statistic for all possible pairs of these tentative local labor markets. This process continues until we have a set of local labor markets for which no possible combination would have a value of this grouping statistic that is less than some arbitrary cutoff. (Without a cutoff, all counties would end up being combined into one local labor market area.) The cutoffs typically used are 0.97 and 0.98.

The algorithm for creating commuting zones tends to prioritize combining two tentative local labor markets if the two markets differ greatly in size. This prioritization occurs because the

volume of commuting between two tentative local labor market pairs depends upon the size of both local labor markets, yet the commuting rate calculated is as a proportion of the smaller member of the pair. Such proportionate differences are more likely to be larger in rural areas, so the algorithm will tend to prioritize combining two rural local labor market areas. Furthermore, once a given grouping gets momentum, it then can absorb other nearby smaller areas readily, because the proportionate size difference will be greater.

The algorithm for creating commuting zones also allows two local labor market areas to be combined even if the commuting rate between them is very small. A cutoff of 0.98 means that the sum of the commuting in either direction between the two local labor market areas that we are considering for combining can be as small as 2 percent of the smaller area, and the areas may still be combined. This results in combining local labor markets that have minimal commuting connections.

Although it is hard to know for sure without having details on the algorithm's operations, these issues may have resulted in implausible CZs, such as the Kalamazoo CZ previously discussed. The rural counties between Kalamazoo and South Bend are readily combined by way of this algorithm, and then Kalamazoo and South Bend are absorbed, even with only minimal commuting connections to the rest of the combined area.

Perhaps because of the large size of some commuting zones, at least some research has found that there are only very small if any spillover effects in cross-county effects within many commuting zones. For example, in my recent paper, I found that for counties in CZs that were average or booming CZs at baseline, the county's employment rate was only affected by demand shocks to the county, and not by demand shocks to the rest of the CZ (Bartik 2024). For counties

in CZs that were highly distressed at baseline, there are some spillover effects—the demand shocks in the rest of the CZ affect the county's employment.

My prior paper then argued that this occurred because job vacancy chains in distressed CZs tend to be filled by more local hiring, versus hiring people moving into the CZ. In such distressed CZs, more local residents are available to be hired, and the CZ is less attractive to inmigrants. As a result, job vacancy chains in distressed CZs are lengthier and can extend throughout the CZ. In contrast, in a CZ that is booming or average at baseline, the job vacancy chains tend to be more likely to be terminated by hiring in-migrants, which reduces spillover effects of a county's demand shocks on the rest of the CZ.

Core-Based Statistical Areas

Local labor markets, in the most commonly used official definition, are termed "corebased statistical areas." These core-based statistical areas are designated by the Office of Management and Budget (OMB 2021). As of 2023, they make up 393 "metropolitan statistical areas" and 542 "micropolitan statistical areas." The distinction between "metro" and "micro" is based on the size of the largest urban area within the core-based statistical area (CBSA), with "metro" applying to cases where the largest urban area has more than 50,000 persons, and "micro" applying to cases where the largest urban area has more than 10,000 persons but less than 50,000 persons.

In all cases, CBSAs consist of counties that contain urbanized areas, together with outlying counties that have sufficient commuting links to these central counties. Out of the 3,144 counties in the United States, there are 393 metro areas, which include 1,186 counties. These 393 metro areas contain 86.2 percent of the U.S. population. The 542 micro areas include 658

counties. Together, these 542 micro areas contain 8.4 percent of the U.S. population. Combined, CBSAs include 1,844 of the 3,144 counties and have 94.6 percent of the U.S. population.

The remaining 1,300 counties, home to 5.4 percent of the U.S. population, are outside the CBSAs. However, the U.S. Bureau of Labor Statistics has "small labor market areas" (LMAs) which use similar commuting-based procedures to classify the remaining areas into labor market areas. A complication is that BLS does not instantly adjust its small LMA definitions. For example, currently the BLS small LMAs are based on the 2010 census and 2006–2010 ACS commuting data, along with the CBSAs derived from that time period. An additional complication is that in New England only, the BLS small LMAs follow town boundaries, not county boundaries. In the rest of the country, the BLS small LMAs usually are only one county in size, because the magnitude of intercounty commuting is insufficient for BLS to group most individual counties into larger labor market areas.

If one peruses the CBSAs, one sees that in many cases the CBSAs seem too large to be plausible local labor `market areas. Many CBSAs are, in fact, too large to be likely to be considered as plausible planning areas for either local economic development programs or local job training programs. At the same time, a smaller number of CBSAs appear to be too small, excluding counties that likely would be included in local planning areas.

To illustrate this problem, I will consider four CBSA examples. Two of these are CBSAs that appear to be "too big": Chicago and Atlanta. The other two examples are CBSAs that appear to be "too small": Detroit and Los Angeles.

Consider the Chicago metro area. This metro area comprises 13 counties, including nine counties in Illinois and four in Indiana (Map 3). Some of these counties appear to have little commuting connection with Chicago. For example, of the 14,556 workers residing in Jasper

County, Indiana, only 3.8 percent work in Cook County (the home county of Chicago). This is not surprising, as the distance from the Jasper County seat of Rensselaer to Chicago makes for a commute of about 84 miles, which Google Maps says at rush hour would take from 1 hour 25 minutes to 2 hours 10 minutes.



Map 3 Areas Covered by Chicago CBSA and Chicago Metropolitan Agency for Planning

NOTE: The 13 counties shown are the Chicago core-based statistical area (CBSA), also known as the Chicago Metropolitan Statistical Area (MSA). The seven cross-hatched counties are those encompassed by the Chicago Metropolitan Agency for Planning (CMAP). SOURCE: Author's compilation.

Perhaps more importantly, this Chicago metro area does not correspond to local planning regions. For example, the Chicago Metropolitan Agency for Planning, which handles local transportation and economic development planning, covers a seven-county area. It eliminates the four counties in Indiana, as well as the outlying Illinois counties of Grundy and DeKalb.

Now, consider the Atlanta metro area (Map 4). This is a sprawling area of 29 counties in Georgia. Some of these 29 counties seem to have little connection to Atlanta. For example, in the Jasper County that is in Georgia, only 3.1 percent of the 5,741 workers living in that county



Map 4 Atlanta CBSA and Atlanta Regional Commission Areas

NOTE: The 29 counties shown are those in the Atlanta Core-Based Statistical Area (CBSA), also known as the Atlanta Metropolitan Statistical Area (MSA). The 11 counties surrounded by a black line make up those encompassed by the Atlanta Regional Commission.

SOURCE: Author's compilation.

commute to Fulton County (Atlanta's home county).¹⁰ According to Google Maps, from the Jasper County seat of Monticello to Atlanta is a distance of 61 miles, which at rush hour takes from 1 hour 5 minutes to 1 hour 40 minutes.

Furthermore, the Atlanta Regional Commission Planning Area consists of only 11 counties. Most of the outlying counties in the official Atlanta MSA are dropped from this locally defined region. The Atlanta Regional Commission does transportation planning, workforce programs, and various housing and community development activities.

But other CBSAs appear to be too small. Consider the Detroit metro area (Map 5). It comprises six counties: Wayne, Oakland, Macomb, St. Clair, Livingston, and Lapeer. But the Detroit MSA excludes Washtenaw County/Ann Arbor, even though 12.3 percent of the 184,500 workers living in Washtenaw County commute to Wayne County. According to Google Maps, the distance from Ann Arbor to Detroit is 43 miles, and the commute at rush hour takes 45 minutes to an hour.

The Detroit metro area may also, simultaneously, be too big. For example, in Lapeer County, only 2.6 percent of its 39,112 resident workers commute to work in Wayne County. According to Google Maps, the distance from Lapeer to Detroit is 58 miles, and the rush-hour commute takes between one and one-and-a-half hours.

Perhaps more importantly, the official Detroit metro-area boundaries do not correspond to locally derived planning areas. The Southeast Michigan Council of Governments (SEMCOG) is a regional planning organization involved in transportation planning, environmental planning,

¹⁰ I have no special fascination with the name "Jasper County." It just so happens that two different CBSAs have a "Jasper County" that is quite remote from the county containing the CBSA's largest city.

Map 5 Detroit CBSA, SEMCOG, and Detroit CSA



NOTE: The 11 counties shown are those in the Detroit Consolidated Statistical Area (CSA). The six cross-hatched counties are those in the Detroit Core-Based Statistical Area (CBSA), also known as the Detroit Metropolitan Statistical Area (MSA). The seven counties in the Southeast Michigan Council of Governments (SEMCOG) are outlined in red. SOURCE: Author's compilation.

and housing and land-use planning. This seven-county region, at variance from the official metro area, drops Lapeer County but adds in Washtenaw and Monroe Counties.

An official federal government alternative to the Detroit metro area is the Detroit Consolidated Statistical Area (CSA), which combines five metro areas. The Detroit CSA adds back in Washtenaw County and Monroe County, which local planners consider to be part of the region. However, the Detroit CSA also includes Lenawee County and Genessee County/Flint. Most people would not consider Flint to be part of the Detroit area. As another example of a "too small" metro area, consider Los Angeles. The Los Angeles metro area consists only of Los Angeles County and Orange County (Map 6).





NOTE: The five counties shown are the Los Angeles Consolidated Statistical Area (CSA). This is sometimes defined as "Greater Los Angeles." The two counties, Los Angeles and Orange, in darker gray with darker outlines, are the Los Angeles Core-Based Statistical Area (CBSA), also known as the Los Angeles Metropolitan Statistical Area (MSA). SOURCE: Author's compilation.

But as such, this Los Angeles metro area does not include the nearby county of San Bernardino. Out of the 808,563 resident workers who live in San Bernardino County, 15.7 percent work in Los Angeles County. According to Google Maps, the distance from San Bernardino County's county seat, San Bernardino city, to Los Angeles is 60 miles, and the trip at rush hour takes from 1 hour 5 minutes to 1 hour 40 minutes. The Los Angeles area does not appear to have organized multicounty planning organizations. But Wikipedia, to use an example, defines "Greater Los Angeles" as the fivecounty area of Los Angeles, Orange, San Bernardino, Riverside, and Ventura. Furthermore, the L.A. Chamber of Commerce appears to draw its membership from the same area. This fivecounty area also coincides with the official Los Angeles Consolidated Statistical Area.

What is going on here? In my view, these "too large" and "too small" local labor market areas occur because of the details of how the Census Bureau defines urbanized areas, how it then sometimes splits and sometimes combines such areas to designate central counties for a CBSA, and the specific criteria then used, which base a county's CBSA assignment on its commuting links to the combined central counties of a CBSA. The underlying problem is that the criteria reflect a philosophy that a local labor market is comprised of a dense central urban area, which outlying suburban counties are then linked to by commuting. But the criteria do not ask whether the underlying central urban area is sometimes too big. As a result, the commuting rate cutoff has to be set so as to prevent CBSAs from growing to ridiculous sizes, and this rules out some important links.

More specifically, the Census Bureau defines an urban area as an area of contiguous dense housing, and then defines its boundaries, but allows for some gaps due to roads, bodies of water, and other reasons. But urban areas can then sometimes be split on a somewhat ad hoc basis if they were not part of the same urban area in the past—this appears to be an attempt to avoid having some urban areas that are clearly too big.¹¹

¹¹ From the Census Bureau's procedures for defining urbanized areas for 2020 in the Federal Register: "Population growth and development, coupled with the automated urban-area delineation methodology used for the 2020 Census, results in large Urban Area Agglomerations (UAAs) that encompass territory defined as separate urban areas for the 2010 Census. If such results occur ... the Census Bureau will apply split criteria.... Eligible UAAs

The central counties of a CBSA then start out as those counties that have at least half their population in the same urban area, or have at least 5,000 population in an urban area of 10,000 or more. These central counties are automatically part of a CBSA, even if there was zero commuting between them. But central counties assigned to different urban areas, and hence initially to different CBSAs, can then be combined to become central counties of a new combined CBSA if, in either direction, at least 25 percent of the resident workers in one set of central counties commute to the other set of central counties, or at least 25 percent of the workers in one set of central counties come from the other set of central counties.

Once these central counties are defined, we then identify the outlying counties of the CBSA. This is done by seeing what outlying counties cross either of the two 25 percent thresholds, calculated to the entire set of central counties for that CBSA: That is, does that outlying county, for example, have at least 25 percent of its resident workers who are commuting to the central county set grouped together?

Therefore, the Chicago metro area, for example, ends up having nine central counties. This includes Lake County and Porter County in Indiana. For this reason, even though Jasper County in Indiana has few commuting links to Chicago/Cook County, it has sufficient commuting to Lake County (20.5 percent of Jasper's resident workers) and Porter County (8.9 percent of its resident workers) to cross the 25 percent threshold. The criteria do not weigh the weakness of the links to Cook County versus the strength of the connections to Lake and Porter Counties in deciding whether to place Jasper County in the Chicago metro area. Crossing the

will be evaluated for splitting where the UAA ... encompasses territory defined as separate urban areas for the 2010 Census and those intersecting areas contain at least 50 percent of the population of each of two or more urban areas for the 2010 Census."

minimum commuting threshold with respect to the combined central counties as a group is enough.

Similarly, the Atlanta metro area ends up having 16 central counties. These central counties include Newton and Rockdale Counties. So even though Jasper County (Georgia) has only weak commuting ties to Fulton County/Atlanta, its commuting levels to Newton and Rockdale Counties (19.4 percent and 11.3 percent of Jasper's resident workers) are enough to cross the 25 percent threshold. The criterion does not weight the weakness of the ties to Fulton County in deciding to put Jasper County, Georgia, into the Atlanta metro area.

In contrast, for Detroit, Washtenaw County's relatively strong links to Wayne County/Detroit (as noted above, 12.3 percent of Washtenaw's resident workers commute to Wayne County) is not enough by itself to cross the 25 percent commuting threshold. The other central counties in this metro area are Oakland and Macomb, and Washtenaw's commuting rates to these two counties (3.7 percent and 0.4 percent, respectively) are insufficient for the sum to cross the 25 percent threshold.

Similarly, for the L.A. metro area, both of the included counties (L.A. and Orange) are central counties. Although San Bernardino County has strong ties to L.A. County (14.5 percent of its resident workers commute to L.A. County), its commuting level to Orange County (4.1 percent) is insufficient for the sum to cross the 25 percent threshold.

Although these federal government procedures are not irrational, they *are* somewhat arbitrary. A metro area can end up accumulating a lot of widely spread central counties, and those counties can then trigger the designation of many outlying counties by increasing the magnitude of the outlying-county commuting rates to the combined set of central counties. Presumably, the 25 percent commuting threshold is used because a lower threshold would result

in clearly much-too-large CBSAs throughout the United States. The result, then, is that in some cases, where a county has relatively strong links to an adjacent county (Washtenaw and Wayne; San Bernardino and Los Angeles), even so, these links are not sufficient for the CBSA approach to group those counties together.

What this procedure lacks is some weighting of the strength of nearby links versus more faraway indirect links. The weakness of the links of outlying counties to the most central county counts for nothing if the links to the combined central counties cross the threshold. And the strength of nearby links counts for nothing if the 25 percent threshold is *not* crossed to the central counties as a group.

The underlying problem is a conceptual problem: is it really right to think of local labor markets as being outlying counties grouped around a set of central counties, which are treated as if they were one entity in deciding on CBSA designations? There is no penalty applied if the links are weak to some of the central counties in the CBSA, as long as the combined commuting rate crosses the threshold.

The details matter as to how both the "central area" and the commuting threshold are defined. For example, the European Union/OECD (Organisation for Economic Co-operation and Development) "Functional Urban Area" definition uses a 15 percent commuting threshold to the "city," but the "city" definition appears to be a far more restrictive unit than having many central counties included in the central area, as the U.S. definition does (Dijkstra, Poelman, and Veneri 2019).

In contrast, France appears to be more like the U.S. in expansively defining "urban units," which form the "urban cluster" to which are attached "commuter municipalities." However, these urban units are defined in terms of municipalities, which may make them smaller

in practice than the U.S.'s central counties. And then the commuting rate to the "urban cluster" must be at least 40 percent of resident workers of the "commuter municipalities," which is a higher bar to meet than the 25 percent cutoff in the United States.¹²

In Canada, "core areas" are defined as areas with a sufficient urban density and size that are adjacent. This is again similar to the U.S. metric, but uses municipalities rather than counties to form core areas. And then adjacent municipalities are combined with these core areas to form "census metropolitan areas" or "census agglomerations" if commuting from these adjacent municipalities to the core areas exceeds 50 percent of the adjacent municipality's resident workers.¹³

All of these details matter in how urban areas are defined, and how adjacent areas are defined, and what commuting thresholds are used. But the U.S. is somewhat unusual in using geographically larger county units to form both central units and suburban areas, and in then using a commuting threshold of only 25 percent to the combined "central counties." As a result, the U.S. definition appears to lean more than the procedures of other countries toward expansively defining metro areas. However, for all these countries, it is unclear exactly what criteria these metro area definitions are trying to maximize, and why the countries choose one set of definitions of core areas or commuting thresholds over another set of criteria.

MOVING BEYOND CURRENT LOCAL LABOR MARKET DEFINITIONS BY ESTIMATING INTERCOUNTY SPILLOVERS

In contrast to current local labor market definitions, this paper seeks a new basis for such definitions, in empirical estimates of intercounty spillovers of local job shocks. More

¹² See <u>https://en.wikipedia.org/wiki/Urban_area_(France)</u>.

¹³ See <u>https://www12.statcan.gc.ca/census-recensement/2021/ref/dict/az/Definition-eng.cfm?ID=geo009</u>

specifically, these new local labor market definitions are based on estimated effects on a county's employment-to-population ratio (employment rate) of both job shocks to its own county and job shocks to nearby counties. These job-shock effects are allowed to depend on intercounty commuting rates. Using these estimated effects of a county's job shocks on employment rates in the county itself and in nearby counties, labor market definitions are then derived that seek to balance two competing criteria: 1) capturing more of the total spillovers in other counties of a job shock in one county, and 2) having a large average effect of job shocks within the defined local labor markets. Although these new local labor market definitions are similar to currently used definitions in that they are based on commuting rates, these new definitions differ in being explicitly based on how these commuting rates are found to affect intercounty effects on an important labor market outcome, the county's employment rate. As already mentioned, I label these as "spillover-based local labor markets," or SLMs.

This section of the paper explains the specific empirical model and data used. After this section, empirical estimates of the model are then presented. These empirical estimates are then used to estimate spillovers between all of the 3,000-plus counties in the contiguous United States. These estimated spillover effects are one of the paper's main outputs: the estimates provide important information to policymakers and researchers: for any pair of counties, what is the effect of a job shock in one county on the other's employment rate? For example, this might provide some basis for deciding who should pay for a county's economic development program, based on plausible benefits of job creation in that county on other counties' employment rates. Even without local labor market definitions, these estimates are useful.

After the empirical estimates are presented, these estimates are used to define new local labor markets for the contiguous United States. This new definition, based on SLMs, are compared on various criteria with current local labor market definitions.

Estimating Equation

The model is a nonlinear regression estimated using cross-section and time-series data on 570 larger counties (those of greater than 65,000 population) from 2005–2006 to 2018–2019. The model relates the dependent variable—the annual change in the natural logarithm of an age-adjusted employment rate for the county—to the main independent variables of interest, which are current and lagged values of job shocks to the county and its 30 nearest counties, with these job shocks measured proportionately to employment in the dependent variable county. Job shocks to the county and the 30 nearest counties are allowed to flexibly depend on the own-county or cross-county commuting rates, with the flexibility leading to the nonlinearity. The 30 nearest counties are aggregated together into one variable, using empirically determined weights on the intercounty commuting rate. The regression also includes some supply-side control variables—e.g., percentage in different education groups or ethnic groups.

The estimating equation can be written as follows:

(2)
$$\ln(E_{kt}/P_{kt}) - \ln(E_{kt-l}/P_{kt-l}) = B_0 + B_k(L)(C_{kk}/E_{kw} + C_{kk}/E_{kr})^{t}(J_{kl} - J_{kt-l})/J_{kt-l} + B_s(L)\sum_s (C_{ks}/E_{sw} + C_{sk}/E_{sr})^{g}(J_{st} - J_{st-l})/J_{kt-l} + \sum_x B_x X_k + \sum_t B_t D_t + \varepsilon_{kt}$$

Here:

- E_{kt}/P_{kt} is the age-adjusted employment-to-population ratio in county k and year t.
- $B_k(L)$ and $B_s(L)$ indicate that there are both current and lagged values of the commutingweighted shocks to own-county k jobs and the 30 nearest county s jobs. Note that the same coefficients are applied to all of the 30 nearest counties, whose job shocks are summed and then weighted by commuting rates taken to a particular power g.

- *C_{ks}*, *C_{sk}*, and *C_{kk}* are commuting from county *k* to county *s*, county *s* to county *k*, and county *k* to itself.
- The commuting from county k to county s (C_{ks}) is divided by employment in county s by place of work, as measured in the commuting data (E_{sw}), to get a commuting rate, and the commuting from county s to county k (C_{sk}) is divided by employment in county s by place of residence, as measured in the commuting data (E_{sr}), to get another commuting rate. For county k itself, its own commuting to itself (C_{kk}) is divided both by county k's employment by place of work in the commuting data (E_{kw}) and by county k's employment by place of residence in the commuting data (E_{kw}) to get two slightly different measures of a county's own-commuting rate.
- These commuting rates are then allowed to affect the influence of job shocks by being taken to two separate powers. Power *f* applies to the own-county sum of the two commuting rates. Power *g* applies to the other county *s* sum of the two commuting rates between *s* and *k*. It is important to note that the same power *g* is used for all of the 30 nearest counties *s* that are included in the regression. This allows these 30 counties to be summed together. This use of powers implicitly assumes that if commuting flows are zero between two counties, the effects of a job shock in county *s* on employment rates in county *k* will be zero. On the other hand, there is no easy way to allow each of the 30 nearest counties *s* to have a different effect that is allowed to vary totally freely, as there is not a natural way to define an ordering of the 30 counties.¹⁴
- *J*_{st} and *J*_{kt} are independent measures of jobs, to be detailed further below, in county *s* in year *t* and county *k* in year *t*, respectively. Note that the year-to-year changes in jobs are divided, for both job shocks to *k* and to *s*, by last year's jobs in county *k*, to be compatible with the dependent-variable focus on employment rates in county *k*. Appendix B shows that it makes sense to have a functional form in which such a job shock—measured in proportional change relative to county *k*'s employment—is then weighted by the commuting weight, relative to county *k* employment, in affecting county *k*'s employment rate. Given the county *k* employment denominator in measuring the job shock, and the county *s* and the size of county *k* in terms of employment matter in determining the effects of a job shock to county *s* on county *k*.
- X_k is any one of several supply-side controls for characteristics of county k in the 2000 census.
- D_t is a set of dummy variables for the year t, each with its own coefficient.

¹⁴ One could order the 30 counties by how close they are by county centroid distances to county k, but for one county k, the third-closest county might, for example, be closer by centroid distances than the second-closest county for some other county k. More feasibly, as an alternative to my using powers of the commuting rate, one could group counties s by their commuting rates, and allow different effects of job shocks by commuting category.

Now I turn to more details about the specific data used for these variables, the rationale for including these variables in this form, and some alternatives that might be considered in future work.

Dependent variable. The dependent variable is measured from published U.S. Census Bureau data on the employment-to-population ratio of 13 different age groups in each county. (The age groups are 16–19, 20–21, 22–24, 25–29, 30–34, 35–44, 45–54, 55–59, 60–61, 62–64, 65–69, 70–74, and 75+.) The employment rates are age-adjusted averages for each county, arrived at by using the national share of population in each age group as of 2019 to weight the age-specific employment rates for each county. This results in an age-adjusted employment rate that controls for differences over county or over time in employment rates because of differences in the age mix over space or time or both. But this measure is arguably better than merely using the prime-age employment rate—which "controls" partially for age by merely looking at the ages 25–54 group—because it allows for the possibility that a lot of the variation in employment rates due to job shocks may occur in groups more on the margin of employment, which may be younger or older age groups.

Possible alternatives for future work include examining effects on the employment rates of particular groups, such as persons with less than a four-year college degree, or Black workers or Hispanic workers. Perhaps the spillover effects of jobs across counties—and therefore the appropriate definition of local labor markets—differ for different demographic or socioeconomic groups.

Another alternative would be to look at other labor market outcomes, such as real wages per hour. However, hourly wages would be harder to measure at a county level from aggregate census data. One could measure hourly wages using the ACS microdata, and then using

probabilistic assignment to locate workers in a particular county, based on what Public Use Microdata Area (PUMA) they were in. As PUMAs typically number at least 100,000 persons, this would probably require restricting estimation to counties exceeding 100,000 or 200,000 in population.

In addition, it is not obvious how to measure real wages in a county in the presence of commuting. One could measure housing prices in the county and rely on previous estimates of how overall local prices vary with housing prices. But with commuting, persons obviously have the option of living in nearby counties, which have different housing prices. Housing prices within a "local housing market"—which might be similar to a local labor market—may vary because of local neighborhood amenities. Such amenities should ideally be controlled for in measuring local housing prices, but this would be difficult to do.

Instead, this paper relies on the notion that employment rates are a key labor market outcome, which will be highly correlated with real wages. In some local labor market models, the local employment rate is the key driver of the local real wage. At one extreme, Amior and Manning (2018) have an argument—and an accompanying theoretical model supporting that argument—that "the employment rate can serve as a sufficient statistic for local well-being." I wouldn't go quite that far, but the local employment rate is extremely important.

Time period. As already mentioned, the time period of estimation ranges from 2005–2006 to 2018–2019. The 2005 start point is the first year for which we have employment rate data for counties available from the American Community Survey on an annual basis, which is the methodology used here: annual changes in employment rates. The 2019 endpoint is chosen because it is prior to the pandemic. In 2020, the pandemic created problems in data collection for the American Community Survey. In addition, that year the pandemic created large and place-

varying shocks to the employment rate, which were often temporary. It is unclear whether trends in employment rates from this period would be predictive for more normal periods.

However, an alternative would be to continue using annual data going forward. In addition to adding data, this would encompass a period during which remote work has become more important. One might even want to do estimates that look only at 2021 and following years. Perhaps intercounty spillovers are quite different from 2021 on than they were in the 2005–2019 period. Perhaps local labor market definitions should differ in today's world, compared to the world of 2019.

Sample. The sample is made up of all counties in the contiguous United States (i.e., excluding Alaska and Hawaii) that are greater than 65,000 in population for all years from 2005 to 2019. I apply the 65,000 restriction because the census only reports annual geographic-unit data for geographic units of 65,000 population and above.

This definition comprises 570 of the 3,080 counties in the contiguous United States. These 570 counties had 81.4 percent of all Year 2019 employment by place of work, and 77.8 percent of all 2020 population.¹⁵

One alternative is to also consider smaller counties. This could be done if, instead of using annual data, we reformulated the model to use five-year data; these five-year averages are reported by the Census Bureau for most geographic units, regardless of size. We could use data for all counties from the long form of the 2000 census and then subsequent five-year periods

¹⁵ These percentages are out of the contiguous U.S. total.
from the ACS: 2005–2009, 2010–2014, 2015–2019, etc.¹⁶ This would allow estimates to see if intercounty spillovers differ for smaller counties.

More generally, we could also estimate the model but allow for intercounty spillovers and local labor market definitions to vary in a variety of county characteristics. The effects of job shocks in own county and nearby counties could be interacted with county population, for example.¹⁷ Interaction effects also could be explored within the region of the country. Finally, because Bartik (2024) found that within-CZ spillovers varied with a CZ's baseline employment rates, one might explore interactions with the baseline employment rate in the country or in nearby counties.

Job shock. The job shock is the change in total employment in the county as measured by the U.S. Bureau of Economic Analysis.¹⁸ This goes beyond wage and salary employment to include, for example, self-employment. The decision to use total employment, rather than just wage and salary employment, is rationalized by the increased importance of independentcontractor employment and other alternative work arrangements.

As is well known, the change in jobs in a geographic area can be due to either demand or supply. Demand-induced job shocks and supply-induced job shocks might have quite different effects on the employment rate. If a county's employment is increasing due to factors directly

¹⁶ Detailed geographic data were in the past provided by the long form of the decennial census, but starting in 2005, such data were annually provided by the ACS. However, as the ACS annual sample is smaller, these detailed data are only reported for smaller geographic units, those of less than 65,000 in population, in the form of five-year averages.

¹⁷ Another alternative is to explore how estimates vary when the regression is weighted by county population. The specification used here is unweighted. However, I prefer explicitly exploring how estimates vary with county population.

¹⁸ Using the BEA employment data requires using their county definitions. In Virginia, BEA combines some independent cities (which the census treats as separate counties) with their surrounding or next-door county. In my view, the BEA's definitions of counties in Virginia are more consistent with other states than is true of the census's definition of Virginia counties.

boosting labor demand—the area becomes more attractive for business location, or the area's specialized industries are doing better nationally—then this increase in labor demand, with the local population relatively fixed in the short run, will tend to increase the employment rate. If a county's employment is increasing due to factors boosting labor *supply*—the area becomes more attractive to potential in-migrants due to some factor such as improved amenities, or the U.S. is experiencing in-migration of persons from countries that already are differentially located in the area—then as population grows, it may reduce employment rates even while it increases employment.

Why then, in the current paper, do I simply use job shocks, without trying to isolate demand shocks to jobs? Using job shocks as measured is simpler, but is this simplicity purchased at the cost of biased estimates?

One rationale for using job shocks without trying to isolate demand shocks is that in practice, when one uses annual job shocks on the right-hand side, estimates that use job shocks (versus estimates that instrument for job shocks using demand shifters) tend to yield similar estimates when the dependent variable is annual changes in employment rates. This result is found, for example, in Bartik (1991).

My 1991 book originated what became known as the "Bartik instrument" for local labor demand shocks.¹⁹ This instrument is the predicted change in employment due to a geographic area's baseline industrial mix, along with the national growth rate of different industries.

¹⁹ To be clear, I obviously didn't originate shift-share analysis. The "Bartik instrument" is the sum of the national growth and share effects from shift-share. What I did do in Appendix 4.2 of the book is point out that the differences across places in this "Bartik instrument"—the share effect—will be driven by industries whose location quotient varies across places, and these industries are quite likely to be export-based industries. Therefore, this variable is a good instrument for "demand shocks" to a place because of shifts in national demand for a place's export-based industries. This is not intuitively obvious, given that the national growth effect and share effect depend on all industries, including non-export-based industries.

Appendix 4.2 of Bartik (1991) showed that this instrument proxied for shifts in national demand for a geographic area's specialized export-base industries.

What is sometimes forgotten is that Bartik (1991) found that the instrumented estimates were not statistically or substantively different from noninstrumented estimates when the dependent variable was the change in local employment rates. In contrast, instrumented estimates—"demand-induced job growth"—did show different effects from job shocks in general for some measures of real wage rates and real per capita earnings.

One possible explanation for these results is that much or most of short-run shocks to local job growth might be due to demand-side factors, such as how an area's specialized industries are doing nationally.²⁰ Industry location will be more malleable in the long run than in the short run.

However, why then is there a difference between the employment-rate results and the real wage- and real earnings-dependent variables? One reason could be that supply shocks to local population do not in fact seem to cause much variation in local employment rates. Many studies suggest that in the short run, shifts in local population seem to shift local employment by about the same percentage.²¹ Possible explanations for this include the following:

 Local population shocks may also be a demand shock, as people buy goods and services in part produced and distributed with local labor.

²⁰ And this may even hold for estimated cumulative effects when we include current job growth and lags to job growth. The estimated effects of any given shock to job growth hold the other growth shocks constant. The common trend in all these growth shocks may be supply driven, but the regression is looking at the annual growth variations around that trend. If the annual variations are demand driven, then even without instruments, the regression can measure the effects of demand-driven cumulative growth trends.

²¹ Bartik (2020) briefly summarizes the research findings, and Bartik (2019) provides a more extensive review of the relevant research literature, which includes Muth (1971); Greenwood and Hunt (1984); Beaudry, Green, and Sand (2018); Amior and Manning (2018); and Howard (2020).

 Local population shifts may differentially affect younger people, who may start small businesses and contribute more to agglomeration economy effects.

Why might population shifts still affect real wages and real earnings? Perhaps because the supply shocks hit lower-wage industries (retail) and lower-wage groups (young people). Ideal real-wage measures would fully control for these industry-mix and age-mix effects, but this is hard to do completely.

At any event, in this preliminary paper, it seems fine to simply look at all job shocks. Subsequent work might distinguish between demand shocks and supply shocks.

Such distinctions might be done in one of two ways. First, a demand-shock instrument, such as the Bartik instrument, could be used to instrument for the actual demand shocks. This approach would simply see how intercounty spillovers vary when we look only at demandinduced variation in jobs.

Second, a reduced-form approach could be used, in which the right-hand-side variable is the Bartik instrument. In that case, the model would be estimating *more* than labor market spillovers of demand-induced job increases; it would also be estimating local economy spillovers. The Bartik instrument proxies for shifts in national demand for a geographic area's specialized export-based industries. Therefore, part of the cross-county effect of the Bartik instrument when it is used by itself as a right-hand-side variable would be due to "multiplier" effects of the instrument on jobs in nearby counties (Bartik and Sotherland 2019). This might increase cross-county effects, and it might also increase the size of "local economic area" definitions based on these cross-county effects.

In other words, the reduced-form approach with export-based industry demand shocks is really estimating a different type of cross-county spillover than is done when one estimates the

effects of either job shocks or instrumented job shocks. Therefore, future work might want to consider the results from such a reduced-form approach. Local area definitions based on "local economy spillovers" might be larger than local area definitions based on "local labor market spillovers."

Supply-side controls. One way to increase the likelihood that the job shocks reflect demand shocks is to control for possible supply-side variables that might be correlated with both county job growth and county trends in employment rates. The regression includes controls for the following supply-side county variables:

- natural logarithm of county population in the year 2000
- from the 2000 census, measures of the fraction of the population that is foreign born and the fraction that is Black
- also from the 2000 census, measures of the fraction of the population 25 and older that has a four-year college degree or more, and the fraction of the population that has a high school degree or more

One could imagine that these variables might cause bias by being correlated with both job-growth and employment-rate trends. For example, if the foreign-born population tended to increase its employment rate during the 2005–2019 period compared to the non-foreign-born population, and if counties with a higher percentage of foreign-born persons in 2000 tended to attract more population growth and hence have more job growth due to increased immigration in the 2005–2019 period, then this control helps avoid biases due to this omitted supply-side variable.

Commuting rates. The intercounty commuting numbers, as well as the corresponding denominator figures for county employment by place of work or residence, are from published tables by the Census Bureau, based on pooled data from the ACS from 2006–2010. This time period is near the beginning of the period encompassed in the estimation, 2005–2019.

As already noted, one alternative is to use a later sample period, when the commuting numbers may reflect differences due to the rise of remote work.

A further obvious possible change would be to allow the commuting rates in either direction (from *s* to *k*, or vice versa) to have different effects. The current specification sums them and takes the sum to some power. Perhaps commuting from *k* to *s* has more (or fewer) effects, compared to commuting from *s* to *k*, on the spillover effects of jobs in county *s* on employment rates in county *k*.

One could also allow the powers f and g to change with the lag length. That is, currently, for example, the 30 nearest counties' job shocks are summed after weighting by the commuting sum taken to the power g, and that power g is the same for weighting the current job shock to s, as well as the lags to the job shock. But one could imagine that how the effects of job shocks vary with commuting rates might change over time.

The commuting rate's functional form could be made more flexible—perhaps by making the powers f and g vary as the commuting rate varies.

In addition, the commuting-rate interaction variable used here assumes that the interaction between the dependent variable—the change in county k's employment rate—and the job shock to county s, depends only on the direct commuting between county s and county k. Yet it could also depend upon the indirect commuting between the two counties. A job created in county s may be taken by someone living in county m who currently works in county m, and the probability that this occurs may depend upon commuting rates from m to s. This opens up a job vacancy in county m, and the probability that this vacancy is filled by someone in county k may depend on the commuting rate between counties k and m.

Therefore, future work should see if the product of commuting rates for intermediate counties also matters to how job shocks to county *s* affect employment rates in county *k*. This is complicated, because with 30 nearby counties, the number of intermediate commuting-rate connections is very high. We can summarize this with some weighted number, but the resulting calculated number is likely to be highly correlated with the direct commuting rate between *s* and *k*. But despite these possible complications, exploring indirect commuting links should be on the agenda for future work.²²

Lag length. The lag length in the equation for allowing for effects of job shocks to county k, and to county s, are assumed to be the same. The lag length is set at allowing for nine lags. This lag length comes from preliminary equations exploring all lag lengths from zero (only for current shocks) to 11 lags, but in a specification in which the powers f and g were set equal to one. The nine-lag specification minimized the Akaike information criterion. The lag length was chosen with powers f and g restricted to 1 because this regression is linear. The specification with powers allowed to vary is quite computer-intensive given its nonlinearity.

Given the lags, the cumulative effect of a job shock in county s on county k after any number of lags is given by summing the coefficients up to that lag length. The summed coefficient is then multiplied by the coefficient term (the sum of the two commuting rates) taken to the estimated power g.

Interpretation of the estimates. Given how the equation is specified, the resulting estimates of the effects of a job shock at a particular lag length represent, as of that lag length, what proportion of a job shock to county s (or county k) leads to increases in employment in

 $^{^{22}}$ Of course, we could also allow for three-way indirect connections, and in fact for the entire matrix of commuting rates across all counties, in determining how job shocks to one county *s* affect another county *k*.

county k due to increases in the employment rate in county k.²³ For a given county s, this proportional employment-rate-effect estimate can be calculated for all possible counties k and compared, or it can be summed to give total employment increases due to higher employment rates for all counties k due to job shocks to county s.

The estimates can also be multiplied by the ratio of employment by place of work in county s to employment by place of residence in county k, to give the percentage increase in employment in county k due to a percentage job shock to county s. For a given county k, this elasticity estimate can be compared across all counties s. The summation here is less meaningful, as it imagines that all counties s have the same percentage increase, which is not perhaps the most interesting scenario.

Both the absolute employment-rate effect of *s* on *k* and the percentage effect might be of interest. For example, the absolute employment-rate effect might be multiplied by some dollar benefit figure—reflecting the average social benefits expected if one more person gets a job—to get a total social benefit measure. This might be compared with the costs of job creation in county *s*, which might be some cost per job created times the number of jobs created.²⁴ The model then shows how the benefits of a job shock to *s* are distributed across counties. The sum of these benefits across counties might correspond to willingness to pay dollars into an economic development program to increase job growth in county *s*. But the resulting effects will be small if county *k* is small relative to county *s*, and large if county *k* is large relative to county *s*. The elasticity estimates show how a policy change with percentage effects on county *s*'s jobs affects

 $^{^{23}}$ Intuitively, both the left-hand side and right-hand side divide by some version of employment in county *k*. Appendix B provides a more elaborate explanation.

²⁴ The appendix to Bartik (2024) explores such models. See also Appendix B in the current paper.

employment in percentage terms in county k. This will tend to be larger (smaller) if county s is

larger (smaller) relative to county k.

ESTIMATED SPILLOVER EFFECTS

Table 1 presents the core spillover-model estimates.

i teur est counties		
	Own-county coefficients	30 nearest county coefficients
	(county k)	(counties s)
Power for commuting rate	3.029	0.9925
	(0.796)	(0.0991)
Immediate effect	0.0470	0.3267
	(0.0213)	(0.0927)
1 year	0.0472	0.3649
•	(0.0221)	(0.1018)
2 years	0.0436	0.2937
•	(0.0208)	(0.0944)
3 years	0.0392	0.3299
•	(0.0189)	(0.0991)
4 years	0.0272	0.2001
•	(0.0144)	(0.0781)
5 years	0.0202	0.1588
•	(0.0123)	(0.0728)
6 years	0.0291	0.1859
•	(0.0151)	(0.0767)
7 years	0.0293	0.0620
•	(0.0152)	(0.0680)
8 years	0.0123	0.1076
-	(0.0107)	(0.0704)
9 years	0.0171	0.0111
-	(0.0113)	(0.0606)

Table 1 Estimated Cumulative Effects on a County's Employment Rate of Job Shocks to Own County and 30 Nearest Counties

NOTE: Sample is 570 counties > 65,000 in population, 2005–2006 to 2018–2019, or 7,980 observations. Standard errors in parentheses below estimated coefficients. Standard errors clustered at county level. Regression is unweighted. Regression also includes year dummies and "supply-side controls" for ln(county population), fraction Black, fraction foreign born, fraction college grads, and fraction high school grads. Original specification has lags. This table shows cumulative effect of summing coefficients—that is, the effects after *t* years of a once-and-for-all job shock. Estimates use ACS employment-rate data and commuting-rate data, BEA employment data, and controls for various county demographics from the census, as described in text. SOURCE: Author's calculations.

Looking at these estimates, it is noteworthy that the power for own-county commuting is much larger than the power for other counties' commuting. This means that the employment-rate effects of a shock to the own county varies much more with the commuting rate than the employment-rate effects of job shocks to other counties. The power for other counties' commuting rates is very close to 1, both statistically and substantively. That is, the effect of job shocks to other counties s on county k's employment rate is roughly proportional to the commuting rate between the two counties, when that commuting rate is measured relative to county s's total employment. If a county s2 has half the amount of commuting with county k of county s1, a job shock of the same size to county s2 will have half the influence on county k as a job shock to county s1.

The coefficients on the different lag lengths show that cumulative effects are statistically significant on own-county job shocks, at the 5 percent level, up to the third lag. The cumulative effect after seven lags is statistically significant at the 10 percent level. For other counties, the cumulative effect of a job shock is statistically significant at the 5 percent level up to six lags. However, in terms of point estimates, the other county job shocks decrease more going from immediate effects to nine lags than is true of own-county effects.

The magnitude of commuting, together with the power terms and the cumulative coefficients, determines the magnitude of the effects of a job shock to k or s on the employment rate in k. A little further on, we will see what this means for employment-rate effects for the 3,080 counties, at empirically observed magnitudes of the commuting rates. As one would expect, the own-county commuting-rate sum is typically much greater than the other-county commuting-rate sum. For example, across the 3,080 counties, the own-county commuting-rate sum has an average of 1.408 (the average commuting rate for own county is 0.704 or 70.4 percent), whereas the average commuting rate of the next-highest county among the 30 nearest counties is 0.240 (an average commuting rate of 0.12 or 12 percent).²⁵

²⁵ Unweighted rates. Rates weighted by county employment by place of work are 1.473 and 0.217.

However, it is of interest to see how a job shock of county k or s varies at the same commuting-rate volume. In general, for most lag lengths and values of the commuting rate, the effect of a job shock in county s will be greater than a job shock to county k, when measured at the same commuting rate.²⁶

Why does this occur? One possible hypothesis: the extent to which a job shock to any county *s* affects the employment rate in county *k* depends upon the marginal probability that the job will be filled by a person in county *k*. The commuting rate could be argued to measure, or at least reflect, the average probability that a job in *s* will be filled by someone in *k*. It's possible there is a tendency for the marginal probability that a job will be filled by a person in his or her own county to be below the average probability. There is an asymmetry here between own county *k* and other counties *s*. The marginal probability of filling a vacancy within the own county may be below the average probability implied by the own-county *k* commuting rate. For other counties *s*, it is also true that the marginal probability of filling the vacancy within county *s* is below the average probability. But this implies that the marginal probability of filling the vacancy from county *k* will be greater than the summed commuting rates from *s* to *k*. That is, it implies that commuting rates within county *k* overstate the marginal probability that jobs will be filled by residents of county *k*, whereas commuting rates from county *s* to county *k* understate the marginal probability that jobs in county *s* will be filled by residents of county *k*.

The marginal probability of going out-of-county to fill jobs may be higher for several reasons. First, over time, commuting may be increasing. Second, over time, more jobs may be created on the outskirts of counties as employment sprawls out.

²⁶ Appendix C presents some calculations.

The greater variation of employment-rate effects with the commuting rate for own county k, compared to other counties s, might also be explained by this hypothesis. If the marginal probabilities of going out-of-county to fill jobs are higher than the average probabilities implied by commuting rates, then for county s the marginal probability that the job is filled by county k, compared to the average probability associated with the commuting rate between k and s, reflects that county k is just one of several other counties whose residents might fill the job. This marginal probability will vary less because other counties than k might fill the job in county s. In contrast, for own county k, all of the increased out-of-county hiring will go to reducing the marginal probability of in-county hiring below the average probability associated with the commuting-rate measure.

Generating dk/ds Estimates for All 3,080 County Pairs in the Contiguous United States

I then use these estimates to create estimates for all 3,080 counties in the contiguous United States for the effects of a shock to employment in counties *s* or *k* on employment in county *k* due to increases in county *k*'s employment rate. The estimated effect is based on the summed 2006–2010 commuting rate between county *k* and county *s*, or between county *k* and itself, taken to the estimated powers from Table 1, and then multiplied by the discounted present value of the 10 appropriate cumulative-effect measures. The estimated effect is then averaged as a proportion of what the effect would be if it was 1 for all cumulative-effect years.²⁷

²⁷ That is, for county *s* (county *k*), the power is 0.9925, (3.029), and the sum of the discounted present value, at a 3 percent real discount rate, of the 10 cumulative effects discounted back to the current shock period *t* and divided by the number 1 discounted in the same way, is 0.2133 for county *s* and 0.0321 for county *k*. Each cumulative-effect coefficient B is discounted back to the present, and the sum of these discounted coefficients is then divided by the sum of the present value if each B coefficient was one. This is a discounted average annual cumulative effect. This discounted average annual cumulative effect is then multiplied by the commuting-rate term taken to the appropriate power.

Such a specification assumes that the effect after the ninth lag is zero, or at least negligible after discounting. This is a conservative assumption. The point estimates show some cumulative effects after the ninth lag, although statistically these effects are not significantly different from zero.

This discounting approach can be rationalized as the appropriate way to average if one assumes that for each added job in a county due to a higher employment rate there is some dollar benefit, due not only to higher earnings but also to other benefits of higher employment rates (e.g., higher real wages, lower substance abuse, lower crime, lower family breakups, etc.). Then an appropriate valuation of the benefits versus costs of job creation should compare the present-value costs of job creation with the present-value benefits of job creation. This will take the form of some dollar figure times the present value of employment increases due to a higher employment rate.

This procedure yields a 3,080-by-3,080 matrix of cross-county effects. This paper's release will include a copy of this matrix as an Excel file, Table E1, which can be examined for any county pair. I will examine some examples below for some specific groups of counties.

Table 2 presents some summaries of these estimated employment-rate effects for all 3,080 counties. I present effects weighted by each county's employment by place of work. Counties differ dramatically in size. What we should be focused on is what our estimates imply for the average job shock and its relative own-county effects versus spillover effects.²⁸

As shown in the table, the total effect—including both the effect on the own county, and the effect on other counties—averages a little over 0.2. That is, a shock of 10 jobs ends up, on average over 10 years, increasing local employment rates, totaled over various counties, by a

²⁸ Unweighted descriptive statistics are similar to the weighted statistics.

Weighted by county employment by place of work							
	Total, all counties	Own-county effect	Ratio of own to total (%)				
Mean	0.229	0.115	50.4				
Standard deviation	0.012	0.058	24.6				
Minimum	0.213	0.004	1.2				
Maximum	0.328	0.246	96.4				
10th percentile	0.219	0.040	16.8				
25th percentile	0.220	0.064	28.4				
50th percentile	0.225	0.114	52.3				
75th percentile	0.236	0.157	69.9				
90th percentile	0.247	0.197	83.4				

 Table 2 Effects of Shocks to One County's Employment on Its Own Employment Rate and That of Other Counties (*dk/ds*)

SOURCE: Author's estimates, based on Table 1 and commuting rates.

little more than two jobs. The remaining eight of the jobs would increase local population—that is, increase net migration. Such a total effect is consistent with the research literature, which shows that local job shocks after 10 years or so tend to be reflected at about 20 percent in employment-rate effects, 80 percent in population effects (Bartik 1991, 2020, 2024).

This total effect does not differ much across counties. The implication is that the jobs must go somewhere—commuting adds up to 100 percent—so the employment-rate effect occurs somewhere because of the job shock. As already mentioned, this finding should be tested against specifications that allow the total effect to vary across regions of the country, or with the county's baseline employment rate.

The own effect, however, does vary a lot across counties, and consequently the owncounty percentage share of the total effect, also varies greatly across counties. The own effect averages 50 percent of the total effect. But there is quite a bit of variation—the own-county effect at the 10th percentile is 17 percent of the total effect, and at the 90th percentile is 83 percent. This own-effect variation obviously implies a corresponding variation of the spillover effect. That is, the estimates imply quite a large variation in the extent to which job shocks have spillover effects across counties. Some counties are such that their job shocks mainly affect their own employment rates and not those of other counties. Other counties have much larger spillover effects compared to own-county effects.

What about spillover effects on specific counties? Table 3 looks at the spillover effects in the five largest counties, other than the own county. The focus is on the ratio to the own-county effect and how this varies across different own counties.

Table 3 Ratio of Five Largest Spillover Effects to Own-County Effects and All Spillover Effects

						Ratio of sum of 5 largest spillover- county effects
	Ratio, largest	Ratio, 2nd	Ratio, 3rd	Ratio, 4th	Ratio, 5th	to total
	to own	largest to own	largest to own	largest to own	largest to own	spillover effect
	(%)	(%)	(%)	(%)	(%)	(%)
Mean	38.7	17.9	11.2	7.5	5.2	80.3
Standard deviation	16.4	6.6	4.3	3.2	2.5	9.4
Minimum	9.0	1.6	0.0	0.0	0.0	37.8
Maximum	369.9	119.8	34.9	22.1	14.4	100.0
10th percentile	21.7	10.0	5.4	3.2	2.0	67.5
25th percentile	26.8	13.5	8.2	5.0	3.2	74.4
50th percentile	35.7	17.5	11.2	7.4	4.9	81.5
75th percentile	47.3	21.9	14.1	9.7	6.9	87.3
90th percentile	61.3	26.2	16.9	11.6	8.7	91.4

NOTE: All statistics are weighted by county employment by place of work. SOURCE: Derived by author from estimates used in Table 2.

As Table 3 shows, the average largest spillover effect of another county is around 39 percent of the own-county effect. But at the 90th percentile, it goes up to around 61 percent. The next-largest county effect averages 18 percent of the own-county effect. Therefore, we see that spillover effects on specific counties are often large compared to own-county effects.

In addition, the five largest spillover counties average 80 percent of the spillover from all other counties of one county's job shocks. This share of the total spillover effect varies from 68 percent at the 10th percentile up to 91 percent at the 90th percentile. Therefore, for most

counties, most of the spillover effect of the county's job shocks on other counties is found in the five counties with the largest spillover effects.

Generating dlnk/dlns Estimates for All 3,080 Contiguous U.S. County Pairs

I also constructed estimates of the (log) percentage effects of a job shock to any U.S. county on the (log) percentage change in employment due to employment-rate effects in any other U.S. county. This simply multiplies the dk/ds numbers by the ratio of employment by place of work in the county being shocked (county *s*, which may include county *k*) to employment by place of residence in the county *k* whose employment-rate increase we are looking at. This ratio of employment by place of work in county *s* to employment by place of residence in county *k* is taken from the 2006–2010 commuting data from the American Community Survey.

This paper's release will include an Excel workbook that reports the full dlnk/dlns 3080by-3080 matrix, in Table E2.

The dlnk/dlns matrix is arguably less policy relevant than the dk/ds matrix because it does not tell us the spillover effects in comparable form for a given change in employment in county s. The sum of the percentage effects on county k of a percentage shock to county s cannot be meaningfully summed across the k counties, as the percentage numbers represent different magnitudes. For a particular county k, one can sum and compare the percentage effects on k across different counties s of percentage shocks to these counties s. The sum represents the effects of a percentage shock to all other counties s on county k. A comparison shows the relative percentage effects on county k of percentage shocks to other counties. If one imagined that some policy change in a county s (a given change in the business tax rate, or a given change in the zoning rules) would cause a percentage change in county s's employment, then the percentage effects on county k show the relative effects of similar policy changes in different counties s.

However, it should be noted that given the different scale of different counties *s*, a given policy change, such as a reduction in business tax rates, would have costs that likely scale with county s's size.

Table 4 shows some summary statistics, calculated across all 3,080 counties k, of own percentage effects versus total effects. As mentioned, the total effects represent the effects of a percentage job shock to all counties s. Given the vast differences in county size, these estimates are weighted by county k's employment, so that the estimates represent the effects for a typical job in county k.²⁹

		Weighted by county k's emp	loyment
	Total	Own	<u>Ratio (%)</u>
Mean	0.227	0.114	48.9
Standard deviation	0.046	0.067	25.8
Minimum	0.013	0.002	1.1
Maximum	2.038	0.249	96.6
10th percentile	0.181	0.029	14.3
25th percentile	0.201	0.051	24.8
50th percentile	0.228	0.110	48.7
75th percentile	0.248	0.173	71.4
90th percentile	0.260	0.203	83.5

 Table 4 Percentage Effects on a County's Employment Rate Due to Percentage Shocks to Own and Other Counties' Employment

SOURCE: Author's calculations, based on estimates in Table 1, commuting rates, and county employment numbers.

As the table shows, these percentage effects in total add up to much more variation than is true in Table 2. Part of this is because for smaller counties k, the percentage effects can be quite large. In addition, if a county has nearby counties s that are quite large, the percentage effects also can be quite large.

²⁹ Unweighted descriptive statistics are similar.

Looking at Particular Groups of Counties

To illustrate what these matrices look like for particular county groupings—and to see

what they mean for the strength of group interactions—I now look at three groupings of

counties: 1) New York City's five counties, 2) the Detroit metro area plus Washtenaw County,

and 3) the Los Angeles Consolidated Statistical Area.

Table 5 shows the five counties of New York City.

 Table 5 Effects on Employment in County k of Job Shock to s, Absolute Effects and Percentage Effects, New York City Counties

County k	County <i>k</i> Employment by Employment							
name	workplace k	by residence s	Bronx	Kings	New York	Queens	Richmond	Sum
	•		Pane	l A: <i>dk/ds</i>	· · ·		· · · · · · · · · · · · · · · · · · ·	
Bronx	483,914	698,216	0.039	0.008	0.025	0.011	0.003	
Kings	1,216,186	1,687,826	0.017	0.056	0.043	0.040	0.044	
New York	3,159,320	1,122,846	0.095	0.086	0.048	0.083	0.058	
Queens	1,072,078	1,630,354	0.022	0.038	0.040	0.037	0.010	
Richmond	188,499	315,426	0.001	0.010	0.005	0.002	0.064	
		Sum	0.174	0.199	0.160	0.175	0.178	
	•		Panel I	B: dlnk/dlns			· · · · · ·	
Bronx	483,914	698,216	0.027	0.015	0.113	0.017	0.001	0.173
Kings	1,216,186	1,687,826	0.005	0.040	0.080	0.025	0.005	0.155
New York	3,159,320	1,122,846	0.041	0.093	0.135	0.080	0.010	0.358
Queens	1,072,078	1,630,354	0.006	0.029	0.077	0.025	0.001	0.137
Richmond	188,499	315,426	0.002	0.038	0.054	0.008	0.038	0.140

NOTE: Kings County is Brooklyn, New York County is Manhattan, and Richmond County is Staten Island. SOURCE: Author's calculations, based on Table 1, commuting rates, and county employment numbers.

One can see the largest interactions by reading across the columns. If the two counties are of dramatically different sizes, the sizable interactions will show up in the *dk/ds* column for the smaller county, which shows the effect on the larger county's employment of shocks to the smaller county. In that same case for dramatically different county sizes, the *dlnk/dlns* matrix has the sizable interactions show up most obviously in the larger county's column.

Based on the dk/ds figures in Panel A, one sees that Bronx County has sizable effects in absolute terms on Manhattan, followed by Queens; Brooklyn has sizable effects on Manhattan

and then Queens; Manhattan has sizable effects on Brooklyn and Queens; Queens has sizable effects on Manhattan, followed by Brooklyn; and Staten Island has sizable spillovers on Brooklyn and Manhattan. The percentage effects in Panel B show sizable percentage effects of the Bronx on Manhattan; sizable effects of Brooklyn on Manhattan, followed by Staten Island and Queens; sizable effects of Manhattan on all of the other four counties; sizable effects of Queens on Manhattan, followed by Brooklyn; and Staten Island is not big enough for its percentage effects to be sizable. Essentially, the model suggests large interactions of Manhattan, Brooklyn, Queens, and the Bronx with each other, with Staten Island interacting more with Manhattan and Brooklyn. Thus, the model clearly implies—as it should—that the New York local labor market at least should encompass the five city counties. Employment rates in one New York City county depend heavily on one or more of the other New York City counties.

Table 6 considers the six counties designated by OMB as the Detroit metro area, plus Washtenaw County (Ann Arbor), which I argued seems to have close commuting connections to Wayne County (Detroit). As shown in Panel A, Lapeer County job shocks have high absolute spillover effects on employment rates in Oakland and Macomb Counties; Livington job shocks have high absolute effects on Oakland, Washtenaw, and Wayne Counties; Macomb job shocks have high effects on Oakland and Wayne Counties; Oakland has high effects on Wayne and Macomb; St. Clair has high absolute effects on Macomb; Washtenaw has high absolute effects on Wayne; and Wayne has high absolute effects on Oakland. In percentage terms, Lapeer, Livingston, and St. Clair Counties are too small to have high-percentage effects on the other four counties. Macomb has high-percentage effects on Wayne and Macomb; Washtenaw has high-percentage

effects on Livingston; and Wayne has high-percentage effects on Oakland, Washtenaw, and

Macomb.

County k	Employment	Employment								
name	by workplace k	by residence s	Lapeer	Livingston	Macomb	Oakland	St. Clair	Washtenaw	Wayne	Sum
		-		Panel A:	dk/ds					
Lapeer	33,526	51,593	0.052	0.000	0.003	0.003	0.005	0.000	0.000	
Livingston	93,503	146,989	0.001	0.043	0.001	0.007	0.000	0.016	0.004	
Macomb	455,428	533,776	0.029	0.004	0.066	0.044	0.063	0.002	0.027	
Oakland	1,010,712	871,512	0.056	0.061	0.077	0.071	0.013	0.017	0.062	
St. Clair	65,713	86,438	0.011	0.000	0.013	0.001	0.104	0.000	0.001	
Washtenaw	274,917	225,596	0.001	0.039	0.001	0.005	0.000	0.091	0.014	
Wayne	978,461	920,039	0.006	0.034	0.056	0.073	0.011	0.056	0.097	
		Sum	0.155	0.181	0.217	0.205	0.197	0.182	0.204	
	·			Panel B: d	lnk/dlns					
Lapeer	33,526	51,593	0.034	0.000	0.029	0.063	0.006	0.001	0.006	0.139
Livingston	93,503	146,989	0.000	0.027	0.003	0.051	0.000	0.030	0.025	0.136
Macomb	455,428	533,776	0.002	0.001	0.056	0.083	0.008	0.001	0.049	0.200
Oakland	1,010,712	871,512	0.002	0.007	0.040	0.082	0.001	0.005	0.069	0.207
St. Clair	65,713	86,438	0.004	0.000	0.066	0.016	0.079	0.000	0.012	0.178
Washtenaw	274,917	225,596	0.000	0.016	0.002	0.023	0.000	0.111	0.061	0.213
Wayne	978,461	920,039	0.000	0.003	0.028	0.080	0.001	0.017	0.103	0.232

Table 6 Interactions among Michigan Counties in Detroit Area

SOURCE: Author's calculations, based on Table 1, commuting rates, and county employment numbers.

Overall, these data show very large interactions between Oakland and Macomb, and between Oakland and Wayne, and with slightly lower connections between Macomb and Wayne. Any reasonable local labor market definition would have to group these three counties. Lapeer, Livingston, St. Clair, and Washtenaw all have connections more with one or another of the big three counties. It is not obvious why one would want to group Lapeer, Livingston, and St. Clair with the core three counties of Wayne, Oakland, and Macomb, and not also group Washtenaw with these three large counties.

From a Michigan political perspective, the large interaction effects between Oakland County and Wayne County are notable. Historically, there were political tensions between Oakland County and Detroit (Wayne County).³⁰ The long-time Oakland County executive,

Brooks Patterson, who served as county executive from 1992 until his death in 2019, was noted for wanting to do very little to help Detroit. For example, Paterson frequently opposed regional projects such as mass transit. For a sample of Patterson's attitudes, consider a 2014 *New Yorker* article (by Paige Williams, colorfully titled "Drop Dead, Detroit!). The article quoted Brooks Patterson as saying, "Anytime I talk about Detroit, it will not be positive. Therefore, I'm called a Detroit basher. The truth hurts, you know? Tough shit" (Williams 2014).

Patterson argued that there was very little needed interaction between Oakland County and Detroit:

I used to say to my kids, "First of all, there's no reason for you to go to Detroit. We've got restaurants out here." They don't even have movie theatres in Detroit—not one. I can't imagine finding something in Detroit that we don't have in spades here. Except for live sports. We don't have baseball, football. For that, fine—get in and get out. But park right next to the venue—spend the extra twenty or thirty bucks. And, before you go to Detroit, you get your gas out here. You do not, *do not*, under any circumstances, stop in Detroit at a gas station! That's just a call for a carjacking.

But, as Table 6 shows, there are quite large interactions between Oakland County and Wayne County (Detroit), in that job shocks to one county have employment-rate effects on the other county that are almost as large. The *New Yorker* article quotes "urban theorist" Richard Florida as saying that Oakland County residents need "to stop the nonsense of thinking they can survive without the city." At the least, more jobs in Wayne County/City of Detroit boost employment rates in Oakland County. For example, as shown in Table 6, for every 100 jobs created in Wayne County, the employment rate in Oakland County goes up by 6.2 jobs. This increase represents almost as large of an effect on Oakland County employment rates as creating

³⁰ Oakland County has shifted politically in recent years, becoming more Democratic and less Republican (Gray 2020).

100 jobs in Oakland County itself, which has an effect of increasing the Oakland County employment rate by 7.1 jobs. Thus, if Oakland County is willing to devote resources to increase jobs in Oakland County in order to help Oakland County residents get jobs, it should be also willing to devote resources to increase jobs in Wayne County. To put it another way, Oakland County residents benefit little from redistributing jobs from Wayne County to Oakland County. The two counties have common interests in creating jobs through shared economic development policies.

Table 7 shows the five counties in the Los Angeles Consolidated Statistical Area. The Census Bureau classifies Los Angeles and Orange Counties as one metro area, San Bernardino and Riverside as another metro area, and Ventura as a third. Above, I suggested that San Bernardino might have a lot of commuting ties to Los Angeles.

Looking at absolute spillover effects of a given job shock to one county on employment rates in another, Los Angeles County is so big that its main effects are contained within the county itself. Orange County has sizable absolute spillover effects on Los Angeles County, Riverside County on San Bernardino, San Bernardino on Los Angeles and Riverside, and Ventura on Los Angeles. In percentage terms, L.A. has sizable percentage effects on Ventura, Orange, and San Bernardino; Orange and Ventura have few sizable percentage effects; and Riverside and San Bernardino have sizable percentage effects on each other.

Overall, it is unclear why one would want to group Los Angeles with Orange, but not with San Bernardino and Ventura.

	Employment	Employment						
County k name	by workplace k	by residence s	Los Angeles	Orange	Riverside	San Bernardino	Ventura	Sum
			Panel A	A: dk/ds				
Los Angeles	6,582,546	6,384,996	0.197	0.053	0.018	0.051	0.061	
Orange	2,307,110	2,178,785	0.018	0.140	0.022	0.013	0.001	
Riverside	1,094,493	1,326,972	0.003	0.012	0.119	0.044	0.001	
San Bernardino	1,074,771	1,175,495	0.009	0.007	0.043	0.104	0.001	
Ventura	475,232	531,575	0.005	0.000	0.000	0.000	0.146	
		Sum	0.232	0.213	0.202	0.212	0.210	
	•	-	Panel B:	dlnk/dlns				
Los Angeles	6,582,546	6,384,996	0.203	0.019	0.003	0.009	0.005	0.239
Orange	2,307,110	2,178,785	0.053	0.149	0.011	0.006	0.000	0.219
Riverside	1,094,493	1,326,972	0.016	0.021	0.098	0.035	0.000	0.171
San Bernardino	1,074,771	1,175,495	0.050	0.014	0.040	0.096	0.000	0.200
Ventura	475,232	531,575	0.063	0.001	0.000	0.001	0.131	0.196

Table 7	Interactions among	California C	ounties in Los	Angeles Area

SOURCE: Author's calculations.

USING SPILLOVER EFFECTS TO CREATE LOCAL LABOR MARKET DEFINITIONS

These spillover effects are now used to create local labor market definitions. These definitions are based on an algorithm that weighs the advantages of capturing more total spillovers by expanding local labor market sizes, versus the disadvantages of the resulting lower average spillovers. This section first explains the algorithm and how it is implemented, on both intuitive appeal and the resulting labor market definitions. Then we explore the labor market definitions in some specific cases, and how they match up to plausible local planning areas. Finally, we compare these "spillover-based local labor markets" (SLMs) with the U.S.'s current local labor market definitions.

Algorithm for Measuring Total Spillovers and Average Spillovers for a Given Local Labor Market Definition

The total spillover effect associated with a given set of local labor market definitions, which group counties into local labor markets and assign every county in the contiguous United States to one of these local labor markets, will be measured in this paper by the following equation:

(3) Total effect =
$$\sum_{k \in \mathbb{N}} \sum_{k \in \mathbb{N}} \sum_{s \in \mathbb{N}} \sum_{k \in \mathbb{N}} \sum_{k \in \mathbb{N}} \sum_{k \in \mathbb{N}} \sum_{s \in \mathbb{N}} \sum_{k \in \mathbb{N}} \sum_{s \in \mathbb{N}} \sum_{k \in \mathbb{N}} \sum_{s \in \mathbb{N}} \sum_{k \in \mathbb{N}} \sum_{k \in \mathbb{N}} \sum_{s \in \mathbb{N}} \sum_{k \in \mathbb{N}} \sum_{k \in \mathbb{N}} \sum_{s \in \mathbb{N}} \sum_{k \in \mathbb{N}} \sum_{s \in \mathbb{N}} \sum_{k \in \mathbb{N$$

Here, l indexes the particular local labor market. B_{sk} is the estimated absolute effect of a job shock to county *s* on county *k* (i.e., B_{sk} equals dk/ds), where county *s* includes own-county *k* effects. E_s is employment by place of work in county *s*.

The rationale for this total effect is that it weights the effects of s on k in a given local labor market definition by baseline employment in county s. This assumes that the spillover effects of larger counties are more important. The particular functional form in which *Es* enters linearly can be rationalized as assuming that the probability of a job shock to any county is proportional to its size. This measure is calculated for each local labor market, indexed by *L*, and then summed over all local labor markets *L*, which together comprise all 3,080 counties in the contiguous United States.

If all counties were each their own separate local labor market, we would get a summation of 23,061,617. If instead we assume that all 3,080 counties are treated as *one* labor market, the summation is almost twice as great, at 45,953,310.

To further interpret these numbers, if we wanted to get the average shock effect if the probability of a shock to *s* is proportional to county *s*'s size, we would divide by total employment in the BEA's employment measure for all 3,080 counties. That total employment

figure is 200,279,252. The resulting average within local labor market effect is 0.115 if each county is its own local labor market, and 0.229 if there is just one U.S. local labor market.³¹

As this suggests, and as a perusal of the equation shows, this total spillover effect will always go up if we make local labor markets bigger.

Any average spillover measure needs to somehow penalize making local labor markets larger. The particular average spillover measure that is used in this paper works by dividing the total effect by the employment size by place of work in the local labor market, and then summing this measure across all local labor markets:

(4) Average effect =
$$\sum_{l} \sum_{k \text{ in } l} (1/E_l) \sum_{s \text{ in } l} E_s * B_{sk}$$
.

Here, the only difference from the total measure is that we divide the within-local-labormarket spillover by the total employment by place of work in the local labor market, here written as E_l .

If each county were its own local labor market, this average measure would sum over all 3,080 counties to 306.9877. If the entire contiguous U.S. were treated as one local labor market, this average measure would sum to almost zero, at 0.2294.

If one looks at the average-effect measure, it is not inevitable that this measure will go down as local labor market sizes increase. But it will usually tend to go down if we add more counties to a current local labor market definition. It will go down assuming that as we add additional counties to a local labor market definition, the sum of the ($E_s * B_{sk}$) measure within a

³¹ By no coincidence, these also equal the weighted own-county and total effects for dk/ds in Table 2.

local labor market grows more slowly than the overall size of employment in the local labor market, El.³²

One can show that when this average effect is divided by the number of counties—that is, by 3080—this measure for each local labor market represents the total spillover effect "standardized" for the local labor market's size relative to the size of the average county. Thus, we can write

(5) (Average effect/3,080) =
$$(1/3080) \sum_{l} \sum_{k \text{ in } l} (1/E_l) \sum_{s \text{ in } l} E_s * B_{sk}$$

= $\sum_{l} (E_l/E_n) \sum_{k \text{ in } l} (A/E_l) (1/E_l) \sum_{s \text{ in } l} E_s * B_{sk}$.

Here, E_n is total national employment, and $A = E_n/3080$ is average employment per county. So for each local labor market, this measure represents the average spillover effects when we "standardize" the effect by multiplying by the ratio of average county employment size (A) to the local labor market's size. We then take a weighted average of this across all local labor markets by calculating a weighted sum using each local labor market's share of total national employment as weights, (E_l/E_n) .

Divided by 3,080, this measure indicates that the standardized average, when each county is its own local labor market, is 0.100 = 306.9877/3080. When the entire contiguous United States is one local labor market, the standardized average effect is less than 0.0001.

³² A similar alternative to dividing by the sum of E_s in a local labor market to penalize creating bigger local labor markets is to instead divide by the sum of E_k —that is, to divide by the local labor market's employment by place of residence rather than its employment by place of work. This could be rationalized as "averaging" the percentage effect with a weighting of E_k . Thus, for each county pair we have $dlnk/dlns = B_{sk}$ times (E_s/E_k). We can multiply this by E_k and get the same total sum we got before. We can then calculate an average effect by dividing each local labor market's total by the sum of all E_k within that local labor market. In practice, I suspect the two methods yield similar results. Perhaps normalizing by the sum of employment by place of residence is less likely to add smaller counties with net outward commuting to a local labor market, as adding such a county will push the local labor market's employment by place of residence up by a higher percentage than it would the local labor market's employment by place of work.

The total effect can be redefined similarly. If we multiply and divide by total employment in each defined local labor market, then divide the result by total national employment, we get

(6) Total effect/
$$E_n = \sum_{l} (E_l/E_n) \sum_{k \text{ in } l} (1/E_l) \sum_{s \text{ in } l} E_s * B_{sk}$$

Thus, when reparametrized, the total effect and average effect represent a weighted average of effects within each labor market of shocks, using each local labor market's share of total national employment (E_l/E_n) . Both total effect and average effect look at effects within each local labor market of the labor market's different county shocks, when shocks are assumed to occur proportionately to each county's share of total local labor market employment (E_s/E_l) . The total effect simply looks at the effect on the employment rate in the local labor market of such defined shocks—that is, *Bsk* is simply weighted by (E_s/E_l) and then summed over all counties *k* in the local labor market where such shocks have effects. The average effect looks at the effects when adjusted for the size of the local labor market by weighting by its size relative to some reference size, that is by dividing the average county size by the local labor market size, which is given by the expression (A/E_l) .

Why control for the local labor market's size in the average effect? One reason is that the cost of coordinating and managing local labor market policies may vary with the size of the local labor market. As a local labor market becomes larger, it becomes increasingly difficult to develop, gain approval for, and implement local labor market policies. The problems, interests, and specific needs of different counties and other areas within the local labor market become more diverse, which renders policymaking more difficult. Therefore, there should be some penalty if a higher employment-rate effect requires a larger local labor market size.

In addition, a higher average effect means there are greater spillovers within the local labor market. For a particular county k, job shocks to other counties within the local labor market will have effects on county k that are more comparable in size to how county k is affected by its own county job shocks. Counties within the overall area share more common interests.

Ideally, one would determine the relative weights on the total effect, and the average effect, based on some explicit model of how the benefits and costs of a local labor market definition vary with the extent of employment rate effects that are captured, versus the size of the local labor market. One could imagine that such a model might have a functional form in which the size of the local labor market enters into the benefit-cost model differently from the way it does as parameterized above, where it enters as 1 over the local labor market size. The functional form might have some quite different ways in which a local labor market size enters. For example, one can imagine that local labor market size might not have any negative effects, or even have positive effects, if we are considering increases from very small local labor market sizes to slightly larger local labor market sizes. And diseconomies of scale might become severe at some point, even more severe than implied by the current functional form. In future work, I hope to explore plausible ways in which average local labor market size might affect the costs of a particular labor market definition, based on reasonable estimates of how the costs of policy development, approval, and implementation might vary with labor market size. For the moment, I simply use the total and average size definitions given above, and I use weights that seem to yield plausible results.

Specifically, for scaling the total effect, I choose to pick as a "natural unit" the total effect that occurs when all counties are combined into one local labor market, which is the maximum

total effect. For the average effect, I use, as a natural unit for scaling, the average effect when all counties are separate local labor markets, which is close to a maximum for this measure.³³

Therefore, I seek to maximize the following weighted average:

(7) Weighted average =

(Total effect from a given local labor market definition/45,953,310) plus W * (Average effect from a given local labor market definition/306.9877) = "total percentage measure" + W * "average percentage measure."

I try three possible weights for W: 1, 2, and 3. These have some intuitive appeal, as I will shortly explain. I then pick the weight that yields the most reasonable results, which turns out to be 3.

To consider the intuitive appeal: Suppose some local labor market definition could come close to capturing the entire spillover effect. This would increase the total measure from around 23 million to around 46 million, or about a 50 percent increase relative to the maximum total effect (of 46 million) when the contiguous U.S. is one labor market. The weights mean the following: A weight of 1 on the average effect means that I am willing to adopt such a local labor market definition even if the average effect drops by 50 percent from its near maximum when all counties are separate local labor markets. This seems extreme. A weight of 2 on the average effect says a doubling of the total spillover from 23 million to 46 million is worth it if the average effect drops by no more than 25 percent from its value when all counties are separate. That weighting seems more plausible. A weighting of 3 means I am willing to do a grouping that doubles the size of the total effect if the average effect declines by no more than

³³ To clarify, the total effect is given by Equation (3), the average effect by Equation (4).

one-third of 50 percent, or about 17 percent, from the average effect when all counties are separate. That also seems like a plausible weighting.

But our intuitions need to be tested against results, at which point we are able to reflect upon the plausibility of the local labor market definitions that are created. If the resulting local labor market definitions create local labor market planning regions that seem too large to be plausible, we must reconsider a weighting. What I find is that a weighting of 1 or 2 on the average effect, relative to the total effect, results in the New York and Philadelphia areas being combined into one local labor market. I don't find that plausible.³⁴ It takes a weight of close to 3 to get New York and Philadelphia to be separated.

But back to implementing this maximization exercise. It is computationally infeasible to actually calculate the local labor market definitions that must maximize this weighted sum. There are simply too many possible combinations of the 3,080 counties that would have to be tested for this to be feasible. Instead, we follow a step-by-step maximization process that should yield local labor market definitions that come close to maximizing the weighted sum.

Specifically, suppose we have a tentative set of local labor market definitions, with estimates for dk/ds between each local labor market k and each local labor market s. The starting set is 3,080 local labor markets—i.e., each county is its own separate local labor market.

We consider each possible local labor market combination of two counties—or rather, we consider all those in which there is any positive spillover between the two local labor markets. As can be seen from the definitions of the average and total effect, they sum up effects over all labor markets of terms that can be separately calculated for each local labor market. Therefore, in looking at how a given recombination of two tentative local labor markets into a larger local

³⁴ My opinion may be biased, because I was born and spent my childhood in the Philadelphia area.

labor market affects the total percentage measure and average percentage measure summed over all local labor markets, we can simply look at these terms calculated as a percentage for the two tentative local labor markets versus their combination. All other local labor markets can be ignored.

The approach, then, at that step picks the local labor market combination that maximizes the increase in the Total Percent Measure + Weight * Average Percent Measure. The total percentage measure change will always be positive, and the average percent measure change will usually be negative.

After we pick this new definition of local labor markets, we recompute dk/ds between this new local labor market and all other local labor markets. This is possible using the original county interactions. The new dk/ds recomputes them assuming that if there is a shock to individual counties within each local labor market, the shock occurs with a probability proportional to the size of each county, as measured by employment by place of work. This assumption allows us to calculate a weighted average effect between the new local labor market that was created and all other local labor markets.

We then take these new local labor market definitions and recompute all possible combinations of the new tentative local labor market definitions. We once again pick the combination that maximizes the weighted percentage sum of the total measure and average measure. This may be a combination that already was computed in a prior stage, or it may involve the local labor market that was just defined.

This process continues until we cannot find a combination of any two local labor markets that increases the weighted percentage sum. We assume that this is close to the maximum possible. I doubt whether it mathematically *has* to be the maximum, although I lack a proof of

that proposition. Perhaps there is some movement of two counties from one local labor market to another that would be better. But I suspect it is unlikely that it is far from the maximum.

This approach has some similarities to existing local labor market definitions in that it builds up local labor markets by gradually combining counties. But there are two crucial distinctions:

First, rather than being based on definitions of urban areas or commuting rates, this approach is explicitly based on estimated county-to-county spillovers.

Second, in deciding on how closely connected a county or other local labor market area is with some other county or local labor market area, this approach explicitly considers the connections between all the counties in each local labor market area. In contrast, many of the past approaches, once they have combined two local labor market areas, simply aggregate total commuting, regardless of county. My approach also aggregates *dk/ds* to the local labor market level, but it weights the county spillovers by the size of the counties within each local labor market area, on the grounds that the labor market shocks to the larger counties and their spillover effects should matter more.

NEW LOCAL LABOR MARKET DEFINITIONS: SPILLOVER-BASED LOCAL LABOR MARKETS (SLMS)

So, what do these "spillover-based local labor markets" (SLMs) look like? Do they correspond better to local planning areas? What are some statistics on how well they capture total spillovers while keeping average within-area spillovers high? We consider such descriptive information first, before then turning to more detailed comparisons of SLMs with BEA economic areas, CZs, and CBSAs. As a reminder, all of these descriptions are based on the triple-weighted algorithm, in which we seek to maximize a weighted sum of percentage total and average effects using a triple weighting on the average versus the total effect.

The first issue considered is whether these SLMs better match local planning areas. The mismatch between CBSAs/CZs/BEA areas and local planning areas was noted above, and it seems like a key problem. If local labor market definitions are not useful for local planning, perhaps they should be revised so that government data are more relevant to local policy.

Under this SLM approach, Kalamazoo County is now its own SLM, with no other counties attached. This accords with the current metro-area definition. In the past, the Kalamazoo County metro area has sometimes included Van Buren County to the west, and has sometimes included Calhoun County (Battle Creek) to the east. But the SLM approach definitely does not try to combine Kalamazoo County with more remote population centers, as the BEA areas did by combining Kalamazoo with Mecosta County (Big Rapids), or as CZs did by combining Kalamazoo with St. Joseph County, Indiana (South Bend). From my own observations of Kalamazoo, there is not much planning that occurs between Kalamazoo and any of its surrounding counties.

The Chicago SLM definition merely consists of the same seven counties in Illinois that are part of the Chicago Metropolitan Agency for Planning. As mentioned above, the Chicago metro area is a much larger 13-county region that includes four counties in Indiana.

The Atlanta SLM is limited to 11 counties, versus the 29 counties in the Atlanta metro area. The Atlanta Metro Regional Commission also has 11 counties, and 10 of them also make up the Atlanta SLM—the difference being that the SLM drops Rockdale County in the southeast of the area and adds Paulding County in the northwest of the area.

The Detroit SLM does add in Washtenaw to the CBSA definition but lops off Lapeer and St. Clair from the CBSA. Adding in Washtenaw is consistent with SEMCOG, but SEMCOG also includes Monroe and St. Clair, which are not in the SLM. SEMCOG agrees with the SLM in that it does not include Lapeer.

The Los Angeles SLM is identical to the Los Angeles Consolidated Statistical Area in having five counties: the two counties of the L.A. metro area (L.A. and Orange) plus the two counties of the Riverside–San Bernardino metro area and the one county of the Ventura metro area. This is identical to the area that Wikipedia calls "Greater L.A.," and from which the L.A. Chamber of Commerce appears to draw membership.

More broadly, I looked at the biggest 15 CBSAs in population and compared their county compositions with the corresponding SLMs, as well as with any local planning agency definitions. Table 8 shows the results.

As Table 8 shows, the New York SLM is fairly similar to the New York CBSA. Los Angeles, Chicago, Atlanta, Riverside–San Bernardino, and Detroit have already been discussed. The Dallas and Houston SLMs lop off a few outlying counties from the corresponding CBSAs. The District of Columbia SLM lops off outlying counties from the District of Columbia CBSA, but combines the D.C. area with the Baltimore area. The Philadelphia SLM drops off three more remote Delaware counties from the corresponding Philadelphia CBSA. The Miami, Phoenix, and Seattle SLMs are identical to the corresponding CBSAs. The Boston SLM adds in and substitutes some different counties for those that are in the Boston CBSA. Because counties are not active governmental entities in New England, the planning area there would not be defined in terms of counties, so trying to find comparable planning areas is challenging.

	CBSA counties	SLM counties	SLM counties compared to CBSA counties
NY	23	24	Subtracts Pike (PA); adds in NJ counties of Warren and Mercer (Trenton, Princeton).
LA	2	5	5 county area same as CSA: adds 2 county Riverside-San Bernardino to LA-Orange, also adds in Ventura County. Same as "Greater LA" in Wikipedia.
Chicago	13	7	Cuts off all 4 counties in IN (Lake, Porter, Jasper, Newton), and 2 small outlying IL counties (DeKalb, Grundy), CMAP region same as new SLM.
Dallas	11	8	Cuts off 3 counties of Wise, Parker, Hunt
Houston	9	7	Cuts off two more remote counties of Austin and Liberty
Atlanta	29	11	Metro Regional Commission also 11 counties, but drops Paulding, adds in Rockdale.
DC	25	16	But different—combined with Baltimore, less outlying
Philadelphia	11	8	Lops off 3 Delaware counties
Miami	3	3	Identical!
Phoenix	2	2	Identical!
Boston	7	9	Adds Worchester and Bristol, subs Hillsborough for Strafford. Worcester is its own metro area, and Bristol is part of Providence MSA. Hillsborough is Manchester MSA.
Riverside-San Bernardino	2	5	Part of 5 county LA SLM
San Francisco	5	7	Wikipedia claims most local planners use 9 county area. SLM adds Santa Clara and Solano to MSA. Does not include Napa and Sonoma that are in 9 counties. Santa Clara is its own MSA
Detroit	6	5	Compared to CBSA, SLM lops off St. Clair and Lapeer, adds in Washtenaw (Ann Arbor). SEMCOG also includes Washtenaw, but also differs from SLM in including Monroe and St. Clair.
Seattle	3	3	Identical!
Minneapolis/St. Paul	15	9	SLM version adds Wright and Sherburne on to 7 county Metro Council

Table 8 Comparing County Composition for 15 Largest CBSAs Versus New SLM Definitions

San Francisco is interesting because Wikipedia claims that local planners use a ninecounty area, which is considerably larger than the five-county CBSA. The San Francisco SLM goes partway toward the nine-county planning area by adding two counties to the five-county CBSA. Unlike the CBSA, the new San Francisco SLM includes Silicon Valley, and in particular it includes Santa Clara County, which the Census Bureau, however, counts as a separate CBSA. One observer is on record as regarding the current Census Bureau separation of San Francisco and Silicon Valley as "weird."³⁵

The Minneapolis–St. Paul SLM cuts down on the size of the corresponding CBSA by eliminating six outlying counties, including several counties in Wisconsin. The Twin Cities have a relatively powerful Metro Council, which provides services such as metro transit and wastewater services, as well as administering a tax-base sharing system. The SLM adds two counties to the Metro Council counties but is much closer to the Metro Council's area of jurisdiction than is true of the CBSA.

The overall impression given, at least from these relatively large areas, is that SLMs do indeed correspond more closely to local planning areas than CBSAs do. In many cases, this involves slimming down the area's size compared to CBSAs (Chicago, Atlanta, the Twin Cities), but in other cases it involves increasing the area's size compared to CBSAs (San Francisco, Detroit, Los Angeles).

The SLM classification used here ends up with 2,752 SLMs in the contiguous United States, of which 170 are multicounty SLMs and 2,582 are single-county SLMs. Table 9 shows the number of SLMs by the number of counties they include, with the percentage of the population by number of counties also shown. As this table demonstrates, although most U.S. counties are single-county SLMs, 59 percent of the U.S. population lives in multicounty SLMs.

Map 7 shows the 170 multicounty SLMs in dark gray, and it includes the county boundaries for the remaining single-county SLMs. As the map shows, the eastern two-thirds of

³⁵ Prominent pollster Nate Silver: "It's pretty weird to consider San Francisco and Silicon Valley to be separate metro areas...." (Silver 2024).
		Population of SLMs		
Number of counties		with that number of	Percentage of total	Average population
in SLM	Number of SLMs	counties	population	size of SLMs
24	1	20,578,908	6.3	20,578,908
16	1	8,502,154	2.6	8,502,154
11	1	5,042,605	1.5	5,042,605
9	2	10,076,615	3.1	5,038,308
8	2	12,826,347	3.9	6,413,174
7	3	22,716,938	6.9	7,572,313
6	4	9,158,734	2.8	2,289,684
5	5	27,008,480	8.2	5,401,696
4	7	11,973,003	3.6	1,710,429
3	27	35,406,051	10.8	1,311,335
2	117	30,994,313	9.4	264,909
More than 1	170	194,284,148	59.0	1,142,848
1	2,582	134,976,472	41.0	52,276
All SLMs	2,752	329,260,620	100.0	119,644

Table 9 Number of SLMs and SLM population by SLM county type

NOTE: The 24-county SLM is New York, the 16-county SLM is D.C., and the 11-county SLM is Atlanta. SOURCE: Author's calculations.

the country tends to have more multicounty SLMs. This is in part because Eastern counties are geographically smaller and packed together.

As this map also shows, in many cases these "slimmer" SLMs also have some adjacent SLMs that are not combined. For example, this is true of the Chicago and Atlanta SLMs, which, as mentioned, are slimmed down around their core counties, but then have some adjacent SLMs.

In my view, this result is desirable. These adjacent SLMs might be combined with the larger core SLM if we were defining local economies that are linked in part by multipliers because of supplier linkages. As already mentioned, future extensions of this model will consider local-area definitions that depend on how shocks to export-based labor demand have effects on nearby county employment rates, which might define local economies. But here we are attempting to define local labor markets based on actual shocks to employment in a county and the extent to which those shocks are propagated to nearby counties' employment rates. There could well be "local economies," linked by supplier multipliers, that contain several local labor markets, in which the shocks to each county's employment are mostly contained within each

Map 7 Multicounty SLMs in Dark Gray, Single-County SLMs in Light Gray



SOURCE: Author's calculations.

local labor market. This could hold true even if the demand shocks to a county's export-based employment might have effects that are more geographically spread. A local economy can reasonably be larger than a local labor market.

As part of this paper's release, two Excel workbooks show more details on each SLM. One table, Table E3, lists in each row, for each SLM, its overall Census 2020 population, employment by place of work, employment by place of residence, and the number of counties in the SLM. It arbitrarily assigns a Federal Information Processing Standard (FIPS) code and name to each SLM based on its largest-population county. The row then lists the counties in the SLM, ordered by population size from left to right, and lists for each county the FIPS code, county name, Census 2020 population, employment by place of work, and employment by place of residence.

The other table, Table E4, is an x-by-x matrix that shows for each SLM the value of dk/ds for the SLM itself, and the cross values for all other SLMs. In other words, it seeks to address two questions: how does a shock to employment by place of work affect the employment rate in the SLM itself, and how much does it spill over into surrounding SLMs?

Based on this information, the SLM classification results in total spillover captured within SLMs of 78.4 percent of the maximum spillover captured if the entire contiguous U.S. was treated as one local labor market. The SLM classification results in an average spillover for SLMs that sums to 98.5 percent of the average figure if all counties in the contiguous U.S. were their own local labor market. The weighted average is 93.4 percent. This is superior to the weighted average figures for either all counties separately (87.5 percent) or all counties together (25.0 percent), by a lot. Is it the true maximum? That is unclear, but I suspect it is close.

Table 10 presents some descriptive statistics on SLM population. Obviously, SLMs vary greatly by population. Half of the U.S. population lives in SLMs that exceed 1.25 million in population, but a quarter live in SLMs below 171,000.

Mean	4,349,308	
Standard deviation	6,213,548	
Minimum	64	
Maximum	20,578,908	
10th percentile	44,843	
25th percentile	171,415	
50th percentile	1,246,225	
75th percentile	6,674,991	
90th percentile	18,644,680	

Table 10 Descriptive Statistics on Population of SLMs, Weighted by Population

SOURCE: Author's calculations on SLMs, using Table 1 estimates and Census 2020 population.

Table 11 presents descriptive statistics on the *dk/ds* effects for SLMs, both in total and within the SLM. Consistent with what previously has been said, on "average" (when weighted), SLMs comprise over three-quarters—around 78 percent—of the total employment effects of an SLM job shock. But half of U.S. jobs are in SLMs in which 85 percent or more of the total employment effects of a job shock are contained within the SLM. Comparing these results to Table 2, we see that SLMs dramatically improve the capture of employment effects of job shocks.

 Table 11
 Descriptive Statistics for SLMs for Total Effect, Own Effect, and Percentage Own for dk/ds, Weighted by SLMs' Employment by Place of Work

	Total <i>dk/ds</i>	Own <i>dk/ds</i>	% own/total (%)
Mean	0.229	0.180	78.1
Standard deviation	0.009	0.048	20.0
Minimum	0.213	0.007	2.3
Maximum	0.307	0.246	97.3
10th percentile	0.220	0.099	44.9
25th percentile	0.223	0.156	69.9
50th percentile	0.228	0.198	85.4
75th percentile	0.235	0.217	93.0
90th percentile	0.245	0.223	95.0

SOURCE: Author's calculations on SLMs, which are defined based on Table 1 and on BEA employment data.

Table 12 presents some information on the 30 largest SLMs by population. These include the variables from the prior table, as well as number of counties in the SLM.

These 30 largest SLMs comprise almost half of the total U.S. population—or, more precisely, 46.2 percent. As can be seen in the table, in 29 of the 30 largest SLMs, the SLM boundaries contain within the SLM over 80 percent of the total spillover effects of job shocks. And in 16 of these 30 SLMs, the SLM captures over 90 percent of total spillovers.

		Number			
	SLM	counties in			
SLM name	population	SLM	Total effect	Own effect	% own/total
Kings, NY	20,578,908	24	0.235	0.222	94.4
Los Angeles, CA	18,644,680	5	0.229	0.223	97.1
Cook, IL	8,577,735	7	0.228	0.212	93.2
Fairfax, Fairfax City + Falls Church, VA*	8,502,154	16	0.246	0.226	91.8
Dallas, TX	7,320,577	8	0.222	0.207	93.0
Santa Clara, CA	7,138,758	7	0.223	0.203	91.3
Harris, TX	7,000,445	7	0.229	0.217	94.8
Middlesex, MA	6,674,991	9	0.229	0.211	91.8
Miami-Dade, FL	6,138,333	3	0.228	0.219	96.2
Philadelphia, PA	5,505,770	8	0.228	0.194	85.2
Fulton, GA	5,042,605	11	0.241	0.209	86.3
Maricopa, AZ	4,845,832	2	0.250	0.243	97.3
Wayne, MI	4,515,297	5	0.221	0.199	89.8
King, WA	4,018,762	3	0.224	0.209	93.3
Hennepin, MN	3,401,624	9	0.235	0.214	90.8
San Diego, CA	3,298,634	1	0.248	0.230	92.6
Hillsborough, FL	2,980,760	3	0.225	0.204	91.0
Denver, CO	2,905,164	6	0.250	0.222	89.1
Cuyahoga, OH	2,477,506	6	0.224	0.191	85.4
Multnomah, OR	2,340,512	4	0.221	0.202	91.2
Orange, FL	2,289,420	3	0.222	0.185	83.2
Clark, NV	2,265,461	1	0.255	0.245	96.1
Sacramento, CA	2,206,197	3	0.223	0.184	82.5
Travis, TX	2,140,272	3	0.224	0.199	88.9
Bexar, TX	2,009,324	1	0.239	0.205	85.8
Jackson, MO	1,964,189	6	0.231	0.204	88.4
St. Louis, MO	1,937,704	4	0.233	0.196	83.9
Fairfield, CT	1,822,254	2	0.219	0.155	71.1
Wake, NC	1,818,938	4	0.224	0.183	81.5
Allegheny, PA	1,814,590	3	0.224	0.186	83.0

	Table 12	Within-SLM	Effect versus	Total Effect.	30 La	rgest SLMs
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SOURCE: SLMs calculated as described in text. Name of SLM is name of SLM county with largest population.

But many SLMs are much smaller, and they often comprise only one county. Table 13 provides some illustrative data on 30 smaller SLMs: the 10 surrounding the 50th percentile, the 10 around the 25th percentile, and the 10 near the 10th percentile, population weighted, of the SLM population distribution.

As can be seen in Table 13, SLMs near the median of the SLM population distribution also tend to be multicounty areas, and also tend to capture over 70 percent of spillover effects. On the other hand, the smaller SLMs, those at the 25th or 10th percentiles of the population

	SLM				
SLM name	population	# of counties	Total effect	Own effect	% own/total
Panel A: 10 counties just	st above and b	elow 50th perce	ntile of populat	ion of SLMs	
Hamilton, OH	1,671,934	4	0.2273	0.1772	77.9
Davidson, TN	1,649,114	5	0.2249	0.1859	82.7
Mecklenburg, NC	1,579,553	3	0.2221	0.1607	72.4
Milwaukee, WI	1,574,731	4	0.2246	0.1949	86.8
Duval, FL	1,487,237	3	0.2263	0.2033	89.8
Oklahoma, OK	1,246,225	3	0.2236	0.1939	86.7
Hartford, CT	1,213,531	3	0.2242	0.1614	72.0
Salt Lake, UT	1,185,238	1	0.2293	0.1741	75.9
Virginia Beach (Independent city), VA	1,139,136	5	0.2415	0.2072	85.8
Shelby, TN	1,115,058	2	0.2313	0.1955	84.5
Panel B: 10 counties just	st above and b	elow 25th perce	ntile of populat	ion of SLMs	
Shawnee, KS	178,909	1	0.2287	0.1700	74.3
Licking, OH	178,519	1	0.2237	0.0677	30.3
Muskegon, MI	175,824	1	0.2192	0.1248	56.9
Bay, FL	175,216	1	0.2414	0.2103	87.1
Lee, AL	174,241	1	0.2187	0.1024	46.8
Alamance, NC	171,415	1	0.2186	0.0994	45.5
Kootenai, ID	171,362	1	0.2256	0.1609	71.3
McLean, IL	170,954	1	0.2293	0.1721	75.1
Clarke, GA	170,470	2	0.2288	0.1300	56.8
Pitt, NC	170,243	1	0.2263	0.1602	70.8
Panel C: 10 counties just above and below 10th percentile of population of SLMs					
Lawrence, IN	45,011	1	0.2182	0.1018	46.6
Polk, WI	44,977	1	0.2197	0.0897	40.8
Macoupin, IL	44,967	1	0.2255	0.0647	28.7
Washington, MS	44,922	1	0.2306	0.1771	76.8
Branch, MI	44,862	1	0.2191	0.0939	42.9
Wood, TX	44,843	1	0.2231	0.0731	32.8
Henderson, KY	44,793	1	0.2196	0.0892	40.6
Warren, MS	44,722	1	0.2222	0.1407	63.3
Beaufort, NC	44,652	1	0.2185	0.1089	49.8
Phelps, MO	44,638	1	0.2214	0.1366	61.7

Table 13: SLM Characteristics for Selected SLMs

SOURCE: Author's calculations based on SLM definitions described in text. Population figures are for 2020.

distribution, tend to be single-county SLMs. In some cases, and particularly for those near the 10th percentile, the total spillover-effect capture is less than half the total effects.

Why are these single-county SLMs not combined with other nearby SLMs to capture more spillovers? The most common case is a situation such as for Macoupin County, Illinois. Macoupin County has spillover effects scattered across numerous nearby counties, but has no particularly strong ties to any of these nearby counties. The largest spillover effect of Macoupin County is on Madison County, Illinois, at 0.0493. Furthermore, Madison County has a *dk/ds* for Macoupin County, Illinois, of only 0.0093. Hence, for many of these rural counties, although they are connected by commuting links to other counties sufficiently for there to be spillover effects of job shocks, these commuting patterns, and hence spillover effects, are quite diverse. Capturing more of these spillover effects by combining counties would require combining many counties, which would lower the average effects of spillovers quite a bit. Therefore, the algorithm says not to make such combinations. One can see this as confirming the notion that a local labor market, to make sense defined as such, requires some core of concentrated employment, rather than having employment by place of work be widely dispersed.

The other case is one in which a small county is adjacent to a much larger SLM. For example, Licking County, Ohio, is adjacent to what is named in my data as the "Franklin County, Ohio" SLM, but which is perhaps better known as the Columbus, Ohio, area. Licking County, Ohio, actually is part of the Columbus MSA in official government statistics. So why doesn't this paper's algorithm combine Licking County into the larger Columbus-area SLM?

Licking County job shocks do have large estimated effects on the Franklin SLM, at 0.1152. But job shocks to the Franklin SLM have only small effects on Licking County, at 0.0103, whereas the Franklin SLM's "own effect" is 0.1879. The algorithm essentially notices that adding in Licking County would lower the size-adjusted average effect because of the small spillover from the Franklin SLM to Licking County. Hence, the algorithm opts to keep Licking County separate to avoid diminishing size-adjusted average SLM effects in the Columbus-area SLM.

One possible reaction to these results is some skepticism about whether it is desirable to treat all counties as necessarily being part of any defined local labor market, either for research purposes or maybe for policy purposes. Based on the algorithm used in this paper, there are

many individual counties whose spillover effects on other nearby counties are sufficiently diffuse that these counties are not grouped together, as there is not a high average effect of job shocks in such county groupings. But in at least some of these single counties, it is also true that less than half of the employment rate effects of a job shock to that county occur within the county. So, for research and policy purposes, neither a single-county definition nor a multicounty grouping will yield high average effects of local job shocks. The local labor market concept, originally developed in the context of a metro area with a job center, may not really be applicable to many remote rural counties.

Therefore, for some research and policy purposes, analysts may want to set a minimum "spillover capture" percent for what percentage of the employment rate effects of a local job shock are contained within the defined local labor market. Table 14 shows how many SLMs would be included if one were to set various spillover-capture cutoffs, and what percentage of employment by place of work and population would be included in the resulting set of SLMs. As Table 14 shows, if we set a minimum cutoff that half the employment-rate effects of an SLM job shock must be captured within the SLM, we end up with 1,261 SLMs exceeding this cutoff, out of the total of 2,752 defined SLMs. But these 1,261 SLMs include almost 88 percent of total U.S. jobs, and about 84 percent of the U.S. population. If one is willing to have lower cutoffs down to 20 percent, we can capture almost all SLMs, at 2,495. But if one imposes a very stringent cutoff of 80 percent, the number of SLMs meeting this cutoff is only 258, although these 258 SLMs still contain around 64 percent of U.S. jobs and 60 percent of the U.S. population.

Alternatively, future work might explore whether it makes sense to add a penalty for a local labor market being too small to fully exploit economies of scale in delivering public

		% of U.S. jobs in SLMs	% of U.S. population in
Cutoff (%)	# of SLMs exceeding cutoff	exceeding cutoff (%)	SLMs exceeding cutoff (%)
95	7	10.0	9.8
90	58	39.2	36.6
85	145	52.4	49.3
80	258	63.8	59.9
75	384	69.2	65.0
70	533	74.9	70.5
65	691	78.3	74.0
60	858	81.8	77.7
55	1,055	85.2	81.5
50	1,261	87.6	84.1
45	1,459	89.9	86.7
40	1,696	92.5	89.9
35	1,929	94.8	92.7
30	2,125	96.4	94.8
25	2,326	97.8	96.7
20	2,495	98.7	98.1
15	2,649	99.5	99.3
10	2,729	99.9	99.9
5	2,730	99.99	99.997
No cutoff	2,752	100.0	100.0

 Table 14 Number and Cumulative Employment and Population of SLMs at Different Cutoffs for Minimum

 Spillover Percentage within SLM

SOURCE: Author's calculations, based on procedures described in text.

services. The current algorithm assumes that a larger-sized local labor market is always penalized, all else being equal. This assumption may be questioned. Some research finds that economies of scale in local public services do exist but are exhausted at low levels of population—in many studies, at populations of 10,000 or less (Gómez-Reino, Lago-Peñas, and Martinez-Vazquez 2023). If some penalty for local labor markets below this scale was included, some of the very smallest single-county local labor markets would be combined, and thereby would capture a higher share of employment-rate effects from job shocks. Alternatively, in addition to production economies of scale, there may be economies of scale in doing planning, which might require different data to estimate. Is local planning of a better quality if the planning area is not very small, at least up to some point, as the local planning group may be better able to adequately staff any local plan? I do not pursue these "economies of scale or planning" options in the current paper, which outlines the idea of deriving local labor markets from estimated spillovers. As an initial demonstration of this idea, it seems better to use consistent weighting procedures to define local labor markets, rather than simply rigging the scheme to ensure larger local labor markets.

COMPARING SLMS WITH OTHER LOCAL LABOR MARKET DEFINITIONS

But how do SLMs compare with other local labor market definitions? We first compare how closely the SLM definitions match other local labor market definitions in classifying counties into local labor markets. We then consider how the SLM definitions compare with other definitions in how much they capture total percentage effects and average percentage effects as estimated in this paper. Finally, we consider how the SLM definitions compare with other definitions in capturing commuter flows, relative to the average size of SLMs.

How Closely Do SLMs Match Other Local Labor Market Definitions?

For matching, we do three comparisons. All three are based on comparing all pairs of counties that are in the same local labor market under one local labor market definition (Definition A) and seeing whether they are in the same local labor market under another local labor market definition (Definition B). The three comparisons use different weightings of the different pairs.

Under some local labor market definition, each local labor market has a number of pairs in that labor market. For example, if a local labor market has only two counties, county x and county y, there is only one pair, xy. If a local labor market has three counties—counties x, y, and z—then there are three pairs in that local labor market: xy, xz, and yz. More generally, for a local labor market with m counties, the number of possible county pairs is one-half of the factorial of *m*, or (0.5 times *m*!). For a given local labor market definition, we then consider all of the multiple-county local labor markets, as well as all the possible pairs in each of those local labor markets. The number of possible pairs will be the sum of $(m_j!/2)$ over all of the *j* local labor markets that are multiple counties.

Under the first comparison, we look at all possible pairs under Definition A, to see whether they are in the same local labor market under Definition B, and then calculate what percentage that are in A are in the same local labor market under Definition B. We then reverse this, to see what percentage of the possible pairs in the same local labor market under labor market Definition B are actually in the same local labor market under Definition B.

Under the second comparison, we do the same mapping of possible pairs in Definition A to Definition B, and vice versa, but we weight each pair by the sum of employment by place of work in each pair.

Under the third comparison, we again do these mappings of what pairs are in the same local labor market under both labor market definitions, but we weigh each pair by the mathematical product of the two counties' employment by place of work.

Each of these three comparisons can be rationalized as corresponding to a particular thought experiment. Comparison 1, equal weighting, corresponds to randomly choosing two counties, k and s, then conditioning on whether they are in the same local labor market under Definition A, then asking what is the probability that they are in the same local labor market under Definition B, and then doing the reverse, going from Definition B to Definition A. Comparison 2, in which we weight a county pair (k,s) by the sum of the employment in k and s, corresponds to putting all possible pairs in the same local labor market under Definition A in a basket, then randomly drawing a pair from the basket with a probability equal to the total size of

that pair. Comparison 3, in which we weight a county pair (k,s) by the product of employment in k times employment in s, corresponds to randomly choosing two jobs, then conditioning on those two jobs being *both* in two different counties *and* in the same local labor market under Definition A. The probability of that corresponding to a particular county pair (k,s) will then be proportional to the product of employment in k times employment in s.

More intuitively, Comparison 1 puts the most weight on whether smaller counties are grouped similarly under both definitions, Comparison 2 puts the most weight on whether big counties are grouped similarly with either small or big counties under both definitions, and Comparison 3 puts the most weight on whether pairs in which both counties are big are grouped the same under both definitions. Consider possible pairs that involve counties of size x and 10x. The possible pairs are (x,x), (x,10x) and (10x,10x). Under the equal weighting of Comparison 1, all of these are weighted equally, and since there are more small counties than large counties, the smaller counties will dominate the comparison. Under Comparison 2, the sum of the two counties, the relative weights are 2, 11, and 20, so the pairs involving the bigger counties are weighted much higher than the pairs involving only small counties. Under Comparison 3, the product of the three counties, the relative weights are 1, 10, and 100, so the pairings involving two big counties for the three counties.

For comparison of the BEA areas and CZs with these new SLMs, I will use the entire contiguous United States, and will use the most recent BEA areas and CZs. But for the comparison between the new SLMs and CBSAs, I will use the 2013 CBSA definitions (2010-based definitions) and focus only on the contiguous United States outside New England. I do so for two reasons.

First, for a comparison with SLMs, it is best to use a comparison that similarly classifies all counties into local labor markets. The official CBSAs do not include all counties, but the U.S. Bureau of Labor Statistics has county-based small labor market areas that classify into small, local labor market areas in counties outside the CBSAs. But the current BLS small LMAs are designed to be compatible with the 2013 CBSA definitions, and they use only counties outside New England. (In New England, the BLS's small LMAs are based on towns and townships, which would be difficult to reconcile with the SLM definitions, which are based on counties.)

Second, for a comparison with SLMs, the 2013 CBSA definitions are based on the same 2006–2010 ACS commuting data as the SLM definitions. Hence, this comparison is a fairer one.³⁶

Table 15 shows these unweighted and weighted comparisons between the SLMs, versus the BEA areas, CZs, and CBSAs.³⁷ As can be seen, SLMs are clearly "slimmer" than these other definitions if we use weightings that put the most emphasis on how small counties are grouped into local labor markets. For example, if two randomly chosen counties are in the same SLM, their probability of being in the same CBSA is 81.7 percent. In contrast, if two randomly chosen counties are in the same CBSA or small labor market area, their probability of being in the same SLM is only 23.3 percent. Even more extremely divergent statistics occur, showing that SLMs group together many fewer small counties than is true for CZs or BEA areas. SLMs are more parsimonious in adding small counties to labor market definitions, as well as in grouping small counties together.

³⁶ The most recent CZ definition is also based on 2006–2010 commuting data. The BEA economic area definitions from 2004 are based on older data, but are the most recent available.

³⁷ As part of this paper's release, I include matrices for all contiguous U.S. counties in which counties are in the same SLM, BEA area, or CZ (Matrices E5, E6, E7). I also include matrices for non–New England counties for SLMs, and CBSAs/BLS small labor market areas (Matrices E8 and E9). These might be useful for some researchers.

	Equal weights		k + s weights		k * s weights	
	SLM pairs in	Other pairs in	SLM pairs in	Other pairs in	SLM pairs in	Other pairs in
	other (%)	SLM (%)	other (%)	SLM (%)	other (%)	SLM (%)
CBSAs	81.7	23.3	82.0	53.6	78.3	88.4
CZs	67.1	7.9	59.9	36.1	64.0	82.1
BEA	99.6	1.2	99.996	16.1	99.99997	59.5

Table 15 Comparing SLMs with Other Local Labor Market Definitions

SOURCE: Author's calculations using SLMs from this study, and other local labor market definitions.

In contrast, if we look at how big counties are grouped with each other, the "k * s weighting" SLMs are in some sense "bigger" than CBSAs or CZs, but not than BEA areas. For example, under this weighting, which puts emphasis on whether two big counties are together, the weighted probability that a CBSA pairing is in the same SLM is 88.4 percent. In contrast, for these big-counties-together weightings, the weighted probability that such big SLM pairs are in the same CBSA is only 78.3 percent. This reflects that for some local labor markets involving relatively large counties, such as San Franciso, Los Angeles, and Detroit, the SLM definition includes more big counties together.

The weighting that puts more emphasis on how big counties are paired with either small or big counties (the "k + s" weighting) shows results that are in-between. But on the whole, it shows that SLMs are "smaller" than these other groupings. In SLMs, fewer small counties are added on to big-county-dominated SLMs. This finding was already anticipated by some of the comparisons above—for example, the Atlanta area, the Chicago area, and the Minneapolis–St. Paul area all have fewer smaller counties added in under the SLM definition compared to the CBSA definition.

Overall, the SLM definition is more similar to the CBSA definition than it is to either the CZ definition or the BEA definition. But the SLM definition in many respects is quite different

from all three of these other definitions in being slimmer. It does this by not adding as many small counties together or combining them with larger local labor market areas.

How Different Local Labor Market Definitions Perform in both Capturing Total Spillovers and Having High Average Spillovers

In addition to looking at similarities or differences in what counties are grouped, I examine whether the different labor market definitions do a good job of capturing the strongest local labor market spillovers, in the sense of not only capturing more total spillovers but also having large average internal spillovers. This will be done by, first, assuming that the *dk/ds* figures estimated here are the best way of capturing these spillovers, and that the percentage total and percentage average figures calculated above are meaningful figures to look at for any local labor market definition. But I will then go on to consider criteria that might be relevant even if one ignores the spillover estimates. These criteria operate on the premise that a local labor market should try to include more commuting flows while keeping its size down.

We do comparisons of SLMs with BEA economic areas and CZs for the *entire* contiguous U.S.. To compare SLMs with CBSAs, we compare SLMs with CBSAs plus BLS-defined small LMAs (labor market areas) for the contiguous U.S, excluding New England. (As explained above, the BLS-defined small LMAs in New England do not follow county boundaries, and so including New England would not yield comparable county-based areas.) We use our estimated *dk/ds* numbers for each county in the contiguous U.S. to generate *dk/ds* numbers for each set of local labor market definitions. (These tables will be electronically available with the report as Matrices E10 (BEA EAs), E11 (CZs), E12 (SLMs, dropping any New England county, a variant of E4), and E13 (CBSAs plus small LMAs for non–New England counties in the contiguous U.S.). We then compute our average percentage measure, our total percentage measure, and our weighted average for each definition.

As shown in Table 16, based on the triple-weighting average criteria, single-county labor markets are superior to combining the United States into one local labor market. Half of the total employment-rate effects of job shocks are captured within single counties, and the average effect goes down to zero if we go to a single national labor market.

	Total % captured	Average % captured	Weighted sum (%)			
Panel A: Contiguous United States						
Single-county labor markets	50.2	100.0	87.5			
SLMs	78.4	98.5	93.4			
CZs	86.6	36.5	49.0			
BEA areas	94.3	12.1	32.7			
Entire U.S. as one labor market	100.0	0.1	25.1			
Panel B: Non-New England contiguous United States						
Single-county labor markets	50.7	100.0	87.7			
SLMs	78.6	98.6	93.6			
CBSAs	82.7	89.1	87.5			
Entire U.S. one labor market	100.0	0.1	25.1			

Table 16 Different Local Labor Market Definitions Compared by Total and Average Percentage Captured

NOTE: Percentages for total are divided by total if all counties are in one labor market, either in the entire contiguous U.S. (Panel A) or the contiguous U.S. outside New England (Panel B). Percentages for average are divided by the average figure if each county is its own labor market, either in the entire contiguous U.S. (Panel A) or the contiguous U.S. outside New England (Panel B). Weighted average triple weights average percentage versus total, which equals (1* total column + 3 * average column) / 4. SOURCE: Author's calculations.

As already mentioned, SLMs do considerably better than single-county local labor markets at capturing more spillovers: they increase the percentage captured from around 50 or 51 percent to 78 or 79 percent, depending on whether one looks at the entire contiguous U.S. or excludes New England. SLMs also do very well in having large internal average job-shock effects: these average effects are almost 99 percent of what we would get from single-county local labor markets. Overall, SLMs have a weighted average that is better than single-county local labor markets, and much better than combining the entire U.S. into one labor market. Finally, we note that SLMs are likely better than single-county labor markets or one U.S. labor market under *various* weighting schemes, not just the triple weighting. For example, simply adding up the total percentage and the average percentage would still find the SLM definition to be superior.

The CZ local labor market definition does much better than the single-county definition in capturing more spillovers, as it captures over 86 percent. However, the average shock effect within CZs is quite low, at less than 37 percent of what is obtained under a single-county definition. The weighted sum for the CZ areas is somewhat better than that of combining the entire United States into one labor market, but is distinctly inferior to treating each county as its own local labor market.

Compared to the CZ definition, the SLM definition is distinctly preferable in terms of the weighted sum. The CZ definition does capture somewhat more spillovers (87 percent versus 78 percent). But the average within-area job-shock effect is much greater for the SLM versus the CZ definition, at 99 percent versus 37 percent.

Similar comments apply to an even greater degree to the BEA local labor market definition, whether compared to the single-county labor market definition, the U.S. one-labormarket definition, or the SLM definition. The BEA definition captures most spillovers but has very low internal average effects. It is distinctly inferior to the SLM definition and even to the single-county definition, and is little better than the results obtained by treating the entire U.S. as one local labor market.

The CBSA definition is more competitive in achieving the goal of capturing more spillover effects but also of having high average within-labor-market effects. CBSAs capture considerably more spillovers than do single-county local labor markets (83 percent versus 51 percent), and they have average internal effects that are 89 percent of what is achieved by singlecounty local labor markets. The triple-weighting algorithm, which prioritizes high average

effects, ranks CBSAs as being roughly similar in the algorithm score to using single-county local labor markets, and as being much better than treating the entire United States as one local labor market.

However, SLMs are ranked more highly than CBSAs by the triple-weighted algorithm, with a weighted score of 94 percent versus 88 percent. SLMs are slightly worse than CBSAs at capturing spillovers (79 percent versus 83 percent), but significantly better at having a higher average internal labor market effect, at 99 percent versus 89 percent.

SLMs would rank higher than CBSAs under any weighting scheme that puts significant weight on average internal effects. A little calculation shows that SLMs weight higher than CBSAs as long as the internal average effect is weighted at least 40.4 percent as much as the total effect.³⁸

How Different Local Labor Market Definitions Do at Capturing Commuting Flows without Unduly Expanding

As can be seen in Table 16, the SLM approach does better at the weighted percentage measure, as one would expect—that is what it is designed to do. Other local labor market definitions do slightly better at the total percentage measure, but disproportionately much worse at the average percentage measure.

But you might say the game is rigged: of course other local labor market definitions do not maximize a measure that SLMs are designed to maximize. One alternative sometimes used to evaluate local labor market definitions looks at what percentage of commuting flows they encompass—i.e., what percentage of resident workers in the local labor market also *work* in the

³⁸ I.e., a weight of 1 upon the total effect and 40.4 percent on the average effect, or, alternatively, a weight of 69.7 percent on the total effect and 30.3 percent on the average effect.

local labor market, and what percentage of those working in the local labor market also *reside* in the local labor market? Of course, it is trivial to see that this measure could be maximized by classifying the U.S. as one labor market. So, implicitly, we want to capture a lot of commuting, while keeping average population or employment size of the local labor markets down as much as possible. Can we capture a lot of commuting without inordinately expanding local labor market size?

To do this, for each local labor market definition, Table 17 measures what percentage of commuting flows that definition captures, out of total commuting in the contiguous United States (or, for CBSAs, in the contiguous United States outside of New England).³⁹ We then "normalize" this percentage by dividing it by a factor that is proportional to the average employment size of local labor markets under a particular definition. Specifically, we divide the commuting percentage captured by the ratio of the number of average jobs in each local labor

 Table 17 Percentage of Commuting Flows Captured within Local Labor Markets, Compared to Local Labor Market Size, under Different Labor Market Definitions

Contiguous United States					
	Single-county				
	LM	SLM	CZ	BEA	U.S.
% of commuting flows	72.7	87.6	92.7	96.9	100.0
# of LMs	3080	2752	608	177	1
Average job size of LMs	65,026	72,776	329,407	1,131,521	200,279,252
% commuting normalized by	72.7	78.3	18.3	5.6	0.03
average job size					
Non-New England contiguous U	nited States				
	Single-county				
	LM	SLM	CBSA		Non-NE U.S.
% of commuting flows (%)	72.9	87.7	90.2		100.0
# of LM	3013	2698	2150		1
Average job size of LM	63,157	70,530	88,507		190,290,976
% commuting normalized by average job size (%)	72.9	78.5	64.4		0.03

NOTE: "Normalized" commuting percentage is the percentage of commuting flows captured, divided by the ratio of (average job size of local labor market definition / average job size of single-county definition). SOURCE: Author's calculations.

³⁹ For the ease of other researchers, I use the published 2006–2010 commuting statistics to provide commuting flows in Matrix E14, which will be electronically available with this report.

market under that definition to the number of average jobs in each local labor market if each county was its own local labor market.

As Table 17 shows, a single-county local labor definition already captures about 73 percent of commuting flows in the United States. A majority of Americans live and work in the same county.

However, SLMs significantly increase commuting flows captured, up to around 88 percent. And SLMs on average are only slightly greater in size than the single-county local labor market definition.

CBSAs do only slightly better than SLMs, increasing commuting-flow capture to around 90 percent. And CBSAs are on average bigger.

CZs and BEA areas do still better than SLMs, capturing 93 percent and 97 percent of total commuting flows, respectively. But these areas are much bigger than SLMs. If there characteristically exist some political problems or planning problems in "too large" local labor markets, CZs and BEA areas will have many more such problems.

Overall, SLMs seem to do the best job of capturing most commuting flows without creating too many inordinately large local labor markets.

A final note: the comparison of Table 17 with Table 16 shows that single-county local labor markets capture a higher share of commuting flows than they do of spillovers. This is probably due to estimates that show that in terms of impact on "own county" k, a given volume of commuting in "other county" s is more predictive of effects on county k's employment rate than the same volume of commuting in "own county k" (See the discussion above of Table 1; also see Appendix C). As previously discussed, this pattern may occur because marginal

increases in jobs in any county may be more likely to affect employment rates in other counties than is suggested by the average commuting flows across counties of existing jobs.

This pattern illustrates again the advantages of looking at estimated spillover effects to construct local labor markets, rather than just using commuting flows. For example, if we just used commuting flows to define local labor markets—with some positive weight on capturing more commuting flows, and some negative weight on making the labor market bigger—it seems likely that local labor markets would be defined to be somewhat smaller than SLMs. But if local labor market definitions are designed to capture labor markets, it seems better to base the definitions on labor market spillovers rather than simply mechanically seeking to capture commuting flows.

CONCLUSION

This paper develops new local labor market definitions, based on job shocks' spillovers across counties. These new definitions—spillover-based local labor markets, or SLMs—have several advantages compared to current local labor market definitions such as BEA economic areas, commuting zones, and core-based statistical areas. SLMs do a better job of capturing more spillovers while keeping average within-area spillovers high. SLMs also do a better job of capturing more capturing most commuting flows without making local labor markets unreasonably large. Finally—and in my opinion most importantly—SLMs tend to correspond more closely with official local planning regions. Researchers should take seriously the decisions of state and local policymakers about spatial areas that are useful as planning regions. Such real-world planning decisions reflect local judgments about when spillovers are large enough to justify the many

political and planning costs of seeking to reconcile the diverse interests of a larger geographic area.

This paper's SLMs are meant to be a pilot effort toward better local labor market definitions. This pilot project should be tested in various ways. Researchers should see whether this new definition finds, in independent analyses, that demand or supply shocks to the overall SLM, holding constant demand or supply shocks to the county, are consistently important in explaining county labor market outcomes. Furthermore, this paper's SLMs should generally yield larger estimates of demand-shock elasticities compared to using other local labor market definitions. With a better grouping of counties with strong interactions, there will be less of a problem from mixing in counties with weak interactions, or from failing to include counties with strong interactions—either of which biases estimated effects of demand shocks toward zero.

Perhaps more importantly, policymakers in various regions of the country should see whether the new SLMs pass a "sniff test": Do they seem intuitively plausible in terms of how local policymakers understand the size and shape of their own local labor market? Do these new SLMs correspond to local areas within which it is possible to make the case that local residents share strong common interests in local area job creation? Local labor market definitions are ultimately justified by being relevant to both research and policy.

If these SLM definitions are better, they should be used for both research and policy. For research, the resulting estimates should be more reliable. For policy purposes, the resulting SLMs would then be more relevant not only for local planning, but for federal and state targeting of local labor markets. If the federal government or state governments are seeking to target economic development programs or job training programs toward local labor markets that are "distressed," such targeting should be based upon accurate local labor market definitions.

These pilot definitions also could be extended in various ways. These extensions have

already been alluded to, but they include the following:

- Models should be estimated that look at spillover effects on different socioeconomic and demographic groups, and that then define local labor markets based on those spillovers. For example, are local labor market definitions that are based on spillovers for workers with less than a four-year college degree, or for Black workers, much different from these pilot definitions, which are based on all workers?
- Models should be estimated that allow the size of own effects and spillovers to vary with local area distress. As discussed in Bartik (2024), there is some evidence that local job-vacancy chains are geographically more extensive in more distressed local labor markets. If so, how does this alter local labor market definitions?
- Spillover models and local labor market definitions should be developed that use post-2020 data. Are local labor market definitions much altered by the recent increase in remote work?
- Spillover models and local labor market definitions should be developed that rely on using demand-shock instruments, or using reduced-form demand-shock specifications. Does instrumenting with demand-shock instruments make much difference? Do reduced-form demand-shock specifications, which are really estimating the combination of local economy multiplier spillovers plus labor market spillovers, lead to significantly larger definitions of "spillover-based local economies" (SLEs), compared to SLMs?
- How sensitive are spillover models and the resulting local labor market definitions to alternative ways of defining commuting interactions, such as separately including incommuting and out-commuting, or of including indirect commuting through intermediate counties?

Local labor market definitions are too important, for both research and policy, to be based on ad hoc procedures whose merits are not widely discussed in the research and policy communities. Local labor market definitions should be based on spillovers, and on algorithms that are explicit about what the resulting local labor market definitions are trying to maximize and why this maximization makes sense. This paper's pilot estimates are meant both to provide better local labor market definitions to be used now, and to encourage further research to improve such definitions for the future.

APPENDIX A

Misspecifying Local Labor Market Size Is Likely to Lead to Underestimation of the Total Effects of Labor Demand Shocks

This appendix provides some intuitive econometrics arguments for why either underestimating or overestimating the size of local labor markets is likely to lead to underestimation of the total employment rate effects of local labor demand shocks.

For the sake of simplicity, imagine a world in which all the geographic places we are considering combining into larger local labor market units are the same size at baseline in terms of both employment and population. However, these various geographic places may experience different job shocks, all of which are assumed to be demand-generated.

We imagine that there are 2z such initial places, which we consider grouping into z larger local labor markets. Each labor market pair includes a county we call k, and one we call s.

Suppose that we measure the change in the natural log of the employment rate over some time period, which we write as dln(E/P), with a *k* subscript for place *k*, and an *s* subscript for place *s*. *E* stands for employment, and *P* for population. We also observe during this time period some demand shocks to jobs in place *k* and place *s*, which we write as dln(J), with subscripts for place *k* and place *s*.

We wish to accurately measure the total effects of a job shock to place k on employment rates in both place k and place s, and the total effects of a job shock to place s on employment rates in both place k and place s. This will play a role in benefit-cost analyses of job creation policies.

Suppose initially that the true model for how employment rates in both k and s evolve is given by the following two equations:

- (A1) $dln(E/P)_k = B_0 + B_1 * dln(J_k) + B_1 * dln(J_s);$
- (A2) $dln(E/P)_s = B_0 + B_1 * dln(J_k) + B_1 * dln(J_s).$

Here, the d in front of the variables indicates we are considering changes over some time period.

This model implies that place k's and place s's labor markets are fully integrated, in that a job shock of the same size in either place has the same effects on employment rates in either labor market.

A benefit cost model of a shock to J_k would have costs given by

(A3) Costs = $m * dJ_k$, where *m* is the cost of creating one job.

A similar equation would apply to a shock to J_s .

Benefits would depend on the change in E/P due to the job shocks in each place, or

(A4) Benefits =
$$w * d(E/P)_k * P_k + w * d(E/P)_s * P_s$$
.

Here, we look at how the probability of obtaining a job changes, and we assume that applies to the baseline population in each area, P_k and P_s . The factor *w* might be the wages of jobs, adjusted downward by the opportunity costs of work time for individuals, and adjusted upward by the social spillover benefits of people becoming employed—lower crime and substance abuse, more stable families and better child development, etc.

If we directly estimated both Equations (A1) and (A2), we could accurately estimate the benefit/cost ratio of (A4) to (A3). For small changes, or as an approximation, (A1) can be rewritten as

(A5) $d(E/P)_k/(E/P)_k = B_0 + B_1 * (dJ_k/J_k) + B_1 * (dJ_s/J_s)$.

A similar equation applies to place *s*.

E is employment by place of residence at baseline, and J is employment by place of work at baseline. For simplicity's sake, we assume that at baseline the two are the same.

Then the effects of the shock dJ_k on the employment in place k is

(A6) $P_k * d(E/P)_k = B_1 * (dJ_k)$.

And using the equation for place s, the effect of a shock dJ_k to place k on the employment in place s is

(A7)
$$P_s * d(E/P)_s = B_1 * dJ_k$$
.

Therefore, the benefit/cost ratio for a job shock to J_k is

(A8) Benefits/costs = $w * 2B_1/m$.

But suppose we instead decide to define the k and s places in each of these pairs as separate local labor markets. We estimate the following equation:

(A9) $dln(E/P)_k = C_0 + C_1 * dln(J_k)$.

What will the C_1 estimate be? To find out, we look at Equation (A1) and calculate the expected value of $dln(E/P)_k$ conditional on $dln(J_k)$ only.

We get

(A10) Expected value of $dln(E/P)_k$ conditional on $dln(J_k) =$

 $B_0 + B_1 * dln(J_k) + B_1 * expected value of dln(J_s) conditional on dln(J_k).$

The linear expected value of $dln(J_s)$, conditional on $dln(J_k)$, comes from an imaginary auxiliary regression, which will have a constant term of H_0 and a slope term of H_1 . This slope term H_1 would generally be expected to have a value of less than one. That is, a higher shock to lnJ_k will be positively correlated with a higher shock to lnJ_s —these are two counties that are next to each other and are highly integrated—but not one for one.

Therefore, we expect the estimated coefficient C_1 on $dln(J_k)$ to equal

(A11) $C_1 = B_1 + B_1 * H_1$,

which is more than B_1 but less than $2B_1$.

Thus, the regression that omits the paired county *s* will overestimate the effects of shocks to J_k on $(E/P)_k$. However, the benefit-cost ratio will now be estimated as

(A12) Benefits/costs = $w * (B_1 + B_1 * H_1)/m$.

That is, we overestimate the effects of job shocks to J_k on place k, but we totally omit the effects of job shocks to J_k on place s. The omission of the spillover benefits more than offsets the overestimation of the direct effect on place k.

But what if we instead combined each county pair *k* and *s* and estimated equations of the following form:

(A13) $dln(E/P)_{s+k} = F_0 + F_1 dln(J_{s+k})$.

What will F_1 equal?

(A14) $\operatorname{dln}(E/P)_{s+k}$ will approximately equal (1/2) * $\operatorname{dln}(E/P)_k + \frac{1}{2} * \operatorname{dln}(E/P)_s$.

That is, its coefficients will be the average of the coefficients from each of the separate equations.

We now consider what we get when estimating $dln(E/P)_k$ as a function of $dlnJ_{s+k}$ rather than the two separately, or

(A15) $dln(E/P)_k = G_0 + G_1 * dln(J_{s+k})$.

Note that Equation (A1) can be rewritten as

(A16) $dln(E/P)_k = B_0 + B_1 * (dln(J_k) + dln(J_s))$.

Note that $dln(J_{s+k})$ approximately equals $(1/2) * dln(J_k) + \frac{1}{2} * dln(J_s)$. Therefore, the estimated G_1 will be approximately equal to $2B_1$. A similar argument applies to the equation for $dln(E/P)_s$ as a function of $dln(J_{s+k})$. Therefore, the resulting coefficient F_1 would be expected to equal $2B_1$. And the resulting equation will yield a benefit/cost ratio that is correct for the effects of a job shock.

To sum up: we can correctly estimate the benefit-cost ratios of job shocks when there are equal spillovers across place pairs, either by directly estimating both direct effects and spillover effects by separate estimates by place, or by combining the paired places into larger local labor markets. However, if we incorrectly undersize the local labor markets and omit possible spillover effects, we will overestimate the direct effects of job shocks but underestimate the benefit-cost ratio of job shocks by omitting spillover effects.

Suppose instead we are in a different universe, with no spillovers. The correct equation for how shocks to k and s affect employment rates in k is

(A17) $dln(E/P)_k = B_0 + B_1 dln(J_k),$

and a similar equation for place s.

Then, if we do regressions where we treat each place as its own labor market, even if we include $dln(J_s)$ in the regression, we should correctly estimate the coefficient B_1 on $dln(J_k)$ and estimate 0 on the other potentially paired county. And the correct benefit-cost ratio will be

(A18) Benefits/costs = $w * B_1/m$.

But what if we instead mistakenly grouped together the k and s counties and estimated

(A19) $dln(E/P)_{s+k} = H_0 + H_1 * dln(J_{s+k})$

Again, $dln(E/P)_{s+k}$ will be the average coefficient from regressing $dln(E/P)_k$ on $dln(J_{s+k})$ and also regressing $dln(E/P)_s$ on $dln(J_{s+k})$.

But now the true regression is found in Equation (A17). The best linear prediction of (A17) based on $dln(J_{k+s})$ is

(A20) $dln(E/P)_k = B_0 + B_1$ * (best linear prediction of $dln(J_k)$ conditional on $dln(J_{k+s})$.

This auxiliary regression will be

(A21) $dln(J_k) = R_0 + R_1 * dln(J_{k+s})$.

We expect the coefficient R_1 to be less than 1, as job shocks to k and s are positively correlated, but not perfectly so. Therefore, the estimated coefficient H_1 above will equal $B_1 * R_1$, where R_1 is less than one. So, we would underestimate the benefit-cost ratio to the extent to which R_1 is less than one. Given these underestimation biases, there are two ways that one can get correct benefitcost ratios for how to compare job creation costs with the benefits from more jobs due to higher employment rates. The first is to do what the current paper does: explicitly estimate a model that includes possible spillover effects across places. But, as this paper has implied, this is easier said than done. Any such model needs to put some restrictions on how spillovers propagate across places, as the current paper does. Many researchers would not want to spend time exploring the optimal spatial pattern of spillovers.

The second way is to rely on someone else's estimation of local labor market models that create labor market definitions that have small spillovers across places but large spillovers within places. That is the type of local labor market definitions that this paper seeks to construct. We must steer between the dangers of both Scylla and Charybdis—that is, between both the danger of "too small" local labor markets and that of "too large" local labor markets.

APPENDIX B

Rationale for Functional Form for Estimating Effects of Job Shocks to County s on Employment Rates in County k

This appendix rationalizes the functional form used in this paper, which is the estimating Equation 2 in the main text:

(2)
$$\ln(E_{kt}/P_{kt}) - \ln(E_{kt-1}/P_{kt-1}) = B_0 + B_k(L)(C_{kk}/E_{kw} + C_{kk}/E_{kr})^f (J_{kt} - J_{kt-1})/J_{kt-1} + B_s(L)\sum_s (C_{ks}/E_{sw} + C_{sk}/E_{sr})^g (J_{st} - J_{st-1})/J_{kt-1} + \sum_x B_x X_k + \sum_t B_t D_t + \varepsilon_{kt} .$$

More specifically, what I want to rationalize is why it makes sense to define the dependent variable as the change in county k's logged employment rate and to define the job shocks in counties k and s as proportional to the base job level in county k, and why the commuting rates are defined relative to employment in the county of the job shock. The rationalization is not based on a highbrow theoretical model, but rather more on lowbrow intuition.

What we're interested in measuring is, "What are the effects on employment rates in county k per the change in job shocks to county s?" (Without loss of generality, county s could include county k). As outlined in a prior section, the benefits of a change in d(E/P) in county k would be

(B1) benefits of change in E/P in county $k = w * d(E/P)_k * P_k$.

And the costs of a change in jobs in county *s* would be

(B2) Costs = $m * dJ_s$.

The benefit-cost ratio would then be the ratio of the two, or

(B3) Benefits of employment rate increase in county k / costs of job creation in county $s = [w * d(E/P)_k * P_k] / [m * dJ_s]$.

Therefore, the question is, "What functional form would make sense for linking county k's employment rate to job creation in county s through commuting rates?"

To address this, consider that the reason we think employment rates in county k have "benefits" is that the increase in the overall employment rate, which is what we measure, is not simply due to changes in the composition of the local population, but rather reflects a change in employment of the population living in k at baseline. In other words,

(B4)
$$d(E/P)_k = f(dE_{ok}/P_k)$$
.

Here, f() is some positive monotonic function, and E_{ok} is the employment of the population originally residing in k at the baseline period. We can imagine that this might take the form

(B5) $d(E/P)_k = F_0 + F_1 * (dE_{ok}/P_k)$, where F_1 is positive.

Now, how will a shock to J_s affect E_{ok} ? The probability that a given job shock to county s will affect the employment of the original baseline population of county k might be some function of the proportion of jobs by place of work in county s that are filled by commuters from county k, or C_{ks}/E_{sw} . At an extreme, we might assume that it would equal this "average probability" of a job in s being filled by residents in county k times some other term that reflects how the marginal job might be filled differently from the average job, and a term that reflects the proportion of jobs that might go to county k residents that are filled by the original residents. The

probability that a given job shock to county *s* will affect the employment of the baseline population of county *k* might also be a function of the proportion of workers living in county *s* who currently commute to county *k*, or C_{sk}/E_{sr} , as some of these commuters may leave their jobs in county *k* to take the new jobs in county *s*. Again, at the extreme, it might be equal to the probability that a current commuter to county *k* will take the job, which might be equal to the current commuting rate times some positive factor, times the probability that an original resident of county *k* will take the resulting job vacancy.

Therefore, with some substitution, we might assume that the change in $(E/P)_k$ for a small change in employment in county *s*, the partial derivative, can be described by

(B6)
$$d(E/P)_k = F_0 + F_1 * (dE_{ok}/P_k) = h(C_{ks}/E_{sw}, C_{sk}/E_{sr}) * (dE_s/P_k)$$
.

Here, we assume for the moment that employment in county *s* is measured in the same way as in county *k*, which is as the number of people holding jobs, which I signify by using E_s and not J_s on the right-hand side. In contrast, in the empirical work, J_s is measured as the number of jobs, which is obviously not the same concept. I will substitute in J_s later on.

For this paper's particular model, I assume for simplicity's sake that the h() function takes the form $B_s(L)\sum_s (C_{ks}/E_{sw} + C_{sk}/E_{sr})^g$ for all counties *s*, and for each lagged shock to jobs in county *s*. That is, the two commuting terms are simply added and taken to the power *g* for all counties. As long as *g* is positive, this ensures that the commuting-rate term is always monotonically positive—that is, as commuting rates between *k* and *s* increase, the effects of a job shock to county *s* on *k* go up. An exception: I allow job shocks to county k on itself to have effects in which the commuting rate of county k to itself is taken to a different power f and allowed to also be different at different lags.

However, I want to further modify this functional form to deal with two issues. First, I want to manipulate it so that I don't have population on both sides of the equation. Having the same variable on both sides of the equation can lead to biased estimates due to measurement error, which will induce correlation between the independent variables and the disturbance term.

Second, I also want to modify it so that the right-hand-side variable measuring shocks to jobs does not change for different dependent variables. As noted in the paper, I intend in future work on this project to look at how job shocks affect employment rates for specific groups. If we used the population of each group in the denominator, we would have a different measure of job shocks for each group, which seems undesirable.

To get to our final functional form, I note that $dln(E/P)_k$ approximately equals $d(E/P)_k/(E_k/P_k)$ for small changes, and I multiply both sides of the equation by (P_k/E_k) . This gets us a functional form in which we have $dln(E/P)_k$ as a dependent variable. On the right-hand side, the independent variables take the following form:

(B7) Right-hand side:
$$B_s(L)\sum_s (C_{ks}/E_{sw} + C_{sk}/E_{sr})^g (E_{st} - E_{st-1})/E_{kt-1}$$

But this functional form still has a right-hand-side variable with terms such as E_{kt-1} that are on both sides of the equation, and that can cause problems due to measurement error. In addition, the employment terms on the right-hand side reflect not only employers' decisions, but workers' decisions about whether to work one job or more than one job, and this seems undesirable if one is trying to isolate labor demand. Therefore, I adopt a reduced form in which I substitute $(J_{st} - J_{st-1})/J_{kt-1}$ for $(E_{st} - J_{st-1})/J_{kt-1}$

 E_{st-1}/E_{kt-1} . The percentage job shock defined by the number of workers holding jobs is assumed to be some multiple, presumably close to 1, of the job shock defined by the number of jobs. The ratio of the two is absorbed into the *B* coefficients. The costs of the job creation policy are then measured in terms of the number of jobs created, and the benefits in terms of the number of jobs held. The empirical estimation shows how shocks in different counties to the number of jobs affect the number of jobs held by residents in county *k*. The estimation equation measures the change in the ln(employment rate) on the left-hand side using ACS data, and the percentage job shock on the right-hand side using BEA data. This minimizes problems due to measurement error.⁴⁰

For future reference: if we look at the employment rates of specific groups using this methodology with a different dependent variable and the same independent variables, the coefficients *B* will also absorb a proportionality factor (E_{kt-1}/E_{ikt-1}) in which the *i* subscript indicates that the ACS employment number is for demographic group *i*. In other words, to get to the form in which we have an overall employment job shock, we must include that ratio, as we are multiplying both sides of the equation by P_{ikt-1}/E_{ikt-1} . In this case, if we want to compare the job gains and their benefits for group *i* with the overall costs of job creation, one would take the

⁴⁰ I measure the denominator term J_{kt-1} using employment by place of work in the BEA data. One could argue for using employment by place of residence, but a time series on this by county is not available in the BEA data. One can measure at a point in time the ratio of employment by place of residence to employment by place of work, using ACS data on commuting, which, again, looks at whether people have jobs, not the number of jobs. For the 3,080 counties, using the 2006–2010 commuting data, this ratio averages 1.20 when unweighted, and 1.00 when weighted by employment by place of work. The 10th to 90th percentile range is 0.89 to 1.62 in the unweighted data, and 0.77 to 1.29 in the weighted data. So it seems unlikely that changing the denominator to be employment by place of residence would make much of a difference to the regressions. In any event, there is no time series available using the BEA employment concept for employment by place of residence.

estimated coefficients on $(J_{st} - J_{st-1})/J_{kt-1}$ and then divide by this proportionality factor, which would shrink the estimated benefits relative to the total job costs.
APPENDIX C

Employment-Rate Effects of Own County versus Other Counties, at Different versus Similar Commuting Rates

The equations estimated in this paper allow this paper's commuting rate to have different effects for the "own county" versus other counties. Going back to the estimating equation, this commuting rate is

 $(C_{kk}/E_{kw} + C_{kk}/E_{kr})$ for own county k, and

 $(C_{ks}/E_{sw} + C_{sk}/E_{sr})$ for other counties s.

Here, C_{kk} , C_{ks} , and C_{sk} are for commuting within county k, commuting from county k to county s, and commuting from county s to county k. E_{kw} , E_{kr} , E_{sw} , and E_{sr} are employment by place of work in county k, by place of residence in county k, by place of work in county s, and by place of residence in county s. This commuting rate is then taken to a separate power for own county k and other counties s, and then multiplied by different coefficients for county k versus counties s for different lags of job shocks to county k and counties s.

The commuting rate has quite different typical values for k and s. The unweighted average commuting rate for county k is 1.408 and, for the county s with the highest commuting rate, an average of 0.240. The 10th and 90th percentile intervals do not overlap—the 10th percentile for county k for the commuting rate is 1.058, and the 90th percentile for the largest county s is 0.4696. However, there is some overlap at more extreme values: the minimum for county k is 0.4955, and the maximum for a county s is 1.0669.

To see what these commuting rates imply for employment-rate effects at similar commuting rates, I compute the implied present-value effect at five values: 0.240, 0.50, 0.75,

1.00, and 1.408. In doing this comparison, it should be kept in mind that 0.240 and 1.408 are purely hypothetical comparisons. At the mean for the largest county *s* of 0.240, no county *k* has so low a value. And at the mean for the own county *k* of 1.408, no county *s* has so large a value. In contrast, the values 0.50, 0.75, and 1.00 are values that are sometimes, although rarely, observed for both county *k* and county *s*.

By discounted present value, I mean that I compute the employment-rate effect at each lag from zero to nine, and then calculate the discounted sum of these current and lagged effects using a 3 percent discount rate. This is compared with the discounted present value that would occur if all effects were 1, to get an implied annual average discounted value. This was the same calculation used in the text for calculating the dk/ds matrix for counties.

Table C1 shows the results. As Table C1 shows, if we compare the k effect at the k mean (1.408) with the s effect at the s mean (0.240), the k effect is higher: 0.0905 versus 0.0517.

Table C1 Comparing k and s Employment-Rate Effects of Job Shock at Similar Commuting Rates

Value of commuting variable	0.240	0.500	0.750	1.000	1.408
k employment-rate effect	0.0004	0.0039	0.0134	0.0321	0.0905
s employment-rate effect	0.0517	0.1072	0.1603	0.2133	0.2995

SOURCE: Author's calculations.

But at possible overlapping values, the *s* effect is greater. For example, if the own-county commuting rate is 0.750, the effect of a job shock in county *k* on county *k*'s employment rate is 0.0134. But at that same commuting rate of 0.750, the effect of a job shock in county *s* on county *k*'s employment rate is 0.1603, which is about 12 times greater.

As argued in the text, the most persuasive explanation of this is that marginal employment shocks tend to have more influence outside the county than average current employment does. This marginal argument implies that a job shock to county k will have a lesser effect on county k's employment rate, whereas a marginal shock to county s will have a lesser effect on county s, and therefore a greater effect on counties such as county k.

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