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Do Jobs Follow People or People Follow Jobs? A Meta-Analysis of Carlino-Mills studies

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Abstract

The workhorse model for examining the classic question as to whether "jobs follow people or people follow jobs" is the simultaneous equations model of regional employment and population by Carlino and Mills (1987). By performing a meta-analysis of 321 study results from 64 so-called "Carlino–Mills studies", we address two research questions: how varied are the population–employment interaction results of these studies, and why do these results differ? In terms of the variation in results, we find that the results are highly divergent, but that more results point towards "jobs following people" than towards "people following jobs". When it comes to the reasons for the variation in results, we find that the results are mostly shaped by the geographic location, spatial resolution, and population and employment characteristics present in the data, as well as by the model's specification, its functional form and by the spatial weight matrix specification. In contrast, the time period of the data and the inclusion or exclusion of a spatial autoregressive lag in the model do not influence the results. Together, the findings of this study help make sense of the existing population–employment interaction literature and can inform future studies about the research design issues that need special consideration.

Key words: population–employment interaction, jobs–people causality, simultaneous equations, adjustment model, Carlino–Mills model, meta-analysis

Introduction

In the urban and regional literature, few questions raise as much interest –and controversy– as the classic question of whether "jobs follow people or people follow jobs" (Borts and Stein, 1964; Muth, 1971; Steinnes and Fisher, 1974). This question links to several debates, such as whether people primarily move for amenities and quality-of-life factors or for economic reasons (e.g., Partridge, 2010), whether the residential location decision is made before or after the job location decision (e.g., Deding, Filges, & Van Ommeren, 2009), and whether employment locations are really exogenous to residential locations (as assumed in the monocentric city model) or whether there is also a reverse effect (e.g., De Graaff, Van Oort, & Florax, 2012b). In addition, the question is asked in relation to the validity of the opposing regional restructuring and deconcentration theories (e.g., Bierens & Kontuly, 2008), and the longstanding bigger question as to whether growth is primarily driven by (labour) supply or (labour) demand (e.g., Freeman, 2001). Finally, the question plays a central role in policy discussions as to whether catering to the wishes of firms and improving the business climate of a place is a better strategy than catering to the wishes of people and improving the people climate of a place when aiming to stimulate local or regional growth (e.g., Florida, 2002; Storper & Scott, 2009).

In recent years, numerous empirical studies have tried to answer the jobs–people causality question. Yet, despite all these research efforts, the literature appears to be no closer to settling the debate and providing insights that are useful for theorizing, modelling, and policymaking. If anything, the controversy has only deepened since the results obtained have apparently included greater variety and become more difficult to make sense of.

Surprisingly, considering the importance of the question and the current state of knowledge, no efforts have yet been made to synthesize and integrate the results of the many available studies on population-employment interactions. Maybe it has been felt that a systemic literature review would serve no useful purpose as it would only confirm what is already widely believed, namely that the results obtained by these studies are mixed and inconclusive at best. However, we suspect that researchers have refrained from comparing the results from different studies because of the considerable heterogeneity in the data and methodologies used. This heterogeneity not only makes comparison complicated, it also gives the impression that the results are unique to individual studies, and therefore not amenable to summarizing. Whatever the reason, the absence of a systematic literature review means we are not getting the most out of these studies. In particular, it remains unclear which factors are responsible for the apparent wide divergence in research findings and, consequently, whether the ambiguity surrounding the population–employment interaction issue would disappear if these factors were accounted for. For example, are the critical factors related to data sampling, and do the differences in research findings reflect real-world variations in the nature of population–employment interaction (e.g., across space and time), or are they related to the selection of particular methodologies, and does the variation in findings reflect a scientific artificiality, or maybe both? Without understanding *why* the research findings

are *what they are*, the population–employment interaction literature is likely to retain the impression of being highly elusive. Moreover, with no clear answers provided to guide policy, and apparently unending calls for further research, the literature ultimately runs the risk of being viewed as trivial.

In this study, we use an increasingly popular quantitative literature review technique known as meta-analysis to answer two questions: exactly how varied are the findings of studies that address whether "jobs follow people or people follow jobs" and which factors explain this variation? A meta-analysis or "the analysis of analyses" involves the application of statistical techniques to collections of empirical findings from previous studies with the purpose of integrating, synthesizing, and making sense of them (Glass, 1976). Compared to a conventional narrative state-of-the-art literature review, a meta-analysis is more systematic and objective in the selection and weighting of studies. Given that study results are quantified as data and statistical techniques are applied, a meta-analysis can also deal with a virtually unlimited number of studies and generate more powerful insights than can be achieved using narrative review techniques. The most attractive aspect of a meta-analysis, at least for this study, is that it offers the opportunity to conduct a meta-regression analysis. In such an analysis, study results can be directly linked to data sampling, methodologies, and other aspects of the studies incorporated. By assessing marginal effects, insights can be obtained into the robustness of study results and into the factors that explain most of the variation within them. Such insights not only help to understand the existing body of research, but also inform future studies about research design issues that warrant special consideration.

In the meta-analysis in this study, we focus exclusively on studies that have used the workhorse model, i.e. the simultaneous equations model of regional employment and population developed by Carlino and Mills (1987), to examine the classic question of whether "jobs follow people or people follow jobs". Although this model is by no means the only methodology used, and has been criticized (see Rickman, 2010), it is by far the most widely used and most recognized methodology, and provides sufficient comparable studies to perform a meta-analysis.

The remainder of this paper is organized as follows. We start with a discussion of studies that would be considered relevant for our meta-analysis, followed by a description of the econometric model used in these studies. We then describe how we selected studies and present the variation in research findings from these studies. Subsequently, we discuss the factors that might explain this variation, and then describe the results of a regression analysis in which the impacts of these factors are formally tested. Finally, we summarize the main findings of our study and discuss possible avenues for further research.

Literature review

The interest in the jobs–people causality question spans some forty years during which time different techniques and data have been used to answer the question. In essence, two main periods can be distinguished. In the late-1960s, the question was first raised and a variety of techniques were advanced in a small and fragmented group of studies.

This was largely the situation until the late-1980s, since when the number of research studies has rapidly grown and there has been relatively little disagreement over the choice of methodology. The dividing line between these two periods can be linked to the publication of *The Determinants of County Growth* by Carlino and Mills (1987), which marked a radical departure from previous causality studies in two respects.[1] First, the study by Carlino and Mills was the first to conduct a US nationwide analysis of population–employment interactions on a very detailed spatial scale (i.e., at the county level). Before this, the jobs–people causality question was mostly examined for metropolitan areas, and then often not using detailed zonal data but data aggregated into central city and suburban areas. Second, and even more importantly, it was the first study to investigate these interactions using a simultaneous equations model similar to the one introduced by Steinnes and Fisher (1974) but with a lagged adjustment framework built in. With the introduction of this now classic model, a methodology became available that was not only based on sound theoretical foundations and straightforward to use, it was also highly versatile and multifunctional.

Initially, the model developed by Carlino and Mills (referred to as the CM model hereafter) was mainly used to shed light on the wide range of potential regional growth determinants. Later, starting with Boarnet (1992, 1994a, 1994b), spatial cross-regressive lags were integrated that opened up the possibility of assessing population–employment interactions across locations. Several years later, Bao (1996) used the model to investigate possible backwash and spread effects by integrating interaction terms that revealed whether population–employment interactions differed among rural areas because of the size and growth of neighbouring urban core and urban fringe areas. Also for the first time, spatial autoregressive lags were added to investigate alternative forms of spatial interaction, namely direct spillover effects in population growth and in employment growth across locations (Vias, 1998). By the beginning of this century, a spatial econometric system with both cross-regressive and autoregressive lags had been introduced in which both population–employment interactions across space and direct spillover effects could be examined (see Henry, Schmitt, & Piguet, 2001). Also, Feser and Isserman (2006) used model estimates with different spatial lags to reveal the range and distance decay of the spillover effects from urban, rural, and mixed urban/rural areas. In a novel application of the CM model, Cho, Kim, Clark, and Park (2007) later integrated locally weighted regression techniques to investigate whether the relationships found in the model were consistent or varied across space.

With the increasing availability of data, the CM model has also been increasingly used in studies of subgroups of jobs and people. Initially, these studies simply compared the results of different model estimations to assess whether the location determinants that affect population and employment as a whole differ between subgroups. Later, extended CM models with multiple employment and/or population equations were developed to account for interactions among subgroups. For example, Vias (1998) investigated the

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[1] To illustrate the importance attached to this publication, it was identified by Isserman (2004) as the most cited regional science article of 1987.

link between basic and non-basic industries, while Deitz (1998) examined whether the locations of particular professional groups were affected by the locations of other professional groups. Using spatial econometric CM models, Schmitt, Henry, Piguet, and Hilal (2006), Abildtrup, Piguet, and Schmitt (2012), and De Graaff, Van Oort, and Florax (2012a, 2012b) investigated intra-industry linkages, inter-industry linkages, and linkages with the population for various sectors of the economy, while Zhang and Guldmann (2010) also focused on the interactions within and among ethnic population subgroups. Hoogstra (2012) also used a spatial econometric CM model, this time focussing on interactions within and among gender-specific employment subgroups.

The CM model has also become a popular tool for investigating possible causal relationships other than those between population and employment. For example, several studies have focused on possible feedback simultaneities of population and employment with income or wages (e.g., Carruthers & Mulligan, 2008; Dudensing & Barkley, 2010; Mills & Lubuele, 1995). Various other relationships have also been considered, involving variables such as the value and stock of agricultural land (Hailu & Brown, 2007), housing values and land area (Woo, 2007), and entrepreneurship (Mojica-Howell, Whittaker, Gebremedhin, & Schaeffer, 2012). More recent studies have also adopted CM models but without population and/or employment variables. The relationships investigated in these studies include those between migration, housing stock, and employment (Vermeulen & Van Ommeren, 2009), employment and gross domestic product (Ke & Feser, 2010), quality of life and population (Royuela, 2011), non-farm proprietorships and income (Krishnapillai & Kinnucan, 2012), in-migration, out-migration, income, employment, and public services (Gebremariam, Gebremedhin, Schaeffer, Phipps, & Jackson, 2012), creative employment and air traffic (Neal, 2012), and births, deaths, and the persistence of firms (Brown, Lambert, & Florax, 2013).

Given that the CM model can separate out the impacts of population–employment interactions, spatial linkages, etc. from other growth factors, it offers great possibilities for policy and impact analysis. These possibilities were first recognized by Luce (1994) who employed a CM model to examine the impact of different types of taxes and government spending on local growth patterns. Later, Bollinger and Ihlanfeldt (1997) used a CM model to evaluate the impact of Atlanta's MARTA rail system, while Duffy-Deno assessed the impacts of endangered species protection (1997a), state parks (1997b), and wilderness preservation (1998) on rural county growth in the US Intermountain West. In recent years, more policy-related studies have gradually been conducted, measuring the effects on growth of economic and environmental policies (Li, 2006), urban containment policies (Woo, 2007), highway investment (Funderburg, Nixon, Boarnet, & Ferguson, 2010), and growth management programmes (Boarnet, McLaughlin, & Carruthers, 2011). In another group of studies, policy implications played a central role in studies using a CM model to assess whether social capital (Callois & Schmitt, 2010), competitiveness (Dudensing & Barkley, 2010), and amenities (e.g. Waltert, Schulz, & Schläpfer, 2011) can stimulate economic growth. More recently, in a somewhat different study than those focussing on the impacts on growth, Kim and Hewings (2013) estimated CM models for forty different US metropolitan areas in an

attempt to reveal the effect of land use regulations on population–employment interactions.

Finally, a few studies have explicitly considered the dynamic properties of the CM model and have used it as a forecasting or scenario analysis model. The first, and until recently the only, example of such a study was conducted by Mills and Lubuele (1995). They estimated a CM model to make projections for the population, employment, and income of US metropolitan areas for the year 2000. Twelve years later, in another study of these metropolitan areas, Carruthers and Mulligan (2007) estimated a CM model to forecast land absorption in these areas beyond the year 1997. De Graaff et al. (2012a) more recently explored the possibilities of using such simulations to predict the impacts of an exogenous shock. They compared the future distributions of jobs and people in and around the Dutch city of Almere in 2028 under a base scenario (without an exogenous shock) and under a policy scenario that foresaw the building of 60,000 additional dwellings in this city. Similarly, Kim and Hewings (2012) generated future growth trajectories for municipalities in the Chicago metropolitan area up to 2040 under three different national economic growth scenarios. The novelty of this study was that they used the CM model as part of a multi-level framework that also included a regional input–output model.

In our meta-analysis, we will focus exclusively on studies that have used a CM model (hereafter referred to as CM studies or the CM literature) because this is by far the most widely used and most recognized methodology for answering the question whether "jobs follow people or people follow jobs". What is more, given that the CM model has become one of the main workhorses in the urban and regional literature, this model in itself certainly presents an interesting case for investigation. Finally, despite the group of studies that have used this model being sufficiently homogenous to permit comparison, it is also quite large and diverse. While at face value this may seem to complicate matters, it makes these studies particularly suited to being investigated by the meta-regression techniques that we apply in this study.

Admittedly, the CM model is not the only methodology that has been used to investigate whether jobs follow people or people follow jobs. Further, the model has drawn severe criticisms, most notably because the identification of the simultaneous equations system is often problematic because of the lack of good instruments and that, therefore, the results may not be reliable (e.g., Rickman, 2010). Were it not for the need to select a clearly recognizable group of comparable studies, our meta-analysis might well have been broader and included studies that used alternative methodologies such as time series techniques. Inferences could then have been made, such as whether vector autoregressive models produce different results to simultaneous equations models. Here, it is important to note that different approaches do exist, and that the question whether one approach is perhaps more fitting than another is outside the scope of this particular study. In response to the criticism that the CM model very much relies on the use of appropriate instruments, we do investigate whether, and to what extent, the results are affected by the exclusion of several types of control variables.

Econometric model

The CM methodology is essentially based on two main ideas. One is that the location choices made by firms and by households are affected by each other and by a variety of other exogenous variables that influence profits and utility levels across locations. The other is that firms and households in changing locations move towards a state of equilibrium (in which profits and utility levels are the same everywhere), but that the adjustments towards equilibrium occur with a time lag. For this reason, CM models are frequently referred to as partial adjustment models, lagged adjustment models, or disequilibrium adjustment models.[2] The idea that population and employment are not fully adjusted to each other is reflected by the inclusion of a time-lagged population [employment] variable on the right-hand side of the population [employment] equation. The magnitude of the parameter estimates for these variables reveals the speed of adjustment towards equilibrium and whether the assumption of lagged adjustment process is justified. The idea that population and employment are jointly determined is reflected by the inclusion of an endogenous employment [population] variable on the right-hand side of the employment [population] equation. A positive and significant parameter estimate for the endogenous employment variable in the population equation can be taken as confirmation that "people follow jobs". Similarly, a positive and significant parameter estimate for the endogenous population variable in the employment equation can be taken as evidence that "jobs follow people".

In reality, there is no such thing as *the* CM model, as there are many different specifications that fit the description above. Equations (1) through (6) below describe an econometric framework that encompasses the most commonly used specifications and that reveals the most fundamental differences between them.[3]

$$\bar{E}_t = \alpha_0 + \alpha_1 E_{t-1} + \alpha_2 (I + \bar{W}_1)\bar{P}_t + \alpha_3 \bar{W}_2 \bar{E}_t + \alpha_4 S_{t-1} + u_t \tag{1}$$

$$\bar{P}_t = \beta_0 + \beta_1 P_{t-1} + \beta_2 (I + \bar{W}_1)\bar{E}_t + \beta_3 \bar{W}_2 \bar{P}_t + \beta_4 T_{t-1} + v_t \tag{2}$$

$$\bar{E}_t = E_t - \delta_1 E_{t-1} \tag{3}$$

$$\bar{P}_t = P_t - \delta_2 P_{t-1} \tag{4}$$

$$\bar{W}_1 = \delta_3 W \tag{5}$$

$$\bar{W}_2 = \delta_4 W \tag{6}$$

where P [E] is a population [employment] variable; S [T] is a vector of control variables affecting employment [population]; I and W represent an identity matrix

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[2] The theoretical foundations of the model are extensively described in many other studies and are not further discussed here. For more details, we refer to Carruthers and Mulligan (2007), and Mulligan, Vias, and Glavac (1999).

[3] For simplification, the framework does not include multiple equations for subgroups of jobs or people, or additional equations for other possible dependent variables such as income or wages.

and a spatial weight matrix, respectively; α and β are estimable parameters, or vectors of estimable parameters; u and v are stochastic error terms; the δ terms are scalars that are either 0 or 1; and subscripts t refer to time.

The fundamental differences in the model specifications above are shown in the different values of the scalars δ_1, δ_2, δ_3, and δ_4 in Equations (3) through (6). The values of δ_1 and δ_2 reflect whether the key population and employment variables on the left-hand and the right-hand sides of the equations are measured as changes ($\delta_1 = \delta_2 = 1$) or as end-of-period levels ($\delta_1 = \delta_2 = 0$). A value of 1 for δ_3 indicates that the specification takes the form of a spatial cross-regressive system in which each equation includes the spatial lag of the dependent variable from the opposite equation (Rey & Boarnet, 2004). In such systems, the population [employment] in a location is modelled as a function of the employment [population] in the same and in neighbouring locations that together make up the labour market zone. A value of 1 for δ_4 indicates that the model has the form of a spatial autoregressive system in which a spatial lag is included to control for spatial dependence within rather than across the equations. Table 1 presents a taxonomy of model specifications used in the literature based on the different values for δ_1, δ_2, δ_3, and δ_4.

< insert Table 1 somewhere here>

Studies and results
Following the discussion as to what constitutes the CM methodology, the next step in the meta-analysis is to retrieve relevant studies. We initially used the *Google* and *Google Scholar* search engines to select all documents that referred to the studies of Carlino and Mills (1987) or Boarnet (1994a, 1994b), or that included keyword combinations such as "jobs follow people", "people follow jobs", "intra-regional", "intra-urban", or "adjustment model". Using the same set of keywords, we also scanned the internet databases of *EconLit* and *ProQuest*. Subsequently, we extracted all the research studies, screened the references used in these studies, searched for other publications by the same authors, and contacted several authors to ask for additional information. Based on a quick scan of the identified research studies, we rejected all those that were not econometric studies written in English. We then used Equations (1) and (2) to objectively decide whether the econometric models used in the remaining studies satisfied the criteria for involving a CM model specification. Here, over thirty studies were excluded because either a reduced form CM model (i.e., without endogenous variables) was estimated, the employment or population variables were defined differently across equations, or the CM model did not include a population or employment equation. As a further filtering step, we only selected studies that gave a full account of the parameter estimates and standard errors. The final issue encountered was that the information provided in peer-reviewed journal articles and in working papers, research reports, theses, and dissertations was often very similar because the latter were preliminary versions of the former. To avoid double counting, we decided to include only those working papers,

research reports, etc. that provided some unique information for our database.[4] At the end of this sifting process, we were left with 64 CM studies, from which we were able to retrieve a total of 321 results in the form of parameters that revealed the relationship between population and employment, i.e., α_2 and β_2 in Equations (1) and (2).

In this study, we are only interested in what these parameter estimates tell us about the direction of the relationship (i.e., whether jobs follow people or people follow jobs). Therefore, we focussed only on the sign and statistical significance of the estimated parameter values and distinguished four categories of research findings.

1. <u>NI</u> (No Interaction): Neither α_2 or β_2 are significant at conventional statistical levels or they do not display the expected positive sign: i.e., "jobs do not follow people and people do not follow jobs";
2. <u>JP</u> (Jobs follow People): Only α_2 is positive and significant;
3. <u>PJ</u> (People follow Jobs): Only β_2 is positive and significant;
4. <u>DC</u> (Dual Causality): Both α_2 and β_2 are positive and statistically significant, i.e., "jobs follow people and people follow jobs".

In Figure 1, we address the variation in results by investigating the signs of parameter values at the 1%, 5%, and 10% significance levels. By including a range of significance levels, we consider the possibility that the distribution of results is influenced by the chosen cut-off value in determining whether the estimated parameter values are different from zero. We also take into account the possibility that sets of estimation results based on the same dataset might be more similar than those being based on different datasets. Therefore, in addition to an unweighted sample of study results, we also present the distribution of results for a weighted sample of study results in which the weights reflect the number of model estimations that have been performed on overlapping datasets. The 321 estimation results included in our sample are based on a total of 150 completely different datasets (in terms of region, time period, and population and employment types). Of these datasets, 106 datasets have been used in single model estimations and 44 datasets have been used in multiple model estimations (for example, in the most extreme case, 45 model estimations were performed on census tract data from US Orange County for the years 1980-1990). By applying weights, we avoid sets of estimation results based on overlapping datasets overly contributing to the analysis. In our analysis, the results are given weights that add up to 308/150 = 2.14 per dataset (for example, the 45 results for "Orange County, 1980-1990" are each given a weight of 321/ (45*150) ≈ 0.0446).[5]

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[4] Here, 'unique' is taken to mean that a study must show a different value for at least one of the variables included in our meta-regression analysis.

[5] In our study, weighting by dataset makes more sense than weighting by study, the approach usually employed in meta-analytical studies (see Bijmolt & Pieters, 2001). In our sample, several CM studies had utilized the same data, and so the results of these studies are quite likely to be similar. Note, however, that results are not necessarily similar within individual studies because the same subset of

< insert Figure 1 somewhere here>

Figure 1 shows that the distribution of results does indeed vary with different significance levels. In more detail, 245, or roughly three-quarters, of the 321 observations give the same results irrespective of whether a 10%, 5%, or 1% significance level is used. However, in 46 cases the result changes when using a 1% level (rather than a 5% or 10% level), and 27 cases give a different result at the 10% level (in comparison to the 5 and 1% levels). Finally, in three instances, inferences about the population–employment relationship are completely different at each of the 10%, 5%, and 1% significance levels.

Naturally, using a 1% significance level is more likely to produce parameters that indicate "no interaction" than when applying 5% and especially 10% significance levels, while the opposite is true for results indicating "dual causality". While the changing number of significant results for these statistical categories comes as no surprise, it is interesting to see from Figure 1 that the increase in "no interaction" is substantially greater than the decrease in "dual causality" as increasingly conservative significance levels are applied. When it comes to the results that indicate one-way causality, from population to employment or from employment to population, the effect of using different significance level is harder to predict. From Figure 1, it can be seen that results that indicate "people follow jobs" are little affected by significance level. However, where studies indicate that "jobs follow people", while there is little difference between the 5% and 10% level results, there is a noticeable decline when the significance level drops from 5% to 1% that is similar to the decrease seen with the results that indicate "dual causality".

Overall, Figure 1 confirms the generally held, but previously untested, perception that the findings of studies on whether "jobs follow people" or "people follow jobs" are very mixed. That said, more of the findings point towards "dual causality" than towards "jobs following people" or "people following jobs". Further, considerably more results point towards "jobs follow people" than indicate "people follow jobs". Our weighting of the results does not appear to have made much of a difference unless the proportion of results indicating "dual causality" has increased at the expense of those indicating "no interaction". After weighting, "dual causality" is the largest category when significance is determined at the 10% and the 5% levels but "no interaction" remains the largest category at the 1% level, albeit less so than with the unweighted sample.

The variation in results displayed in Figure 1 reinforces the argument made at the start of this study that more needs to be understood about the impact of data sampling and methodological choices. For example, the fact that more findings point towards "jobs

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data are not always used across the various model estimations. Later in our meta-regression analysis, we address this overlap of data when we control for possible interdependency among the study results.

follow people" than towards "people follow jobs" may be due to the fact that most studies use data from a specific country, such as the US, or data that refer to a particular time period such as the 1980s. Similarly, it may be that a specific methodology more often yields results indicating "jobs follow people". In other words, while the observation that the results of population–employment interaction studies are mixed is valid, it is more important to understand what is behind the variation in results. It is this issue that we turn to next.

Study features

Essentially, a distinction can be made between three broad categories of factors that can be expected to explain the variation in population-employment interaction findings across the CM literature, namely (1) data-related *substantive* factors that reflect real-world variations in the nature of population-employment interaction, (2) *methodological* factors that reflect the impact of differences in research design and possible distortion, bias, or artificialness in the study results, and (3) *external* factors that are not about the impact of data sampling or methodological choice, but related to the characteristics of the researcher(s) or the publication outlet.

First, addressing data-related substantive study features, it can reasonably be hypothesized that the results of CM studies will vary because different regions, time periods, and population and employment groups are analysed, and because the analyses are performed on different spatial scales. Indeed, one of the most prominent assumptions made in the literature is that the direction of the population-employment interaction is not the same everywhere. This assumption is also one of the main reasons for the continuing application of CM studies – given this variability, it is almost impossible to generalize the results from existing studies (or to transfer the results from one site to another). Indeed, evidence provided by Hoogstra, Florax, and Van Dijk (2011) and Kim and Hewings (2013), in which the CM model was respectively tested on data from different localities in the Netherlands and different US metropolitan areas, supported the idea of spatial heterogeneity in the population–employment relationship. In terms of the spatial resolution of data, studies focusing on the modifiable area unit problem (Openshaw, 1984) have repeatedly shown that model parameter estimates can fluctuate significantly and even exhibit sign reversal at different levels of aggregation. Also, and more specific to population–employment interactions, the suggestion has been made that intra-regional applications of the CM model are especially likely to generate statistically insignificant parameter estimates (Hoogstra et al., 2011). This is both because of the difficulty in controlling for spillover effects and also because firms and households probably adjust to each other on the regional, rather than the local, scale when it comes to labour markets. Regarding possible temporal changes in the population–employment relationship, it has been suggested that, with the transition from a manufacturing-based society towards a service-oriented one in which knowledge, information, and creativity are key, the balance has shifted from "people follow jobs" to "jobs follow people" (see, e.g., Florida, 2002). Finally, as also discussed in the Literature Review section, several CM studies have already focused on possible differences in the nature of population-

employment interactions between subgroups of jobs and people (see, e.g., Abildtrup et al., 2012; De Graaff et al., 2012a, 2012b; Hoogstra, 2012). These studies clearly indicate that applying the CM model to total population and employment data may conceal important differences between subgroups, and especially between jobs in population-related service industries and those in export-driven manufacturing industries.

The possible effects of certain methodological choices have been the subject of considerable speculation, and some systematic research has been conducted (e.g., Boarnet, Chalermpong, & Geho, 2005; Hoogstra et al., 2011; Mulligan et al., 1999). The conclusion emerging from these studies is that different applications of the CM model can produce very different results, even if exactly the same data are investigated. Focusing on these methodological features could reveal crucial insights for future studies as to which methodological issues need careful consideration. Moreover, we may find out whether differences in the quality of the modelling (and the possibility that the estimation results obtained are unreliable) can go a considerable way in explaining the wide divergence in findings across the CM literature. For example, it could be that models without spatial autoregressive lags, with only two equations, or without certain control variables suffer from an 'omitted variables bias'. Similarly, suggestions have been made that estimating a log-linear CM model is preferable to a regular linear CM model because logarithmic transformations usually provide a better fit to the data (see, e.g., De Graaff et al., 2012a, 2012b; Hoogstra 2012; Vermeulen & Van Ommeren, 2009).

The possible impact of external factors, and particularly the publication status of a study, has been regularly investigated in meta-analytical studies. Although the publication in which a study appears does not in itself affect the research outcomes, it may reflect the selection criteria and reporting proclivities of the authors, reviewers, and editors who decide if and how a study will be published (Cooper, Hedges, & Valentine, 2009).

On the basis of the hypotheses outlined above and the data that can be extracted from the available CM literature, we distinguish four data-related factors that may offer additional information about possible real-world variations in the population–employment relationship. First, concerning the geographical characteristics of the data, a distinction is made between model estimations on data from the US Pacific (71 observations), from the US Mountain West and Midwest (48), from the US Northeast and South (75), non-US (mostly European) data (78), and data covering the entire US (49). Second, addressing the spatial resolution of the data, we distinguish between small (62), intermediate (188), and large area observations (77).[6] Third, concerning the

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[6] Cut-off values of 2.9 and 607.9 square miles were used to distinguish between these different area observations, which were determined by calculating the mean and standard deviation of the average land area size (in natural log square miles) of the spatial observations from 321 datasets. Note that spatial areas such as US census tracts and US counties may significantly differ in size. For example, only US census tracts in highly urbanized areas tend to be classified as small area observations and only US counties in rural areas fall under large area observations. For most of the CM studies, external Internet data sources were used to obtain the necessary information on area size.

temporal characteristics of the data, we distinguish between data from the 1970s and 1980s (157) and from the 1990s and 2000s (164). Finally, regarding the population and employment characteristics of the data, a straightforward distinction is made between data for subgroups of jobs and/or people (58) and aggregated "total" employment and population data (263).

Note that on the basis of the information that is available it is difficult to determine exactly why the direction of the population-employment relationship is not necessarily the same everywhere. In order to be able to explain possible spatial heterogeneity in the relationship, information is needed about the industry structure, the composition of the labour force, land use regulations, and other features of the regions under investigation. In the absence of such information, we can only conclude whether the jobs-people causality direction varies among the US regions, the US taken as a whole, and regions outside the US, and not relate this to variables that reflect differences in regional characteristics. Further, the information provided in the CM studies does not allow a very detailed investigation of possible time and group effects. Ideally, we would, for example, have made a distinction between basic population-related employment services and more traditional export-based industries.

In addition to the substantive factors, we also include several factors that might reveal possible *methodological* sources of distortion, bias or artificialness in the study results. First, based on the taxonomy presented in Table 1, we make a distinction between three different CM model specifications: one in which both the RHS and LHS endogenous variables are measured as end-of-period levels (i.e., specifications a, d, and e in Table 1; 54 observations), another in which these variables are measured as changes and as end-of-period levels respectively (i.e., specifications b and g in Table 1; 49 observations), and one in which both these variables are measured as changes (i.e., specifications c, f, and h in Table 1; 218 observations). Second, a division is made between those applications of the CM model in which these variables are expressed in terms of population and employment densities or shares (i.e., population and employment numbers standardized by area size or by total population and employment size; 106 observations) and those using absolute numbers (215). Third, concerning the inclusion of a spatial cross-regressive lag and the specification of the spatial weight matrix *W*, we distinguish two categories: models in which the RHS endogenous variables include a spatial cross-regressive lag that is calculated in conjunction with a flow matrix (53) and those models in which the RHS endogenous variables either lack a spatial cross-regressive lag or have a lag that is calculated in conjunction with a standard inverse distance or fixed distance based weight matrix (268). Fourth, considering the functional form of the CM model, we distinguish between non-linear (mostly logarithmic) specifications (81) and linear specifications (240). Next, we distinguish between model specifications with (52) and without (269) spatial autoregressive lags, and between model specifications with three or more dependent variables (66) and the more common two-equation systems (255). Further, we distinguish between model specifications that either exclude or include one or more variables to capture (a) land use or spatial policies

(186 versus 135), (b) income, wages, or rents (126 versus 195), and (c) various economic characteristics such as the industry structure and productivity (105 versus 216).[7]

Finally, to assess a possible publication bias in the results of the CM studies, we incorporate a single external study factor that divides studies published in peer-reviewed academic journals (217) from studies reported in working papers, book chapters, dissertations, and other documents (104).

Meta-regression analysis

Following the separate discussions of study outcomes and selected study-specific factors, we proceed with an examination of the impact of each of the selected factors on the distribution of study outcomes. Given that we have four discrete outcomes that have no natural ordering, our analysis takes the form of a multinomial logistic regression. Using a multinomial logit model, the dependent variables are the log odds, or logits, of an outcome relative to another outcome. Also, for each factor variable that is included on the right-hand side of the equations, one level is omitted and this functions as a comparator. Accordingly, the estimated regression coefficients reveal the change in log odds, or the additive effect of each level relative to the omitted level (for which the coefficient is 0).

Rather than focusing on estimated regression coefficients, we prefer to summarize the results of the multinomial logit model in terms of marginal effects. Marginal effects can be calculated following the estimation of the multinomial logit model by holding the explanatory variables at their sample means**.** Generally, marginal effects provide a similar qualitative picture to using estimated regression coefficients but can be easier to interpret (as they do not depend on the chosen baseline category). For the factor variables, they simply measure the change in the probability of a particular outcome in the form of a discrete change (in terms of percentage points) from the base level. By comparing percentage points across outcomes and study features, insights can be gained as to which outcomes are mostly affected and which features make the greatest difference.

Here, it is important to be aware that population-employment interaction findings that are based on the same data are not independent of each other. Consequently, treating them as independent would deflate standard errors and result in artificially small p values. To avoid this risk, we estimated the multinomial logit model with clustered standard errors (the standard errors were adjusted for 150 data clusters; see also footnote 5). A further stringent assumption of a multinomial logit model is that the outcome

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[7] Initially, we also considered a range of other categories of location-specific variables, including natural amenities and recreational facilities, demographic characteristics (e.g., age and ethnic composition), labour market characteristics (e.g., unemployment and skill levels), and location characteristics (e.g., central locations and distance to urban core). These categories turned out to be non-significant predictors and were therefore excluded from the final model.

categories have the property of independence of irrelevant alternatives (IIA). For this assumption to be valid, the odds ratio for each specific pair of outcomes must not change by the exclusion (or inclusion) of an alternative outcome. We investigated whether this assumption was justified by also estimating a multinomial probit model since these do not rely on the IIA assumption. The estimated marginal effects of this latter model were similar to those obtained using a multinomial logit model (this was not unexpected given that the four categories are very dissimilar and not likely substitutes for one another).

In the discussion below, we concentrate on the results of the logistic regression using the population-employment interaction findings at the conventional 5% significance level. We also ran the logit model on study outcomes that revealed these interaction findings at less and more stringent significance levels (10% and 1%). The results of these alternative model estimations, which are broadly similar to those presented below, are not included for space reasons but are available upon request. Table 2 summarizes the marginal effects that are calculated from the multinomial logit model (for descriptive statistics and chosen baseline categories, see Appendix A; for estimated regression coefficients, see Appendix B).

< insert Table 2 somewhere here>

Starting with the substantive study factors, the marginal effects displayed in Table 2 clearly indicate that the region being investigated has a major impact on the findings related to the direction of the population–employment interaction, and in particular on the finding of "dual causality". More specifically, when data from the entire US are used to estimate the CM model, the probability that the estimated model parameters will point towards "dual causality" is about 80% higher than when data from the US West, the US East, or from outside the US are used. A reasonable conclusion to draw is that the region covered by the data must be significantly large and varied (in terms of industries, workers, and economic and living conditions) for the parameters of the CM model to point towards two-way interaction. Further, Table 2 reveals some noteworthy differences between sub-regions of the US. Whereas the "no interaction" outcome is common in the US West findings, the US East seems to be more associated with "people follow jobs". Apparently, people in the US East (consisting of the Northeast, Midwest and South) are more likely to move because of economic motives. It is also interesting to note that the interaction running from people to jobs (i.e., "jobs follow people") appears to be more characteristic of regions outside the US than those in the US. When we hold all other explanatory variables constant at their means, our model predicts a 47.6% increase in the probability of finding "jobs follow people" using non-US data than data covering the entire US. Since the non-US data mostly comes from Europe, this finding is perhaps not particularly surprising given earlier findings. Studies by Blanchard and Katz (1992) for the US and by Decressin and Fatas (1995) for Europe clearly show that adjustments in the labour market mainly occur through migration in the US whereas, in Europe, changes in regional participation are much more significant. In Europe, housing markets are

usually very tight and there is greater social security, which alongside cultural differences means that people are generally less mobile than people in the US.

The results also show that population-employment interaction findings are not the same at different spatial levels of analysis. In line with expectations, we found that applying the CM model with small area observations (such as urban census tracts) has a significantly greater chance of finding "no-interaction" than applications on medium area observations (+61.4%) and especially large area observations (+77.8%). Conversely, with large area observations (such as US metropolitan areas or US rural counties) there is a nearly 70% higher probability of finding "people follow jobs" than with small or medium area observations. Compared to other observations, medium area observations (such as US municipalities and most US counties) are nearly 50% more likely to point towards "dual causality". Evidently, and perhaps unsurprisingly, migration is a much more important adjustment mechanism at larger spatial scales where the distance between job and residential location may be too large to resolve by commuting.

The results also reveal that using aggregate population and employment data rather than data referring to specific subgroups of jobs and people has a major influence on the findings. Perhaps surprisingly, when data referring to subgroups are used, there is a substantially greater chance of finding "no interaction" (by 72.9%), and less likelihood of finding either "jobs follow people" or "dual causality". A possible explanation for this finding is that studies using subgroups relatively often focus on manufacturing and other traditional industries rather than on population-related consumer services.

When we assessed the influence of the time characteristics present in the data and controlled for the impact of other factors, we found that the predicted probabilities of each outcome were very similar for data from the 1970s or 1980s and for data from the 1990s or 2000s. This result contradicts the commonly held idea that the balance has shifted from "people follow jobs" to "jobs follow people" (see, e.g., Florida, 2002). It could be that such a shift has still not fully materialized, or that the time periods used here are too broad to capture such a shift. In comparison, Partridge, Rickman, Olfert, and Ali (2012) found that migration patterns in the US fundamentally changed during the 1990s and 2000s and that, post-2000, US labour markets have become similar to those in Europe in the sense that reductions in local unemployment and/or increases in local labour force participation have replaced migration as the primary labour supply response to spatially-asymmetric labour demand shocks. It is also possible that shifts from "people follow jobs" to "jobs follow people" have taken place but only in certain places (such as the urban creative centres suggested by Florida, 2002) that have not been extensively studied in the existing CM literature and therefore not reflected in our meta-analysis.

Turning to the impact of methodological study factors, it can be seen from Table 2 that all factors, except for the inclusion or exclusion of a spatial autoregressive lag, demonstrate (at least at the 10% significance level) significant marginal effects. Here, using a CM model specification that focuses on the relationship between population and employment levels, rather than on changes therein, shows the greatest impact. Depending on which model specification is used, the predicted probability of a particular

outcome can vary by as much as 70.0% (for jobs follow people). Further, the outcomes very much depend on whether the model focuses on population and employment densities or sizes, whether or not a flow matrix is used to calculate spatial cross-regressive lags, the functional form of the model, and, to a lesser extent, on the number of equations/dependent variables included in the model. When using densities, non-linear functional forms, 2+ equations systems, and flow matrices, there is less likelihood of finding "no interaction" and a greater chance of finding "dual causality". While these differences suggest that it is probably better to use densities, non-linear functional forms, and advanced models in which more variables than just population and employment are endogenous, there are reasons why this might not be the case with using a flow matrix. It has been argued that a flow matrix that is based on commuting data is better at capturing the true spatial labour market relationships than default matrices that reflect geographic distances (Boarnet et al., 2005). However, because a flow matrix is inherently more endogenous, the greater probability of "dual causality" may also reflect an inbuilt bias.

When we consider the impact of particular location-specific control variables included in the CM model, we see that the marginal effects, shown in Table 2, have a rather diffuse pattern. Whereas including variables that capture land-use patterns or spatial policies has only a minor effect on the results, the effects of including economic variables and especially income variables are more profound. Also, whereas the inclusion of economic variables such as industry structure and productivity decreases the probability of finding statistically insignificant parameter estimates, the opposite is true for the inclusion of income and wage variables. The fact that the parameter estimates are more likely to be insignificant when income or wage variables are included suggests that these variables have a mediating effect, and that the correlation between population and employment is not always due to a direct causal relationship.

Finally, regarding a possible impact of the publication outlet of a study, Table 2 shows that there are no major differences in the results published in peer-reviewed journal articles and those reported in working papers, dissertations, book chapters, and the like. As such, there is no evidence that academic journals are biased towards the publication of statistically significant results or that unfavourable (i.e., statistically questionable) results are refused publication. If anything, it appears that journal articles are less likely to report "dual causality", albeit only at the 10% significance level.

Conclusions
The meta-analysis of CM studies conducted in this study has clearly shown a wide variation in empirical findings related to the question of whether "jobs follow people or people follow jobs". As such, it confirms the widely held but, until now, not systematically tested belief that the evidence provided by studies is mixed and inconclusive. Further, the meta-analysis has shown that these apparently inconsistent results can to a large extent be explained by the different data samples used. Of the four substantive study features included in the analysis, three aspects appear to influence the outcomes of CM studies: the geographic location of the data, the spatial resolution of the

17

data, and the population and employment characteristics of the data. In contrast, no evidence was found that the outcomes differ when data from different time periods are analysed.

The meta-analysis also reveals that population–employment interaction findings not only vary because of differences in data sampling, but also because of differences in methodology. In other words, even if exactly the same data were to be investigated, CM studies could produce different findings depending on how the CM model is being used. Of the several methodological study features examined in the analysis, the choice in the CM model specification as to whether to measure the relationship between population and employment in terms of changes or end-of-period levels has the greatest impact. Further, the functional form of the model and the specification of the weight matrix used to calculate spatial cross-regressive lags also have a major influence on the outcomes. Of less, but still significant, importance are whether the key variables in the model measure population and employment in absolute numbers or in numbers standardized by area size (i.e., densities), the number of equations in the model, and whether or not the model includes variables to control for land use or spatial policies, income or wages, and the economic characteristics of places. No evidence was found that including a spatial autoregressive lag in the CM model makes any difference to the results.

Based on the findings from this study, the following suggestions for future research can be made. First, this meta-analysis provides clear evidence that researchers should always use models that allow for the possibility that the causality between jobs and people is running in multiple directions. Second, the conclusion that variations in population–employment interaction findings are partly due to differences in methodology suggests that researchers should test their results against alternative model and variable specifications. While it is likely that researchers already do this, we would encourage the routine reporting of these robustness tests rather than only reporting "the most plausible" results. Ideally, researchers would also include some form of sensitivity analysis in their reporting so that fellow researchers can also benefit from these insights. Third, with regard to future applications of the CM model, the findings obtained here suggest that non-linear models with more than two equations and with a focus on population and employment densities offer an improvement over the more regularly used simpler CM models. While these advanced models are naturally more difficult to implement, researchers are less likely to come up with insignificant estimates for the parameters that reveal the impact of population on employment and vice versa. Fourth, regarding the inclusion of location-specific variables to identify the system of equations, our findings indicate that researchers can trust the accuracy of their population-employment interaction findings provided their model includes variables that capture land-use patterns or spatial policies, and especially variables that capture economic conditions (e.g., industry structure and productivity) and income or wages. In comparison, in terms of having an impact on the results, it does not appear to be important whether variables are included to capture natural amenities and recreational facilities, demographic characteristics (e.g., age and ethnic composition), labour market characteristics (e.g., unemployment and skill levels), or location characteristics (e.g.,

18

central locations and distance to urban core areas). Fifth, the meta-analysis has shown that population–employment interaction findings are very sensitive to the spatial weight matrix chosen in spatial cross-regressive systems. This is a potentially important insight. It supports the conclusion of Boarnet et al. (2005) that, if the question of jobs-people causality is central to the investigation, the specification of the weights matrix is crucial and more important than, for example, the range of location-specific variables included in the model. They also concluded that a flow matrix based on commuting data is close to the theoretical ideal and should therefore ideally be used. Here we would add a note of caution in that, while it is true that such a weight matrix probably better captures spatial interactions than default distance-based matrices, the weighting elements are less exogenous to the model and might lead to bias in the results.

Further, with regard to future research, it might be interesting to repeat the meta-analysis conducted in this study in a few years' time. By then, the number of CM studies will have increased significantly, which will allow a more detailed investigation of possible subgroup, temporal, and spatial differences in the population–employment relationship. In the shorter term, insights into such differences might also be obtained by extended primary research. Kim and Hewings (2013), for example, conducted this type of research to examine spatial differences in population–employment interactions across US metropolitan areas. In their study, these spatial differences were linked to variations in land use regulation, although without the use of statistical techniques that are employed in a meta-analysis. For the future, it would be valuable to generate a dataset with population–employment interaction findings for different locations, and in addition include information on land-use regulation and collect information on a range of other location-specific characteristics (such as industry structure, access to amenities, technological development, and labour force composition) that could explain the variation in the findings. By then carrying out a regression analysis, it should be possible to draw more definitive conclusions as to why the direction of the population–employment interaction is not the same everywhere. It is these spatial differences that first need to be understood if the population–employment interaction literature is to progress, and to provide insights that could usefully inform policymaking.

It is important to remember that the meta-analysis in this study has exclusively focused on studies that have used a simultaneous equations model with adjustment lags. Although this model has become the mainstream methodology in population-employment interaction research, this does not necessarily mean that it is superior to other methodologies. As argued by Rickman (2010), among others, time series techniques are possibly more appropriate for investigating how shocks in labour demand or labour supply affect population and employment movements, and these techniques may also allow a more detailed investigation of the actual time lags before people and firms react. The field would significantly benefit from studies that compare results when different techniques are applied with the same dataset (such as in a recent study by Tervo, 2016). Finally, an ongoing concern is the difficulty in finding suitable instruments to identify a system of simultaneous equations. As was shown in our study, the inclusion or exclusion of particular variables may significantly influence the results and it is

important that future studies pay greater attention to this. Ideally, in future studies, the suitability of instruments should be explicitly tested and the reader be informed about the robustness of the results to guard against possible use of weak instruments.

References

Abildtrup, J., Piguet, V, & Schmitt, B. (2012). Does the agro-food industry impact on changes in regional employment and population? The case of Denmark. *Food Economics*, *9*, 145–156. doi:10.1080/2164828X.2012.757220

Bao, S. (1996). Restructuring in functional economic areas: A GIS based study of rural linkages to urban areas in selected southern regions (Unpublished doctoral dissertation). Clemson University, South Carolina.

Bierens, H. J., & Kontuly, T. (2008). Testing the regional restructuring hypothesis in Western Germany. *Environment and Planning A*, *40*, 1713–1727. doi:10.1068/a39341

Blanchard, O. J., & Katz, L. F. (1992). Regional evolutions. *Brookings Papers on Economic Activity*, *1*, 1–76. Retrieved from http://scholar.harvard.edu/lkatz/files/regional_evolutions.pdf

Boarnet, M.G. (1992). Intra-metropolitan growth patterns: The nature and causes of population and employment changes within an urban area (Unpublished doctoral dissertation). Princeton University, New Jersey.

Boarnet, M. G. (1994). An empirical model of intrametropolitan population and employment growth. *Papers in Regional Science*, *73*, 135–152. doi:10.1111/j.1435-5597.1994.tb00607.x

Boarnet, M. G. (1994b). The monocentric model and employment location. *Journal of Urban Economics*, *36*, 79–97. doi:10.1006/juec.1994.1027

Boarnet, M. G., McLaughlin, R. B., & Carruthers, J. I. (2011). Does state growth management change the pattern of urban growth? Evidence from Florida. *Regional Science and Urban Economics*, *41*, 236–252. doi:10.1016/j.regsciurbeco.2010.12.004

Boarnet, M. G., Chalermpong, S., & Geho, E. (2005). Specification issues in models of population and employment growth. *Papers in Regional Science*, *84*, 21–46. doi:10.1111/j.1435-5957.2005.00002.x

Bollinger, C. R., & Ihlanfeldt, K. R. (1997). The impact of rapid rail transit on economic development: The case of Atlanta's MARTA. *Journal of Urban Economics*, *42*, 179–204. doi:10.1006/juec.1996.2020

Borts, G. H., & Stein, J. L. (1964). *Economic growth in a free market*. New York, NY: Columbia University Press.

Brown, J. P., Lambert, D. M., & Florax, R. J. G. M. (2013). Firm birth, death and persistence: Creative destruction and the spatial distribution of U.S. manufacturing establishments, 2000-2006. *Economic Geography*, *89*, 203–206. doi:10.1111/ecge.12014

Callois, J. M., & Schmitt, B. (2009). The role of social capital components on local economic growth: Local cohesion and openness in French rural areas. *Review of*

Agricultural and Environmental Studies, *90*, 257–286. Retrieved from https://core.ac.uk/download/pdf/6714249.pdf

Carlino, G. A., & Mills, E. S. (1987). The determinants of county growth. *Journal of Regional Science*, *27*, 39–54. doi:10.1111/j.1467-9787.1987.tb01143.x

Carruthers, J. I., & Mulligan, G. F. (2007). Land absorption in U.S. metropolitan areas: Estimates and projections from regional adjustment models. *Geographical Analysis*, *39*, 78–104. doi:10.1111/j.1538-4632.2006.00696.x

Carruthers, J. I., & Mulligan, G. F. (2008). A locational analysis of growth and change in American metropolitan areas. *Papers in Regional Science*, *87*, 155–172. doi:10.1111/j.1435-5957.2007.00162.x

Cho, S. H., Kim, S. G., Clark, C. D., & Park, W. M. (2007). Spatial analysis of rural economic development using a locally weighted regression model. *Agricultural and Resource Economics Review*, *36*, 24–38. doi:10.1017/S1068280500009424

Cooper, H., Hedges, L. V., & Valentine, J. C. (Eds.). (2009). *The handbook of research synthesis and meta-analysis*. New York, NY: Russell Sage Foundation.

Decressin, J., & Fatas, A. (1995). Regional labor market dynamics in Europe. *European Economic Review*, *39*, 1627–1655. doi:10.1016/0014-2921(94)00102-2

Deding, M., Filges, T., & Van Ommeren, J. (2009). Spatial mobility and commuting: The case of two-earner households. *Journal of Regional Science*, *49*, 113–147. doi:10.1111/j.1467-9787.2008.00595.x

De Graaff, T., Van Oort, F. G., & Florax, R. J. G. M. (2012a). Regional population–employment dynamics across different sectors of the economy. *Journal of Regional Science*, *52*, 60–84. doi:10.1111/j.1467-9787.2011.00753.x

De Graaff, T., Van Oort, F. G., & Florax, R. J. G. M. (2012b). Sectoral heterogeneity, accessibility and population–employment dynamics in Dutch cities. *Journal of Transport Geography*, *25*, 115– 127. doi:10.1016/j.jtrangeo.2012.06.013

Deitz, R. (1998). A joint model of residential and employment location in urban areas. *Journal of Urban Economics*, *44*, 197–215. doi:10.1006/juec.1997.2067

Dudensing, R. M., & Barkley, D. L. (2010). Competitiveness of southern metropolitan areas: The role of new economy policies. *Review of Regional Studies*, *40*, 197–226. Retrieved from http://journal.srsa.org/ojs/index.php/RRS/article/view/208/163

Duffy-Deno, K. T. (1997a). Economic effect of endangered species preservation in the non-metropolitan West. *Growth and Change*, *28*, 263–288. doi:10.1111/1468-2257.00059

Duffy-Deno, K. T. (1997b). The effect of state parks on the county economies of the West. *Journal of Leisure Research*, *29*, 201–224. Retrieved from http://www.nrpa.org/globalassets/journals/jlr/1997/volume-29/jlr-volume-29-number-2-pp-201-224.pdf

Duffy-Deno, K. T. (1998). The effect of federal wilderness on county growth in the Intermountain Western United States. *Journal of Regional Science*, *38*, 109–136. doi:10.1111/0022-4146.00084

Feser, E., & Isserman, A. (2006). Harnessing growth spillovers for rural development: the effects of regional spatial structure (Report to USDA Rural Development, University of Illinois). Retrieved from https://works.bepress.com/edwardfeser/26/

Florida, R. (2002). *The rise of the creative class, and how it's transforming work, leisure, community and everyday life*. New York, NY: Basic Books.

Freeman, D. G. (2001). Sources of fluctuations in regional growth. *The Annals of Regional Science*, *35*, 249–266. doi:10.1007/s001680000037

Funderburg, R. G., Nixon, H., Boarnet, M. G., & Ferguson, G. (2010). New highways and land use change: Results from a quasi-experimental research design. *Transportation Research A*, *44*, 76–98. doi:10.1016/j.tra.2009.11.003

Gebremariam, G. H., Gebremedhin, T. S., Schaeffer, P. V., Phipps, T. T., & Jackson, R. W. (2012). Employment, income, migration and public services: A simultaneous spatial panel data model of regional growth. *Papers in Regional Science*, *91*, 275–298. doi:10.1111/j.1435-5957.2011.00388.x

Glass, G. V. (1976). Primary, secondary, and meta-analysis of research. *Educational Research*, *5*, 3–8. Retrieved from http://www.jstor.org/stable/1174772

Hailu, Y. G., & Brown, C. (2007). Regional growth impacts on agricultural land development: A spatial model for three states. *Agricultural and Resource Economics Review*, *36*, 149–163. doi:10.1017/S1068280500009503

Henry, M. S., Schmitt, B., & Piguet, V. (2001). Spatial econometric models for simultaneous systems: Application to rural community growth in France. *International Regional Science Review*, *24*, 171–193. doi:10.1177/016001701761013169

Hoogstra, G. J. (2012). Gender, space, and the location changes of jobs and people: A spatial simultaneous equations analysis. *Geographical Analysis*, *44*, 47–64. doi:10.1111/j.1538-4632.2011.00833.x

Hoogstra, G. J., Florax, R. J. G. M., & Van Dijk, J. (2011). Determinants of variation in population–employment interaction findings: A quasi-experimental meta-analysis. *Geographical Analysis*, *43*, 14–37. doi:10.1111/j.1538-4632.2010.00806.x

Isserman, A. M. (2004). Intellectual leaders of regional science: A half-century citation study. *Papers in Regional Science*, *83*, 91–126. doi:10.1007/s10110-003-0178-7

Ke, S., & Feser, E. (2010). Count on the growth pole strategy for regional economic growth? Spread–Backwash Effects in Greater Central China. *Regional Studies*, *44*, 1131–1147. doi:10.1080/00343400903373601

Kim, J. H., & Hewings, G. J. D. (2012). Integrating the fragmented regional and subregional socioeconomic forecasting and analysis: A spatial regional econometric input–output framework. *Annals in Regional Science*, *49*, 485–513. doi:10.1007/s00168-011-0468-y

Kim, J. H., & Hewings, G. J. D. (2013). Land use regulation and intraregional population–employment interaction. *The Annals of Regional Science*, *51*, 671–693. doi:10.1007/s00168-013-0557-1

Krishnapillai, S., & Kinnucan, H. (2012). The impact of automobile production on the growth of non-farm proprietor densities in Alabama's counties. *Journal of Economic Development*, *37*, 25–46. Retrieved from http://www.jed.or.kr/full-text/37-3/2.pdf

Li, C. (2006). The effects of local economic and environmental policies on county population and employment growth (Unpublished doctoral dissertation). Ohio State University, Columbus.

Luce, T. F. (1994). Local taxes, public services, and the intrametropolitan location of firms and households. *Public Finance Quarterly*, *22*, 139–167. doi:10.1177/109114219402200201

Mills, E. S., & Carlino, G. A. (1989). Dynamics of county growth. In A. Anderson, D. Batten, B. Johansson, & P. Nijkamp (Eds.), *Advances in spatial theory and dynamics* (pp. 195–206). Amsterdam: North-Holland.

Mills, E. S., & Lubuele, L. S. (1995). Projecting growth of metropolitan areas. *Journal of Urban Economics*, *37*, 344–360. doi:10.1006/juec.1995.1018

Mojica-Howell, M. N., Whittaker, W. L., Gebremedhin, T. G., & Schaeffer, P. V. (2012). Examining the bidirectional relationship between entrepreneurship and economic growth: is entrepreneurship endogenous? In T. Burger-Helmchen (Ed.), *Entrepreneurship: Born, made and educated* (pp. 283–316). Rijeka: InTech.

Mulligan, G. F., Vias, A. C., & Glavac, S. M. (1999). Initial diagnostics of a regional adjustment model. *Environment and Planning A*, *31*, 855–876. doi:10.1068/a310855

Muth, R. F. (1971). Migration: chicken or egg? *Southern Economic Journal*, *57*, 295–306. doi:10.2307/1056181

Neal, Z. (2012). Creative employment and jet set cities: Disentangling causal effects. *Urban Studies*, *49*, 2693–2709. doi:10.1177/0042098011431282

Openshaw, S. (1984). *The modifiable areal unit problem*. Norwich: Geo Books.

Partridge, M. D. (2010). The dueling models: NEG vs amenity migration in explaining U.S. engines of growth. *Papers in Regional Science*, *89*, 513–536. doi:10.1111/j.1435-5957.2010.00315.x

Partridge, M. D., Rickman, D. S., Olfert, M. R., & Ali, K. (2012). Dwindling U.S. internal migration: Evidence of spatial equilibrium or structural shifts in local labor markets? *Regional Science and Urban Economics*, *42*, 375–388. doi:10.1016/j.regsciurbeco.2011.10.006

Rey, S. J., & Boarnet, M. G. (2004). A taxonomy of spatial econometric models for simultaneous equations systems. In L. Anselin, R. J. G. M. Florax, & S. J. Rey (Eds.), *Advances in spatial econometrics: Methodology, tools and applications* (pp. 99–119). Berlin: Springer.

Rickman, D. S. (2010). Modern macroeconomics and regional economic modeling. *Journal of Regional Science*, *50*, 23–41. doi:10.1111/j.1467-9787.2009.00647.x

Royuela, V. (2011). Modelling quality of life and population growth. The case of the Barcelona metropolitan area. *Spatial Economic Analysis*, *6*, 83–109. doi:10.1080/17421772.2010.540034

Schmitt, B., Henry, M. S., Piguet, V., & Hilal, M. (2006). Urban growth effects on rural population, export and service employment: Evidence from Eastern France. *Annals of Regional Science*, *40*, 779–801. doi:10.1007/s00168-006-0069-3

Steinnes, D. N., & Fisher, W. D. (1974). An econometric model of intraurban location. *Journal of Regional Science*, *14*, 65–80. doi:10.1111/j.1467-9787.1974.tb00430.x

Storper, M., & Scott, A. J. (2009). Rethinking human capital, creativity and urban growth. *Journal of Economic Geography*, *9*, 147–167. doi:10.1093/jeg/lbn052

Tervo, H. (2016). Do people follow jobs or do jobs follow people? The case of Finland in an international context. *The Journal of Regional Analysis and Policy*, *46*, 95-109. Retrieved from http://www.jrap-journal.org/pastvolumes/2010/v46/jrap_v46_n1_a7_tervo.pdf

Vermeulen, W., & Van Ommeren, J. (2009). Does land use planning shape regional economies? A simultaneous analysis of housing supply, internal migration and local employment growth in the Netherlands. *Journal of Housing Economics*, *18*, 294–310. doi:10.1016/j.jhe.2009.09.002

Vias, A. C. (1998). An analysis of population and employment growth in the nonmetropolitan Rocky Mountain West, 1970–1995 (Unpublished doctoral dissertation). Arizona University, Tucson.

Waltert, F., Schulz, T., & Schläpfer, F. (2011). The role of landscape amenities in regional development: Evidence from Swiss municipality data. *Land Use Policy*, *28*, 748–761. doi:10.1016/j.landusepol.2011.01.002

Woo, M. (2007). Impacts of urban containment policies on urban growth and structure (Unpublished doctoral dissertation). Ohio State University, Columbus.

Zhang, S., & Guldmann, J. M. (2010). Accessibility, diversity, environmental quality and the dynamics of intra-urban population and employment location. *Growth and Change*, *41*, 85–114. doi:10.1111/j.1468-2257.2009.00517.x
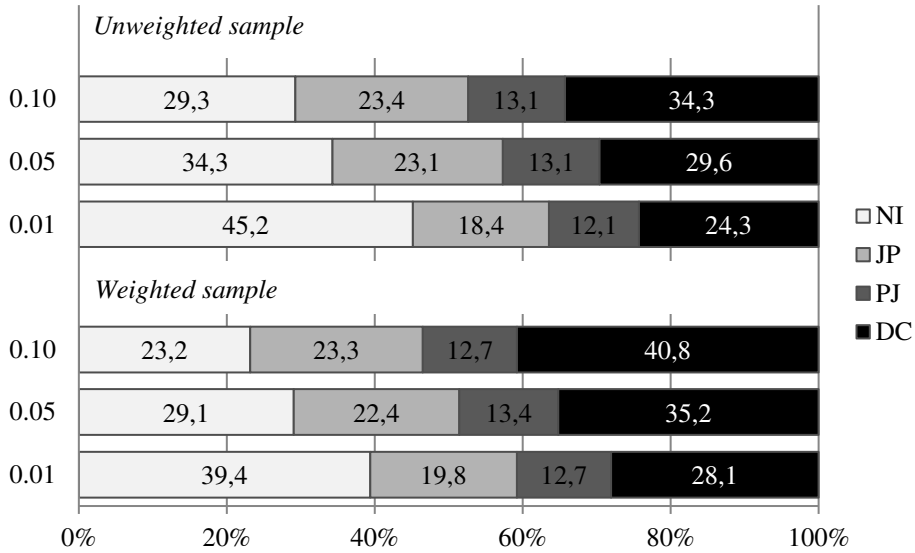
Figure 1. Distribution of study results (in %) for weighted and unweighted samples at various significance levels (vertical axis)

Table 1. Taxonomy of Carlino–Mills model specifications

	$\bar{E}_t/\bar{P}_t$	$\bar{E}_t/\bar{P}_t$(RHS)	$\bar{W}_1$	$\bar{W}_2$	
	δ_1/δ_2*	δ_1/δ_2*	δ_3**	δ_4***	Introduced by:
a	0	0	0	0	Carlino & Mills (1987)
b	1	0	0	0	Mills & Carlino (1989)
c	1	1	1	0	Boarnet (1992)
d	0	0	1	0	Luce (1994)
e	0	0	0	1	Vias (1998)
f	1	1	1	1	Henry et al. (2001)
g	1	0	0	1	Carruthers & Mulligan (2008)
h	1	1	1	1	Kim (2008)

Note: LHS (RHS) refers to variables on the left-hand-side (right-hand side) of the equations.
* 0 = population/employment *levels* and 1 = population/employment *changes*. ** 0 = *without* spatial cross-regressive lags and 1 = *with* spatial cross-regressive lags. *** 0 = *without* spatial autoregressive lags and 1 = *with* spatial autoregressive lags. See also Equations (1) – (6).

Table 2. Estimation results - multinomial logit model (marginal effects at means)

	NI	JP	PJ	DC
Substantive study factors				
US West	**.586** (.103)	.149 (.099)	*.100* (.049)	**-.835** (.097)
US East	**.329** (.094)	.137 (.137)	**.369** (.139)	**-.835** (.109)
Non-US	*.226* (.091)	*.476* (.189)	.098 (.116)	**-.800** (.134)
Small area obs.	**.614** (.137)	-.150 (.143)	.025 (.070)	**-.489** (.124)
Large area obs.	-.164 (.109)	-.050 (.281)	**.692** (.260)	**-.478** (.135)
1970s + 1980s data	.092 (.076)	-.111 (.112)	.026 (.107)	-.007 (.085)
Subgroups	**.729** (.085)	**-.329** (.098)	-.102 (.064)	**-.298** (.079)
Methodological study factors				
LHS & RHS levels	**-.256** (.100)	**.700** (.144)	**-.309** (.081)	-.134 (.115)
RHS changes & LHS levels	.127 (.396)	.238 (.295)	**-.296** (.086)	-.069 (.183)
Densities	**-.256** (.095)	-.161 (.117)	.104 (.135)	*.313* (.158)
Non-linear func. form	*-.217* (.091)	*-.260* (.106)	-.100 (.086)	**.576** (.155)
Flow matrix	**-.381** (.052)	-.083 (.142)	-.066 (.108)	*.530* (.210)
With SAR	.086 (.131)	.033 (.164)	-.080 (.090)	-.038 (.087)
2+ Equations	*-.249* (.121)	-.119 (.183)	.120 (.122)	.248 (.238)
Land use variables incl.	.119 (.086)	.000 (.090)	-*.144* (.078)	.025 (.073)
Income variables incl.	**.384** (.112)	-.252 (.172)	-.090 (.126)	-.043 (.143)
Economic variables incl.	**-.254** (.091)	*.212* (.108)	.042 (.099)	.000 (.126)
External study factors				
Non-journal article	.083 (.095)	-.193 (.119)	-.088 (.077)	*.198* (.120)

Standard errors shown in parentheses. Bold = significant at the 1% level; bold-italic = significant at the 5% level; italic = significant at the 10% level. NI = No Interaction, JP = Jobs follow People, PJ = People follow Jobs, DC = Dual Causality. See Appendix A for reference categories.

Appendix A. Distribution of study results across selected study features (in %)

	NI	JP	PJ	DC	n
Substantive study factors					
US West	56.7	24.0	9.6	9.6	104
US East	24.4	22.2	20.0	33.3	90
Non-US	35.9	28.2	11.5	24.4	78
Entire US*	2.0	14.3	10.2	73.5	49
Small area obs.	80.6	8.1	9.7	1.6	62
Medium area obs.*	29.1	23.6	14.3	33.0	182
Large area obs.	9.1	33.8	13.0	44.2	77
1970s + 1980s data	41.4	21.7	12.7	24.2	157
1990s + 2000s data*	27.4	24.4	13.4	34.8	164
Subgroups	50.0	24.1	12.1	13.8	58
Total pop/emp data*	30.8	22.8	13.3	33.1	263
Methodological study factors					
LHS & RHS levels	22.2	61.1	7.4	9.3	54
RHS changes & LHS levels	10.2	18.4	10.2	61.2	49
LHS & RHS changes*	42.7	14.7	15.1	27.5	218
Densities	17.9	21.7	17.0	43.4	106
Sizes*	42.3	23.7	11.2	22.8	215
Non-linear functional form	19.8	16.0	7.4	56.8	81
Linear functional form*	39.2	25.4	15.0	20.4	240
Flow matrix	24.5	15.1	18.9	41.5	53
Other*	36.2	24.6	11.9	27.2	268
With SAR	26.9	13.5	5.8	53.8	52
Without SAR*	35.7	24.9	14.5	24.9	269
2+ Equations	31.8	7.6	12.1	48.5	66
2 Equations*	34.9	27.1	13.3	24.7	255
Land use variables included	44.4	23.7	11.1	20.7	135
Land use variables excluded*	26.9	22.6	14.5	36.0	186
Income variables included	21.5	25.6	14.4	38.5	195
Income variables excluded*	54.0	19.0	11.1	15.9	126
Economic variables included	35.6	26.4	12.0	25.9	216
Economic variables excluded*	31.4	16.2	15.2	37.1	105
External study factors					
Non-journal article	47.1	21.2	10.6	21.2	104
Journal article*	28.1	24.0	14.3	33.6	217

NI = No Interaction, JP = Jobs follow People, PJ = People follow Jobs, DC = Dual Causality. Study results are at the 5% significance level. * reference categories in the multinomial logit model.

Appendix B. Estimation results of multinomial logit model (regression coefficients)

	Logit JP vs NI		Logit PJ vs NI		Logit DC vs NI	
Intercept	*2.637*	(1.591)	1.264	(1.483)	**5.116**	(1.753)
Substantive study factors						
US West	***-2.812***	(1.186)	***-2.384***	(1.090)	**-6.564**	(1.368)
US East	-2.306	(1.651)	-.648	(1.388)	**-6.002**	(1.527)
Non-US	-.921	(1.539)	-1.468	(1.708)	**-5.281**	(1.577)
Small area obs.	*-2.393*	(1.284)	-1.005	(.935)	**-5.199**	(1.515)
Large area obs.	1.277	(1.883)	**4.102**	(1.540)	-1.616	(1.825)
1970s + 1980s data	-.658	(.502)	-.150	(.681)	-.325	(.543)
Subgroups	**-4.195**	(1.358)	**-2.591**	(.876)	**-5.908**	(1.649)
Methodological study factors						
LHS & RHS levels	**3.355**	(1.055)	-1.043	(1.087)	.488	(1.469)
RHS changes & LHS levels	.584	(1.695)	-2.579	(1.585)	-.776	(2.038)
Densities	.364	(.659)	*1.544*	(.861)	***2.345***	(.990)
Non-linear functional form	-.312	(.693)	.251	(.992)	**2.890**	(.999)
Flow matrix	**2.115**	(.631)	***2.003***	(.788)	**4.121**	1.077
With SAR	-.144	(.773)	-.745	(.790)	-.466	(.633)
2+ Equations	.610	1.098	*1.639*	(.887)	2.072	1.341
Land use variables included	-.370	(.463)	*-1.178*	(.676)	-.235	(.575)
Income variables included	**-2.248**	(.802)	*-1.925*	(1.036)	-1.677	(1.020)
Economic variables included	*1.532*	(.602)	.958	(.682)	.720	(.836)
External study factors						
Non-journal article	-0.997	(.721)	-.786	(.575)	.642	(.715)

Number of observations = 321; Wald chi^2 (54) = 1137.90; Prob > chi^2 = 0.0000; Log likelihood = -275.75059; Pseudo R^2 = 0.3549. The robust standard errors are shown in parentheses (adjusted for 150 data clusters). Bold = significant at the 1% level; bold-italic = significant at the 5% level; italic = significant at the 10% level. See Appendix A for reference categories and the meaning of outcome categories NI, JP, PJ, and DC.