Location, Location, Location

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ABSTRACT

We use data from the Longitudinal Employer-Household Dynamics program to study the causal effects of location on earnings. A model with fixed effects for workers and for the interaction of industry and commuting zone (CZ) provides a good approximation to observed earnings changes as people move between CZ's and/or industries, though it takes several quarters to adjust to new labor markets. Additional returns to previous work experience in the largest U.S. cities are small. We find some indication of match effects between places and industries, and of local agglomeration effects, but these are small and explain only a small fraction of CZ-average wage differences. In contrast, worker skills, captured by the individual fixed effects in our model, vary widely between locations and explain about 2/3 of the observed earnings differences across CZ's. Fitting separate models for college and non-college workers we find very similar local wage premiums. The degree of assortative matching across CZs is much larger for college-educated workers, however, leading to a positive correlation between CZ size and the college-high school wage gap that is driven by sorting *within* the college workforce. Differences in local housing costs more than offset the corresponding earnings premiums, suggesting that workers who move to larger CZ's have lower net-of-housing consumption.

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There are large, persistent differences in earnings across cities and regions. Larger cities tend to have higher average earnings (Behrens, et al., 2014; Eeckhout et al., 2014) and higher returns to education (Autor, 2019; Davis and Dingel, 2019), but there are also wide disparities between cities of similar size. The source of these differences is a perennial issue in economic geography.

In a simple Roback (1982)-style model of spatial equilibrium, nominal wages in different places reflect productivity gaps: otherwise employers will move. Several explanations have been offered for place-based productivity gaps. One is that they arise from sorting of high-skilled people to preferred places (e.g., Behrens et al., 2014). A second is that they derive from the concentration of productive industries (e.g., Ellison and Glaeser, 1997; Rosenthal and Strange, 2004). A third is that local pay differences reflect the causal effects of the places themselves, arising from endogenous factors like population density or human capital (Ciccone and Hall, 1996; Duranton and Puga, 2004; Glaeser and Gottlieb, 2009; Diamond, 2016), or from exogenous factors like geography or climate.

These explanations have sharply different predictions for the impacts of worker mobility. A sorting-based explanation implies that mobility has no effect on the earnings of movers. In contrast, theories based on industry composition or place-based factors imply that productivity and wages rise when people move to larger or higher-wage places. They also have distinct implications for policy. An industry-based explanation implies that regions could benefit by attracting clusters of high-wage industries, providing a rationale for tax subsidies (e.g., Greenstone, Hornbeck, and Moretti 2010). Likewise, endogenous externalities suggest a role for policies to increase local population or attract highly skilled workers (Moretti 2004a,b). Externalities arising from fixed factors like climate, on the other hand, leave less room for policy.

Despite several decades of research there is surprisingly little consensus on the relative importance of these three explanations, or even on the simple question of whether movers experience systematic wage changes that are correlated with conventionally estimated place effects. A seminal study by Glaeser and Maré (2001) found a mixed pattern of evidence on the effects of moving into or out of metropolitan areas, depending on the data set and direction of the move.[1] Subsequent studies using much larger administrative data sets from outside the U.S. (Combes et al., 2008; de la Roca and Puga, 2017; Dauth et al., 2018) have found evidence of skill-based sorting *and* place effects that both contribute to observed earnings differentials.

In this paper we use data from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program to follow individuals as they move across commuting zones (CZs). We use changes in earnings surrounding moves to identify the causal effects of places on earnings.[2] Generalizing the specification of Combes et al. (2008), we model log nominal earnings as a function of permanent individual effects, time-varying person characteristics, and a fully interacted set of CZ × industry effects. We allow the effects of a given place to vary across industries, capturing potential returns to local specialization and/or other forms of non-separability.

In a first methodological contribution we use event-study style comparisons of earnings before and after a move to show that mobility is approximately exogenous with respect to transitory earnings fluctuations, and with respect to idiosyncratic gains (or "match effects") from specific CZs or industries. These findings parallel recent evidence for firm-to-firm mobility (see Card et al. 2018 for a survey) and allow us to obtain approximately unbiased estimates of the CZ × industry effects using a standard two-way fixed effect framework. Although our baseline specification does not allow for dynamic effects of early-career experience in larger CZ's (a focus of de la Roca and Puga, 2017), we explore this in augmented specifications. We find imprecisely estimated and relatively modest dynamic effects. We

[1] Appendix Figure 1 presents a visual summary of Glaeser and Maré's main results. They used the Panel Study of Income Dynamics and the National Longitudinal Study of Youth, both of which have relatively small samples. A later study by Gould (2007) concluded that gains for migration are confined to high-education workers.
[2] CZs are meant to capture regions within which workers commute. Unlike metropolitan statistical areas (MSAs), they cover the entire country, including both urban and rural areas. The locations of some workplaces in the LEHD are imputed. As discussed below, however, we find that the effects of any imputation errors are negligible.

also find that the static place effects from a dynamic specification are nearly identical to those from our baseline specification.

Our second contribution is to characterize the role of industry in CZ average wage differences. We decompose place-by-industry effects into a combination of place effects, industry effects, and a match (or interaction) effect that could arise from local specialization. We find significant earnings differences across industries (Krueger and Summers 1988), and across places, but only small match effects – i.e., close to additive separability in the contributions of place and industry. The match effects vary with local industry shares (reflecting possible agglomeration effects) but on net contribute only 1-2% to the variation in average wages across CZ's.

Our third contribution is to identify the effects of skill-based sorting on observed earnings differences across CZs. About two-thirds of the variation in raw earnings differences across CZs is attributable to differences in the person effects of a CZ's workers, while about one third is attributable to CZ earnings premiums. As in France (Combes et al., 2008), Spain (de la Roca and Puga, 2017), and Germany (Dauth et al., 2018), we find that higher earnings-capacity workers are more likely to live in high wage CZ's, a pattern that magnifies the inequality in average earnings differences across CZ's. Similar conclusions hold with respect to ***CZ size***: About two-thirds of the earnings premium associated with working in a larger CZ reflects worker sorting, while one-third arises from the size premium. We also find that larger places have more dispersion in skills (Eeckhout et al., 2014), and a greater degree of assortative matching between high skilled workers and high-return industries (Dauth et al., 2018).

Our fourth contribution is to explore differences in the effects of different CZ's on the earnings of more- and less-educated workers. In simple cross-sectional models, college-educated workers appear to receive larger returns from living in larger or higher-wage cities, a fact that has received much attention in the recent literature (e.g., Autor, 2019; Davis and Dingel, 2019, 2020). But such comparisons are potentially confounded by differences in unobserved skills within education groups. To address this concern we estimate separate models for college and non-college workers. We find very similar average place effects for the two groups, but much greater assortative matching of highly-skilled college workers to larger or higher-wage places (consistent with Diamond, 2016). This differential sorting explains 90% of the observed correlation between CZ size and the return to college in cross-sectional models.[3]

Finally, we conclude by examining housing cost differences across CZs, and the associated differences in real earnings. We find large elasticities of housing costs with respect to CZ mean wages and log size – more than enough to offset the corresponding effects on nominal earnings. Thus, movements to larger or higher-wage locations yield reductions in real income. In a Roback-style model this could arise if more productive places have higher amenities that offset their higher cost of living.

Our work is related to three main literatures. The first is a set of recent studies that, following Glaeser and Mare (2001), use large administrative data sets from outside the U.S. to separate the effects of place from the non-random sorting of workers.[4] Combes et al. (2008) estimate models on French data that include fixed effects for workers, employment areas, and industry. De la Roca and Puga (2017) estimate models for Spain that include fixed effects for workers, urban areas (UA's), and measures of cumulative work experience in larger UAs. Both studies conclude that about one-half of the locational premium for larger areas is attributable to sorting of higher-earning workers. Dauth et al. (2018) estimate models for Germany that include fixed effects for workers and *establishments* and conclude that up to three quarters of the wage premium for working in a larger city reflects worker quality and enhanced sorting between workers and firms. We contribute to this literature by providing the first estimates from administrative data for the U.S., and by carefully evaluating the underlying assumptions

[3] Our data cover 2010-2018, and do not allow us to examine how either sorting or CZ effects have changed over recent decades, as suggested by Autor (2019).
[4] A related set of papers use a similar strategy but derive from the intergenerational mobility literature. See, e.g., Chetty and Hendren (2018a,b) and Finkelstein, Gentzkow, and Williams (2016, 2021).

in our own and previous specifications, including additive separability between the person, place, and industry effects, the role of match effects, and the impact of dynamic returns to locational choices.

Second, we relate to the large literature in urban economics on market size elasticities and the returns to agglomeration (Rosenthal and Strange, 2004; Baum-Snow and Pavan, 2012; Behrens et al., 2014; Eekhout et al., 2014). A related literature considers the impact of high-wage employers or industries on local economic development (Greenstone, Hornbeck, and Moretti 2010; Kline and Moretti 2014) or worker location choices (Diamond, 2016). We contribute to this literature by showing that there is substantial sorting of higher-skilled workers to larger, higher-wage CZ's. Controlling for worker skills and national industry wage premiums, we find that local industry structure, industry-based agglomerations, and match effects explain only a small additional share of CZ wage differences. However, the sorting of higher-skilled (and more highly educated) workers to higher-paying industries is greater in larger CZ's, suggesting an important benefit to local agglomeration (Dauth et al., 2018).

Finally, our work is related to the literature beginning with Abowd, Kramarz and Margolis (1999) that examines firm-specific pay differences. Studies in this vein focus on *firms* or *plants* as the unit of analysis and, with the notable exceptions of Dauth et al. (2018) and Combes et al. (2008), have ignored the role of geography. We show that there is an important geographic component in wage setting that adds a roughly constant pay premium for workers in all industries.

II. Geographic earnings premiums in the U.S.

In Roback's (1982) benchmark model of locational equilibrium, representative-agent workers derive equal utility from the packages of wages, rents, and amenities offered in each local labor market, while firms derive equal profits. Ignoring the role of land in production, nominal wage differences across locations therefore reflect productivity differences, while rents offset any differences in nominal wages net of consumption amenities. We focus below on nominal earnings differences across places: thus we interpret our results as reflecting productivity differences across places. In our final section, however, we examine local housing costs, and show that higher nominal wage cities have much higher housing costs and consequently lower real wages, consistent with these cities offering both productive and consumption amenities that are offset by higher rents.

To help frame our analysis, we begin by estimating the wage differentials for different commuting zones (CZ's), using data from the 2010-2018 American Community Surveys (ACS). Commuting zones are intended to approximate integrated labor market areas, with each CZ comprised of one or more complete counties. There are 741 CZs in the United States. Details of our sample and basic summary statistics are presented in the Appendix. We relate y_{ic}, the log hourly wage of worker *i* in CZ *c*, to a set of individual controls X_{ic} [5] and CZ fixed effects ψ_c:

$$y_{ic} = \psi_c + X_{ic}\beta + u_{ic} \tag{1}$$

Using (1), the mean log wage in a given CZ, $\bar{y}_c$, is just the sum of the average observed components $(\bar{X}_c\hat{\beta})$ and an estimated CZ effect $(\hat{\psi}_c)$. We emphasize that $\hat{\psi}_c$ includes unobserved skill factors in CZ *c*, as well as any locational premium for that CZ.

Figure 1 graphs these two components, each normalized to have mean zero, against the CZ mean log wage for 688 CZ's. The x-axis extends about 70 log points from the lowest-wage CZ's to the 3 three highest-wage CZ's (San Francisco, San Jose, and Washington DC). The blue dots in the figure, representing $\bar{X}_c\hat{\beta}$, slope gently upward (slope = 0.27), confirming that workers in higher-wage CZ's have higher observed skills (particularly education). The red dots, representing $\hat{\psi}_c$, rise much more quickly (slope=0.73), implying that most of the variation in mean wages is due to unobserved factors. The relative slopes imply that that observed skills account for only about one quarter of the across-CZ variation in mean wages.

[5] Our controls include education, experience, race/ethnicity, and country of origin for immigrants, all interacted with female gender.

In our ACS sample average wages are higher in larger labor markets, with an estimated size elasticity of 0.072 (standard error=0.003).[6] This can also be decomposed into components attributable to average observed characteristics $(\bar{X}_c\beta)$ and unobserved factors, including place premiums $\hat{\psi}_c$. Less than 20% of the size elasticity is attributable to observed characteristics

As has been emphasized by Autor (2019) and Davis and Dingel (2019, 2020), CZ wage premiums also vary by education. When we fit separate versions of equation (1) for people with lower and higher education, we find that the elasticity with respect to city size is substantially larger for workers with some college (around 0.086) than those with no college (around 0.015) – an issue we explore in more detail below.

A large literature has developed around the importance of local industry structure in determining the success of different cities (e.g., Ellison and Glaeser, 1997). To provide an initial look at this issue we fit an extended version of equation (1) that included dummies for 20 major industries. We then extracted just the industry component of this skill index, creating a "mean industry composition effect" for each CZ (i.e., a pay-premium-weighted average of the shares of workers in each industry). This has a surprisingly small standard deviation across CZ's (0.012) and only a very small elasticity with respect to log size (coefficient = 0.002), suggesting that differences in industry composition have little power to explain CZ wage differences or the CZ-size premium. When we repeat this exercise using more detailed 4-digit industries we continue to find a small degree of variation across CZ's and a slight relationship with CZ size (elasticity= 0.004). As we will discuss in more detail below, these findings foreshadow one of the main conclusions of our paper, which is that industry composition effects are not a major driver of CZ wage premiums in the U.S. labor market.

A key limitation of a model like (1) is that some part of the variation in $\hat{\psi}_c$ is surely due to differences in unmeasured worker skills. In the remainder of the paper we therefore use LEHD panel

[6] Here and below we measure CZ size by the number of 16-66 year olds in the pooled 2010-2016 ACS samples.

data that allow us to follow workers as they move across CZs and separate permanent earnings differences among workers from any causal place effects. We start with a brief overview of the LEHD data before describing our approach in more detail.

III. Longitudinal Earnings Data from LEHD

LEHD data are derived from quarterly earnings reports provided by employers to state unemployment insurance (UI) agencies, which are then assembled by the Census Bureau into a national data set. The core data set includes total wages paid by a given employer to each worker in a quarter and a few characteristics of workers and establishments, including industry and location (discussed below). This is supplemented with information on workers and employers collected from other sources (e.g., decennial census and ACS files, linked at the individual level; see Abowd et al., 2009). The LEHD covers about 95% of private sector employment, as well as state and local government employees, but excludes federal employees, members of the armed services, and self-employed workers. From 2010 forward it includes data from all 50 states.

A limitation of the LEHD is that there is no information on job start/end dates or on hours of work. To help screen out part-time jobs and/or interrupted job spells we exclude person-employer-quarters (PEQs) with earnings below $3,800 (roughly the earnings from a full-time job at the federal minimum wage), quarters where an individual had multiple jobs, and any *transitional* quarters (the first and last quarter of any person-employer spell). We then select PEQs for workers age 22-62 from 2010Q1 to 2018Q2. We drop workers who are observed for less than 8 quarters in this period, and PEQs with unknown industry and/or establishment location.

Finally, we divide people into 30 mutually exclusive 3.33% subsamples. We pool the first 3 of these as our main estimation sample, which we refer to as our *A sample*. We pool the next 3 to form the *B sample*, which we use together with the A sample to estimate measurement-error-corrected second moments. In some exercises below we use one or more of the remaining subsamples to form instrumental variables. We also use a subsample of PEQ's for individuals whose education has been measured in the ACS and linked to LEHD.

We use the industry code and location of the establishment in a PEQ to assign workers to an industry and CZ in each quarter. We retain 735 of the 741 CZ's defined by Tolbert and Sizer (1996), omitting a handful of very small CZs.[7] In some analyses we further restrict the sample to the 688 CZs identified in our ACS analysis described above. The (size-weighted) correlation between CZ-mean log quarterly earnings from our LEHD A-sample and CZ-mean log hourly wages from our ACS sample is 0.94.

A potential concern with the LEHD is that the assignment of workers to establishments owned by the same firm in the same state, and thus to both CZ and industry, is imputed.[8] The Census Bureau uses a multiple imputation procedure to assign such addresses, and we used the 10 available imputations to classify PEQs as "high certainty" (all 10 imputations result in the same CZ and 2-digit industry) or not. We then refit most of our models described below using only records for the subset of high-certainty PEQs (see the Appendix for more details). All our results are highly robust to using only this subset.

For our primary analyses, we use 24 "2-digit" industries based on the first two digits of the establishment NAICS code.[9] This yields roughly 18,000 CZ-industry cells. Since many CZs are small and some industries are also relatively small, not all CZ-industry cells are populated. In some analyses, we limit attention to the (roughly) 300 CZ's that have workers in each industry in our A sample. We also

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[7] The omitted CZs are not connected by mobility to other CZs in at least one of our 3.33% subsamples.

[8] As discussed in Vilhuber (2018), the Census Bureau supplements the UI data with the locations of all establishments owned by a given firm in a state, and with worker residential addresses, and uses these to impute establishments for each worker.

[9] Under this classification, construction comprises 1 industry, manufacturing comprises 3 industries, and hotels, restaurants and cultural/recreation facilities comprise 1 industry. Industry codes are imputed to establishments in the LEHD using the procedures described in Vilhuber and McKinney (2014).

explore richer specifications using more detailed 4-digit NAICS industries, with 312 unique codes. For these analyses, we limit attention to the 50 largest CZs.

In some analyses we focus on wage dynamics around mobility events (i.e., changes in CZ and/or industry), and restrict to samples that allow us to focus on these. Here, we limit attention to workers who switch CZ-industry cells only once in our sample, with stable jobs in the same CZ-industry cell for at least 5 consecutive quarters before and after the switch. Because many moves involve periods of non-employment, we allow up to 6 quarters of non-employment between the origin CZ-industry cell and the destination cell.[10]

Table 1 presents some characteristics of our LEHD samples, including the fraction observed in different numbers of CZ's and industries over the sample period. We also show the mean and standard deviation of the estimated person effects from our models (discussed below), which provide a simple index of skill (on a log scale). The first column presents results for the full sample, while column 2 shows our estimation sample. Workers in the estimation sample have similar mean earnings, age, fraction female and fraction foreign-born as the broader LEHD population, but are somewhat less mobile. Columns 3-6 classify this sample by whether people are observed in multiple CZs and/or industries. People who change CZs but stay in the same industry have somewhat above average person effects, while those who stay in the same CZ but change industry have below average person effects. Finally, column 7 summarizes our event study sample of people with exactly one move between CZ-industry cells. This group is a little younger and a little less likely to be female. About 45% change CZ, while 55% change industry but not CZ.

[10] Transitional quarters are considered non-employment when computing this gap. Thus, we allow workers to have no UI-related work for up to four quarters between the last quarter of their origin job spell and the first quarter of their destination spell.

An initial look at the impacts of mobility

We use our event study sample to conduct a descriptive analysis of earnings changes associated with moves between CZs. We construct an adjusted earnings measure as the residual from a regression of quarterly earnings on time effects and a polynomial in age. Then, following Card, Heining, and Kline (2013) (hereafter CHK), we classify CZ's into quartiles based on average earnings, yielding 16 origin/destination pairs. Figure 2 plots the means of adjusted wages by quarter relative to the move for the subsets of movers originating from CZs in the top and bottom quartiles.[11]

The figure shows that pre-move earnings are quite stable, with no sign of pre-move shocks. Post-move earnings tend to grow slightly, especially in the first 2 quarters after a move, suggesting that hours or wages on new jobs take a few quarters to ramp up.[12] The changes in earnings for different origin/destination groups suggest a causal effect of places: people who move to higher-wage quartile CZs tend to see earnings increases, while those who move to lower-wage CZs tend to see declines. The identity of the destination CZ also helps predict the level of pre-move earnings for workers from the same origin group. People from origin quartile 1 who will move to a quartile 4 CZ, for example, earn more before the move than those who will move to quartiles 1, 2 or 3. A simple explanation for this pattern is dynamic sorting based on the permanent component of a worker's ability: i.e., higher skilled workers from a given origin CZ are more likely to move up the ladder than their lower-skilled colleagues.

IV. Methods

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[11] Recall that we exclude transitional quarters and allow for several quarters of non-employment between them. Thus, there may be as many as 6 quarters between the last observation in the origin CZ (labeled -1) and the first one in the destination (labeled +1).

[12] Glaeser and Maré (2001) emphasized the possibility of an adjustment process for movers. As can be seen in Appendix Figure 1, their NLSY sample shows that it takes about a year to get to the new level of earnings for people who enter or leave a metro area.

In this section we present our methodology for using the LEHD data to study locational wage differences. We begin by presenting our two-way fixed effects model and discussing some of the key specification issues in this model. Next we present our approach for analyzing the role of industry differences in CZ-average wages. Then we discuss our approaches to assessing differences between more- and less-educated workers and to examining city size effects.

Two-way fixed effects model

Building on Abowd, Kramarz, and Margolis (1999), we assume that log earnings are generated by an additive model with worker fixed effects, time-varying worker characteristics, and a fully interacted set of CZ-by-industry effects. Specifically, letting y_{it} represent the log of observed earnings of worker i in quarter t, and letting $cj(i,t)$ represent the CZ-industry cell for worker i in quarter t, our baseline model is:

$$y_{it} = \alpha_i + \psi_{cj(i,t)} + X_{it}\beta + \epsilon_{it}. \tag{2}$$

Here, α_i is a fixed effect that captures the time-invariant skills (measured or unmeasured) of worker i, X_{it} is a vector of time-varying characteristics (age and calendar time effects), and ψ_{cj} is an additive wage premium or discount for jobs in CZ c and industry j.[13] The error term ϵ_{it} captures all other factors, including transitory worker-specific earnings shocks, transitory industry- or CZ-wide shocks, and any person-specific match effect associated with working in the specific CZ and industry combination.

Ordinary least squares (OLS) applied to equation (2) will yield unbiased estimates of the CZ-industry premiums if the $\epsilon_{it}{}'s$ are orthogonal to the sequence of CZ-industry choices made by worker i -- an "exogenous mobility" assumption. As noted by CHK, there are two main threats to this assumption. The first is that mobility may be correlated with transitory earnings shocks – as could happen if workers who experience negative earnings shocks tend to move to lower-paying CZ's. Such

[13]The person effects and CZ-industry effects have to be normalized. For expositional convenience it is useful to assume that the CZ-industry-effect for a low-wage industry in a small CZ is normalized to 0.

threats would be revealed in Figure 2 by temporary dips or peaks prior to a move (Ashenfelter, 1978). We see little evidence of such patterns.

A second threat is that mobility across industries and/or CZs is driven in part by idiosyncratic match effects. Under exogenous mobility, equation (2) implies that the expected change in earnings for a worker who moves from CZ/industry pair (c, j) to CZ/industry pair (d, k) is $\psi_{d,k} - \psi_{c,j}$, while the expected change in earnings for a worker who moves in the opposite direction is $\psi_{c,j} - \psi_{d,k}$ -- i.e., equal in magnitude but opposite in sign. If mobility is partly driven by match effects, however, this symmetry prediction will fail. It is even possible the average earnings gains are positive for movers in both directions (as is often assumed in Roy (1951)-style sectoral choice models). We present more analysis of symmetry in gains and losses below. However, we can already see support for the symmetry prediction in Figure 2. In particular, the gains for movers from quartile 1 CZ's to quartile 4 CZ's are (roughly) equal and opposite to the losses for movers from quartile 4 CZ's to quartile 1 CZ's.

Evaluating the Specification

We take several approaches to evaluating the functional form of equation (2) and the assumption of exogenous mobility.

First, we examine the residuals from equation (2), looking for evidence that the mean residuals for high or low skilled workers (classified by the estimated value of α_i) are larger in magnitude for jobs in high or low premium CZ-industry cells (classified by the estimated value of ψ_{cj}).

Second, we examine average wage changes for workers moving from one CZ-industry cell to another, and compare these with the prediction from the model. As noted, with exogenous mobility the mean predicted change in earnings for a worker who moves from CZ/industry pair (c, j) to CZ/industry pair (d, k) is $\Delta_{dk,cj} = \psi_{d,k} - \psi_{c,j}$. We construct the average observed wage changes for different groups of movers and compare these to the predicted changes from our model, $\widehat{\Delta}_{dk,cj} = \hat{\psi}_{dk} - \hat{\psi}_{cj}$. To address problems caused by sampling error in the $\hat{\psi}'s$, we use a split sample procedure, instrumenting

$\widehat{\Delta}$ for movers in sample A with an estimate of $\widehat{\Delta}$ derived from models fit to observations not included in Sample A.

Third, as discussed below, we estimate model (2) separately for more- and less-educated workers, using subsets of the LEHD data set that have education information from other Census surveys. We verify that estimates of ψ_{cj} for higher- and lower-educated workers are very highly correlated, implying that the functional form of the pooled model, with additive separability of individual and CZ-industry effects, is (approximately) correct.

Equation (2) assumes that only a worker's current industry and CZ matter for determining her current wage. As noted by de la Roca and Puga (2017), however, is possible that work experience in certain locations (e.g., the biggest cities) affects wages in all subsequent jobs. To explore such dynamic effects, we re-estimate model (2), controlling for the number of quarters of previous employment (regardless of where that work was done), and for quarters of previous employment in specific sets of CZ's (e.g., the 10 largest or 25 largest CZ's), interacted with indicators for where the worker is currently located. While we find some evidence of dynamic effects, they are relatively small and imprecisely estimated, and their addition leads to little change in the estimated contemporaneous effects for working in different CZ's. Accordingly, for most of our analysis we use the simpler specification without such dynamic effects.

Decomposing Mean Earnings Differences Across CZ's and the Variance of Individual Earnings

Assuming that the specification of equation (2) is valid, we can use it to decompose differences in mean wages across CZ's. Averaging across workers and time periods, we get:

$$\bar{y}_c = \bar{\alpha}_c + \Psi_c + \bar{X}_c\beta \tag{3}$$

where $\bar{\alpha}_c$ – the mean of the person effects for workers in the CZ – summarizes the average skill of the workforce, $\Psi_c \equiv \sum_j s_{cj}\psi_{cj}$ (where s_{cj} is the share of employment in industry *j* in CZ *c*) represents an average locational premium, and $\bar{X}_c\beta$ represents a coefficient-weighted average of the time-varying effects (which we expect to be nearly constant across CZ's). This decomposition differs from the simpler one based on (1) because we can use the fixed effects for each worker to measure both the observed and *unobserved* components of skill.

We can also use (2) to estimate the share of the variance of individual wages that is attributable to locational premiums. Omitting subscripts, we obtain:

$$V(y) = V(\alpha) + V(\psi) + V(X\beta) + 2cov(\alpha,\psi) + 2cov(\alpha,X\beta) + 2cov(\psi,X\beta) + V(\epsilon) \tag{4}$$

A similar equation characterizes the decomposition of the variance of CZ mean earnings into the variances and covariances of the terms in (3). Of particular interest are the relative magnitude of $V(\psi)$ and $cov(\alpha,\psi)$ (or, respectively, of $V(\Psi)$ and $cov(\bar{\alpha}\,,\Psi)$), which measures the tendency of higher-skilled workers to live in CZ's that pay higher wage premiums.

The terms on the right-hand side of (4) can be estimated by a plug-in procedure. Past studies of *firm* wage setting, however, have noted that estimation errors in α and ψ will lead to biases, potentially overstating $V(\psi)$ and understating $cov(\alpha,\psi)$ (e.g., Andrews et al. 2008; Kline et al., 2020). To address such concerns we use a simple two-sample procedure. Specifically, we estimate equation (2) on subsample A, obtaining parameter estimates $\{\hat{\alpha}_i^A, \hat{\beta}^A, \hat{\psi}_{cj}^A\}$, and again on subsample B, obtaining estimates $\{\hat{\alpha}_i^B, \hat{\beta}^B, \hat{\psi}_{cj}^B\}$. We then construct new estimates $\hat{\alpha}_i^{A(B)}$ of the person effects for workers in subsample A using the CZ-industry effects from the B sample, and form the following estimators:[14]

$$\begin{gathered}\widehat{V(\alpha)} = cov\left(\hat{\alpha}^A, \hat{\alpha}^{A(B)}\right);\ \widehat{V(\psi)} = cov\left(\hat{\psi}^A, \hat{\psi}^B\right) \\ \widehat{V(X\beta)} = cov\left(X\hat{\beta}^A, X\hat{\beta}^B\right);\ \widehat{cov(\alpha,\psi)} = cov\left(\hat{\alpha}^A, \hat{\psi}^B\right) \\ \widehat{cov(\alpha,X\beta)} = cov\left(\hat{\alpha}^A, X\hat{\beta}^B\right);\ \widehat{cov(\psi,X\beta)} = cov\left(\hat{\psi}^A, X\hat{\beta}^B\right)\end{gathered} \tag{5}$$

Since subsamples A and B are independent, these estimators are unbiased.

<u>*Decomposing city and industry effects*</u>

[14] Specifically, $\hat{\alpha}_i^{A(B)} = \frac{1}{T_i}\sum_t y_{it} - \hat{\psi}_{cj(i,t)}^B - X_{it}\hat{\beta}^B$ where T_i is the number of earnings observations for individual *i.*

Next we consider the structure of the locational wage premiums in (2). We focus on three related questions: (i) Do some CZ's pay higher wages for workers in all industries? (ii) Is the average wage premium for certain cities partly due a higher share of jobs in industries that tend to pay more everywhere (e.g., finance in NYC)? (iii) Do industry wage premiums vary by CZ, and if so is this variation associated with more employment in sectors with higher local returns – a local concentration effect that could also contribute to average wage premiums.

We begin with a simple regression of the estimated CZ-industry effects $\hat{\psi}_{cj}$ on CZ dummies and industry dummies:

$$\hat{\psi}_{cj} = \theta_c + \mu_j + e_{cj} \ . \tag{6}$$

The R-squared of this model provides an initial indication of the importance of CZ-industry match effects, which are captured in the residual term e_{cj} along with any sampling error in $\hat{\psi}_{cj}$.

To distinguish the sampling error component, we fit equation (6) using estimates of $\hat{\psi}_{cj}$ from our B sample. We then take the residuals and include them as a control function in an expanded model for $\hat{\psi}_{cj}$ from our A sample. The gain in explanatory power associated with the addition of this control function can be used to estimate the true variance in the CZ-industry match effects in ψ_{cj}. We also estimate specifications that include the share of employment in industry *j* in CZ *c* (or the log of this share) as an additional regressor in (6). The coefficient on this variable measures the extent to which match effects are related to the local size of an industry, reflecting potential agglomeration effects.

Next, we turn to an Oaxaca (1973) style analysis of the average wage premiums in different CZ's – the Ψ_c components in equation (3). Let w_c represent the share of national employment in CZ c, let $\bar{s}_j$ represent the share of national employment in industry *j,* and let $\bar{\psi}_j$ represent a weighted average of the wage premiums for industry *j*: $\bar{\psi}_j = \sum_c w_c \psi_{cj}$.[15] The city average wage premium can then be decomposed as:

$$\Psi_c = k + \underbrace{\sum_j \bar{s}_j(\psi_{cj} - \bar{\psi}_j)}_{1} + \underbrace{\sum_j(s_{cj} - \bar{s}_j)\bar{\psi}_j}_{2} + \underbrace{\sum_j(s_{cj} - \bar{s}_j)(\psi_{cj} - \bar{\psi}_j)}_{3}. \qquad (7)$$

where $k \equiv \sum_j \bar{s}_j \bar{\psi}_j$ represents the average industry premium earned by workers in a representative CZ with national-average industry shares, and is constant across CZ's.

Term 1 on the right-hand side of (7) is a share-weighted average of the gap between the industry premium earned in CZ *c* and the corresponding national average industry premium, $(\psi_{cj} - \bar{\psi}_j)$. This measures the average locational premium for the CZ. Term 2 represents the excess share of workers in different industries $(s_{cj} - \bar{s}_j)$, weighted by the national average wage premium in each industry. This measures the effect attributable to the presence of typically higher- or lower-wage industries in CZ *c*, or the contribution of industry composition to the CZ's average earnings premium. Finally, term 3 arises from a correlation between the share of an industry in a given CZ and any excess local wage premium in that industry, and will reflect local agglomeration effects.

To illustrate, consider the example of New York City, which is well known to contain a disproportionate concentration of finance industry employment. Term 1 would be larger if finance *and other sectors* pay more in NYC than do jobs in the same sectors in the average CZ. Term 2 would be larger if NYC has a relatively large share of workers in finance, which is highly paid everywhere. Finally, term 3 would be larger if industry-specific pay premiums in NYC are higher in the industries (like finance) where NYC workers are more likely to be employed.

To summarize the implications of equation (7) we calculate the variances and covariances of the 3 non-constant terms on the right hand side, and compute the shares of each term in the overall

[15] Note that we use a fixed set of city weights to define the national average wage premiums for each industry, rather than using industry-specific city weights. This choice simplifies the interpretation of the interaction term in our decomposition.

variance of Ψ_c. The variance of term 1 measures the importance of CZ differences in the average pay premiums. In the additively separable case where $\psi_{cj} = \theta_c + \mu_j$, this term is just the variance of θ_c. The variance of term 2 reflects the variation across CZ's in the relative presence of "high premium" industries – those that pay more in all CZ's. This term will be close to 0 if all CZ's have the same industry composition, or if compositional differences are uncorrelated with average wage premiums. Finally, the variance of term 3 reflects the importance of local specialization that is correlated with local pay premiums. This term will be zero if ψ_{cj} is additively separable (with no local match effects), <u>or</u> if an industry's share of jobs in a CZ is uncorrelated with the match effect. One of the covariances is also of interest. One model of industry agglomeration effects might be that expansions of employment in high-wage industries raise wages not just in those industries but across all industries in the CZ. This would appear as a positive covariance between term 2 and term 1.

<u>Geographic variation in the return to education</u>

Next, we examine differences in the returns to education across places. The starting point for this analysis is the observation that the gap in wages between more- and less-educated workers tends to be bigger in cities with higher average wages (or in larger cities). Equation (3) allows us to disentangle the sources of the pattern: Is it due to the fact that CZ-average wage premiums are different for higher- and lower-educated workers? Or to differences in the unobserved skills of more- and less-educated workers in different cities, which can be captured by the person effects in an AKM-style framework but remain unobserved in simple cross-sectional wage models?

We begin by estimating our earnings model separately for high- and low-education workers, defining the former as those with at least some college education, and the latter as those with only high school or less.[16] Denoting education by e, the AKM model for education group e (e=H, L) is:

[16] We use education data collected in the ACS and linked to LEHD, which are available for about 10% of all workers in LEHD. See Abowd et al. (2009).

$$y_{iet} = \alpha_i + \psi^{e}_{cj(i,t)} + X_{it}\beta^{e} + \epsilon_{iet}.$$

We construct the averages of α, X, and y for each education group in each CZ-industry, $\bar{\alpha}_{ce}$, $\bar{X}_{ce}$, and $\bar{y}_{ce}$. Last, we define the share of group-e workers in CZ c who work in industry j as s_{cje} (with $\sum_j s_{cje} = 1$ for each c and e).

Generalizing equation (3), the education gap in CZ c, $\bar{y}_{cH} - \bar{y}_{cL}$, can be written as:

$$\bar{y}_{cH} - \bar{y}_{cL} = (\bar{\alpha}_{cH} - \bar{\alpha}_{cL}) + (\bar{X}_{cH}\beta^{H} - \bar{X}_{cL}\beta^{L}) + (\Psi_{cH} - \Psi_{cL}) \quad (8)$$

where $\Psi_{cH} = \sum_j s_{cjH}\psi_{cjH}$ and $\Psi_{cL} = \sum_j s_{cjL}\psi_{cjL}$ are the CZ-average wage premiums for high and low educated workers, respectively. The first term in (8) reflects the gap in average human capital between high- and low-education workers in the CZ, the second term reflects differences in the covariate effects for the two groups, and the third reflects difference in the average pay premiums for the two groups.

Generalizing equation (7) we can decompose the third term:

$$\Psi_{cH} - \Psi_{cL} = \underbrace{\sum_j s_{cj}\big(\psi_{cjH} - \psi_{cjL}\big)}_{1} + \underbrace{\sum_j \big(s_{cjH} - s_{cjL}\big)\psi_{cj}}_{2}$$
$$+ \underbrace{\sum_j \big(s_{cjH} - s_{cj}\big)\big(\psi_{cjH} - \psi_{cj}\big) - \big(s_{cjL} - s_{cj}\big)\big(\psi_{cjL} - \psi_{cj}\big)}_{3}, \quad (9)$$

where ψ_{cj} is the CZ-industry premium from a pooled model for the two education groups. The first term in (9) reflects an average "education premium" in the CZ (i.e., a weighted average of the difference in pay premiums for high and low educated workers in the same industry in that CZ); the second term is an industry composition effect, reflecting the relative shares of the two groups in higher premium industries; and the third is a variant of the interaction effect in equation (7) with components reflecting the *relative* clustering of high- versus low-education workers in industries with a higher or lower local industry premium for that group.

Combining (8) and (9) yields a decomposition of the return to education in CZ c into five components, one of which (the $X\beta$ term) we expect to be quite small. We use this for two purposes.

First, we explore which of these components account for the association of the local return to education with the CZ average wage level by regressing each component separately on CZ mean wages. Second, we decompose the across-CZ variation in $\bar{y}_{cH} - \bar{y}_{cL}$ into the variances of each of the five components (plus covariances). To the extent that the wage gap between college and high school workers in a CZ reflects differential premiums for the two groups, we expect the first term in (9) to play an important role in both exercises. To the extent that the wage gap is driven by differential selection among the high- and low-education workers in a given CZ, however, we expect the first term in (8), involving $\bar{\alpha}_{cH} - \bar{\alpha}_{cL}$, to play a predominant role.

Decomposing the Effects of CZ Size

As a final exercise we follow a long tradition in urban economics and explore the sources of the tendency for average wages to rise with city size (e.g., Behrens et al. 2014; Eeckhout et al. 2014). Equation (3) implies that if we fit a simple regression model like

$$\bar{y}_c = \delta_0 + \delta_1 \log(Size_c) + \xi_c \tag{10}$$

then the size premium δ_1 can be decomposed into the sum of elasticities of $\bar{\alpha}_c$, Ψ_c, and $\bar{X}_c\beta$ with respect to size, reflecting respectively a skill component, a true size premium adjusted for skill differences, and observable differences (which we expect to be negligible). –We can further decompose the skill-adjusted size premium into the sum of the elasticities of three terms in equation (7) with respect to CZ size. We can also conduct a similar set of analyses separately for high- and low-educated workers, allowing us to decompose the effect of CZ size on the college-high school wage gap.

V. Results

The basic decomposition

We estimate the two-way fixed effects model (2) using our main analytic (A) sample and our alternative (B) sample. Table 2 presents the terms of the variance decomposition given by equation (4). We use for this the cross-sample technique described in equation (5); we show, however, in Appendix

Table 2 that simple plug-in estimates are nearly identical, reflecting the fact that we are estimating a relatively modest number of CZ × industry effects given our sample sizes.

Column 1 of Table 2 presents the standard deviations and correlations between the various terms in equation (3). Column 2 shows the implied variance shares of each component. The standard deviation of log quarterly earnings in our analysis sample is 0.654, and the associated variance is 0.428. About 74% of this variance is attributable to the person effects, 2.2% to the CZ-industry effects, and 5.3% to the time-varying covariates (age and time effects). Another 5.4% is attributed to the positive covariance between the person effects and the CZ-industry effects, while the covariances involving $X_{it}\hat{\beta}$ are negligible. Finally, about 14% of the overall variance in log quarterly earnings is unexplained (implying an R-squared coefficient for the model of about 86%).

The variance shares from our two-way fixed effects model are not too different from the shares that have been estimated in previous two-way fixed effects models of worker and firm pay components (e.g., CHK), though the estimated contribution of the CZ-industry effects in our application is a little lower than is typically estimated for the firm effects in the worker-firm literature, while the residual component is larger. This is not too surprising given that pay differences between employers in the same industry and location will be captured by the firm effects in typical applications of the AKM model, but are part of the residual in our model.

In Columns 3-6 of Table 2, we average the terms of (2) to the CZ-by-industry level (columns 3-4) and the CZ level (columns 5-6) and then apply the same decomposition to these averages. The importance of person effects falls when the data are aggregated, but they still account for 53% of the variance of earnings across CZ-industry cells and 47% of the variance across CZ's. In contrast the variance contribution of the estimated CZ-industry effects rises from 2.2% at the individual level to 12.5% at the CZ-industry mean level and 19.6% at the CZ-mean level. Even more remarkably, the share of the variance attributable to the covariance between person effects and CZ-industry effects rises from

5.4% at the individual level to 30.8% at the CZ-industry mean level and to 34.7% at the CZ-mean level, implying that high-person-effect workers tend to work in high-Ψ_c CZs.[17]

An alternative to the decomposition in columns 5 and 6 of Table 2 is a covariance decomposition based on equation (3): $var[\bar{y}_c] = cov[\bar{y}_c, \bar{\alpha}_c] + cov\left[\bar{y}_c, \widehat{\Psi}_c\right] + cov[\bar{y}_c, \bar{X}_c\beta]$. The relative contributions of the covariance terms are just the regression coefficients from (weighted) regressions of the mean person effects and CZ average wage effects on CZ-average wages. (The third covariance term is approximately 0). These coefficients are 0.62 and 0.38, indicating that over 60% of the variation in mean CZ earnings is attributable to differences in worker skill characteristics captured in $\bar{\alpha}_c$, while under 40% is attributable to differences in local wage premiums, $\widehat{\Psi}_c$. As noted in the discussion of Figure 1, a similar exercise based on a cross-sectional model fit to the ACS shows that observed skills can account for only 27% of the variation in mean CZ wages. Clearly, inferences about skill-based sorting need to take account of both observed and unobserved skills.

To help visualize the implications of our model, Figure 3 presents two simple maps. The upper panel shows the locations of larger CZ's with mean log wages in each of three terciles, as estimated from our ACS sample. The lower panel shows the classification of the same CZ's into terciles of the estimated average CZ premium – i.e., $\widehat{\Psi}_c$. For reference, Appendix Table 3 shows the characteristics of CZ's in each tercile, as well as those with very high (top 10) and very low (bottom 10) estimated CZ effects.[18]

The maps illustrate two key points. First, higher wage CZ's tend to be on the coasts, though there are also some high wage CZ's in more rural but resource-rich areas (such as Western North

[17] The variance shares of CZ average wages in column 6 are not too different from the variance shares of labor market mean wages reported by Dauth et al (2018) for West Germany, though Dauth et al. start with an AKM model with worker and establishment effects and aggregate that model to the labor market area. Specifically, they report that the shares explained by person effects, establishment effects, and the covariance of person and establishment effects are 39.8%, 23.6% and 41.7%, respectively.

[18] For disclosure reasons we cannot report individual CZ averages. The top 10 CZs are Anchorage, AK; Bakersfield, CA; Bismarck, ND; Hobbs, NM; Minot, ND; New York, NY; Odessa, TX; San Francisco, CA; San Jose, CA; and Seattle, WA. The bottom 10 CZs are Columbia, MO; Florence, SC; Gainesville, FL; Hattiesburg, MS; Monett, MO; Ocala, FL; Springfield, MO; St. George, UT; Traverse, MI; and West Plains, MO.

Dakota). Second, CZ's with higher (or lower) premiums tend to have higher (or lower) average wages. This reflects both the direct effect of the pay premiums and the indirect effect arising from assortative matching of highly skilled workers to higher-premium CZ's. Indeed, using equation (3) to calculate the effect of an increase in the average local wage premium, we find that a CZ with a 1 percentage point higher CZ effect has average wages that are 1.88 percentage points higher, since (ignoring the covariates):

$$\frac{\partial E[\bar{y}_c|\Psi_c]}{\partial\Psi_c} = \frac{\partial\bar{\alpha}_c}{\partial\Psi_c} + 1 = \rho(\bar{\alpha}_c, \Psi_c)\frac{\sigma(\bar{\alpha}_c)}{\sigma(\Psi_c)} + 1 = 1.88$$

There are, however, some interesting exceptions to this pattern. Florida has mostly middle or upper tercile average wages but bottom tercile CZ effects. There are also some resource-intensive CZ's (e.g., on the Texas Gulf Coast and in the Permian Basin) that have high CZ effects but only average earnings.

Validating the Specification

As noted in Section IV, for OLS to provide unbiased estimates of the coefficients in our two-way fixed effects model we need exogenous mobility (EM) – moves across CZs and industries have to be uncorrelated with the error term ϵ_{it} in (2). In this section we report some simple tests of EM. To foreshadow our results, we find that EM can be rejected, but that departures from the patterns predicted by EM tend to be small.

Figure 4 presents average earnings by quarter relative to the date of a move, separately for those who move across different categories of CZ-industry cells. It closely parallels Figure 2, but categorizes CZ-industry cells based on their estimated wage premiums rather than on mean earnings. We limit attention to the event study sample described in Table 1, excluding movers who change industry but stay in the same CZs. As in Figure 2, we show only the earnings profiles for movers from the top and bottom quartiles.

Under exogenous mobility, the expected change in earnings from period -1 to period 1 for a person who moves from a typical CZ-industry cell in quartile q_k to a typical CZ-industry in quartile q_h is

$E[\psi_{cj}|\psi_{cj} \in q_h]$-$E[\psi_{cj}|\psi_{cj} \in q_k]$. Thus, it should be approximately symmetric – a move from quartile 4 to 1 should yield about as large a drop in earnings as the increase from a move from 1 to 4.[19] The figure indicates that this prediction largely holds in the data. Moreover, we see again that earnings are flat prior to a move and but adjust a bit more slowly following a move, increasing for several quarters.

Appendix Figure 2 shows the wage residuals from model (2) for the same groups of movers. For movers who leave quartile 1, we tend to see negative residuals in the first post-move quarter, indicating that they have not achieved the full earnings gain the model predicts. But by the second quarter after a move, the residuals are much closer to 0, and within a year the mean residuals are all less than 1% in magnitude. In contrast, movers who leave quartile 4 have positive residuals in every quarter after the move. In the next section we explore one potential explanation for this pattern, which is that movers from upper quartile CZ's receive a return to their experience in these places, as suggested by de la Roca and Puga (2017). We find some evidence of this effect, though the estimated dynamic effects of previous work experience in the largest CZ's are modest-sized and at best only marginally significant.

Figure 5 presents another approach to validating the model (2). Here, we divide CZ-industry cells into vingtiles based on their estimated average earnings premiums, and plot the average change in log earnings from period -1 to period 1 for movers in each of the 400 possible origin and destination cells against the predicted change in ψ_{cj} given the origin and destination vingtiles. Since the CZ-industry effects are estimated with error we use an IV approach to predict the change in $\hat{\psi}_{cj}$ for movers in our A sample based on estimates of ψ_{cj} derived from models fit to the 27 other 3.33% samples.[20] Across all 400 transitions, the (instrumented) slope is almost exactly 1.0 (0.996, standard error=0.0132), suggesting that the two-way fixed effects model does a good job of capturing the average effect of moves. There is some evidence that the model over-predicts the size of losses for movers who are

[19] People who move from quartile 4 to quartile 1 may originate from different CZs within the 4th quartile than the CZ's that are the destinations for movers from quartile 1 to quartile 4.
[20] Results are nearly indistinguishable if we use the B sample to construct the instrument.

predicted to lose 5-15% of earnings, and over-predicts the gains for those who are predicted to gain 10-20%, but overall the model fits the data relatively well.

Figure 6 explores this lack of symmetry further, by comparing the average changes for “upward” movers to the average changes for the symmetric “downward” movers. Earnings fall by a bit less for the downward movers than would be expected from the increase for the upward movers, especially when the move is between CZs with similar estimated premiums, but the symmetry violations are modest.

We also conducted the analysis in Figure 5 separately for workers in the top and bottom terciles of the distribution of α_i, to probe for violations of additive separability. The slope across the origin-destination cells for movers in bottom tercile is 0.980 (standard error = 0.015), while the slope for movers in the top tercile is 0.978 (s.e. = 0.026). The fact that both of these are very close to 1 suggests that the CZ effects estimated in our pooled model are highly predictive of the earnings gains and losses for workers with lower or higher skills, supporting the additive structure of our basic model.

Finally, in Appendix Figure 3 we plot mean residuals by decile of the person and CZ-industry effect distributions. As has been found in previous applications of the AKM model, we find positive mean residuals at the bottom corner of the distribution, corresponding to the lowest values for α_i and ψ_{jc}, and negative mean residuals at the top corner. But the mean residuals are quite small (absolute value < .005) indicating that the model violations are typically small and unsystematic.

Overall, our investigation indicates that equation (2), with its implicit assumptions of additive separability and exogenous mobility, fits the data well, though there are some violations of the exogenous mobility assumption, particularly in the first few quarters after a move, that could be incorporated in future work.

Dynamic effects

De la Roca and Puga (2017) argue that work experience in larger urban areas builds human capital and raises subsequent earnings, leading to a dynamic return to location choices. Such heterogeneity could lead to biases in the estimated person and CZ-industry effects from our baseline specification (2), which does not incorporate any dynamic effect of location-specific experience. To investigate the magnitude of these biases, we estimated a set of models that included 4 additional control variables: (i) cumulative quarters of work for each individual (as measured from the start of our LEHD panel); (ii) cumulative quarters of work in larger CZ's; (iii) an interaction of cumulative work experience with an indicator for currently working in a larger CZ; (iv) an interaction of cumulative work experience in larger CZ's with an indicator for currently working in a larger CZ. These models generalize De la Roca and Puga's (2017) specification slightly by allowing the returns to overall experience and "big city" experience to be valued differently in larger CZ's.

The estimated coefficients on these extra controls are shown in Table 3 for two different definitions of "larger CZ's": the 10 largest CZ's (column 1); and the 25 largest CZ's (column 2).[21] We present estimated standard errors for the dynamic effects that are clustered by the first CZ in which an individual is observed in our sample.

The results point to two main conclusions. First, cumulative work experience in any CZ has a relatively strong, statistically significant effect on earnings, with an implied return of 0.007-0.008 per quarter or around 3 log points per year of work.[22] Second, experience in a larger CZ has an additional positive effect of about 0.0014 to 0.0018 per quarter (0.6 to 0.7 log points per year) outside larger CZs, though the incremental effects are imprecisely estimated. The estimates in column 1, for example, imply that an individual with 5 years of continuous experience in a top-10 CZ would earn about 3.6% higher earnings (with a standard error of 3.2%) if she moved to a non-top-10 CZ. The two specifications differ

[21] The 10 largest (in order) are Los Angeles; New York; Chicago; Washington DC; Northern NJ; Houston; Philadelphia; Boston; San Francisco; and Atlanta. The CZ's around the top 25 cutoff are San Jose (#23), Cleveland (#24), St. Louis (#25), Pittsburgh (#26), and New Orleans (#27).

[22] Because our model also includes controls for both age and calendar quarter, the experience main effects are identified by variation in the cumulative number of quarters of employment over the period covered by our sample, so reflect in part consistency of labor force attachment.

somewhat on how experience is valued in larger CZ's. The model in column 1 suggests that general experience is valued more in top 10 CZ's, but top-10 experience is if anything more beneficial in non-top-10 CZs. In contrast, the results in column 2 suggest that general experience and top-25 CZ work experience are both valued about the same in top-25 CZ's as elsewhere.

To assess the likely degree of bias in the estimates from our baseline models that exclude dynamic experience effects, we regressed the estimates of $\hat{\psi}_{cj}$ and $\hat{\Psi}_c$ from the dynamic specifications in Table 3 on the corresponding estimates from our main specification. To account for correlated sampling errors in the two sets of estimates (both of which are based on our A sample), we again instrument the estimated parameters from our main specification using corresponding estimates from our B sample. The resulting regression coefficients, shown in the bottom rows of Table 3, are very close to 1.0 in all cases, suggesting that there is little systematic bias from using the estimates from our main specification. We also conducted our main decomposition exercises using the estimates from the dynamic specifications and found nearly identical results to those from our main specification. Taking these results together with the relatively small size of the implied dynamic effects from the specifications in Table 3, and their statistical imprecision, we decided to focus on the estimates from the simpler static specification (2) in the remainder of this paper.

The role of industry

Next we explore the role of industry in the estimated ψ_{cj} effects obtained from equation (2). Of particular interest are three issues: the extent to which industry and place effects are additively separable; the role of industry composition in explaining locational wage differentials; and the contribution of industry agglomeration and/or local specialization effects to CZ wage differences.

We begin by using equation (6) to explore potential interactions between industry and place effects. Table 4 reports models for the estimated $\psi_{cj}'s$ that include CZ effects (column 1), industry effects (column 2), and both set of effects (column 3). The R-squared statistics show that 43% of the variation in $\hat{\psi}_{cj}$ can be explained by CZ, while 46% can be explained by industry. Remarkably, the combined explanatory power of the two sets of effects is 88.4%, just 0.6 percentage points less than the sum of that explained in columns 1 and 2. The implication is that place and industry factors are nearly orthogonal, so the CZ-wide component of ψ_{cj} is similar whether we control for industry or not.

Nevertheless, the fact that the R-squared of the model in column 3 is less than 100% means that estimated pay differences across industries vary by CZ – i.e., that there are "match effects" in $\hat{\psi}_{cj}$. Whether this reflects true variation in ψ_{cj} depends on the sampling errors in the $\hat{\psi}'_{cj}s$. To isolate the true match effect component, we re-estimated the model with CZ and industry effects using our B sample and computed the residual, $\hat{e}^{B}_{cj}$. We then add this as an additional explanatory variable in the model for sample A. The coefficient on the residual measures the correlation between $\hat{e}^{A}_{cj}$ and $\hat{e}^{B}_{cj}$, i.e., the reliability of estimated match effects. The results, presented in column 4, show that the coefficient on $\hat{e}^{B}_{cj}$ is a relatively high 0.88. This estimate implies that true match effects between place and industry account for about 10% of the variance of ψ_{cj}.[23]

Having established this fact, we next check whether the variation in match effects is driven by industry agglomerations. In the final two column of Table 4, we return to the specification from column 3 but add a control for s_{cj} – industry *j's* share of employment in the CZ. We experiment with using s_{cj} (in column 5) or $log(s_{cj})$ (in column 6).[24] Column 5 indicates that a one percentage point increase in an industry's local employment share is associated with about a 0.24 percent increase in relative earnings

[23] The 0.886 reliability of the estimated match effects implies that true match effects account for about 88% of the residual component of CZ-industry effects after controlling for CZ dummies and industry dummies. The R-squared of 0.884 in column 3 of Table 4 implies that the residual component is about 12% of the variance in estimated CZ-industry effects. Since the standard deviation of the estimated CZ-industry effects is 0.097 (Table 2, column 3), the standard deviation of the true match effects is approximately 0.031, accounting for about 10% of the variance in the true (sampling error corrected) CZ-industry effects.
[24] Because the model includes CZ fixed effects, controlling for the log employment share is equivalent to controlling for the log number of workers in the industry in the CZ.

in that industry, on top of the nationwide industry wage premium, while column 6 indicates that a one percent increase in industry employment in a CZ is associated with a 0.023 percent increase in relative earnings. (Note that these coincide for an industry with ten percent of employment in the CZ at baseline.[25]) Thus, each is consistent with the presence of local agglomeration effects. However, the goodness of fit increases only slightly relative to the model in column 3. Indeed, a comparison of the R-squared coefficients suggest that industry size differences explain only about 1% of the overall variation in CZ-industry effects. We conclude that although local agglomeration is associated with higher earnings, the net effect is small because industry shares do not vary enough across CZ's.[26]

To explore this further, in Table 5 we turn to the formal decomposition of CZ-mean effects given by equation (7). As shown in the first row of the table, pure locational wage premia (term 1 in equation 7) account for just over 100% of the variation in Ψ_c. Industry composition effects (term 2 in equation 7) explain only 1.5%. Moreover, the industry composition effect is negatively correlated with the pure locational component, implying that high wage industries are slightly more concentrated in areas with low *average* location wage effects – and cutting against the idea that agglomerations of employment in high-wage industries lead to across-the-board earnings increases in the CZ. This negative covariance more than fully offsets the small positive variance contribution of local composition differences. Finally, specialization of CZs in industries where the CZ has a comparative pay advantage (the interaction effects in term 3 of equation 7) explains just under 1% of the overall variation in Ψ_c, consistent with their incremental R-squared in the simpler models in Table 4.

[25] This assumes that growth in the industry's employment does not induce growth in the CZ's overall workforce. If overall employment grows by r% for each 1% increase in industry employment, the two coincide when $s_{jc}(1\text{-}r)$ = 0.1.

[26] We have also explored specifications like those in columns 5 and 6 that allow the industry share coefficient to differ for tradeable vs. non-tradeable industries. The coefficient is slightly larger for tradeable industries, but not substantially so, and there is no meaningful increase in the goodness of fit.

A concern with the conclusion that industry composition and agglomeration effects are relatively small is that we may not be accounting for industry in enough detail. Our baseline estimates are based on "2-digit" industry coding with 24 sectors, a categorization that may be too coarse to capture many well-known industry agglomerations (e.g., furniture in North Carolina). The LEHD has 4-digit industry codes, but since many smaller CZ's have few or no workers in the smaller sectors it is infeasible to expand our baseline model to finer industries.[27] Instead, we explore this by limiting attention to the 50 largest commuting zones, which include 58% of the workers in our sample. We re-estimate our baseline model in these larger CZ's using four-digit industries. Reassuringly, we find that CZ average person effects ($\bar{\alpha}_c$) based on an expanded industry definition are very highly correlated with those from our baseline model ($\rho = 0.999$), indicating that the apportionment of CZ earnings differences into person and place-by-industry effects is highly robust to industry coding.

Columns 2 and 3 of Table 5 show results based on equation (7) for the 50 largest CZs. Column 2 reproduces the results in column 1 using our baseline 2-digit industry classification for these larger CZ's. The results are quite similar to those for the overall set of CZ's. Column 3 then redoes the analysis using 4 digit industries. Here we find a slightly larger covariance between average CZ earnings premiums and the average interaction effect, but substantively the results are very similar to those in column 1.

In addition to the granularity of industries, there are several other concerns that might be raised about the analysis in Tables 4-5. One is that we may be incorrectly assigning workers to CZ's and/or industries because of establishment imputation errors in the LEHD data. As discussed above, we can assess this by limiting our analysis to observations where we are confident of the CZ and industry assignments. Results of our analyses of this subsample are nearly identical to those from our main specification. (See Appendix Table 4 for the alternative version of Table 2).

[27] Our decomposition methods rely on having positive shares of employment in each CZ-industry cell.

A second concern is that our main specification, which ignores dynamic effects of work experience in larger CZ's, leads to biases in the implied contribution of local industry structure. To address this we used the estimated CZ-industry effects from the models in Table 3 to redo the decomposition of equation (7). Again, we found results that are very close to our main specification.

A third concern is that our LEHD sample may over-weight individuals who are observed moving in our sample window. We investigated this concern by evaluating the components of the variance decompositions in Table 2 separately for people who are observed in the same CZ throughout our sample. The results, reported in Appendix Table 4, are quite similar for those for our overall sample, leading us to believe that alternative sampling schemes would yield similar results.

A fourth potential concern is that we do not account for occupational differences in our analysis. Although the LEHD lacks information on occupations, we don't believe that such controls are necessary. Many occupations (like nurse or attorney) reflect the skills and training that a worker brings to the job. Such characteristics are absorbed in the person effects in our model. Many occupations are also closely associated with specific industries (e.g., auto mechanics in the car repair sector). Our analysis in Table 4 showed that our main conclusions are highly robust to using detailed (4 digit) industry effects to define the pay premiums in equation (2). Finally, insofar as workers gain or lose access to *specific* occupations when they change CZ's (such as when a teacher's aide moves to a place with lower credentialing requirements and obtains a position as a classroom teacher) the consequent wage changes are reasonably considered to be part of the causal place effect.

Overall, the evidence in Tables 4 and 5 shows that 95% or more of the variation in CZ-specific average wage premiums is attributable to place effects that are common across industries, rather than to the confounding effects of industry structure. Consistent with local agglomeration theories, industry wage premiums <u>are</u> higher in places where an industry employs a higher fraction of local workers, but on net these effects contribute only about 1-2% of the overall cross-CZ variation in average wage premiums.

This relatively small role for agglomeration may seem inconsistent with some existing studies, such as Greenstone, Hornbeck, and Moretti (2010) (hereafter, GHM). GHM find that the opening of a "million dollar" manufacturing plant leads to a 13% increase in the number of manufacturing plants in the county and to a 6% increase in employment at incumbent plants, for an approximately 19% total increase in manufacturing employment. They also find that a plant opening leads to a 2.7% increase in manufacturing wages (with a standard error of 1.4%). Our estimates (from column 6 of Table 4) imply that a 19% increase in employment would lead to a 0.4% rise in manufacturing wages relative to other industries in the CZ, fully adjusted for the quality of workers.[28] Thus, while our estimates are smaller than GHM's *point estimate* of the total wage effect of a new plant, they are well within the confidence interval for their estimate.

Local differences in returns to education

Next we turn to an exploration of differences in the return to education across commuting zones. In order to implement the analysis described in equations (8) and (9), we have to re-estimate our two-way fixed effects models separately on samples of low and high educated workers. We start with our full LEHD sample, finding people who were interviewed in the ACS at some point in the 2001-2017 period, were age 30 or older when interviewed, and provided their education. This subsample represents about 14% of our full analysis sample, somewhat larger than our 10% A sample. We then define two groups: people with no more than 12 years of completed schooling (the low education group) and people with at least some college (the high education group).

[28] Moreover, we find that ψ_{jc} is positively correlated with $\bar{\alpha}_{jc}$ conditional on CZ and industry fixed effects, suggesting that the increase in manufacturing employment would attract higher-α workers to the industry in the CZ. Assuming that the education controls that GHM include in their wage regression do not fully capture α, this would represent an additional component of their estimated wage effect.

Appendix Table 5 provides a summary of the estimation results for two-way fixed effects models fit to these two samples. The results for the education subgroups are very similar to those for our pooled sample. At the individual level the variance of the person effects accounts for around three quarters of the overall variance of earnings, regardless of sample, while CZ-industry effects and their covariance with the person effects account for another 7-10%.

When we look at the aggregated implications of the estimates for the two education groups, however, an interesting pattern emerges. For lower-educated workers, CZ-industry effects account for a noticeably larger share of the variance of mean earnings across CZ-industry cells and CZ-average cells, while for higher-educated workers, variation in the person effects accounts for a larger share of these variances. There is also a notable difference in the degree of assortative matching across CZ's: the correlation between mean person effects and the average CZ wage premiums is 0.42 for lower-educated workers but 0.65 for higher-educated workers.

A key question for interpreting these differences is whether the estimated CZ-industry effects are approximately the same for the two education groups, or substantially different. To assess this, we regressed the estimated effects for the lower-educated group ($\hat{\psi}_{cjL}$) on the corresponding estimates for the higher-educated group ($\hat{\psi}_{cjH}$). We find that the two sets of effects are very highly correlated: the estimated regression coefficient is 0.991 (standard error=0.014). To see whether this high correlation masks small but systematic differences at the CZ level, we construct $\hat{\Psi}_{cL} = \sum_j s_{cj}\hat{\psi}_{cjL}$ and $\hat{\Psi}_{cH} = \sum_j s_{cj}\hat{\psi}_{cjH}$, using the <u>same set</u> of CZ-industry weights for both education groups (based on the combined sample) and then regress $\hat{\Psi}_{cL}$ on $\hat{\Psi}_{cH}$. Again, we obtain an estimated slope very close to 1 (0.988, standard error=0.073).[29] We conclude that the CZ-industry wage premiums for lower- and

[29] One might be concerned that the estimated CZ-industry effects are estimated with error. To address this we also estimated the two sets of models by IV. We split the college sample into two groups, estimated two sets of $\hat{\psi}_{cjH}$'s , and used one set as the instrument for the other. In both cases the IV estimate is very similar to the OLS estimate, and very close to 1.0.

higher-educated workers are very similar, consistent with our baseline model (which assumes a constant effect for both groups).

With this background we turn to equations (8) and (9), which decompose the CZ-level earnings gap between high- and low-education workers, $\bar{y}_{cH} - \bar{y}_{cL}$, into the difference in mean person effects between high- and low-education workers, differences in the covariates (age and time), and differences in the CZ-industry effects. Columns 1 and 2 of Table 6 present regressions of the CZ-level wage gap $\bar{y}_{cH} - \bar{y}_{cL}$ and each of its components on the mean log wage in the CZ (as measured from the ACS). As shown by the 0.644 estimate in the first row, higher-wage CZ's have much larger education wage gaps: a 30 log point increase in the mean wage in the CZ (equivalent of moving from Houston to San Francisco) is associated with a 20 log point widening of the college-high school wage gap. When we decompose the source of this divergence using equation (8), we find that 94% (0.604/0.644) is attributable to differences in person effects, while only 6% (0.042/0.644) is due to differences in the local wage premiums. This is further confirmation that CZ-industry premiums are very similar for lower and higher educated workers.

Interestingly, as shown in rows 5-7, the small net contribution of differential CZ-industry effects arises from two competing forces: on average, the share-weighted gap in CZ-industry premiums for higher- and lower-educated workers (term 1 in equation 9) is smaller in high-wage cities (regression coefficient = -0.068); but the gap in industry employment shares between the two groups, weighted by the average wage premium for the industry (term 2 in equation 9) is larger (regression coefficient = 0.092). Thus, to the extent that CZ-industry premiums contribute to the widening of the college-high school gap in higher-wage cities, it is because of greater assortative matching of college workers to higher-paying industries (consistent with Dauth et al., 2018), and not because of a higher return to education in those CZ's.

Columns 3 and 4 of Table 6 use the same five-part decomposition, this time exploring the overall variation in the CZ-level return to education. We see a generally similar pattern here. Differences in the person effects of more- and less-educated workers explain 78% of the variation in the apparent return to education, while differences in the share-weighted gap in returns explains 7.5%. There are also some important covariance components. Most importantly, there is a positive covariance between the difference in person effects of the two education groups and the relative industry composition effect. In CZ's with a larger skill gap between college and high school workers, college workers are more likely to work in high-premium industries: a pattern that reinforces the overall importance of the differential selectivity of college versus non college workers.

The CZ size gradient

Finally, we turn to an exploration of CZ size premiums, using the framework of equation (10). The first row of Table 7 shows that the elasticity of mean earnings in our LEHD sample with respect to CZ size is 0.0765 – very similar to the estimate based on ACS data discussed in Section II (0.072). Rows 2 and 3 decompose earnings into a skill component ($\overline{\alpha}_c$) – which accounts for 66% of the overall size elasticity -- and a CZ effect (Ψ_c) – which accounts for one-third. This decomposition is quite different than that obtained using observed skills in the ACS, where (as noted in Section II) over 80% of the size elasticity was attributable to factors other than observed skills. As shown in rows 5 and 6, larger CZ's tend to have a higher share of very highly skilled workers (with person effects in the top decile of the overall distribution) but the same share of very low-skilled workers (with person effects in bottom decile) as smaller CZs. They also have more overall dispersion in skills.

In rows 8-11 we use the decomposition of equation (7) to dig further into the sources of the relationship between the city-average wage premium, Ψ_c, and log CZ size.[30] Here we see that the CZ-

[30] To analyze the components of equation (6) we have to limit attention to CZ's that have workers in every industry. In this subset the elasticity of the CZ-average wage component (Ψ_c) with respect to log size is slightly larger (0.0317) than in the overall sample of CZ's (0.026).

specific premium component ($\sum_j \bar{s}_j(\psi_{cj} - \bar{\psi}_j)$) drives the entire effect. Once again, industry composition effects and interactions between local industry-specific premiums and the local share of workers in the industry are unimportant.

Row 12 returns to the question of whether the degree of sorting between high wage workers and high wage industries varies across CZ's. Classifying CZ's by size we see a significant positive relationship: a 100 log point increase in CZ size is associated with a rise of +0.0612 in the correlation between the mean person effects in an industry and the average premium paid by that industry nationally (i.e., $\rho(\overline{\alpha}_{jc}, \overline{\psi}_{j})$). This confirms Dauth et al.'s (2018) findings in Germany regarding the role of market size in enhancing sorting.

In Table 8 we examine the relationships between log size and the components of the return to education. Panels a and b examine non-college and college workers separately, while Panel c examines the gap between the two. Comparing the first row of Panel a with that of Panel b, we see that the elasticity of earnings with respect to city size is much larger for more educated workers (0.1020) than for less educated workers (0.0386). Thus, as shown in the first row of Panel c, the gap in wages between the two education groups rises with CZ size (coefficient=0.0612).

Next, in row 2 of each panel we examine the component of mean earnings for each education group that is attributable to worker skills. Among less-educated workers mean skills have a modestly positive elasticity with respect to CZ size (0.0198). Among more educated workers the elasticity is over 3 times bigger (0.0744): thus the gap in skills between a typical worker with some college education and a worker with high school or less education is sharply rising with size (elasticity = 0.0540). In contrast, the CZ wage premiums for better-educated workers are only slightly more elastic with respect to CZ size than the premiums for less-educated workers (0.0287 versus 0.0193).

Most of rise in the education wage gap across larger cities is therefore attributable to the greater selectivity of the college-education workforce in larger cities, rather than to the tendency for larger CZ's to raise wages more for higher-educated workers. When we look more deeply into the three components of the difference in CZ wage premiums identified in equation (9) (row 3 of Panel c), we see that virtually all of this is attributable to the differences in relative industry composition for the two education groups (consistent with the results in columns 3 and 4 of Table 6).

To summarize: higher wages in larger CZ's are driven by a combination of more highly skilled workers (66%) and a "size premium" (33%). The overall CZ size premium – which in our framework represents a weighted average of premiums for different industries – is very similar across industries. However, we also see that in larger CZ's higher-skilled workers are more likely to work in higher-paying industries. When we classify workers by education, we see that the differential sorting of high skilled workers to larger CZ's is particularly important within the college workforce. Thus, what appear to be higher average wages for college workers in larger CZ's is mainly due to the higher skills of college workers in those places. The size premium for college-educated workers is only slightly larger than that for high school workers. And interestingly, this greater premium arises because the most highly skilled college workers are more likely to work in high paying industries in the larger CZ's, consistent with the sorting pattern we see across the overall workforce.

VI. Earnings and the cost of living

So far we have considered decompositions of nominal earnings, unadjusted for local differences in the cost of living. But there are large and persistent differences in housing costs between places (see e.g., Moretti, 2013). Many of the coastal cities identified in Figure 5 with high causal effects on earnings have relatively high housing costs. A natural question is how the causal earnings effects that we identify relate to differences in local costs – does moving to a larger city mean an increase in real earnings, or are the increased nominal earnings offset by higher costs?

Diamond and Moretti (2021; hereafter *DM*) use detailed expenditure and price data to construct price indexes and measures of real consumption for different income and education groups in different CZ's. They find that the size elasticity of the cost of living is approximately 0.04 for higher- and lower-educated workers.[31] Comparing this with the size elasticities of nominal income, they conclude that nominal earnings differences roughly compensate for the higher cost of living in larger cities for better-educated workers, but not for less-educated workers. They are careful to point out, however, that their comparisons effectively assume that there are no skill differences between workers in a given education group in different CZ's. Our analysis suggests that in fact college educated workers in larger cities have substantially higher skills: roughly three quarters of the 0.102 size elasticity of average earnings for college workers in Table 8 is due to differences in worker skills and only one quarter (0.029) reflects a causal place effect. Comparing the causal effect of size to the elasticity of the cost of living, the implication is that the causal effect of moving from a smaller city to a larger city is to *reduce* real earnings, even for college graduates.

To investigate these issues more directly, we use rents and housing costs information from the ACS to explore how housing costs vary with CZ size. Table 9 presents regressions of four CZ-level housing measures (mean log home values for homeowners and mean log rents for renters, each unadjusted and then adjusted for housing characteristics[32]) on log CZ size. We find that the elasticity of housing costs with respect to log size is around 0.2 or larger. Because housing typically represents at least one-third of a household's budget, these estimates imply that nominal wages would have to exhibit a size elasticity

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[31] DM's Figure 13 reports expenditure and real consumption size elasticities for workers in 3 education groups. The difference in these elasticities is the size elasticity of the cost of living index, which is 0.040 for workers with college education, 0.042 for workers with exactly high school education, and 0.043 for high school dropouts.
causal effects on nominal earnings, so the result holds for lower-skill workers as well.

[32] The quality adjustment models include controls for type of unit (with five classes of apartment building size), number of bedrooms and of total rooms, year of construction, indicators for utilities included in rent (for rents only), and an indicator for whether the owner has a mortgage (homeowner model only). The model for rents has an R2 of 0.34, while that for home values has R2=0.50.

of 0.07 or more to keep up with the cost of living. But the estimate in Table 7 shows that the size elasticity of the CZ average wage premium (for all education groups) is 0.026, less than 40% of the magnitude needed to match the rise in the cost of living. We conclude that housing costs consume more than 100% of the nominal earnings gain that a typical worker obtains from moving to a larger CZ. Accounting for the other components of consumption studied by Diamond and Moretti (2021) would only strengthen this result.

An interesting question, beyond the scope of this paper, is how this can be sustained. In the standard Roback (1982) framework, causal effects of places on nominal earnings imply differences in productivity. But why would workers prefer to live in high-productivity cities if they will need to give up more than all of the earnings advantage of those cities in higher housing costs? One potential explanation consistent with Roback (1982) is the presence of consumption amenities (Albouy 2011; Albouy, Cho, and Shappo 2021). Our evidence suggests that these amenities must be more valuable in larger CZs, offsetting the reductions in real wages for workers in these more productive places.

VII. Concluding Remarks

We have used an earnings model with a combination of individual worker effects and additive premiums for different commuting zone/industry combinations to address longstanding questions about the impact of place on labor market outcomes in the U.S. This class of two-way fixed effect models, originated by Abowd, Kramarz and Margolis (1999), has proven very useful in answering questions about the role of firms in wage determination (Card et al., 2018). While versions of this approach have been used in France (Combes et al., 2008), Spain (de la Roca and Puga, 2017), and Germany (Dauth et al., 2018), ours is the first to apply it to the U.S., using data from the Census Bureau's LEHD program.

We first show that a model with additive premiums for different commuting zone (CZ) and industry combinations provides a relatively good summary of the main patterns in the data, and can be estimated by simple OLS methods without too much concern for biases arising from either the strategic timing of moves or idiosyncratic match effects in earnings that drive mobility decisions. We find some evidence of the kind of dynamic returns to "big city" experience highlighted by de la Roca and Puga (2017) but the addition of this channel has little impact on the static returns to different CZ's.

A key advantage of our specification, which generalizes models with only worker and place effects (or with additive worker, place, and industry effects) is that we can carefully assess the role of industry in mediating observed place effects in average earnings. Such effects can arise in two main ways. First, there can be a pure compositional effect if some CZ's have a higher fraction of high-wage industries. More subtly, there can be an interaction effect if the earnings premiums for different industries vary across places and employment is locally concentrated in industries with a larger local premium. We find very small roles for either mechanism. In fact, CZ × industry pay premiums are approximately separable: only about 10% of the variation in these premiums is due to CZ-specific premiums. Moreover, we find only small interaction effects arising from the concentration of employment in sectors with a local pay premium. Wages are higher in locally agglomerated sectors, by an amount consistent with previous work (e.g., Greenstone, Hornbeck, and Moretti 2010), but industry composition does not vary enough across CZs to generate large differences in the weighted average of pure industry effects. Importantly, these conclusions are highly robust to the definition of industry. Comparing models with only 24 industries with models with close to 300, we reach nearly identical conclusions.

As in the AKM-related literature, we measure worker skills by the worker's fixed effect in the earnings model. We find that this measure of skill varies far more widely across CZ's than a more traditional measure based on observable characteristics like education, age and gender. Consistent with work in France, Spain and Germany we find that the main explanation for high wage places is the presence of high wage people. Comparing larger and smaller CZ's, for example, two thirds of the size elasticity of mean earnings is attributable to the presence of higher skilled workers. The tendency for high-wage workers to work in high-wage places magnifies overall earnings inequality in the market as a whole and represents an important feature of locational equilibrium.

We find two interesting sources of variation in the degree of assortative matching. First, college-educated workers are more highly sorted to larger and higher-wage CZ's than their less educated counterparts. Nearly all of the higher "return to college" that is observed in higher-wage (or larger) places is attributable to the presence of college workers with the highest unobserved skills in those places. The differences in sorting are consistent with Diamond (2016), though her model ignores unobserved skills and treats earnings differences as causal. Second, we find that the sorting within CZ's of high wage workers into high wage industries is enhanced in larger places. This confirms a similar finding by Dauth et al. (2018) in Germany, and illustrates a potential benefit of increased market size for the overall productivity of the economy.

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Table 1: Characteristics of Samples Derived from Longitudinal Employer-Household Dynamics (LEHD) Data Base

	All LEHD Obs. (1)	Estimation Sample (2)	Subgroups of Estimation Sample: CZ & Ind. Stayers (3)	CZ Stayer Ind. Mover (4)	CZ Mover Ind. Stayer (5)	CZ & Ind. Mover (6)	Event Study Sample (7)
Share with Quarterly Earnings ≥ $3800	0.837	1	1	1	1	1	1
Mean Earnings (if ≥ $3800)	16,050	16,600	16,890	15,210	18,500	16,300	17,420
Mean Age	41.11	42.51	44.82	40.11	40.96	38.79	39.95
Fraction Female	0.492	0.472	0.497	0.465	0.476	0.405	0.438
Fraction Foreign Born	0.167	0.163	0.167	0.175	0.148	0.143	0.144
Number of CZ's during Sample Period:							
1 CZ	0.631	0.731	1	1	0	0	0.454
2 CZ's	0.231	0.201	0	0	0.825	0.712	0.546
3+ CZ's	0.138	0.068	0	0	0.175	0.288	0
Number of 2-digit Industries during Sample Period:							
1 Industry	0.495	0.630	1	0	1	0	0.282
2 Industries	0.263	0.257	0	0.775	0	0.616	0.719
3+ Industries	0.242	0.113	0	0.225	0	0.385	0
Mean Number of Quarters Observed	21.39	22.49	24.12	21.22	22.43	19.76	10
Mean Est. Person Eff.		9.419	9.434	9.338	9.526	9.405	9.492
(std. dev.)		(0.561)	(0.568)	(0.540)	(0.568)	(0.548)	(0.542)
Number P-Q obs (millions)	368.70	255.80	140.00	46.94	21.05	47.80	12.30
Number Persons (millions)	17.24	11.37	5.80	2.21	0.94	2.42	1.23

Notes: Sample includes person-quarter (PQ) observations for indivduals age 22-62 with at least 8 quarters of employment in the LEHD 2010Q1 to 2018Q2. Quarterly observations for individuals with multiple employers are excluded, as are the first and last (transitional) quarters of any spell with the same employer, and quarters for which industry or location information is missing. Estimation sample in column 2 drops quarters with <$3800 in earnings. Event study sample only uses 5 quarters of earnings before a move and 5 quarters after.

Table 2: Summary of Estimated Two-Way Fixed Effects Models

	Person-quarter level		CZ-industry level		CZ level	
	Std. Dev. or Correlation	Var. Share	Std. Dev. or Correlation	Var. Share	Std. Dev. or Correlation	Var. Share
	(1)	(2)	(3)	(4)	(5)	(6)
Log earnings or mean log earnings	0.654	1.000	0.275	1.000	0.145	1.000
<u>Variance components (std. deviations in odd-number columns, variance shares in even-numbered columns)</u>						
Person effects	0.561	0.736	0.199	0.526	0.100	0.472
CZ-industry effects	0.097	0.022	0.097	0.125	0.064	0.196
Covariate index (Xβ)	0.150	0.053	0.015	0.003	0.005	0.001
Residual	0.243	0.138	0.000	0.000	0.000	0.000
<u>Covariance components (correlations in odd-number columns, variance shares in even-numbered columns)</u>						
Person/CZ-industry	0.211	0.054	0.593	0.308	0.563	0.347
Person/Covariates	-0.010	-0.004	0.387	0.032	-0.029	-0.001
CZ-industy/Covariates	0.026	0.002	0.256	0.010	-0.297	-0.009

Notes: Table shows variance decompositions based on equation (4). Columns 1-2 pertain to the variance of individual quarterly earnings. Columns 3-4 pertain to the variance of mean earnings by CZ-industry cell. Columns 5-6 pertain to the variance of mean earnings by CZ. Entries in columns 1-3-5 for "variance components" are standard deviations of earnings component indicated in row heading; for "covariance components" are the estimated correlations of the indicated variance components. Entries in columns 2-4-6 are variance shares explained by variance or covariance components. Variance components are estimated using two-sample method described in equation (5) -- see text.

Table 3: Estimation Results for Dynamic Specifications

	Large CZ Definition:	
	10 Largest CZ's (1)	25 Largest CZ's (2)
A. Estimated Effects of Work Experience from Dynamic Specification:		
1. Work Experience in any CZ	0.0080	0.0076
(quarters of experience)	(0.0001)	(0.0002)
2. Work Experience in Large CZ	0.0018	0.0014
(quarters of experience)	(0.0016)	(0.0009)
3. In Large CZ × Work Experience	0.0011	-0.0003
	(0.0015)	(0.0008)
4. In Large CZ ×	-0.0015	0.0003
Work Experience in Large CZ	(0.0004)	(0.0002)
B. Regress CZ-ind. Effect from Dynamic Model on Effect from Main Specification:		
5. Estimated Slope Coefficient (IV)	0.990	0.989
(CZ-industry effects)	(0.001)	(0.001)
6. Estimated Slope Coefficient (IV)	0.972	0.972
(Average CZ effects)	(0.006)	(0.005)

Notes: Panel A shows estimated regression coefficients for experience terms from dynamic two-way fixed effects specification. In column 1, "large CZ experience" is previous quarters of work in one of the 10 largest CZ's. In column 2, "large CZ experience" is previous quarters of work in one of the 25 largest CZ's. Standard errors, clusted by the first CZ in which a person is observed in our sample, in parentheses. Panel B shows estimated regression coefficients from IV regression of estimated CZ-industry effects (row 5) or average of CZ effects (row 6) on corresponding estimate from our main specification. Instrumental variable is corresponding effect estimated using B sample. Robust standard errors in parentheses.

Table 4: Simple Linear Regression Models for Estimated CZ-Industry Effects

			Models with CZ and Industry Effects:			
	CZ Effects only	Industry Effects only	no other controls	plus residual from model for Sample B	plus local emp. share of industry	plus log of local emp. share of industry
	(1)	(2)	(3)	(4)	(5)	(6)
Residual from model with CZ + industry, fit to Sample B	--	--	--	0.878	--	--
(standard error)				(0.008)		
Share (or log share) of CZ emp. in Industry	--	--	--	--	0.243	0.023
(standard error)					(0.019)	(0.001)
R-squared	0.433	0.457	0.884	0.973	0.891	0.895
RMSE	0.073	0.072	0.033	0.016	0.032	0.032

Notes: Table shows goodness of fit and estimated regression coefficients from regression of estimated CZ-industry effects on CZ effects (column 1), industry effects (column 2), and CZ and industry effects (columns 3-6). Model in column 4 also includes the estimated residual from regression model in column 3 (with CZ and industry effects), fit to Sample B. Models in columns 5-6 inclide the share (or log share) of CZ employment in the industry. Models are fit to person-quarter data after assigning estimated CZ-industry effect and all control variables to each person-quarter observation.

Table 5: Decomposition of Variance of Average CZ Earnings Premium

	All CZ's	Top 50 CZ's Only	
	2-digit industries	2-digit industries	4-digit industries
	(1)	(2)	(3)
Standard Dev. of Average CZ premium	0.063	0.061	0.062
Decomposition (variance shares):			
Var(Average Earnings Premium)	1.003	0.978	0.958
Var(Composition Effect)	0.015	0.010	0.007
Var(Interaction Effect)	0.008	0.003	0.006
Cov(Earnings Premium, Composition Effect)	-0.027	-0.010	-0.009
Cov(Earnings Premium, Interaction Effect)	0.002	0.025	0.039
Cov(Composition Effect, Interaction)	0.000	-0.006	0.000

Notes: Table shows decomposition of the variance of estimated average CZ wage premium, based on equation (7) in text. Decomposition in column 1 uses main LEHD sample and 24 2-digit industries to define CZ-by-industry effects. Decompositions in columns 2 and 3 are restricted to observations in 50 largest CZ's only. Decomposition in column 2 uses 24 2-digit industries to define CZ-by-industry effects; decomposition in column 3 uses 312 4-digit industries to define CZ-by-industry effects.

Table 6: Components of Wage Gap Between High- and Low-Education Workers

	Regression Models Relating Wage Gap and Components to Mean Log Wage in CZ		Variance Decomposition of Wage Gap	
	Coefficient (1)	Standard error (2)	Std. Dev. or Correlation (3)	Var. Share (4)
Wage gap (high- versus low-education workers)	0.644	(0.051)	0.109	1.000
Components of Wage Gap (column 3 = std. dev.)				
Difference in mean person effects	0.604	(0.049)	0.096	0.782
Difference in covariate indexes	-0.003	(0.005)	0.005	0.002
Difference in mean CZ wage effect:				
Total	0.042		--	--
Within-industry wage gap	-0.068	(0.028)	0.030	0.075
Industry sorting	0.092	(0.007)	0.016	0.021
Interaction	0.018	(0.002)	0.004	0.001
Covariance Terms (column 3 = correlation of terms)				
Cov(Person effects, cov. index)	--	--	-0.127	-0.010
Cov(Person effects, within-industry gap)	--	--	-0.226	-0.109
Cov(Person effects, industry sorting)	--	--	0.755	0.195
Cov(Person effects, interaction)	--	--	0.576	0.039
All other covariance terms	--	--	--	0.004

Notes: Columns 1 and 2 show coefficient and standard error from univariate regression of CZ-specific value of wage gap term identified in row heading on mean log wage CZ (estimated from ACS). Columns 3 and 4 show components of a decomposition of the variance of the estimated CZ wage gap between high-education and low-education

Table 7: Summary of Relationships Between CZ Outcomes and Log CZ Size

	Estimated Coefficient (1)	Standard Error (2)
1. log quarterly earnings	0.0765	(0.0092)
Basic Decomposition of Mean Log Earnings (All CZ's)		
2. Mean person effects	0.0505	(0.0095)
3. CZ wage effect	0.0260	(0.0031)
4. Percent of size effect due to skills (row 2/1)	*66.0*	
Measures of Dispersion in Skill Composition (All CZ's)		
5. Share in decile 1 skill/person effs.	-0.0041	(0.0032)
6. Share in decile 10 skill/person effs.	0.0228	(0.0032)
7. Standard deviation of person effs.	0.0288	(0.0019)
Components of Average CZ Wage Effect (CZ's with All Industries)		
8. CZ-average Wage Effect	0.0317	(0.0035)
9. CZ-specific premium component	0.0341	(0.0033)
10. Industry composition component	-0.0010	(0.0003)
11. Interaction component	-0.0015	(0.0005)
Degree of Assortative Matching within CZ (CZ's with All Industries)		
12. Within-CZ skill-match correlation (correl. of person effect and industry effect)	0.0612	(0.0012)

Notes: Each entry is a coefficient from a separate univariate regression of the outcome indicated by the row heading on the log of workforce size in the CZ. "All CZ's" refers to 688 CZ's; CZ's with All Industries refers to a subset of CZ's which have workers in all 24 NAICS industries in all our replication samples. All models are weighed by CZ size. See text for explanation of components of average CZ wage effect and within-CZ skill-match correlation.

Table 8: Components of the Return to Education and Log CZ Size

	Estimated Coefficient (1)	Standard Error (2)
a. Outcomes for less-educated workers (education ≤12)		
1. log earnings (earnings > 3800)	0.0386	(0.0056)
2. Mean skill index/person effects	0.0198	(0.0046)
3. CZ wage effect	0.0193	(0.0024)
4. Share of size effect due to skills (row 2/1)	*51.3*	
b. Outcomes for more-educated workers (education>12)		
1. log earnings (earnings > 3800)	0.1020	(0.0083)
2. Mean skill index/person effects	0.0744	(0.0087)
3. CZ wage effect	0.0287	(0.0031)
4. Share of size effect due to skills (row 2/1)	*72.9*	
c. Earnings Gap between more and less educated workers		
1. gap in log earnings	0.0612	(0.0030)
2. Mean skill index/person effects	0.0540	(0.0050)
3. CZ wage effect components		
Relative wage premium component	-0.0018	(0.0029)
Compositional component	0.0075	(0.0007)
Interaction component	0.0015	(0.0001)

Notes: See notes to Table 7. Each entry is a coefficient from a separate univariate regression of the outcome indicated by the row heading on the log of workforce size in the CZ. The sample includes 688 CZ's; all models are weighed by CZ size.

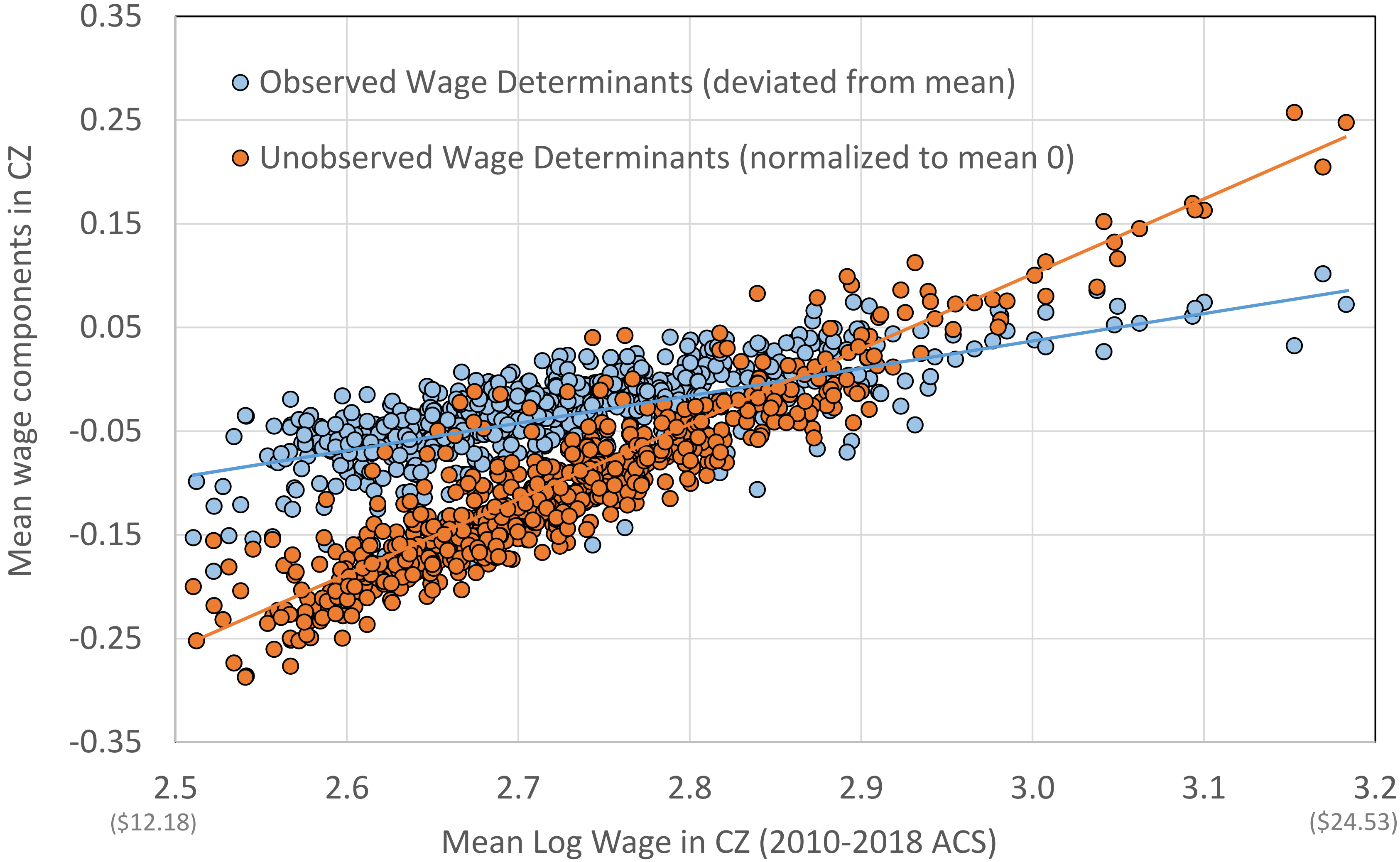
Table 9: Elasticities of Home Values and Rents with respect to CZ Size

	All CZ's (1)	Largest 50 CZ's (2)
House Prices (log of home value for owners)		
Unadjusted log home value	0.25	0.38
	(0.01)	(0.08)
Quality Adjusted log home value [a]	0.22	0.42
	(0.01)	(0.08)
Monthly Rent (log of rent for renters)		
Unadjusted log monthly rent	0.17	0.19
	(0.01)	(0.04)
Quality Adjusted log monthly rent [a]	0.18	0.23
	(0.01)	(0.04)

Note: Table entries are regression coefficients (and standard errors) from weighted OLS regressions of CZ-average housing price measure in row heading on constant and log of number of workers in CZ. Regressions are weighted by number of workers in CZ. Sample in column 1 is set of 678 CZ's in 2018 5-year ACS with non-missing data. Sample in columns 2 is 50 largest CZ's.

[a]Quality adjustment obtained by regressing log home value (or monthly rent) on indicator for type of housing unit, number of bedrooms, log of total number of rooms, year of construction, and indicator for mortgage (for home values) or set of indicators for inclusion of utility costs (for rents).

Figure 1: Observed and Unobserved Components of CZ Mean Log Wages, 2010-2018 ACS



Note: sample contains 688 CZ's based on 1990 CZ definitions (Alaska is excluded). Observed wage determinants represent fitted values from a regression model of log hourly wages that includes education, experience, gender, race/ethnicity, country of origin, and CZ effects, and are deviated from their weighted mean. Unobserved wage determinants are estimated CZ effects from the regression model. Weighted mean of CZ effects is constrained to 0. Fitted lines shown are from weighted OLS regressions.

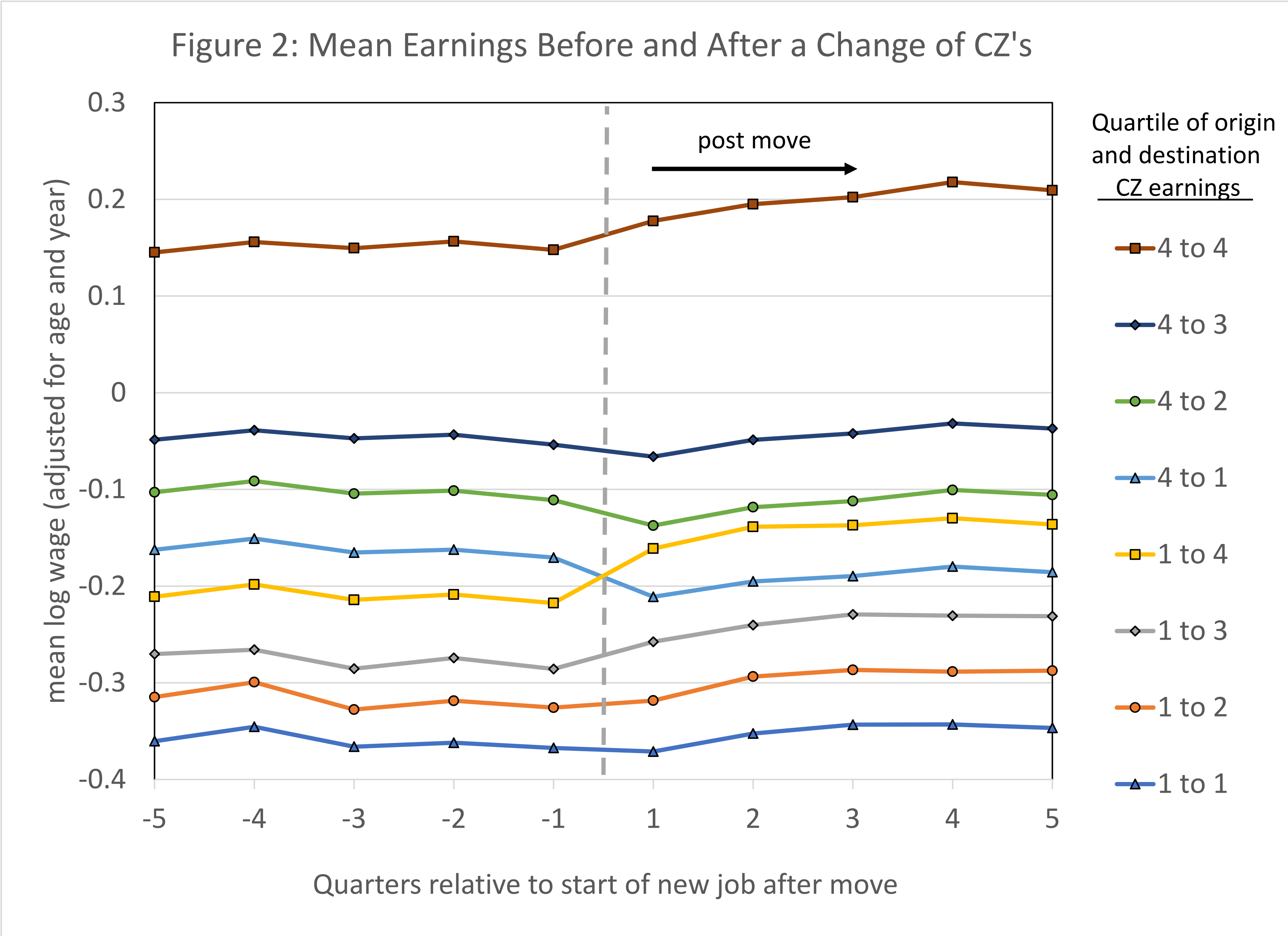
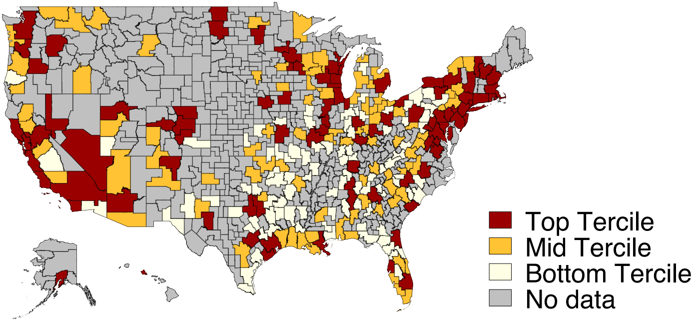


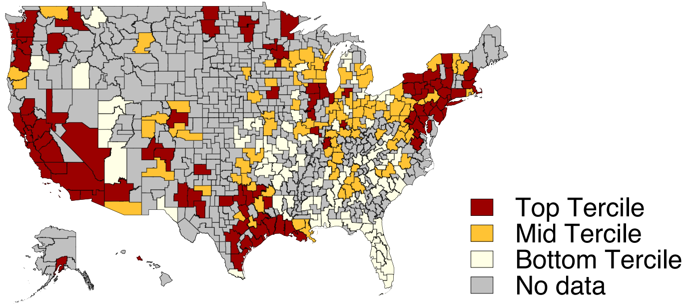
Figure 2: Mean Earnings Before and After a Change of CZ's
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
mean log wage (adjusted for age and year)
post move
-5
-4
-3
-2
-1
1
2
3
4
5
Quarters relative to start of new job after move
Quartile of origin and destination CZ earnings
4 to 4
4 to 3
4 to 2
4 to 1
1 to 4
1 to 3
1 to 2
1 to 1

Figure 3: Map of CZ's by Terciles of Wages and CZ Effects

a. Wages (ACS)



b. CZ Effects (LEHD)



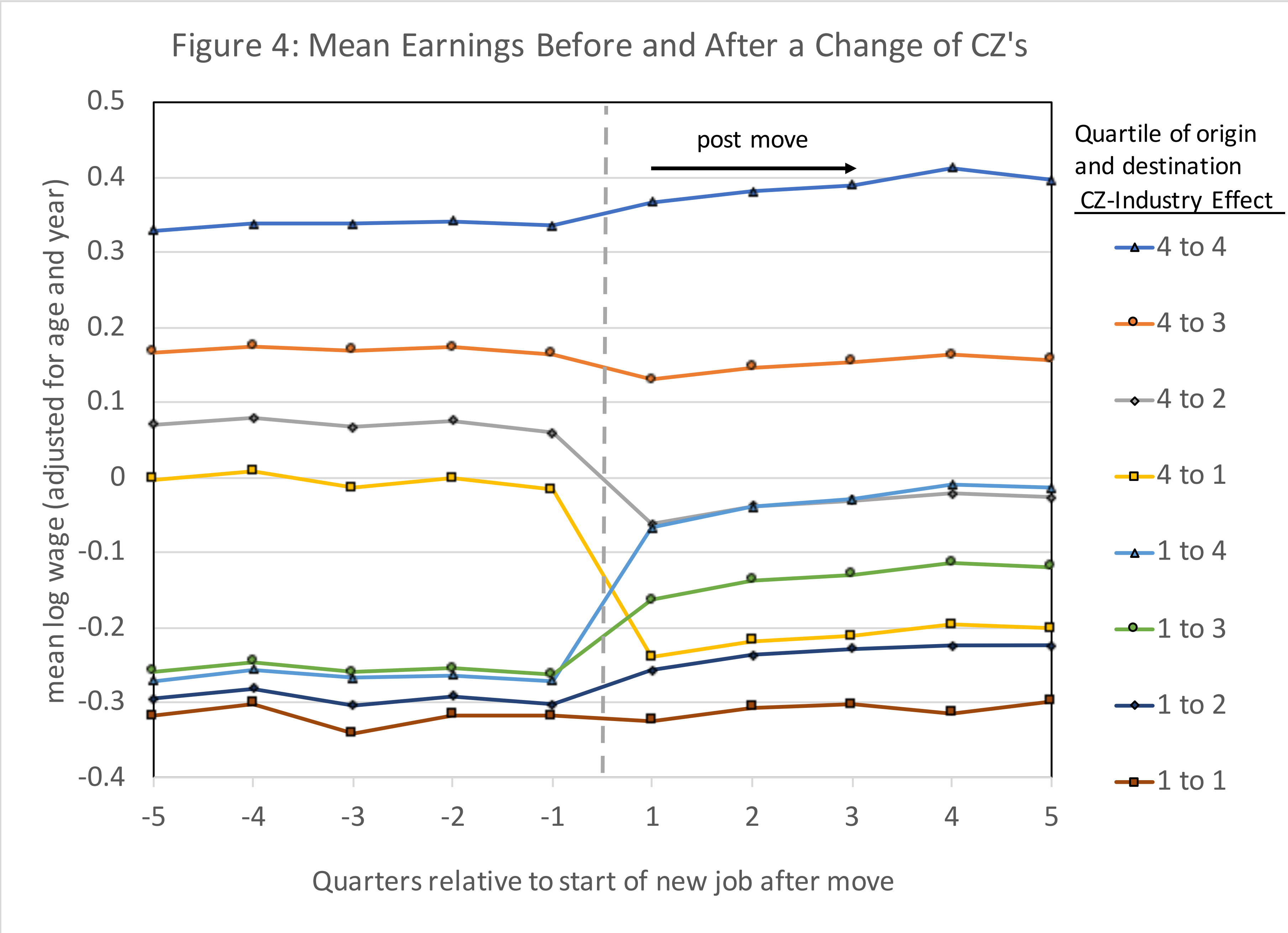


Figure 4: Mean Earnings Before and After a Change of CZ's
mean log wage (adjusted for age and year)
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
post move
Quartile of origin
and destination
CZ-Industry Effect
4 to 4
4 to 3
4 to 2
4 to 1
1 to 4
1 to 3
1 to 2
1 to 1
-5
-4
-3
-2
-1
1
2
3
4
5
Quarters relative to start of new job after move

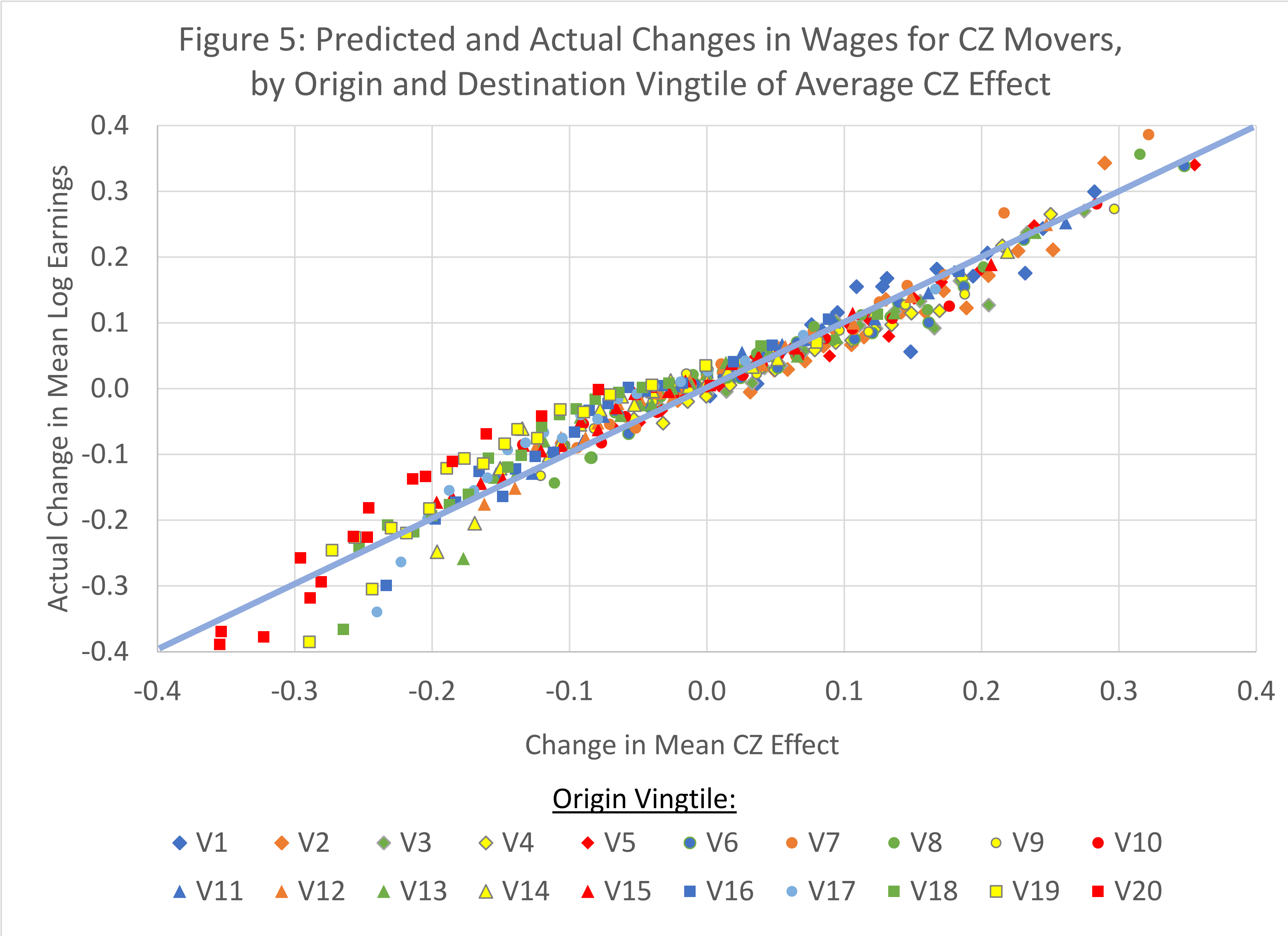
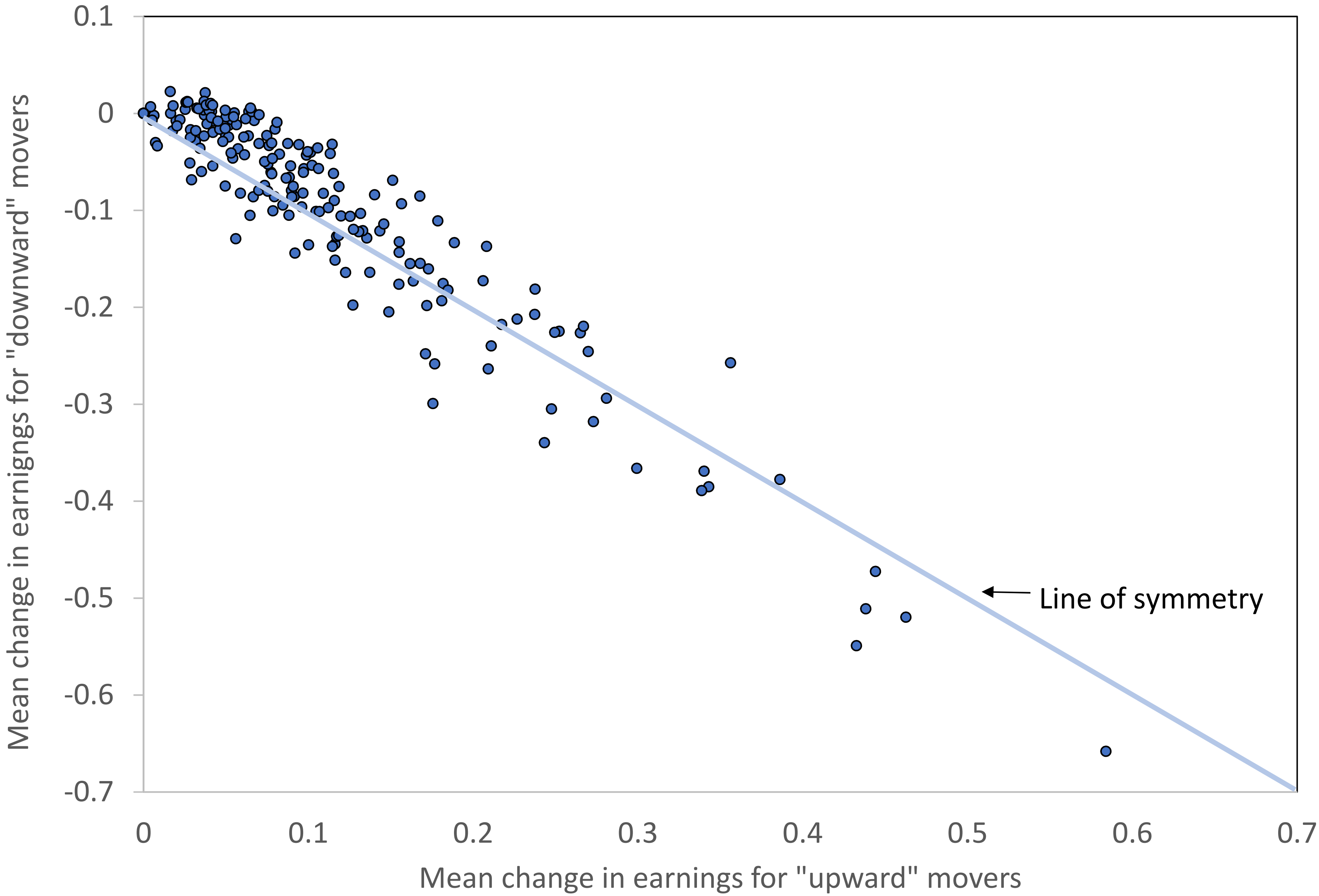


Figure 5: Predicted and Actual Changes in Wages for CZ Movers,
by Origin and Destination Vingtile of Average CZ Effect
Actual Change in Mean Log Earnings
0.4
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.4
-0.4
-0.3
-0.2
-0.1
0.0
0.1
0.2
0.3
0.4
Change in Mean CZ Effect
Origin Vingtile:
V1
V2
V3
V4
V5
V6
V7
V8
V9
V10
V11
V12
V13
V14
V15
V16
V17
V18
V19
V20

Figure 6: Evaluation of Symmetry for CZ changers



Appendix Table 1: Descriptive Statistics for Commuting Zones: 2010-2018 American Community Survey

	All CZ's		Largest 50 CZ's		Univariate Regression on Log(Workforce Size)		
	Mean	(Std. Dev)	Mean	(Std. Dev)	Coeff.	(Std. Err)	R-sq.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a. Mean Worker Characteristics							
Mean Log Hourly Wage	2.863	(0.141)	2.944	(0.113)	0.069	(0.003)	0.519
Mean Share BA+	0.324	(0.083)	0.371	(0.065)	0.039	(0.002)	0.485
Mean Years Education	13.615	(0.461)	13.798	(0.417)	0.142	(0.011)	0.209
Mean Share Immigrants	0.167	(0.123)	0.231	(0.117)	0.060	(0.002)	0.523
Mean Share Black Non-Hisp.	0.119	(0.094)	0.129	(0.076)	0.011	(0.002)	0.028
Mean Share Asian Non-Hisp.	0.056	(0.056)	0.080	(0.054)	0.023	(0.001)	0.360
Mean Share Hispanic	0.168	(0.152)	0.209	(0.142)	0.044	(0.004)	0.180
Mean Share White Non-Hisp.	0.658	(0.189)	0.582	(0.164)	-0.077	(0.004)	0.364
b. Decomposition of mean wages from regression model [a/]							
CZ wage residual	0.000	(0.109)	0.062	(0.087)	0.055	(0.002)	0.572
CZ predicted wage	2.863	(0.050)	2.882	(0.048)	0.013	(0.001)	0.152
c. Add 2-digit Industry Effects to wage model							
CZ wage residual	0.000	(0.105)	0.060	(0.084)	0.054	(0.002)	0.573
CZ predicted wage	2.863	(0.054)	2.884	(0.052)	0.015	(0.001)	0.165
d. Add 4-digit Industry Effects to wage model							
CZ wage residual	0.000	(0.102)	0.057	(0.083)	0.052	(0.002)	0.566
CZ predicted wage	2.863	(0.057)	2.887	(0.053)	0.017	(0.001)	0.185
Mean (4-digit) Ind. Composition Effect	0.186	(0.017)	0.193	(0.016)	0.004	(0.000)	0.142
Share of Total Sample	1.000		0.583				

Notes: Sample in columns 1-2 includes 11,733,554 observations in 688 Commuting Zones in the American Community Survey (ACS), 2010-18 (excluding Alaska). All statistics are weighted using ACS population weights. Regression models in columns 5-7 are fit to CZ-means of row variable using log(CZ workforce size) as explanatory variable, and weighting by sum of ACS weights for workers in CZ.

[a/] See text for description of regression model. Model includes controls for education, gender, potential experience, country of birth.

Appendix Table 2: Comparison of Variance Decompositions of Two-Way Fixed Effects Models: Plug-In versus Cross-Sample Methods

	Individual Level				CZ-industry Level				CZ Level			
	Plug-in		Cross-sample		Plug-in		Cross-sample		Plug-in		Cross-sample	
	Std Dev or Correl.	Var. Share	Std Dev or Correl.	Var. Share	Std Dev or Correl.	Var. Share	Std Dev or Correl.	Var. Share	Std Dev or Correl.	Var. Share	Std Dev or Correl.	Var. Share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Overall wage/mean wage	0.654	1.000	0.654	1.000	0.275	1.000	0.275	1.000	0.145	1.000	0.145	1.000
<u>Variance components</u>												
Person effects	0.561	0.736	0.561	0.736	0.200	0.528	0.199	0.526	0.100	0.475	0.100	0.472
CZ-industry effects	0.097	0.022	0.097	0.022	0.097	0.126	0.097	0.125	0.064	0.195	0.064	0.196
Covariate index (Xβ)	0.150	0.052	0.150	0.053	0.015	0.003	0.015	0.003	0.005	0.001	0.005	0.001
Residual	0.243	0.138	0.243	0.138	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
<u>Covariance components</u>												
Person/CZ-industry	0.209	0.053	0.211	0.054	0.585	0.302	0.593	0.308	0.558	0.339	0.563	0.347
Person/Covariates	-0.010	0.004	-0.010	-0.004	0.389	0.031	0.387	0.032	-0.024	-0.001	-0.029	-0.001
CZ-industy /Covariates	0.026	0.002	0.026	0.002	0.256	0.010	0.256	0.010	-0.293	-0.009	-0.297	-0.009

Notes: See note to Table 3. Table shows variance decompositions based on equation (3) using Plug-in method or cross-sample method. Columns 1-4 pertain to the variance of individual quarterly earnings. Columns 5-8 pertain to the variance of mean earnings by CZ-industry cell. Columns 9-12 pertain to the variance of mean earnings by CZ. Entries in odd-numbered columns for "variance components" are estimated standard deviations of earnings component indicated in row heading; entries in odd-numbered columns for "covariance components" are the estimated correlations of the indicated variance components. Entries in even-numbered columns are variance shares explained by variance or covariance components.

Appendix Table 3: Mean Log Earnings and Components of Earnings for Groups of CZ's

	Ranked By Mean CZ Effect (ψ_c)				Grouped By Tercile of Mean CZ Effect (ψ_c)		
	Top 10		Middle				
	All	Large Urban	Resource	Range	Bottom 10	Lowest	Middle	Top
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean Log Earnings	9.32	9.70	9.46	9.32	9.18	9.24	9.32	9.41
	(0.11)	(0.11)	(0.07)	(0.10)	(0.08)	(0.08)	(0.07)	(0.12)
Mean Person Effect	9.18	9.40	9.19	9.18	9.13	9.15	9.18	9.21
(normalized)	(0.08)	(0.06)	(0.06)	(0.08)	(0.08)	(0.07)	(0.07)	(0.09)
Mean CZ-industry Effect	0.09	0.24	0.23	0.08	0.00	0.04	0.08	0.14
(normalized)	(0.05)	(0.04)	(0.03)	(0.04)	(0.01)	(0.02)	(0.01)	(0.04)
Mean Covariates	0.05	0.05	0.04	0.05	0.05	0.05	0.05	0.05
	(0.01)	(0.00)	(0.02)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)

Notes: standard error of mean in parentheses. CZ-industry effects are normalized to have mean 0 in bottom 10 CZ's.

Appendix Table 4: Comparison of Variance Decopositions for Main Sample, No CZ-Industry Uncertainty Sample, and Non-mover Sample

	Person-quarter level			CZ-industry level			CZ level		
	Main Sample	No Uncertainty of CZ-Industry	Stayers Only	Main Sample	No Uncertainty of CZ-Industry	Stayers Only	Main Sample	No Uncertainty of CZ-Industry	Stayers Only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variance of log earnings/ mean log earnings	0.654	0.655	0.652	0.275	0.270	0.273	0.145	0.143	0.144
<u>Variance shares</u>									
Person effects	0.736	0.744	0.742	0.526	0.537	0.534	0.472	0.465	0.470
CZ-industry effects	0.022	0.023	0.022	0.125	0.133	0.128	0.196	0.195	0.199
Covariate index (Xβ)	0.053	0.051	0.051	0.003	0.003	0.003	0.001	0.001	0.001
Residual	0.138	0.137	0.136	0.000	0.000	0.000	0.000	0.000	0.000
<u>Covariance component shares of variance</u>									
Person/CZ-industry	0.054	0.050	0.053	0.308	0.297	0.301	0.347	0.355	0.337
Person/Covariates	-0.004	-0.006	-0.005	0.032	0.023	0.029	-0.001	-0.005	0.001
CZ-ind/Covariates	0.002	0.001	0.002	0.010	0.007	0.009	-0.009	-0.011	-0.007

Notes: Table shows variance decompositions based on equation (4). Columns 1-3 pertain to the variance of individual quarterly earnings. Columns 4-6 pertain to the variance of mean earnings by CZ-industry cell. Columns 7-9 pertain to the variance of mean earnings by CZ. Results in columns 1-4-7 are for the main estimation sample, and repeat information from Table 2. Results in columns 2-5-8 are for the subsample of observations with no uncertainty about the current CZ-industry cell. Results in columns 3-6-9 are for the subset of individuals in the main estimation sample that remain in the same CZ. First row gives the standard deviation of earnings or mean earnings. Remaining rows give variance shares.

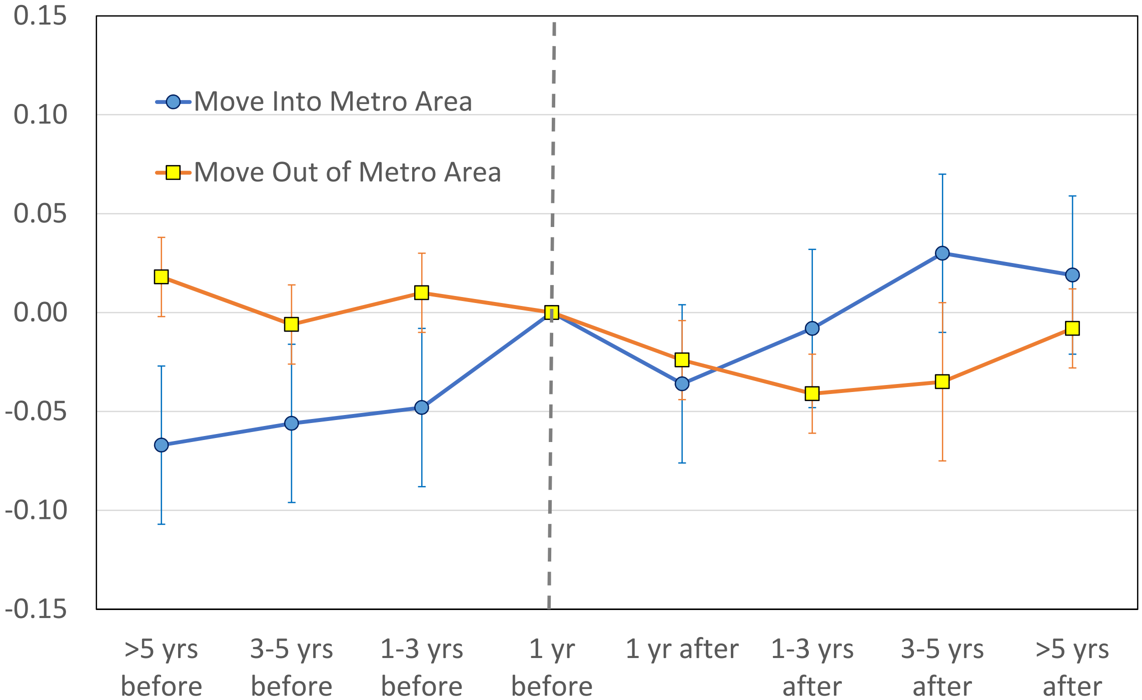
Appendix Table 5: Estimated Two-Way Fixed Effects Models for Low/High Education Workers

	Person-quarter		CZ-industry level		CZ level	
	Std. Dev. or Correlation	Var. Share	Std. Dev. or Correlation	Var. Share	Std. Dev. or Correlation	Var. Share
	(1)	(2)	(3)	(4)	(5)	(6)
A. Low Education (No More than High School) Subsample						
Log earnings or mean log earnings	0.518	1.000	0.229	1.000	0.098	1.000
Variance components (std. dev. in cols. 1-3-5, var. shares in cols. 2,4,6)						
Person effects	0.445	0.737	0.157	0.470	0.056	0.334
CZ-industry effects	0.101	0.038	0.101	0.196	0.060	0.379
Covariate index (Xβ)	0.110	0.045	0.011	0.002	0.005	0.003
Residual	0.202	0.153	0.000	0.000	0.000	0.000
Covariance components (correlations in cols. 1-3-5, var. shares in cols. 2,4,6)						
Person/CZ-industry	0.193	0.065	0.548	0.333	0.422	0.300
Person/Covariates	-0.102	-0.037	-0.024	-0.002	-0.148	-0.009
CZ-industy/Covariates	0.000	0.000	0.006	0.000	-0.102	-0.007
B. High Education (Some College or More) Subsample						
Log earnings or mean log earnings	0.685	1.000	0.282	1.000	0.180	1.000
Variance components (std. dev. in cols. 1-3-5, var. shares in cols. 2,4,6)						
Person effects	0.599	0.764	0.210	0.557	0.131	0.531
CZ-industry effects	0.095	0.019	0.095	0.114	0.066	0.135
Covariate index (Xβ)	0.132	0.037	0.011	0.002	0.005	0.001
Residual	0.256	0.140	0.000	0.000	0.000	0.000
Covariance components (correlations in cols. 1-3-5, var. shares in cols. 2,4,6)						
Person/CZ-industry	0.225	0.054	0.640	0.322	0.646	0.346
Person/Covariates	-0.042	-0.014	0.070	0.004	-0.171	-0.007
CZ-industy/Covariates	0.005	0.000	0.063	0.002	-0.275	-0.006

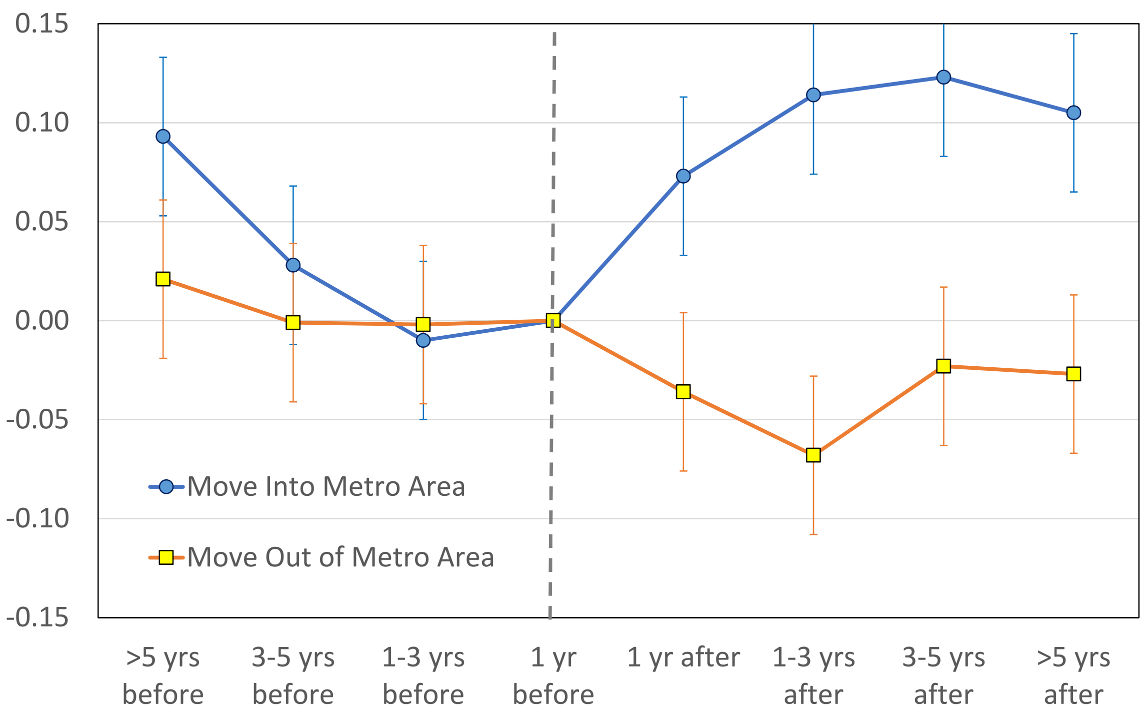
Notes: See note to Table 2. Columns 1-2 pertain to the variance of individual quarterly earnings. Columns 3-4 pertain to the variance of mean earnings by CZ-industry cell. Columns 5-6 pertain to the variance of mean earnings by CZ. Entries in columns 1-3-5 for "variance components" are standard deviations of earnings component indicated in row heading; for "covariance components" are the estimated correlations of the indicated variance components. Entries in columns 2-4-6 are variance shares explained by variance or covariance components. Variance components are estimated using two-sample method -- see text.

Appendix Figure 1: Wage Changes for Movers in and out of Metro Areas (Glaeser and Mare, 2000)

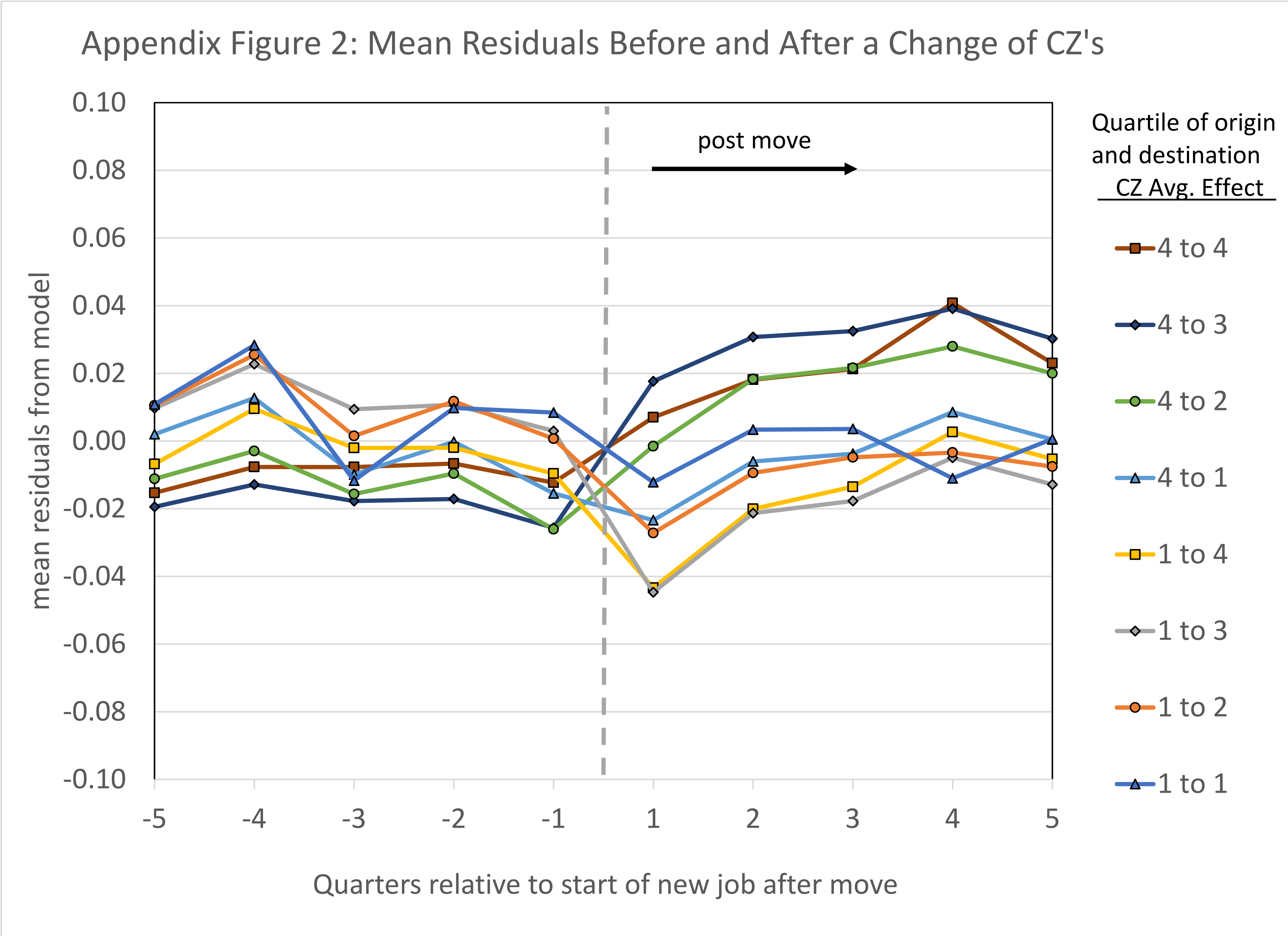
A. PSID Data



B. NLSY Data



Note: from Glaeser and Mare (2000, Table 5, columns 2 and 4). 95% confidence intervals shown with vertical bars.


Appendix Figure 2: Mean Residuals Before and After a Change of CZ's
mean residuals from model
0.10
0.08
0.06
0.04
0.02
0.00
-0.02
-0.04
-0.06
-0.08
-0.10
post move
-5
-4
-3
-2
-1
1
2
3
4
5
Quarters relative to start of new job after move
Quartile of origin and destination CZ Avg. Effect
4 to 4
4 to 3
4 to 2
4 to 1
1 to 4
1 to 3
1 to 2
1 to 1

Appendix Figure 3: Mean Residuals by Decile of Person Effect and CZ/Industry Effect