The Global Value of Cities

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Abstract

We estimate the economic value of each city around the world. We obtain a dataset of detailed job histories of 513 million workers in 220,000 cities across 191 countries. We track job spells for these workers, with information on start and end dates, establishment name, location, job title, and effective salary. We use an event-study movers design, conditional on individual and time fixed effects, with tests for pre-trends. We show that moving to a higher (average) wage city leads to a substantial jump in earnings. The distinctly global nature of our analysis allows us to measure internal and cross-border moves, while simultaneously estimating what makes a city more productive, and which countries have large gains from spatial re-sorting of workers. When moving across international borders, 90% of the change in wages can be attributed to city effects, whereas within countries about 35% of the wage change is because of city effects. Richer countries show more ability-based sorting, and so less of the wage differentials in high-income countries can be attributed to city effects. City effects are correlated with economic structure, whereby cities with more diverse industries have larger city effects. More populated cities are more productive, suggesting agglomeration economies. The variance in city effects within countries highlights the potential gains from migration. These gains increase as countries develop, and their human capital stock grows.

Keywords: City wage premia, movers design, spatial sorting, wage differentials

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1 Introduction

What are the income gains from moving a software engineer from Kansas City to San Francisco? Or from Bangalore to San Francisco? Answering this question is challenging as simple wage differences across cities could reflect the sorting of individuals based on skill. To isolate the true value of a city on worker's earnings, we would need to track cross-city moves for a large number of workers. We are now able to do this by leveraging a unique new database of high-skilled worker job histories for 513 million workers in 220,000 cities around the world. With the help of an event-study movers design that exploits worker movement across cities (Finkelstein et al., 2016; de La Roca and Puga, 2017; Card et al., 2023b) we ask: are the large disparities in city wages across the globe primarily driven by sorting on skill (Young, 2013; Behrens et al., 2014; Combes et al., 2008), or do cities themselves have a meaningful impact on a worker's earnings (Ciccone and Hall, 1996; Diamond, 2016; Glaeser and Gottlieb, 2009; Card et al., 2023b)?[1]

In this paper, we distinguish between *city effects* and *individual-level sorting*. City effects capture a city's productivity, its firm activity, the types of jobs, technology, infrastructure, and agglomeration forces it may have. Whereas systemic sorting of those with higher abilities, to preferable places merely reflects the preferences of high-ability individuals. Distinguishing between these explanations has meaningful implications for how facilitating the movement of people can affect aggregate income. If city effects are indeed important, then migration from low-productive to high-productive cities can raise aggregate productivity. If, instead, sorting on abilities is the primary driver of wage differentials, then cities may instead focus on attracting high-ability workers.

We first estimate city effects for 123,431 cities around the world. We estimate event-study designs based on those who migrate between cities, and isolate what fraction of the wage differentials between any two pairs of cities are because of city effects. Next, we investigate what city features are associated with higher city wage premia. How much of the city effects are a reflection of the nature of economic activity, the types of firms, and industries? We seek to unpack how a city's economic structure is associated with the city effects. Finally, we aim to understand how the potential gains from spatial re-allocation within a country varies across the economic development process. The variance in wage premia across cities, within a country reflects how greater internal migration may potentially lead to higher aggregate incomes via workers sorting to high-wage cities. We study how this potential gain from spatial sorting is associated with a country's geographic and economic structure.

We obtain global data on 700 million LinkedIn users that track the movements of 513 million workers across 220,000 cities around the world. Our data include job location, job titles, firm/establishment names, and the start and end date of each work spell. We construct individual level panels using the full job histories of individuals. LinkedIn data capture relatively high-skilled individuals. Complementary data on 200 million salaries across a wide variety of sources, by precise

[1] Pritchett (2017) argues "Mostly in the world there aren't poor people. There are people in poor places."

location, job title, tenure, seniority, company (establishment), allow us to track predicted wages, adjusted for purchasing power parity, for individuals. An important feature of our data is that we observe precise granular location information, regardless of where a firm is headquartered. This allows us to track the movements of individuals across cities across the world, and their corresponding changes in job status, titles, seniority, type of work, and effective salaries. We use this information to understand how moving to a particular city affects individual outcomes.

We first begin with an event-study analysis of changes in individual wages associated with moves across cities.[2] Conditional on individual, time, and time-since-move fixed effects, we study how moving to a higher-wage city affects an individual's earnings. This design has a few distinct advantages. It allows us to condition on individual effects, capturing all time-invariant characteristics of an individual. Further, it allows us to check for pre-existing trends in the lead-up to a move, to determine whether the move was prompted by positive or adverse wage shocks. Importantly, our method needs to assume that any wage shocks that occur at the time of the move are not correlated with individual-by-city match-specific components. If this were to happen systematically, we would likely see pre-trends in our event study graphs.

We then exploit the variation captured in the event study to estimate city effects using a model where log wage is a combination of an individual worker fixed effect, a city fixed effect, and a vector of time-varying controls, including indicators for year relative to move for migrants (Finkelstein et al., 2016).

Our analysis highlights six facts. First, there is stark regional heterogeneity in average city-level wages across the world. These reflect regional incomes (city-level wages are lower in Africa and South Asia, in comparison to Europe), country borders (there are sharp jumps at the US-Mexico border), and also within-city regions (coastal USA has higher-wage cities than the midwest).

Second, we examine the sample of cross-city movers (as they help estimate city effects), and find that most moves are concentrated to relatively higher-wage cities. That is, individuals are far more likely to move to a relatively richer city than a relatively poorer one. When looking at cross-country moves, individuals are far more likely to move to a city in the top income quintile of cities in the destination country.

Third, we estimate event-study specifications at the individual-move level to see how wages for workers change for different kinds of moves. We show that for international moves, 90% of the wage gains are attributable to city effects. Whereas, for within-country moves, only about 35% of the gains are attributable to the value of cities. As such, country effects are important, but city effects are far from negligible. The event studies do not suggest any pre-trends, and are robust to various controls.

Fourth, we find substantial heterogeneity in the share of geographic wage variation explained by city effects. Specifically, we find that city effects account for a large share of variation in wages

[2]The closest in methodology is Finkelstein et al. (2016) who study health outcomes as older Medicare individuals move across the US.

among cities across the world, but explain less within-country variation. Additionally, the extent of within-country variation explained by city effects varies across countries. This has important implications for potential gains from migration in different contexts. Importantly, for regions within a country, the relationship is flatter, even as the country-level relationship is relatively steeper. This reflects the fact that regions have stark differences in incomes, and much ability-based sorting may occur within regions.

Fifth, we correlate these isolated city effects, and find some stark relationships. City-level diversity and complexity in industrial composition are strongly correlated with larger city effects. In contrast, cities with few concentrated industries have lower city effects. Further, larger cities have higher city effects, suggesting meaningful agglomeration economies. We also examine the types of jobs a city has, and find that cities that have more skilled and senior-level jobs have higher city effects. These patterns not only validate our methods for estimating city effects, but also help answer an age-old question in urban economics: what makes a city more productive?

Sixth, we study how the potential gain from spatial sorting varies across the development process. We estimate the variance of city effects within a country's borders. A larger variance suggests more potential gains from internal migration. That is, large city effect differentials imply that in moving individuals to high-impact cities can raise aggregate productivity. We find, in fact, that the variance in city effects is actually larger in richer countries, with larger cities and more urbanization. These potential gains are also higher in countries that have higher college enrollment and literacy, reflecting that skilled internal migration can unlock large aggregate gains in various countries across the world.

These findings have important implications for recent debates on the value of locations. A recent and important starting point of our work is Card et al. (2023b), who use AKM methods to isolate gains from locations within the US. The distinctly global nature of our analysis creates certain advantages. It allows us to not only study city effects within countries across the world, but also cross-country and cross-region movements. These moves reflect important nuances. First, cross-border moves have much larger wage gains. This speaks to important work on the gains from migration, much of which has focused on internal migration within one country (Bryan and Morten, 2019; de La Roca and Puga, 2017; Dauth et al., 2022; Card et al., 2023b) or country-level gains (Amanzadeh et al., 2024). Second, our global analysis allows us to understand how the potential gains from re-allocating workers across space vary greatly across countries around the world. This reflects recent work on how potential potential gains from re-allocating inputs in firms and sectors (Hsieh and Klenow, 2009; Gollin et al., 2014). Additionally, the methods we use are different from Card et al. (2023b), as our event-study design allows us to cleanly test for pre-trends that would be indicative of violations of the identification assumptions (Finkelstein et al., 2016).

Next, we unpack the correlates of these city effects, to hint at work on why some cities are more productive than others. Finally, we speak to the debate on whether the disparities in city wages reflect ability-biased sorting (Young, 2013; Behrens et al., 2014; Combes et al., 2008), or whether locations have a causal impact on earnings (Ciccone and Hall, 1996; Diamond, 2016; Glaeser and Gottlieb, 2009; Card et al., 2023b). We do find a substantial role for ability-based sorting, whereby city effects can only explain about 35% of the wage differentials across cities within a country. Yet, we argue that these are non-negligible city effects, and are correlated meaningful measures of economic structure.

Our paper is organized as follows. Section 2 describes the data, and how we construct our estimating sample. Section 3 provides some descriptive facts about the distribution of wages in cities across the world, and on migration patterns between different types of cities. Section 4 describes our empirical strategy for our event-study analysis and estimating city effects. Section 5 shows our event-study results. Section 6 discusses the estimated city effects and their implications for heterogeneity in gains from different types of migration. Section 7 unpacks what explains these city effects, and the distribution of city effects across countries. Section 8 concludes.

2 Data

The data for our primary analysis comes from Revelio Labs, which provides detailed data from public professional networking websites, including LinkedIn. While our data contains harmonized individual-level data from other sites in addition to LinkedIn, we will focus our discussion on LinkedIn data since that is a large majority of our users. LinkedIn contains over 700 million professional profiles which are created by users by entering their personal education and employment histories. We primarily work with the employment information users provide, which contains the location of the job, job titles, firm names, and the start and end date of each entry. By leveraging the start and end date of each position, we are able to construct user-level panels that allow us to follow the same user across the entirety of their work history. Our data from Revelio Labs covers over 500 million accounts from 180 countries as of late 2023.

The type of individuals with LinkedIn profiles are different than the general population. While LinkedIn has profiles with extremely varied histories, highly educated individuals and those with white-collar jobs are overrepresented in our data. We, therefore, view our analysis as informative of the dynamics of earnings across space for the relatively high skilled.

Additionally, countries have varying degrees of LinkedIn use, even among the college-educated individuals in the country. As noted in Amanzadeh et al. (2024), the ratio of college-educated individuals to LinkedIn users across countries is heterogenous, with countries in Central and East Asia particularly unlikely to use LinkedIn. Although this could complicate matters when analyzing certain questions, most of our analysis will focus on estimating the city wage premia within a single country at a time.

In order to measure the salary of individuals, we make use of supplementary imputed wage data from Revelio Labs. We observe an individual's imputed salary for each job position on their profile. Wages are estimated using job titles broken down into 1500 categories, company-specific information, geographical economic information such as median housing values and unemployment rates,[3] position-specific information such as tenure and seniority, and company identifiers. Documentation provided by Revelio explains that wages are imputed using a regression-based model on a dataset of over 200 million salaries across a wide variety of sources. In order to provide imputed wages globally, predictions are adjusted across countries according to Purchasing Power Parity as well as differences in wages across job categories between each country and the US. Finally, wages are adjusted for country-specific inflation. The imputed wages in our data behave similarly to observed wages (Amanzadeh et al., 2024).

A highlight of our data is that we observe granular location information for individual positions. When creating a position entry in a profile, users are asked to provide the location of that job or education experience. By observing this information, we are able to match individuals to specific cities around the world. An advantage of using the user-provided location information is that we are able to specifically identify where individuals are working even if they work for a multi-establishment firm, including multinational firms. Our global coverage is extensive, with over 220,000 cities in our data. Figure 1b plots each city in our dataset with over 100 users by its average salary. While the large differences in income across countries make it difficult to identify within-country variation, Figures 2a and 2d highlight the richness of our city-level data. In addition to the large number of cities across both countries, these figures match the fact that we observe higher wages in wealthier regions of both countries, such as California and New England in the USA.

We take several steps to construct our primary sample of users for our analysis. For all work positions with no listed end date–which populate as "present" on LinkedIn–we assign an end date that is equal to the date Revelio Labs collected the data at the end of 2023. We then expand the data from the user-by-position level to user-by-year level by creating yearly entries based on the start and end date of positions. We apply a growth rate of 3%, which roughly matches the average year-on-year growth rate of salaries in the US, backward from the end date of the position for each previous year. Our results are robust to also simply using a constant wage and log interpolation between the estimated start and end salaries. Because our analysis only requires users that move between cities at some point in their careers, we then restrict our sample to all users that appear in two cities throughout our time period.[4]

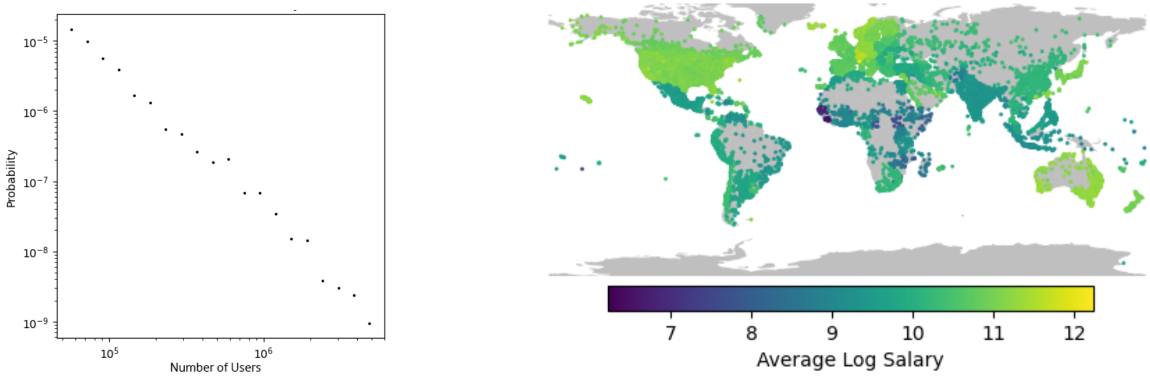
3 Descriptive Facts: Salaries Across the Globe

We describe certain key aspects of our data before estimating city effects. The distribution of users across cities also follows recognizable patterns. Figure 1a shows that a large fraction of users are concentrated in a few major cities, while most cities have significantly fewer users, following

[3]Thus, while the wages are expected to capture information relevant to location, there is not a mechanical city effect added to the estimated wages.

[4]Our current sample excludes individuals who have worked in more than two cities during their careers. This is because we want to avoid concerns regarding return migration or falsely attributing wage gains to the wrong location based on the order of moves.

Figure 1: The Distribution of LinkedIn Users and Wages Across the World



(a) Cities by Number of Users

(b) Average Log City Wages, Global

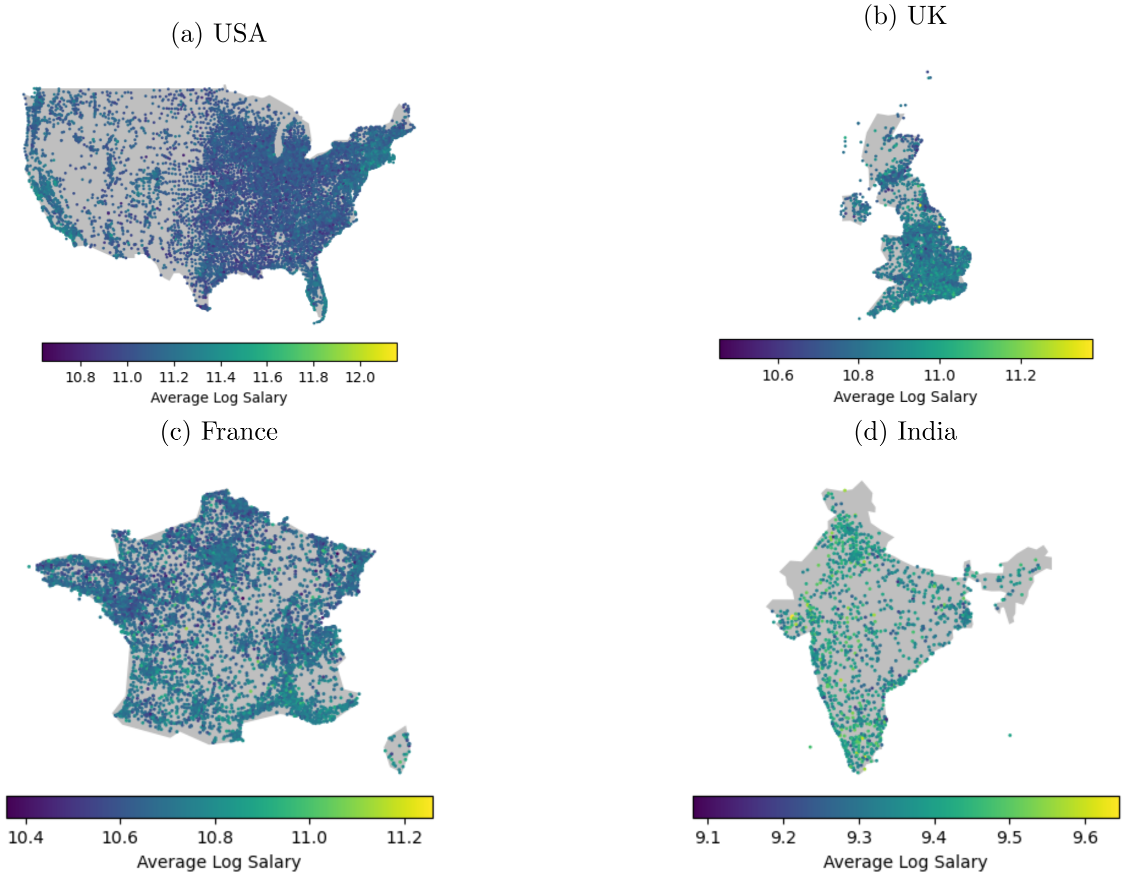
Notes: The left panel shows the density of cities by the number of LinkedIn users. The x-axis is on a log scale and shows the number of LinkedIn users present in our database. The vertical axis is the probability that a city has a certain number of users. The right panel shows the average wages calculated in each city in our data (on a log scale), across the world.

a power-law distribution. This reflects the observed population distribution patterns across cities globally (Düben and Krause, 2021).

Average Wages by City: Figure 1b plots the distribution of average city-level wages in cities around the world. A few key patterns emerge. First, on the coverage, the database has wide coverage in all countries. The blank grey zones correspond with less populated parts of the globe. Second, there is large regional heterogeneity in wages, as one may expect, with the low end of the wage distribution appearing in Africa and South Asia, and the high end appearing in Europe. Third, country borders are starkly visible in certain parts, highlighting the possibly large gains from cross-border migration. This is particularly evident, for instance, in the border between Mexico and the US, or between North Africa and Southern Europe. And last, while a bit harder to see, there is meaningful variation within countries as well. For instance, even though almost all US cities have high average salaries, even in the US, there are much higher-earning cities.

To explore the within-country variation better, we examine certain countries in isolation, allowing the legend color range to vary by country. We show these maps in Figure 2, after picking countries across the development spectrum. The maps show the regional variance within countries, while also highlighting the density of our city coverage (despite restricting the sample to cities with more than 100 users). For instance, while there are relatively higher wages along the coasts than in the Midwest, there are pockets of cities in the Midwest with high-salary cities as well. The UK seems to have more relatively high-wage cities in the south, where it is also relatively denser in terms of coverage. France's richest cities seem to agglomerate around Paris in the north, while the west has relatively lower wages. In India, the southern and western parts of the country have rela-

Figure 2: Geographic distribution of average city salaries by country



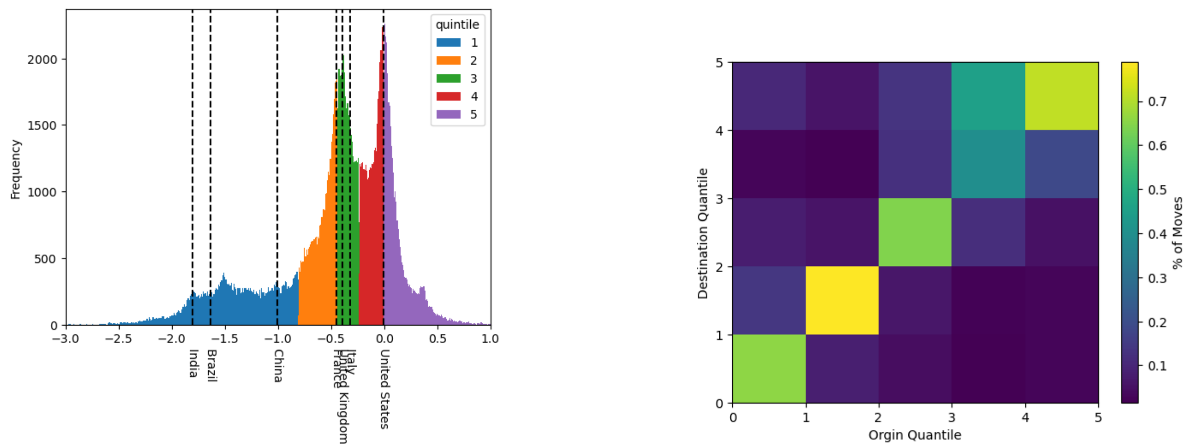
Notes: The maps plot average log(salaries) in each city. Legend scale varies by country. Sample restricted to cities with more than 100 LinkedIn users.

tively more high-wage cities, with the central and eastern parts showing some lower-wage centers. Importantly, the range (on a log scale) varies greatly across the income spectrum.

Movers and Transition Matrices: Our estimation will rely on workers who move across cities. We describe this sample of movers, and the moves that they do. Figure 3a first shows the distribution of movers by origin income. There are more moves seen at higher ends of the city-income distribution. We divide cities into 5 quintiles to more easily examine transitions across location income quintiles.

In the next panel, Figure 3b shows the transition matrix of all recorded cross-city moves, with the origin city quintile being on the horizontal axis, and the destination quintile on the vertical axis. Most moves lie along the diagonal. This, perhaps, reflects the fact that most moves are within countries, and that country borders matter greatly for city-level income differences. Yet, there does seem to be some mobility from the fourth (origin) quintile to the fifth (destination) quintile as well, suggesting some potentially higher mobility at the upper middle-income range of origin cities.

Figure 3: Movers Sample: Income Quintiles and Transition Matrices



(a) Wage Distribution of Locations by Movers

(b) Transition Matrices (All Moves)

Notes: The left panel shows the density of movers by average city wages at the origin. We also show the distribution for 5 equally-sized city-level wage quintiles of the data. The right panel shows the joint distribution of moves by origin and destination city wage quintile.

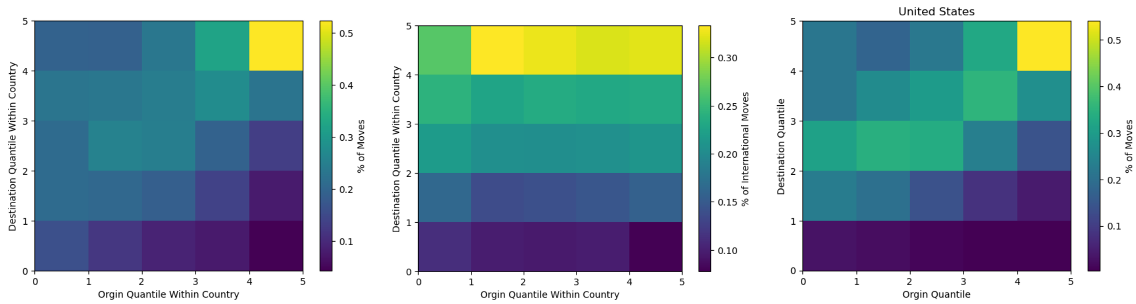
Finally, in Figures 4a to 4c, we examine transitions within and across borders. First, in Figure 4a, we study within-country moves. The north-west triangle of the graph being brighter than the south-east suggests that most moves are to higher-wage cities, from lower-wage cities. That is, individuals are less likely to move to a lower-wage city, within a country. The top right grid being distinctly higher density suggests, for instance, that those in the top quintile of origin cities are only more likely to move to other cities in the top quintile (and very unlikely to move to cities in the bottom quintile).

Figure 4b looks at the subset of moves that occur across country borders. The axes are the income quintiles within an origin or destination country. For instance, if a person migrates from India to the US, it plots the density for the income quintile of the Indian city, relative to all Indian cities on the origin x-axis, and the income quintile of the US city, relative to US cities on the destination y-axis. The high density in the top row suggests that when individuals cross borders, regardless of what type of city they come from, they choose to migrate to a high-income city in the destination country. That is, for international migrants, whether they come from low or high-income origins, their destination city is relatively wealthy compared to other cities in the destination country. In contrast, the bottom row being low density suggests immigrants are much less likely to choose relatively poorer cities among destination-country cities.

Finally, in Figure 4c, we look at the US transition matrix. This reflects the average within-country transition matrix, whereby individuals are more likely to transition up, and move to relatively higher-wage cities. Again, the high density on the top-right grid shows that those who leave quintile 5 cities are most likely to move to another quintile 5 city.

These patterns together suggest that individuals do seek out higher-wage cities. Below, we aim

Figure 4: Transition Matrices for Migrants



(a) Within Country Moves (b) Cross Border Moves (c) US: Transition Matrix

Notes: The figures show the transition matrices for within-country moves (left panel), cross-border moves (middle panel), and the US (right panel). The cross-border moves plot the income quintiles within a country. That is, for a person migrating from India to the US, it plots the density for the income quintile of the Indian city, relative to Indian cities (x-axis origin) and the income quintile of the US city, relative to US cities (y-axis destination).

to better understand whether these cities are higher wage because high-ability people sort into them, or because they make individuals more productive.

4 Empirical Strategy

In this section, we outline our methodology for examining the role of cities in locational wage differences. First, we conduct an event-study analysis of changes in individual wages associated with moves between cities. Next, we employ a 'mover-based' design (Finkelstein et al., 2016; Card et al., 2023a) using a fixed-effects specification to separate city effects from the non-random sorting of workers. This approach is closely related to the literature on estimating firm-wage premia, which utilizes matched worker-firm data (Abowd et al., 1999; Card et al., 2013). Our main analysis restricts the data to workers who moved exactly once (movers).

4.1 Event-Study Representation

If wage variation across cities is primarily driven by sorting, individuals moving between cities would not necessarily experience systematic changes in their wages. Conversely, if city-specific wage premiums exist, individuals moving to cities with higher average wages for other workers would experience wage gains. In comparison, those moving to cities with lower average wages would face wage losses.

To investigate this empirically, we first define δ_i that denotes the difference in average log wages between the mover's destination and origin city. Specifically, for mover i, whose origin and destination cities are $o(i)$ and $d(i)$, respectively:

$$\delta_i = \bar{y}_{d(i)} - \bar{y}_{o(i)} \tag{1}$$

Where $\bar{y}_j$ denotes the average of $\bar{y}_{jt}$ across t, and $\bar{y}_{jt}$ is the expectation of outcome y_{it} across workers living in city j in year t. Following Finkelstein et al. (2016), the event-study specification that follows is:

$$y_{it} = \alpha_i + \tau_t + I_{r(i,t)} + \theta_{\mathrm{r}(i,t)}\delta_i I_{r(i,t)} + \eta_{it} \tag{2}$$

where y_{it} is the log wage of individual i in calendar year t. α_i is an individual fixed effect that captures time-invariant skills of worker i and τ_t controls for calendar year fixed effects. $I_{r(i,t)}$ is a vector for relative-years, where for mover i who moves in year t^* relative year $r(i,t) = t - t^*$. The relative-year specific coefficients $\theta_{\mathrm{r}(i,t)}$ are our main parameters of interest. They capture changes in y_{it} around the move, scaled by δ_i.

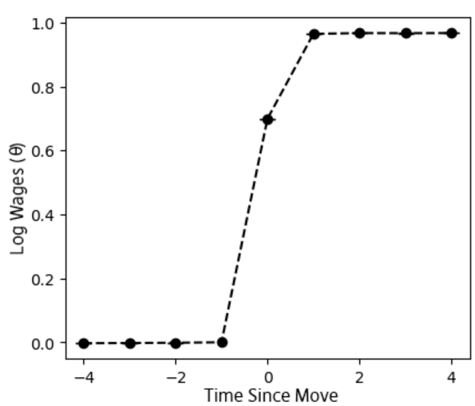
4.2 Estimating City Effects

We assume that the log wage y_{it} of individual i in year t is the sum of a worker component α_i, a city component $\psi_{\boldsymbol{J}(i,t)}$, time-varying characteristics $(\tau_t, x'_{it}\beta)$, and an error component ϵ_{it} :

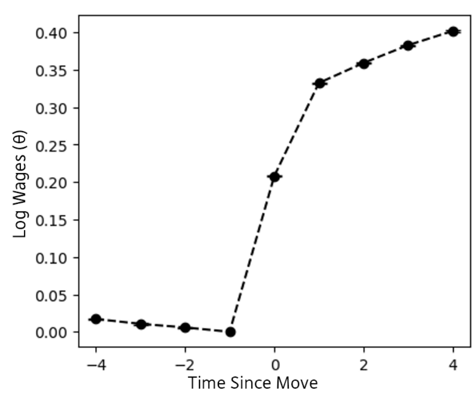
$$y_{it} = \alpha_i + \tau_t + \psi_{\boldsymbol{J}(i,t)} + x'_{it}\beta + \epsilon_{it}. \tag{3}$$

The function $\boldsymbol{J}(i,t)$ gives the city where worker i was employed in year t. α_i captures time-invariant individual-specific characteristics, τ_t controls for calendar year fixed effects. $x'_{it}\beta$ controls for year relative to move. Including relative year effects accounts for the possibility that the decision to move is correlated with wage shocks - for instance, when laid-off workers relocate to seek employment.

Figure 5: Event Study for International and Internal Movers



(a) International Movers, N = 18,025,420



(b) Internal Movers, N = 89,844,550

Both estimation samples are subset to only include individuals that worked in the year prior to moving ($t = -1$). Standard errors clustered at the user level.

Our model does not allow for wage shocks that occur precisely at the time of a move and are correlated with $J(i,t)$ and match-specific components between cities and individuals. This is analogous to the 'exogenous mobility' assumption in the AKM literature (Abowd et al., 1999;

Card et al., 2013). An example of a violation of this assumption would be if workers experiencing negative wage shocks respond by moving to cities with high city premiums. In such cases, part of the shock's effect might be misattributed to the effect of moving, leading to an overestimation of city effects. While we cannot completely rule out this bias, our event-study analysis helps evaluate its magnitude. Specifically, wage trends correlated with origin and destination city effects would likely manifest as pre-trends in the event-study analysis from Section 4.1. The additive separability assumption rules out interactions between individual and city effects. We provide tests for various assumptions below.

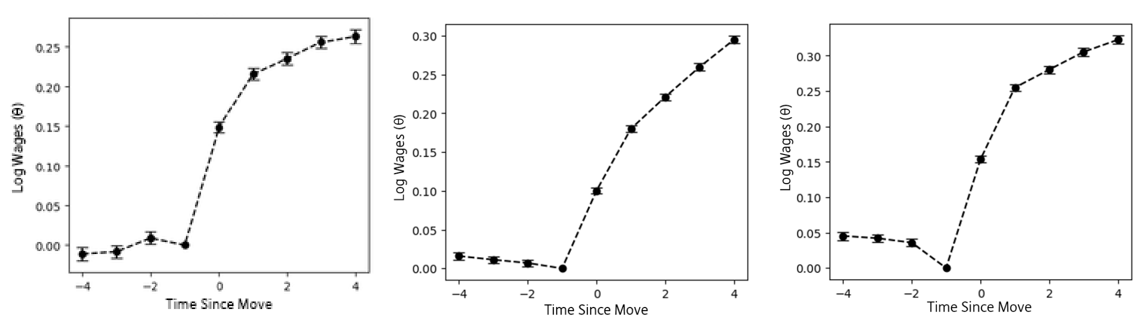
5 Event Studies

5.1 Event-Study Analysis

We present our event study results from Equation 2 for different populations of movers in our sample. On the y-axis, we plot estimated coefficients $\theta_{r(i,t)}$ for the corresponding relative year $r(i,t)$ on the x-axis. $\theta_{r(i,t)}$ captures changes in wages relative to the years surrounding the move, scaled by the difference in average wages between the mover's destination and origin cities. We normalize the value for $r(i,t)$ = -1 to 0.

Figure 5a plots estimated coefficients $\theta_{r(i,t)}$ for individuals whose origin and destination city are located in different countries ('international movers'). The figure shows a sharp discontinuous jump in the year of the move, from 0 to approximately 0.9. This implies a city-effect share of $\approx$ 90% in the observed variation in wages across cities internationally (Finkelstein et al., 2016), and suggests large potential wage gains for international moves, irrespective of individual-level skills.

Figure 6: Event Study for Internal Movers, Developed Economies



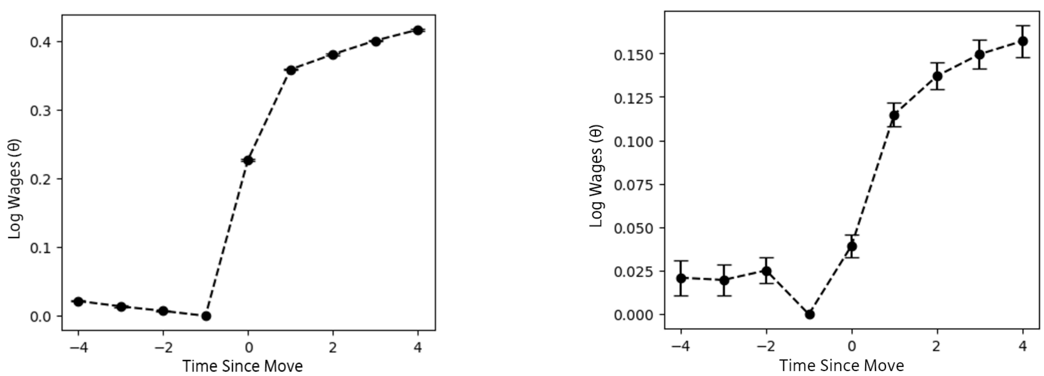
(a) Italy, N = 3,508,589 (b) UK, N = 5,704,159 (c) France, N = 6,260,064

All estimation samples are subset to only include individuals that worked in the year prior to moving ($t = -1$). Standard errors clustered at the user level.

Figure 5b shows the results for movers who move to cities within the same country as their origin. The jump from 0 to 0.35 around the move implies the city share of 35% in the observed variation in wages across cities in this sample. The sample for internal movers contains moves across 123,431 cities, while the international moves are across 56,422 cities.

As such, city effects are quite meaningful. Yet, the much larger effects for cross-border moves suggest country effects are extremely important too. That is, moving from Bangalore to San Francisco is likely to have a much larger impact on one's earnings than moving from Omaha to San Francisco, partly because moving from India to the US also has a big impact on a worker's earnings.

Figure 7: Event Study for Internal Movers, USA and India



(a) USA, N = 41,211,648

(b) India, N = 4,594,549

All estimation samples are subset to only include individuals that worked in the year prior to moving ($t = -1$). Standard errors clustered at the user level.

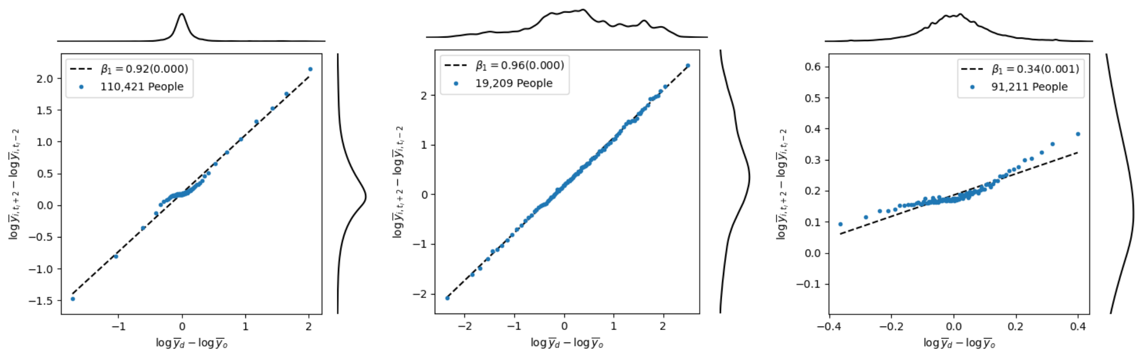
Figure 6 and 7 plot the event study figures for a sample of developed and developing countries. The post-move increase in earnings is larger for richer countries. This indicates that cities explain a larger share of wage variation across cities in developed countries than in developing countries. In other words, individual-level factors are likely to play a relatively greater role in determining wages in developing countries compared to developed countries, whereas cities play a relatively important role in determining earnings in rich countries. The presence of some post-move trends implies that δ_i is positively correlated to wage growth after the move.

5.2 Average Gains by Origin-Destination Pair

The event study graphs show stark increases in earnings, as a function of the origin-destination wage differential. In this section, we describe the relationship between the difference in wages in the two years prior to moving to wages in the two years after a move and the average wage differential at the origin-destination pair level ($\delta_i \equiv \bar{y}_{d(i)} - \bar{y}_{o(i)}$).

This exercise is informative of how we go from the event-study estimates to the city effects. Essentially, the event study graphs plot an average jump in wages for individuals who move between cities. Yet, we may expect that this average hides a fair bit of heterogeneity, and non-linearities based on the origin-destination wage differentials. For instance, individuals moving between two rich cities may see a different proportionate gain (as a fraction of the wage differentials between the two cities), than individuals moving from a poor to rich city.

Figure 8: Change in Wages by Difference in Pairwise City Wages



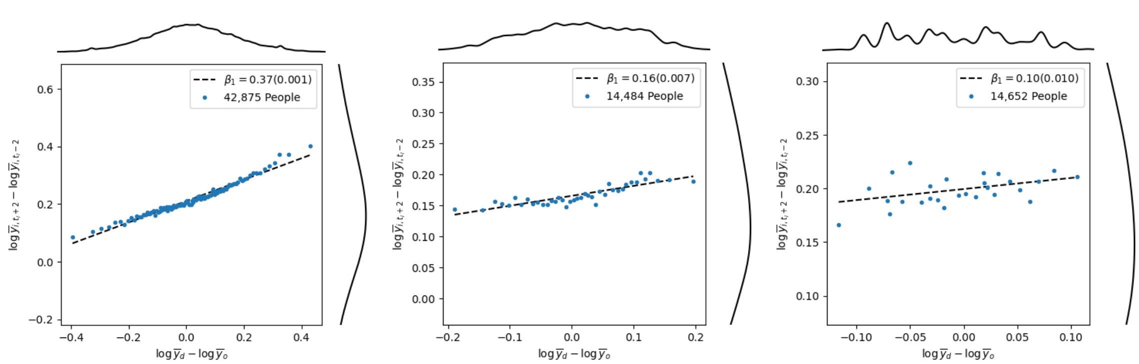
(a) Full Sample (b) International Moves (c) Internal Moves

We plot the difference in wages two periods before and after the move (y-axis) vs the difference in origin and destination average salaries corresponding to the move (x-axis). The left panel is for all moves. The middle panel for international moves. And the right panel for within-country moves. External axes plot the density of observations.

Figure 8a plots the relationship between the jump in wages for an origin-destination pair (y-axis), and the corresponding origin-destination average salary differential (x-axis). We plot the line of best-fit over this relationship, the slope of which should be similar to the size of the average jump in the event-study graphs. We also plot the density of observations on the axes.

The relationship in Figure 8a is roughly linear, with a flatter portion around the center. This may reflect the fact that most of the moves around the center of the graph are for within-country moves with smaller wage differentials, while the larger wage differentials reflect cross-border moves. Since country borders create stark wage differences (relative to within-country city differentials), moving across countries can lead to potentially larger gains. We investigate this relationship further in Figures 8b and 8c.

Figure 9: Change in Wages by Difference in Pairwise City Wages



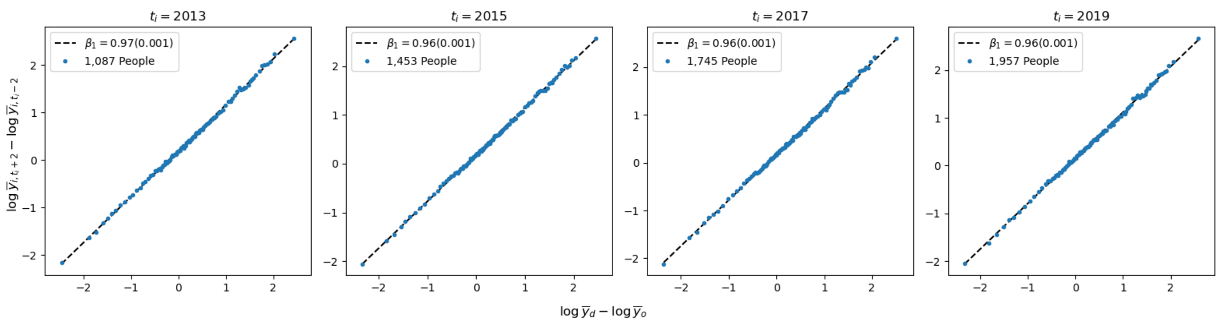
(a) USA (b) UK (c) India

We plot the difference in wages two periods before and after the move (y-axis) vs the difference in origin and destination average salaries corresponding to the move (x-axis). External axes plot the density of observations.

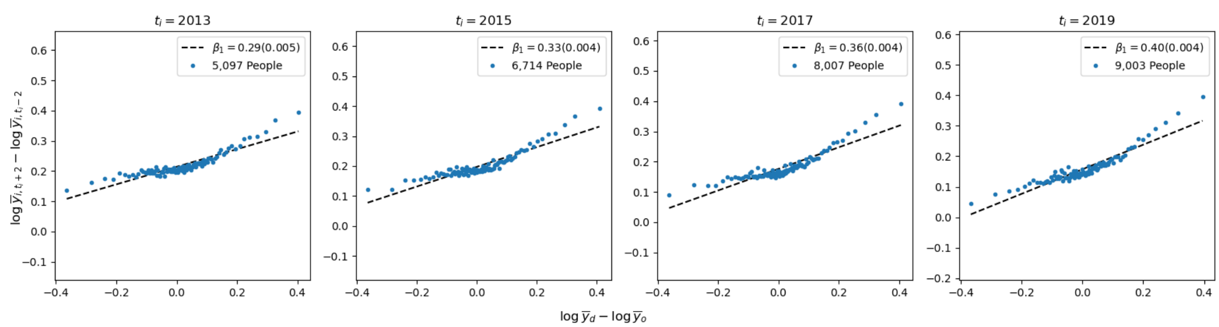
Indeed, the international moves (Figure 8b) show a stark (almost one-to-one) relationship with average city wage differences. The wage differential between Bangalore and San Francisco reflects the fact that, on average, when a worker moves between these cities, they will earn substantially more: almost the entire average wage difference. In contrast, for internal moves (Figure 8c), the relationship is a lot flatter (a slope of 0.34). Individuals that move between Omaha and San Francisco, will see a relatively smaller increase in their wages, as a fraction of the wage differential between the two cities.

These patterns reflect the fact that, given the (relatively) low migration barriers between Omaha and San Francisco, there has already been substantial internal migration whereby high-ability individuals have sorted to co-locate in one of the cities. That is, a fair amount of the wage differential between Omaha and San Francisco, reflects ability-based sorting. Furthermore, the steep relationship in Figure 8a is largely driven by cross-border moves.

Figure 10: Changes in Wages by Difference in City Wages, Over Time



(a) International Moves



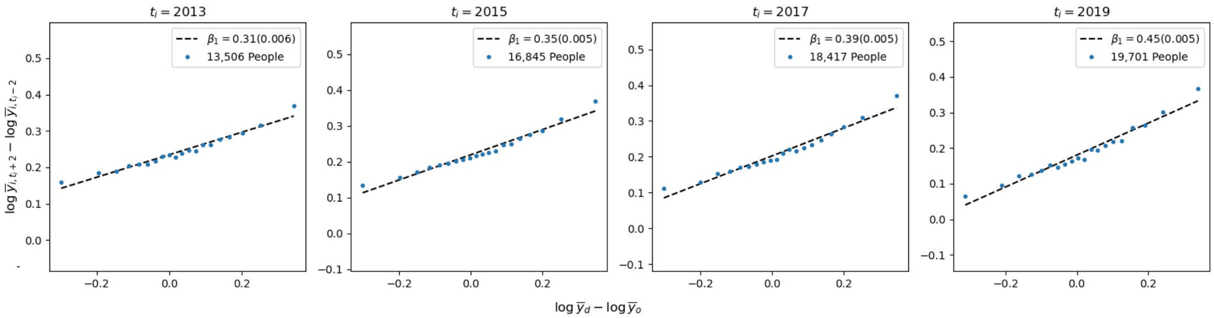
(b) Internal Moves

We plot the difference in wages two periods before and after the move (y-axis) vs the difference in origin and destination average salaries corresponding to the move (x-axis), by year of move. The left panel is for international moves, and the right panel for within-country moves.

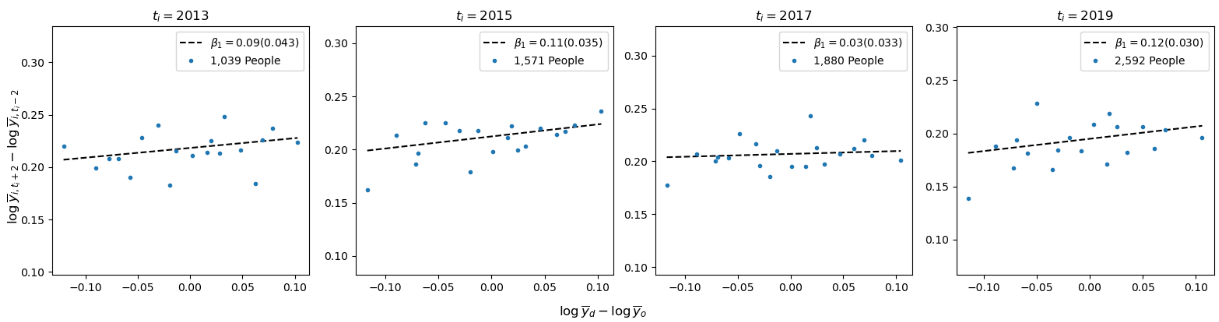
Next, we conduct the same exercise, within countries. Figure 9a shows a slope of 0.37, reflecting a similar size of the event study jump on average. This slope (and so the event study coefficient) is much flatter for a country like India. Figure 9c shows a slope of about 0.1. This suggests, that within India, ability-based sorting may play a substantially more important role in driving pairwise city wage differentials. Someone who moves internally in the US, will see a substantially larger rise in wages (as a fraction of the pairwise city wage differential), than someone who moves within

India.

Figure 11: Changes in Wages by Difference in City Wages, US and India



(a) USA



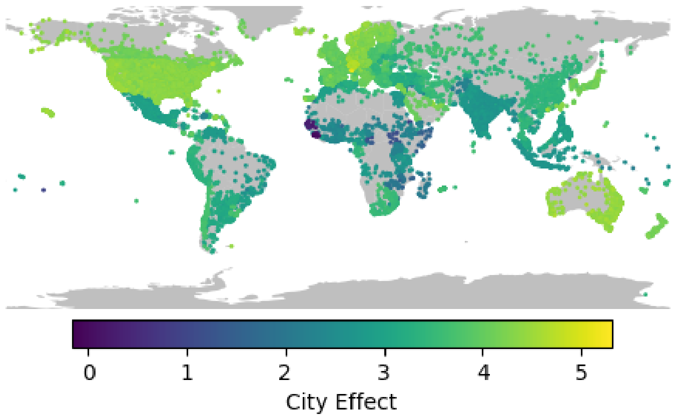
(b) India

We plot the difference in wages two periods before and after the move (y-axis) vs the difference in origin and destination average salaries corresponding to the move (x-axis), by year of move. The left panel is for international moves, and the right panel for within-country moves.

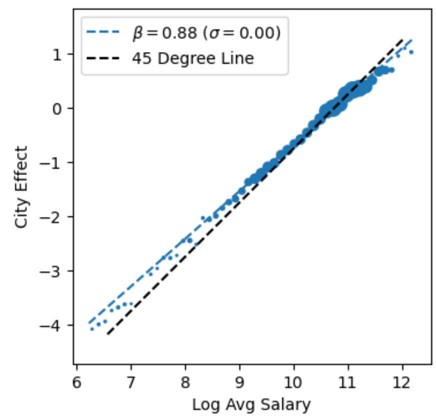
We also find that this relationship between wage gains and city wage differentials is not static over time. Figures 10 and 11 plot the same relationship between wages gains before and after a move against origin and destination wage differentials, but now disaggregated by the year of move. While this relationship is constant for international moves, Figure 10b reveals that there has been a steady increase over time in the relationship between wage gains and city wage differentials for internal moves; between 2012 and 2018 we find that–for a move between locations with a given wage differential–the average increase in wages before and after a move has increased nearly 40%. This relationship could reflect the growing importance of city effects in determining productivity or increasing frictions, such as urban congestion and housing supply, that have limited the role that sorting by ability across space plays. Although we do see a clear trend when grouping all internal moves, it is not uniform across countries. Figures 11a and 11b plot this relationship for the United States and India, respectively. We find that the relationship for the US looks similar to the general trend; however, we find virtually no changes in the relationship between wage gains from a move and city differentials in India over time. This suggests that one factor that could be limiting urbanization in India is that cities are having a small role in increasing productivity of individuals.

6 City Effects

Figure 12: City Effects, Global



(a) Estimated City Effect



(b) Log City Wages vs City Effect

Panel (a) plots the city effects ψ_J estimated using Equation 3, using the same sample as the event study analysis in Figure 5a. Panel (b) plots the relationship between the Log City Effect and the Log Average City Salary, where points are equally spaced across the distribution and the size of each point is proportional to the fraction of cities in each wage bin. $N = 8,025,420$

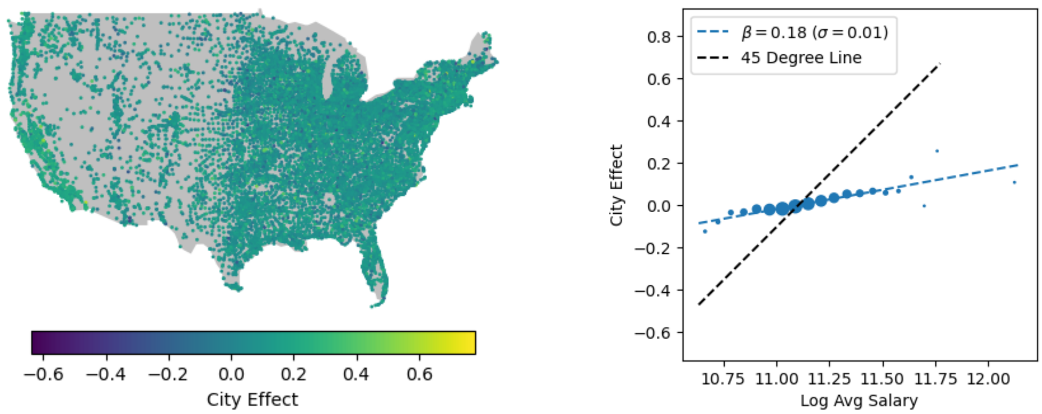
We use our movers' sample and Equation 3 to estimate the city effects for each city around the world. To comprehensively understand the economic implications of these city effects, we conduct several analyses. First, we plot the estimated city effects for all cities worldwide based on international movers (Figure 12) and compare these with city effects derived from within-country movers (Figures 13, 14, 15). This comparison highlights the extent to which national borders influence city effects. To further disaggregate within-country differences, we examine regional variations in city effects, using the United States as a case study (Figure 16). Finally, we investigate the differences in the distribution of city effects across countries due to their implications for heterogeneity in potential returns to higher internal migration.

Collectively, these comparisons help us shed light on the importance of city effects under varying migration costs: international moves across countries, moves across cities in the same country (both within and across regions), and within-country moves for different countries. Subsequently, in Section 7, we explore what underlying economic primitives are reflected in our estimated city effects and the variance in city effects across countries.

6.1 City Effects Across and Within Countries

In Figure 12a, we plot our estimated city effects on a map. They do roughly reflect the map of average wages by city in Figure 1b, once again highlighting the importance of regions and country borders. Figure 12b plots the correlation between city effects and average wage premia. These are strongly positively correlated for cities across the world. A correlation of 0.88 indicates that cities

Figure 13: City Effects, USA



(a) Estimated City Effect (b) Log City Wages vs City Effect

Panel (a) plots the city effects ψ_J estimated using Equation 3, using the same sample as the event study analysis in Figure 6a. Panel (b) plots the relationship between the Log City Effect and the Log Average City Salary, where points are equally spaced across the distribution and the size of each point is proportional to the fraction of cities in each wage bin. $N = 41,211,648$

play a significant role in explaining wage differentials across the globe, highlighting the importance of city-specific factors in shaping economic outcomes.

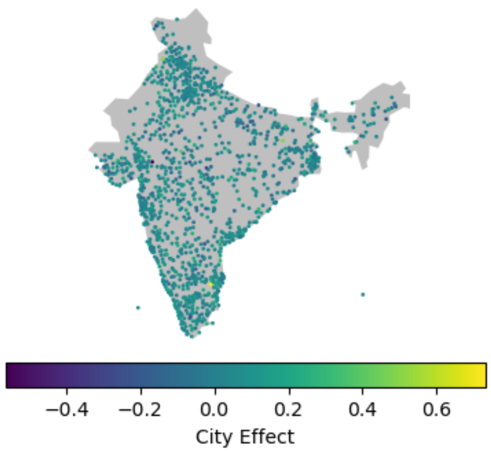
In Figures 13 and 14 we look at the example of only within-country internal moves for the US and India. The flatter relationship between city effects (y-axis) and average city salaries (x-axis) for the US ($\beta = 0.18$) and India ($\beta = 0.31$) suggests that city effects explain a much smaller share of the city wage differentials within a country than international wage differentials ($\beta = 0.88$). The variance in city effects is smaller than the variance in city-level average wages. We see similar results for city effects for the UK and France (Figure 15).

These results are consistent with our event study results from Figure 5. Overall, our results demonstrate that potential wage gains from international migration dwarf the potential gains from internal migration. Additionally, the varying slopes observed in the country-level graphs (USA, India, UK, and France) suggest that the extent to which city effects explain wage differentials is not uniform across countries. These differences imply that the potential economic benefits of internal migration, particularly in terms of wage gains, depend significantly on the country-specific context. For instance, in countries where city effects play a larger role in determining wages, internal migration may offer greater opportunities for wage gains. We investigate the variance in city effects across countries systematically in Section 7.2.

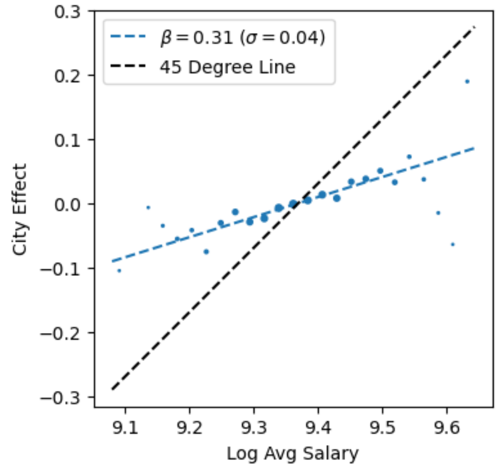
6.2 Regions Within Countries

Regions play a crucial role in shaping wage differentials. This is evident, for example, when comparing the coastal United States to the Midwest, where each region exhibits distinct income levels.

Figure 14: City Effects, India



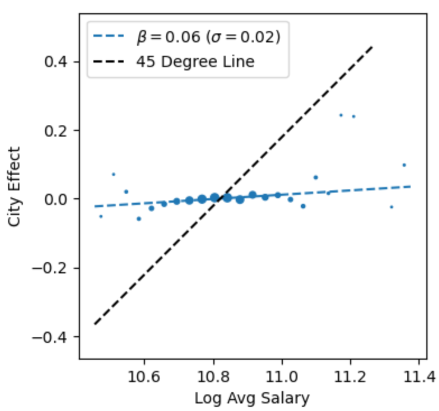
(a) Estimated City Effect



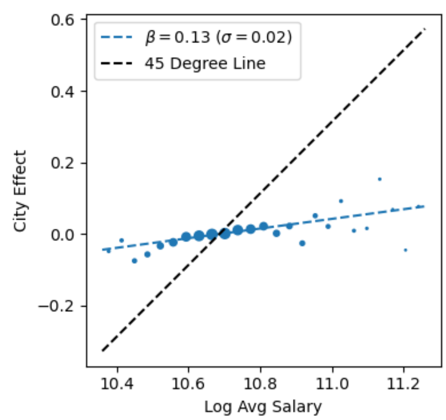
(b) Log City Wages vs City Effect

Panel (a) plots the city effects ψ_J estimated using Equation 3, using the same sample as the event study analysis in Figure 7b. Panel (b) plots the relationship between the Log City Effect and the Log Average City Salary, where points are equally spaced across the distribution and the size of each point is proportional to the fraction of cities in each wage bin. $N = 4,594,549$

Figure 15: City Effects, UK and France



(a) UK



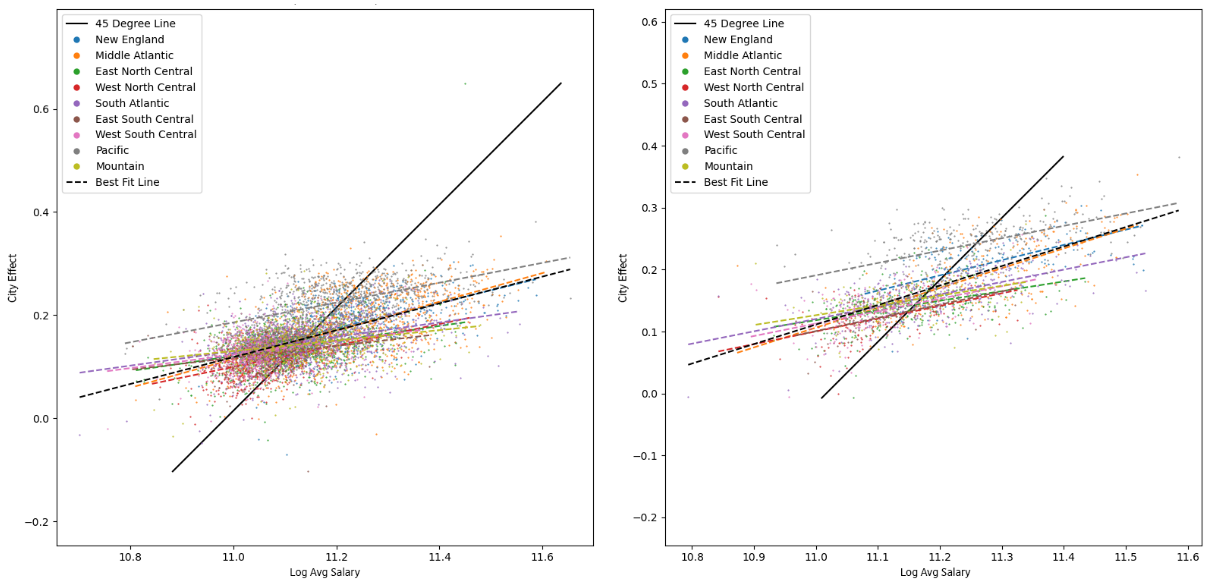
(b) France

Each panel plots the relationship between the Log City Effect and the Log Average City Salary, where points are equally spaced across the distribution and the size of each point is proportional to the fraction of cities in each wage bin.

Migration patterns also tend to be concentrated within regions, leading to two important implications. First, substantial sorting of individuals based on abilities is likely to occur within regions, rather than across regions. Second, this contributes to a distinctive relationship between city effects and average salaries: within regions, this relationship is relatively flat, but when observed across the entire country, it becomes significantly steeper.

Figures 16a and 16b illustrate this pattern. Within each region of the US, the relationship

Figure 16: City effects by region, USA



(a) Effects by US Regions (with mid-sized cities) (b) Effects by US Regions (only larger cities)

Figures plot the city effects by region of the US, and the overall fit line. The left panel includes all cities with more than 1000 users. The right panel includes all cities with more than 10,000 users. The bold black line is a 45-degree line. The black dotted line is a country-level line of best fit.

between city effects and average salaries is nearly flat. However, because some regions are systematically wealthier than others, the relationship for the entire country becomes steeper, as reflected by the dotted black line.

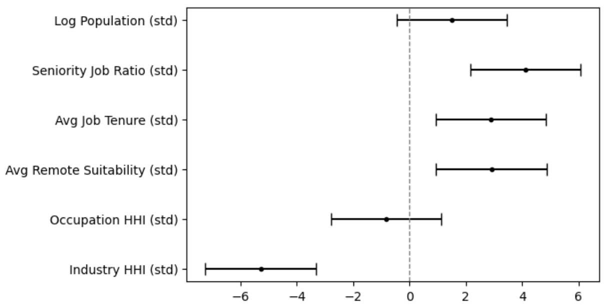
These aggregation phenomena are likely present in other parts of the world as well, particularly in countries where some regions are consistently richer than others and migration occurs predominantly within regions. This observation also helps explain why the slope of the relationship is steeper in our global analysis compared to the within-country analysis.

7 What Explains the City Effects and Their Distribution

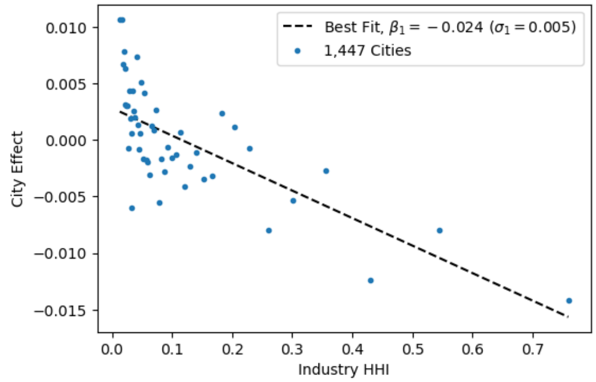
7.1 Explaining the City Effects

We next turn to confirming that our estimated city effects are associated with observable factors that we believe would impact the effect of a city on earnings. Using the full sample of LinkedIn users, we construct a measure of the industrial diversity of a city based on employee job classifications, the ratio of job titles in a city that are identified as senior positions, the average job tenure, and the average remote suitability of positions. Additionally, we obtain a measure of the current population of each city by merging our cities with the publicly available data available at GeoNames. We estimate the relationship between city effects and each of these variables, and include region fixed

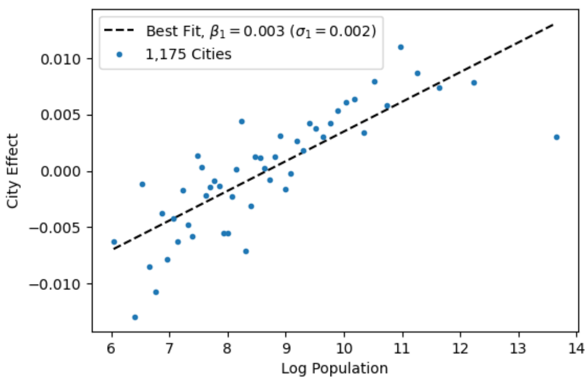
Figure 17: Correlates with City Effects



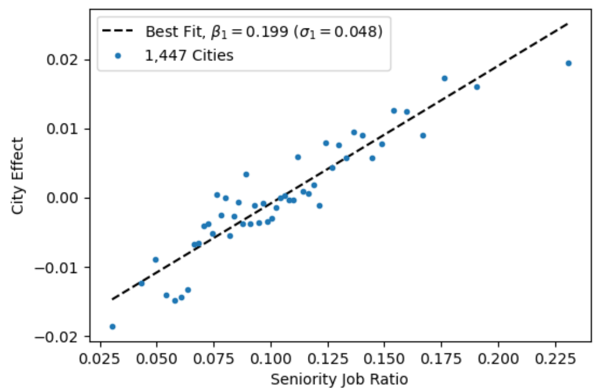
(a) Correlates of City Effects



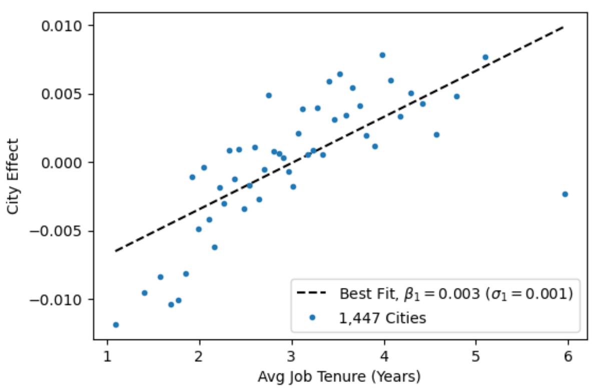
(b) Industrial Diversity



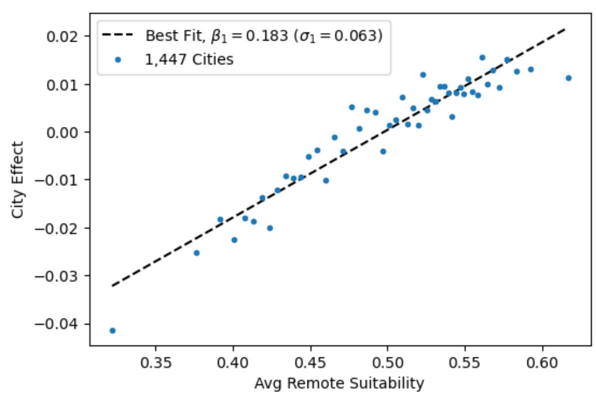
(c) Population



(d) Senior job positions



(e) Average Job Tenure



(f) Job Remote Suitability

Notes: We plot the city-level correlation between city characteristics and city effects with the inclusion of region fixed effects. Industrial diversity is the Hirschmann Herfindahl Index (HHI) of industry-wise employment. Log(population) is the city's population. Senior job positions, is the ratio of job titles in the LinkedIn data that are in senior positions. Average job tenure is the average number of years workers stay at a job. Job remote suitability is a measure of whether the job-title-by-industry is conducive to remote work (based on job postings of remote work). Standard errors are clustered at the country level.

effects to control for heterogeneity in all of these variables over space.[5]

Figure 17a plots the standardized coefficients from our estimation while Figures 17b- 17f present binned scatter plots for each relationship. Consistent with conventional theories of agglomeration economies, we find that cities that are larger and have more modern firms (proxied by remote suitability) have higher estimated city effects. These patterns reflect other work that argues how city density and large populations facilitate knowledge sharing, with spillovers that drive city incomes (Duranton and Puga, 2004; Rosenthal and Strange, 2004).

Next, in Figure 17b, we find that cities with a lower industrial HHI have a wider variety of economic activity with room for productive spillovers, which is associated with larger city effects. The complexity and diversity of the economic structure allows for linkages between sectors, and network externalities can facilitate higher city income growth. In contrast, a mono-centric industrial structure is associated with lower city effects, suggesting that cities that rely on just a handful of industries are less likely to be productive.

Finally, we test how skill-based agglomeration affects city growth. Previous work argues how knowledge sharing and innovation may result from the higher density of skilled workers (Moretti, 2004). In our data, we measure various aspects of skilled jobs, by looking at their seniority, whether they are suitable for remote work, and whether they are stable. We find that cities with the most skilled, stable, jobs with senior positions also see increased city effect estimates.

Our results highlight that our estimated city effects are strongly associated with multiple measures of city productivity, and are highly robust to the inclusion more granular country fixed effects.

These findings have important implications for policymakers wishing to unpack what makes a city more productive? Cities that attract high-skill workers, a diverse set of industries, and maintain skilled, stable jobs may be likely to see productivity gains.

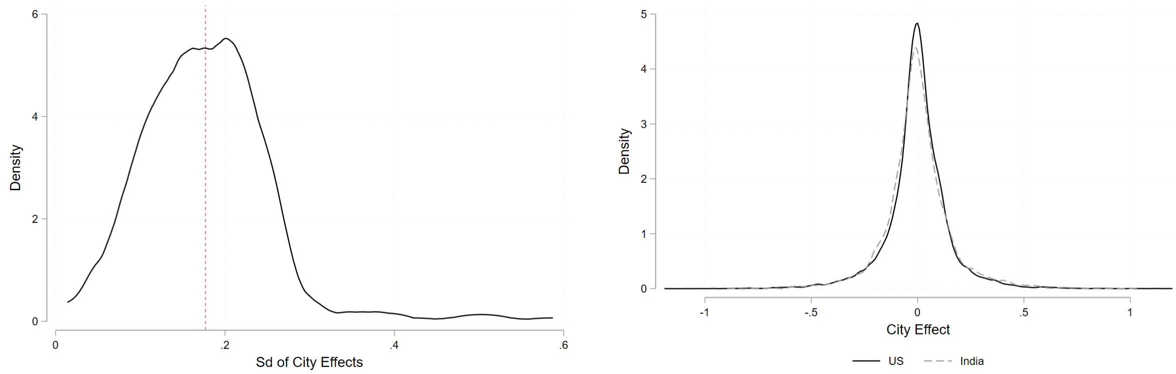
7.2 Heterogeneity of Variance of City Effects by Country

The global scope of our dataset provides a unique opportunity to assess whether potential returns to internal migration vary significantly between countries. If the distribution of city effects were uniform across countries, individuals moving from a city in the 25th percentile to one in the 75th percentile within any country would experience comparable wage gains, regardless of the country. However, when the distribution of city effects is narrower in one country (e.g., country X) compared to another (e.g., country Y), the economic returns to such migration would be considerably lower in country X. This highlights the critical role of cross-country heterogeneity in city effect distributions in shaping the potential wage benefits of internal migration and returns to reducing migration constraints (Bryan and Morten, 2019).

We uncover substantial variation in the distribution of city effects across countries. Figure 18a

[5]We identify 15 regions in our data: Arab States, Central America and the Caribbean, Central and Western Asia, Eastern Asia, Eastern Europe, Northern Africa, Northern America, Northern Europe, Pacific Islands, South-Eastern Asia, Southern America, Southern Asia, Southern Europe, Sub-Saharan Africa, and Western Europe

Figure 18: Distribution of City Effects

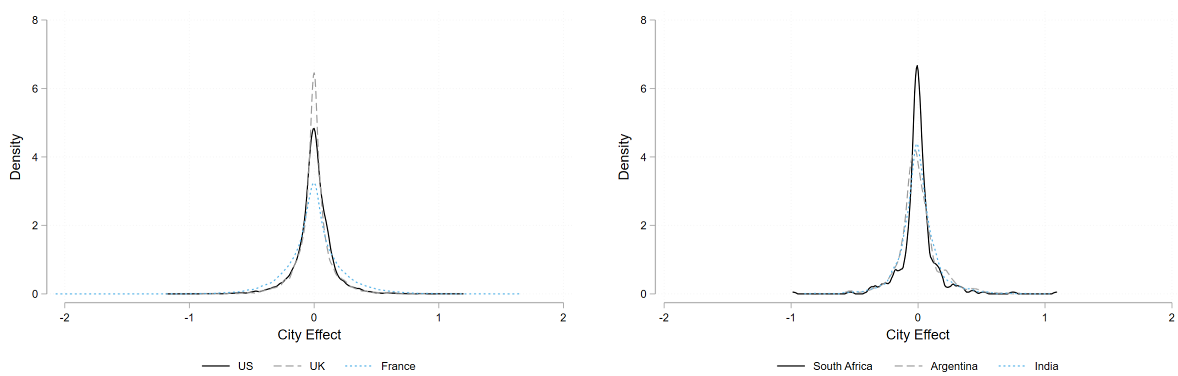


(a) Distribution of Sd of City Effects (b) City Effects Distribution, USA and India

Panel (a) plots the density plot of the standard deviation of city effects estimated using Equation 3 across countries. The distribution indicates that the variance of city effects varies meaningfully across countries. Panel (b) shows the distribution of city effects for the USA and India. We recenter the country level distributions, as the city effects for each country are only identified up to a constant term.

plots the global distribution of each country's standard deviation in city effects. While the average standard deviation of city effects at the country level is 0.18, Figure 18a reveals significant global variation in our estimated city effects. That is, certain countries have a tight distribution of city effects, with few potential gains from relocating workers across cities. On the other (right end) of the global distribution, certain countries have a wide range of city effects, suggesting that there facilitating migration to high productive cities can improve aggregate incomes substantially.

Figure 19: City Effects Distribution, Across Countries



(a) City Effects Distribution, Developed Countries (b) City Effects Distribution, LMICs

Panel (a) plots the distribution of city effects for a sample of developed countries - USA, UK, and France. Panel (b) plots the distribution of city effects for a sample of LMICs - South Africa, Argentina, and India.

Indeed, our findings indicate that the potential returns to internal migration differ considerably between countries, depending on the underlying distribution of city effects. For instance, countries with a higher dispersion of city effects may offer greater economic incentives for individuals to migrate internally, whereas in countries with lower dispersion, the benefits of such migration might be more constrained.

Figure 18b demonstrates that we can also directly compare the distribution of city effects across countries. They are both large countries, with somewhat similar distributions in city effects. The gains from internal migration are likely to also be somewhat similar.

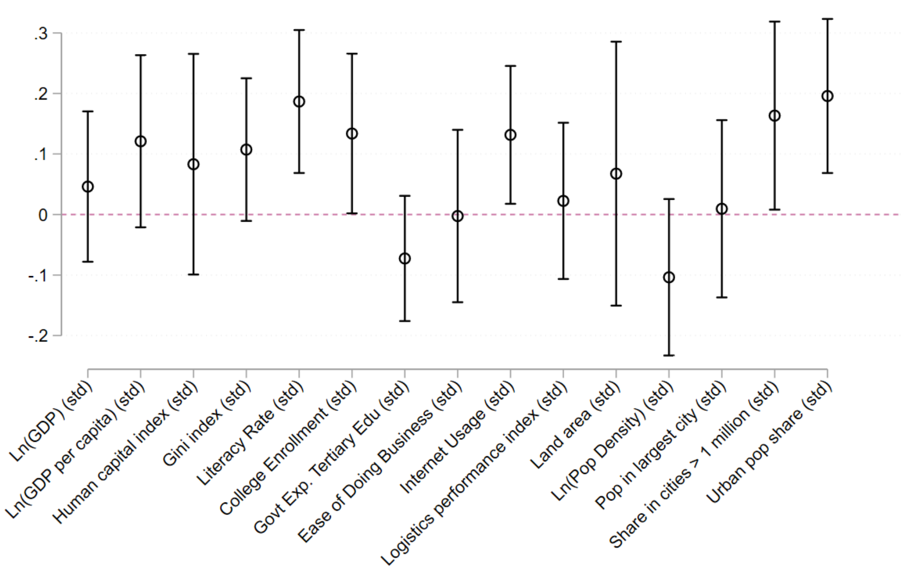
In Figure 19, we investigate the differences in distribution within groups of countries as well. We plots the distribution of city effects for multiple countries in our sample; while it appears that more developed countries have a higher variance in their city effects, it is also clear that there are other factors that could explain the differences in variation across countries.

For instance, looking at developed economies, the UK has a much tighter distribution of city effects than France. This suggests that the aggregate gains from internal re-sorting of workers will be higher in France, than in the UK. Similarly, among middle-income countries, we find that the distribution of city effects is a lot tighter in a country like South Africa, than it is in Argentina or India, implying that there are relatively limited aggregate gains from internal migration in South Africa.

We evaluate which country-level economic factors are correlated with higher variances of city effects in a country below.

7.3 Explaining the Variance in City Effects

Figure 20: Relationship Between Country Aggregates and Variance of City Effects



Here, we examine the country-level factors that correlate with the variance of city effects that we estimate. All explanatory variables come from the World Bank's World Development Indicators and are calculated as the average value of each variable over the last 10 years. Given the heterogeneity in country sizes in our sample, our preferred specification weights each country by its population.

We look at three important sets of variable categories: income and size, human capital, and urbanization. Figure 20 plots the estimated coefficients for the relationship between the standard deviation of city effects of a country with each of our explanatory variables, while Table 1 displays the regression results of several variables of interest, split between categories capturing a country's income and human capital, respectively.[6]

Overall, we find that wealthier countries have higher variances in their city effects. A higher variance of city effects implies that there would be larger gains from reallocating individuals from low-productivity cities to high-productivity cities within a country. Thus, returns to internal migration in LMICs might be low, consistent with previous work (Bryan and Morten, 2019).

Table 1: Country Income and Variance in City Effects

Panel A: Country Income	Sd of city effects (std)			
Ln(GDP per capita) (std)	0.1210*			
	(0.0726)			
Gini index (std)		0.1073*		
		(0.0601)		
Share in cities > 1 million (std)			0.1634**	
			(0.0793)	
Land area (std)				0.0675
				(0.1112)
Unique Countries	200	165	118	203

Panel B: Human Capital	Sd of city effects (std)			
Human capital index (std)	0.0831			
	(0.0930)			
Literacy Rate (std)		0.1867***		
		(0.0603)		
College Enrollment (std)			0.1338**	
			(0.0673)	
Internet Usage (std)				0.1316**
				(0.0581)
Unique Countries	157	147	178	199

Relationship between within-country SD of city effects and standardized country characteristics.
Standard errors in parentheses clustered at the country level and countries weighted by population.
* $p < .1$, ** $p < .05$, *** $p < .01$

Highly-educated countries (as measured by higher literacy rates and college enrollment) have

[6] These results are robust to not weighting the relationship. We find similar, statistically significant, associations between rates of urbanization and the variance of city effects, and the relationship between human capital and city effects is qualitatively similar.

relatively higher variances as well, suggesting that skilled internal migration may reap large benefits, by allocating skills to locations where they are more productive. Not surprisingly, more unequal countries have higher variances as well, reflecting the fact that overall income inequality also manifests in spatial inequality.

Finally, countries with higher urbanization rates also have larger potential gains from internal migration. We measure this by looking at the share of the population in urban areas, and the share in cities that have more than a million individuals. Urban centers reflect potential gains from agglomeration, and differences in city effects reflect how more migration to a certain large centers may raise country-level GDP. In contrast, rural heavy countries may currently have fewer large urban centers that gain reap agglomeration benefits.

8 Conclusion

Our study provides new insights into the economic value of cities by leveraging a unique dataset of detailed job histories from 513 million workers in 220,000 cities across 191 countries. Through an event-study design, we isolate the causal impact of city effects on individual wages, disentangling the role of geographic productivity from ability-based sorting. Our findings underscore the substantial role cities play in shaping earnings, particularly across international borders, where city effects account for up to 90% of observed wage differences. Within-country moves, while also significant, show a more modest contribution of city effects, at approximately 35%.

We find that city effects are strongly associated with industrial diversity, city size, and the prevalence of high-skill jobs, reinforcing the importance of agglomeration economies. Notably, the variance in city effects increases with a country's level of development, suggesting greater potential gains from internal migration in richer economies. These results highlight the dual role of cities as hubs of productivity and magnets for skill, while also pointing to barriers that constrain the realization of these benefits, particularly in developing countries.

Our findings contribute to the broader literature on the economic value of cities, spatial inequality, and migration by illustrating how city-level productivity interacts with national and regional contexts to shape labor market outcomes. Facilitating migration can potentially allow workers to move to more productive cities and raise aggregate incomes. Policymakers aiming to foster economic mobility should consider both reducing barriers to migration and enhancing the productivity of lagging cities. Future research could explore the mechanisms driving these city effects, such as infrastructure investments, governance quality, and social networks, to better inform urban development policies.

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