A Human Capital Theory of Who Escapes the Grasp of the Local Monopsonist

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Abstract

Over the last thirty years, there have been significant changes in several empirical measures of local labor market monopsony power. A monopsonist has a profit incentive to offer lower wages to local workers. High skilled mobile workers can avoid these lower wages by moving to other more competitive local labor markets. We explore several empirical implications of a Roy Model of heterogeneous worker sorting across local labor markets. Counties with concentrated labor markets are predicted to experience a "brain drain" over time. Using data over four decades we document this deskilling and loss of high-income workers associated with local monopsony power. An implication is that labor market competition complements product market competition to foster faster city growth. Going forward the rise of work from home may act as a substitute for migration by high-skill workers from monopsony markets.

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Introduction

Local labor markets experiencing a rise in monopsony power face the possibility that large local firms can benefit by paying workers lower wages. Labor economists have argued that rising monopsony power has contributed to earnings inequality and inflated firm profits (Manning 2003, 2006, 2009, 2011). Given a geographic area defined by finite commuting speeds, workers cannot credibly search across a wide number of employers. Apart from moving, this limits their best response in the face of monopsony. Mobility frictions arise from a number of sources. Urban economic research demonstrates that home ownership is associated with lower migration rates (Oswald 2019). Those who have built up location-specific investments in social networks and have families who have matched with friends and good schools are more hesitant about moving away to another local labor market offering greater opportunities (Glaeser et al. 2002, Deryugina et al. 2018). If local labor market concentration is persistent over time, an implication of Glaeser et al. (2002) is that young individuals growing up in concentrated local markets anticipating a future desire to move will have more incentive to invest in human capital and less incentive to invest in social capital.

Workers also differ with respect to their gains from migrating. Going back to Sjaastad (1962), economists have understood that migration is an investment and those with a longer expected work horizon have a larger present discounted value of earnings gains from moving. The Roy Model (1950, 1951) of local labor markets offers an additional insight. As pointed out by Heckman and Scheinkman (1987), the fundamental role of bundling—that an individual must sell all attributes to a single local labor market—can mean that individual skill factor prices (i.e. for brains and muscle and personality) are not equalized across space.

This variation in skill prices has an important implication for the role of monopsony at one's origin location as a migration push factor. If a worker with plenty of brain power faces "exploitation" for this skill at theorigin location, then the opportunity cost of remaining there is high when the worker can move to another more competitive local labor market where the skill price reflects the urban agglomeration effects emphasized in the urban economics literature (Glaeser 2012, Moretti 2004a, 2004b).

In this paper, we use the Roy Model to explore how different workers adapt when they face monopsony power in their origin's local labor market. In locations featuring high levels of local monopsony power, skilled individuals have an incentive to move away. As these workers depart, and other skilled workers do not move in (because they anticipate that they would be underpaid if they move there), the average skill level of the monopsony locations declines.

We use standard measures of monopsony in a county/decade panel data set covering the last 40 years to examine this hypothesis. We document four main results. First, counties facing greater monopsony power have slower population growth. Second, such counties are "deskilling" by losing younger and more educated individuals. Third, the fraction of these counties tax filers that are "high income" is reduced. Finally, moves and commuting between counties in the same commuting zone increase with the employment concentration of the origin county and decrease with the employment concentration of the neighboring destination county.

There is an expanding literature estimating the impact of monopsony on worker wages and earnings (Qiu and Sojourner 2019, Azar et. al. 2022 and Rinz 2022). In Kahn and Tracy (2024), we document that, all else equal, home prices are also lower in local labor markets featuring greater employer concentration. If spatially tied amenities are exogenously determined (i.e. local climate conditions), then this adjustment in local house prices in the face of monopsony power would help to attenuate any demographic shifts induced by monopsony.[1]

In this paper, we study net migration rates as well as commuting, and the resulting shifts in the demographic composition and the income distribution of counties over time in response to changes in local employment concentration. The compensating differentials of lower house prices and rents in response to local employment concentration documented in Kahn and Tracy (2024) generate differential incentives for renters versus owners to commute to escape lower monopsonistic wages. Documenting that both house prices and skill distributions adjust in the face of changes in monopsony power indicates that both mechanisms are active as markets re-equilibrate.

Our study builds on the seminal Ehrlich and Becker's (1972) study of self-protection. In their model, a decision maker faces a tradeoff between making a costly investment to offset risk ex-ante, or to take the gamble and ex-post rely on market insurance to transfer resources. In our local monopsony setting, migration to another local labor market represents a type of self-protection. We argue that there is heterogeneity in the propensity to exercise this option because the expected

[1] If local amenities are a function of the local poverty rate, then more complicated spatial equilibrium dynamics emerge. Urban research has documented that the combination of durable housing supply and declining housing demand acts to create a poverty magnet effect (Glaeser and Gyourko 2005).

present discounted value of this choice is an increasing function of one's general human capital and expected work horizon.

Our human capital hypothesis has implications for testing for the economic incidence of local monopsony power. This paper's reduced form evidence supports the claim that cross-sectional hedonic wage studies measuring the wage loss due to local monopsony power are subject to selection bias concerns. As we discuss below, these studies seek to instrument for local monopsony power to address concerns about firm locational choice. However, these studies do not address the related concern about worker locational choice—that is, worker wages are only observed in the markets where they choose to live. Our migration evidence suggests that areas featuring local monopsony power deskill over time. Additionally, the low rents and the relatively low returns to skill attract less educated workers. Federal transfer programs that pay a fixed nominal amount offer greater purchasing power in places where rents are lower and local service prices are cheaper (Notowigigdo 2020).

There is a large literature examining what explains differences in growth across cities. Innovation is seen as an important determinant of growth. Porter (1990) stresses that competition in product markets provides strong incentives for firms to innovate and adopt new technologies in order to survive. Consequently, innovation is more likely in markets with many small firms who must compete or perish even though they do not receive the full value of their innovations (Jacobs, 1969). Contrasting Silicon Valley and Route 128, Saxenian (1994) finds that smaller firms are less hierarchical and have cultures that are more conducive to entrepreneurship and innovation. Glaeser et al. (1992, 2015) find supporting evidence that cities with more competitive product markets proxied by smaller firm sizes grow faster.[2]

Innovation requires not only strong incentives and flexible organizational structures to undertake costly and risky investments, but also the human capital necessary to produce and utilize new ideas. Our findings illustrate a complementary channel in which local labor market competition helps cities retain the human capital needed to support innovation (see also Gennaioli et al., 2013). As local labor market competition diminishes, cities experience a brain drain that limits entrepreneurship and subsequent growth.

In the final section of the paper, we introduce an emerging practice that could have important implications. Since the COVID crisis, the rise of work from home (WFH) has started to

[22] See also Rosenthal and Strange (2003, 2010) and Agrawal et al. (2014).

shift America's economic geography. An expansion of WFH would open up a new opportunity for skilled workers to live in a local monopsony area in order to consume its services and amenities, but not to work there and suffer from its lower wages.[3] This unbundling of place of work from place of residence would have implications going forward such that high amenity, monopsonized places would be less likely to "deskill". Furthermore, if marginal workers are WFH, then capitalization of amenities will occur only through land prices with wages no longer adjusting for amenity differences (Brueckner et al. 2023). This would shift the relative incidence of capitalization between employed and retired households (Gyourko and Tracy 1991). The expansion of WFH is a development of potential interest for future research.

Recent Empirical Research on Local Monopsony Power on Wages

Empirical work on the effects of monopsony must start with a measure of the firm's degree of monopsony power in a market. Theory points to the elasticity of labor supply facing an employer as the proper measure of monopsony power. However, as Manning (2003) notes "… a good estimate of the elasticity of the labor supply curve facing the firm seems very elusive… (page 96)." With a few exceptions that estimate monopsony power using the sensitivity of a firm's turnover rate to its wage (see for example Bamford 2021 and Hirsch et al. 2022), most of the empirical work on monopsony has relied on measures of employment concentration for a given definition of the firm's market. That is, the empirical analysis "… leads one back towards the concerns of the 'traditional' monopsony model—how large is a firm *relative to its labor market*…" (Kuhn 2003, page 376).

There is a growing literature that examines the effect of monopsony on worker wages, earnings and skill mix. Qiu and Sojourner (2019) find that increasing concentration reduces the share of college-educated workers in the affected sector. They find that controlling the human capital characteristics of workers substantially reduces the conditional impact of concentration on wages. Similarly, Azar et al.(2022) using job posting data from CareerBuilder.com find that increasing employment concentration from the 25th to the 75th percentile is associated with a 5 percent (OLS)

[3] Work from home by lowering commuting costs would also increase the labor supply elasticity facing monopsonists reducing their ability to extract rents. This can be illustrated using Barro's (2024) circular Hotelling model, but switching the context to workers commuting to employers. If all workers had the same value of leisure, the elasticity of labor supply would reflect differential commuting costs based on distances from the monopsonist.

and 17% (IV) decline in wages. They report that controlling for job titles (a proxy for worker quality) lowers the estimated impact of concentration on wages. Finally, Rinz (2022) finds that the negative effect of local employment concentration on wages is concentrated on lower income workers. These findings indicate that the lower earnings associated with monopsony reflect both a wage effect and a skill mix effect. We incorporate this finding into our Roy model.

The Roy Model's Relevance for Local Monopsony Research

We examine the effects of local labor market concentration using a Roy model (Roy 1950, 1951) in which each worker is treated as a bundle of sector-specific skills. A city where one or more firms are exercising monopsony power in one sector generates a different ratio of skill factor prices than in a city facing perfect labor market competition. We use the Roy model to highlight the subset of workers who choose to remain after a monopsony employer enters the city and the resulting change in the allocation of workers across sectors within the city and between cities. We document that when worker skills are positively correlated across sectors and labor markets, the "exploited sector" in a monopsony city will suffer a "brain drain" to other sectors in the city as well as due to migration out of the city. Thus, this formulation of the Roy model captures the finding in the literature that the lower average wages in the monopsony sector reflects both the downward pressure on wages due to monopsony power and a composition shift as the skill level of workers in this sector declines.

The Economic Incidence of Monopsony in a Roy Model with Sectoral Choice

When workers differ with respect to their skills, the rise of monopsony power will induce behavioral change at the extensive margin and workers will re-sort across sectors and labor markets. The early Rosen/Roback (Rosen 1979, Roback 1982) literature on compensating differentials abstracted from explicitly considering the assignment of heterogeneous workers to sectors (based on skill) in local markets.[4]

Assume that workers in a local labor market are heterogeneous in their ability. The labor market consists of two sectors. Each worker's (indexed by i) ability is given by a pair of sector-

[4] The value of a statistical life literature (started by Thaler and Rosen 2004) is a first cousin of the Rosen/Roback model. In that literature, researchers seek to estimate the compensating differential for working in a riskier job (Viscusi 1993). Hwang et al. (1992) investigate the hedonic assignment of heterogeneous workers to risky and safe jobs.

specific abilities $\left(a_{i1}, a_{i2}\right)$.[5] These abilities have a joint distribution in the local labor market. In a competitive local market, each sector consists of many employers who pay a common sector specific ability wage, w_k. A worker is paid a wage equal to the ability wage in that sector times that worker's sector specific ability, $w_{ik} = w_k a_{ik}$.

Assume initially costless mobility between sectors within a local market, but that movement between labor markets is prohibitively expensive. In this case, each worker will select the sector of employment in their local market that provides the higher wage. That is, worker *i* will select sector 1 if $w_1 a_{i1} > w_2 a_{i2}$ or $w_1 / w_2 > a_{i2} / a_{i1}$. As illustrated in Figure 1, self-selection implies that the skill price ray with slope w_1 / w_2 divides the joint distribution of skills in a local market such that workers with skill pairs below the ray will select to work in sector 1, while workers with skill pairs above the ray will select to work in sector 2.

Positive correlation in skill attributes across sectors

For illustration, we will label sector 1 as "Retail" and sector 2 as "Mfg". Assume that the two skill abilities are positively correlated and that the variance of abilities in manufacturing is higher than in retail.[6] Let the ability wages w_1^c and w_2^c represent a competitive equilibrium where, given the selection of workers across the two sectors induced by these ability wages, firms make zero profits selling their output. With this joint distribution of abilities, self-selection leads the manufacturing sector to attract, on average, higher quality workers than in the retail sector. While high ability workers in manufacturing would also tend to be high ability in retail, as shown in Figure 1, the larger variance of ability in manufacturing allows many of these high skilled workers to earn more in manufacturing.

Consider now the entry into the local labor market of a large retail employer that displaces the existing small retailers. Once the small retail employers have exited, the large retail employer acts as a monopsonist. The assignment of workers to sectors implies that the large retail employer faces an upward sloping supply curve of workers that is indexed to the ability wage paid in manufacturing.

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[5] We treat these skill vectors as exogenous. However, the structure of local labor markets may also influence the incentives for firms and workers to invest in human capital. Becker (1962) points out that a monopsonist may have a greater incentive to invest in firm- (sector-) specific human capital.
[6] The Roy model can be analyzed using any assumption on the joint distribution of worker sector-specific skills. We explore the case of a positive correlation and differential variance to align the Roy model to the empirical findings discussed earlier.

Acting as a monopsonist, the retail employer reduces the ability wage paid in retail, $w_1^m < w_1^c$, so that its marginal revenue product of labor equals its marginal factor cost.

Holding constant the ability wage in manufacturing, the lower ability wage in retail rotates the skill price ray downward as shown in Figure 1. With costless sectoral mobility within the local market, this induces workers with ability pairs between the two rays to reallocate from the retail to the manufacturing sector thereby reducing total retail employment. Wages fall for those workers who remain in the retail sector. For a worker with retail skill a_{i1} who remains in the retail sector, the wage decline is proportional to the vertical distance between the two skill price rays at a_{i1}. In addition, the average ability of workers in retail is lower under the monopsony retailer than it was under the earlier competitive retail sector. So, consistent with the findings in the literature, the decline in average retail earnings reflects the combination of the lower skill wage paid by the monopsonist and the lower average ability of workers remaining in the retail sector.

The Roy model also provides insights for the relative wage effects of a monopsonist between workers who switch sectors and those who remain in retail. For a worker with retail skill a_{i1} who switches to manufacturing, the wage decline is proportional to the height of the original skill price ray at a_{i1} less the worker's skill level in manufacturing, a_{i2}. Workers with retail skill a_{i1}who remain in retail suffer a wage loss proportional to the vertical distance between the two skill price rays at a_{i1}. For a given skill level in retail, then, the wage loss for workers who remain in retail is greater than the wage loss for workers who switch to manufacturing.[7]

Whether this is the new equilibrium depends on if the manufacturing sector for this local market is a price taker in the broader manufacturing market. If this is the case, then the ability wage in manufacturing is not affected by the influx of additional workers. An implication in this case is that for workers who were already working in manufacturing, the entry of the monopsonist in the retail sector does not affect their wages. In contrast, if the local manufacturing sector is not a price taker, then the expanded output due to the influx of workers from the retail sector will result in a lower skill wage in manufacturing. This shifts the supply curve facing the monopsonist and will reduce the overall movement of workers into manufacturing.

[7] In contrast, Neal (1995) finds that industry switchers tend to suffer greater wage losses than industry stayers following a job displacement.

Our analysis ignores the housing market and assumes that rents and house prices remain unaffected by the exercise of monopsony power. With migration, monopsony power can be thought of as a location disamenity that must be compensated for to retain (or attract) workers in that local labor market. Capitalization of the monopsony effect into lower house prices affects all homeowners regardless of whether they experience a lower wage from the monopsonist. In Kahn and Tracy (2024), we study the real estate capitalization effect of local monopsony and document that home prices are lower in areas where local labor market concentration is higher. In that paper, we implicitly assume that all workers are homogeneous.

Mobility Across Labor Markets

We now relax the assumption that movement between labor markets is prohibitively costly. As before, we maintain our focus on the labor market and do not incorporate equilibrium effects from the housing market. For simplicity, assume that moving between labor markets entails a fixed cost which we can represent as a flow cost to the worker. Now consider a Roy model where we have a "local" sector and an "other labor market" sector representing outside labor market opportunities. As before, we assume that worker skills are positively correlated across these two sectors with a higher variance in the other labor market sector.

A monopsonist enters the local sector driving down the skill price in that local labor market. This is illustrated in Figure 2. Again, the flow costs of moving represent the costs per period of moving that recoup the fixed moving costs over a specified number of years. Adding mobility costs strengthens the selection effect on skill relative to costless cross-sector migration within the local labor market. Individuals between the solid red and blue lines have an incentive to exercise the "outside" option of migrating to another labor market. Given the assumed fixed costs of moving, the associated flow costs will be lower for younger workers who have a longer expected career to amortize the mobility costs. This indicates that migration will also be skewed to younger as well as more skilled workers.

An alternative to moving is for a worker impacted by a local monopsonist to continue to reside in the county but to commute to a neighboring county. There are tradeoffs between moving and commuting and the relative tradeoffs differ for homeowners and renters. Moving entails fixed costs that must be amortized over time but provides the worker with a broader set of employers to search over. Commuting avoids the up-front fixed cost and instead imposes a potentially much lower flow commute cost. The worker also retains the option to move in the future. A downside of commuting is that it limits the set of firms that the worker can search over. The commute option may be relatively attractive to workers with significant location-specific investments—such as kids in schools, a social network and amenities that match the worker's preferences. In addition, the lower rents resulting from higher employment concentration in a local market create a differential incentive for renters to commute to a neighboring county to work. This allows the worker to benefit from the lower housing costs but to avoid the lower monopsonistic wage.[8]

Imperfect knowledge of outside options could create a friction to the mobility predicted from the Roy model. If workers affected by a monopsonist underestimate the wages that they could earn in an alternative sector or alternative labor market, then this will diminish observed mobility, (see Jäger et al., 2024). However, if these biases are attenuated with additional education, then this will accentuate the skill-bias in the mobility flows between sectors and markets, (Benjamin et al., 2013).

Location Amenities

We now consider the effects of allowing local markets to differ with respect to the amenities that they offer residents. The Rosen/Roback framework results in these amenities being capitalized into higher house prices and lower wages so that the marginal household is indifferent between staying or moving.

With heterogeneity in preferences for these amenities, some households will earn locational rents. That is, these households would have been willing to pay more for access to these amenities than the willingness to pay by the marginal household and therefore what is priced into houses and wages. The existence of locational rents generates an additional friction to moving for these inframarginal households.

In this case, the mobility response to monopsony power would vary across local markets depending on the degree to which these locational rents exist in these markets. Holding other factors constant, monopsonists in localities with relatively high amenities would face relatively more

[8] See Kahn and Tracy (2024). Homeowners do not face this additional incentive to commute since they suffer the lower house price regardless of whether they are working or retired and, if working, whether they commute or not.

inelastic labor supply. This increases the incentive for the monopsonist to further lower the skill price to appropriate some of these locational rents. This moves our analysis back closer to our initial assumption of no migration between local markets. This is similar to Brueckner and Neumark (2014) where local public sector unions instead of local monopsonists attempt to appropriate locational rents through collective bargaining.

The presence of amenities and locational rents adds another dimension to the selection effect associated with migration in response to a monopsonist. What is important is the nature of the correlation (if any) between worker skills and preferences for the amenities. If high skilled workers tend to have stronger (weaker) preferences for the amenities, then this will mitigate (exacerbate) the de-skilling associated with the exercise of monopsony power.

The Main Hypothesis and Our Data Sources

Our empirical research focuses on testing the hypothesis that local labor markets that feature greater levels of monopsony power experience a "brain drain". That is, these local labor markets shrink in population, have fewer young and better educated people as these individuals migrate away or commute to other labor markets offering greater economic opportunities and, consequently, have a lower share of high-income residents. Our empirical strategy presents a type of revealed preference analysis as we focus on quantity adjustments. Is the population shrinking in local monopsony areas? Are they deskilling? We explore these questions by constructing a county/decade panel data set and standard measures of local monopsony power.

Constructing County Level Employment Concentration

We use the public releases of County Business Patterns (CBP) data from 1980, 1990, 2000, and 2010.[9] The CBP data provides the total county employment and the number of establishments in each size category for the week of March 12th. The CBP covers roughly 6 million single-unit establishments and 1.8 million multi-unit establishments. The CBP data excludes most government employment.

[9] This 40-year range of the data is dictated by the CBP reporting. Prior to 1976, the CBP did not break out the number of establishments with 1,000 or more employees which adversely impacts the quality of the standard employment concentration measures. Starting in 2017 the CBP censors more of the data available in the public use files.

Over these four decades the list of employee size categories provided are: 1-4, 5-9, 10-19, 20-49, 50-99, 100-249, 250-499, 500-999, 1,000-1,499, 1,500-2,499, 2,500-4,999, 5,000+. Table 1 provides the share of establishments in each size category when we pool across counties and years. The distribution of establishments and employment by size is extremely skewed. More than half of all establishments are less than 5 persons in size and nearly three quarters are less than 10 persons. At the same time, establishments of 1,000 or more employees make up less than 1 percent of total establishments but account for over 13 percent of total employment. The task is to use this information to allocate to establishments the county employment across these categories. We can then calculate for each county standard measures of employment concentration.[10]

We start with the case of a county that has no establishments in the upper open size category (5,000 or more). We use annual data on the national number of establishments and total employment by size category to calculate the conditional mean number of workers per establishment in each size category.[11] We then proportionately scale these conditional mean number of workers for the county so that the sum the estimated employment levels across size categories equals the total county employment.

For counties that have one or more establishments in the upper open size category, we start by allocating county employment across the closed size categories using the annual conditional mean establishment size by category from the national data. We then check to see if the remaining number of employees for the county equals or exceeds 5,000 times the number of establishments that the county has in the open interval. If this is not the case, then we create a flag for that county. We then calculate the distribution of implied employment levels at the largest establishments for those counties where the flag is not turned on in that year. For counties where the flag is turned on, we assign to each of its large establishments an employment level indicated by the 10th percentile of this distribution. We then proportionately scale the employment sizes for the closed size categories in that county so that the estimated total county employment equals the actual employment.

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[10] More precise measures of employment concentration using the actual number of employees in each establishment would require access to the confidential version of the CBP data through a Census Research Data Center.

[11] See: https://www.bls.gov/web/cewbd/table_f.txt

Using the county-level data on imputed establishment sizes we construct twomeasures of employment concentration. These are the Herfindahl index (HHI) and the share of total county employment accounted for by the top 10 establishments.

Demographic Data

We use county level demographic data from 1980, 1990, 2000, 2010 and 2020. The U.S. Census Bureau annually releases unbridged population estimates for five-year age groups and race at the county level.[12] The Census Bureau does not release bridged race estimates by single year of age at the county level due to concerns about the reliability of these estimates. We collapse these age groups into four age categories: 26-35, 36-45, 46-55, 56-65. We omit the share of individuals 25 or younger and older than 65 from our analysis. We combine this with data on educational attainment by county for adults aged 25 and older.[13]

Since 2011, the Internal Revenue Service Statistics of Income program (IRS SOI) provides annual data on the county-level distribution of adjusted gross income (AGI) among tax filers. The upper interval is for AGI of $200,000 or higher. We use this data to measure a county's aggregate AGI as well as the distribution of its AGI. The IRS also reports cases where a household changes the residence associated with their tax returns. We use this data to look at the ratio of movers to stayers between counties within a commuting zone. We also calculate the fraction of a county's AGI that moves.

The final data consists of commuting flows between counties for 1970 to 2000 based on Census data. The data was compiled by Stephen Redding (Redding, 2022).[14] For county pairs within a commuting zone we calculate the fraction of commuters relative to resident non-commuting individual in the origin county.

A limitation of our analysis is that we do not explicitly incorporate local wages and local rents into our analysis.[15] In Kahn and Tracy (2024), we document the negative relationship between local monopsony measures and local home prices. Rather than explicitly modeling the logic chain

[12] See https://seer.cancer.gov/popdata/download.html
[13] See https://www.ers.usda.gov/data-products/county-level-data-sets/download-data/
[14] The link for the data is: U.S. County-County Commuting Flows | NBER
[15] Introducing endogenous wages and rents into the migration model would considerably complicate the model. Given that migrants consider their current and future wages and rents in each location before moving, a researcher would have to take a strong stand on how people form expectations of wages and rents in each location. Lower expected rents in a monopsony county would tend to diminish outmigration (especially for less skilled workers).

such that local monopsony power lowers local wages and local rents and then studying how heterogeneous workers respond to the spatial price incentives induced by local wage and rental variation, we focus on the reduced form relationship of exploring the Roy Model's implications for migration flows away from monopsony local labor markets.

Estimation Results

We start by examining the demographic and income distribution dynamics of a county's population over time. We focus on decade changes in a county's population, age and educational distribution, and how these changes in human capital vary with 10-year lagged measures of local labor market monopsony power. Upfront, we acknowledge that we do not attempt to estimate an equilibrium model that features price adjustment. If local wages and rents adjust in the face of monopsony power, then the observed demographic shifts we study will be attenuated because lower rents in monopsony areas will partially compensate "exploited" workers.

We estimate the following decade-based panel regression specification shown in (1) for each of our two measures of county employment concentration. Let D_{ijt} be a demographic measure (age or education) for county i in Commuting Zone j in year t and ΔD_{ijt} the 10-year change in that demographic measure. In addition, let M_{it-10} denote the degree of local monopsony power and is the 10-year lag value of either the log of the county-level HHI or the Share Top 10 employment concentration.[16] To facilitate comparisons across the two measures we report standardized coefficients. We include Commuting Zone effects (α_j) and decade effects (τ_t). Including Commuting Zone effects accounts for any amenity and other persistent service/tax differences across local markets and decade effects account for longer-term trends that may affect mobility frictions.

$$\Delta D_{ijt} = \beta_0 + \beta_1 M_{it-10} + \alpha_j + \tau_t + \varepsilon_{ijt} \qquad (1)$$

One concern with our empirical specification is that a secular decline in a local market may result in both a rise in employment concentration as firms go out of business and subsequent migration of talent due to diminished employment opportunities. For example, the opening of trade with China and its impact on the Rust belt, see Autor et al. (2013). However, the timing of trade

[16] Using a 10-year lag in employment concentration avoids any local cyclical effects that may impact employment concentration and contemporaneous employment and wages.

with China and the dynamics of employment concentration do not line up. In addition, in Kahn and Tracy (2024) we find no difference in the effects of employment concentration on house prices between "rust-belt" and "non-rust-belt" counties contrary to a secular decline hypothesis. As noted above, the decade time effects should also help control for any secular trends affecting migration.

More generally, a concern is that left-out factors in specification (1) could affect both the lagged employment concentration and the current demographic makeup of a locality. This would impart a left-out variable bias on the OLS coefficient estimate on employment concentration. For example, in Kahn and Tracy (2024) we found that locations that won a "million-dollar" plant experienced a subsequent increase in employment concentration. If the large influx of investment capital from winning a major plant location contest is complementary with higher skilled workers, then winning a new plant would impart a positive correlation between employment concentration and the local skill mix. Similarly, states with more binding minimum wage laws would be less attractive locations for monopsony firms as these wage floors restrict their ability to extract labor rents. If these same locations are relatively more attractive to less skilled workers, then this would again impart a positive correlation between employment concentration and the education mix of a locality that is not directly due to employment concentration.

A separate concern is that we use the public rather than the confidential CBP data to construct our county-level employment concentration variables. As discussed earlier, this introduces measurement error in these concentration measures. This measurement error varies across counties and years. Left unaddressed, this would lead to attenuation bias in our estimates of the effect of employment concentration on the variables of interest.

To address these concerns, we adopt a version of the IV strategy used in Rinz (2022). We divide counties into 20 groups based on their population in 1970. This is 10 years prior to when we start tracking changes in the demographic makeup of counties. For each county-level observation in our estimation sample, we calculate the average of the employment concentration for that county's group in that year less that county's own employment concentration.[17] We use this adjusted group average as an instrument for that county's employment concentration.

[17] Rinz (2022) instrumented the HHI in a commuting zone/industry by the employment weighted average of HHI across commuting zones for the same industry. We use a county's population size group in place of Rinz's industry groupings.

This instrument will pick up general changes in employment concentration that are shared by other Counties in the same size group, but that do not reflect specific factors impacting the county in question. This alleviates the concern raised by the two examples above as they would not be captured in the group-level movements in average employment concentration. In addition, to the extent that the measurement error is idiosyncratic across counties, the average employment concentration for a population category will reflect less measurement error. Using the group average (less the employment concentration for the county) as an instrument will help to address the measurement error in the estimated concentration measures. The data indicate a strong correlation over time between county-level employment concentration and their group average employment concentration.

Table 2 presents the IV results for county population growth over a decade as well as the decade change in the age distribution within a county. We report results for four different age brackets ranging from ages 26 to 65. For each specification, we report the percentage point change in that age category in response to a one-standard deviation change in employment concentration. We also translate this into the corresponding percent change relative to the sample average employment share for that age category. The OLS results are provided in the Appendix and are uniformly smaller in magnitude as compared to the IV results. This is consistent with the issues of left-out variable bias and measurement error discussed earlier.

The first two specifications of Table 2 show that counties and time periods with higher levels of employment concentration experience slower population growth over the next 10 years. Both measures of employment concentration produce similar estimates indicating that a one-standard deviation increase in employment concentration is associated with around a 1 to 1.4 percentage point slower population growth relative to other counties in the same commuting zone after controlling for the aggregate rate of population growth over the decade.

Kahn and Tracy (2024) report that controlling for county employment and per capita income, house prices decline with increases in current employment concentration. Lower housing costs helps to reduce out migration resulting from higher local employment concentration As we will show, this lower population growth is associated with a de-skilling of the local labor market which, combined with an inelastic supply of existing housing (Glaeser and Gyourko 2005), can put additional downward pressure on house prices.

The remaining specifications in Table 2 examine the effects of higher levels of employment concentration on the decade change in the age distribution in a county. Again, the results are very similar for both measures of employment concentration. The age distribution in counties and time periods with higher levels of employment concentration shifts over the next 10 years towards older workers. For example, a one-standard deviation increase in employment concentration is associated with around a 11 basis point decline in the share of individuals 26 to 35, and a 22 basis point increase in the share of individuals 56 to 65. This is consistent with the prediction from the Roy model with mobility frictions. Younger individuals have lower levels of location-specific investments and a longer expected working career to amortize the costs of moving making them more responsive to monopsony power in their current local market.

In Table 3 we examine how monopsony affects the decade change in the skill distribution in a county as proxied by the educational attainment of its residents. We focus on four educational categories: less than high school, high school graduate, some college, and college graduate or higher. The table has a similar structure to Table 2 in that we present standardized effects both in percentage point and percent changes relative to means for each education category.

As we found in Table 2 for the age distribution, the results for the education distribution are very similar across both employment concentration measures. Looking at Table 3, the data indicate that a county and time period with a higher level of employment concentration will experience a downward shift in share of highly educated residents over the next decade. A one-standard deviation increase in employment concentration is associated with around a 22 to 28 basis point (or 1.2 to 1.6 percent of the average college or more share) decrease in the share of individuals with a college or more education. The education distribution shifts towards individuals with a high school or some college education. In contrast, the data indicate that a one standard deviation increase in local employment concentration reduces the share of residents with less than a high school education by 65 basis points. One possible explanation is if the employment reductions imposed by monopsonists are concentrated at the very low end of the education spectrum.

To examine the effect of employment concentration on a county's income distribution, we use the IRS SOI data to compute a county's aggregate AGI per tax filer and the distribution of tax filers by AGI intervals between 2011 and 2021. Given the shorter time period covered by this data, we restrict ourselves to overlapping 5-year changes in a county's aggregate AGI per tax filer and the distribution of AGI. We again control for commuting zone effects and year effects and continue to use a 10-year lag in the county employment concentration. As in all of our sepecifications, we estimate the standard errors clustering on the county. Our IV estimates shown in Table 4 indicate that a one-standard deviation in either measure of employment concentration reduces 5-year change in aggregate county AGI per filer by 8 basis points. In addition, a county's higher employment concentration is associated with a decline in the county's share of high income filers. A one standard deviation in employment concentration is associated with a 12 to 14 basis point (or 2 percent of the average share) 5-year) in the fraction of filers in the $200,000 or higher AGI bracket. Similar to the earlier findings for the change in a county's education distribution, higher local employment concentration is associated with a 5-year decline in the lowest (<$75k) AGI category. This indicates that the documented brain drain associated with higher employment concentration shown in Tables 2 and 3 leads to both a loss in county average AGI and a relative loss of high-income residents in a county.

To check the robustness of these findings we expanded the specification in Table 4 to include predicted county average job growth for the period from 2000 to 2016. These are Bartik-style county demand shocks calculated using a county's industry composition in 2000 and national employment growth by industry.[18] The results are provided in Appendix Table A4. The county predicted job growth is significant for the highest AGI category. Including this additional control variable slightly attenuates our estimated employment concentration effects but they remain economically and statistically significant.

As an additional robustness check for the results provided in Tables 2 to Table 4, we include the average temperature in February and July for a county.[19] Temperature is an important element of the "weather" amenity offered by a location. The temperature variables were generally significant in the regressions on a county's age and education distribution but not on its income distribution. However, the local employment concentration measures remain statistically and economically significant.

Given that people build up social capital where they live, many people face high psychic migration costs as a function of distance from their current location. The U.S Census creates commuting zones (CZA) because there are adjacent counties that one can commute to from another nearby county. The possibility of migrating to a county in the same CZA that features a more competitive labor market offers the opportunity for a worker to avoid the monopsonist's grasp while staying in touch with one's social network. Alternatively, a worker can continue to live in the

[18] For details on the construction and a different application see Bartik (2024). We thank Tim Bartik for providing us with the data.
[19] We thank Robert Huang for providing us with this data.

monopsony county and commute to the more competitive local labor market in the same CZA. We use two different data sets to explore these adaptation strategies.

We shift our attention in Tables 5 and 6 to mobility across counties within a commuting zone. In Table 5 we focus on households that move between counties while in Table 6 we focus on households that commute between counties. Looking at movers in Table 5, the dependent variable is the fraction of movers between an origin county and a destination county (within the same commuting zone) expressed as a fraction of resident non-moving households in the origin county. Now we control for the employment concentration in both the origin and the destination county. We continue to include commuting zone effects and year effects and as before use instrumented 10-year lags of county employment concentration.

Looking first at movers as a fraction of non-moving residents, Table 5 indicates that holding constant the employment concentration in the destination county that a one-standard deviation increase in the employment concentration in the origin county increases the fraction of movers to the destination county by roughly one-third. Holding constant the employment concentration in the origin county, a one-standard deviation increase in the employment concentration in the destination county reduces the fraction of movers by 84 to 89 percent. We find similar results when we look at the fraction of the origin county aggregate AGI that moves to a destination county. The higher sensitivity of moving to the destination employment concentration may reflect that households thinking of making a within commuting zone typically have more than one county to select from as a destination.

Table 6 explores the alternative option to moving for households trying to "escape" the rent extraction from a local monopsonist. Rather than moving, a worker may instead choose to remain a resident of the origin county and commute to a destination county. This may make sense if the household enjoys the amenities and services provided in the origin county and/or has made significant location specific investments. The data indicate that the fraction of commuters responds positively to the origin county employment concentration and negatively to the destination county employment concentration. Now, though, the relative effects are stronger for the origin county. This may reflect the finding in Kahn and Tracy (2024) that higher employment concentration is associated with lower rents and house prices. A renter facing higher local employment concentration can benefit from lower rents but avoid the associated lower wage by commuting to a neighboring county. This would increase their commuting sensitivity to the employment concentration in their current county.

The panel data on county age and education characteristics, income distribution, moving and commuting and their relation to employment concentration shows that these characteristics to a county adjust over time to changes in the level of employment concentration in that market. Higher levels of employment concentration are associated with slower population growth and a deskilling in the local labor market over time—younger, more educated and higher income individuals choose to either move or commute to alternative markets to sell their skills.[20]

Implications for Estimating Monopsony Wage Effects

Our empirical results establish that moving or commuting out of a local labor market is one of the adjustment mechanisms in response to an increase in monopsony power in a local market. The data also indicate that this mobility is not random, but rather is skills based. Controlling for this changing skill distribution is important for identifying the effect of monopsony on the skill prices. The overall wage effect associated with an increase in monopsony power will be a combination of the monopsony effect on the skill prices and the shift in the composition of skills. This is consistent with the empirical literature discussed earlier that finds controlling for observed skill attributes tends to attenuate the estimated monopsony "wage effect."

While our empirical analysis focused on observed skill attributes, a similar logic applies to unobserved (to the researcher but not to the employer) skill attributes of workers. If we assume that, on average, the distribution of unobserved skill abilities in a local market is positively related to the distribution of observed skills, then a prediction from the Roy model would be that growing monopsony power in a local market would also lead to deskilling along unobserved skill attributes creating a selection bias challenge for empirical work.

Understanding the effect of monopsony on wages is an important empirical question. This estimation is more complicated if monopsony induces self-selection of workers across sectors and labor markets. Our long-run regression findings support the operation of this adjustment process. This implies that, in addition to controlling for workers' observed skills, researchers estimating the monopsony wage effects also likely need to control for endogenous sample selection on

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[20] Our analysis is based on semi-aggregated data that focuses on the marginal distributions of worker characteristics. Future work could explore using micro longitudinal data to study the effect of monopsony on the joint distribution of age, education, income and racial composition in local labor markets.

unobservable skills. A standard approach is the Heckman selection model (Heckman 1979). The challenge in implementing this approach is to model the distribution of skills in a county and identify one or more variables that shift this distribution but can be excluded from the wage specification. Accounting for shifts in both the observed and unobserved skill distribution in response to monopsony power is important for isolating the effect of monopsony on skill prices.

Implications for Public Policy

The Biden Administration has considered public policies intended to protect workers against expropriation risk. On July 9, 2021, President Biden signed an historic executive order on Promoting Competition in the American Economy. That order underscored the importance of competition in the labor market, stating that "a competitive marketplace creates more high-quality jobs and the economic freedom to switch jobs or negotiate a higher wage." The order tasked the Treasury Department to investigate the effects of a lack of labor market competition on the United States labor market. A 2022 report issued by the Department of Treasury summarized the evidence. [21]

The benefits of anti-trust policy for workers hinges on whether such workers have access to strategies to protect themselves from exploitation. In our past research, we have documented that rents are lower in local labor markets featuring more concentrated industry (Kahn and Tracy 2024). Our explanation for this finding relates to the fact that there are always a set of young people who have not planted roots and can move to areas offering economic opportunities. If a local labor market indeed does feature monopsony, then skilled workers will not move there, and the mobile residents will move elsewhere. This dynamic lowers local housing demand in monopsony markets and this lowers equilibrium rents in the area. In this sense, migration acts as a self-protection strategy protecting workers from exploitation. If everyone could easily migrate away from a concentrated local labor market, then this diminishes the social benefits of aggressive anti-trust regulation.

In recent years, a second adaptation strategy has emerged. In our emerging hybrid/WFH economy, the option to telecommute offers a new margin of adjustment. The continued advancement of technology and the rise of WFH have the potential to discipline monopsony power

[21] https://home.treasury.gov/system/files/136/State-of-Labor-Market-Competition-2022.pdf

by reducing search frictions (Kuhn 2003, 2004) and effectively unbundling place of work and place of residence (Brueckner et al., 2023). Both developments have the ability to increase the effective labor supply elasticity facing a monopsonist, thereby limiting the ability of the monopsonist to generate economic profits by lowering the skill price

Liquidity constraints may also reduce the ability of households to move away from concentrated labor markets. These households would like to move to take advantage of higher earnings prospects in alternative labor markets but do not have the financial resources to cover the moving and transition costs. Relaxing these liquidity constraints would increase the labor supply elasticity facing monopsonists.

The Federal government could assist in these situations by offering a "job mobility" loan (Ludwig and Raphael 2010). To qualify for the loan, an individual would have to document a job offer in an alternative labor market that pays a higher monthly income. The government would provide a 5-year loan where the monthly payment and interest (P&I) must be less than 80 percent of the increase in monthly earnings.[22] The loan rate would be the 5-year Treasury rate plus 2 percent. These loans would be managed by private servicers who would collect and remit payments to the Treasury.

As an illustration, consider an individual who is making $55,000 per year (around the 40th percentile). The individual receives a job offer that pays 10 percent more than the current job. The maximum monthly P&I on a job mobility loan would be $367. If we use a loan rate of 5.79 percent (5-year Treasury rate of 3.79 plus 2 percent), the maximum loan amount is around $19,000. This would significantly relax any liquidity constraints facing the individual.

Conclusion

Using four decades of data on county demographics and employment concentration, we show that counties and time periods with higher levels of employment concentration suffer slower population growth and a brain drain over the next decade. This manifests itself in the loss of younger, more educated and higher income workers in the county. This deskilling of the county labor force induces a sample selection challenge for researchers attempting to measure the effect of

[22] This limit implies that the monthly P&I can be paid out of the additional after-tax monthly income for most individuals. The maximum percentage could be set at a value different from 80 percent.

monopsony on skill prices in local markets. Researchers need to account for the changes in observed and unobserved skills in the local market induced by the exercise of monopsony power.[23]

The Rosen/Roback model along with the Roy model extension allowing for heterogenous skilled workers share a common bundling assumption that individuals must live and work in the same local market. Improved transportation systems can relax this constraint to a degree, but commuting costs (money and time) still limit the practical distances between place of work and place of residence. These two models present both a human capital and a social capital theory of who escapes the local monopsonist. Those individuals endowed with skills that are greatly valued by other local labor markets and those with few local social network ties are the least likely to remain in an area featuring monopsony. Migration and cross-county commuting represent the two major strategies for adapting to local monopsony risk.

Prior empirical research on the role of competitive markets and city growth (Glaeser et al. 1992, 2015) assumed a national labor market. This work examines how more competitive local product markets as proxied by smaller firm sizes is associated with faster city growth. Our work highlights a second complementary channel in which competition supports city growth working through local labor markets. Less competitive local labor markets experience a loss of human capital necessary to generate sustained innovation and adoption of ideas. Competition in both labor and product markets combine to support entrepreneurship and city employment growth.

Our analysis of the role of population migration as a check on local monopsony power has policy implications for how local and Federal agencies regulate large firms. Migration rates are highest for younger, more educated people. This means that older, less educated workers are more exposed to monopsony risk. This demographic differential has important implications for the crafting of competitive labor market policies.

[23] A similar skills-based migration between countries is documented in Amanzadeh et al., 2024. These authors also look at return migration back to the origin country. Future research could examine whether within country migration induced by monopsony leads to future return migration when workers retire.

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Table 1. Establishment Size Distribution

Employment Size Category	Percent of Total Establishments	Percent of Total Employment
1 – 4	54.85	6.21
5 – 9	19.29	8.34
10 – 19	12.43	10.92
20 – 49	8.33	16.39
50 – 99	2.84	12.69
100 – 249	1.59	15.53
250 – 499	0.41	9.21
500 – 999	0.16	7.02
1,000 – 1,499	0.04	3.38
1,500 – 2,499	0.03	3.54
2,500 – 4,999	0.015	3.37
5,000+	0.006	3.39

Notes: County Business Pattern data, 1976 – 2016.

Table 2. The Effects of Employment Concentration on Change in Population and Age Distribution of Counties

	ΔLog(Pop)		Δ% Age 26-35		Δ% Age 36-45		Δ% Age 46-55		Δ% Age 56-65	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
10-year lag	–0.97		–0.110		–0.116		–0.066		0.217	
log(HHI)	(0.23)		(0.019)		(0.017)		(0.012)		(0.016)	
(1-sd change)			[–0.86]		[–0.87]		[–0.52]		[1.87]	
10-year lag Top		–1.45		–0.108		–0.116		–0.060		0.220
10 Share		(0.22)		(0.019)		(0.018)		(0.013)		(0.016)
(1-sd change)				[–0.86]		[–0.87]		[–0.47]		[1.89]
R-square	0.55	0.56	0.59	0.59	0.70	0.70	0.82	0.82	0.62	0.62

Notes: Dependent variables are 10-year changes. Standardized IV coefficients with standard errors in parentheses. Percent of group mean in square brackets. Standard errors are calculated clustering on Counties. Decade and Commuting Zone fixed effects are included. Data for 1990, 2000, 2010 and 2020. Sample size 9,154
Standard deviation of 10-year lag log(HHI) = 1.11
Standard deviation of 10-year lag Top 10 Share = 0.17

Table 3. The Effects of Employment Concentration on Change in Education Makeup of Counties

	Δ% < HS		Δ %HS		Δ % Some College		Δ % College+	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
10-year lag log(HHI)	–1.080		0.462		0.941		–0.287	
(1-sd change)	(0.053)		(0.043)		(0.044)		(0.041)	
	[–0.053]		[0.012]		[0.035]		[–0.016]	
10-year lag Top 10 Share		–1.020		0.385		0.356		–0.220
(1-sd change)		(0.064)		(0.047)		(0.050)		(0.043)
		[–0.050]		[0.011]		[0.032]		[–0.012]
R-square	0.48	0.48	0.31	0.31	0.28	0.28	0.22	0.22

Notes: Dependent variables are 10-year changes. Standardized IV coefficients with standard errors in parentheses. Percent of group mean in square brackets. Standard errors are calculated clustering on Counties. Decade and Commuting Zone fixed effects are included. Data for 1990, 2000, 2010 and 2020. Sample size 9,167
Standard deviation of 10-year lag log(HHI) = 1.11
Standard deviation of 10-year lag Top 10 Share = 0.17

Table 4. Effects of Employment Concentration on county Average AGI and AGI Distribution

	ΔLog(AGI/Filer)		Δ% <$75k		Δ% $75-$100k		Δ% $100-$200k		Δ% >$200k	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
10-year lag log(HHI)	–0.008		–0.306		0.135		0.313		–0.141	
(1-sd change)	(0.001)		(0.034)		(0.021)		(0.022)		(0.020)	
			[–0.004]		[0.015]		[0.030]		[–0.054]	
10-year lag Top 10		–0.008		–0.309		0.152		0.281		–0.124
Share (1-sd change)		(0.001)		(0.035)		(0.025)		(0.024)		(0.019)
				[–0.005]		[0.017]		[0.027]		[–0.048]
R-square	0.56	0.57	0.56	0.56	0.26	0.26	0.43	0.43	0.55	0.55

Notes: Dependent variables are 5-year changes. Standardized IV coefficient with standard errors in parentheses. Percent of group mean in square brackets. Standard errors are calculated clustering on Counties. Decade and Commuting Zone fixed effects are included. Data for 2011 to 2021. Sample size 18,168
Standard deviation of 10-year lag log(HHI) = 1.11
Standard deviation of 10-year lag Top 10 Share = 0.17

Table 5. Employment Concentration and County-to-County Moves Within a Commuting Zone (IV)

	Movers as Fraction of County Filers		Movers as Fraction of County AGI	
	Origin	Destination	Origin	Destination
10-year lag log(HHI)	0.186	–0.517	0.159	–0.406
(1-SD change)	(0.012)	(0.015)	(0.011)	(0.013)
	[32.27]	[–89.67]	[34.90]	[–88.87]
R-square	0.28		0.20	
10-year lag Share Top 10	0.216	–0.487	0.186	–0.381
(1-SD change)	(0.004)	(0.004)	(0.004)	(0.004)
	[37.42]	[–84.37]	[40.69]	[–83.41]
R-square	0.28		0.20	

Notes: Standardized IV coefficients with standard errors in parentheses. Standard errors are calculated clustering on Counties and shown in parentheses. Percent of group mean in square brackets. Year and Commuting Zone fixed effects are included. Data for 2012 through 2021. Number of observations = 97,281
Standard deviation of 10-year lag log(HHI) origin = 1.17, destination = 0.17
Standard deviation of 10-year lag Top 10 Share origin = 0.15, destination = 0.14

Table 6. Fraction of Commuters Between Counties in a Commuting Zone (IV)

	Origin	Destination
10-year lag log(HHI)	4.759	–1.522
(1-SD change)	(0.152)	(0.087)
	[146.44]	[–46.82]
R-square	0.049	
10-year lag Share Top 10	4.840	–1.685
(1-SD change)	(0.148)	(0.086)
	[148.93]	[–51.45]
R-square	0.057	

Notes: Dependent variable is the ratio of the number of residents who commute between the origin and destinations county divided by the number of resident non-commuters in the origin county. Standardized IV coefficients with standard errors in parentheses. Standard errors are calculated clustering on Counties. Percent of group mean in square brackets. Decade and Commuting Zone fixed effects are included. Data for 1990 and 2000. Sample size 97,281.
Standard deviation of 10-year lag log(HHI) origin = 1.29, destination = 1.34
Standard deviation of 10-year lag Top 10 Share origin = 0.30, destination = 0.27

Figure 1. Impact of Monopsony on Worker Assignment Across Sectors– positive correlation in skills

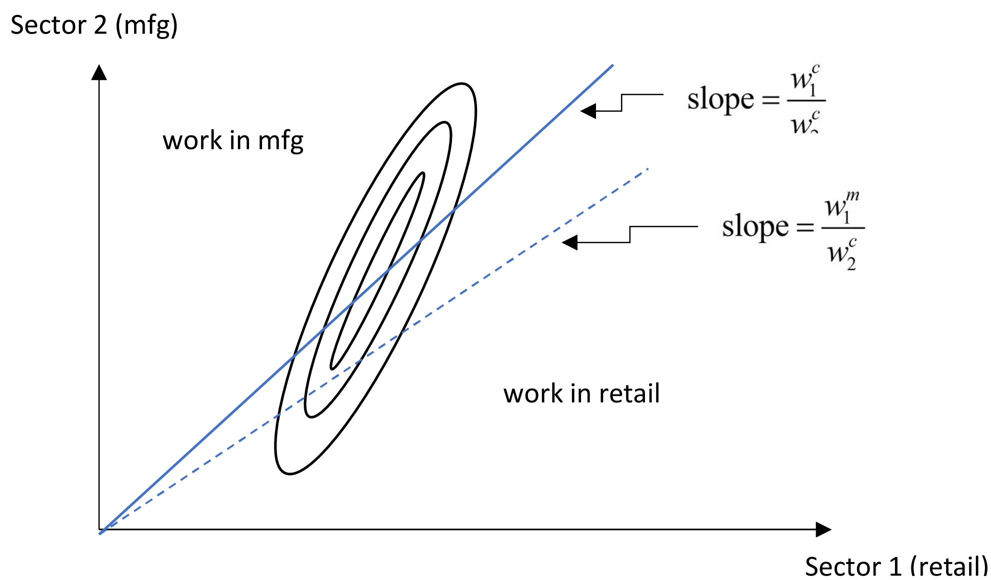
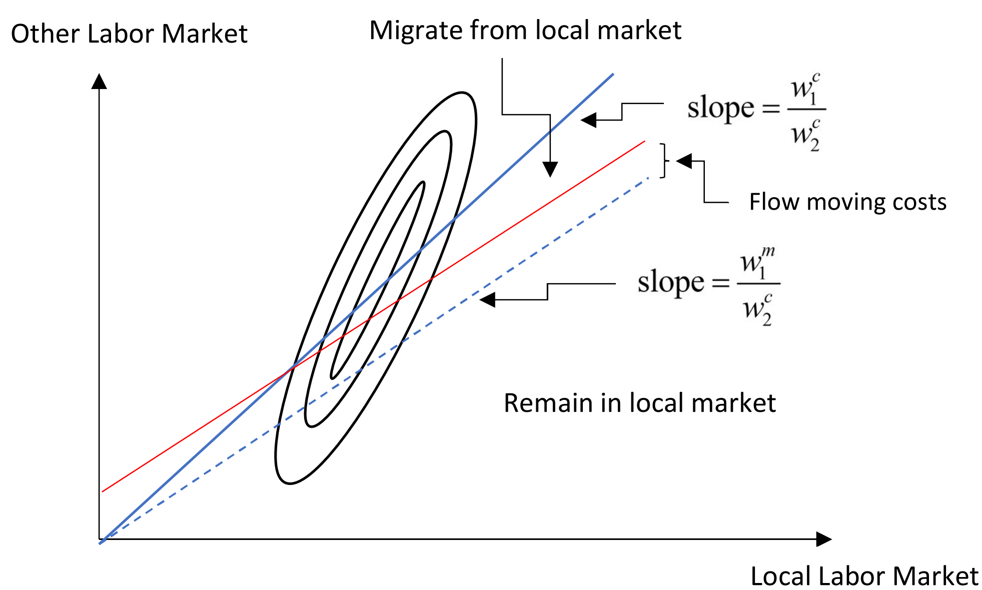


Figure 2. Impact of Monopsony on Worker Migration Across Labor Markets



Appendix:

Table A1. Descriptive Statistics

Variable	Mean	Standard Deviation
% Age 26 – 35	12.67	2.54
% Age 36 – 45	13.34	2.15
% Age 45 – 55	12.67	2.24
% Age 56 – 65	11.59	2.78
% Less than High School	20.44	10.67
% High School Graduate	34.66	6.72
% Some College	27.04	6.56
% College+	17.85	8.75
% < $75k	77.91	7.31
% $75 - $100k	8.98	1.89
% $100 - $200k	10.49	4.13
% > $200k	2.62	2.29
Movers as Fraction of County Filers	0.58	0.67
Movers as a Fraction of County AGI	0.46	0.67
Commuters as a Fraction of Residents	3.25	10.88

Table A2. Effects of Employment Concentration on Population and Age Distribution of Counties

	ΔLog(Pop)		Δ% Age 26-35		Δ% Age 36-45		Δ% Age 46-55		Δ% Age 56-65	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
10-year lag log(HHI)	–0.015		–0.025		–0.014		–0.037		0.120	
(1-sd change)	(0.002)		(0.016)		(0.013)		(0.012)		(0.013)	
			[–0.002]		[–0.001]		[–0.003]		[0.010]	
10-year lag Top 10		–0.018		–0.019		–0.011		–0.030		0.129
Share (1-sd change)		(0.002)		(0.017)		(0.014)		(0.013)		(0.013)
				[–0.002]		[–0.001]		[–0.002]		[0.010]
R-square	0.56	0.56	0.60	0.60	0.68	0.70	0.82	0.76	0.62	0.62

Notes: Dependent variables are 10-year changes. Standardized OLS coefficients with standard errors in parentheses. Percent of group mean in square brackets. Standard errors are calculated clustering on counties. Decade and Commuting Zone fixed effects are included. Data from 1990, 2000, 2010 and 2020. Sample size 9,154
Standard deviation of 10-year lag log(HHI) = 1.11
Standard deviation of 10-year lag Top 10 Share = 0.17

Table A3. Effects of Employment Concentration on Change in Education Makeup of Counties

	Δ% < HS		Δ %HS		Δ % Some College		Δ % College+	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
10-year lag log(HHI)	–0.678		0.384		0.556		–0.263	
(1-sd change)	(0.043)		(0.037)		(0.037)		(0.032)	
	[–0.040]		[0.011]		[0.019]		[–0.014]	
10-year lag Top 10 Share		–0.640		0.394		0.502		–0.257
(1-sd change)		(0.056)		(0.042)		(0.041)		(0.033)
		[–0.037]		[0.011]		[0.017]		[–0.013]
R-square	0.49	0.49	0.31	0.31	0.29	0.29	0.22	0.22

Notes: Dependent variables are 10-year changes. Standardized OLS coefficients with standard errors in parentheses. Percent of group mean in square brackets. Standard errors are calculated clustering on counties. Decade and Commuting Zone fixed effects are included. Data from 1990, 2000, 2010 and 2020. Sample size 9,167
Standard deviation of 10-year lag log(HHI) = 1.11
Standard deviation of 10-year lag Top 10 Share = 0.17

Table A4. Effects of Employment Concentration on Change in County Average AGI and AGI Distribution

	ΔLog(AGI/Filer)		Δ% <$75k		Δ% $75-$100k		Δ% $100-$200k		Δ% >$200k	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
10-year lag log(HHI)	–0.008		–0.297		0.115		0.305		–0.123	
(1-sd change)	(0.001)		(0.036)		(0.022)		(0.024)		(0.021)	
			[–0.004]		[0.013]		[0.029]		[–0.047]	
10-year lag Top 10		–0.008		–0.301		0.135		0.272		–0.106
Share (1-sd change)		(0.001)		(0.036)		(0.026)		(0.025)		(0.020)
				[–0.004]		[0.015]		[0.026]		[–0.041]
5-year lag Predicted	–0.009	–0.008	0.243	0.231	–0.547	–0.505	–0.212	–0.273	0.516	0.547
County Job Growth	(0.009)	(0.009)	(0.208)	(0.211)	(0.105)	(0.108)	(0.152)	(0.153)	(0.120)	(0.119)
R-square	0.56	0.56	0.56	0.56	0.26	0.27	0.43	0.43	0.55	0.55

Notes: Dependent variables are 5-year changes. Standardized IV coefficient with standard errors in parentheses. Percent of group mean in square brackets. Standard errors are calculated clustering on Counties. Decade and Commuting Zone fixed effects are included. Data for 2011 to 2021. Sample size 18,162
Standard deviation of 10-year lag log(HHI) = 1.11
Standard deviation of 10-year lag Top 10 Share = 0.17

Table A5. Effects of Employment Concentration on County Avg AGI and AGI Distribution

	ΔLog(AGI/Filer)		Δ% <$75k		Δ% $75-$100k		Δ% $100-$200k		Δ% >$200k	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
10-year lag log(HHI)	–0.008		–0.047		0.118		0.100		–0.172	
(1-sd change)	(0.001)		(0.024)		(0.017)		(0.017)		(0.014)	
			[–0.001]		[0.013]		[0.008]		[–0.057]	
10-year lag Top 10		–0.009		–0.044		0.139		0.079		–0.174
Share (1-sd change)		(0.001)		(0.028)		(0.024)		(0.020)		(0.013)
				[–0.006]		[0.015]		[0.007]		[–0.057]
R-square	0.56	0.56	0.56	0.56	0.26	0.26	0.44	0.44	0.55	0.55

Notes: Dependent variables are 5-year changes. Standardized OLS coefficients with standard errors in parentheses. Percent of group mean change in square brackets. Standard errors are calculated clustering on counties. Decade and Commuting Zone fixed effects are included. Data for 2011 to 2021. Sample size 18,474
Standard deviation of 10-year lag log(HHI) = 1.13
Standard deviation of 10-year lag Top 10 Share = 0.17

Table A6. Employment Concentration and county-to-County Moves Within a Commuting Zone

	Movers as Fraction of County Filers		Movers as Fraction of County AGI	
	Origin	Destination	Origin	Destination
10-year lag log(HHI)	0.160	–0.330	0.137	–0.272
(1-SD change)	(0.008)	(0.009)	(0.007)	(0.008)
	[27.79]	[–57.23]	[30.14]	[–59.66]
R-square	0.33		0.22	
10-year lag Share Top 10	0.185	–0.301	0.158	–0.248
(1-SD change)	(0.007)	(0.008)	(0.007)	(0.007)
	[32.03]	[–52.31]	[34.70]	[–54.35]
R-square	0.33		0.23	

Notes: Standardized OLS coefficients with standard errors in parentheses. Standard errors are calculated clustering on counties and shown in parentheses. Percent of group mean change in square brackets. Year and Commuting Zone fixed effects are included. Data for 2012 through 2021. Number of observations = 78,591
Standard deviation of 10-year lag log(HHI) origin = 1.17, destination = 1.17
Standard deviation of 10-year lag Top 10 Share origin = 0.15, destination = 0.14

Table A7. Fraction of Commuters Between Counties in a Commuting Zone

	Origin	Destination
10-year lag log(HHI)	3.026	–0.894
(1-SD change)	(0.108)	(0.063)
	[94.24]	[–27.86]
R-square	0.061	
10-year lag Share Top 10	3.161	–1.077
(1-SD change)	(0.115)	(0.064)
	[98.45]	[–33.55]
R-square	0.069	

Notes: Dependent variable is the ratio of the number of residents who commute between the origin and destinations county divided by the number of resident non-commuters. Standardized OLS coefficients with standard errors in parentheses. Standard errors are calculated clustering on counties. Percent of group mean in square brackets. Decade and Commuting Zone fixed effects are included. Data for 1990 and 2000. Sample size 97,281.
Standard deviation of 10-year lag log(HHI) origin = 1.29, destination = 1.34
Standard deviation of 10-year lag Top 10 Share origin = 0.16, destination = 0.16