# Concentrating on His Career or Hers?: Descriptive Evidence on Occupational Co-agglomeration in Dual-Earner Households

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**Abstract**

The desire to co-locate induces married couples to choose occupations that are either clustered in similar labor markets or dispersed across labor markets. Using new indices of occupational co-agglomeration, I document that geographic concentration of occupations has increased significantly since the 1980s, and the likelihood that married couples' occupations are clustered in similar labor markets has increased. Being well-matched to one's spouse in terms of occupational clustering is positively associated with earnings for women and secondary earners. These positive associations are stronger for individuals in occupations with higher costs of re-skilling and are associated with higher mobility for couples starting in sub-optimal labor markets.

**JEL Codes: J1, J16, R23.**

**Keywords: economic geography, family economics, gender, agglomeration economies**

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# 1 Introduction

Households headed by two working adults have become increasingly common in the United States, making locational compatibility within a household an important mechanism to consider in modeling joint job search. A couple has locationally compatible careers if the places that are desirable for one spouse's career are desirable for the other's. For households with two-earners, the desirability of a given location will depend on the availability of quality jobs in not only one's own chosen career in that location, but also whether one's spouse can find a high quality job in the same location. This restriction may not matter for couples whose jobs are dispersed throughout the country uniformly but can cause frictions for job searchers in occupations or industries with strong ties to a certain region, which I will refer to as "locationally-concentrated" occupations.

In this paper, I explore how the geographic concentration of occupations in the United States has increased over the last 40 years and the implications of this increase for dual-earner households in locationally concentrated occupations. To do this, I develop a measure of locational compatibility of spouses' occupations based on an index of co-agglomeration used in urban economics (e.g., Ellison and Glaeser, 1997; Gabe and Abel, 2011; Gabe and Abel, 2016; Moretti, 2011) which typically measures the extent to which certain industries and occupations cluster by region and in my setting measures the clustering of within-households occupational pairings. Past work has used urban areas as a proxy for labor markets with more job opportunities for both spouses, but this method cannot address regional asymmetries in labor market thickness by occupation. This new application of the co-agglomeration index provides a method of measuring how easily a couple can co-locate that allows for heterogeneity by occupation and by region. I document that occupational concentration has increased over time. Though this increased concentration could result in more couples being locationally mismatched over time if spouses are in occupations concentrated in different regions, I show that occupational co-agglomeration within households has increased over time. This means that not only are individuals in more geographically concentrated careers, but they are also more likely to be married to someone whose job is clustered in a similar location. This is primarily driven by large increases in co-agglomeration among couples who both have a college degree, consistent with past work (e.g., Costa and Kahn, 2000) documenting that solving a joint location problem for dual-earner careers is more crucial for couples with two degrees than those without college degrees.

Next, I explore how being in more locationally compatible occupations, as measured by the index of co-agglomeration of the occupations of a husband and wife, is related to the earnings of men and women by household type. I show that scoring higher on the co-agglomeration index is positively associated with earnings and the relationship is stronger for women, with a one-S.D. increase in the co-agglomeration index corresponding to a 1.8% increase in earnings for women and a 0.6% increase in earnings for men. When I split the households into male-primary earner and female-primary earner households, I find that this relationship is driven by women being more likely to be the secondary earner. In a household where the wife earns more than 50% of household income, occupation locational compatibility is now significantly associated with men's earnings on the order of a 2.3% increase in earnings for a one S.D. increase in the co-agglomeration index. These results are consistent with the theoretical assumptions of the Mincer (1978) model of migration in which households for whom career prospects are not correlated across location are more likely to have the secondary earner end up sub-optimally matched following a move and experience lower wages post-move.

While these results are suggestive of spouse-based location frictions playing a role in lower earnings for women, they should be interpreted as descriptive in nature, not causal. I cannot rule out the possibility that women's selection into either occupation, location, or spouses are driven by unobservable characteristics that also result in lower earnings. For example, someone who intends to eventually become a stay-at-home parent may both earn less and also be more willing to marry someone whose occupation is less locationally compatible with their own. While I cannot fully rule out all alternative explanations, I conduct a series of analyses that provide additional support for the importance of locationally compatible occupations.

I show that these frictions have a stronger association with earnings when a person cannot easily resolve the location incompatibility by switching fields. I first show that the results are stronger for sub-groups who have higher field-specific human capital, such as those with a college degree. I also show that the effects are stronger in licensed occupations which is a concrete example of a type of occupation with higher entry costs. This is particularly true for women; for women in licensed occupations, a one-S.D. increase in the co-agglomeration index is associated with a 2.8% increase in earnings relative to a 1.6% increase for non-licensed occupations. Next, I test whether the relationship holds when I use measures of co-agglomeration based on college major which is typically chosen before one knows the field of one's spouse. I find that the association between income and college major co-agglomeration is of the same magnitude as the occupation-based co-agglomeration: a one-S.D. increase in the college major co-agglomeration index is associated with a 1.8% increase in earnings for women and a 2.3% increase in earnings for women who are the secondary earner. Lastly, I test whether more locationally concentrated occupations are associated with women's labor force participation rates, routinization of tasks, social meaning, and job flexibility and find that while locationally concentrated occupations are weakly less flexible as measured by the Goldin (2014) index, they are uncorrelated with other characteristics that might drive occupational selection.

I next show that examining whether these results are consistent with predictions from Mincer (1978). If the spouses' occupations are concentrated in similar labor markets, one would expect that it would be easier for them to move. Consistent with this theory, I provide suggestive evidence that the positive correlation between co-agglomeration and earnings is driven by mobility by documenting that the correlation is stronger for households living outside their birth states. I then show that being in a sub-optimal labor market, as measured by that occupation being under-represented in your current labor market, is associated with lower earnings, but that a spouse's match to the labor market only correlates with women's income. Lastly, I show that households with higher co-agglomeration are more likely to have moved if one or both of the spouses were in a sub-optimal labor market for their occupation prior to the move.

This paper relates to three main literatures: the literature on household location choice and women's earnings, the literature within urban economics on skill concentration across locations, and the literature within labor economics on how occupational choices impact women's earnings.

First, this paper contributes to the broader literature on how spatial frictions in a household can contribute to gender differences in earnings. The results in this paper are consistent with the framework developed in Mincer (1978)'s model of dual earner location choice.[1] In this model, having two sets of location preferences to consider in utility maximization results in lower migration rates for dual-earner households and a higher likelihood that one spouse is living in a location that is individually sub-optimal for their career (even if it is optimal for the household as a whole). The frictions associated with family ties are smaller if a couple's preferences and earnings profiles are locationally compatible. Mincer suggests two different ways that a married couple's migration decision may approach that of a single mover: either one spouse's average earnings is much higher than the other's, in which case that spouse's preferred location will win out, *or* the spouses' earnings across locations are highly correlated.

Due to gender differences in earnings, many papers on family location choice have focused on the impacts of the first case – the role of primary earners versus secondary earners. Past research has shown that household moves are typically initiated by job opportunities for the husband and married women are more likely to experience earnings losses following a long-distance move (e.g., LeClere and McLaughlin, 1997; Boyle et al., 2001; Cooke, 2003; Nivalainen, 2004; Boyle et al., 2009; Guler and Taskin, 2013; Gemici, 2011; Venator, 2025; Jayachandran et al., 2024). Structural models of dual-earner migration have explored how relative bargaining power (Gemici, 2011; Jayachandran et al., 2024), women's rising labor force participations (Braun et al., 2021), and the gender wage gap (Guler and Taskin, 2013) impact dual-earner location choices

[1] Though there are more recent theoretical models such as Lundberg and Pollak (2003) which move beyond the unitary model of the households in migration decision, newer models generally differ from Mincer in the mechanism that determines the outcome of the household problem, not the causes of location-based frictions, which is the focus of this paper. As such, the remainder of the paper will use Mincer (1978) as the primary theoretical reference paper.

through this first channel of relative spousal earnings. However, there has been less research focused on the second prediction of Mincer's theory: correlation between wages and offers, rather than absolute level of wages of one earner, may be a driver of how a household chooses where to live. A smaller literature (Foerster and Ulbricht, 2023, Venator, 2025) models the role of co-location frictions associated with the timing and location of offers in impeding dual-earner migration, but neither paper models what creates these frictions in the first place. This paper documents that occupations' concentration across space create correlations of job opportunities across space that impact men's and women's earnings differently. Specifically, this paper uses occupation as a proxy for location preferences, allowing a more granular look at how each spouses' human capital impact a household's location frictions. My findings suggest that occupation choice and how occupations vary across space matter for joint location decisions, indicating a additional mechanism that future work modelling occupation or location choice in a household setting should consider incorporating.

Past work (Costa and Kahn, 2000; Compton and Pollak, 2007; Mariotti et al., 2017; Simon, 2019) has documented that educational attainment of one or both spouses impact the location choices of dual-earner couples. Costa and Kahn (2000) show that households led by two college-educated spouses, so-termed 'power couples', are more likely to locate in urban areas which are more likely to have thick labor markets across fields to mitigate the co-location problem. Compton and Pollak (2007) later showed that mobility to urban areas is driven primarily by husbands' education rather than college-college pairings and that higher rates of power couples in urban areas are more attributable to couple formation in urban areas. These papers and the literature that followed on migration patterns of 'power couples' use only a coarse distinction of skills: college-educated or non-college-educated. For the purposes of understanding a couple's locational compatibility, education may not be the ideal way of assigning skill types. Compton and Pollak (2007) note in their paper that one reason women's college education may less correlated with household migration is because "many college-educated individuals, women especially, are in occupations that are relatively portable and are not concentrated in large urban areas." I show that within the college-educated group, there is wide variation in levels of locational-concentration, ranging from jobs such as human resources managers which have fairly similar geographic concentration across labor markets to jobs such as actuaries who have thick labor markets in the Connecticut-New York area, Los Angeles, Chicago, and Minneapolis and thin markets elsewhere.

A smaller literature (McKinnish, 2008; Shauman, 2010; Benson, 2014; Benson, 2015; Alonzo, 2022) has attempted to classify occupation-based geographic constraints and the relationship between the mobility of an occupation and each spouse's earnings. This paper is most similar to Benson (2014; 2015) which develops a model of marriage, migration, and occupational choice in which individuals choose either geographically concentrated occupations or disperse occupations, marry, and then choose where to locate. He demonstrates that the equilibrium of such a model is for one gender to specialize into geographically specific occupations and the other to choose a geographically disperse occupation, due to the possibility that a couple will end up locationally mismatched if they both choose geographically concentrated occupations. Though this latter paper is closest in spirit to the current exercise, Benson (2014; 2015) implicitly assumes that couples cannot choose geographically constrained careers that align and does not allow for any correlation in location-based returns by occupation. The current paper complements this literature by shifting the focus from the geographic constraints associated with a single occupation to the compatibility of spouses' geographic constraints. Mincer's model emphasizes that the household migration decision is dependent on how correlated spouses' earnings are across locations. To test this prediction of Mincer's model, I need a measure that would capture not just whether one's occupation is geographically constrained, but rather whether the husband and wife have compatible geographic constraints. By creating the measure of co-agglomeration, I am able to consider not just concentration, but also match between where spouses' careers are concentrated as a locational constraint.

Second, the results in this paper are related to the economics of agglomeration. A large literature in economics documents that urban areas with higher concentrations of similar firms and/or workers are associated with higher productivity and wage premiums.[2] Much of this literature focuses on agglomeration and co-agglomeration of industries, measured at the firm level in cross-sectional data. This paper departs from that literature by instead measuring concentration of workers within labor markets by occupation, which measures how similar skills are concentrated in similar places rather than how production of similar products are concentrated together. Past similar work includes Gabe and Abel (2011) and Gabe and Abel (2016) which respectively document cross-sectional patterns in occupational agglomeration and co-agglomeration. Gabe and Abel (2011) documents that wage gains associated with agglomerated occupations are primarily concentrated in innovation or creative occupations, rather than care, service, or production fields. Similarly, Goldman et al. (2019) documents occupational agglomeration within industries showing that high skill occupations such as research and development exhibit higher rates of occupational agglomeration. Likelihood of co-agglomeration is driven by the likelihood that two occupations share similar skills, rather than industrial concentration or input-output relationships between skill types and production (Gabe and Abel, 2016).

This paper contributes to the literature on skill agglomeration in two ways. First, I document trends over time in occupational concentration, as well as documenting how much of the changes in these trends are

[2] For an overview of the theory and empirics of agglomeration economics, see Duranton and Puga (2004) and Rosenthal and Strange (2004) respectively

due to occupations themselves being more concentrated versus selecting into more concentrated occupations. Second, I document trends in selection into agglomerated occupations by gender and education, as well as selection into co-agglomerated occupation pairs within households, which to my knowledge previously has not been studied. This paper's results suggest an additional explanation for why similar skill types may cluster together: highly skilled couples are both more likely to have similar knowledge and skill backgrounds and are incentivized to choose locales where they can both work.

Lastly, a large literature has documented the factors driving gender gaps in earnings (see Goldin (2014); Olivetti and Petrongolo (2016); Blau and Kahn (2017) for systematic reviews of this literature). Selection into different types of occupations is often cited as one factor driving lower earnings for women. In a decomposition of the gender wage gap, Blau and Kahn (2017) show that selection into occupation accounted for about one-third of the aggregate gender wage gap in 2010 compared to only about 10% of the gap in 1980. Past research documents that women's labor supply and choice of occupation are more sensitive to non-wage amenities related to flexibility, such as standardized work hours without overtime requirements (e.g., Goldin and Katz, 2016; Cortés and Pan, 2019), ability to work from home (e.g., Mas and Pallais, 2017), shorter commuting times (e.g., Le Barbanchon et al., 2021; Gu et al., 2024), and part-time options (e.g., Wiswall and Zafar, 2018). This paper introduces a new type of flexibility that may make occupations more attractive to women: locational flexibility. Occupations that are more evenly distributed throughout the country make it easier for secondary earners to find jobs that are compatible to their spouse's preferred labor market. I show that women are more likely to sort into occupations that are less concentrated on average and the co-agglomeration with spouses' occupation is more strongly correlated with women's earnings.

# 2 Measuring Spousal Match

To better understand how spousal occupation-location compatibility impacts a couple's location choices and earnings, I will be using measures typically used to measure the extent of industrial agglomeration: locational Gini coefficients, which measure the relative spatial concentration of U.S. industries, and an index of pairwise co-agglomeration, which measures the extent to which two pairs of industries are concentrated within the same region. While regional economics literature classically has used these measures for understanding what industries and firms benefit from co-locating in a region, I am adapting these measures to understand which skills or occupations make it easier for spouses to co-locate in a given region. The measures I use are adapted from the work of Gabe and Abel (2011) and Gabe and Abel (2016) on how geographically concentrated occupations are more likely to require specific or unique skill sets and from the work of Ellison and Glaeser (1997) on how different industries benefit from co-locating in similar regions.

## 2.1 Data

For all analyses, I use the 5% state sample of the 1980, 1990, and 2000 Decennial Censuses and the 1% sample of the 2006-2019 ACS sourced from the US Census Integrated Public Use Micro-Data Series (IPUMS) data (Ruggles et al., 2023), restricted to individuals between the ages of 25 to 64 for whom I observe both occupation and location. I use this sample to calculate the measures described below.

For the regression analyses, I then restrict the sample further to married couples living in the same household for whom I observe household earnings greater than zero, where earnings are defined as earnings from wages and salary, adjusted to 2014 dollars. I only include the head of household and their spouse in the sample, dropping any married couples living in the same household as the head of household. Because the measures of concentration vary at the occupational level, I exclude individuals for whom one or both spouses do not have a reported occupation (i.e., occupation reported as 'unknown').[3] In my sample, the average age for both men and women is mid-forties with men being slightly older than women. About one-third of the sample have a college degree and within household, about 18% of households have both spouses having a college degree and around 20% have at least one college degree.

While I am theoretically agnostic about the role of gender in determining individual's choice of occupation (and therefore how concentrated one's occupation is), in my sample, men are more likely to be the primary earner, both in terms of overall earnings and in terms of hours per week worked. To the extent that factors other than earning power, such as gender norms, drive who gets to control location choice, I might expect that there is some interaction between primary earner and gender that is important to capture when thinking about the predictions of this model. I therefore run analyses split both by gender of the spouse and by primary earner status. In all analyses, I define a spouse as the primary earner or 'breadwinner' if they earned more than fifty percent of household income in the last year.

[3]Those unemployed or temporarily out of the labor force are included; the Census asks such workers to report their most recent occupation if they have been employed within the last five years. An alternative to excluding those not working is to assume that the co-agglomeration index is 0 for households in which one spouse does not work, under the assumption that not-working has no locational concentration. Appendix Table A-1 redoes the primary analysis using this measure; the results are substantively unchanged.

## 2.2 Measure #1: Occupational Concentration

To measure occupational concentration, I compute a locational Gini coefficient at the three-digit level of IPUMS' standardized 1990 occupation classication (OCC1990) codes which allow me to link comparable occupation groups across decades.[4] I define a labor market as a commuting zone, which is defined as in Dorn (2009) to be geographic clusters of U.S. counties that are characterized by strong within-cluster and weak between-cluster commuting ties. I first calculate the share of individuals employed in each occupation by commuting zone as well as each commuting zone's total share of national employment. From this, I am able to calculate the locational Gini coefficient for occupation $k$ and year $t$ as follows:

$$
\begin{aligned}
\theta_{kt} &= \frac{\left[\frac{1}{n(n-1)}\right] \sum_{i=1}^{n} \sum_{j=1}^{n} |x_{ikt} - x_{jkt}|}{4 \frac{1}{n} \sum_{i=1}^{n} \ x_{ikt}} \qquad (1) \\
i, j &= \text{U.S. commuting zones, where } i \neq j \text{ and } n = 741 \\
x_{ikt} &= \frac{\text{commuting zone i's share of employment in occupation k in year t}}{\text{commuting zone i's share of total employment in year t}}
\end{aligned}
$$

The locational Gini ranges from 0, when an occupation is dispersed across the country in a pattern similar to the distribution of all employment, to 0.5 when an occupation is geographically concentrated in a single commuting zone. Figure 1 plots the agglomeration index against the proportion college educated separately for men (squares) and women (circles), weighted by the number employed in each occupation. Highly concentrated occupations span the educational distribution: for example, actuaries are almost exclusively college-educated but have a similar agglomeration value to textile machine operators which are exclusively non-college graduates. While there is a positive correlation between education and agglomeration, some of the most concentrated occupations (i.e., $\theta > 0.35$) are majority non-college.

## 2.3 Measure #2: Spousal Occupation Match

The prior measure describes how concentrated an individual's occupation is, but does not provide the key piece of information necessary for testing our understanding of the impacts of inter-household occupational match: are the occupations of a married couple concentrated in the same place or different places? For

[4] Appendix Section A.2 replicates the analyses of trends over time in agglomeration and coagglomeration and the primary regression specifications using four alternative measures: (1) two-digit occupational code in the ACS to ensure trends aren't due to level of aggregation; (2)metropolitan area by three-digit occupation code in the Current Population Survey to ensure trends aren't affected by the switch from Decennial Census to ACS; (3) three-digit occupations restricted to standardized codes that correspond to non-changing codes in the 1980-2000 Census to ensure that time series patterns aren't driven by new occupations and mismatch between the 1990 measure and contemporaneous occupation codes; and (4) a sample omitting commuting zones below the 5th percentile of population to ensure the measure isn't skewed by small locales.

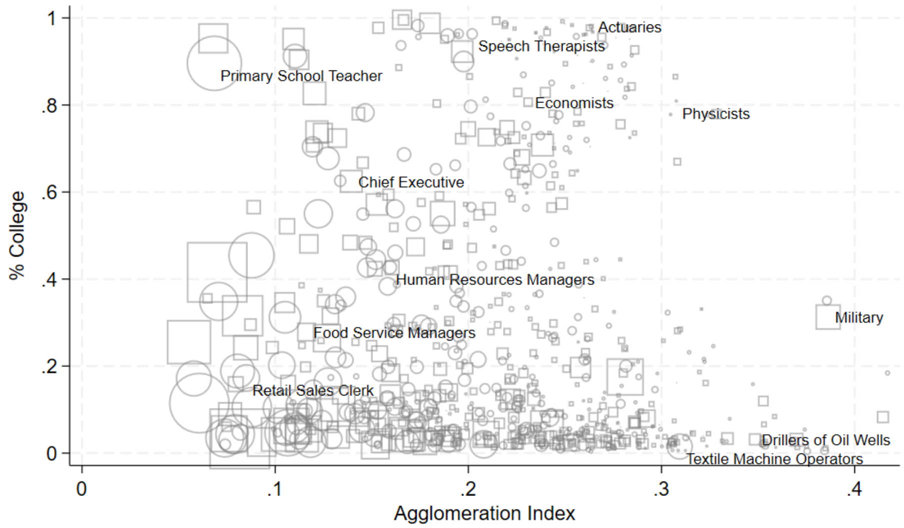



Figure 1: Agglomeration By Education and Gender
Notes. This figure plots the average agglomeration index for each occupation against the college education rate seperately for men (squares) and women (circles), weighted by the number of men and women in that occupation.

that, I need a measure of co-agglomeration. If both spouses' careers have high agglomeration levels but are concentrated in the same geographic region, I would not expect geographic mismatch for the trailing spouse in a move. In contrast, if spouses both have highly agglomerated occupations but are optimally located in different regions, I would expect the opposite. An index of co-agglomeration tells us not just if two occupations are both geographically concentrated, but if they are concentrated in similar places or different places.

The co-agglomeration index for occupations is adapted from the work of Ellison and Glaeser (1997) and Gabe and Abel (2016) and is calculated as:

$$\begin{aligned} \gamma_{k,l,t} &= 1000 * \frac{\sum_{i=1}^{n}(s_{i,k,t} - t_{it})(s_{i,l,t} - t_{it})}{(1 - \sum_{i=1}^{n} t_{it}^2)} \quad (2) \\ i &= \text{commuting zone, n= 741} \\ s_{i,k(l),t} &= \text{commuting zone i's share of employment in occupation k (l) in year t} \\ t_{it} &= \text{commuting zone i's share of total employment in year t} \end{aligned}$$

Using the same data previously used to calculate the locational Gini, I calculate a matrix of values for each occupation-pair and year. Positive values of the index indicate that occupations are agglomerated in similar places; values near zero indicate that the occupations have no tendency to co-agglomerate (i.e., one or both occupations are disperse); negative values indicate that the occupations are agglomerated in different places. The multiplier of 1000 re-scales the index to levels that are easier to read – without the scaling, most occupation pairs have a $\gamma$ value less than 0.001.

# 3 Historical Trends in Occupational Concentration

Before analyzing how a household's occupation locational compatibility impacts their earnings and migration decisions, I first show how measures of occupational agglomeration have varied over time and across genders. Have occupational clusters by commuting zone become more common over time, increasing the amount of agglomeration and therefore increasing the importance of husbands and wives sorting into locationally compatible careers?

## 3.1 Locational Gini Trends

Table 1 reports the mean value of $\theta$, the occupation locational Gini, by decade, gender, and college education. The first row, 'Across Occupations,' takes the mean value across the three-digit occupation groups. Because this is an average across occupations rather than people, these means are unweighted by the number of workers within an occupation and describe how occupational agglomeration has increased without accounting for how people may select across occupations due to concentration. While occupational concentration was flat from 1980 to 2000, the average Gini increased significantly throughout the 2000s and 2010s.

When I consider how individuals sort across occupations and take the average $\theta$ value across men and women, there is a clear upward trend in both men and women's occupational agglomeration values, but the increase in occupational concentration is smaller than the increase seen in the row unweighted by population. This suggests that while occupations have gotten more concentrated, less people are selecting into concentrated occupations in the 2000s. From 1980 to 2016-19, the average locational Gini for men increased by 0.042 which is equivalent to a 30% or a 0.54 standard deviation increase in value. Similarly, women's occupational concentration levels increased across decades, but are consistently lower than men's, meaning that the growth in concentration represents a larger gain relative to the mean in 1980 (38% or 0.68 standard deviations). The size of the gender gap in Gini values is constant over time. I next split the sample by education level and show that there is no consistent statistically significant difference between those with and without a college degree, though the growth in concentrated jobs is slightly larger for college-educated women than non-college-educated women.

How much of the growth of concentration from 1980 to 2019 is attributable to occupations becoming more concentrated versus people selecting into more concentrated occupations at higher rate? To answer this question, I assign observations in 2019 the agglomeration values their occupation would have had in 1980 and re-calculate the average locational Gini. The average of the index would have been 0.142 for men and 0.124 for women using 1980s values, both of which are similar to the values actually observed in 1980. This suggests that changes over time in occupational concentration are not due to people actively selecting into different occupations, but instead occupations becoming more clustered over time.

Appendix Section A.2 discusses how these trends differ if occupations are defined at the two-digit level rather than the three-digit level, are measured in the Current Population Survey, are measured using occupations that have non-changing occupation definitions across decades, or omit small commuting zones which may skew the measure. Levels of occupational agglomeration are lower when occupations are defined more broadly with two-digits, and the growth in selection into agglomerated occupations is weaker. This is perhaps unsurprising: as occupation groups encompass more types of workers, it is less likely that it will be under-represented within any given commuting zone. However, even with the broader occupational definitions, there remains a statistically significant difference in selection into concentrated occupations across genders, with men having higher scores on the locational Gini than women in all decades. Using the CPS sample, I show that the growth in occupational concentration still exists in data with a consistent measure across all years and that the switch from the Decennial Census to the ACS cannot explain the increase in concentration in the 2000s. Third, while I do use an occupational definition that is consistent across years in the primary specification, one might be concerned that the 1980 occupations mapped onto the standardized code are different conceptually than the 2010 occupations in that code. To test this, I restrict the occupations to the set of occupations which do not either add new occupations to the standardized code or remove occupations from the code. I see similar patterns in agglomeration over time among these occupations, suggesting that the growth in concentration is not due to changing occupations over time. Lastly, one concern with using a Locational Gini as a measure of agglomeration is that it will over-categorize occupations that are over-represented in small commuting zones as concentrated. To address this, I re-calculate the measure omitting commuting zones with bottom 5th percentile populations.[5] Concentration is increasing at a similar rate in this sample, suggesting that any skew induced by small commuting zones does not impact overall trends over time.

[5] I also discuss the benefits of locational Gini relative to HHI in Appendix Section A.2.4.

Table 1: Occupation Locational Gini Over Time, Gender, and Educational Groups

| | 1980 | 1990 | 2000 | 2006-2010 | 2011-2015 | 2016-2019 | Change 1980-2019 |
|---|---|---|---|---|---|---|---|
| Across Occupations | 0.200 | 0.204 | 0.195 | 0.247 | 0.255 | 0.253 | 0.053*** |
| Across Men | 0.138 | 0.135 | 0.132 | 0.171 | 0.180 | 0.180 | 0.042*** |
| Across Women | 0.117 | 0.114 | 0.108 | 0.150 | 0.160 | 0.162 | 0.045*** |
| *Gender Gap* | 0.021+ | 0.021* | 0.024** | 0.020* | 0.021* | 0.018* | -0.003 |
| College Men | 0.137 | 0.137 | 0.136 | 0.170 | 0.181 | 0.181 | 0.044*** |
| Non-College Men | 0.139 | 0.134 | 0.130 | 0.171 | 0.180 | 0.179 | 0.041*** |
| *College Gap, Men* | -0.002 | 0.004 | 0.007 | -0.000 | 0.001 | 0.001 | 0.004 |
| College Women | 0.108 | 0.114 | 0.111 | 0.151 | 0.162 | 0.164 | 0.057*** |
| Non-College Women | 0.120 | 0.114 | 0.107 | 0.150 | 0.158 | 0.161 | 0.041*** |
| *College Gap, Women* | -0.012 | -0.001 | 0.004 | 0.002 | 0.004 | 0.004 | 0.016+ |

Notes: This table reports the mean value of the locational Gini for different sub-groups by year with column 1-3 reporting average values for each Decennial Census year and columns 4-6 reporting means across five-year groupings using American Community Survey year. Panel A reports mean by occupation, unweighted by number of workers within an occupation. Panel B reports means by gender, weighted using IPUMS person weights; Panel C and D report the same separately for those with a college degree versus those without. Stars indicated significance of difference across years/gender/education-level, calculated by regressing concentration on gender, year, or education with standard errors (not reported) clustered at the occupation level: $\dagger p < 0.10$ * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$.

## 3.2 Co-agglomeration Index Trends

Table 2 reports the mean value of $\gamma$, the index of co-agglomeration, by decade, educational pairings of the spouses, and gender of the primary earner.[6] The first row reports the mean value across occupation pairs (i.e., one observation per occupation pair) whereas the remaining rows report the mean value accounting for the proportion of couples in each pairing. By comparing the values across occupations versus across households, I can gauge how much of the growth in co-agglomeration is attributable to occupations becoming increasingly jointly concentrated versus couples sorting into well-matched occupations. The unweighted mean is significantly higher in 2016/19 relative to 1980, but the increase is not monotonic across decades. In contrast, the household-weighted co-agglomeration index is higher than the unweighted mean in all decades and does increase monotonically. This suggests that while some of the increase in couples being in locationally compatible careers may be attributable to changes in how occupations are concentrated across labor markets, a larger portion of the increase is attributable to couples being more likely to sort into co-agglomerate occupations either by choosing to marry someone in a more compatible career or by changing occupations to better match their spouse.

Variation in how locationally compatible spouses are in terms of occupation also varies by education. To calculate gaps between educational pairings, I restrict the sample to married couples with either both

[6]Appendix section A.2 shows that these results do not differ substantively depending on occupation definition or data sample.

spouses with a college degree or both without and regress the co-agglomeration index on a dummy for both having a degree; standard errors are clustered at the occupational pairing level. Households with two college-educated spouses have significantly higher values on the co-agglomeration index across all decades and the degree of occupation-location compatibility amongst college-educated 'power couples' has increased over time. Couples that are mismatched in terms of education also seem to be increasingly mismatched in terms of occupation-location compatibility over time, with significant declines in the index between 1980 and 2019 for spouses with different education. The lowest values on the index are for households with a college-educated wife and a non-college-educated husband. Households in which neither spouse has a college degree have stable, but low values on the index.

Table 2 also reports values of the index conditional on which spouse earns more. Households with the husband as the primary earner have significantly lower values on the index and these gaps are increasing over time. While both types of households are increasingly co-agglomerated, the index is increasing for male breadwinner households less than for female breadwinner households, though the difference in growth is not statistically significant

Table 2: Co-Agglomeration Index Over Time, Educational Pairings, and Breadwinner Gender

| | 1980 | 1990 | 2000 | 2006-2010 | 2011-2015 | 2016-2019 | Change 1980-2019 |
|---|---|---|---|---|---|---|---|
| Across Occupations | 0.163 | 0.130 | 0.092 | 0.125 | 0.198 | 0.220 | 0.057*** |
| Full Sample | 0.167 | 0.175 | 0.186 | 0.190 | 0.241 | 0.274 | 0.107*** |
| Both Spouses College | 0.309 | 0.363 | 0.464 | 0.405 | 0.566 | 0.625 | 0.317*** |
| Husband College, Wife Non-College | 0.188 | 0.170 | 0.193 | 0.106 | 0.139 | 0.139 | -0.049* |
| Husband Non-College, Wife College | 0.096 | 0.079 | 0.082 | 0.061 | 0.074 | 0.055 | -0.041+ |
| Husband Non-College, Wife Non-College | 0.140 | 0.143 | 0.110 | 0.137 | 0.140 | 0.157 | 0.017 |
| *Diff. Both College to No College* | 0.169*** | 0.220*** | 0.354*** | 0.268*** | 0.427*** | 0.469*** | 0.300*** |
| Husband Breadwinner | 0.158 | 0.170 | 0.185 | 0.179 | 0.219 | 0.245 | 0.087*** |
| Wife Breadwinner | 0.209 | 0.192 | 0.187 | 0.213 | 0.283 | 0.329 | 0.120*** |
| *Difference by Breadwinner Gender* | -0.051* | -0.022 * | -0.002 | -0.034** | -0.065*** | -0.084 *** | -0.033 |

Notes: This table reports the mean value of the co-agglomeration index over time for the full married sample, by education of spouses, and by gender of the primary earner. The first row reports the average co-agglomeration between occupation pairings, unweighted by the proportion of couples in each occupation pairing. The remaining rows report the means weighted by the proportion of households in each pairing and IPUMS household weights. Difference across groups calculated by regressing the index on an indicator for group-type. Stars indicate significance of difference across gender with standard errors (not reported) clustered at the occupation level: $\dagger p < 0.10$ * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$.

Taken together, these measures demonstrate that the US labor market has become increasingly geographically segmented over time, with occupational concentration increasing and households sorting into more locationally compatible pairings over time. This paper is not the first to document increasing occupational or industry concentration; a large literature in urban economics (e.g., Moretti (2012); Rosenthal and Strange (2004)) has documented the growth of skill clusters in particular urban areas, established that knowledge spill-overs encourage similar firms and workers to sort into these clusters, and discussed the technological changes that drive increasing concentration. However, the growth in married couples sorting into locationally compatible occupations has not previously been documented. Notably, while the increased concentration of occupations does not seem to be driven by sorting into concentrated occupations, the co-agglomeration of occupations within households has grown at a faster rate than the unweighted co-agglomeration of occupations.

These trends are consistent with a number of other labor market trends previously documented in the literature. First, we would anticipate that location compatibility would become more important as the full-time labor force participation of women increases, resulting in an increase in dual-earner households. As household income is more evenly split between two spouses, it becomes more costly for a household to be locationally mismatched, encouraging men and women to consider career compatibility when choosing spouses and occupations. Second, past research has documented an increase in assortative matching among couples, both in terms of greater educational homogamy (Schwartz and Mare, 2005) and earnings homogamy (Greenwood et al., 2014). The patterns shown in this paper are also suggestive of increasing assortation in marriage: because occupations tend to be more co-agglomerated when the skills and knowledge used in those occupations are more similar (Gabe and Abel, 2016), increases in co-agglomeration are indicative of couples increasingly marrying spouses in occupations that require similar skills and marrying spouses with similar location preferences.

# 4 Locational Compatibility and Earnings

Mincer's model of dual-earner migration suggests that spouses with more highly correlated earnings should find it easier to move and that such households will be less likely to move to locations that are poor fits for the tied mover (typically the secondary earner). In this context, this suggests that how co-agglomerated spouses' occupations are should have stronger association with earnings for the secondary earner, due to the secondary earner being more likely to be mismatched if they are in a concentrated career that does not match that of their spouse. To test this prediction, I regress logged earnings (measured as the natural log of annual income from wages and salary in 2014 dollars) on the co-agglomeration index value for a couple, the agglomeration index value for each spouse, a set of covariates, and location, occupation, and year fixed effects:

$$\ln(W_{ijkt}) = \beta_1 \gamma_{k_F,k_M,t} + \beta_2 \theta_{k_M,t} + \beta_3 \theta_{k_F,t} + \beta_4 X_i + \zeta_j + \zeta_{k_F} + \zeta_{k_M} + \zeta_t + \epsilon_{ijkt} \quad (3)$$

$\gamma_{k_F,k_M}$ is the index of co-agglomeration for household $i$ with husband in occupation $k_M$ and wife in occupation $k_F$, normalized such that a one standard deviation increase is equivalent to $\gamma$ increasing by one. $\theta_{kt}$ refers to the locational Gini evaluated at each spouse's occupation $k$ in year $t$, also standardized. $X_i$ is a vector of covariates, including levels of education of each spouse, the interaction of the education levels of the spouses, a quadratic of age for each spouse, a dummy for whether each spouse is white, number of children, state of birth dummies, and a constant. $\zeta_j$ is a commuting zone fixed effect, $\zeta_{k_F}$ is a fixed effect for occupation of the wife, $\zeta_{k_M}$ is a fixed effect for occupation of the husband, and $\zeta_t$ is a fixed effect for year. All standard errors are clustered at the occupation-level of the focal spouse.

Note, $\gamma$ does not vary by location. This means that the effects of the index on earnings are not endogenous to the actual location choices made by households; $\gamma$ is instead a potential push factor for mobility, where the geographic distribution of a household's chosen occupation combination makes such moves more or less feasible. With the fixed effects for occupation and years included, identification of $\beta_1$ comes from variation over *occupation pairs* over time, and any bias in the coefficients come from two possible sources which are discussed further in section 5: (1) unobserved factors that were changing over time for occupation pairs that are correlated with changes over time in how those occupations are jointly geographically distributed at the national level or (2) couples' selection into more/less co-agglomerated occupation pairs.

Table 3 reports the results of these regressions with columns 1 and 2 for all men and women, columns 3 and 4 for households in which the husband is the primary earners, and columns 5 and 6 for households in which the wife is the primary earner.[7] Being in an occupation that is locationally compatible with one's spouse is associated with higher earnings for both genders, but the effect is stronger for women. A standard deviation increase in the co-agglomeration index is associated with approximately 1.8 percent higher earnings for women, whereas there is a much smaller association of co-agglomeration for men.[8] However, as previously noted, the effects of co-agglomeration on each spouses earnings are not inherently gendered, but instead should depend on who is the primary earner and who is the secondary earner.

When the husband is the primary earner, the effect of co-agglomeration on the wife's income is positive, larger, and significant ($\beta_1 = 0.022$) whereas the effect on the husband is small and non-significant. When the wife is the primary earner, the co-agglomeration index's relationship with male earnings is now positive and significant, with a one standard deviation in the index being associated with a 2.3 percent change in male earnings. The size of the association for women is still positive, but small and no longer significant. These

[7]Appendix Tables A-4, A-7, A-10, and A-12 report the same regressions for measures based on the four alternative occupational concentration definitions; patterns of earnings by co-agglomeration are similar.

[8]For context, the change in the co-agglomeration index from 1980 to 2016/19 is equivalent to a 0.08 S.D. increase, meaning that the increase in locational compatibility over this forty year period is associated with 0.14 percent higher earnings for women.

regressions suggest that being well-matched to one's spouse in terms of location-occupation concentration matters more for the secondary earner, regardless of gender.

Table 3: Relationship between Locational Compatibility and Earnings, By Gender and Breadwinner Type

| | All HHs | | Male Primary Earner HHs | | Female Primary Earner HHs | |
|---|---|---|---|---|---|---|
| | Men, ln(Earn) | Women, ln(Earn) | Men, ln(Earn) | Women, ln(Earn) | Men, ln(Earn) | Women, ln(Earn) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Coag. Index | 0.006*** | 0.018*** | -0.001 | 0.022*** | 0.023*** | 0.001 |
| | (0.001) | (0.003) | (0.001) | (0.003) | (0.003) | (0.001) |
| Aggl. Index, Men | -0.030+ | -0.013** | -0.023+ | -0.018*** | -0.020 | -0.011** |
| | (0.015) | (0.004) | (0.012) | (0.005) | (0.018) | (0.004) |
| Aggl. Index, Women | -0.003 | 0.024 | -0.004* | 0.026 | 0.006 | -0.000 |
| | (0.002) | (0.028) | (0.002) | (0.026) | (0.005) | (0.013) |
| Observations | 10,469,120 | 10,469,120 | 7,796,791 | 7,796,791 | 2,672,326 | 2,672,326 |

Standard errors clustered at the occupation level; $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Note. This table reports regressions of log income (in real 2014$) on the index of co-agglomeration ($\gamma$), the indices of agglomeration for each gender ($\theta_M$ and $\theta_F$), demographic controls including dummies for own and spouse's education, interaction dummies for spousal education, a quadratic of own and spousal age, dummies for whether own or spouse's race is white, number of children and fixed effects for state of birth, commuting zone, occupation of each spouse, and year. Column 1 and 2 are for all married men and women, respectively. Column 3 and 4 are restricted to households in which the husband is the primary earner, defined as making more than 50% of household income. Column 5 and 6 are restricted to households in which the wife is the primary earner.

These regressions also show no significant association between women's occupational agglomeration and earnings once one controls for spousal match. In contrast, a husband being in a more concentrated occupation has a negative association with both men and women's earnings, which contrasts with the expectation that being in an agglomerated occupation should increase earnings for men. However, recall that agglomeration is only associated with higher earnings if one is in the 'correct' location that matches one's occupation. A couple can score highly on agglomeration and co-agglomeration measures, but still be locationally mismatched if they have not moved to the optimal location for their occupational pairing. This means that agglomeration will only be positively associated with earnings if a person is agglomerated and well-matched to their location.

# 5 The role of occupation choice

While these results are consistent with spousal occupation match acting as a friction that impacts secondary earners, I cannot rule out the possibility that those who select into occuptions associated with worse locational compatibility differ on unobservables that drive earnings. These selection forces complicate the claim that being better matched drives higher earnings– is it the case that being well-matched drives higher earnings or is it the case that individuals who are more productive for unobserved reasons are more likely to choose occupations that are compatible to their spouse's occupation?

Because of the difficulty of finding an instrument that drives both selection of spouse and occupation that is uncorrelated with unobserved drivers of earnings, I instead provide additional support for the hypothesis that location compatibility is a driver of earnings by testing whether the correlation between earnings and co-agglomeration differs for sub-groups for whom we would expect these frictions to bind more. The frictions associated with the dual-earner location problem will matter the most for earnings in situations where it is difficult to resolve locational incompatibility by switching careers. If a couple realizes after falling in love that their preferred living situation and career paths aren't compatible, they have a few options. They could end up in the situation previously described, in which one member of the couple takes the earnings hit associated with being mismatched. Alternatively, one or both of the spouses could change their occupation to resolve the incompatibility, possibly by selecting into a different concentrated occupation that matches their spouse or by selecting into a disperse career. The couple could also separate– either before or after marriage – in the hopes that they can find a different partner with more compatible career plans. The patterns of spousal match in terms of agglomeration and co-agglomeration by gender, education, and household breadwinner in section 2 are all a result of this process of spouse and occupation selection.

## 5.1 Does locational compatibility matter if you can switch occupations?

Switching occupations may induce bias in the association between earnings and the locational compatibility measures, and it is not clear which direction that bias will be. On one hand, the spouses who do not select out of a low compatibility career may have fewer transferable or general skills that would allow them to change occupations and earn less for this reason. In this case, high productivity workers who marry a mismatched spouse will select out of their occupation into a disperse occupation and low productivity workers will stay in their mismatched occupation. I would then be over-estimating the impacts of being co-agglomerated with one's spouse on earnings. On the other hand, spouses who do not select out of a low compatibility career may have stronger occupation-specific skills, leading me to under-estimate the relationship between co-agglomeration and earnings. How the correlation changes across types of workers can provide suggestive evidence for the direction of bias in these estimates. To test this, I re-run the regression specified in equation 3 separately for college-educated and non-college educated and for those in occupations which require licenses.

Occupations that require a college degree or an occupational license are more likely to have occupation-specific human capital requirements and high upfront costs for entry into an occupation. For example, an actuary – one of the more concentrated careers as shown in Figure 1 – requires a person to get a bachelor's degree, often in actuarial science or business statistics, as well as an associate actuarial certification. Licenses often require an individual to spend both time and money to qualify for a license. Switching out of such a career because one's spouse gets a job in a sub-optimal labor market for actuaries results in the loss of a great deal of occupation-specific human capital. These explicit costs of entry into the profession make the costs of switching occupations much higher. In addition, many licenses are state-specific, making it more difficult for individuals to adjust to a poor match by moving to a new labor market. A recent analysis from Johnson and Kleiner (2020) finds that those in licensed occupations are 36 percent less likely to move across states than those in other occupations. For this analysis, I define a person as being in a licensed occupation if their occupation falls into the twenty-two licensed occupations identified by Johnson and Kleiner (2020). While Johnson and Kleiner then divide these occupations into occupations licensed at the state-level versus those licensed at the national-level, I group all types into one category, as both national licenses and state licenses indicate that the person will have a high cost of switching occupations in response to their spouse's locational preferences.[9]

Because college degrees and occupational licenses are both associated with higher occupation switching costs, we would expect that the correlation for this group would be less biased by the sorting patterns described above, allowing us to understand whether occupational sorting to match one's spouse on the basis of unobserved productivity biases the estimates upwards or towards zero. Panel A of Figure 2 reports the coefficients on the co-agglomeration separately by gender and education level; Panel B reports the coefficients separately by gender and licensing. Appendix Tables A-13 and A-14 report the full regression results.

For both men and women, co-agglomeration has a stronger and positive relationship with earnings for those with a college degree, though I cannot reject that the coefficients are equal in a t-test of equality of coefficients. The effect is strongest for college-educated women, for whom a one standard deviation increase in the co-agglomeration index is associated with 2.0 percent higher relative earnings. Similarly, the co-agglomeration index is more strongly associated with higher earnings for both genders if in a licensed occupation, and we can reject that coefficients are equal across groups in a t-test of equality of coefficients for men at the $p < 0.01$ level and for women at the $p < 0.10$ level. Once again, this relationship between co-agglomeration and earnings is largest for women in occupations with high switching costs: for those in licensed occupations, a one standard deviation increase in the co-agglomeration index is associated with 2.7 percent higher earnings compared to 1.7 percent for those in non-licensed occupations. This suggests

[9]The criteria for whether an occupation is considered licensed is as follows: (1) uniquely identifiable using ACS occupation codes, (2) universally licensed in all states, and (3) entry into the occupation requires licensure, so all members of an occupation must be licensed. Regressions run separately by state and national licenses show similar results; I cannot reject that the coefficients are equal across specifications.

that spousal-location match is a stronger driver of earnings for women than men, but occupations with higher costs to switching occupations impact the relationship similarly across genders. More importantly, the stronger association for those in occupations that are hard to switch out of suggests that selection on unobservables into concentrated/disperse occupations actually biases the coefficients towards zero and the true effect of locational compatibility is likely underestimated in these regressions.

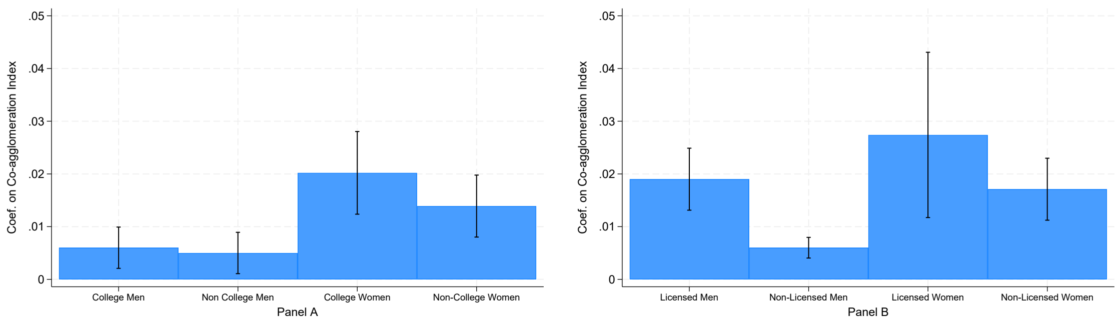



Figure 2: Coefficients on Co-agglomeration, by Education and Occupational Licensing
Notes. This figure plots the coefficients on the co-agglomeration index from a regression of log earnings on the index of co-agglomeration, the indices of agglomeration for each gender, demographic controls including a quadratic of own and spousal age, dummies for own and spouse's education (own omitted in Panel A),dummies for whether own or spouse's race is white, number of children, and fixed effects for state of birth, commuting zone, major of each spouse, and year. Panel A shows results separately by education level of the spouse and Panel B shows results separately by occupational licensing. 95% confidence intervals with standard errors clustered at the own occupation level.

## 5.2 Do skills that are acquired pre-marriage exhibit the same pattern?

An alternative way to address the selection bias caused by switching occupations is to proxy for skills with a measure that cannot be changed post-marriage. While there are still potential selection issues related to whom one marries, college majors are usually completed prior to marriage and are a measure of a set bundle of skills that one cannot easily change once in the workforce. The downsides to using this measure are that 1) it limits the analyses to those with a college degree, 2) it is a measure of skills that may have a weaker relationship to labor market returns particularly for older workers, and 3) major information was not collected prior to 2009. Nonetheless, college major agglomeration and co-agglomeration measures allow me to test whether my results are robust to alternative measures of how skills cluster across labor markets. If the correlation between earnings and co-agglomeration remains using this measure, this suggests that the relationship is not driven solely by occupational sorting on ability.

Using data from the 2009 through 2019 ACS, I re-calculate the agglomeration index and the co-agglomeration index using detailed college major field as the group of interest. The most agglomerated majors match up closely with college-educated occupations which were also heavily agglomerated: geological engineering, nuclear engineering, and astronomy are all some of the most agglomerated majors whereas business management, psychology, and nursing are all some of the least agglomerated majors.

Using these measures of skill concentration, I regress log earnings for men and women on the major co-agglomeration index, each spouse's major agglomeration index, demographic controls, commuting zone fixed effects, each spouse's major fixed effects, and year fixed effects. I run these regressions separately by gender and household breadwinner type. Table 4 reports the results of these regressions.

Table 4: Relationship between College Major Location Compatibility and Earnings

| | All HHs | | Male Primary Earner HHs | | Female Primary Earner HHs | |
|---|---|---|---|---|---|---|
| | Men, ln(Earn) | Women, ln(Earn) | Men, ln(Earn) | Women, ln(Earn) | Men, ln(Earn) | Women, ln(Earn) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Coag. Index | 0.009 | 0.018** | 0.004 | 0.020*** | 0.023* | 0.007 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.010) | (0.005) |
| Aggl. Index, Men | -0.004 | -0.006* | 0.001 | -0.007 | -0.011 | -0.005 |
| | (0.013) | (0.003) | (0.012) | (0.005) | (0.008) | (0.004) |
| Aggl. Index, Women | 0.000 | -0.017* | -0.005* | -0.025** | 0.005 | 0.007 |
| | (0.002) | (0.008) | (0.002) | (0.009) | (0.004) | (0.007) |
| Observations | 1,495,372 | 1,495,372 | 1,007,717 | 1,007,717 | 487,655 | 487,655 |

Standard errors clustered at the major level; $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Notes. This table reports regressions of log income (in real 2019$) on the index of college major co-agglomeration , the indices of college major agglomeration for each gender, demographic controls including a quadratic of own and spousal age, dummies for whether own or spouse's race is white, number of children, and fixed effects for state of birth, commuting zone, major of each spouse, and year. Column 1 and 2 are for all married men and women, respectively. Column 3 and 4 are restricted to households in which the husband is the primary earner, defined as making more than 50% of household income. Column 5 and 6 are restricted to households in which the wife is the primary earner.

Though the magnitudes differ some from the measures using occupation, the sign of the coefficients and the gender differences in the coefficients are very similar to those in previous analyses.[10] Spousal match in terms of college major match has a stronger positive association with earnings for women, with a one-S.D. increase in the college major co-agglomeration index being associated with a 1.8% increase in earnings for women versus a non-significant 0.9% increase for men. As previously, this gender difference seems to be driven by gendered patterns in who is the secondary earner. When the wife is the primary earner, the association is significantly larger for men and is smaller and only non-significant for women. These results demonstrate that the link between spouses' locational compatibility of skills and earnings are robust to different methods of measuring the spouses' skill sets and career opportunities across labor markets.

[10]The magnitude differences come primarily from the year restriction rather than the use of college major. Coefficients are similar to the results for 2006-2019 in Figure 3 and Appendix Table A-15.

### 5.3 Alternative explanations: Correlates of Concentrated Occupations

Though the previous results suggest that the positive association between co-agglomeration and earnings is not solely driven by selection into occupation pairs, the correlation could still be biased if there are other factors correlated with changes in occupational pairings' geographical distribution over time. For example, women's labor force participation increased over the time span of the sample. If women differentially entered occupations that are more or less concentrated, then growth over time in the co-agglomeration index may be correlated with growth over time in labor force participation, and the coefficients may be picking up the impacts of women's increased attachment to the labor force in concentrated occupations. I conduct three exercises to test for this.

First, I calculate the average labor force participation rate by women's reported occupation and year and then test whether it is correlated with the measures of agglomeration. To do this, I collapse the data set by women's occupation and year and regress the standardized agglomeration index ($\theta$) on the proportion of women not working within that occupation and year and regress the agglomeration index on the proportion of women not working along with occupation and year fixed effects. I find that the proportion of women working in a given occupation is uncorrelated with the concentration of their or their spouse's occupation[11]

Second, I estimate the primary regression specification separately for the Decennial Census sample (2000 and earlier) and the ACS sample (2006 and later). By 2000, women's labor force participation levels had stabilized, meaning that if the results are driven solely by changing patterns of labor force participation over time, we would expect the results in the ACS to be non-significant. Figure 3 and Appendix Table A-15 report the results of this regression. While the coefficients are higher in the pre-2000 sample, there is still a statistically significant positive correlation between co-agglomeration and earnings for women and secondary earnings in the post-2000 sample. The lower correlation is suggestive of declines over time in how important having a locationally compatible occupation to one's spouse is, possibly due to changing patterns of women's labor force participation or to changing norms about the relative contribution of men and women to household earnings.

Finally, I test whether concentrated occupations have other characteristics that may explain the gender differences in likelihood of choosing a locationally constrained occupation. Past work shows that women's occupation choice is more influenced by job amenities such as hours flexibility (Goldin, 2014; Goldin and Katz, 2016; Cortés and Pan, 2019) or social meaning (Burbano et al., 2024; Maestas et al., 2023) and

[11]To give a sense of magnitude, a ten-percentage point increase in the proportion of women not working in an occupation is associated with 0.01 standard deviation in the concentration of their spouse's occupation and the association is not statistically significant.

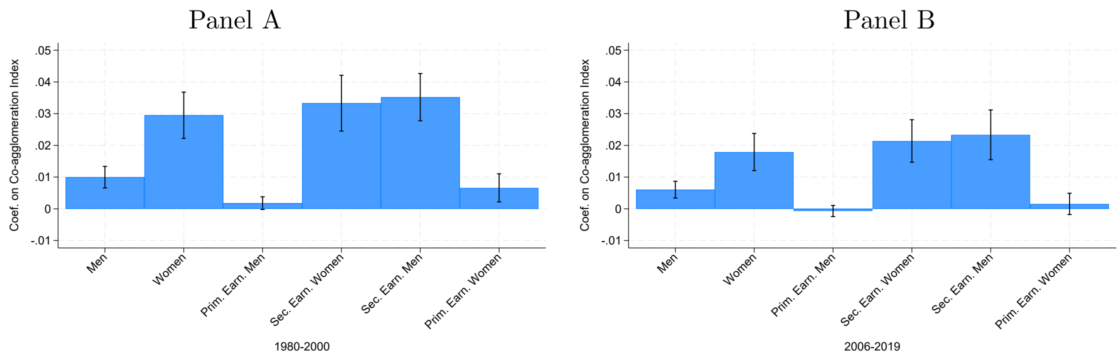



Figure 3: Coefficients on Co-agglomeration, by Time Period, Gender, and Breadwinner
Notes. This figure plots the coefficients on the co-agglomeration index from a regression of log earnings on the index of co-agglomeration, the indices of agglomeration for each gender, demographic controls including a quadratic of own and spousal age, dummies for own and spouse's education, interaction dummies for spousal education, dummies for whether own or spouse's race is white, number of children, and fixed effects for state of birth, commuting zone, major of each spouse, and year. Panel A is restricted to the Decennial Census samples (1980, 1990, and 2000) and Panel B is restricted to the ACS samples (2006-2019). Primary earner is defined based on which spouse makes more than 50% of household income. 95% confidence intervals with standard errors clustered at the own occupation level.

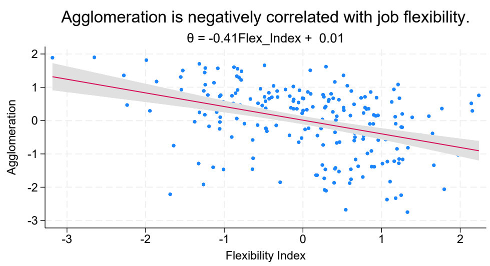
that women were more likely than men to shift out of routine task-intensive occupations when faced with automation (Cortés et al., 2024). If locationally concentrated jobs are more likely to be inflexible or routine-task intensive jobs, the changes over time in the pay-offs to being in concentrated, well-matched occupations could come from changes in the availability and wage premium associated with these jobs over time.

Figure 4 shows a scatter plot of the agglomeration index against indices measuring flexibility (Goldin, 2014), job meaningfulness (Maestas et al., 2023), and routine task intensity (Autor and Dorn, 2013).[12] Occupations that are more locationally concentrated are less likely to be flexible jobs as defined in the (Goldin, 2014) index, but have statistically insignificant relationships with routine task intensity and meaning of the job. Given that both hours flexibility and locational flexibility are characteristics that allow women to balance their careers with their household's needs, it is perhaps unsurprising that they would be correlated. To the extent that women choose more disperse occupations due to job amenities that are constant across time, occupation fixed effects will control for the general tendency of these occupations to offer these amenities. Because co-agglomeration index varies by occupational pairings overs time, this correlation only biases our regressions if an occupation's flexibility changes over time and sorting into flexible occupations is related to the geographic concentration of the spouse's occupation.[13]

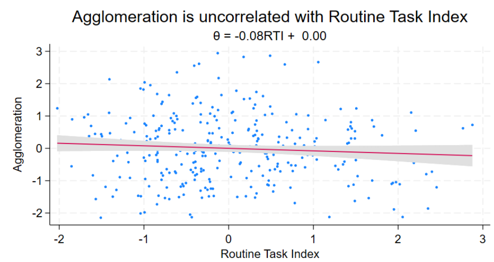
[12] Appendix Section A.3 provides additional information on creation of these indices.

[13] Because all three of these indices are measured at specific points in time, I cannot test whether changes in flexibility, routine tasks, or social meaning over time are correlated with changes in the agglomeration index over time.

Panel A




Panel B




Panel C

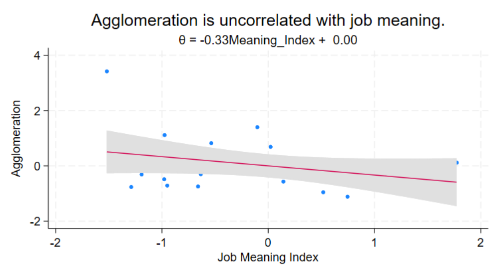



Figure 4: Correlates of Agglomeration

Notes. This figure shows a scatter plot and line of best fit for the correlation between the standardized agglomeration index and three indices of job characteristics. Panel A shows an index of job flexibility (Goldin, 2014), Panel B shows an index of routine task intensity (Autor and Dorn, 2013), and Panel C shows an index of job meaning (Maestas et al., 2023). The first two are measured at the three-digit occupation-level, measured using OCC1990, and the third is measured at the two-digit occupation-level. Further details on index creation in Appendix Section A.3.

# 6 The role of geographic mobility

A key prediction of the Mincer (1978) model of dual-earner migration is that households whose career prospects are correlated across geographies will be more mobile. Higher earnings for co-agglomerated households could then come from these households being better able to move to higher earning labor markets or from non-co-agglomerated households being more likely to stay in low-paying labor market because there isn't an alternate market that both spouses can agree on. For example, if one member of a household experiences a lay-off, they may better be able to search for a job across labor markets if they are co-agglomerated with their spouse's occupation.[14] To bolster my claim that having co-agglomerated careers impacts earnings in part by making mobility easier, I present three exercises.

First, if these results are driven by reduced labor mobility frictions, we would expect that the correlation between co-agglomeration and earnings would be stronger for couples who are more mobile. To test this, I re-run the earnings regression separately for those who are living in their state of birth (less mobile) and those who are not living in their state of birth (more mobile). I focus only on women as they are the spouse for whom the measure has the strongest effects and estimate the regression separately for all women, women who are secondary earners, and women who are primary earners.[15] Table 5 reports the results. I see that the correlation is stronger for women who are not living in their state of birth (i.e., mobile households), consistent with the hypothesis that co-agglomeration relates to earnings because being well-matched to your spouse buffers against income losses associated with being a trailing spouse. This is true even for mobile women who are primary earners unlike in the full sample where the correlation was small and non-significant.

Second, the Mincer (1978) model predicts that when spouses have differing preferred locations, the higher earning spouse's preferred labor market will drive location choice resulting in lower earnings for the trailing spouse. This would be consistent with the primary earner's earnings being uncorrelated with their spouse's occupation-location match, but the secondary earner's earnings depending on their spouse's match. To test how earnings relate to joint locational compatibility, I create a measure of whether a given labor market is a 'well-matched' market for an occupation using the sub-component of the locational Gini which represents the relative share of those in employed in an occupation in a commuting zone, $x_{ikt}$ ( see eq. 1). A high value of $x_{ikt}$ indicates that the occupation $k$ occurs more often in commuting zone $i$ than one would expect given the labor market's population share, a middling value indicates that the occupation is about as common as one would expect given the population share in commuting zone $i$, and a low value indicates

[14] In a study of mobility in Norway, Huttunen et al. (2018) find that while lay-offs increase moves across labor markets, the effect of a lay-off on mobility is about 20% smaller if married. They do not explore whether this effect varies by spouse occupation.

[15] Households living in their home state are 8% more likely to have a male primary earner.

Table 5: Relationship between Co-Agglomeration and Earnings, by Home Status

| | All Women | | Secondary Earner Women | | Primary Earner Women | |
|---|---|---|---|---|---|---|
| | Non-Home | Home | Not Home | Home | Not Home | Home |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Coag. Index | 0.022*** | 0.015*** | 0.025*** | 0.019*** | 0.004** | -0.001 |
| | (0.003) | (0.003) | (0.003) | (0.004) | (0.001) | (0.002) |
| Aggl. Index, Men | -0.012+ | -0.00753+ | -0.017* | -0.015** | -0.010+ | -0.003 |
| | (0.006) | (0.004) | (0.007) | (0.005) | (0.005) | (0.005) |
| Aggl. Index, Women | 0.023 | 0.026 | 0.026 | 0.028 | -0.0001 | -0.001 |
| | (0.032) | (0.028) | (0.030) | (0.026) | (0.013) | (0.013) |
| Observations | 3,409,46 | 6,104,846 | 2,543,567 | 4,553,754 | 865,973 | 1,551,085 |

Standard errors in parentheses
$^{+}\ p < 0.10$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Notes. This table reports regressions of log income (in real 2019$) on the index of co-agglomeration, the indices of agglomeration for each gender, demographic controls including a quadratic of own and spousal age, dummies for whether own or spouse's race is white, number of children, and fixed effects for state of birth, commuting zone, major of each spouse, and year. Column 1 and 2 are for women who are not and are living in their state of birth, respectively. Column 3 and 4 are the same restricted to households in which the wife is the secondary earner, defined as making more than 50% of household income. Column 5 and 6 is the same, restricted to households in which the wife is the primary earner.

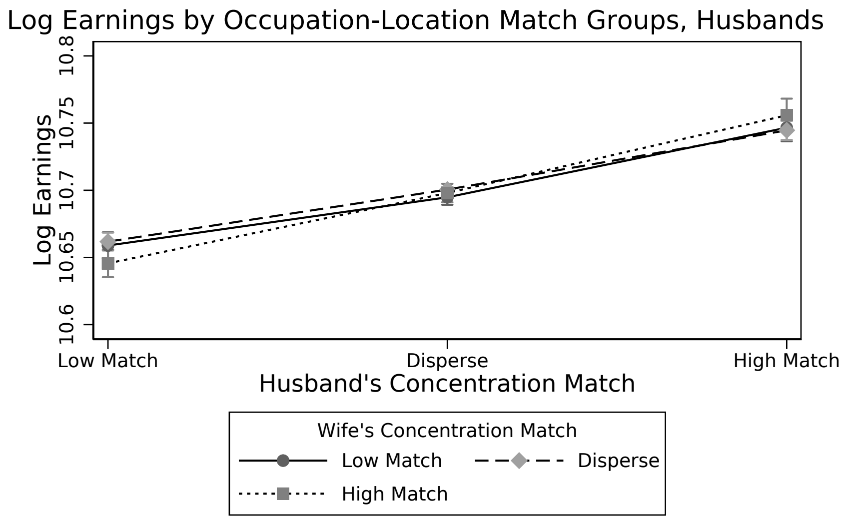
the occupation is relatively rare in that labor market.

I define a person as being in an 'under-represented' occupation for their commuting zone if their occupation-location's $x_{ikt}$ is below the 15th percentile of the distribution of $x_{ikt}$ in year $t$, a 'disperse' occupation if their occupation's $x_{ikt}$ is between the 15th and the 85th percentile, and an 'over-represented' occupation if their occupation location's $x_{ikt}$ is greater than the 85th percentile.[16] I then regress log earnings on the indicators for being in an occupation over-represented in the person's current labor market (High) or under-represented in their current labor market (Low) interacted with the same measures for their spouse, as well as the same controls and fixed effects as in the primary regression specification. I then predict the average log earnings for each husband-wife occupation-location match pairing at the average values of the controls and plot them in Figure 5.

For both men and women, earnings are increasing in how heavily concentrated their own occupation is in the commuting zone – those in commuting zones where their occupation is over-represented relative to overall employment earn more than those in disperse occupations who in turn earn more than those whose occupations are under-represented in their commuting zone. Men and women differ however in how their spouse's occupation-match impacts their own earnings. For men, there is little difference in how much they earn conditional on their wife's occupation-location match; they earn slightly more if their wife is well-

[16]The analyses are not sensitive to choosing alternative cut-offs such as 10% or 20%.

Panel A




Panel B

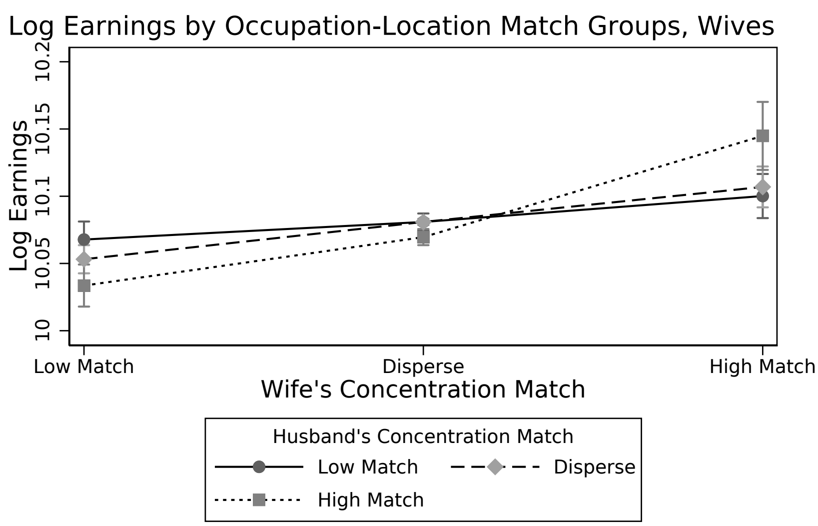



Figure 5: Average Earnings by Spousal Occupation-Location Match

Notes. This figure plots the predicted log earnings for men (Panel A) and women (Panel B) from a regression of log earnings on indicators for living in a commuting share with high, medium, and low relative shares of one's occupation, controls for own and spouse's age, age squared, education level, and race, own and spouse occupation fixed effects, year fixed effects, and commuting zone fixed effects. 95% confidence intervals with standard errors clustered at the own occupation level.

matched across all own-occupation-location match groups. In contrast, women's earnings vary not only due to their spouse's match but also through the interaction of their own match with their spouses. Like men, women's earnings are highest in a High-High pairing. Unlike men, however, being married to a husband whose occupation is over-represented in the labor market results in worse outcomes for women unless their occupation is also highly concentrated there. Women in commuting zones where their occupation is under-represented earn significantly less if their husband is well-matched than if he is a 'Low' or 'Disperse' type. This aligns with Mincer (1978)'s model predictions in which the primary earner determines the location choice when couples have mismatched location preferences, resulting in a null correlation between primary earners' earnings and spouses' location-occupation match and the secondary earner having lower earnings only if their location-occupation match differs from their spouse. [17]

Lastly, I examine whether being more locationally compatible influences decisions of whether to move and whether such couples move away from locations that are unsuitable for their occupation. A positive correlation with co-agglomeration and earnings could come not only from couples who are locationally compatible being better able to move to a better labor market when in a sub-optimal labor market, but also from locationally incompatible couples moving less even when in a sub-optimal labor market for one or both spouses' career. To test this, I regress measures of mobility on the co-agglomeration indices, interacted with an indicator for whether each spouse's occupation was over- or under-represented in the prior year's commuting zone. Because the Decennial Census and the ACS measure past mobility differently, I run separate regressions for pre- and post-2000. In the Decennial Census (2000 and earlier), moves are defined as living in a different commuting zone than five years prior. The second measure, only available for the 2006-2019 ACS samples, is an indicator for if the household moved across commuting zones in the last year. Table 6 reports the results of these regressions.

[17] Because choice of location is endogenous to the economic opportunity, the differences in patterns of earnings by spousal match and gender could also be driven by different sorting on unobservables. If households are more likely to move to/stay in mismatched locations when one spouse has lower unobserved productivity or low attachment to the labor force, this could be the case.

Table 6: Relationship between Locational Compatibility and Migration

| | (1)<br>Overall | (2)<br>High-Match | (3)<br>Low-Match | (4)<br>Overall | (5)<br>High-Match | (6)<br>Low-Match |
|---|---|---|---|---|---|---|
| Coag. Index | -0.00137 | $0.005^{**}$ | $-0.004^{***}$ | -0.0003 | $0.002^{***}$ | $-0.001^{**}$ |
| | (0.005) | (0.005) | (0.001) | (0.000436) | (0.0004) | (0.0003) |
| Over-Rep., W × Coag. Index | | $-0.005^{***}$ | | | $-0.002^{***}$ | |
| | | (0.001) | | | (0.001) | |
| Over-Rep, M× Coag. Index | | -0.004 | | | $-0.001^{*}$ | |
| | | (0.003) | | | (0.001) | |
| Both Over-Rep× Coag. Index | | -0.003 | | | $-0.003^{**}$ | |
| | | (0.003) | | | (0.001) | |
| Under-Rep., W × Coag. Index | | | $0.015^{***}$ | | | $0.002^{**}$ |
| | | | (0.001) | | | (0.001) |
| Under-Rep., M × Coag. Index | | | $0.007^{***}$ | | | $0.002^{**}$ |
| | | | (0.002) | | | (0.001) |
| Both Under-Rep × Coag. Index | | | $-0.005^{+}$ | | | -0.001 |
| | | | (0.003) | | | (0.001) |
| Observations | 5,834,233 | 5,834,233 | 5,834,233 | 4,437,317 | 4,437,317 | 4,437,317 |
| Mean Migration Rate | 0.353 | 0.353 | 0.353 | 0.095 | 0.095 | 0.095 |

Standard errors in parentheses; $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Note. This table reports regressions of measures of mobility on the index of co-agglomeration ($\gamma$) and interactions with being in an occupation that was over-represented in their previous commuting zones or underepresented, demographic controls including dummies for own and spouse's education, interaction dummies for spousal education, a quadratic of own and spousal age, dummies for whether own or spouse's race is white, number of children, and fixed effects for state of birth, commuting zone, occupation of each spouse, and year. Column 1-2 is an indicator for having moved across commuting zones in the last five years and is run on the Decennial Census 1980, 1990, and 2000. Column 4-6 is an indicator for having moved across commuting zones in the last year and is run on the ACS 2006-2019. Standard errors are clustered at the occupation level

I find that higher values on the co-agglomeration index are positively correlated with mobility if we control for previous locations' match type. In columns 2 and 5, I interact co-agglomeration with an indicator for whether the household's occupation was over-represented in the prior commuting zone, meaning that the coefficient on co-agglomeration alone represents the effects of being well-matched to your spouse for households in which the previous labor market was sub-optimal for their occupations. Columns 3 and 6 show the inverse. For those who were in occupations poorly-matched to their starting labor market, a one-standard deviation increase in the co-agglomeration index is associated with a 0.5 pp (1.4%) higher five-year mobility rate and a 0.2 pp (2.1%) higher one-year mobility rate. For those whose occupations were well-matched to the prior location, having higher locational compatibility decreases mobility, consistent with these couples having already achieved their preferred optimal location. Though the direction of these correlations are consistent with Mincer's theory, the magnitude is relatively small and indicates that locational compatibility only plays a small role in mobility.

# 7 The role of marriage markets

In the literature on educational power couples, Compton and Pollak (2007) show that dual-college couples are more likely to be located in big cities due to couples forming there, rather than locational constraints driving such couples to both to big cities. This raises the question: are spouses choosing occupations/spouses strategically to adjust to these locational constraints or are they instead only co-agglomerated because they are more likely to find a locationally compatible spouse in their local labor market? If the former is true, we would expect to see those in occupations under-represented (over-represented) in their labor market marry people who are also under-represented (over-represented) whereas if the latter is true, we would expect to see both under-represented and over-represented occupation holders marrying those in over-represented occupations.

I test whether those who are poorly matched to a location are more likely to marry an under-represented, a disperse, or a over-represented spouse, using the same indicators as in Table 6. I fit a multinomial logistic regression where the outcome is the probability that one's spouse is each of those types as a function of own's type, own type interacted with own and spouse's education, and controls for a quadratic of own age and spouse's age, indicators for whether own race and spouse's race are white, and controls for number of children. I then predict how much more likely a person of a poorly matched or a well-matched type is to marry each type relative to a disperse type. Table 7 reports the results.[18]

Those who are in under-represented occupations are not more likely to match to disperse or over-represented occupations. The results are more in-line with positive assortation with those whose own type is under-represented being more likely to match to another under-represented person and vice versa for over-represented types. The patterns are more pronounced for those who are recently married, suggesting that the assortation is not driven by changing locations or occupations following marriage. This finding differs from that of Compton and Pollak (2007); if the pairings were driven by availability of spouse in a labor market, we'd expect all types to be most likely to marry the over-represented type. It is, however, suggestive of couples sorting into marriages on the basis of occupation-location compatibility as both types are less likely to marry a spouse in an occupation-location type that is locationally incompatible to their own.

[18] I report separately for men and women who have married in the last five years which better reflects the person's compatibility at time of marriage prior to moving or changing occupations. These results are restricted to observations post 2008 which is the first year that IPUMS reports year of marriage.

Table 7: Probability of Matching to Spouse of Each Type, relative to Disperse Type

| | Spouse Type | Men | Women | Men, < 5 yr. | Women, < 5 yr. |
|---|---|---|---|---|---|
| | Under-represented | 0.055 | 0.059 | 0.066 | 0.066 |
| | | (0.0002) | (0.0003) | (0.001) | (0.001) |
| Own Type: | Disperse | -0.053 | -0.069 | -0.063 | -0.074 |
| Under-represented | | (0.0003) | (0.0003) | (0.001) | (0.001) |
| | Over-represented | -0.002 | 0.011 | -0.003 | 0.008 |
| | | (0.0002) | (0.0003) | (0.001) | (0.001) |
| | Under-represented | 0.005 | -0.027 | 0.001 | -0.033 |
| | | (0.0002) | (0.0003) | (0.001) | (0.001) |
| Own Type: | Disperse | -0.094 | -0.111 | -0.108 | -0.128 |
| Over-represented | | (0.0003) | (0.0003) | (0.001) | (0.002) |
| | Over-represented | 0.089 | 0.138 | 0.107 | 0.161 |
| | | (0.0002) | (0.0003) | (0.001) | (0.002) |

Note. This table reports marginal effects from a multinomial logistic regression where the outcome is occupational match type of one's spouse (under-represented, disperse, over-represented) and the regressor of interest is own match type where disperse is the omitted category. Values reported are the marginal probability of marrying a spouse of type X for under-represented and over-represented individuals relative to disperse individuals. Standard errors are calculated using delta method and are not clustered. Regressions include controls for college degree of each spouse, an indicator for whether each spouse is white, a quadratic of age for each spouse, and presence of children in the households Column 1 and 2 are for all married men and women; Column 3 and 4 are for married men and women for whom we observe year of marriage and they were married within five years of the survey.

# 8 Conclusion

This study highlights two important facts about occupation choice in the context of dual earner households' joint-decision about where to live.

First, I document historical trends in how clustered occupations are and how men and women sort differently across occupational concentration levels. Occupational concentration has increased since 1980 and there is a consistent gap in average concentration level of men and women's occupations. Within households, the average co-agglomeration of husbands' and wives' occupations has increased over time, and there are large gaps by educational assortative matching. Households with two college-educated spouses are also more likely to be well-matched in terms of occupational concentration locations than those with two non-college-educated spouses, and the households with educational mis-match (i.e., only one spouse with a college degree) have the lowest values on the co-agglomeration index.

Second, this study departs from past research's focus on education as a predictor of the location choice of dual-earner couples to instead focus on occupation. I present a new application of co-agglomeration indices, using this measure as an indicator of the locational compatibility of spouses and demonstrating that locational compatibility of spouses is strongly associated with earnings for women. This is in large part due to women being more likely to be the secondary earner in the household. By separating the role of breadwinner from gender, I am able to show that secondary earners typically bear the brunt of geographic constraints on income, regardless of gender. These effects are stronger for occupations with high skill barriers to entry, such as occupations which require a college degree or an occupational license.

Taken together, these facts present evidence that one's expectations about one's future spouse are associated with occupation and location choice. The findings in this paper are descriptive in nature; these analyses do not attempt to disentangle how much of the correlation between spousal match and earnings comes from selection into a marriage, into an occupation, or into a location. Future extensions of this work could consider the timing of selection into an occupation versus a relationship; do men and women select majors or training in anticipation of marriage? Or do they switch occupations in response to changes in relationship status? However, even if these correlations are merely an artifact of how people choose their spouse or their career, they indicate that the results of these choices are different in terms of men's earnings relative to women's earnings. In modeling both job search and location choice, it is therefore important to consider differences by gender in how a spouse's occupation impacts a person's choice of where to live and work.

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# A Online-Only Appendix

## A.1 Including non-employed spouses

While the primary specifications focus specifically on households for whom we can observe their occupation to capture behavior of households where both spouses are recently attached to the labor force, one could alternatively consider single-earner households as an extreme version of location compatibility. For these households, the non-earner has no location attachment and the earner can thus more easily optimally locate for their career. I therefore test whether the primary specification holds for an alternative sample in which I assign those who worked less than 5 hours in the last year and are missing an occupation a locational Gini of zero and households where there is at least one such spouse a co-agglomeration value of zero. In practice, I still exclude those with zero income from the regressions as the outcome is log income, but this allows me to include individuals whose spouses were not working and had zero income. In these regressions, I also include dummies for employment in the last year.

Appendix Table A-1 reports the results for the primary regression analysis using this adjusted index specification. The results are similar in sign and magnitude to those in the primary specification in Table 3.

Table A-1: Relationship between Locational Compatibility (Inc. Non-Workers) and Earnings, By Gender and Breadwinner Type

| | (1) All Men | (2) All Women | (3) Prim. Earner Men | (4) Sec. Earner Women | (5) Sec. Earner Men | (6) Prim. Earner Women |
|---|---|---|---|---|---|---|
| Coag. Index | 0.004*** | 0.017*** | -0.001 | 0.022*** | 0.023*** | 0.006** |
| | (0.001) | (0.003) | (0.001) | (0.003) | (0.003) | (0.002) |
| Aggl. Index, Men | -0.033* | -0.014*** | -0.032* | -0.019*** | -0.020 | -0.021*** |
| | (0.016) | (0.004) | (0.014) | (0.005) | (0.018) | (0.004) |
| Aggl. Index, Women | -0.010*** | 0.027 | -0.001 | 0.026 | 0.006 | 0.022 |
| | (0.003) | (0.027) | (0.003) | (0.026) | (0.005) | (0.019) |
| Observations | 14,430,983 | 12,266,334 | 11,758,269 | 7,797,185 | 2,672,711 | 4,469,145 |

Standard errors clustered at the occupation level; $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Notes. This table reports regressions of log income (in real 2014$) on the index of co-agglomeration ($\gamma$) which includes zeros for non-workers, the indices of agglomeration for each gender ($\theta_M$ and $\theta_F$), demographic controls including dummies for own and spouse's education, interaction dummies for spousal education, a quadratic of own and spousal age, dummies for whether own or spouse's race is white, dummies for own and spouse's employment status in previous year, number of children and fixed effects for state of birth, commuting zone, occupation of each spouse, and year. Column 1 and 2 are for all married men and women, respectively. Column 3 and 4 are restricted to households in which the husband is the primary earner, defined as making more than 50% of household income. Column 5 and 6 are restricted to households in which the wife is the primary earner.

## A.2 Robustness to Alternative Measures of Occupation

Geographic concentration of an occupation will differ depending on how one defines an occupation. If occupations are aggregated into larger occupational groupings, one would expend lower concentration and vice versa if occupations are defined based on very narrow definitions. Additionally, the measures of concentration may be impacted by changes across surveys in how occupations are defined. I therefore test four alternative ways of defining occupation to ensure that my results are robust to my choice of categorization.

### A.2.1 Two-Digit Occupation

I first test whether the trends and patterns in occupational agglomeration and co-agglomeration change based on definition of occupation groups by aggregating the IPUMS' 1990 occupational classification into two-digit groups.

Appendix Table A-2 reports trends over time in agglomeration based on two-digit occupations. Similar to the results reported in Table 1, we see that occupations unweighted by number of workers are increasingly concentrated over time, though both the levels and the growth in concentration are lower than when agglomeration is measured at the three-digit level. Additionally, we still see a consistent gender gap in agglomeration with men being more likely to select into concentration occupations. The trends differ from the three-digit analysis primarily in one way: once we adjust for selection into occupation, the levels of agglomeration are fairly constant over time rather than showing significant growth over time. The only group for whom there is a statistically significant growth in agglomeration is college-educated women.

Table A-2: Two-Digit Occupation Locational Gini Over Time, Gender, and Educational Groups

| | 1980 | 1990 | 2000 | 2006-2010 | 2011-2015 | 2016-2019 | Change 1980-2019 |
|---|---|---|---|---|---|---|---|
| Across Occupations | 0.107 | 0.104 | 0.100 | 0.117 | 0.123 | 0.122 | 0.016* |
| Across Men | 0.091 | 0.083 | 0.078 | 0.090 | 0.093 | 0.094 | 0.002 |
| Across Women | 0.069 | 0.066 | 0.060 | 0.073 | 0.077 | 0.079 | 0.010 |
| *Gender Gap* | 0.022* | 0.018* | 0.018* | 0.017* | 0.016* | 0.015* | -0.007 |
| College Men | 0.095 | 0.089 | 0.083 | 0.096 | 0.098 | 0.099 | 0.004 |
| Non-College Men | 0.090 | 0.081 | 0.076 | 0.087 | 0.090 | 0.091 | 0.001 |
| *College Gap, Men* | 0.005 | 0.008 | 0.007 | 0.008 | 0.008 | 0.008 | 0.003 |
| College Women | 0.067 | 0.070 | 0.065 | 0.079 | 0.083 | 0.084 | 0.017* |
| Non-College Women | 0.069 | 0.064 | 0.058 | 0.069 | 0.073 | 0.075 | 0.006 |
| *College Gap, Women* | -0.002 | 0.006 | 0.007 | 0.010 | 0.010 | 0.009 | 0.011 |

Notes: This table reports the mean value of the two-digit occupation locational Gini for different subgroups by year with column 1-3 reporting average values for each Decennial Census year and columns 4-6 reporting means across five-year groupings using American Community Survey year. Panel A reports mean by occupation, unweighted by number of workers within an occupation. Panel B reports means by gender, weighted using IPUMS person weights; Panel C and D reports the same separately for those with a college degree versus those without. Stars indicated significance of difference across years/gender/education-level, calculated by regressing concentration on gender, year, or education with standard errors (not reported) clustered at the occupation level: $\dagger p < 0.10$ * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$.

Appendix Table A-3 reports trends over time in the co-agglomeration index for the full sample, by education of spouses, and by gender of breadwinner (comparable to Table 2). As with the locational Gini, levels of the co-agglomeration index are lower when occupations are defined at a higher level. Similar to the three-digit occupation specification, co-agglomeration has increased, though it is not statistically significant. The index increases significantly over time for households with two college-educated spouses and decreases for households with only one college educated spouse, though the trends over time are non-significant for this group. Additionally, we see that co-agglomeration is increasing in education, with households with two college-educated spouses having higher average scores than households with two non-college-educated spouses. In contrast to the three-digit definition, there is no longer a statistically significant difference in co-agglomeration for female-breadwinner and male-breadwinner households, though the index is still higher on average for female-breadwinner households.

Table A-3: Two-Digit Co-Agglomeration Index Over Time, Educational Pairings, and Breadwinner Gender

| | 1980 | 1990 | 2000 | 2006-2010 | 2011-2015 | 2016-2019 | Change 1980-2019 |
|---|---|---|---|---|---|---|---|
| Across Occupations | 0.079 | 0.052 | 0.044 | 0.059 | 0.058 | 0.070 | -0.009 |
| Full Sample | 0.064 | 0.076 | 0.088 | 0.092 | 0.104 | 0.115 | 0.051 |
| Both Spouses College | 0.135 | 0.164 | 0.232 | 0.195 | 0.256 | 0.284 | 0.149** |
| Husband College, Wife Non-College | 0.089 | 0.079 | 0.108 | 0.050 | 0.068 | 0.065 | -0.024 |
| Husband Non-College, Wife College | 0.017 | 0.015 | 0.030 | 0.018 | 0.007 | -0.001 | -0.017 |
| Husband Non-College, Wife Non-College | 0.049 | 0.062 | 0.046 | 0.070 | 0.060 | 0.060 | 0.011 |
| *Diff. Both College to No College* | 0.086 | 0.102+ | 0.185*** | 0.124* | 0.195** | 0.224** | 0.137* |
| Husband Breadwinner | 0.062 | 0.082 | 0.096 | 0.116 | 0.128 | 0.134 | 0.047 |
| Wife Breadwinner | 0.075 | 0.081 | 0.082 | 0.093 | 0.112 | 0.128 | 0.053 |
| *Difference by Breadwinner Gender* | -0.013 | -0.006 | 0.008 | -0.001 | -0.011 | -0.020 | -0.007 |

Notes: This table reports the mean value of the co-agglomeration index calculated using two-digit occupations over time for the full married sample, by education of spouses, and by gender of the primary earner. Difference across groups calculated by regressing the index on an indicator for group-type. Stars indicate significance of difference across gender with standard errors (not reported) clustered at the occupation level: $\dagger p < 0.10$ * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$.

Appendix Table A-4 reports the results of the primary regression analysis using the two-digit indices, comparable to Table 3. While the magnitudes of the correlations differ slightly, they do not differ substantively. Being in a co-agglomerated household is associated with higher earnings, and this association is stronger for women and secondary earners regardless of gender.

### A.2.2 Current Population Survey

My primary data set combines three Decennial Censuses (1980, 1990, and 2000) and the American Community Survey (2006 onward) because the Census no longer collects occupation as part of the Decennial Census

Table A-4: Relationship between Two-Digit Occupation Locational Compatibility and Earnings, By Gender and Breadwinner Type

| | (1)<br>All Men | (2)<br>All Women | (3)<br>Prim. Earner Men | (4)<br>Sec. Earner Women | (5)<br>Sec. Earner Men | (6)<br>Prim. Earner Women |
|---|---|---|---|---|---|---|
| Coag. Index | 0.00748*** | 0.0237*** | -0.00197 | 0.0290*** | 0.0254*** | 0.000234 |
| | (0.00179) | (0.00473) | (0.00163) | (0.00525) | (0.00409) | (0.00325) |
| Aggl. Index, Men | -0.0373 | -0.0228*** | -0.0339 | -0.0301*** | -0.0218 | -0.0191*** |
| | (0.0457) | (0.00572) | (0.0352) | (0.00734) | (0.0556) | (0.00451) |
| Aggl. Index, Women | 0.00528 | 0.0122 | -0.0101** | 0.0288 | 0.0113 | -0.0164 |
| | (0.00356) | (0.0312) | (0.00324) | (0.0249) | (0.00781) | (0.0245) |
| Observations | 10,469,126 | 10,469,126 | 7,796,796 | 7,796,796 | 2,672,330 | 2,672,330 |

Standard errors clustered at the occupation level; $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Notes. This table reports regressions of log income (in real 2014$) on the two-digit occupation index of co-agglomeration ($\gamma$), the indices of agglomeration for each gender ($\theta_M$ and $\theta_F$), demographic controls including dummies for own and spouses' education, interaction dummies for spousal education, a quadratic of own and spousal age, dummies for whether own or spouse's race is white, number of children and fixed effects for state of birth, commuting zone, occupation of each spouse, and year. Column 1 and 2 are for all married men and women, respectively. Column 3 and 4 are restricted to households in which the husband is the primary earner, defined as making more than 50% of household income. Column 5 and 6 are restricted to households in which the wife is the primary earner.

starting in 2010 as part of the switch to the short-form-only Census. Given that there is a sharp increase in my measures of agglomeration starting 2006, one might be concerned that this increase is attributable to the change in survey rather than actual trends in occupational concentration. I therefore replicate my results using the March Annual Social Economic Supplements of IPUMS Current Population Survey (CPS-ASEC). The CPS-ASEC is an annual, nationally representative survey of approximately 90,000 households with information on occupation, earnings, and metropolitan area. The smaller size of the CPS-ASEC makes it unsuitable for the primary analyses for two reasons. First, the smallest area of geography is metropolitan area meaning that unlike the Census and ACS in which I can include those in non-metropolitan areas in the analysis, I cannot map all CPS respondents onto a commuting zone. Second, there are too few observations of each occupation in each metropolitan area to be confident in the accuracy of the calculation of co-agglomeration measure, resulting in implausibly large or small values of the co-agglomeration index for some occupation pairings. However, the CPS is continuous across all years, allowing me to check if the increases in concentration hold in a data set that does not change its survey in the mid-2000s. To adjust for the issue of small sample size skewing the measures to be implausibly large magnitudes, the follow replications are run on a sample which drops the top and bottom 5% of the sample in terms of co-agglomeration.

Appendix Table A-5 reports trends over time in agglomeration based on three-digit occupations and metropolitan areas calculated in the CPS. To keep the results comparable to those in Table 1, I report the average value in each decade corresponding the Decennial Censuses and each five-year span corresponding to the ACS periods. As before, we see that occupations are increasingly concentrated over time, and while the increase in concentration between 2000 and 2006-2010 is not as pronounced as in the primary data, there is still an increase, with the measure showing a large jump up from 1980 to 1990, similar values in 1990 and 2000, another jump up between 2000 and 2006-2010, and similar values throughout the mid 2000s and

2010s. The gender gap is not significant in this data set, in part due to the smaller sample size, but is still positive and consistent with men being in more concentrated occupations than women.

Table A-5: CPS Occupation Locational Gini Over Time, Gender, and Educational Groups

| | 1980 | 1990 | 2000 | 2006-2010 | 2011-2015 | 2016-2019 | Change 1980-2019 |
|---|---|---|---|---|---|---|---|
| Across Occupations | 0.189 | 0.218 | 0.211 | 0.225 | 0.234 | 0.230 | 0.041*** |
| Across Men | 0.154 | 0.174 | 0.169 | 0.180 | 0.191 | 0.186 | 0.032*** |
| Across Women | 0.147 | 0.169 | 0.163 | 0.174 | 0.182 | 0.180 | 0.032*** |
| *Gender Gap* | 0.007 | 0.005 | 0.006 | 0.006 | 0.009+ | 0.006 | -0.001 |
| College Men | 0.156 | 0.175 | 0.168 | 0.176 | 0.185 | 0.183 | 0.027*** |
| Non-College Men | 0.154 | 0.174 | 0.169 | 0.181 | 0.192 | 0.186 | 0.033*** |
| *College Gap, Men* | 0.003 | 0.001 | -0.001 | -0.005 | -0.006 | -0.003 | -0.006+ |
| College Women | 0.154 | 0.173 | 0.164 | 0.174 | 0.179 | 0.177 | 0.024*** |
| Non-College Women | 0.147 | 0.168 | 0.163 | 0.174 | 0.182 | 0.180 | 0.034*** |
| *College Gap, Women* | 0.007 | 0.005 | 0.001 | -0.001 | -0.003 | -0.003 | -0.010+ |

Notes: This table reports the mean value of the three-digit occupation by metropolitan area locational Gini for different sub-groups by year with column 1-3 reporting average values for Current Population Survey years averaged across each decade and columns 4-6 reporting means across five-year groupings meant to match the American Community Survey years. Panel A reports mean by occupation, unweighted by number of workers within an occupation. Panel B reports means by gender, weighted using IPUMS person weights; Panel C and D report the same separately for those with a college degree versus those without. Stars indicated significance of difference across years/gender/education-level, calculated by regressing concentration on gender,year, or education with standard errors (not reported) clustered at the occupation level: $\dagger p < 0.10$ * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$.

Appendix Table A-6 reports trends over time in the co-agglomeration index for the full sample, by education of spouses, and by gender of breadwinner (comparable to Table 2). While the increase in the co-agglomeration overall is only marginally significant, the general trend in the full sample is the same: an upward trend in co-agglomeration and higher co-agglomeration among couples with two college degrees.

Table A-6: Co-Agglomeration Index in CPS Over Time, Educational Pairings, and Breadwinner Gender

| | 1980 | 1990 | 2000 | 2006-2010 | 2011-2015 | 2016-2019 | Change 1980-2019 |
|---|---|---|---|---|---|---|---|
| Across Occupations | 0.086 | 0.042 | 0.042 | 0.084 | 0.063 | 0.094 | 0.009 |
| Full Sample | 0.050 | 0.037 | 0.055 | 0.076 | 0.074 | 0.102 | 0.052+ |
| Both Spouses College | 0.194 | 0.191 | 0.213 | 0.260 | 0.231 | 0.239 | 0.045 |
| Husband College, Wife Non-College | 0.111 | 0.089 | 0.083 | 0.141 | 0.106 | 0.135 | 0.023 |
| Husband Non-College, Wife College | 0.056 | 0.041 | 0.044 | 0.067 | 0.049 | 0.078 | 0.022 |
| Husband Non-College, Wife Non-College | 0.032 | 0.021 | 0.042 | 0.055 | 0.058 | 0.083 | 0.051 |
| *Diff. Both College to No College* | 0.161* | 0.170** | 0.171** | 0.205** | 0.173** | 0.156** | -0.006 |
| Husband Breadwinner | 0.049 | 0.034 | 0.053 | 0.076 | 0.072 | 0.102 | 0.053+ |
| Wife Breadwinner | 0.055 | 0.044 | 0.059 | 0.075 | 0.077 | 0.101 | 0.046+ |
| *Difference by Breadwinner Gender* | -0.006 | -0.010 | -0.006 | 0.001 | -0.005 | 0.001 | 0.007 |

Notes: This table reports the mean value of the co-agglomeration index using CPS data over time for the full married sample, by education of spouses, and by gender of the primary earner. Difference across groups calculated by regressing the index on an indicator for group-type. Stars indicate significance of difference across gender with standard errors (not reported) clustered at the occupation level: $\dagger p < 0.10$ * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$.

Appendix Table A-7 reports the results of the primary regression analysis using the CPS sample, comparable to Table 3. While the magnitudes of the correlations differ slightly, they do not differ substantively. Being in a co-agglomerated household is associated with higher earnings and this association is stronger for women and secondary earners regardless of gender.

Table A-7: Relationship between CPS Occupation Locational Compatibility and Earnings, By Gender and Breadwinner Type

| | (1) All Men | (2) All Women | (3) Prim. Earner Men | (4) Sec. Earner Women | (5) Sec. Earner Men | (6) Prim. Earner Women |
|---|---|---|---|---|---|---|
| Coag. Index | -0.00163 | 0.0156*** | -0.00607*** | 0.0192*** | 0.0309*** | -0.00771** |
| | (0.00248) | (0.00354) | (0.00153) | (0.00416) | (0.00661) | (0.00278) |
| Aggl. Index, Men | -0.102** | 0.0161 | -0.0725** | -0.00773 | -0.0721 | -0.0262 |
| | (0.0304) | (0.0235) | (0.0225) | (0.0265) | (0.0572) | (0.0233) |
| Aggl. Index, Women | -0.0411* | -0.0542 | -0.0412** | -0.0828 | 0.0339 | -0.0121 |
| | (0.0205) | (0.0635) | (0.0130) | (0.0604) | (0.0535) | (0.0436) |
| Observations | 267,772 | 267,772 | 199,718 | 199,718 | 68,052 | 68,052 |

Standard errors clustered at the occupation level; $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Notes. This table reports regressions of log income (in real 2014$) in the CPS on the CPS occupation index of co-agglomeration ($\gamma$), the CPS indices of agglomeration for each gender ($\theta_M$ and $\theta_F$), demographic controls including dummies for own and spouse's education, interaction dummies for spousal education, a quadratic of own and spousal age, dummies for whether own or spouse's race is white, number of children and fixed effects for state of birth, metropolitan area, occupation of each spouse, and year. Column 1 and 2 are for all married men and women, respectively. Column 3 and 4 are restricted to households in which the husband is the primary earner, defined as making more than 50% of household income. Column 5 and 6 are restricted to households in which the wife is the primary earner.

### A.2.3 Consistent Occupation Groups

For the primary analyses, I use the definition of occupations created by IPUMS which standardizes occupations across time based on on the 1990 occupational codes, to allow for comparability across years of the Census. This measure is created by the Bureau of Labor Statistics who trace the proportion of each occupation that broke into more specific occupations or became a larger occupation across Censuses and then created aggregated occupational categories based on these proportions, described further in Meyer et al. (2005). While this harmonized measure allows for comparability across time, one might be concerned that modern occupations are substantively very different from occupations in the 1990s. I therefore re-run all analyses using only occupations which have a consistent single-code across all periods (i.e., if the standardized occupation code corresponds to zero occupations in 2000 or to multiple occupations in 2000 but only one in 1980, I drop that occupation). This drops approximately half of the observations.

Appendix Table A-8 reports trends over time in agglomeration based on consistent single-code three-digit occupations. The overall trends are unchanged from the main analysis. The increase in agglomeration of occupations over time is slightly stronger than in the main sample, though the differences across sample are not statistically significant. In both analyses, women are more likely to be in less concentrated occupations than men and this is true across all decades, education levels, and marital status.

Table A-8: Single Code Three-Digit Occupation Locational Gini Over Time, Gender, and Educational Groups

| | 1980 | 1990 | 2000 | 2006-2010 | 2011-2015 | 2016-2019 | Change 1980-2019 |
|---|---|---|---|---|---|---|---|
| Across Occupations | 0.206 | 0.211 | 0.206 | 0.260 | 0.268 | 0.265 | 0.053*** |
| Across Men | 0.158 | 0.158 | 0.149 | 0.197 | 0.209 | 0.210 | 0.051*** |
| Across Women | 0.115 | 0.115 | 0.106 | 0.152 | 0.163 | 0.167 | 0.052*** |
| *Gender Gap* | 0.043** | 0.043** | 0.043*** | 0.045*** | 0.046*** | 0.042*** | -0.003 |
| College Men | 0.147 | 0.154 | 0.144 | 0.186 | 0.201 | 0.201 | 0.055*** |
| Non-College Men | 0.165 | 0.160 | 0.152 | 0.204 | 0.215 | 0.215 | 0.051*** |
| *College Gap, Men* | -0.018 | -0.006 | -0.008 | -0.017 | -0.013 | -0.014 | 0.004 |
| College Women | 0.097 | 0.105 | 0.102 | 0.146 | 0.158 | 0.162 | 0.066*** |
| Non-College Women | 0.121 | 0.118 | 0.108 | 0.156 | 0.167 | 0.172 | 0.050*** |
| *College Gap, Women* | -0.025 | -0.013 | -0.006 | -0.010 | -0.009 | -0.009 | 0.015 |

Notes: This table reports the mean value of the three-digit occupation locational Gini, restricted to occupations with a consistent single code, for different sub-groups by year with column 1-3 reporting average values for each Decennial Census year and columns 4-6 reporting means across five-year groupings using American Community Survey year. Panel A reports mean by occupation, unweighted by number of workers within an occupation. Panel B reports means by gender, weighted using IPUMS person weights; Panel C and D report the same separately for those with a college degree versus those without. Stars indicate significance of difference across years/gender/education-level, calculated by regressing concentration on gender, year, or education with standard errors (not reported) clustered at the occupation level: $\dagger p < 0.10$ * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$.

Appendix Table A-9 reports trends over time in the co-agglomeration index restricted to occupations that have a consistent single code. These occupations are more co-agglomerated than the full set of occupations, with the average level of the index being about twice that of the primary specification and the growth in the index being higher. As in the primary specification, co-agglomeration is growing over time, higher for those with a college degree, and higher for households with a female breadwinner. These results suggest that the growth in co-agglomeration is not attributable to changes in the number of occupations under a code heading driving increased joint concentration.

Table A-9: Co-Agglomeration Index in Single Code Three-Digit Occ. Over Time, Educational Pairings, and Breadwinner Gender

| | 1980 | 1990 | 2000 | 2006-2010 | 2011-2015 | 2016-2019 | Change 1980-2019 |
|---|---|---|---|---|---|---|---|
| Across Occupations | 0.086 | 0.042 | 0.042 | 0.084 | 0.063 | 0.094 | 0.009 |
| Full Sample | 0.050 | 0.037 | 0.055 | 0.076 | 0.074 | 0.102 | 0.052+ |
| Both Spouses College | 0.194 | 0.191 | 0.213 | 0.260 | 0.231 | 0.239 | 0.045 |
| Husband College, Wife Non-College | 0.111 | 0.089 | 0.083 | 0.141 | 0.106 | 0.135 | 0.023 |
| Husband Non-College, Wife College | 0.056 | 0.041 | 0.044 | 0.067 | 0.049 | 0.078 | 0.022 |
| Husband Non-College, Wife Non-College | 0.032 | 0.021 | 0.042 | 0.055 | 0.058 | 0.083 | 0.051 |
| *Diff. Both College to No College* | 0.161* | 0.170** | 0.171** | 0.205** | 0.173** | 0.156** | -0.006 |
| Husband Breadwinner | 0.049 | 0.034 | 0.053 | 0.076 | 0.072 | 0.102 | 0.053+ |
| Wife Breadwinner | 0.055 | 0.044 | 0.059 | 0.075 | 0.077 | 0.101 | 0.046+ |
| *Difference by Breadwinner Gender* | -0.006 | -0.010 | -0.006 | 0.001 | -0.005 | 0.001 | 0.007 |

Notes: This table reports the mean value of the co-agglomeration index using consistent single-code three-digit occupations over time for the full married sample, by education of spouses, and by gender of the primary earner. Difference across groups calculated by regressing the index on an indicator for group-type. Stars indicate significance of difference across gender with standard errors (not reported) clustered at the occupation level: †$p < 0.10$ * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$.

Appendix Table A-10 reports the results of the primary regression analysis using the consistently coded occupation sample, comparable to Table 3. As was true with the prior measures, using an alternative occupation decision does not substantively change the conclusions of the analysis: locational compatibility is positively associated with higher earnings for women and secondary earners.

Table A-10: Relationship between Consistent Occupation Locational Compatibility and Earnings, By Gender and Breadwinner Type

| | (1) All Men | (2) All Women | (3) Prim. Earner Men | (4) Sec. Earner Women | (5) Sec. Earner Men | (6) Prim. Earner Women |
|---|---|---|---|---|---|---|
| Coag. Index | 0.00251 | 0.0153*** | -0.00181 | 0.0180*** | 0.0218*** | 0.000472 |
| | (0.00165) | (0.00304) | (0.00153) | (0.00362) | (0.00464) | (0.00195) |
| Aggl. Index, Men | -0.0591* | -0.00323 | -0.0350** | -0.0135 | -0.0518 | -0.0209* |
| | (0.0233) | (0.00741) | (0.0118) | (0.00869) | (0.0363) | (0.00923) |
| Aggl. Index, Women | -0.00513 | -0.00612 | -0.0114** | -0.00126 | -0.00338 | -0.00423 |
| | (0.00482) | (0.0205) | (0.00387) | (0.0191) | (0.00905) | (0.0171) |
| Observations | 2114482 | 2114482 | 1506764 | 1506764 | 607715 | 607715 |

Standard errors clustered at the occupation level; $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Notes. This table reports regressions of log income (in real 2014$) in the Census and ACS of the consistent occupation index of co-agglomeration ($\gamma$), the consistent indices of agglomeration for each gender ($\theta_M$ and $\theta_F$), demographic controls including dummies for own and spouse's education, interaction dummies for spousal education, a quadratic of own and spousal age, dummies for whether own or spouse's race is white, number of children and fixed effects for state of birth, metropolitan area, occupation of each spouse, and year. Column 1 and 2 are for all married men and women, respectively. Column 3 and 4 are restricted to households in which the husband is the primary earner, defined as making more than 50% of household income. Column 5 and 6 are restricted to households in which the wife is the primary earner.

### A.2.4 Sensitivity of Locational Gini: Omitting Small CZs and Using HHI

Throughout the paper, I use Locational Ginis and the co-agglomeration index as measures of how locational frictions created by concentration can constrain couples. Both the locational Gini and the co-agglomeration are capturing whether an occupation or occupation pairing is over-represented or under-represented on average across commuting zones. Both measures include as part of the measure a component that re-scales the share of workers in an occupation in a given CZ relative to the overall share of workers in that CZ. This has the benefit of better being able to capture occupations that are geographically constrained through concentration in small or medium-sized labor markets. A measure such as the Herfindahl-Hirschman Index (HHI) which sums squared shares without re-scaling will naturally assign a higher level of concentration for occupations that are over-represented in large urban areas. While this will capture whether an occupation has a lot of options in major urban areas, it won't as easily measure whether an occupation is common in only a few medium or small sized labor markets.

To illustrate this, I calculate the HHI for each occupation and compare the two measures. HHI for an occupation $k$ is defined as:

$$HHI_k = \sum_{n=1}^{N_{CZ}} \left( \frac{\text{Num. of Workers in Occupation } k \text{ in CZ } n}{\text{Num. of Workers in Occupation } k} \right)^2$$

One example of an occupation that HHI will mis-categorize as more concentrated than it is is accountants and auditors. Accountants and auditors are white-collar professions that are spread fairly evenly across the country proportional to the population density of a given labor market, which in the Locational Gini measure means that it is at the 6th percentile and would be categorized as very disperse. However, this occupation is at the 67th percentile of the HHI distribution. This is because population is concentrated, meaning that occupations which occur at a constant rate relative to population will get categorized as concentrated even if being an accountant does not particularly constrain one's choice of where to live given that such jobs exist in most labor markets. Conversely, occupations related to natural resource extraction which tend to be in non-urban areas – which are by definition locationally constrained to labor markets with the natural resource and should score high on the index– are under-estimated with HHI. For example, timber, logging, and forestry workers are at the 71st percentile of the locational Gini distribution but are at the 3rd percentile of HHI. These miscategorizations demonstrate that HHI does not fully capture locational frictions that would make an occupation more or less compatible with a spouses' occupation.

However, one could argue that this isn't the right metric for locational frictions. While it may be the case that accountants are found in most labor markets, one could argue that a large urban market with many accountant jobs but a low relative proportion of accountant jobs is a preferable market to a small market with a similar relative rate of accountants but a lower absolute number. A locational Gini will be particularly misspecified under this interpretation if there are small commuting zones with high relative rates of an occupation. Therefore, I re-calculate the agglomeration measure omitting commuting zones below the 5th percentile of the employed population distribution and re-calculate the trends over time in agglomeration using this measure. I also re-run the primary regression specification omitting those living in these commuting zones and using this re-calculated agglomeration measure. Table A-11 reports the trends over time in the agglomeration measure exclusing small CZs and Table A-12 reports the results of the regression. The results are not substantively different from the results in the main text.

Table A-11: Locational Gini Excluding Small CZs, Over Time, Gender, and Educational Groups

| | 1980 | 1990 | 2000 | 2006-2010 | 2011-2015 | 2016-2019 | Change 1980-2019 |
|---|---|---|---|---|---|---|---|
| Across Occupations | 0.197 | 0.201 | 0.191 | 0.244 | 0.254 | 0.251 | 0.054*** |
| Across Men | 0.134 | 0.131 | 0.128 | 0.166 | 0.177 | 0.177 | 0.043*** |
| Across Women | 0.114 | 0.110 | 0.104 | 0.144 | 0.156 | 0.159 | 0.046*** |
| *Gender Gap* | 0.021+ | 0.021* | 0.024** | 0.021* | 0.021* | 0.018* | -0.003 |
| College Men | 0.134 | 0.135 | 0.133 | 0.166 | 0.178 | 0.179 | 0.045*** |
| Non-College Men | 0.135 | 0.130 | 0.126 | 0.166 | 0.176 | 0.177 | 0.042*** |
| *College Gap, Men* | -0.001 | 0.005 | 0.008 | 0.000 | 0.002 | 0.002 | 0.003 |
| College Women | 0.104 | 0.110 | 0.107 | 0.146 | 0.159 | 0.162 | 0.058*** |
| Non-College Women | 0.116 | 0.110 | 0.103 | 0.143 | 0.154 | 0.158 | 0.041*** |
| *College Gap, Women* | -0.012 | -0.000 | 0.004 | 0.003 | 0.005 | 0.004 | 0.017+ |

Notes: This table reports the mean value of the three-digit occupation locational Gini, restricted to commuting zones larger than the 5th percentile of population, for different sub-groups by year with column 1-3 reporting average values for each Decennial Census year and columns 4-6 reporting means across five-year groupings using American Community Survey year. Panel A reports mean by occupation, unweighted by number of workers within an occupation. Panel B reports means by gender, weighted using IPUMS person weights; Panel C and D reports the same separately for those with a college degree versus those without. Stars indicated significance of difference across years/gender/education-level, calculated by regressing concentration on gender,year, or education with standard errors (not reported) clustered at the occupation level: †$p < 0.10$ * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$.

Table A-12: Relationship between Occupation Locational Compatibility and Earnings Excluding Small CZs, By Gender and Breadwinner Type

| | (1) All Men | (2) All Women | (3) Prim. Earner Men | (4) Sec. Earner Women | (5) Sec. Earner Men | (6) Prim. Earner Women |
|---|---|---|---|---|---|---|
| Coag. Index | 0.006*** | 0.018*** | -0.001 | 0.022*** | 0.024*** | 0.001 |
| | (0.001) | (0.003) | (0.001) | (0.003) | (0.003) | (0.001) |
| Aggl. Index, Men | -0.031* | -0.014** | -0.024* | -0.020*** | -0.022 | -0.010** |
| | (0.015) | (0.004) | (0.012) | (0.005) | (0.018) | (0.004) |
| Aggl. Index, Women | 0.001 | 0.024 | -0.002 | 0.026 | $0.009^{+}$ | 0.004 |
| | (0.002) | (0.027) | (0.002) | (0.025) | (0.005) | (0.014) |
| Observations | 9,969,367 | 9,969,367 | 7,393,398 | 7,393,398 | 2,575,966 | 2,575,966 |

Standard errors clustered at the occupation level; $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Notes. This table reports regressions in a sample exclusing the bottom 5th percentile of CZs in terms of population. I regress log income (in real 2014$) on the occupation index of co-agglomeration ($\gamma$), the indices of agglomeration for each gender ($\theta_M$ and $\theta_F$), demographic controls including dummies for own and spouse's education, interaction dummies for spousal education, a quadratic of own and spousal age, dummies for whether own or spouse's race is white, number of children and fixed effects for state of birth, metropolitan area, occupation of each spouse, and year. Column 1 and 2 are for all married men and women, respectively. Column 3 and 4 are restricted to households in which the husband is the primary earner, defined as making more than 50% of household income. Column 5 and 6 are restricted to households in which the wife is the primary earner.

## A.3 Calculating correlates of agglomeration

In section 5.3, I test whether the locational Gini is correlated with three occupational characteristics: job flexibility, routine task intensity, and social meaning.

To quantify job flexibility, I follow the Goldin (2014) measure of job flexibility, expanded to cover a broader set of occupations including many lower-paying ones not covered in the original analysis. Specifically, I build an occupation-level index as the average of five normalized *NET attributes: "Time pressure", "Contact with others", "Establishing and maintaining interpersonal relationships", "Structured vs. unstructured work", and "Freedom to make decisions". Each characteristic is normalized to have mean 0 and standard deviation 1. I use O*NET responses from 2019 and crosswalk them to using the O*NET taxonomy and the SOC–Census occupational crosswalk from IPUMS to map it to 1990 agglomeration index at the three-digit OCC1990 level. I compute weighted averages based on the number of observations in the source categories.

To measure routine task intensity, I use the measure described in Autor and Dorn (2013) which combines routine, abstract, and manual task intensities into an occupation-level RTI index anchored in 1980. I then map 1980 Census occupation codes to OCC1990 and merge it to the 1980 agglomeration index at the three-digit OCC1990 level.

My measure of social meaning by occupation is based on the American Working Conditions Survey conducted by RAND, described in Maestas et al. (2023). Using the 2015 and 2018 waves, I build an occupation-level index as the average of six questions: "Opportunities to fully use your talents", "The feeling of making a positive impact on your community and society", "A sense of personal accomplishment", "Goals that you aspire to", "The satisfaction of work well done", and "The feeling of doing useful work". I standardize each item to mean 0 and standard deviation 1, then average them to form an occupation-level index, oriented so that lower (more negative) values indicate greater social meaning. Because the survey sample is small and cell sizes for responses at the 3 digit level do not meet minimum cell sizes of 25 responses, I construct the index at the 2-digit SOC level and then merge it to the 2015 and 2018 two-digit SOC agglomeration index in 2015.

## A.4 Additional Tables and Figures

Table A-13: Relationship between Locational Compatibility and Earnings, By Gender and Education Level

| | (1)<br>College Men | (2)<br>Non-College Men | (3)<br>College Women | (4)<br>Non-College Women |
|---|---|---|---|---|
| Coag. Index | 0.006** | 0.005** | 0.020*** | 0.014*** |
| | (0.002) | (0.002) | (0.004) | (0.003) |
| Aggl. Index, Men | 0.005 | -0.024 | -0.016** | -0.005 |
| | (0.016) | (0.017) | (0.006) | (0.005) |
| Aggl. Index, Women | -0.006* | 0.001 | 0.037 | 0.032 |
| | (0.003) | (0.003) | (0.028) | (0.026) |
| Observations | 2,638,345 | 6,909,982 | 2,766,915 | 6,747,465 |

Standard errors clustered at the occupation level; $^{+}$ $p < 0.10$, $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$
Notes. This table reports regressions of log income (in real 2014$) on the index of co-agglomeration ($\gamma$), the indices of agglomeration for each gender ($\theta_M$ and $\theta_F$), demographic controls including dummies for own and spouse's education, interaction dummies for spousal education, a quadratic of own and spousal age, dummies for whether own or spouse's race is white, number of children, and fixed effects for state of birth, commuting zone, occupation of each spouse, and year. Column 1 and 2 are for college-educated and non-college educated men, respectively. Column 3 and 4 are for college-educated and non-college educated women.

Table A-14: Relationship between Locational Compatibility and Earnings, By Gender and Occupational Licensing

| | (1) Licensed Occ., Men | (2) Non-Licensed Occ., Men | (3) Licensed Occ., Women | (4) Non-Licensed Occ., Women |
|---|---|---|---|---|
| Coag. Index | 0.019*** | 0.006*** | 0.027** | 0.017*** |
| | (0.003) | (0.001) | (0.00) | (0.003) |
| Aggl. Index, Men | 0.068 | -0.035* | -0.005 | -0.013** |
| | (0.052) | (0.017) | (0.007) | (0.005) |
| Aggl. Index, Women | -0.009 | -0.005+ | 0.002 | 0.040 |
| | (0.010) | (0.002) | (0.030) | (0.032) |
| Observations | 793,686 | 8,754,643 | 2,009,912 | 7,504,480 |

Standard errors clustered at the occupation level; + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes. This table reports regressions of log income (in real 2014$) on the index of co-agglomeration ($\gamma$), the indices of agglomeration for each gender ($\theta_M$ and $\theta_F$), demographic controls including dummies for own and spouse's education, interaction dummies for spousal education, a quadratic of own and spousal age, dummies for whether own or spouse's race is white, number of children, and fixed effects for state of birth, commuting zone, occupation of each spouse, and year. Column 1 and 2 are for licensed occupations and non-licensed occupations for men, respectively. Column 3 and 4 are the same for women.

Table A-15: Coefficients on Co-agglomeration, by Time Period, Gender, and Breadwinner

| | Panel A: 1980-2000 | | | | | |
|---|---|---|---|---|---|---|
| | All Men | All Women | Prim. Earner Men | Sec. Earner Women | Sec. Earner Men | Prim. Earner Women |
| Coag. Index | 0.009*** | 0.030*** | 0.002 | 0.033*** | 0.035*** | 0.007** |
| | (0.002) | (0.004) | (0.001) | (0.005) | (0.004) | (0.002) |
| Aggl. Index, Men | 0.024 | -0.001 | 0.011 | 0.009 | 0.022 | 0.016 |
| | (0.028) | (0.006) | (0.024) | (0.007) | (0.031) | (0.010) |
| Aggl. Index, Women | -0.018*** | 0.097 | 0.001 | 0.073 | 0.013 | 0.046 |
| | (0.004) | (0.077) | (0.003) | (0.064) | (0.013) | (0.042) |
| Observations | 5,511,145 | 5,494,594 | 4,327,315 | 4,308,721 | 1,183,828 | 1,185,870 |
| | Panel B: 2006-2019 | | | | | |
| | All Men | All Women | Prim. Earner Men | Sec. Earner Women | Sec. Earner Men | Prim. Earner Women |
| Coag. Index | 0.006*** | 0.018*** | -0.001 | 0.021*** | 0.023*** | 0.002 |
| | (0.001) | (0.003) | (0.001) | (0.003) | (0.004) | (0.002) |
| Aggl. Index, Men | -0.004 | 0.004 | -0.003 | 0.003 | -0.0004 | 0.004 |
| | (0.011) | (0.009) | (0.008) | (0.011) | (0.019) | (0.00) |
| Aggl. Index, Women | 0.016** | 0.005 | 0.007+ | 0.006 | 0.025* | 0.003 |
| | (0.005) | (0.013) | (0.004) | (0.015) | (0.010) | (0.011) |
| Observations | 4,037,190 | 4,019,799 | 2,809,038 | 2,788,601 | 1,228,150 | 1,231,198 |

Standard errors in parentheses; + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes. This table reports the coefficients from a regression of log earnings on the index of co-agglomeration, the indices of agglomeration for each gender, demographic controls including a quadratic of own and spousal age, dummies for own and spouse's education, interaction dummies for spousal education, dummies for whether own or spouse's race is white, number of children, and fixed effects for state of birth, commuting zone, major of each spouse, and year. Panel A is restricted to the Decennial Census samples (1980, 1990, and 2000) and Panel B is restricted to the ACS samples (2006-2019). Primary earner is defined based on which spouse makes more than 50% of household income. Standard errors clustered at the own occupation level.