Migration and Proximity Preference in Fertility Decision

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November 10, 2024

Abstract

This paper examines the role of spatial distance from migrants' hometowns in shaping fertility and mobility outcomes. Using U.S. survey data, I demonstrate that the likelihood of having children declines with increasing distance from one's place of origin, suggesting a "proximity preference" in fertility behavior. This preference appears driven by the reduced access to familial support and increased insecurity faced by long-distance migrants, factors that may discourage childbearing. To quantify the impact of this preference on fertility and mobility, I develop a spatial equilibrium model with endogenous fertility decisions. Counterfactual experiments reveal that proximity preference exerts a substantial influence on both mobility and fertility choices, with skilled workers exhibiting a more pronounced proximity preference in fertility limiting their fertility and mobility outcomes. Additionally, my analysis estimates that changes in migration patterns account for approximately 5% of the decline in fertility rates observed since 2000.

1 Introduction

Raising children is a demanding task that requires substantial time and resources, often supplemented by support from extended family. For long-distance migrants, however, this support is limited, as shown in Figure 1, which illustrates the proportion of households with children by skill level across various origin-destination pairs. The figure indicates a decrease in the likelihood of having children as migration distance increases. Migrants moving far from their hometowns are less likely to receive intergenerational

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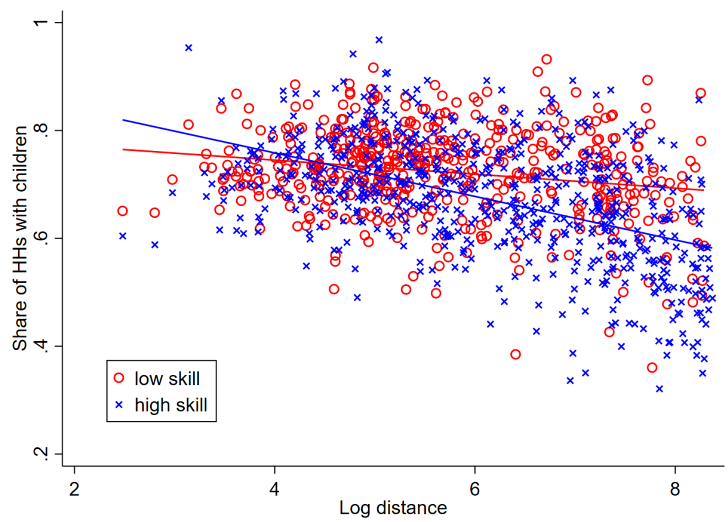


Figure 1: Distance and Child-rearing Share by Skill Levels
Note: Each unit is a state-of-origin by destination city pair, where cities are defined as metropolitan statistical areas (MSA) in 2013. Distance of a unit is the distance in killometer between the population centroid of its state-of-origin and the centroid of its destination MSA. Shares of households with children are obtained by calculating the percentage of women age 35-39 who are residing with their children. High skill refers to individuals who have completed four years of college education. For clarity, this figure restricts the units to those with at least 30 observations. Relaxing this restriction does not change the lines of best fit dramatically. Data: American Community Survey 5-Year Data (ACS 2015-2019).

time transfers, such as child care from their parents, which can discourage them from starting families due to heightened insecurity and lack of support. This phenomenon of distance-related discouragement from child-rearing creates what I term a "proximity preference" in fertility.

The existence of this proximity preference has implications in both fertility and mobility: an improvement in mobility that encourages long-distance migration could drive down fertility, whereas greater extended family support that encourages fertility could bind workers closer to their hometown. To access the extent this proximity preference on fertility and mobility requires a spatial model with endogenous fertility decisions and a proximity preference in fertility.

This paper develops a static spatial equilibrium model that links migration distance to both destination and fertility decisions. Through counterfactual simulations, I demonstrate that proximity preference significantly influences both mobility and fertility. Moreover, the analysis reveals that skilled workers exhibit a stronger proximity preference in fertility, which imposes a greater constraint on their mobility across regions.

The structure of the paper is as follows. Section 2 documents the variation in fertility patterns across U.S. cities, providing descriptive evidence that supports the existence of proximity preference in fertility. Section 3 details the model, integrating fertility decisions into a static spatial equilibrium framework, inspired by the Rosen-Roback model (Rosen, 1979; Roback, 1982). This model incorporates a two-stage decision process: in the first stage, workers select a destination city, influenced by location-specific tastes and migration costs; in the second stage, they make fertility and consumption choices, with distance affecting fertility preferences. Given the observed differences in fertility behavior by skill level, the model also differentiates workers based on skill.

This study focuses on the extensive margin of fertility—the share of households with children—rather than the intensive margin, which considers the number of children per family. My modeling assumptions imply a positive correlation between child-rearing amenity and fertility, which might be at odds with the widely observed quantity-quality tradeoff in fertility. This trade-off suggests higher child-rearing amenities, such as a lower education cost, could increase the investment per child but decrease the overall amount of children. While this tradeoff is widely observed, it is presented mostly in studies discussing the intensive margin of fertility. Aaronson et al. (2014) notes the differences between two margins and argues that the quantity-quality tradeoff does not apply along the extensive margin of fertility. A lower education cost, for example, may decrease the quantity per child-rearing household due to substitution, but would also increase the share of households with at least one child due to lower cost.

In Section 4, I calibrate the model to reflect U.S. data, targeting population, child-rearing shares, rents, and wages across cities and skill levels. Section 5 presents the distribution of estimated child-rearing amenities and examines the influence of proximity preference on both fertility and mobility. The calibration reveals that high-rent cities tend to have lower child-rearing amenities, which in turn suppresses fertility.

The general equilibrium effects of proximity preference are explored through counterfactual scenarios that eliminate this preference in fertility. In both cases, removing proximity preference leads to increased long-distance migration and notable fertility changes, especially in cities with initially low fertility rates.

This paper is most closely related to a rapidly growing literature that uses a quantitative spatial model to study interregional labor mobility (for example, Caliendo et al. 2019, Fan 2019, Fan and Zou 2021, Giannone et al. 2019, Tombe and Zhu 2019). Most studies so far have summarized utility loss from migration into an overarching migration cost and remain agnostic of its composition. My contribution is to separately identify proximity preference in fertility, which would otherwise be summarized into the migration cost, and demonstrate its impact on mobility.

Proximity preference in fertility is closely related to the presence of intergenerational time transfer. The existing literature on this topic focus on time transfer in the form of grandparent-provided child care and find significant effects of having access to such care on the fertility and employment decisions of the second generation (Aassve et al. 2012, Cardia and Ng 2003, Compton and Pollak 2014, Eibich and Siedler 2020). While this intergenerational time transfer requires residing in proximity, few have accounted for its mobility restriction. García-Morán and Kuehn (2017) uses a two-region model to analyze the effect of the availability of grandparent-provided child care on fertility and mobility. They found that greater availability increases fertility and reduces mobility. In comparison, my model remains agnostic about the composition of proximity preference but allows for a richer multi-region geography. Similarly, I found that stronger proximity preference increases fertility and reduces mobility. My contribution is to extend the discussion on intergenerational time transfer to a multi-region setting.

2 Data and Evidences

2.1 Data

American Community Survey (ACS). For main analysis, I use Integrated Public Use Microdata Series (IPUMS) ACS 2015-2019 (Ruggles et al., 2021). ACS is a cross-sectional household survey managed by the U.S. Census Bureau that contains a representative one-percent sample each year. It provides a rich collection of information on the individual level and can identify Public Use Microdata Areas (PUMAs). IPUMS ACS is a streamlined version maintained by University of Minnesota. It features unified coding and additional constructed variables, one of which is Metropolitan Statistical Areas (MSAs). IPUMS ACS 2015-2019 identifies 258 MSAs. In this paper, cities are defined as MSAs.

ACS identifies the number of children currently living in each household. I use this information to infer individuals' fertility status. The model estimation requires fertility statistics on the city-level and on the origin-city-level. The timing of fertility is heterogeneous across regions. To accommodate the variation in timing, when calculating the fertility statistics, I restrict the sample to individuals between age 35-39. Individuals in this age window are likely to have given birth to first-born if they want kids and are not likely to have older kids that live outside of the household. For remaining statistics in the analysis, I use the sample of individuals age 25-45.

ACS identifies the state-level birthplace and MSA-level current residency of each individual. I use these information to construct migration measure. Throughout the paper, distances are defined only among state-of-origin by destination MSA pairs. Distance of a pair is the distance in killometer between the population centroid of its state-of-origin and the centroid of its destination MSA.

2.2 Data Pattern

Substantial variability of fertility exists across cities in the United States. A large share of the variation can be explained by the average rent of the city. Figure 2 plots the child-rearing household share on city-level average housing rent. The negative slope suggests cities with higher rent tend to have lower fertility. Since child-rearing household demands more housing, higher rent would discourage residents from having children.

In my model, child-rearing households would consume more housing indirectly. This allows my model to generate a negative correlation between fertility and rent. Moveover, my model exactly match the fertility pattern across cities by absorbing unexplained variations into child-rearing amenities.

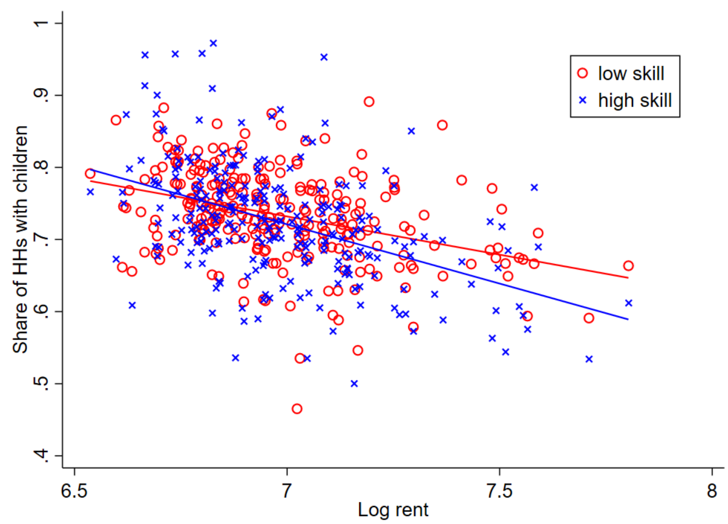


Figure 2: Rent and Child-rearing Share by Skill Levels

Note: Each unit is a metropolitan statistical area (MSA) in 2013. Shares of households with children are obtained by calculating the percentage of women age 35-39 who are residing with their children. Rent is calculated by averaging the rents paid by residents age 25-45. High skill refers to individuals who have completed four years of college education. Data: American Community Survey 5-Year Data (ACS 2015-2019).

Figure 1 suggests that migrants from distant locations would have lower fertility. I verify this pattern with an OLS regression by regressing the household child-rearing dummy on two distance dummies, along with origin and destination fixed effects. Table 1 presents the result. The two distance dummies exclude the group with a distance larger than 1000 km. The estimations indicate that fertility probability decreases over these three distance brackets.

My model allows distance from hometown to influence migrants' fertility decisions through a latent variable that governs the proximity preference in fertility. Model estimations suggest fertility utility decreases over a set of pre-defined distance brackets, which is consistent with the fertility pattern in Figure 1 and Table 1.

Table 1: Fertility and Distance from Origin by Skill Levels

	with children	
	low skill	high skill
	(1)	(2)
dist $<$ 500 km	0.0405	0.0553
	(0.00488)	(0.00434)
$500 \leq$ dist < 1000	0.0302	0.0332
	(0.00724)	(0.00652)
destination MSA FE	✓	✓
state-of-origin FE	✓	✓
N	137217	129873

Note: Sample is restricted to women age 35-39. Data from ACS 2015-2019.

3 Model

3.1 Environment

The model economy is static and consists of J regions, indexed by $j \in \{1, \ldots, J\}$.

Workers are heterogeneous in origins and skill levels $e \in \{L, H\}$. Workers make location, fertility, and consumption decisions in two stages. In the first stage, workers from different origins draw location-specific taste shocks and decide destination cities to settle. In the second stage, workers draw their fertility taste shocks and make fertility and consumption decisions. In this model, I assume workers make location choices before drawing their fertility tastes. Since individuals are more likely to migrate across cities when they are young and unmarried, they are likely to have made their location choices before getting married and drawing their fertility tastes.

3.2 Worker Preferences

3.2.1 The Location Choice of Workers

A worker with skill e from region o chooses d to maximize:

$$\max_{d} \left(\bar{U}^{e}_{o,d} - d^{e}_{o,d} + \varepsilon^{e}_{d} \right).$$

in which $d^{e}_{o,d}$ is the migration cost between regions o and d, $\bar{U}^{e}_{o,d}$ is the expected utility of a person from region o living in region d, and ϵ_d is an idiosyncratic location-specific utility draw generated from a Gumble distribution with mode 0 and dispersion parameter θ^e

Let the number of workers of born in region o be L^{e}_{o}, the number of people moving from region o to region d is $L^{e}_{o} \cdot \pi^{e}_{o,d}$ with $\pi^{e}_{o,d}$ defined by:

$$\pi^{e}_{o,d} = \frac{\exp\left(\theta^{e}\left(\bar{U}^{e}_{o,d} - d^{e}_{o,d}\right)\right)}{\sum_{d} \exp\left(\theta^{e}\left(\bar{U}^{e}_{o,d} - d^{e}_{o,d}\right)\right)}. \tag{1}$$

Given individuals' migration choices, the number of workers in location d is:

$$N^{e}_{d} = \sum_{o=1}^{J} \left[L^{e}_{o} \cdot \pi^{e}_{od} \right]. \tag{2}$$

3.2.2 Consumption and Fertility Decision

Consumption decisions of workers without children

Workers without children enjoy an indirect utility specified as follow:

$$V^{e,N}_{d} \equiv \max_{h} \log\left(A^{e}_{d} \cdot (I^{e}_{d} - r_{d} \cdot h)^{(1-\alpha)} \cdot h^{\alpha} \right).$$

where A^{e}_{d} is the amenities of city d to a worker with skill e, h is the quantity of housing consumed, r_d is the housing price, I^{e}_{d} is the total income to a worker with skill e, and α is the housing share in consumption.

Total income I^{e}_{d} is comprised of labor income W^{e}_{d} and government transfer t, that is,

$$I^{e}_{d} = W^{e}_{d} + t.$$

Under the optimal choice of h, the indirect utility is given by:

$$V_d^{e,N} = c_1 + \log\left(A_d^e\right) + \log\left(I_d^e\right) - \alpha \log\left(r_d\right). \tag{3}$$

in which $c_1 = \log\left((1-\alpha)^{1-\alpha}\alpha^{\alpha}\right)$ is a constant.

Consumption decisions of workers with children

Workers with children enjoy an indirect utility specified as follow:

$$V_{o,d}^{e,W} \equiv \max_{h,m} \log\left(A_d^e \cdot \kappa_{o,d}^e \cdot \left(I_d^e - r_d \cdot h - p_d^e \cdot m\right)^{(1-\alpha-\beta)} \cdot h^{\alpha} \cdot (m)^{\beta}\right).$$

where m is the quantity of child-rearing goods consumed, β is the child-rearing expenditure share, and $\kappa_{o,d}^e$ governments the proximity preference in fertility.

Since parents' education level could substantially impacts their investments in children and the composition of their child-related expenditures, I allow the amenity-adjusted price of child-rearing good p_d^e to vary by both location and skill to account for the different bundle prices workers with different education are facing.

Under the optimal choices of h and m, the indirect utility is:

$$V_{o,d}^{e,W} = c_2 + \log\left(A_d^e\right) + \log\left(\kappa_{o,d}^e\right) + \log\left(I_d^e\right) - \alpha \log\left(r_d\right) - \beta \log\left(p_d^e\right), \tag{4}$$

in which $c_2 = \log\left((1-\alpha-\beta)^{1-\alpha-\beta}\alpha^{\alpha}\beta^{\beta}\right)$ is a constant.

Fertility decisions of workers

In city d, workers decide whether to raise children or not. Specifically, the worker receives an idiosyncratic taste shock for each of the two choices and chooses one to maximize utility. I denote these shocks $\zeta^{e,W}$ for raising children and $\zeta^{e,N}$ for not raising children. These shocks are drawn from the Gumble distribution with dispersion parameter η^e. Concretely, workers solve the following optimization problem:

$$\max_{\{N,W\}} \left\{V_d^{e,N} + \zeta^{e,N}, V_{o,d}^{e,W} + \zeta^{e,W}\right\}$$

Then the expected utility of a person from region o living in region d can be written as:

$$\bar{U}_{o,d}^{e} = -\alpha \log r_d + \log A_d^e + \log I_d^e + \frac{\bar{\gamma}}{\eta^e} + \frac{1}{\eta^e} \log \left(\left[\exp\left(c_1\right)\right]^{\eta^e} + \left[\exp\left(c_2\right) \kappa_{o,d}^{e} \left(p_d^e\right)^{-\beta}\right]^{\eta^e} \right), \tag{5}$$

where $\bar{\gamma}$ is the Euler's constant.

The probability of households with children is

$$f_{o,d}^{e} = \frac{\left[\exp\left(c_2\right) \kappa_{o,d}^{e} \left(p_d^e\right)^{-\beta}\right]^{\eta^e}}{\left[\exp\left(c_1\right)\right]^{\eta^e} + \left[\exp\left(c_2\right) \kappa_{o,d}^{e} \left(p_d^e\right)^{-\beta}\right]^{\eta^e}} \tag{6}$$

Number of households with children is

$$F_d^e = \sum_{o=1}^{J} f_{o,d}^{e} \cdot L_o^e \cdot \pi_{o,d}^{e} \tag{7}$$

3.3 Production

Consumption Good. Consumption good is produced with the following technology:

$$Y_d = K_d^L N_d^L + K_d^H N_d^H, \tag{8}$$

where K_d^e is the regional productivity and N_d^e is the number of workers in location d.

Housing. Housing is produced using consumption good under decreasing return to scale function:

$$H_d = \bar{H}_d \left(Y_d^H\right)^{\epsilon_d}$$

in which $\epsilon_d < 1$ differs across cities. $\bar{H}_d$ captures the overall level of land supply, and Y_d^H is the quantity of consumption good allocated to housing production.

Under perfect competition, the following housing supply equation can be derived:

$$\begin{aligned} r_d &= \frac{1}{\epsilon_d \bar{H}_d \left(Y_d^H\right)^{\epsilon_d - 1}} = \left(\epsilon_d \bar{H}_d^{\frac{1}{\epsilon_d}}\right)^{-1} H_d^{\frac{1-\epsilon_d}{\epsilon_d}} \\ &\Longrightarrow \log\left(r_d\right) = \tilde{H}_d + \frac{1-\epsilon_d}{\epsilon_d} \log\left(H_d\right). \end{aligned} \tag{9}$$

Child-rearing Good. Child-rearing good is produced using consumption good and housing good with the following technology:

$$M_d^e = R_d^e \cdot \left(Y_d^{R,e}\right)^{1-\rho} \left(H_d^{R,e}\right)^{\rho}, \tag{10}$$

where ρ is the housing share of child-rearing good, $Y_d^{R,e}$ and $H_d^{R,e}$ are the quantity of consumption and housing good allocated to the production of child-rearing good for skill e, and R_d^e is the productivity of child-rearing good, which can be interpreted as the child-rearing amenity.

Under perfect competition, the amenity-adjusted price of child-rearing good is:

$$p_d^e = (r_d)^{\rho} \left(R_d^e\right)^{-1}. \tag{11}$$

Transfers and Market Clearing Conditions

The consumption good market clearing condition is:

$$Y_d = Y_d^C + Y_d^{R,L} + Y_d^{R,H} + Y_d^H. \tag{12}$$

The housing market clearing condition is:

$$H_d = \frac{\alpha \left(\sum_e I_d^e \left(N_d^e - F_d^e\right)\right) + (\alpha + \beta \cdot \rho) \left(\sum_e I_d^e F_d^e\right)}{r_d}. \tag{13}$$

The profit in housing markets is rebated to the workers as direct transfer. The amount of transfer is given by:

$$t = \frac{\sum_d (1 - \epsilon_d) r_d H_d}{\sum_{o,e} L_o^e}. \tag{14}$$

3.4 Equilibrium

A competitive equilibrium of the model is a set of prices and allocations such that:

1. Given wages, prices, and government transfers, individual choices are optimal.
   (a) Workers' fertility decisions are characterized by equation (6).
   (b) Workers make optimal migration decisions according to equation (1), where the expected utility of residence $\bar{U}_{o,d}^e$ is given by equation (5).

2. Under the optimal individual decisions, the set of prices and allocations are consistent.
    (a) The number of workers in location d is given by (2).
    (b) The number of workers with children in location d is given by (7).
    (c) Wages are given by equation (8).
    (d) Housing markets clear, i.e., equations (9) and (13).
    (e) Consumption good markets clear, i.e., equation (12)
    (f) The transfer from the rent of land is given by (14).

4 Parametrization

4.1 Parameters Assigned Directly

Land supply elasticities. See Diamond (2016).

Migration elasticity. See Diamond (2016). $\theta^H = 4.976$ and $\theta^L = 3.261$

Housing expenditure share. Set to be the average share among households without children from ACS data. $\alpha = 0.24$.

Child-rearing expenditure share. See Lino et al. (2017). $\beta = 0.39$.

Housing share of child-rearing expenditure. See Lino et al. (2017). $\rho = 0.29$.

4.2 Migration Cost

I assume the following specification for migration cost:

$d^e_{o,d} = \mathbb{I}_{s(o)\neq s(d)} \cdot (\nu^e_0 + \nu^e_1 \cdot \mathbb{I}_{160\leq dist_{s(o),d}<500} + \nu^e_2 \cdot \mathbb{I}_{500\leq dist_{s(o),d}<1000} + \nu^e_3 \cdot \mathbb{I}_{1000\leq dist_{s(o),d}<2000} + \nu^e_4 \cdot \mathbb{I}_{dist_{s(o),d}>2000})$.

where $s(d)$ is the state of destinations d. Due to data limitation, origins o are on the state-level, whereas destinations d are on the MSA-level.

From (5) and (6), I reformulate $\bar{U}^e_{o,d}$ to be a sum of destination-dependent term and a function of observable fertility rate:

$$\bar{U}^e_{o,d} = -\alpha \log r_d + \log A^e_d + \log I^e_d + c_1 + \frac{\bar{\gamma}}{\eta^e} - \frac{1}{\eta^e} \log\left(1 - f^e_{o,d}\right). \tag{15}$$

Substitute (15) into (1) to derive the following specification for estimating $d^e_{o,d}$:

$$\log\left(L^e_o \pi^e_{od}\right) = \lambda^e_o + \lambda^e_d + \tilde{\lambda}^e_o \frac{1}{1 - f^e_{o,d}} - \theta^e d^e_{o,d} + \varepsilon^e_{o,d}. \tag{16}$$

Table 2: Migration Cost Estimates

dep var: $\log\left(L^e_o \pi^e_{od}\right)$	(1) low skill	(2) high skill	(3) low skill	(4) high skill
$\mathbb{I}_{s(o) \neq s(d)}$	-1.526	-1.327	-1.604	-1.329
	(0.153)	(0.125)	(0.143)	(0.123)
$\mathbb{I}_{160 \leq dist_{s(o),d} < 500} \cdot \mathbb{I}_{s(o) \neq s(d)}$	-1.106	-0.878	-1.144	-0.922
	(0.150)	(0.122)	(0.140)	(0.120)
$\mathbb{I}_{500 \leq dist_{s(o),d} < 1000} \cdot \mathbb{I}_{s(o) \neq s(d)}$	-2.031	-1.827	-2.078	-1.855
	(0.151)	(0.121)	(0.140)	(0.120)
$\mathbb{I}_{1000 \leq dist_{s(o),d} < 2000} \cdot \mathbb{I}_{s(o) \neq s(d)}$	-2.482	-2.376	-2.499	-2.393
	(0.150)	(0.121)	(0.140)	(0.120)
$\mathbb{I}_{dist_{s(o),d} > 2000} \cdot \mathbb{I}_{s(o) \neq s(d)}$	-3.014	-2.770	-3.014	-2.792
	(0.152)	(0.122)	(0.142)	(0.120)
destination MSA FE	✓	✓	✓	✓
state-of-origin FE	✓	✓	✓	✓
fertility: $\frac{1}{1 - f^e_{o,d}}$			✓	✓
N	3201	3336	3201	3336

Note: Data are from ACS 2015-2019. Sample includes individuals between age 25 and 45. Each observation is a state-of-origin by destination MSA pair. Standard errors are in parentheses.

4.3 Proximity Preference in Fertility and Fertility Taste

I assume the following specification for proximity preference in fertility: $\kappa^e_{o,d} = \exp(\mu^e_1 \cdot \mathbb{I}_{dist_{s(o),d} < 500} + \mu^e_2 \cdot \mathbb{I}_{500 \leq dist_{s(o),d} < 1000})$.

The following transformation of (6) can be used to estimate $\kappa^e_{o,d}$ and η^e in two stages.

$$\log\left(\frac{f^e_{o,d}}{1 - f^e_{o,d}}\right) = \eta^e\left(c_2 - c_1\right) - \eta^e \beta \log p^e_d + \eta^e \log \kappa^e_{o,d}.$$

First, I use the following specification to obtain $\eta^e \log \kappa^e_{o,d}$:

$$\begin{aligned}\log\left(\frac{f^e_{o,d}}{1-f^e_{o,d}}\right) &= \psi^e_d + \eta^e \log \kappa^e_{o,d} + \varepsilon^e_{o,d} \\ &= \psi^e_d + \eta^e \mu^e_1 \cdot \mathbb{I}_{dist_{s(o),d}<500} + \eta^e \mu^e_2 \cdot \mathbb{I}_{500\leq dist_{s(o),d}<1000} + \varepsilon^e_{o,d}.\end{aligned} \tag{17}$$

Then, I use the following specification to obtain η^e

$$\psi^e_d = \gamma^e - \eta^e(\beta \cdot \rho \log r_d) + g^e(\hat{R}_d) + \varepsilon^e_d \tag{18}$$

where $g^e(\hat{R}_d)$ is a flexible function of child-related amenity proxies.

Table 3: Proximity Preference in Fertility Estimates

	(1)	(2)
dep var: $\log\left(\frac{f^e_{o,d}}{1-f^e_{o,d}}\right)$	low skill	high skill
$\mathbb{I}_{dist_{s(o),d}<500}$	0.220	0.399
	(0.0394)	(0.0384)
$\mathbb{I}_{500\leq dist_{s(o),d}<1000}$	0.109	0.204
	(0.0353)	(0.0347)
destination MSA FE	✓	✓
N	5141	4585

Note: Data are from ACS 2015-2019. Sample includes individuals between age 35 and 39. Each observation is a state-of-origin by destination MSA pair. Standard errors are in parentheses.

Table 4: Fertility Taste Estimates

	(1)	(2)	(3)	(4)
dep var: ψ^e_d	low skill	high skill	low skill	high skill
$\beta \cdot \rho \cdot \log r_d$	-1.760	-1.878	-3.029	-4.128
	(0.883)	(0.997)	(1.233)	(1.374)
Controls				
education			✓	✓
services			✓	✓
N	258	258	258	258

Note: Each observation is a MSA. Depedent variable ψ^e_d is obtained from (17). Standard errors are in parentheses.

4.4 Calibrating the Remaining Parameters Jointly

$\bar{H}_d$, A_d^e, K_d^e, and R_d^e will be calibrated jointly in the model by exactly matching the wage $\hat{W}_d^e$, rent $\hat{r}_d$, number of workers $\hat{N}_d^e$, and fertility $\hat{f}_d^e$ in the data. Calibration requires solving the model. Below I will first introduce the problem of model solving, before present the problem of calibration.

4.4.1 Solving the Model

Problem 1. The following system of equations defines a solution to the competitive equilibrium of the model:

1. (1): migration decision is optimal.
2. (3), (4), and (6): worker utility and fertility decisions are consistent with local incomes, rents, and amenities.
3. (2) and (7): the number of workers with children and the number of workers without children are consistent with population distribution.
4. (8): wages are given by the regional productivity.
5. (9) and (13): housing market clear.
6. (14): government budget balances.

4.4.2 Calibration the Model

Problem 2. The following system of equations calibrates the competitive equilibrium of the model to the data:

1. All equations listed in Problem 1.
2. Average productivity for skill type e in city d equals the wage data: $K_d^e = \hat{W}_d^e$.
3. Rent in city d equals its data counterparts: $r_d\left(\bar{H}_d\right) = \hat{r}_d$.
4. The number of skill e workers in city d equals its data counterpart: $N_d^e\left(A_d^e, R_d^e\right) = \hat{N}_d^e$.
5. The percentage of skill e workers with children in city d equals its data counterpart: $f_d^e\left(A_d^e, R_d^e\right) = \hat{f}_d^e$.

5 Results

5.1 Model Patterns

Figure 2 illustrates that locations with higher rent tends to have lower fertility. Since child-rearing household demands more housing, higher rent would discourage residents from having children. However, it is not clear if variations in housing rent alone can explain the steep negative slope in fertility.

In my model, housing rent impacts fertility through the amenity-adjusted price of child-rearing goods only, which also depends on child-rearing amenities R_d^e. Figure 3 plots the child-rearing amenity on rent. The negative slope suggests that cities with higher housing rent tend to have lower child-rearing amenity, which also contributes to lower fertility.

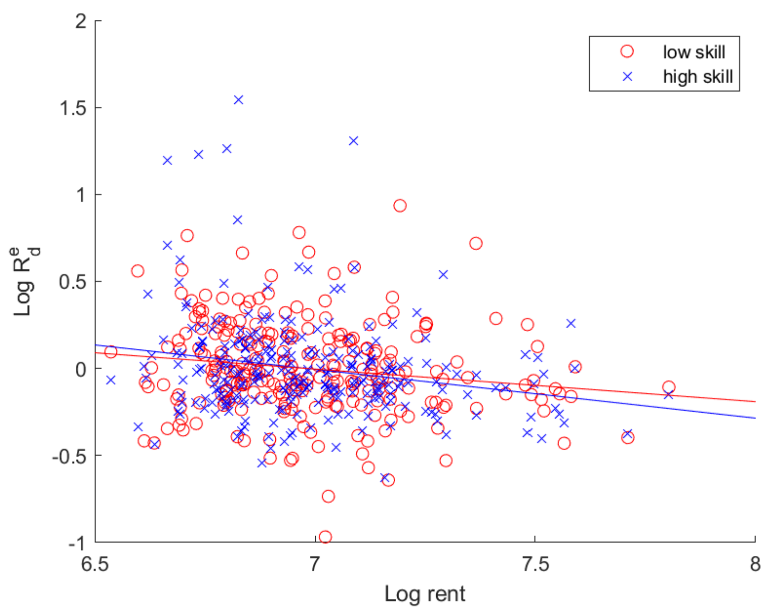
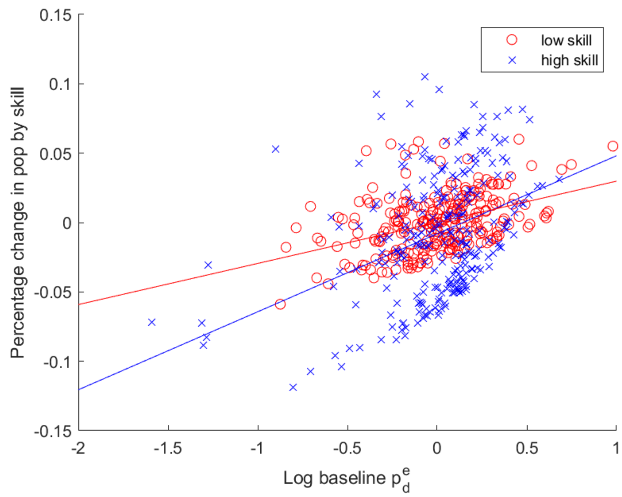


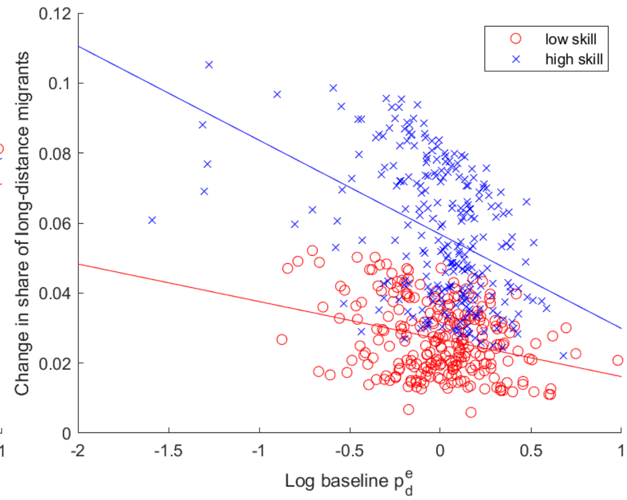
Figure 3: Rent and Child-rearing Amenity (R_d^e)

5.2 The Effects of Proximity Preference

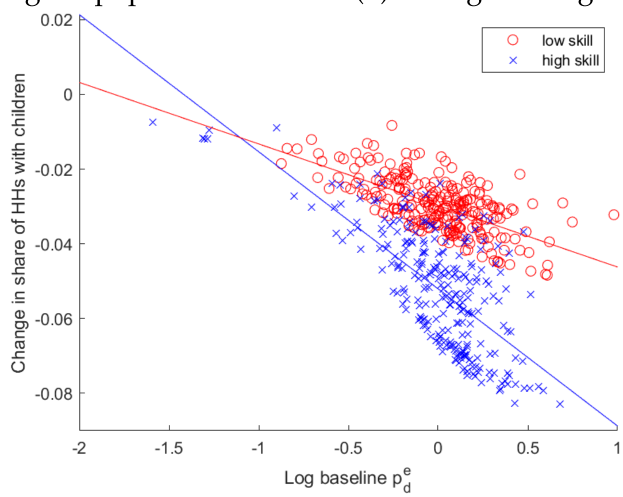
To discuss the effect of proximity preference in fertility, I eliminate it by setting $\kappa_{o,d}^e$ to be a constant and examine the general equilibrium response. For a better illustration, I present two experiments. In the first experiment, I set $\kappa_{o,d}^e = 1$, which forces residents from all origins to make fertility decisions as if they are long-distance migrants. This experiment corresponds to the scenario in which no one has access to any support from the hometown. In the second experiment, I set $\kappa_{o,d}^e = exp(\mu_1^e)$, which forces residents to make fertility decisions as if they are local. This experiment corresponds to the scenario in which everyone has unrestricted access to support from the hometown regardless of distance. My model doesn't generate meaningful differences between partial and general equilibrium responses, so I present only general equilibrium responses.



(a) Percentage change in population



(b) Change in long-distance migrant share



(c) Change in child-rearing HH share

Figure 4: General Equilibrium Effects of Depriving Local Status

Note: This experiment sets $k_{o,d}^e = 1$, so residents from all origins are making fertility decisions as if they are long-distance migrants, who reside more than 1000 km away from their state-of-origin.

Figure 4 presents the city-level changes after the first experiment. These changes are plotted on the amenity-adjusted prices of child-rearing goods. Recall that from (6) child-rearing probability is determined by the price of child-rearing good p_d^e and the proximity preference $\kappa_{o,d}^e$. In the absence of proximity preference, a household moving to cities with higher p_d^e would less likely to have children. Figure 4a plots the city-level percentage change in population. The positive slope suggests populations are moving to cities with higher p_d^e. This migration response would lower the aggregate fertility in the economy.

Figure 4b plots the changes in city-level long-distance migrant share. Here, long-distance migrants are those who reside more than 1000 km away from their state-of-origin. Notice that all cities have a positive change in the long-distance migrant share. This suggests workers travel further from their hometown in the absence of proximity preference in fertility.

Figure 4b examines the change in city-level fertility. The negative slope suggests cities with higher prices experience a larger reduction in fertility. In this experiment, the variations in fertility changes across cities can be attributed completely to the variations of two factors. The first is initial city-level population composition. Cities that initially have a high share of long-distance migrants would be less affected in this experiment, whereas cities that have a low share would be affected more. While my model generates variation in city-level population composition, the composition is only weakly correlated with the city-level prices. As a result, the observed negative slope can be attributed mainly to the second factor: the initial child-rearing rate. Taking the derivative of (6) with respect to κ would derive a decreasing function. This implies that a lower initial value of the child-rearing rate would react more to a change in κ. Since cities with higher prices have lower fertility in my model, they are also the ones that react more to a change in κ.

Figure 5 presents the city-level changes after the second experiment. In comparison, Figure 5a suggests populations are moving away from cities with higher p_d^e. This migration response would increase the aggregate fertility in the economy.

Despite the proximity preference being set to a different constant, Figure 5b illustrates similar changes in city-level long-distance migrant share. This suggests workers travel further from their hometown in the absence of proximity preference in fertility.

The positive slope in Figure 5b suggests cities with higher prices experience a larger increase in fertility. The rationale behind this pattern is the same as the one that has driven the negative slope in Figure 4b. Because cities with higher prices have lower fertility, they are the ones that react more to a change in κ.

The slope in Figure 5b is flatter comparing to that in 4b. Since the initial city-level population composition generated in my model is mostly local, the second experiment has less impact on fertility compared to the first experiment.

References

Aaronson, Daniel, Fabian Lange, and Bhashkar Mazumder (2014) "Fertility Transitions along the Extensive and Intensive Margins," *American Economic Review*, 104 (11), 3701–24.

Aassve, Arnstein, Elena Meroni, and Chiara Pronzato (2012) "Grandparenting and Childbearing in the Extended Family," *European Journal of Population / Revue européenne de Démographie*, 28 (4), 499–518.

Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro (2019) "Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock," *Econometrica*, 87 (3), 741–835.

Cardia, Emanuela and Serena Ng (2003) "Intergenerational time transfers and childcare," *Review of Economic Dynamics*, 6 (2), 431–454.

Compton, Janice and Robert A. Pollak (2014) "Family proximity, childcare, and women's labor force attachment," *Journal of Urban Economics*, 79, 72–90, Spatial Dimensions of Labor Markets.

Diamond, Rebecca (2016) "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000," *The American Economic Review*, 106 (3), 479–524.

Eibich, Peter and Thomas Siedler (2020) "Retirement, intergenerational time transfers, and fertility," *European Economic Review*, 124, 103392.

Fan, Jingting (2019) "Internal Geography, Labor Mobility, and the Distributional Impacts of Trade," *American Economic Journal: Macroeconomics*, 11 (3), 252–288.

Fan, Jingting and Ben Zou (2021) "The Dual Local Markets: Family, Jobs, and the Spatial Distribution of Skills," Working paper.

García-Morán, Eva and Zoë Kuehn (2017) "With strings attached: Grandparent-provided child care and female labor market outcomes," *Review of Economic Dynamics*, 23, 80–98.

Giannone, Elisa, Qi Li, Nuno Paixao, and Xinle Pang (2019) "Unpacking Moving," Working paper.

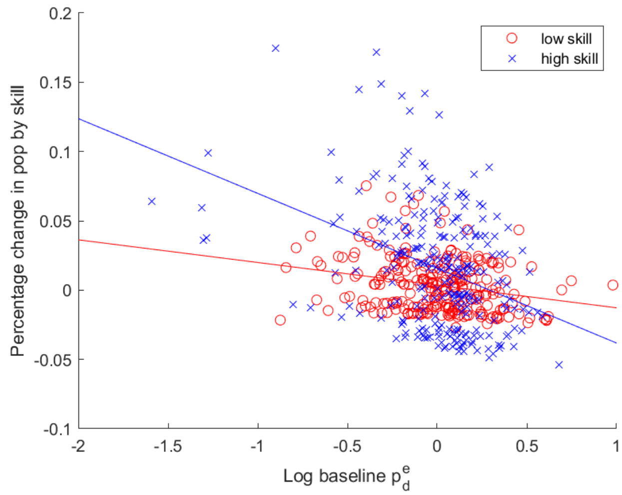
Lino, Mark, Kevin Kuczynski, Nestor Rodriguez, and TusaRebecca Schap (2017) *Expenditures on Children by Families, 2015*: United States Department of Agriculture, Center for Nutrition Policy and Promotion.

Roback, Jennifer (1982) “Wages, Rents, and the Quality of Life,” *Journal of Political Economy*, 90 (6), 1257–1278.

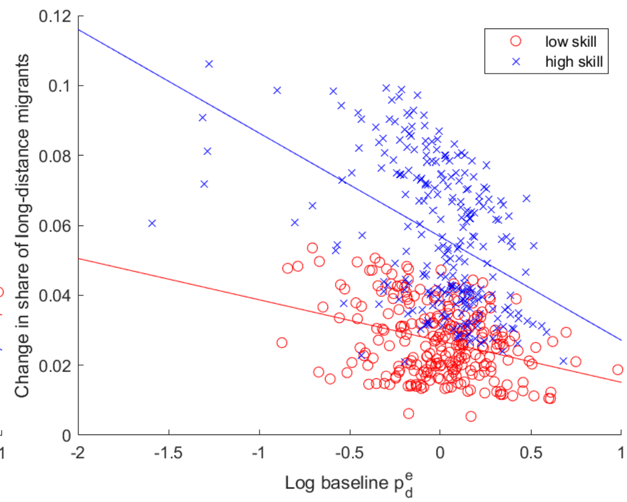
Rosen, Sherwin (1979) “Wage-based Indexes of Urban, Quality of Life,” *Current Issues in Urban Economics*, 74–104.

Ruggles, Steven, Sarah Flood, Sophia Foster, Ronald Goeken, Jose Pacas, Megan Schouweiler, and Matthew Sobek (2021) “PUMS USA: Version 11.0 [dataset],” Minneapolis, MN: IPUMS.

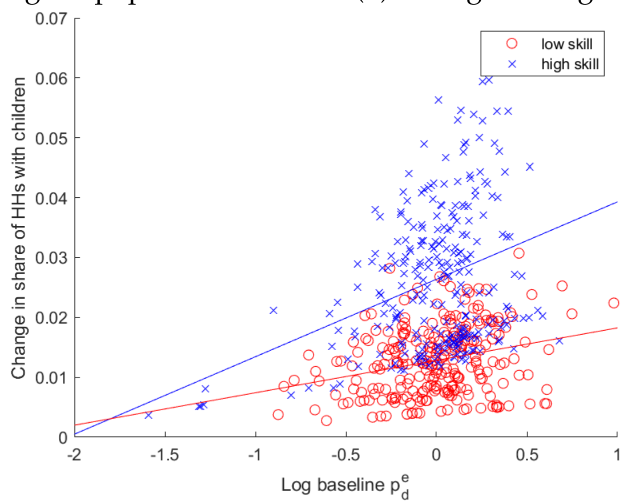
Tombe, Trevor and Xiaodong Zhu (2019) “Trade, Migration, and Productivity: A Quantitative Analysis of China,” *American Economic Review*, 109 (5), 1843–1872.



(a) Percentage change in population



(b) Change in long-distance migrant share



(c) Change in child-rearing HH share

Figure 5: General Equilibrium Effects of Granting Local Status

Note: This experiment sets $k^e_{o,d} = \exp(\mu^e_1)$, so residents from all origins are making fertility decisions as if they are local. In 5b, long-distance migrants refer to those who reside more than 1000 km away from their state-of-origin.