The Preference for Larger Cities in China: Evidence from Rural-Urban Migrants

Chunbing Xing[1] Junfu Zhang[2]

[1] Department of Economics, Beijing Normal University

[2] Department of Economics, Clark University

Outline

1. Motivation
2. Model
3. Data
4. Results

City Size Fascinates Urban Economists

- Why do cities come with different sizes?
- What are optimal/equilibrium city sizes?
- Why do we see a power law distribution of city sizes?

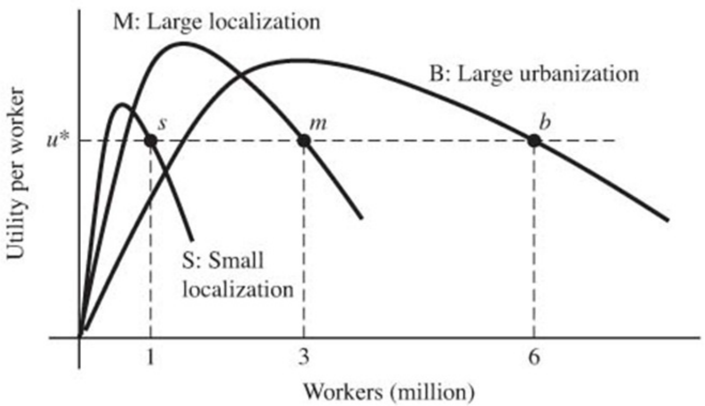
City Size Fascinates Urban Economists

- Why do cities come with different sizes?
- What are optimal/equilibrium city sizes?
- Why do we see a power law distribution of city sizes?

City Size Fascinates Urban Economists

- Why do cities come with different sizes?
- What are optimal/equilibrium city sizes?
- Why do we see a power law distribution of city sizes?

Henderson (1974): Optimal vs. Equilibrium City Size



Government Policies and City Sizes

- Dictatorships produce urban giants: Ades and Glaeser (1995)
- In China, the hukou system controls the movement of population, making it difficult to migrate to large cities.
- Au and Henderson (2006a, 2006b): estimating the inverted U curve using data in China; Chinese cities are mostly on the left side of the peak, i.e., smaller than optimal city size.

Government Policies and City Sizes

- Dictatorships produce urban giants: Ades and Glaeser (1995)
- In China, the hukou system controls the movement of population, making it difficult to migrate to large cities.
- Au and Henderson (2006a, 2006b): estimating the inverted U curve using data in China; Chinese cities are mostly on the left side of the peak, i.e., smaller than optimal city size.

Government Policies and City Sizes

- Dictatorships produce urban giants: Ades and Glaeser (1995)
- In China, the hukou system controls the movement of population, making it difficult to migrate to large cities.
- Au and Henderson (2006a, 2006b): estimating the inverted U curve using data in China; Chinese cities are mostly on the left side of the peak, i.e., smaller than optimal city size.

City Size Policies in China

- Chinese government has tried to contain the growth of large cites and encouraged rural migrants to move to small and medium sized cities.
- On the other hand, government investment has always favored large cities.
- Hypothesis: People in China prefer larger cities.

City Size Policies in China

- Chinese government has tried to contain the growth of large cites and encouraged rural migrants to move to small and medium sized cities.
- On the other hand, government investment has always favored large cities.
- Hypothesis: People in China prefer larger cities.

City Size Policies in China

- Chinese government has tried to contain the growth of large cites and encouraged rural migrants to move to small and medium sized cities.
- On the other hand, government investment has always favored large cities.
- Hypothesis: People in China prefer larger cities.

Goal and Contribution of This Paper

- Implication of the hypothesis: Migrants are willing to give up some income in order to live and work in larger cities.
- The goal of this paper is to estimate the amount of income migrants are willing to give up in exchange for larger cities.
- Contribution: The first paper to quantify people's preferences for larger cities; a useful method to study nonmarket urban amenities in a country with migration restrictions; results have policy implications.

Goal and Contribution of This Paper

- Implication of the hypothesis: Migrants are willing to give up some income in order to live and work in larger cities.
- The goal of this paper is to estimate the amount of income migrants are willing to give up in exchange for larger cities.
- Contribution: The first paper to quantify people's preferences for larger cities; a useful method to study nonmarket urban amenities in a country with migration restrictions; results have policy implications.

Goal and Contribution of This Paper

- Implication of the hypothesis: Migrants are willing to give up some income in order to live and work in larger cities.

- The goal of this paper is to estimate the amount of income migrants are willing to give up in exchange for larger cities.

- Contribution: The first paper to quantify people's preferences for larger cities; a useful method to study nonmarket urban amenities in a country with migration restrictions; results have policy implications.

Related Literature

- In terms of subject matter: Henderson (1974), Au and Henderson (2006a, 2006b), Ades and Glaeser (1995), Zheng, Fu, and Liu (2009), ...
- In terms of methodology: Roback (1982), McFadden (1974, 1978), Timmins (2007), Bayer et al. (2009), Dahl (2002), ...

Related Literature

- In terms of subject matter: Henderson (1974), Au and Henderson (2006a, 2006b), Ades and Glaeser (1995), Zheng, Fu, and Liu (2009), ...
- In terms of methodology: Roback (1982), McFadden (1974, 1978), Timmins (2007), Bayer et al. (2009), Dahl (2002), ...

A Model of Migration Destination Choice

Person i in destination city j maximizes utility:

$$\max U_{ij} = C_{ij}^{\alpha_C} H_{ij}^{\alpha_H} \exp\left[\sum_{k=1}^{K} \beta_k \ln X_{jk} + D_{ij} + \xi_j + \eta_{ij}\right]$$

$$s.t. \quad C_{ij} + p_j H_{ij} = I_{ij}.$$

- C_{ij}: i's consumption of a tradable composite good in city j; its price is normalized to 1. H_{ij}: i's consumption of a non-tradable composite good (including, e.g., housing) in city j; its price is p_j. X_j: a vector of K characteristics (e.g., quality of public facilities) of city j. D_{ij}: distance from i's home to city j.
- ξ_j: unobserved characteristics (e.g., migrant-friendliness) of city j. η_{ij}: i's idiosyncratic component of utility. I_{ij}: i's income in city j.

A Model of Migration Destination Choice

Person i in destination city j maximizes utility:

$$\max U_{ij} = C_{ij}^{\alpha_C} H_{ij}^{\alpha_H} \exp\left[\sum_{k=1}^{K} \beta_k \ln X_{jk} + D_{ij} + \xi_j + \eta_{ij}\right]$$
$$s.t. \quad C_{ij} + p_j H_{ij} = I_{ij}.$$

- C_{ij}: i's consumption of a tradable composite good in city j; its price is normalized to 1. H_{ij}: i's consumption of a non-tradable composite good (including, e.g., housing) in city j; its price is p_j. X_j: a vector of K characteristics (e.g., quality of public facilities) of city j. D_{ij}: distance from i's home to city j.
- ξ_j: unobserved characteristics (e.g., migrant-friendliness) of city j. η_{ij}: i's idiosyncratic component of utility. I_{ij}: i's income in city j.

A Model of Migration Destination Choice

Person i in destination city j maximizes utility:

$$\max U_{ij} = C_{ij}^{\alpha_C} H_{ij}^{\alpha_H} \exp\left[\sum_{k=1}^{K} \beta_k \ln X_{jk} + D_{ij} + \xi_j + \eta_{ij}\right]$$
$$s.t. \quad C_{ij} + p_j H_{ij} = I_{ij}.$$

- C_{ij}: i's consumption of a tradable composite good in city j; its price is normalized to 1. H_{ij}: i's consumption of a non-tradable composite good (including, e.g., housing) in city j; its price is p_j. X_j: a vector of K characteristics (e.g., quality of public facilities) of city j. D_{ij}: distance from i's home to city j.
- ξ_j: unobserved characteristics (e.g., migrant-friendliness) of city j. η_{ij}: i's idiosyncratic component of utility. I_{ij}: i's income in city j.

Indirect Utilities

Optimal choice in city j:

$$C_{ij}^* = \frac{\alpha_C I_{ij}}{\alpha_C + \alpha_H}; \quad H_{ij}^* = \frac{\alpha_H}{\alpha_C + \alpha_H} \frac{I_{ij}}{p_j}.$$

Indirect utility in city j:

$$U_{ij}^* = \left(\frac{\alpha_C}{\alpha_C+\alpha_H}\right)^{\alpha_C} \left(\frac{\alpha_H}{\alpha_C+\alpha_H}\right)^{\alpha_H} p_j^{-\alpha_H} I_{ij}^{\alpha_C+\alpha_H} \cdot \exp\left[\sum_{k=1}^{K} \beta_k \ln X_{jk} + D_{ij} + \xi_j + \eta_{ij}\right]$$

Rescale this utility, let $\alpha \equiv \alpha_C + \alpha_H$ and take log to get:

$$V_{ij} = -\alpha_H \ln p_j + \alpha \ln I_{ij} + \sum_{k=1}^{K} \beta_k \ln X_{jk} + D_{ij} + \xi_j + \eta_{ij}.$$

Indirect Utilities

Optimal choice in city j:

$$C_{ij}^* = \frac{\alpha_C I_{ij}}{\alpha_C + \alpha_H}; \quad H_{ij}^* = \frac{\alpha_H}{\alpha_C + \alpha_H} \frac{I_{ij}}{p_j}.$$

Indirect utility in city j:

$$U_{ij}^* = \left(\frac{\alpha_C}{\alpha_C+\alpha_H}\right)^{\alpha_C} \left(\frac{\alpha_H}{\alpha_C+\alpha_H}\right)^{\alpha_H} p_j^{-\alpha_H} I_{ij}^{\alpha_C+\alpha_H} \cdot \exp\left[\sum_{k=1}^{K} \beta_k \ln X_{jk} + D_{ij} + \xi_j + \eta_{ij}\right]$$

Rescale this utility, let $\alpha \equiv \alpha_C + \alpha_H$ and take log to get:

$$V_{ij} = -\alpha_H \ln p_j + \alpha \ln I_{ij} + \sum_{k=1}^{K} \beta_k \ln X_{jk} + D_{ij} + \xi_j + \eta_{ij}.$$

Indirect Utilities

Optimal choice in city j:

$$C^*_{ij} = \frac{\alpha_C I_{ij}}{\alpha_C + \alpha_H}; \quad H^*_{ij} = \frac{\alpha_H}{\alpha_C + \alpha_H} \frac{I_{ij}}{p_j}.$$

Indirect utility in city j:

$$U^*_{ij} = \left(\frac{\alpha_C}{\alpha_C+\alpha_H}\right)^{\alpha_C} \left(\frac{\alpha_H}{\alpha_C+\alpha_H}\right)^{\alpha_H} p_j^{-\alpha_H} I_{ij}^{\alpha_C+\alpha_H} \cdot \exp\left[\sum_{k=1}^{K} \beta_k \ln X_{jk} + D_{ij} + \xi_j + \eta_{ij}\right]$$

Rescale this utility, let $\alpha \equiv \alpha_C + \alpha_H$ and take log to get:

$$V_{ij} = -\alpha_H \ln p_j + \alpha \ln I_{ij} + \sum_{k=1}^{K} \beta_k \ln X_{jk} + D_{ij} + \xi_j + \eta_{ij}.$$

Indirect Utilities

Following Timmins (2007), we assume this p_j is a linear function of observed city characteristics:

$$\ln p_j = \sum_{k=1}^{K} \lambda_k \ln X_{jk} + \tau_j .$$

Plug this into the indirect utility equation:

$$\begin{aligned} V_{ij} &= \alpha \ln I_{ij} + \sum_{k=1}^{K} (\beta_k - \alpha_H \lambda_k) \ln X_{jk} + D_{ij} + (\xi_j - \alpha_H \tau_j) + \eta_{ij} \\ &= \alpha \ln I_{ij} + \sum_{k=1}^{K} \beta_k^* \ln X_{jk} + D_{ij} + \xi_j^* + \eta_{ij}, \end{aligned}$$

where $\beta_k^* = \beta_k - \alpha_H \lambda_k$ and $\xi_j^* = (\xi_j - \alpha_H \tau_j)$.

Indirect Utilities

Following Timmins (2007), we assume this p_j is a linear function of observed city characteristics:

$$\ln p_j = \sum_{k=1}^{K} \lambda_k \ln X_{jk} + \tau_j .$$

Plug this into the indirect utility equation:

$$\begin{aligned} V_{ij} &= \alpha \ln I_{ij} + \sum_{k=1}^{K} (\beta_k - \alpha_H \lambda_k) \ln X_{jk} + D_{ij} + (\xi_j - \alpha_H \tau_j) + \eta_{ij} \\ &= \alpha \ln I_{ij} + \sum_{k=1}^{K} \beta_k^* \ln X_{jk} + D_{ij} + \xi_j^* + \eta_{ij}, \end{aligned}$$

where $\beta_k^* = \beta_k - \alpha_H \lambda_k$ and $\xi_j^* = (\xi_j - \alpha_H \tau_j)$.

Willingness to Pay for Larger Cities

Denote WTP_i (i's marginal *willingness to pay*) as the amount of money i is willing to give up in order to have one more unit of X_{j1}, city population.

$$WTP_i = \frac{\partial V_{ij}/\partial X_{j1}}{\partial V_{ij}/\partial I_{ij}} = \frac{\beta_1^*}{\alpha}\frac{I_{ij}}{X_{j1}}.$$

Income population-size elasticity:

$$\frac{\Delta I_{ij}/I_{ij}}{\Delta X_{j1}/X_{j1}} \approx \frac{\partial \ln I_{ij}}{\partial \ln X_{j1}} = \frac{\beta_1^*}{\alpha}.$$

Willingness to Pay for Larger Cities

Denote WTP_i (i's marginal *willingness to pay*) as the amount of money i is willing to give up in order to have one more unit of X_{j1}, city population.

$$WTP_i = \frac{\partial V_{ij}/\partial X_{j1}}{\partial V_{ij}/\partial I_{ij}} = \frac{\beta_1^*}{\alpha}\frac{I_{ij}}{X_{j1}}.$$

Income population-size elasticity:

$$\frac{\Delta I_{ij}/I_{ij}}{\Delta X_{j1}/X_{j1}} \approx \frac{\partial \ln I_{ij}}{\partial \ln X_{j1}} = \frac{\beta_1^*}{\alpha}.$$

Income and Migration Cost

Decompose i's income into predicted income and random error:

$$\ln I_{ij} = \ln \hat{I}_{ij} + \varepsilon_{ij}.$$

We construct three dummy variables:

- $d_{ij}^1 = 1$ if city j is in the same province as i's home village, and 0 otherwise.
- $d_{ij}^2 = 1$ if city j is in an adjacent province, and 0 otherwise.
- $d_{ij}^3 = 1$ if city j is in neither i's home province nor one of its adjacent province, and 0 otherwise.

We assume that:

$$D_{ij} = \pi_1 d_{ij}^1 + \pi_2 d_{ij}^2 + \pi_3 d_{ij}^3.$$

Income and Migration Cost

Decompose i's income into predicted income and random error:

$$\ln I_{ij} = \ln \hat{I}_{ij} + \varepsilon_{ij}.$$

We construct three dummy variables:

- $d_{ij}^1 = 1$ if city j is in the same province as i's home village, and 0 otherwise.
- $d_{ij}^2 = 1$ if city j is in an adjacent province, and 0 otherwise.
- $d_{ij}^3 = 1$ if city j is in neither i's home province nor one of its adjacent province, and 0 otherwise.

We assume that:

$$D_{ij} = \pi_1 d_{ij}^1 + \pi_2 d_{ij}^2 + \pi_3 d_{ij}^3.$$

Income and Migration Cost

Decompose i's income into predicted income and random error:

$$\ln I_{ij} = \ln \hat{I}_{ij} + \varepsilon_{ij}.$$

We construct three dummy variables:

- $d_{ij}^1 = 1$ if city j is in the same province as i's home village, and 0 otherwise.
- $d_{ij}^2 = 1$ if city j is in an adjacent province, and 0 otherwise.
- $d_{ij}^3 = 1$ if city j is in neither i's home province nor one of its adjacent province, and 0 otherwise.

We assume that:

$$D_{ij} = \pi_1 d_{ij}^1 + \pi_2 d_{ij}^2 + \pi_3 d_{ij}^3.$$

Step 1: Logit Model

Substitute income and distance equations into utility:

$V_{ij} = \alpha \ln \hat{I}_{ij} + \sum_{k=1}^{K} \beta_k^* \ln X_{jk} + \pi_1 d_{ij}^1 + \pi_2 d_{ij}^2 + \pi_3 d_{ij}^3 + \xi_j^* + \upsilon_{ij}$,
where $\upsilon_{ij} = \alpha \varepsilon_{ij} + \eta_{ij}$.

In principle, at this stage, one could make an assumption about the distribution of υ_{ij} and estimate $(\alpha, \beta_1^*, \ldots, \beta_K^*, \pi_1, \pi_2, \pi_3)$ by maximum likelihood. However, city population size X_{j1} is likely to be correlated with many unobserved city characteristics in ξ_j^*.

Step 1: Logit Model

Substitute income and distance equations into utility:

$V_{ij} = \alpha \ln \hat{I}_{ij} + \sum_{k=1}^{K} \beta_k^* \ln X_{jk} + \pi_1 d_{ij}^1 + \pi_2 d_{ij}^2 + \pi_3 d_{ij}^3 + \xi_j^* + \upsilon_{ij}$,
where $\upsilon_{ij} = \alpha \varepsilon_{ij} + \eta_{ij}$.

In principle, at this stage, one could make an assumption about the distribution of υ_{ij} and estimate $(\alpha, \beta_1^*, \ldots, \beta_K^*, \pi_1, \pi_2, \pi_3)$ by maximum likelihood. However, city population size X_{j1} is likely to be correlated with many unobserved city characteristics in ξ_j^*.

Step 1: Logit Model

Let $\theta_j \equiv \sum_{k=1}^{K} \beta_k^* \ln X_{jk} + \xi_j^*$, then

$$V_{ij} = \alpha \ln \hat{I}_{ij} + \pi_1 d_{ij}^1 + \pi_2 d_{ij}^2 + \pi_3 d_{ij}^3 + \theta_j + \upsilon_{ij}.$$

Assume that υ_{ij} follows an i.i.d. type I extreme value distribution, then Individual i chooses city j with probability

$$\Pr(\ln V_{ij} > \ln V_{ik} \forall k \neq j) = \frac{\exp\left(\alpha \ln \hat{I}_{ij} + \pi_1 d_{ij}^1 + \pi_2 d_{ij}^2 + \pi_3 d_{ij}^3 + \theta_j\right)}{\sum_{s=1}^{J} \exp\left(\alpha \ln \hat{I}_{is} + \pi_1 d_{is}^1 + \pi_2 d_{is}^2 + \pi_3 d_{is}^3 + \theta_s\right)}.$$

Estimate $(\alpha, \pi_1, \pi_2, \pi_3, \theta_1 \ldots, \theta_J)$ by ML:

$$L = \prod_i \prod_{j=1}^{J} \left[\frac{\exp\left(\alpha \ln \hat{I}_{ij} + \pi_1 d_{ij}^1 + \pi_2 d_{ij}^2 + \pi_3 d_{ij}^3 + \theta_j\right)}{\sum_{s=1}^{J} \exp\left(\alpha \ln \hat{I}_{is} + \pi_1 d_{is}^1 + \pi_2 d_{is}^2 + \pi_3 d_{is}^3 + \theta_s\right)} \right]^{\kappa_{ij}}.$$

Step 1: Logit Model

Let $\theta_j \equiv \sum_{k=1}^{K} \beta_k^* \ln X_{jk} + \xi_j^*$, then

$$V_{ij} = \alpha \ln \hat{I}_{ij} + \pi_1 d_{ij}^1 + \pi_2 d_{ij}^2 + \pi_3 d_{ij}^3 + \theta_j + \upsilon_{ij}.$$

Assume that υ_{ij} follows an i.i.d. type I extreme value distribution, then Individual i chooses city j with probability

$$\Pr(\ln V_{ij} > \ln V_{ik} \forall k \neq j) = \frac{\exp\left(\alpha \ln \hat{I}_{ij} + \pi_1 d_{ij}^1 + \pi_2 d_{ij}^2 + \pi_3 d_{ij}^3 + \theta_j\right)}{\sum_{s=1}^{J} \exp\left(\alpha \ln \hat{I}_{is} + \pi_1 d_{is}^1 + \pi_2 d_{is}^2 + \pi_3 d_{is}^3 + \theta_s\right)}.$$

Estimate $(\alpha, \pi_1, \pi_2, \pi_3, \theta_1 \ldots, \theta_J)$ by ML:

$$L = \prod_i \prod_{j=1}^{J} \left[\frac{\exp\left(\alpha \ln \hat{I}_{ij} + \pi_1 d_{ij}^1 + \pi_2 d_{ij}^2 + \pi_3 d_{ij}^3 + \theta_j\right)}{\sum_{s=1}^{J} \exp\left(\alpha \ln \hat{I}_{is} + \pi_1 d_{is}^1 + \pi_2 d_{is}^2 + \pi_3 d_{is}^3 + \theta_s\right)} \right]^{\kappa_{ij}}.$$

Step 1: Logit Model

Let $\theta_j \equiv \sum_{k=1}^{K} \beta_k^* \ln X_{jk} + \xi_j^*$, then

$$V_{ij} = \alpha \ln \hat{I}_{ij} + \pi_1 d_{ij}^1 + \pi_2 d_{ij}^2 + \pi_3 d_{ij}^3 + \theta_j + \upsilon_{ij}.$$

Assume that υ_{ij} follows an i.i.d. type I extreme value distribution, then Individual i chooses city j with probability

$$\Pr\left(\ln V_{ij} > \ln V_{ik} \forall k \neq j\right) = \frac{\exp\left(\alpha \ln \hat{I}_{ij} + \pi_1 d_{ij}^1 + \pi_2 d_{ij}^2 + \pi_3 d_{ij}^3 + \theta_j\right)}{\sum_{s=1}^{J} \exp\left(\alpha \ln \hat{I}_{is} + \pi_1 d_{is}^1 + \pi_2 d_{is}^2 + \pi_3 d_{is}^3 + \theta_s\right)}.$$

Estimate $(\alpha, \pi_1, \pi_2, \pi_3, \theta_1 \ldots, \theta_J)$ by ML:

$$L = \prod_i \prod_{j=1}^{J} \left[\frac{\exp\left(\alpha \ln \hat{I}_{ij} + \pi_1 d_{ij}^1 + \pi_2 d_{ij}^2 + \pi_3 d_{ij}^3 + \theta_j\right)}{\sum_{s=1}^{J} \exp\left(\alpha \ln \hat{I}_{is} + \pi_1 d_{is}^1 + \pi_2 d_{is}^2 + \pi_3 d_{is}^3 + \theta_s\right)}\right]^{\kappa_{ij}}.$$

Step 2: Linear Regression

Estimate $\beta_1^*, ..., \beta_K^*$ from the following linear equation:

$$\theta_j = \sum_{k=1}^{K} \beta_k^* \ln X_{jk} + \xi_j^*.$$

Remember that X_{j1} and unobserved city characteristics ξ_j are likely to be correlated. As a solution, we instrument for X_{j1} using lagged city population.

Step 2: Linear Regression

Estimate $\beta_1^*, ..., \beta_K^*$ from the following linear equation:

$$\theta_j = \sum_{k=1}^{K} \beta_k^* \ln X_{jk} + \xi_j^*.$$

Remember that X_{j1} and unobserved city characteristics ξ_j are likely to be correlated. As a solution, we instrument for X_{j1} using lagged city population.

Correcting Selection Biases in Predicted Income

Predict i's income in city j using i's characteristics:

$$\ln I_{ij} = Z_i \gamma_j + \varepsilon_{ij}$$

Selection biases:

$$0 \neq E\left(\varepsilon_{ij} | \bullet\right) = \ldots = \psi\left(P_{i1}, \ldots, P_{iJ}\right)$$

Correcting the biases:

$$\begin{aligned} \ln I_{ij} &= Z_i \gamma_j + \psi\left(P_{i1}, \ldots, P_{iJ}\right) + e_{ij} \\ &= Z_i \gamma_j + \widetilde{\psi}\left(P_{ij}\right) + e_{ij} \end{aligned}$$

Following Dahl(2002), we estimate P_{ij} nonparametrically and approximate $\widetilde{\psi}$ by polynomial expansion.

Correcting Selection Biases in Predicted Income

Predict i's income in city j using i's characteristics:

$$\ln I_{ij} = Z_i \gamma_j + \varepsilon_{ij}$$

Selection biases:

$$0 \neq E\left(\varepsilon_{ij} | \bullet\right) = \ldots = \psi\left(P_{i1}, \ldots, P_{iJ}\right)$$

Correcting the biases:

$$\begin{aligned} \ln I_{ij} &= Z_i \gamma_j + \psi\left(P_{i1}, \ldots, P_{iJ}\right) + e_{ij} \\ &= Z_i \gamma_j + \widetilde{\psi}\left(P_{ij}\right) + e_{ij} \end{aligned}$$

Following Dahl(2002), we estimate P_{ij} nonparametrically and approximate $\widetilde{\psi}$ by polynomial expansion.

Correcting Selection Biases in Predicted Income

Predict i's income in city j using i's characteristics:

$$\ln I_{ij} = Z_i \gamma_j + \varepsilon_{ij}$$

Selection biases:

$$0 \neq E\left(\varepsilon_{ij} | \bullet\right) = \ldots = \psi\left(P_{i1}, \ldots, P_{iJ}\right)$$

Correcting the biases:

$$\begin{aligned} \ln I_{ij} &= Z_i \gamma_j + \psi\left(P_{i1}, \ldots, P_{iJ}\right) + e_{ij} \\ &= Z_i \gamma_j + \widetilde{\psi}\left(P_{ij}\right) + e_{ij} \end{aligned}$$

Following Dahl(2002), we estimate P_{ij} nonparametrically and approximate $\widetilde{\psi}$ by polynomial expansion.

Identification of Income Equation

Income equation for city j:

$$\ln I_{ij} = Z_i \gamma_j + \psi_1 \hat{P}_{ij} + \psi_2 \hat{P}_{ij}^2 + e_{ij}$$

Z_i: age, age_squared, gender, education. Estimate P_{ij} using age, education, and home region.

Identifying restriction:

Home province can be excluded from the income equation, i.e., does not affect earnings directly.

Identification of Income Equation

Income equation for city j:

$$\ln I_{ij} = Z_i \gamma_j + \psi_1 \hat{P}_{ij} + \psi_2 \hat{P}_{ij}^2 + e_{ij}$$

Z_i: age, age_squared, gender, education. Estimate P_{ij} using age, education, and home region.

Identifying restriction:

Home province can be excluded from the income equation, i.e., does not affect earnings directly.

Identification of Income Equation

Income equation for city j:

$$\ln I_{ij} = Z_i\gamma_j + \psi_1\hat{P}_{ij} + \psi_2\hat{P}_{ij}^2 + e_{ij}$$

Z_i: age, age_squared, gender, education. Estimate P_{ij} using age, education, and home region.

Identifying restriction:

Home province can be excluded from the income equation, i.e., does not affect earnings directly.

The 2005 "Mini Census" Data

- One-percent population survey.
- Detailed information on individual characteristics, income, and housing conditions.
- We have access to a one-fifth subsample of the "mini census" data.

The 2005 "Mini Census" Data

- One-percent population survey.
- Detailed information on individual characteristics, income, and housing conditions.
- We have access to a one-fifth subsample of the "mini census" data.

The 2005 "Mini Census" Data

- One-percent population survey.
- Detailed information on individual characteristics, income, and housing conditions.
- We have access to a one-fifth subsample of the "mini census" data.

The Migrant Sample

- Identify rural-urban migrants: (i) holds a rural hukou but has left the hukou registration place for more than 6 months; (ii) has migrated out of rural area for employment reasons; (iii) is currently living in an urban area; (iv) is between 20 and 60 years old; (v) is currently employed or self-employed; (vi) has non-zero monthly income in current year; and (vii) is a household head in the city
- Keep 158 cities with at least 30 migrants: dropped 53% of prefecture-level cities but only 7% migrants.

The Migrant Sample

- Identify rural-urban migrants: (i) holds a rural hukou but has left the hukou registration place for more than 6 months; (ii) has migrated out of rural area for employment reasons; (iii) is currently living in an urban area; (iv) is between 20 and 60 years old; (v) is currently employed or self-employed; (vi) has non-zero monthly income in current year; and (vii) is a household head in the city

- Keep 158 cities with at least 30 migrants: dropped 53% of prefecture-level cities but only 7% migrants.

Descriptive Statistics on Rural-Urban Migrants

	Mean	Std. Dev.
Female	0.196	0.397
Age	33.02	8.47
Years of schooling	8.938	2.435
Unmarried	0.215	0.411
Self-employed	0.285	0.451
Monthly earnings	1,090	756

Regression Results from the Conditional Logit

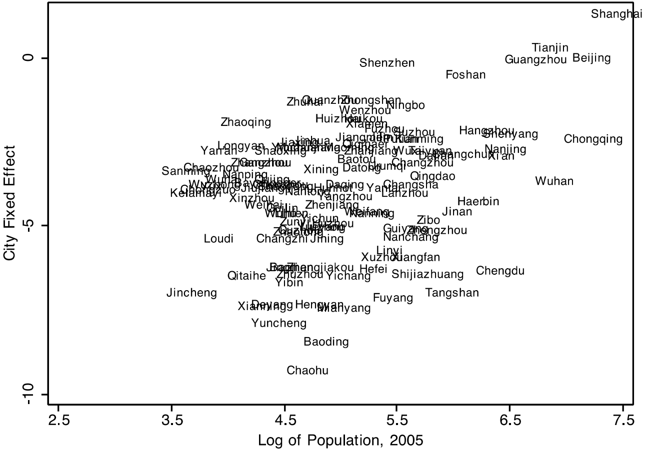
Variable | coefficient name	Coefficient
Utility from income	
Log income | α	0.614 (0.054)
Migration cost (reference group: same province)	
Adjacent province | π_2	-3.301 (0.024)
Non-adjacent province | π_3	-5.137 (0.027)
City fixed effects	Included
Number of cities	158
Number of observations	5,161,228

Standard errors are in parenthesis.

Top Ten Cities by Migrants' Willingness to Pay

Rank	City	Value of $\hat{\theta}_j$
1	Shanghai	1.346
2	Tianjin	0.306
3	Beijing	0.000
4	Guangzhou	-0.058
5	Shenzhen	-0.146
6	Foshan	-0.523
7	Changji	-1.224
8	Zhongshan	-1.240
9	Zhuhai	-1.294
10	Quanzhou	-1.311

Visualize the Relationship between $\hat{\theta}_j$ and Log Population



Descriptive Statistics of City Characteristics (1)

Description	Mean	Std. Dev.
City fixed effects θ_j	-3.979	1.983
Log(population, 10,000 persons)	4.840	0.832
Log(1984 population, 10,000 persons)	4.163	0.848
Log(population density, persons/square km)	6.710	0.880
Log(per capita GDP)	10.163	0.571
Log(unemployment rate)	-3.469	0.625
Log(share of fixed assets investment in GDP)	-0.750	0.363

Descriptive Statistics of City Characteristics (2)

Description	Mean	Std. Dev.
Log(no. of large scale manufacturing enterprises per 10,000 persons)	1.051	0.904
Log(share of domestic firms in large scale manufacturing enterprises)	-0.225	0.250
Log(no. of primary schools per 10,000 persons)	0.788	0.603
Log(no. of colleges per 10,000 persons)	-3.085	0.768
Log(per capita books in public libraries)	4.177	0.835

Descriptive Statistics of City Characteristics (3)

Description	Mean	Std. Dev.
Log(no. of hospital beds per 10,000 persons)	3.917	0.373
Log(per capita paved road area, square meter)	2.079	0.517
Log(industrial particulates emission, 1,000kg/10,000 persons)	5.176	1.228
Average January temperature, 1971-2000	2.150	8.824

Regression Results, OLS

Dependent Variable = city fixed effect ($\hat{\theta}_j$)			
Variables	(1) OLS	(2) OLS	(3) OLS
Log (population, 10,000 persons)	1.413*** (0.312)	1.403*** (0.200)	0.735*** (0.156)
Constant	Yes	Yes	Yes
Region dummies	No	Yes	No
Province dummies	No	No	Yes
Adjusted R^2	0.328	0.556	0.847
No. of observations	119	119	119

Regression Results, IV

Dependent Variable = city fixed effect ($\hat{\theta}_j$)			
Variables	(4) IV	(5) IV	(6) IV
Log (population, 10,000 persons)	1.369*** (0.390)	1.495*** (0.220)	1.271*** (0.222)
Constant	Yes	Yes	Yes
Region dummies	No	Yes	No
Province dummies	No	No	Yes
Adjusted R^2	0.328	0.555	0.694
No. of observations	119	119	119

IV: Log population 1984.

IV Results, Controlling for City Characteristics and Province Dummies

Variables	(1)	(2)
Log(population, 10,000 persons)	1.271*** (0.222)	0.951*** (0.255)
Controls	No	Yes
Constant	Yes	Yes
Adjusted R^2	0.694	0.565
Number of observations	119	119

Controls: Log(per capita GDP); Log(unemployment rate)***; Log(share of fixed assets investment in GDP)*; Log(no. of large scale manufacturing enterprises per 10,000 persons)***; Log(share of domestic firms in large scale manufacturing enterprises)***; province dummies.

IV Results, Controlling for City Characteristics and Province Dummies

Variables	(1)	(3)
Log(population, 10,000 persons)	1.271*** (0.222)	0.637** (0.250)
Controls	No	Yes
Constant	Yes	Yes
Adjusted R^2	0.694	0.789
Number of observations	119	119

Controls: Log(no. of primary schools per 10,000 persons)***; Log(no. of colleges per 10,000 persons); Log(per capita books in public libraries); Log(no. of hospital beds per 10,000 persons); Log(per capita paved road area, square meter)**; province dummies.

IV Results, Controlling for City Characteristics and Province Dummies

Variables	(1)	(4)
Log(population, 10,000 persons)	1.271*** (0.222)	1.341*** (0.246)
Controls	No	Yes
Constant	Yes	Yes
Adjusted R^2	0.694	0.752
Number of observations	119	119

Controls: Log(population density, persons/square km)**; Log(industrial particulates emission**, 1,000kg/10,000 persons); Average January temperature, 1971-2000; Average January temperature squared***; province dummies.

IV Results, Controlling for City Characteristics and Province Dummies

Variables	(1)	(5)
Log(population, 10,000 persons)	1.271*** (0.222)	0.642** (0.250)
Controls	No	Yes
Constant	Yes	Yes
Adjusted R^2	0.694	0.853
Number of observations	119	119

Controls: all.

What Do These Estimates Imply?

- Remember that $\frac{\Delta I_{ij}/I_{ij}}{\Delta X_{j1}/X_{j1}} \approx \frac{\partial \ln I_{ij}}{\partial \ln X_{j1}} = \frac{\beta_1^*}{\alpha}$.
- From the second stage regression $\hat{\beta}_1^* = 0.642$; from the first stage regression $\hat{\alpha} = 0.614$. so, $\frac{\Delta I_{ij}/I_{ij}}{\Delta X_{j1}/X_{j1}} \approx 1$.
- That is, rural-urban migrants are willing to give up about 1% of their earnings in order to work and live in a city with a log population that is 1% higher.

What Do These Estimates Imply?

- Remember that $\frac{\Delta I_{ij}/I_{ij}}{\Delta X_{j1}/X_{j1}} \approx \frac{\partial \ln I_{ij}}{\partial \ln X_{j1}} = \frac{\beta_1^*}{\alpha}$.
- From the second stage regression $\hat{\beta}_1^* = 0.642$; from the first stage regression $\hat{\alpha} = 0.614$. so, $\frac{\Delta I_{ij}/I_{ij}}{\Delta X_{j1}/X_{j1}} \approx 1$.
- That is, rural-urban migrants are willing to give up about 1% of their earnings in order to work and live in a city with a log population that is 1% higher.

What Do These Estimates Imply?

- Remember that $\frac{\Delta I_{ij}/I_{ij}}{\Delta X_{j1}/X_{j1}} \approx \frac{\partial \ln I_{ij}}{\partial \ln X_{j1}} = \frac{\beta_1^*}{\alpha}$.
- From the second stage regression $\hat{\beta}_1^* = 0.642$; from the first stage regression $\hat{\alpha} = 0.614$. so, $\frac{\Delta I_{ij}/I_{ij}}{\Delta X_{j1}/X_{j1}} \approx 1$.
- That is, rural-urban migrants are willing to give up about 1% of their earnings in order to work and live in a city with a log population that is 1% higher.

Why Do Migrants Prefer Larger Cities?

- Give up some income today in exchange for higher future income? Larger cities enable people to accumulate human capital at a faster rate (Combes et al., 2012)? Larger cities offer better life opportunities for future generations?
- Larger cities offer a wider variety of consumption goods?
- Social-family networks (*guanxi*) are less important in larger cities? Less discrimination in larger cities?

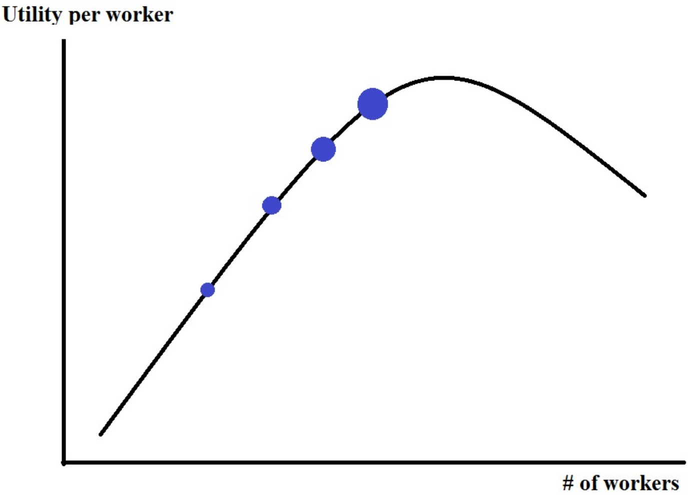
Why Do Migrants Prefer Larger Cities?

- Give up some income today in exchange for higher future income? Larger cities enable people to accumulate human capital at a faster rate (Combes et al., 2012)? Larger cities offer better life opportunities for future generations?
- Larger cities offer a wider variety of consumption goods?
- Social-family networks (*guanxi*) are less important in larger cities? Less discrimination in larger cities?

Why Do Migrants Prefer Larger Cities?

- Give up some income today in exchange for higher future income? Larger cities enable people to accumulate human capital at a faster rate (Combes et al., 2012)? Larger cities offer better life opportunities for future generations?
- Larger cities offer a wider variety of consumption goods?
- Social-family networks (*guanxi*) are less important in larger cities? Less discrimination in larger cities?

Consistent with Findings by Au and Henderson (2006a,b)



Policy Implication 1: Large Instead of Small Cities Should Absorb Rural Migrants?

- Suppose we want to grant an urban hukou to a rural migrant. Presumably, she'll give up her land use right in home village but gain access to subsidized public services.
- With the same amount of net subsidy, migration to a larger city leads to a larger utility gain.
- Only externalities-type of arguments could possibly justify the current policy that encourages migrants to move to small cities.

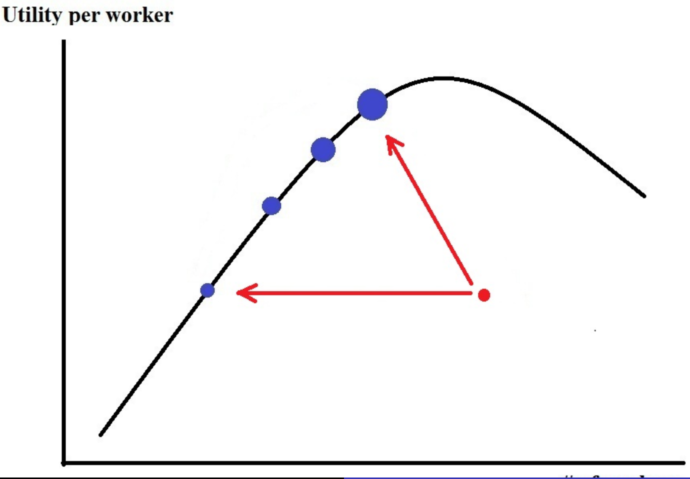
Policy Implication 1: Large Instead of Small Cities Should Absorb Rural Migrants?

- Suppose we want to grant an urban hukou to a rural migrant. Presumably, she'll give up her land use right in home village but gain access to subsidized public services.
- With the same amount of net subsidy, migration to a larger city leads to a larger utility gain.
- Only externalities-type of arguments could possibly justify the current policy that encourages migrants to move to small cities.

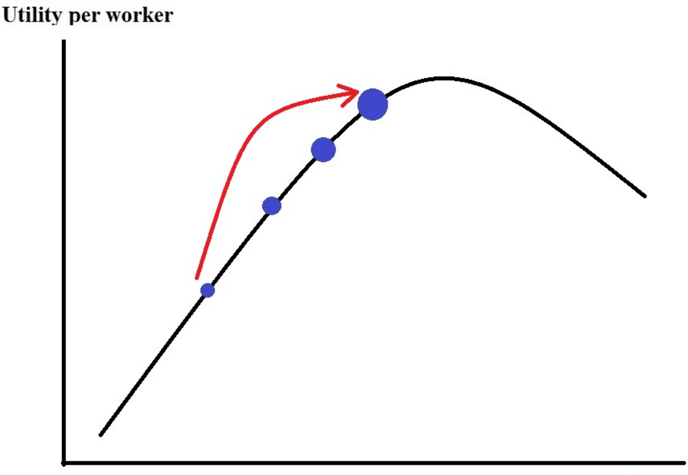
Policy Implication 1: Large Instead of Small Cities Should Absorb Rural Migrants?

- Suppose we want to grant an urban hukou to a rural migrant. Presumably, she'll give up her land use right in home village but gain access to subsidized public services.
- With the same amount of net subsidy, migration to a larger city leads to a larger utility gain.
- Only externalities-type of arguments could possibly justify the current policy that encourages migrants to move to small cities.

Policy Implication 1: Large Instead of Small Cities Should Absorb Rural Migrants?



Policy Implication 2: Large Potential Gains from Lifting Migration Restrictions within Urban Sector



Future Work

- More empirical analysis (longer city population lag, straight-line migration distance, heterogeneous preferences, ...).
- Some simulation studies?
- Any suggestions?

Future Work

- More empirical analysis (longer city population lag, straight-line migration distance, heterogeneous preferences, ...).
- Some simulation studies?
- Any suggestions?

Future Work

- More empirical analysis (longer city population lag, straight-line migration distance, heterogeneous preferences, ...).
- Some simulation studies?
- Any suggestions?