How Restricting Migrants' Job Options Affects Both Migrants and Residents

Wilbur Townsend, UC Berkeley
Corey Allan, Ministry of Business, Innovation and Employment

Can work visas facilitate immigration while protecting residents' wages?

We focus on one aspect of work visa policy: **Requirements that migrants work in certain jobs.**

- 'High-skill' occupations.
- Rural areas or certain cities.
- The agriculture or medical sectors.
- Particular firms.

We ask how these requirements affect **migrant workers**, **resident workers**, and their **employers**.

Specifically: We study New Zealand's Essential Skills work visa. These migrants were **limited to positions for which no New Zealanders were believed to be available**.

Incidence will depend on how firms set wages:

Bargaining?

- Firms bargain with individual workers.
- Weaker outside options decrease migrants' bargaining power and so decrease their wages.
- **Residents only affected insofar as their marginal product is affected.**

Incidence will depend on how firms set wages:

Bargaining?

- Firms bargain with individual workers.
- Weaker outside options decrease migrants' bargaining power and so decrease their wages.
- **Residents only affected insofar as their marginal product is affected.**

Wage-posting?

- Firms commit to position-specific wages.
- A firm's wage choice will depend on the distribution of outside options.
- **Restricting migrants' job options can decrease wages for residents.**

Incidence will depend on how firms set wages:

Bargaining?

- Firms bargain with individual workers.
- Weaker outside options decrease migrants' bargaining power and so decrease their wages.
- **Residents only affected insofar as their marginal product is affected.**

Wage-posting?

- Firms commit to position-specific wages.
- A firm's wage choice will depend on the distribution of outside options.
- **Restricting migrants' job options can decrease wages for residents.**

A fundamental topic in labor economics with implications for the **causes of wage inequality**, the **effects of employment regulations** and the **allocative efficiency** of the labor market (Flinn & Mullins '21; Silbert & Townsend '24).

Today's talk

Reduced-form facts:

- Migrants earn less than other workers — but only because of the jobs they hold.
- Loosening an *individual* migrant's job restrictions does not affect their wages.
- But loosening the restrictions on *all* migrants within an occupation does increase wages.

These facts are consistent with a model in which wages are set through monopsonistic wage-posting.

We estimate such a model:

- Restricting migrants' job options decreases their wages by an average of 8%.
- Most residents are unaffected — but 2.1% have their wage decreased by $\geq$ 2%.
- The restrictions decrease aggregate welfare — mostly because of non-wage amenities.

Existing literature: work visas

- Individual workers' visa status matters little (Wang '21),
- While the overall migrant visa system matters a lot (Naidu, Nyarko & Wang '16; Ahrens, et. al '23; Borjas & Edo '23).

We reconcile these results by **combining analyses of individual- and market-level shocks**.

We also extend this literature by asking how **visa systems affect residents' wages** (Amior & Manning '20; Amior & Stuhler '23; Borjas & Edo '23).

Existing literature: theories of wage-setting

- How workers' outside job options affect their wages (Caldwell & Harmon '19; Caldwell & Danieli '22).
- Other predictions (Carvalho, da Fonseca & Santarrosa '23; Bloesch, Larsen & Taska '22; Hall & Krueger '12; Roussille & Scuderi 24; Rubens & Delabastita '24).

We focus on a novel prediction of wage-posting models:

- *Among workers at the same firm*, an individual's *own* outside option has no effect on their wage,
- But the wage chosen by that firm will depend on the *distribution* of workers' outside options.

Existing literature: structural estimation of labor market power

A large literature estimates labor market power:

- By estimating labor supply elasticities (Manning '03; Lamadon, Mogstad & Setzler '21; Azar, Berry & Marinescu '22; Berger, Herkenhoff & Mongey '22; Kroft, et al. '23; Roussille & Scuderi '23, Sharma '22, ...),
- By estimating production functions (Lamadon, Mogstad & Setzler '21; Yeh, Macaluso & Hershbein '22; Kroft, et al. '23; Delabastita & Rubens '22).

We estimate how **market concentration for one type of worker affects other workers' wages**:

- We abandon the typical assumption that firms are 'strategically small'.
- We assume that firms set constant wages across worker types.
- **Greater concentration for one type of worker** $\implies$ lower labor supply elasticity $\implies$ **lower wages for all workers**.

Existing literature: structural estimation of labor market power

A large literature estimates labor market power:

- By estimating labor supply elasticities (Manning ’03; Lamadon, Mogstad & Setzler ’21; Azar, Berry & Marinescu ’22; Berger, Herkenhoff & Mongey ’22; Kroft, et al. ’23; Roussille & Scuderi ’23, Sharma ’22, ...),
- By estimating production functions (Lamadon, Mogstad & Setzler ’21; Yeh, Macaluso & Hershbein ’22; Kroft, et al. ’23; Delabastita & Rubens ’22).

We estimate production functions in which **different occupations are distinct inputs**:

- Calculate firm-by-occupation marginal products by inverting a markdown equation (Berry, Levinsohn & Pakes ’95; Chan et al. 2024).
- We estimate **firms’ ability to substitute across occupations**.

The Essential Skills Work Visa

- Existed between 2008 and 2022.
- Accounted for 80% of employer-assisted visas, and about 25% of all work visas.
- Covers a broad range of skilled and semi-skilled occupations. Most common: chef, carpenter, dairy cattle farmer.

The Essential Skills visa was limited to positions for which there were ‘no New Zealanders available’.

- For most occupations: must show a ‘genuine attempt’ to recruit New Zealanders
- … but **occupations on an “Essential Skills in Demand list” are exempt**.

Data and sample

We use linked **census**, **tax** and **immigration** data:

- **Census data:** Employment status, hours, occupation, education and demographics, in 2013 and 2018.
- **Tax data:** Worker-month-firm panel of earnings & location.
- **Immigration data:** Spell data on visas held, border movements, and occupations. Entries into resident visa lotteries.

Between **August 2008 to March 2022**: 278m observations across **3.8m workers**.

Among **205k Essential Skills workers**:

- 32% live in Auckland (vs. 27% overall). 54% urban (vs. 51% overall).
- Average age 35. 71% are men.
- 37% have at least a Bachelor's degree (vs. 32% overall).

Today's talk

Reduced-form facts:

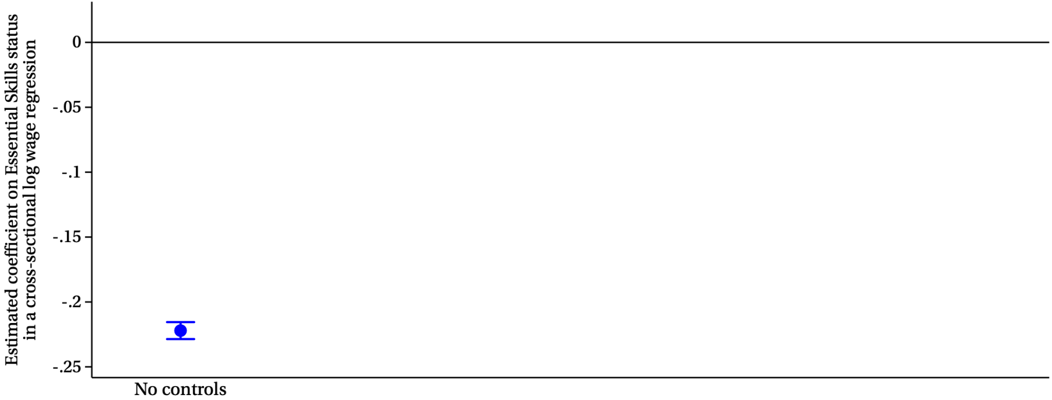
- Migrants earn less than other workers — but only because of the jobs they hold.
- Loosening an *individual* migrant's job restrictions does not affect their wages.
- But loosening the restrictions on *all* migrants within an occupation does increase wages.

These facts are consistent with a model in which wages are set through monopsonistic wage-posting.

We estimate such a model:

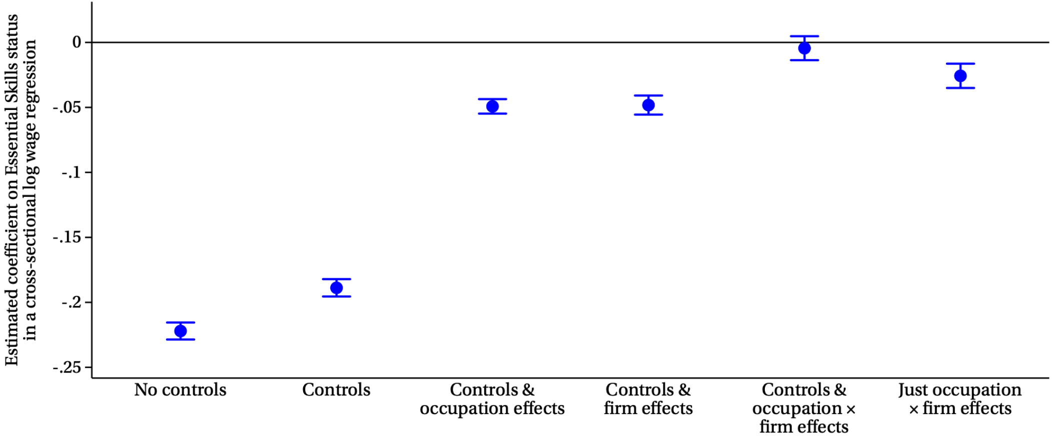
- Restricting migrants' job options decreases their wages by an average of 8%.
- Most residents are unaffected — but 2.1% have their wage decreased by ≥ 2%.
- The restrictions decrease aggregate welfare — mostly because of non-wage amenities.

Migrants earn less than other workers...



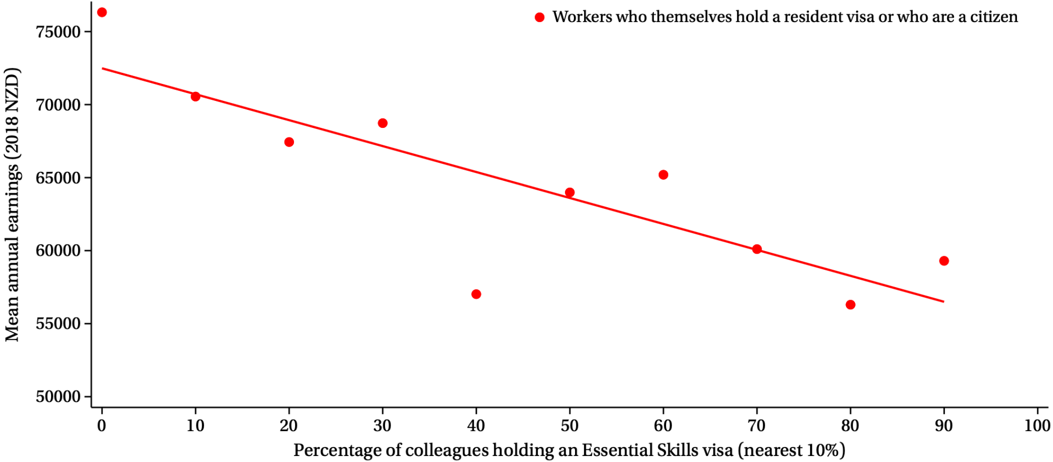
Sample: full-time employees with a unique firm in the 12 months before the 2018 Census. Other samples.

Migrants earn less than other workers... but only because of their jobs



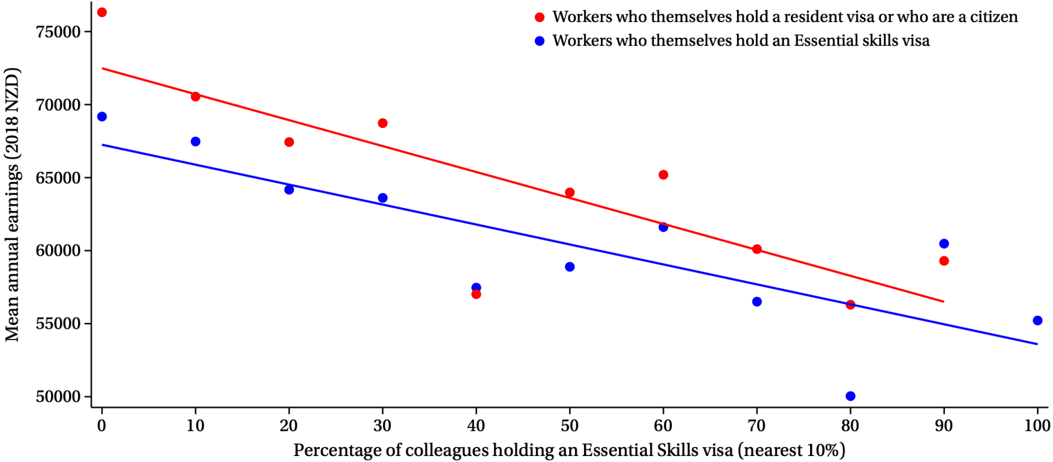
Sample: full-time employees with a unique firm in the 12 months before the 2018 Census. Other samples.

Migrants earn less than other workers... but only because of their jobs



Sample: full-time employees with a unique firm in the 12 months before the 2013 or 2018 censuses.

Migrants earn less than other workers... but only because of their jobs



Sample: full-time employees with a unique firm in the 12 months before the 2013 or 2018 censuses.

Today's talk

Reduced-form facts:

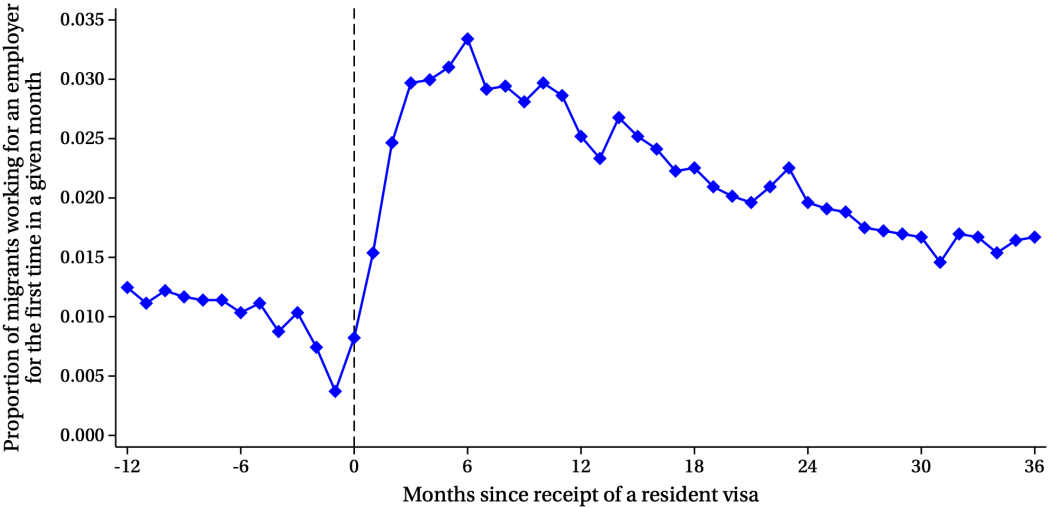
- Migrants earn less than other workers — but only because of the jobs they hold.
- Loosening an *individual* migrant's job restrictions does not affect their wages.
- But loosening the restrictions on *all* migrants within an occupation does increase wages.

These facts are consistent with a model in which wages are set through monopsonistic wage-posting.

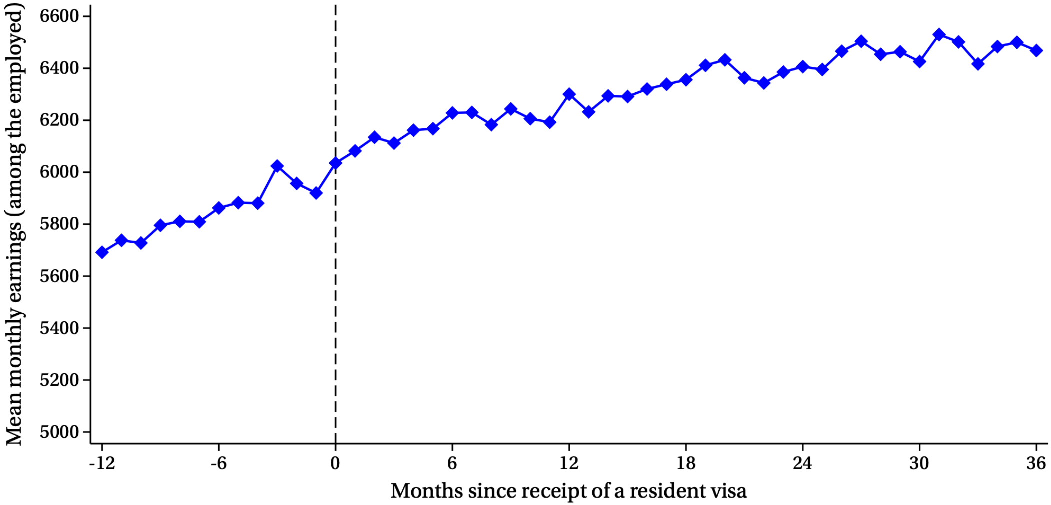
We estimate such a model:

- Restricting migrants' job options decreases their wages by an average of 8%.
- Most residents are unaffected — but 2.1% have their wage decreased by $\geq 2\%$.
- The restrictions decrease aggregate welfare — mostly because of non-wage amenities.

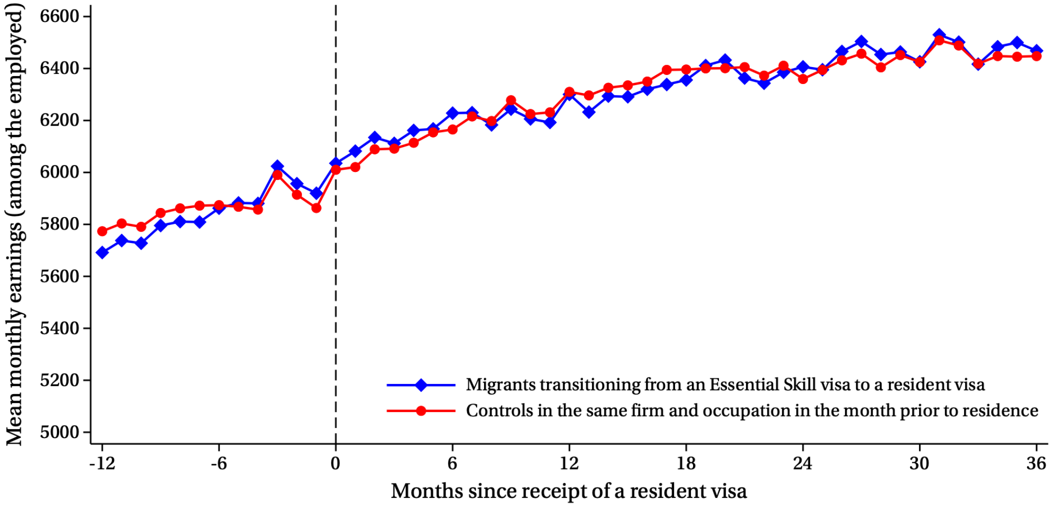
The Essential Skills visa restricts migrants' job options...



…but has no effect on an individual migrant's earnings

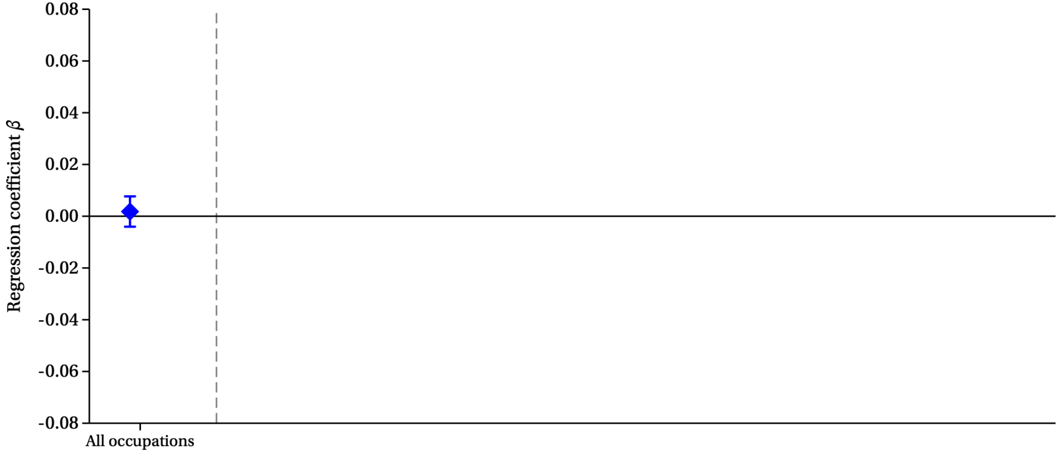


…but has no effect on an individual migrant's earnings



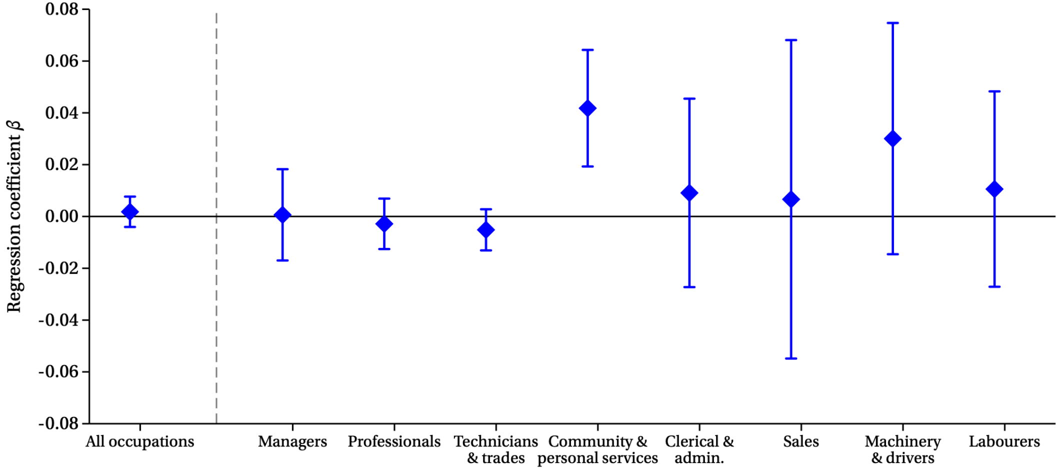
...but has no effect on an individual migrant's earnings

$$\log\left(\text{earnings}_{i,t}\right) - \log\left(\text{control earnings}_{i,t}\right) = \beta + \delta\left(\log\left(\text{earnings}_{i,-1}\right) - \log\left(\text{control earnings}_{i,-1}\right)\right) + e_{i,t}$$



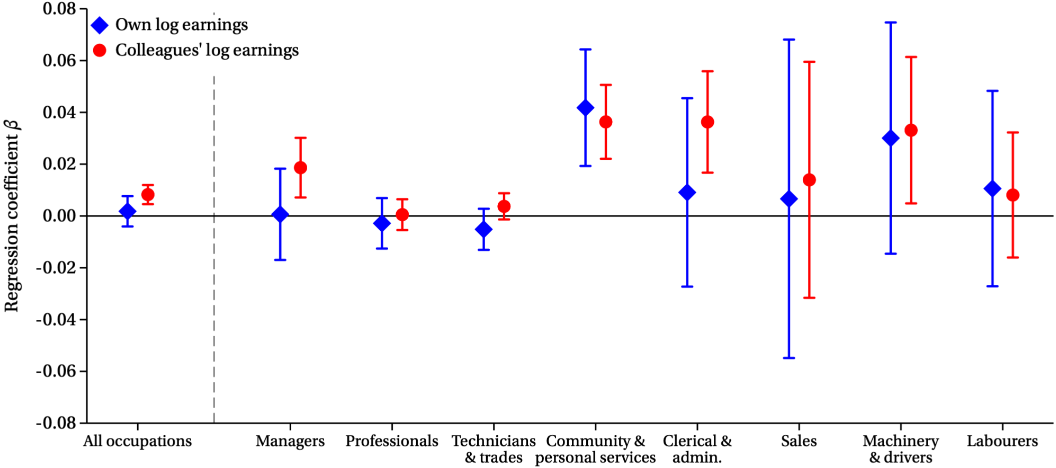
...but has no effect on an individual migrant's earnings

$$\log(\text{earnings}_{i,t}) - \log(\text{control earnings}_{i,t}) = \beta + \delta\left(\log(\text{earnings}_{i,-1}) - \log(\text{control earnings}_{i,-1})\right) + e_{i,t}$$



…but has no effect on an individual migrant's earnings

$$\log\left(\text{earnings}_{i,t}\right) - \log\left(\text{control earnings}_{i,t}\right) = \beta + \delta\left(\log\left(\text{earnings}_{i,-1}\right) - \log\left(\text{control earnings}_{i,-1}\right)\right) + e_{i,t}$$

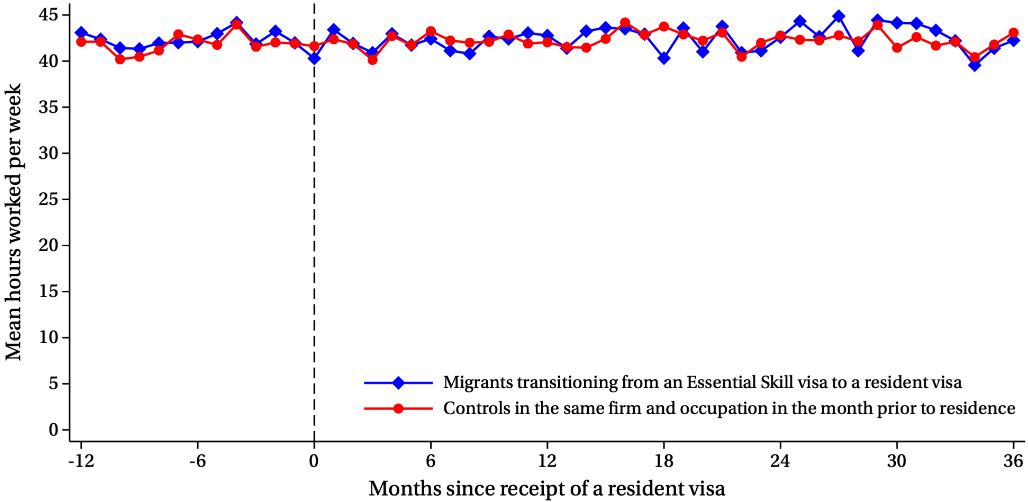


An individual migrant's job restriction does not affect their wage

Concern 1: New residents are able to negotiate better working conditions.

- Solution: *Study self-reported hours of work* in labor force surveys.

Obtaining a resident visa has no effect on hours of work



An individual migrant's job restriction does not affect their wage

Concern 1: New residents are able to negotiate better working conditions.

- Solution: *Study self-reported hours of work* in labor force surveys.

Concern 2: Workers apply for residence in anticipation of **worker-specific** shocks.

- Solution: *Study entrants into visa lotteries.*

The Pacific lottery visas

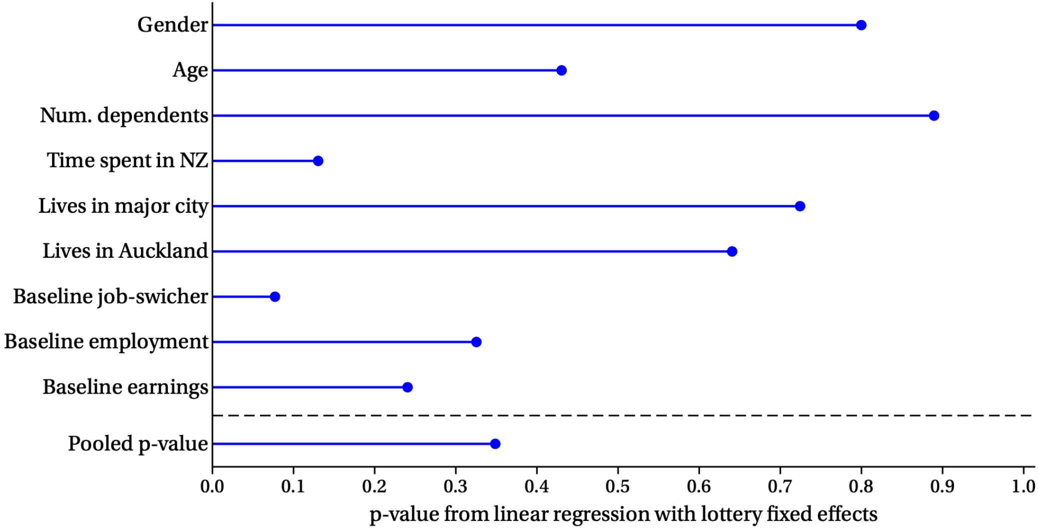
The **Pacific Access Category Resident Visa** and the **Samoan Quota Resident Visa** are New Zealand resident visas allocated by a **random lottery**.

- Citizens of Samoa, Kiribati, Tuvalu, Tonga and Fiji are eligible to enter.
- Typical entrants reside in their home country, but roughly 8% are in New Zealand when the lottery is drawn.

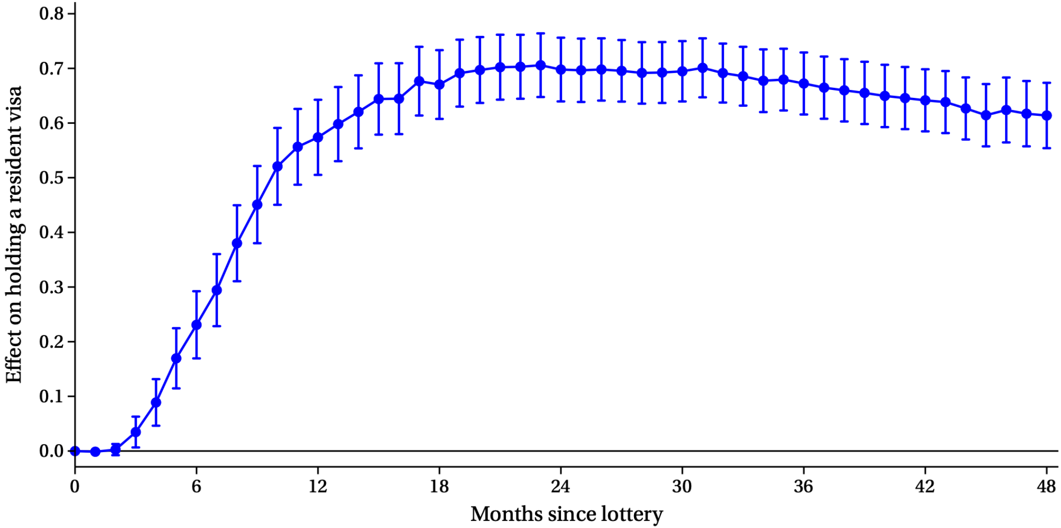
We study those 6501 lottery entries from 3891 individuals who

- **Entered the lottery for a Pacific lottery visa**,
- **While working in New Zealand on an Essential Skills visa**.

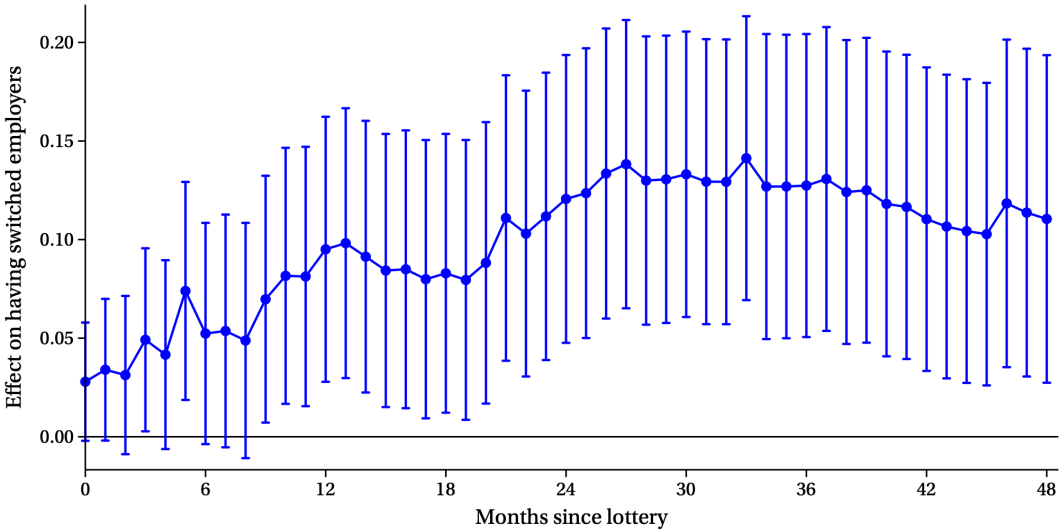
Lottery winners are similar to lottery losers



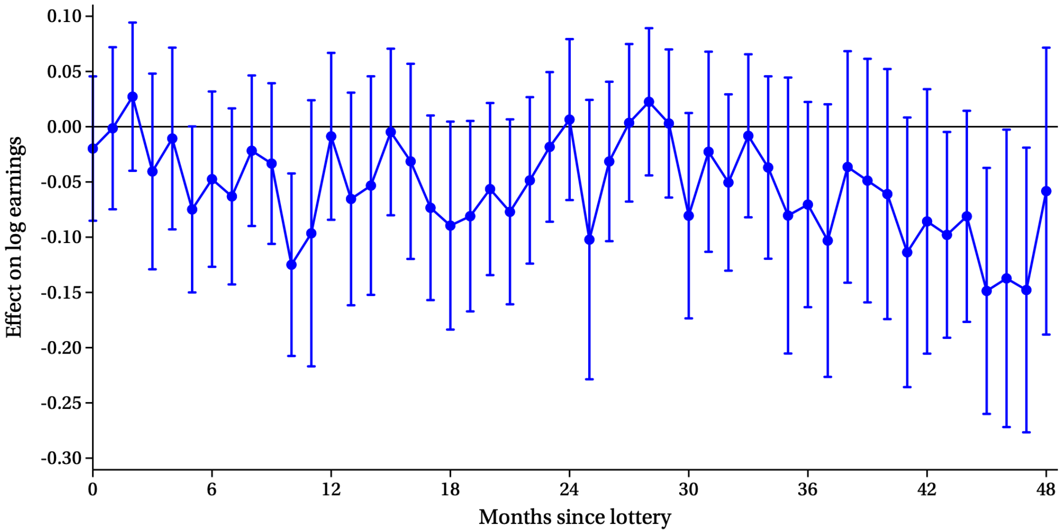
Lottery winners are much more likely to obtain resident visas



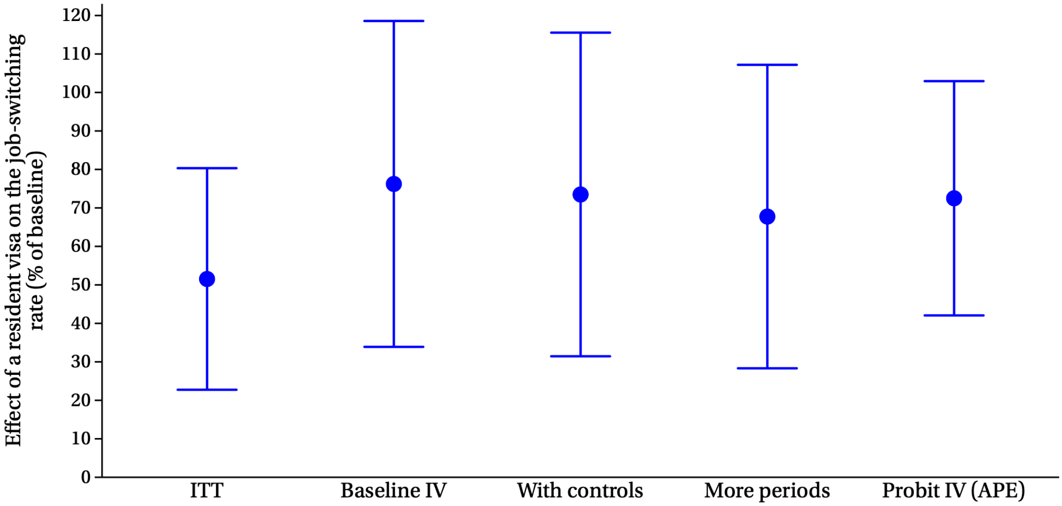
Lottery winners are more likely to switch jobs...



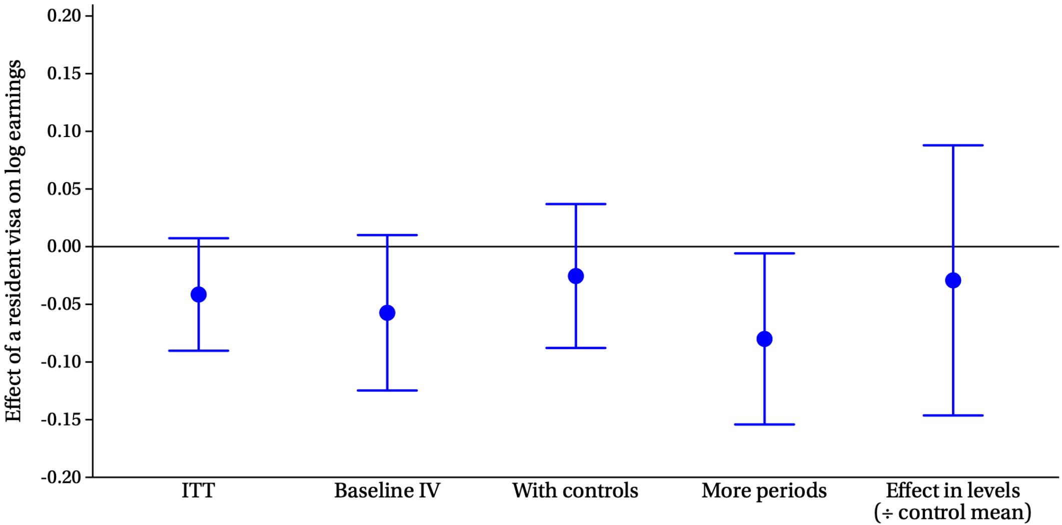
… but earn no more than lottery losers



IV estimates of the effect of a resident visa



IV estimates of the effect of a resident visa



An individual migrant's job restriction does not affect their wage

Concern 1: New residents are able to negotiate better working conditions.

- Solution: *Study self-reported hours of work* in labor force surveys.

Concern 2: Workers apply for residence in anticipation of **worker-specific** shocks.

- Solution: *Study entrants into visa lotteries.*

Concern 3: Our existing estimates include both the effect of outside options on **bargaining**, and the effect of **job-switching**.

- Some new residents may move to **high-amenity but low-wage jobs**

An individual migrant's job restriction does not affect their wage

Concern 1: New residents are able to negotiate better working conditions.

- Solution: *Study self-reported hours of work* in labor force surveys.

Concern 2: Workers apply for residence in anticipation of **worker-specific** shocks.

- Solution: *Study entrants into visa lotteries.*

Concern 3: Our existing estimates include both the effect of outside options on **bargaining**, and the effect of **job-switching**.

- Some new residents may move to **high-amenity but low-wage jobs**
- Solution: Identify the *average treatment effect among job-stayers.*

Do better outside options matter if a worker stays at their original job?

Let $Y_{i,t}(W,M)$ denote i's period-t log earnings, which depends on whether they won the lottery W_i and whether they moved $M_{i,t} = M_{i,t}(W_i)$:

$$Y_{i,t} = Y_{i,t}\left(W_i, M_{i,t}\right) = Y_{i,t}\left(W_i, M_{i,t}(W_i)\right).$$

Do better outside options matter if a worker stays at their original job?

Let $Y_{i,t}(W, M)$ denote i's period-t log earnings, which depends on whether they won the lottery W_i and whether they moved $M_{i,t} = M_{i,t}(W_i)$:

$$Y_{i,t} = Y_{i,t}\left(W_i, M_{i,t}\right) = Y_{i,t}\left(W_i, M_{i,t}(W_i)\right).$$

We are interested in the **average effect of winning a visa lottery, among those who stay at their initial job:**

$$\text{ATE}_{\text{stayers}} \equiv \mathbb{E}\left[Y_{i,t}(1,0) - Y_{i,t}(0,0) \,\middle|\, M_{i,t}(1) = M_{i,t}(0) = 0\right].$$

Problem: Among job-stayers, the lottery is non-random.

Do better outside options matter if a worker stays at their original job?

Let $Y_{i,t}(W,M)$ denote i's period-t log earnings, which depends on whether they won the lottery W_i and whether they moved $M_{i,t} = M_{i,t}(W_i)$:

$$Y_{i,t} = Y_{i,t}\left(W_i, M_{i,t}\right) = Y_{i,t}\left(W_i, M_{i,t}(W_i)\right).$$

We are interested in the **average effect of winning a visa lottery, among those who stay at their initial job:**

$$\text{ATE}_{\text{stayers}} \equiv \mathbb{E}\left[Y_{i,t}(1,0) - Y_{i,t}(0,0) \,\middle|\, M_{i,t}(1) = M_{i,t}(0) = 0\right].$$

Assumption 1 (random lotteries): $\left(M_{i,t}(\cdot), Y_{i,t}(\cdot,\cdot)\right)_t \perp W_i$.

Assumption 2 (monotonicity): $\forall\, i,t : M_{i,t}(1) \geq M_{i,t}(0)$.

Do better outside options matter if a worker stays at their original job?

Let $Y_{i,t}(W,M)$ denote i's period-t log earnings, which depends on whether they won the lottery W_i and whether they moved $M_{i,t} = M_{i,t}(W_i)$:

$$Y_{i,t} = Y_{i,t}\left(W_i, M_{i,t}\right) = Y_{i,t}\left(W_i, M_{i,t}(W_i)\right).$$

We are interested in the **average effect of winning a visa lottery, among those who stay at their initial job:**

$$\text{ATE}_{\text{stayers}} \equiv \mathbb{E}\left[Y_{i,t}(1,0) - Y_{i,t}(0,0) \middle| M_{i,t}(1) = M_{i,t}(0) = 0\right].$$

Assumption 1 (random lotteries): $\left(M_{i,t}(\cdot), Y_{i,t}(\cdot,\cdot)\right)_t \perp W_i$.

Assumption 2 (monotonicity): $\forall\, i,t : M_{i,t}(1) \geq M_{i,t}(0)$.

$\therefore$ We can identify $\mathbb{E}\left[Y_{i,t}(1,0) \middle| M_{i,t}(1) = M_{i,t}(0) = 0\right] = \mathbb{E}\left[Y_{i,t} \middle| M_{i,t} = 0; W_i = 1\right]$.

Do better outside options matter if a worker stays at their original job?

We are interested in the **average effect of winning a visa lottery, among those who stay at their initial job:**

$$\text{ATE}_{\text{stayers}} \equiv \mathbb{E}\left[Y_{i,t}(1,0) - Y_{i,t}(0,0) \,\middle|\, M_{i,t}(1) = M_{i,t}(0) = 0 \right].$$

Challenge: what would *lottery-winning job-stayers* have earnt, had they lost the lottery?

Do better outside options matter if a worker stays at their original job?

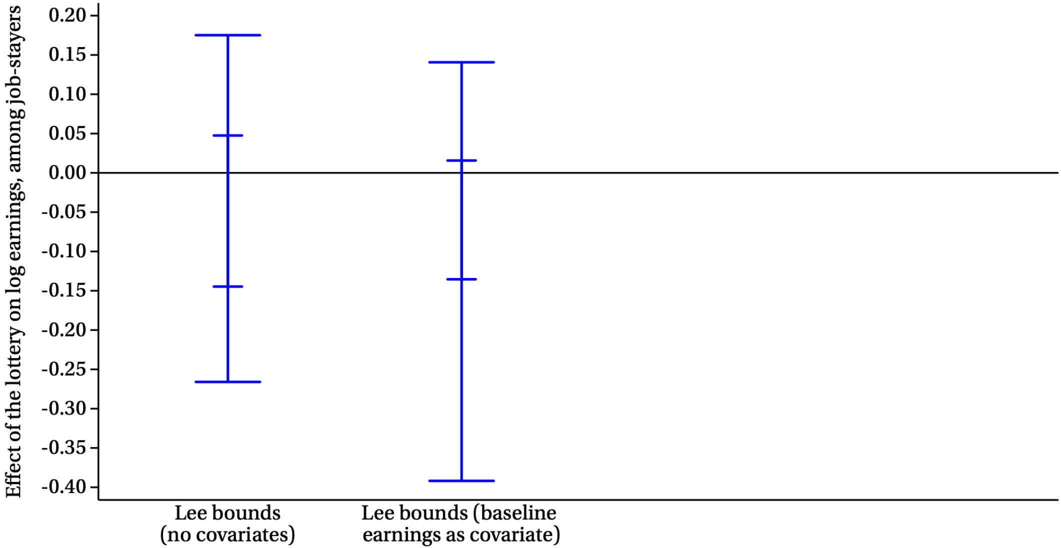
We are interested in the **average effect of winning a visa lottery, among those who stay at their initial job:**

$$\text{ATE}_{\text{stayers}} \equiv \mathbb{E}\left[Y_{i,t}(1,0) - Y_{i,t}(0,0) \middle| M_{i,t}(1) = M_{i,t}(0) = 0 \right].$$

Challenge: what would *lottery-winning job-stayers* have earnt, had they lost the lottery?

Approach 1: Set-identify by dropping the highest or lowest $Y_{i,t}$ among lottery losers (Lee ’09).

Do better outside options matter if a worker stays at their original job?



Do better outside options matter if a worker stays at their original job?

We are interested in the **average effect of winning a visa lottery, among those who stay at their initial job:**

$$\text{ATE}_{\text{stayers}} \equiv \mathbb{E}\left[Y_{i,t}(1,0) - Y_{i,t}(0,0) \,\middle|\, M_{i,t}(1) = M_{i,t}(0) = 0\right].$$

Challenge: what would *lottery-winning job-stayers* have earnt, had they lost the lottery?

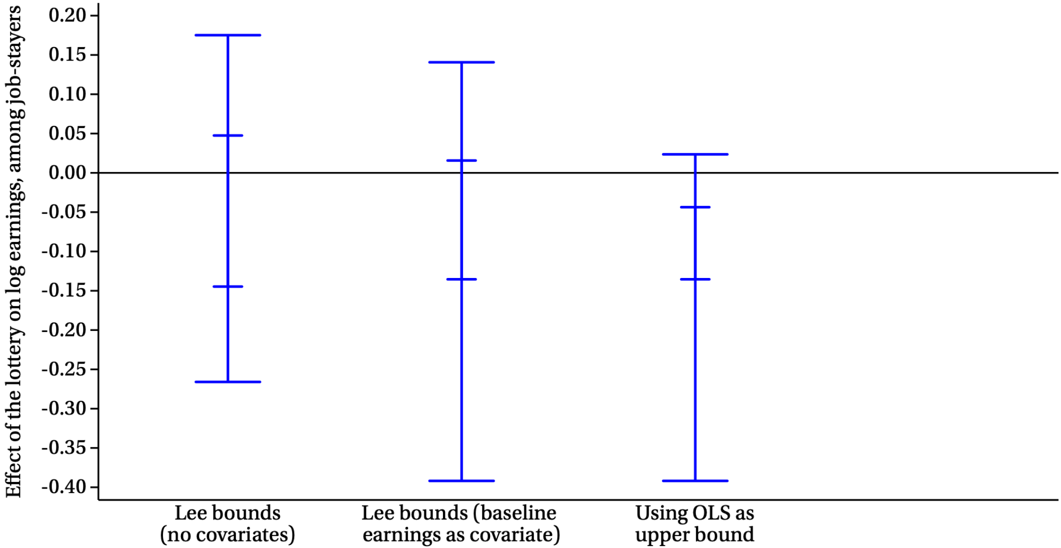
Approach 2: Sharpen the upper bound under the assumption that

$$\mathbb{E}\left[Y_{i,t}(0,0) \,\middle|\, M_{i,t}(0) = 0\right] \leq \mathbb{E}\left[Y_{i,t}(0,0) \,\middle|\, M_{i,t}(1) = 0\right],$$

which implies that OLS is upwards-biased.

$\left(\text{We observe } \mathbb{E}\left[Y_{i,-1} \,\middle|\, M_{i,t}(0) = 0\right] < \mathbb{E}\left[Y_{i,-1} \,\middle|\, M_{i,t}(1) = 0\right].\right)$

Do better outside options matter if a worker stays at their original job?



Do better outside options matter if a worker stays at their original job?

We are interested in the **average effect of winning a visa lottery, among those who stay at their initial job:**

$$\text{ATE}_{\text{stayers}} \equiv \mathbb{E}\left[Y_{i,t}(1,0) - Y_{i,t}(0,0) \,\middle|\, M_{i,t}(1) = M_{i,t}(0) = 0\right].$$

Challenge: what would *lottery-winning job-stayers* have earnt, had they lost the lottery?

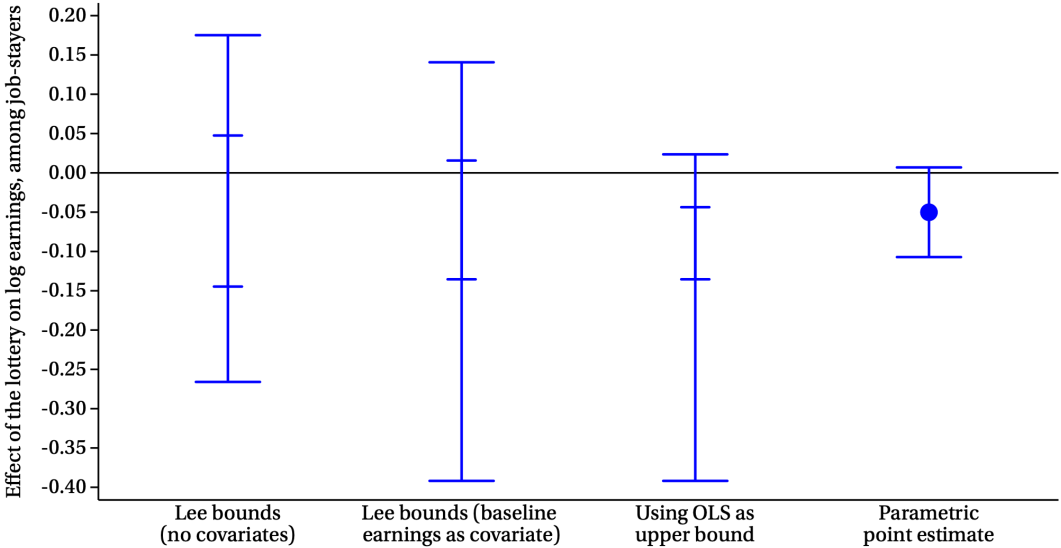
Approach 3: Point-identify by <u>modeling</u> the decision to move.

Key assumption: job-switching is Markovian in counterfactual earnings

$$M_{i,t}(1), M_{i,t}(0) \perp \left(Y_{i,s}(0,0)\right)_{s<t} \mid Y_{i,t}(0,0).$$

$\therefore$ We can infer how job-switching depends on counterfactual earnings from how job-switching depends on baseline earnings.

Do better outside options matter if a worker stays at their original job?



Today's talk

Reduced-form facts:

- Migrants earn less than other workers — but only because of the jobs they hold.
- Loosening an *individual* migrant's job restrictions does not affect their wages.
- But loosening the restrictions on *all* migrants within an occupation does increase wages.

These facts are consistent with a model in which wages are set through monopsonistic wage-posting.

We estimate such a model:

- Restricting migrants' job options decreases their wages by an average of 8%.
- Most residents are unaffected — but 2.1% have their wage decreased by $\geq 2\%$.
- The restrictions decrease aggregate welfare — mostly because of non-wage amenities.

In an occupation, strengthening *all* migrants' job options increases wages

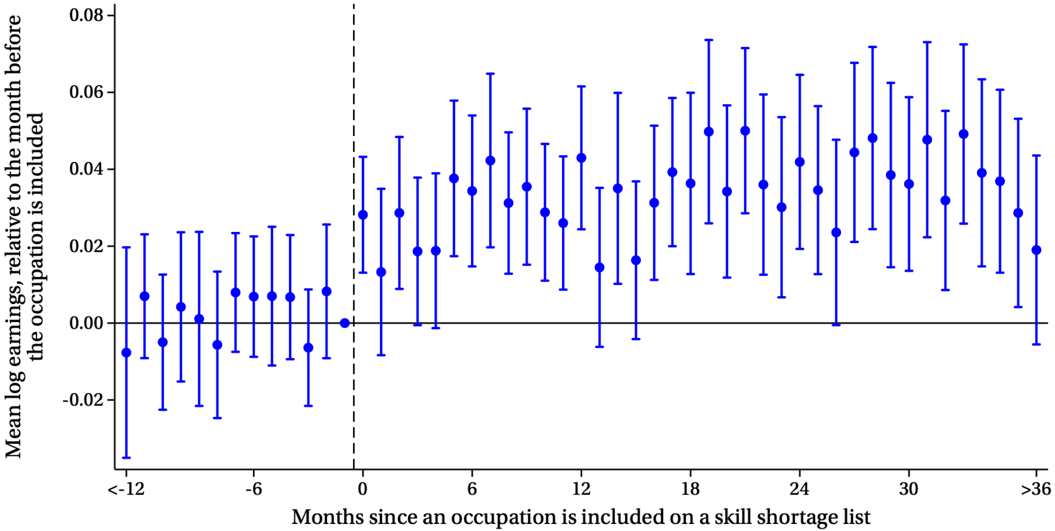
For **occupations on an 'Essential Skills in Demand' list**:

- Prospective employers need not show a 'genuine attempt' to recruit New Zealanders.
- So, **Essential Skills migrants' job options are unrestricted**.

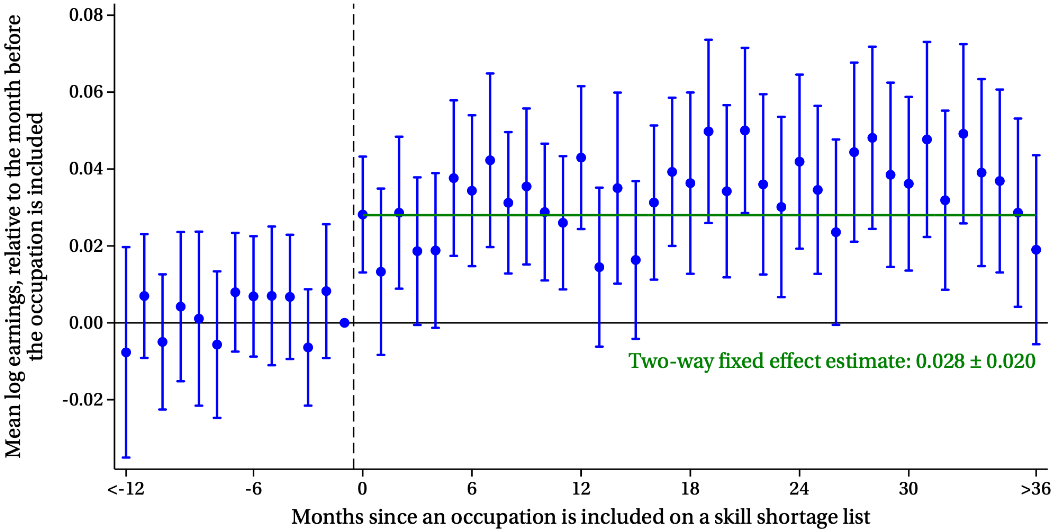
Occupations were added and removed from these lists regularly, often for reasons orthogonal to demand (*e.g.* occupation size).

We ask how wages change when an occupation is listed.

In an occupation, strengthening *all* migrants' job options increases wages

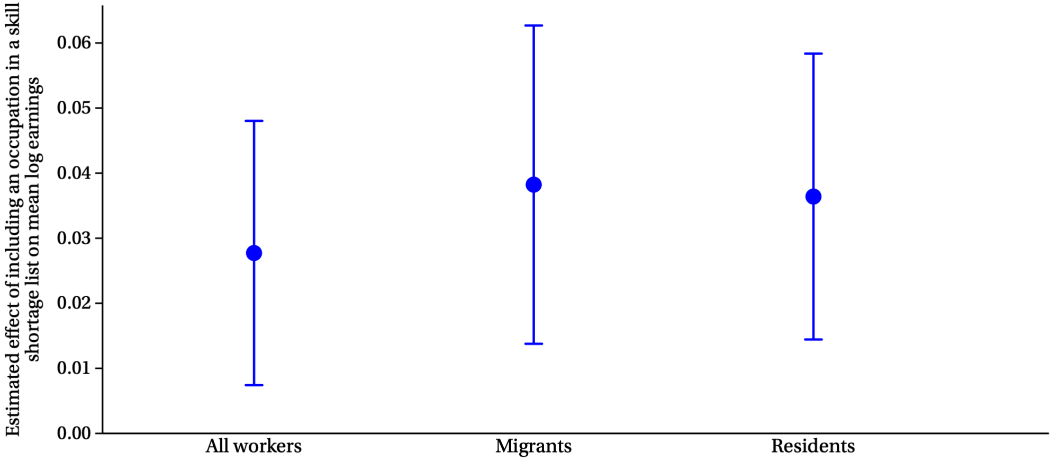


In an occupation, strengthening *all* migrants' job options increases wages

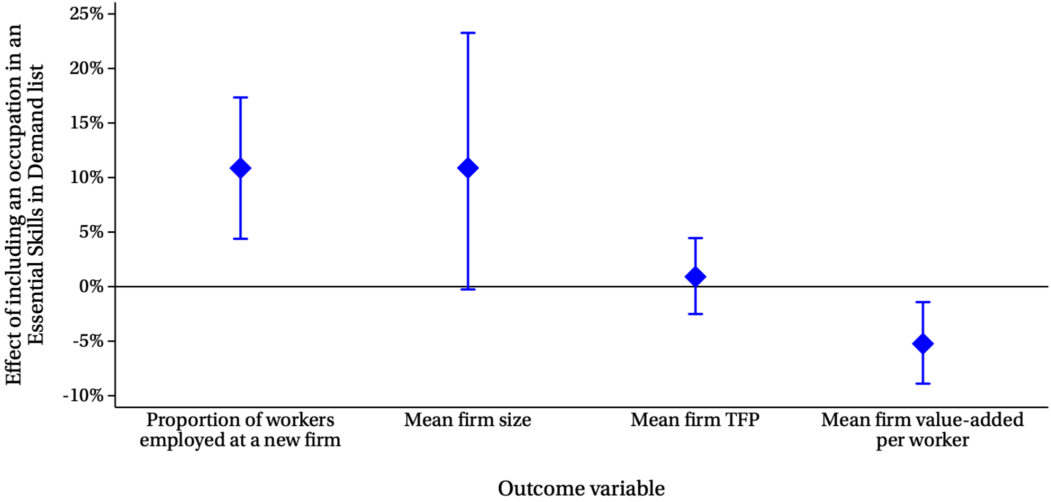


In an occupation, strengthening *all* migrants' job options increases wages

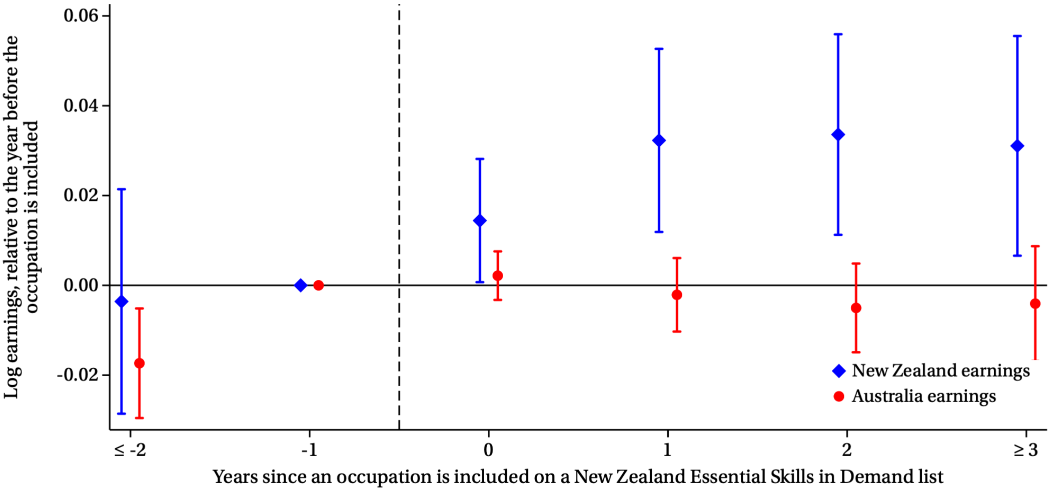
In an occupation, strengthening *all* migrants' job options increases wages



Why does strengthening migrants' job options increase wages?



Using Australian data as a placebo outcome



Point estimate.

Today's talk

Reduced-form facts:

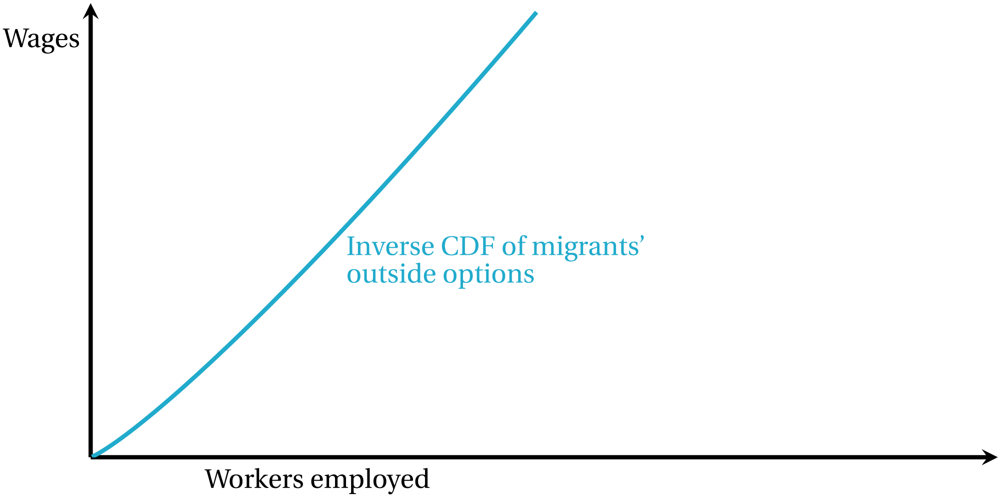
- Migrants earn less than other workers — but only because of the jobs they hold.
- Loosening an *individual* migrant's job restrictions does not affect their wages.
- But loosening the restrictions on *all* migrants within an occupation does increase wages.

These facts are consistent with a model in which wages are set through monopsonistic wage-posting.

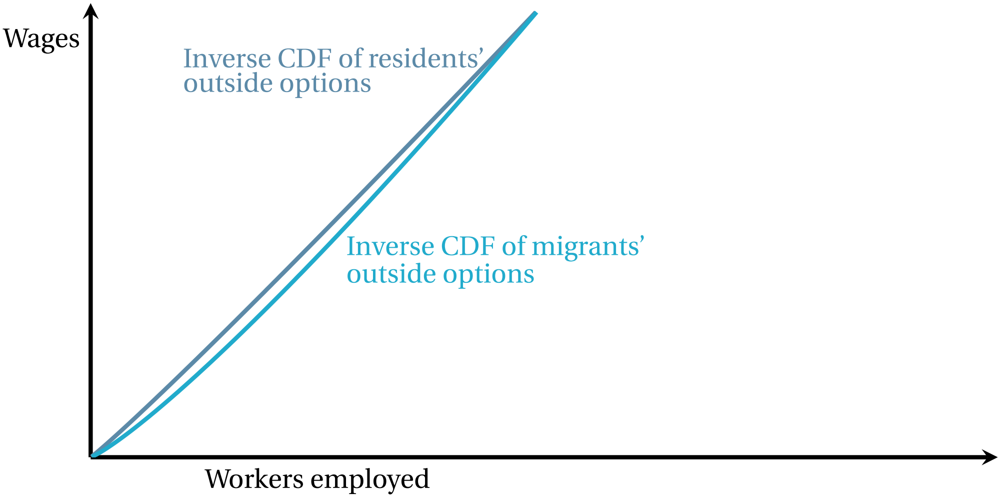
We estimate such a model:

- Restricting migrants' job options decreases their wages by an average of 8%.
- Most residents are unaffected — but 2.1% have their wage decreased by $\geq 2\%$.
- The restrictions decrease aggregate welfare — mostly because of non-wage amenities.

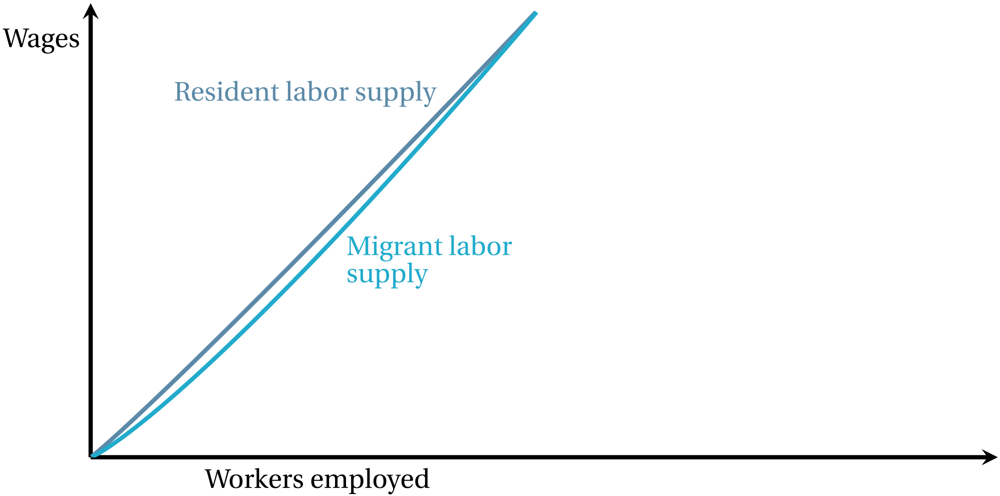
Posted wages when migrants' jobs are *unrestricted*



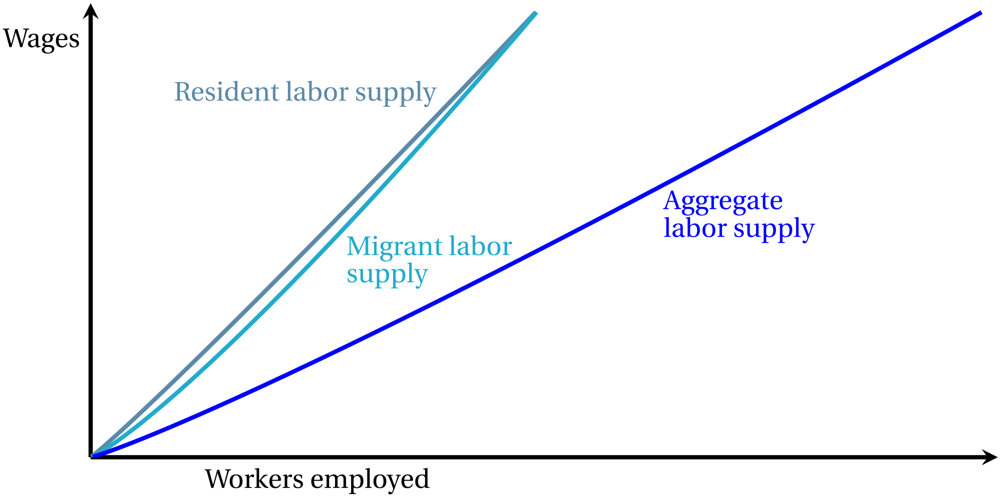
Posted wages when migrants’ jobs are *unrestricted*



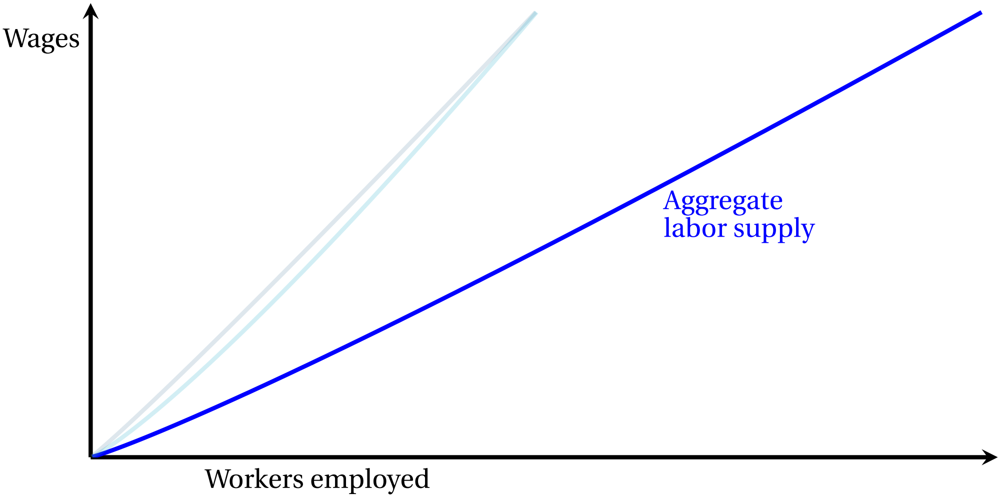
Posted wages when migrants' jobs are *unrestricted*



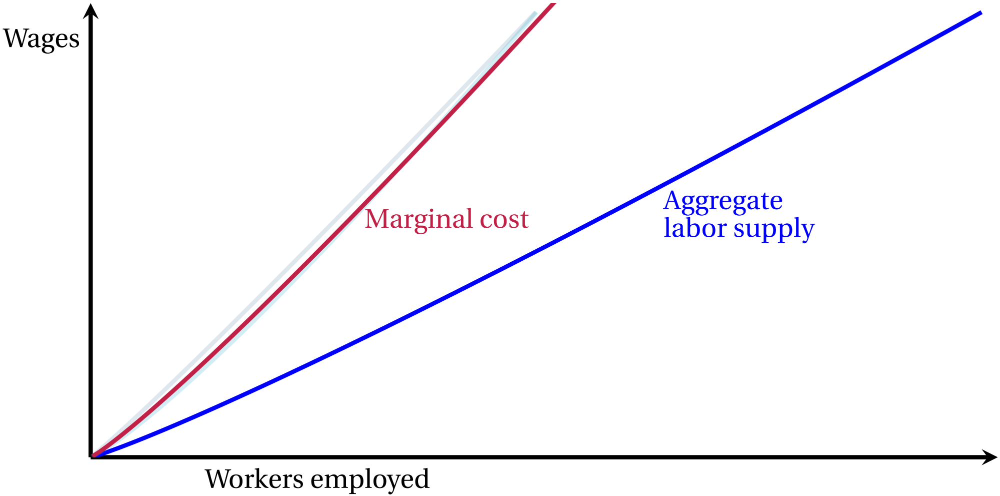
Posted wages when migrants' jobs are *unrestricted*



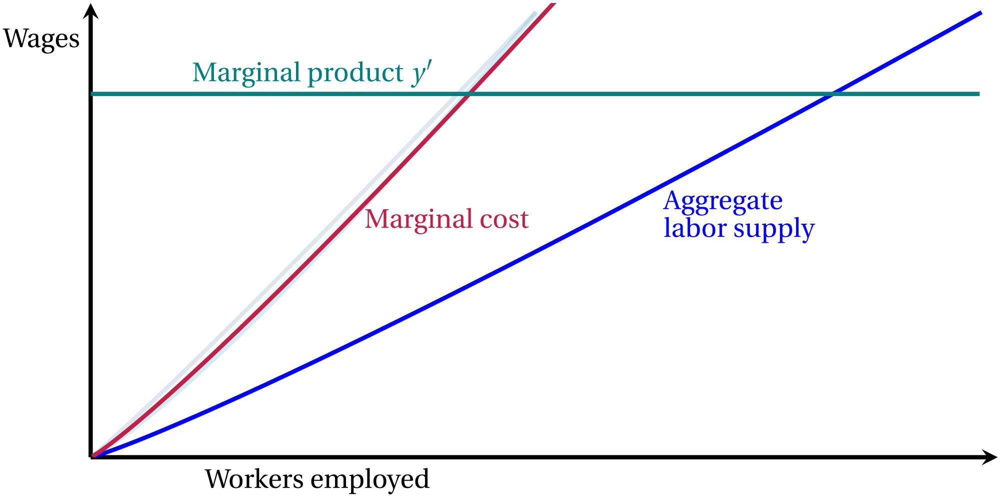
Posted wages when migrants' jobs are *unrestricted*



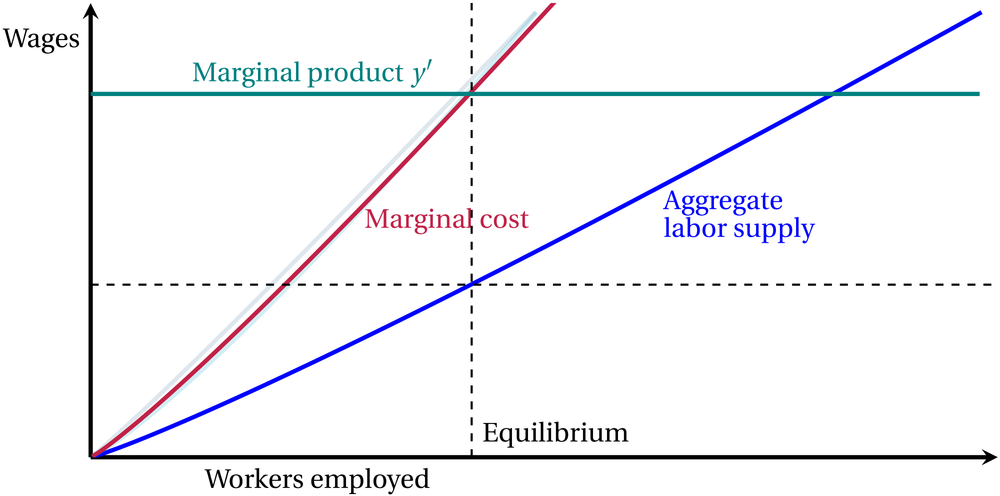
Posted wages when migrants' jobs are *unrestricted*



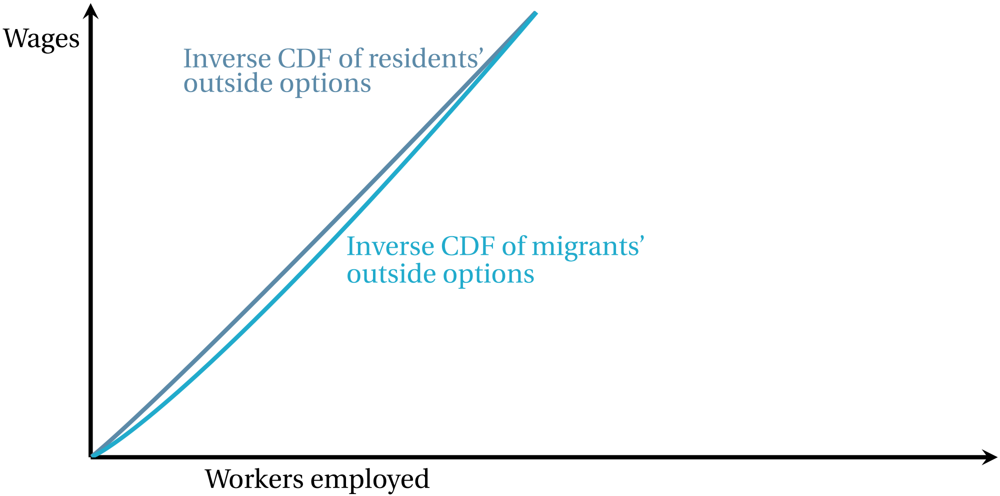
Posted wages when migrants' jobs are *unrestricted*



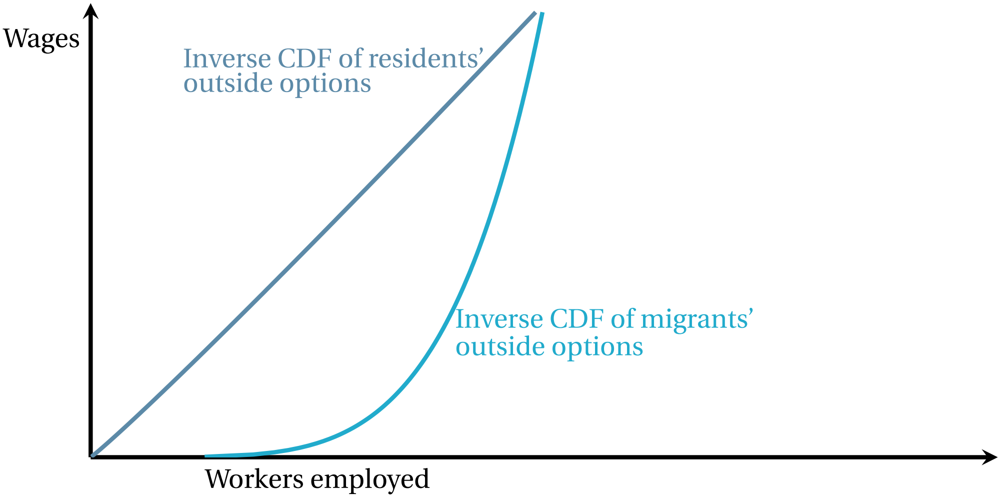
Posted wages when migrants' jobs are *unrestricted*



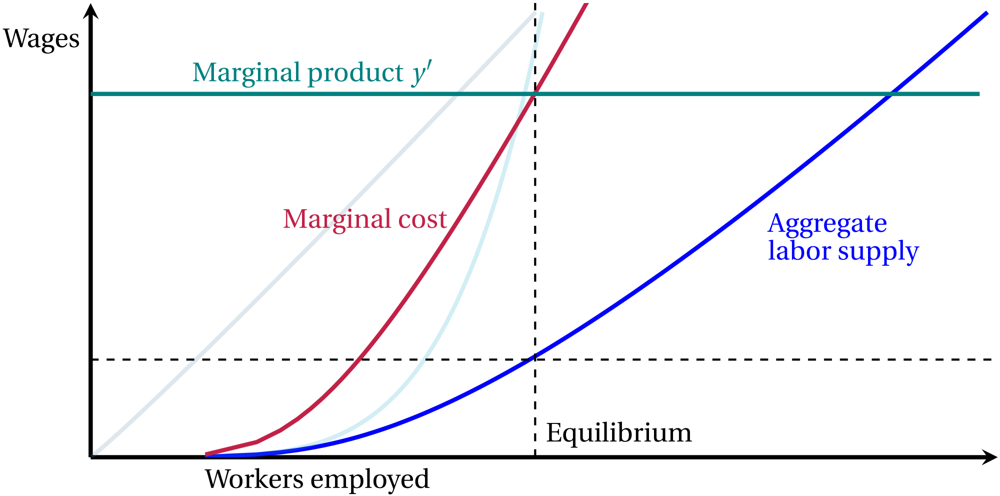
Posted wages when migrants' jobs are *unrestricted*



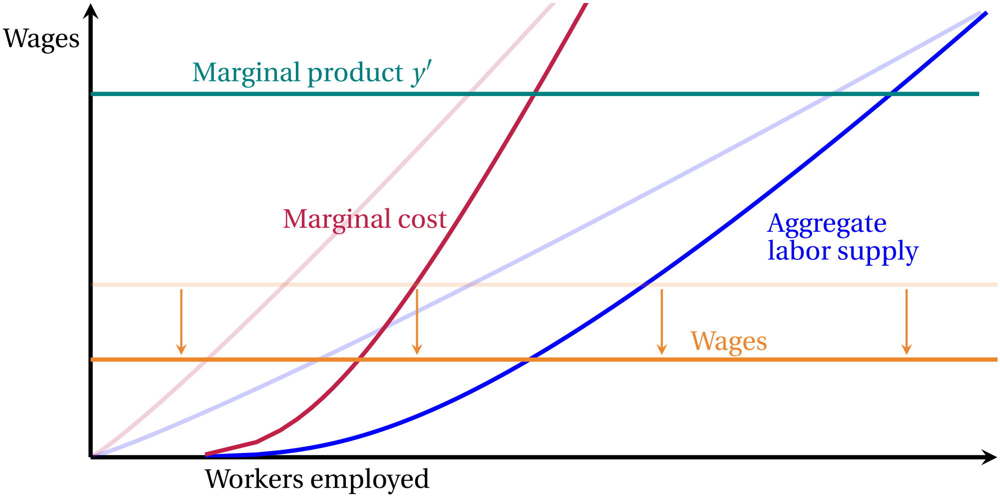
Posted wages when migrants' jobs are *restricted*



Posted wages when migrants' jobs are *restricted*



Restricting migrants' jobs reduces posted wages



Structural model: motivation

Research question: **how does restricting migrants job options affect wages, profits, and welfare?**

Limitation of reduced-form analyses:

- Can’t identify the distribution of effects across workers.
- Firm-level data is noisy and often missing: can’t estimate profit effects.
- Don’t observe non-wage amenities: can’t identify welfare effects.

Structural model: overview

The model is designed to capture two mechanisms.

Restricting migrants' job options will **decrease the elasticity of their labor supply, inducing firms to set less generous wages**.

- Empirical question: how restricted are migrants' job options in practice?
- Estimate workers' willingness to move across firms and space.

Structural model: overview

The model is designed to capture two mechanisms.

Restricting migrants' job options will **decrease the elasticity of their labor supply, inducing firms to set less generous wages**.

- Empirical question: how restricted are migrants' job options in practice?
- Estimate workers' willingness to move across firms and space.

Restricting migrants' job options will **segregate them into certain firms, decreasing their marginal product**.

- Empirical question: How concave is production? How easily can firms substitute across occupations?
- Estimate production functions which account for workers' occupations.

Structural model: primitives

Perfect information, partial equilibrium. Discrete time, but decision-making is static.

In each period, the model comprises a continuum of workers $\mathbf{I}_t$ and finite firms $\mathbf{F}_t$.

Structural model: primitives

Perfect information, partial equilibrium. Discrete time, but decision-making is static.

In each period, the model comprises a continuum of workers $\mathbf{I}_t$ and finite firms $\mathbf{F}_t$.

Each worker $i \in \mathbf{I}_t$ has an **exogenous occupation** $o_{i,t}$ and supplies an **exogenous endowment of labor** $l_{i,t}$ to

$$f_{i,t} = \underset{f \in \mathbf{F}_{i,t}}{\arg\max}\, u_{i,t}\left(w_{f,o_{i,t},t} l_{i,t},\, f\right),$$

where $\mathbf{F}_{i,t}$ is the worker's choice set:

- If i is a *resident*: $\mathbf{F}_{i,t} = \mathbf{F}_{o_i,t}$;
- If i is a *migrant*: $\mathbf{F}_{i,t} = \mathbf{F}_{o_i,t}^{migrant} \subseteq \mathbf{F}_{o_i,t}$.

Structural model: primitives

Perfect information, partial equilibrium. Discrete time, but decision-making is static.

In each period, the model comprises a continuum of workers $\mathbf{I}_t$ and finite firms $\mathbf{F}_t$.

Each worker $i \in \mathbf{I}_t$ has an **exogenous occupation** $o_{i,t}$ and supplies an **exogenous endowment of labor** $l_{i,t}$ to

$$f_{i,t} = \arg\max_{f \in \mathbf{F}_{i,t}} u_{i,t}\left(w_{f,o_{i,t},t} l_{i,t}, f\right),$$

where $\mathbf{F}_{i,t}$ is the worker's choice set:

- If i is a *resident*: $\mathbf{F}_{i,t} = \mathbf{F}_{o_i,t}$;
- If i is a *migrant*: $\mathbf{F}_{i,t} = \mathbf{F}_{o_i,t}^{migrant} \subseteq \mathbf{F}_{o_i,t}$.

A type-x worker has **nested-logit preferences** over firms f in locations c_f with wages w:

$$u_{i,t}\left(W, f\right) = \tau_x \log(W) + \bar{\xi}_{c_f,o_i,x,t} + \frac{1}{\lambda_x}\zeta_{i,c_f,t} + \xi_{f,o_i,x,t} + \epsilon_{i,f,t}; \qquad \zeta_{i,c_f,t}, \epsilon_{i,f,t} \perp l_{i,t}.$$

Structural model: primitives

Perfect information, partial equilibrium. Discrete time, but decision-making is static.

In each period, the model comprises a continuum of workers $\mathbf{I}_t$ and finite firms $\mathbf{F}_t$.

Firms have **CES production functions**:

$$y_{f,t}\left(\left(L_{f,o,t}\right)_{o\in\mathbf{O}_{f,t}}\right) = \left(\sum_{o\in\mathbf{O}_{f,t}} e^{\phi_{f,o,t}} L_{f,o,t}^{\rho}\right)^{\frac{\nu}{\rho}}, \qquad L_{f,o,t} \equiv \int_{i:f_i=f,o_i=o} l_{i,t}\,di.$$

Structural model: primitives

Perfect information, partial equilibrium. Discrete time, but decision-making is static.

In each period, the model comprises a continuum of workers $\mathbf{I}_t$ and finite firms $\mathbf{F}_t$.

Firms have **CES production functions**:

$$y_{f,t}\left(\left(L_{f,o,t}\right)_{o\in\mathbf{O}_{f,t}}\right) = \left(\sum_{o\in\mathbf{O}_{f,t}} e^{\phi_{f,o,t}} L_{f,o,t}^{\rho}\right)^{\frac{\nu}{\rho}}, \qquad L_{f,o,t} \equiv \int_{i:f_i=f,o_i=o} l_{i,t}\,di.$$

Firms post wages $w_{f,o,t}$ in **Bertrand competition**:

$$\vec{w}_{f,t} \in \underset{\vec{w}\in\mathbf{R}^{|\mathbf{O}_{f,t}|}}{\arg\max}\left\{y_f\left(\vec{L}_{f,t}\left(\vec{w};\vec{w}_{-f,t}\right)\right) - \vec{w}'\vec{L}_{f,t}\left(\vec{w};\vec{w}_{-f,t}\right)\right\}.$$

Structural model: equilibrium wages

Profit-maximizing wages will satisfy a standard markdown equation:

$$w_{f,o,t} = \frac{\partial y_{f,t}}{\partial L_{f,o,t}} \left(1 + \frac{1}{\eta_{f,o,t}}\right)^{-1},$$

where $\eta_{f,o,t}$ is the elasticity of labor supply, and the marginal product of labor is

$$\frac{\partial y_{f,t}}{\partial L_{f,o,t}} = \nu \left(\sum_{o' \in \mathbf{O}_{f,t}} e^{\phi_{f,o',t}} L^{\rho}_{f,o',t} \right)^{\frac{\nu-\rho}{\rho}} e^{\phi_{f,o,t}} L^{\rho-1}_{f,o,t}.$$

Structural model: equilibrium wages

Profit-maximizing wages will satisfy a standard markdown equation:

$$w_{f,o,t} = \frac{\partial y_{f,t}}{\partial L_{f,o,t}} \left(1 + \frac{1}{\eta_{f,o,t}}\right)^{-1},$$

where $\eta_{f,o,t}$ is the elasticity of labor supply, and the marginal product of labor is

$$\frac{\partial y_{f,t}}{\partial L_{f,o,t}} = \nu \left(\sum_{o' \in \mathbf{O}_{f,t}} e^{\phi_{f,o',t}} L_{f,o',t}^{\rho} \right)^{\frac{\nu-\rho}{\rho}} e^{\phi_{f,o,t}} L_{f,o,t}^{\rho-1}.$$

Combining these equations, we derive the wage equation

$$\log w_{f,o,t} = \frac{\rho \log \nu}{\nu} + (\rho - 1) \log L_{f,o,t} + \left(\frac{\nu - \rho}{\nu}\right) \log \tilde{L}_{f,t} - \log\left(1 + \frac{1}{\eta_{f,o,t}}\right) + \phi_{f,o,t}$$

where $\tilde{L}_{f,t}$ measures firm-level aggregate labor: $\tilde{L}_{f,t} \equiv \sum_{o \in \mathbf{O}_{f,t}} w_{f,o,t} L_{f,o,t} \left(1 + \frac{1}{\eta_{f,o,t}}\right)$.

Structural model: labor supply

Labor supply *within* locations:

$$\log N^{resident}_{f,o,x,t} = C_{c_f,o,x,t} + \tau_x \log w_{f,o,t} + \xi_{f,o,x,t}$$

Labor supply *between* locations:

$$\log N^{resident}_{c,o,x,t} = C_{o,x,t} + \lambda_x \log\left(\sum_{f \in \mathbf{F}_{c,o,t}} e^{\tau_x \log w_{f,o,t} + \xi_{f,o,x,t}}\right) + \Delta\bar{\xi}_{c,o,x,t}.$$

Structural model: labor supply

Labor supply *within* locations:

$$\log N^{resident}_{f,o,x,t} = C_{c_f,o,x,t} + \tau_x \log w_{f,o,t} + \xi_{f,o,x,t}$$

Labor supply *between* locations:

$$\log N^{resident}_{c,o,x,t} = C_{o,x,t} + \lambda_x \log\left(\sum_{f \in \mathbf{F}_{c,o,t}} e^{\tau_x \log w_{f,o,t} + \xi_{f,o,x,t}}\right) + \Delta\bar{\xi}_{c,o,x,t}.$$

Labor supply elasticity of demographic-x, visa-v workers to firm f:

$$\eta^{v}_{f,o,x,t} = \tau_x\left(1 - (1-\lambda_x)\,\text{regional market share}_{f,o,x,v,t} - \lambda_x \text{national market share}_{f,o,x,v,t}\right)$$

Structural model: labor supply

Labor supply *within* locations:

$$\log N^{resident}_{f,o,x,t} = C_{c_f,o,x,t} + \tau_x \log w_{f,o,t} + \xi_{f,o,x,t}$$

Labor supply *between* locations:

$$\log N^{resident}_{c,o,x,t} = C_{o,x,t} + \lambda_x \log\left(\sum_{f\in\mathbf{F}_{c,o,t}} e^{\tau_x \log w_{f,o,t} + \xi_{f,o,x,t}}\right) + \Delta\bar{\xi}_{c,o,x,t}.$$

Labor supply elasticity of demographic-x, visa-v workers to firm f:

$$\eta^{v}_{f,o,x,t} = \tau_x\Big(1 - (1-\lambda_x)\,\text{regional market share}_{f,o,x,v,t} - \lambda_x \text{national market share}_{f,o,x,v,t}\Big)$$

Overall labor supply elasticity to firm f:

$$\eta_{f,o,t} = \frac{1}{N_{f,o,t}} \sum_{x\in\mathbf{X}} \left(N^{resident}_{f,o,x,t}\eta^{resident}_{f,o,x,t} + N^{migrant}_{f,o,x,t}\eta^{migrant}_{f,o,x,t}\right)$$

Structural model: identification stategy

Key assumption: shocks to the amenity-value of employment $\Delta\xi_{f,o,x,t}$ are orthogonal to both

- productivity shocks $\Delta\phi_{f,o,t}$, and
- lagged productivity shocks $\Delta\phi_{f,o,t-1}$,

Structural model: identification stategy

Key assumption: shocks to the amenity-value of employment $\Delta\xi_{f,o,x,t}$ are orthogonal to both

- productivity shocks $\Delta\phi_{f,o,t}$, and
- lagged productivity shocks $\Delta\phi_{f,o,t-1}$,

Problem: Productivity and amenity-values are both measured using wages.

- Unobserved worker productivity generates measurement error in wages.
- Measurement error in wages introduces a spurious correlation.

Structural model: identification stategy

Key assumption: shocks to the amenity-value of employment $\Delta\xi_{f,o,x,t}$ are orthogonal to both

- productivity shocks $\Delta\phi_{f,o,t}$, and
- lagged productivity shocks $\Delta\phi_{f,o,t-1}$,

Problem: Productivity and amenity-values are both measured using wages.

- Unobserved worker productivity generates measurement error in wages.
- Measurement error in wages introduces a spurious correlation.

Solution: calculate wages in each of two random split-samples. Require e.g. productivity shocks in one sample be orthogonal to amenity shocks in the other sample.

Structural model: a fixed-point estimator

Given candidate values of the labor supply parameters τ_x^0, λ_x^0:

Structural model: a fixed-point estimator

Given candidate values of the labor supply parameters τ_x^0, λ_x^0:

1. Calculate $\eta^v_{f,o,x,t}$: **the labor supply elasticity of type-x occupation-o workers with visa-status** v, given observed market shares and the parameters τ_x^0, λ_x^0.

$$\eta^v_{f,o,x,t} = \tau_x \left(1 - (1 - \lambda_x) \, \text{regional market share}_{f,o,x,v,t} - \lambda_x \text{national market share}_{f,o,x,v,t} \right)$$

Structural model: a fixed-point estimator

Given candidate values of the labor supply parameters τ_x^0, λ_x^0:

1. Calculate $\eta_{f,o,x,t}^{v}$: **the labor supply elasticity of type-x occupation-o workers with visa-status** v, given observed market shares and the parameters τ_x^0, λ_x^0.
2. Calculate $\eta_{f,o,t}$: the **labor supply elasticity of occupation-o workers** to firm f, by aggregating over visa statuses and worker types.

$$\eta_{f,o,t} = \frac{1}{N_{f,o,t}} \sum_{x \in \mathbf{X}} \left(N_{f,o,x,t}^{resident} \eta_{f,o,x,t}^{resident} + N_{f,o,x,t}^{migrant} \eta_{f,o,x,t}^{migrant} \right)$$

Structural model: a fixed-point estimator

Given candidate values of the labor supply parameters τ_x^0, λ_x^0:

1. Calculate $\eta^{\nu}_{f,o,x,t}$: **the labor supply elasticity of type-x occupation-o workers with visa-status** ν, given observed market shares and the parameters τ_x^0, λ_x^0.
2. Calculate $\eta_{f,o,t}$: the **labor supply elasticity of occupation-o workers** to firm f, by aggregating over visa statuses and worker types.
3. Using these labor supply elasticities, calculate **firm-level aggregate labor** $\tilde{L}_{f,t}$.

$$\tilde{L}_{f,t} = \sum_{o \in \mathbf{O}_{f,t}} w_{f,o,t} L_{f,o,t} \left(1 + \frac{1}{\eta_{f,o,t}}\right)$$

Structural model: a fixed-point estimator

Given candidate values of the labor supply parameters τ_x^0, λ_x^0:

1. Calculate $\eta^{v}_{f,o,x,t}$: **the labor supply elasticity of type-x occupation-o workers with visa-status** v, given observed market shares and the parameters τ_x^0, λ_x^0.
2. Calculate $\eta_{f,o,t}$: the **labor supply elasticity of occupation-o workers** to firm f, by aggregating over visa statuses and worker types.
3. Using these labor supply elasticities, calculate **firm-level aggregate labor** $\tilde{L}_{f,t}$.
4. In each split-sample-s, calculate **amenity shocks** $\Delta\hat{\xi}^{s}_{f,o,x,t}$ given observed employment, wages and the parameters τ_x^0, λ_x^0 (Berry '94).

$$\log N^{resident}_{f,o,x,t} = Constant_{x,c_f,t} + \tau_x \log(w_{f,o,t}) + \xi_{f,o,x,t}$$

Structural model: a fixed-point estimator

Given candidate values of the labor supply parameters τ_x^0, λ_x^0:

1. Calculate $\eta^{v}_{f,o,x,t}$: **the labor supply elasticity of type-x occupation-o workers with visa-status** v, given observed market shares and the parameters τ_x^0, λ_x^0.
2. Calculate $\eta_{f,o,t}$: the **labor supply elasticity of occupation-o workers** to firm f, by aggregating over visa statuses and worker types.
3. Using these labor supply elasticities, calculate **firm-level aggregate labor** $\tilde{L}_{f,t}$.
4. In each split-sample-s, calculate **amenity shocks** $\Delta\hat{\xi}^{s}_{f,o,x,t}$ given observed employment, wages and the parameters τ_x^0, λ_x^0 (Berry ’94).
5. Use amenity shocks as instruments to **estimate production parameters** $\hat{\nu}, \hat{\rho}$.

$$\Delta\log\hat{w}^{s}_{f,o,t} + \Delta\log\left(1 + \frac{1}{\eta_{f,o,t}}\right) = (\hat{\rho} - 1)\,\Delta\log\hat{L}^{s}_{f,t} + \left(\frac{\hat{\nu} - \hat{\rho}}{\hat{\nu}}\right)\Delta\log\tilde{L}_{f,o,t} + C_{s,c_f,o,t,x} + \varepsilon_{s,f,o,t,x}$$

Structural model: a fixed-point estimator

Given candidate values of the labor supply parameters τ_x^0, λ_x^0:

5. Use amenity shocks as instruments to **estimate production parameters** $\hat{\nu}, \hat{\rho}$.

$$\Delta \log \hat{w}^s_{f,o,t} + \Delta \log\left(1 + \frac{1}{\eta_{f,o,t}}\right) = (\hat{\rho} - 1)\,\Delta \log \hat{L}^s_{f,t} + \left(\frac{\hat{\nu} - \hat{\rho}}{\hat{\nu}}\right)\Delta \log \tilde{L}_{f,o,t} + C_{s,c_f,o,t,x} + \varepsilon_{s,f,o,t,x}$$

- Our instrument for $\Delta \log \hat{L}^s_{f,t}$ is $\Delta \hat{\xi}^{-s}_{f,o,x,t}$.
- Our instrument for $\Delta \log \tilde{L}_{f,o,t} = \Delta \log \sum_{o \in \mathbf{O}_{f,t}} e^{\log w_{f,o,t} + \log L_{f,o,t} + \log\left(1 + \frac{1}{\eta_{f,o,t}}\right)}$

  is $\Delta \log \sum_{o \in \mathbf{O}_{f,t}} e^{E^*\left[\log w_{f,o,t} + \log L_{f,o,t} + \log\left(1 + \frac{1}{\eta_{f,o,t}}\right) \middle| \hat{\xi}^{-s}_{f,o,x,t}\right]}$,

  where $E^*[Y|X]$ is the linear projection of Y on X.

Structural model: a fixed-point estimator

Given candidate values of the labor supply parameters τ_x^0, λ_x^0:

5. Use amenity shocks as instruments to **estimate production parameters** $\hat{\nu}, \hat{\rho}$.
6. Use $\hat{\rho}, \hat{\nu}$ to calculate productivity shocks in each sample $\hat{\phi}^s_{f,o,t}$.

$$\hat{\phi}^s_{f,o,t} = \log \hat{w}^s_{f,o,t} + \log\left(1 + \frac{1}{\eta_{f,o,t}}\right) - \frac{\hat{\rho}\log\hat{\nu}}{\hat{\nu}} + (1-\rho)\log\hat{L}^s_{f,o,t} + \left(\frac{\rho-\nu}{\nu}\right)\log\tilde{L}_{f,t}$$

Structural model: a fixed-point estimator

Given candidate values of the labor supply parameters τ_x^0, λ_x^0:

5. Use amenity shocks as instruments to **estimate production parameters** $\hat{\nu}, \hat{\rho}$.
6. Use $\hat{\rho}, \hat{\nu}$ to calculate productivity shocks in each sample $\hat{\phi}^s_{f,o,t}$.
7. Use productivity shocks as instruments to **estimate labor supply parameters** $\hat{\tau}_x, \hat{\lambda}_x$.

$$\Delta \log N^{resident}_{f,o,x,t} = \hat{\tau}_x \Delta \log \hat{w}^s_{f,o,t} + C_{s,x,c_f,t} + \Delta \xi_{f,o,x,t}$$

- Our instrument for $\Delta \log \hat{w}^s_{f,o,t}$ is $\Delta \hat{\phi}^{-s}_{f,o,t-1}$.

Structural model: a fixed-point estimator

Given candidate values of the labor supply parameters τ_x^0, λ_x^0:

5. Use amenity shocks as instruments to **estimate production parameters** $\hat{v}, \hat{\rho}$.
6. Use $\hat{\rho}, \hat{v}$ to calculate productivity shocks in each sample $\hat{\phi}^s_{f,o,t}$.
7. Use productivity shocks as instruments to **estimate labor supply parameters** $\hat{\tau}_x, \hat{\lambda}_x$.

$$\Delta \log N^{resident}_{c,o,x,t} = \hat{\lambda}_x \Delta \log \left(\sum_{f \in \mathbf{F}_{c,o,t}} e^{\tau_x^0 \log \hat{w}^s_{f,o,t} + \hat{\xi}^s_{f,o,x,t}} \right) + C_{s,o,x,t} + \Delta \bar{\xi}_{c,o,x,t}$$

- Our instrument for $\log \left(\sum_{f \in \mathbf{F}_{c,o,t}} e^{\tau_x^0 \log \hat{w}^s_{f,o,t} + \hat{\xi}^s_{f,o,x,t}} \right)$

  $$\text{is } \log \left(\sum_{f \in \mathbf{F}_{c,o,t}} e^{\tau_x^0 E^* \left[\log \hat{w}^s_{f,o,t} \middle| \hat{\phi}^{-s}_{f,o,t} \right]} \right),$$

  where $E^* \left[Y | X \right]$ is the linear projection of Y on X.

Structural model: a fixed-point estimator

Given candidate values of the labor supply parameters τ_x^0, λ_x^0:

5. Use amenity shocks as instruments to **estimate production parameters** $\hat{v}, \hat{\rho}$.
6. Use $\hat{\rho}, \hat{v}$ to calculate productivity shocks in each sample $\hat{\phi}^s_{f,o,t}$.
7. Use productivity shocks as instruments to **estimate labor supply parameters** $\hat{\tau}_x, \hat{\lambda}_x$.

Our estimate is the fixed point $\hat{\tau}_x\left(\tau_x^0, \lambda_x^0\right) = \tau_x^0; \qquad \hat{\lambda}_x\left(\tau_x^0, \lambda_x^0\right) = \lambda_x^0$.

Conduct inference using an equivalent GMM representation, with two-way clustering across firms and occupations.

Structural model: data

Years: Use annual data 2014-2022 (when occupation is generally observed).

Wages: Estimate wages using full-time workers with a unique firm. Estimate wage-bills using all workers.

Worker types: Born in New Zealand vs. born overseas.

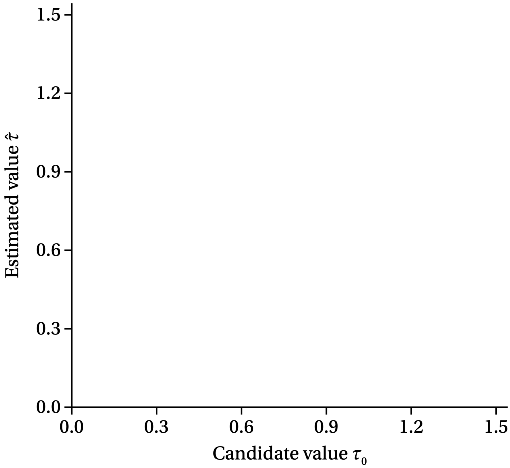
Locations: Functional urban areas.

Firms: Enterprise × location.

Structural model: a fixed point estimator

First, assume τ_x and λ_x are constant across types.

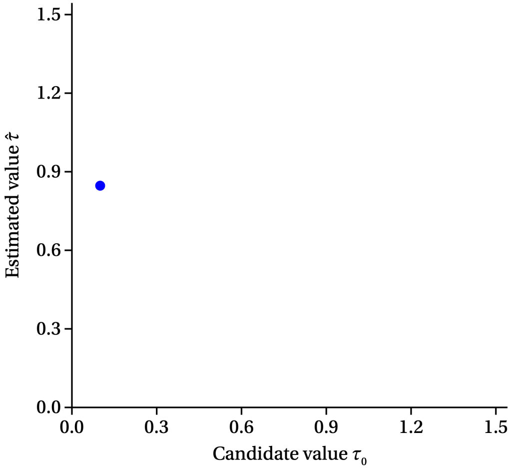
λ_0	τ_0	$\hat{\rho}$	$\hat{\nu}$	$\hat{\tau}$	$\hat{\lambda}$
0.13	0.1	0.989	0.996		



Structural model: a fixed point estimator

First, assume τ_x and λ_x are constant across types.

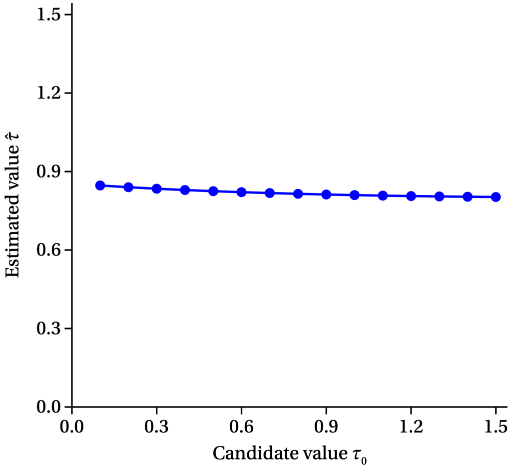
λ_0	τ_0	$\hat{\rho}$	$\hat{\nu}$	$\hat{\tau}$	$\hat{\lambda}$
0.13	0.1	0.989	0.996	0.847	0.140



Structural model: a fixed point estimator

First, assume τ_x and λ_x are constant across types.

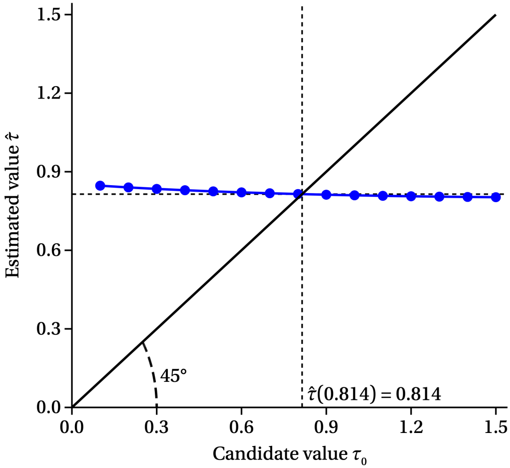
λ_0	τ_0	$\hat{\rho}$	$\hat{\nu}$	$\hat{\tau}$	$\hat{\lambda}$
0.13	0.1	0.989	0.996	0.847	0.140
0.13	0.2	0.980	0.988	0.840	0.139
0.13	0.3	0.970	0.980	0.834	0.137
0.13	0.4	0.960	0.972	0.829	0.136
0.13	0.5	0.951	0.965	0.825	0.134
0.13	0.6	0.941	0.957	0.821	0.133
0.13	0.7	0.931	0.949	0.818	0.132
0.13	0.8	0.921	0.942	0.815	0.131
0.13	0.9	0.911	0.934	0.812	0.131
0.13	1.0	0.900	0.926	0.810	0.130
0.13	1.1	0.889	0.918	0.808	0.129
0.13	1.2	0.879	0.909	0.806	0.129
0.13	1.3	0.868	0.901	0.805	0.129
0.13	1.4	0.856	0.893	0.804	0.129
0.13	1.5	0.845	0.884	0.803	0.129



Structural model: a fixed point estimator

First, assume τ_x and λ_x are constant across types.

λ_0	τ_0	$\hat{\rho}$	$\hat{\nu}$	$\hat{\tau}$	$\hat{\lambda}$
0.13	0.1	0.989	0.996	0.847	0.140
0.13	0.2	0.980	0.988	0.840	0.139
0.13	0.3	0.970	0.980	0.834	0.137
0.13	0.4	0.960	0.972	0.829	0.136
0.13	0.5	0.951	0.965	0.825	0.134
0.13	0.6	0.941	0.957	0.821	0.133
0.13	0.7	0.931	0.949	0.818	0.132
0.13	0.8	0.921	0.942	0.815	0.131
0.13	0.9	0.911	0.934	0.812	0.131
0.13	1.0	0.900	0.926	0.810	0.130
0.13	1.1	0.889	0.918	0.808	0.129
0.13	1.2	0.879	0.909	0.806	0.129
0.13	1.3	0.868	0.901	0.805	0.129
0.13	1.4	0.856	0.893	0.804	0.129
0.13	1.5	0.845	0.884	0.803	0.129



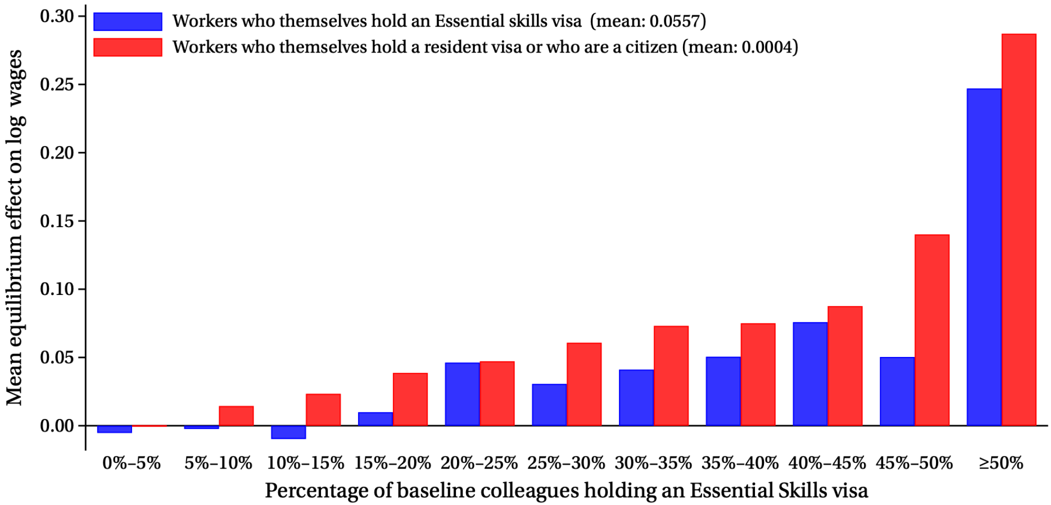
Structural model: estimates

	Homogeneous coefficients	Heterogeneous coefficients	
Labor supply estimates		NZ-born	foreign-born
τ (labor supply elasticity for an atomistic firm)	0.814	0.845	0.751
	[0.197]	[0.208]	[0.183]
λ (workers' willingness substitute across space)	0.131	0.118	0.153
	[0.008]	[0.008]	[0.010]
Production function estimates			
ρ (firms' ability to substitute across occupations)	0.919	0.919	
	[0.019]	[0.019]	
ν (returns to scale)	0.940	0.940	
	[0.014]	[0.014]	

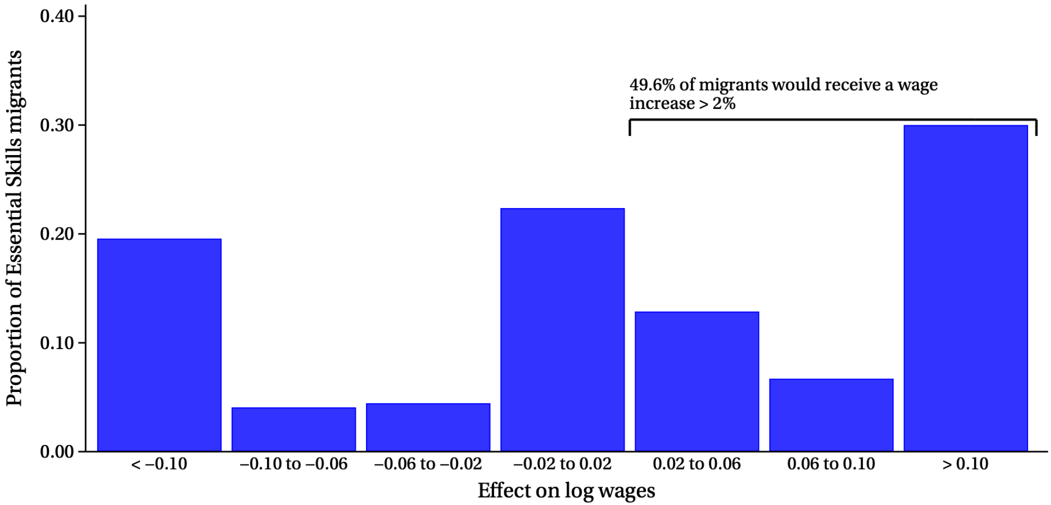
The equilibrium effect of allowing migrants to work at any firm

1. Use only 2018 cross-section, assume constant worker productivity.
2. Calculate productivity as in estimation.
3. Calculate amenities – imputing when necessary.
4. Treating labor as continuous, solve for the actual equilibrium and a counterfactual equilibrium in which migrants' job options are unrestricted.
5. Allocate discrete workers to actual and counterfactual firms using a ***NOVEL ALGORITHM FOR NESTED EXTREME VALUE RANDOM VARIABLES.***

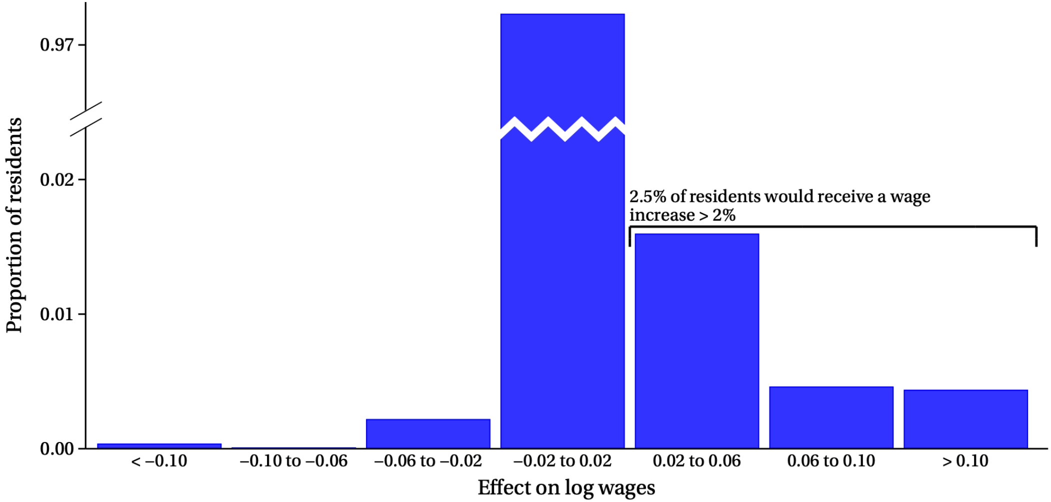
The equilibrium effect of allowing migrants to work at any firm



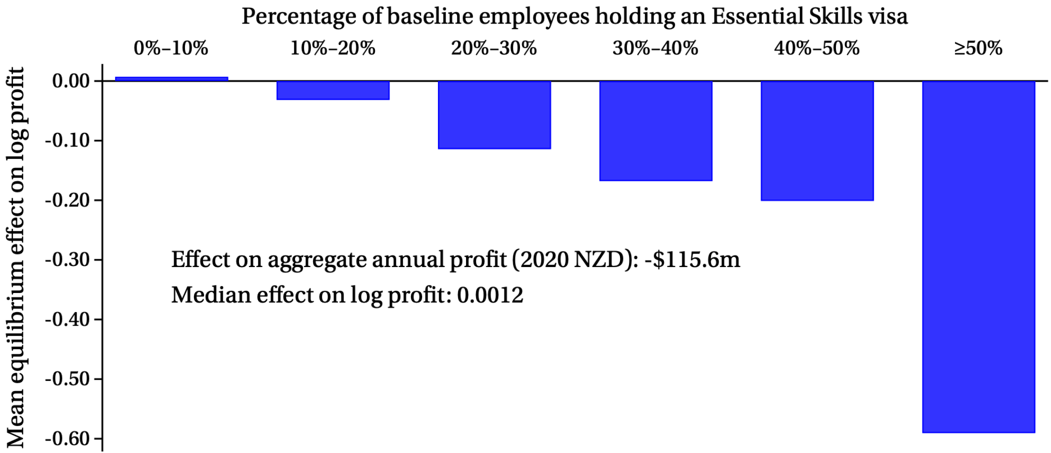
The equilibrium effect of allowing migrants to work at any firm



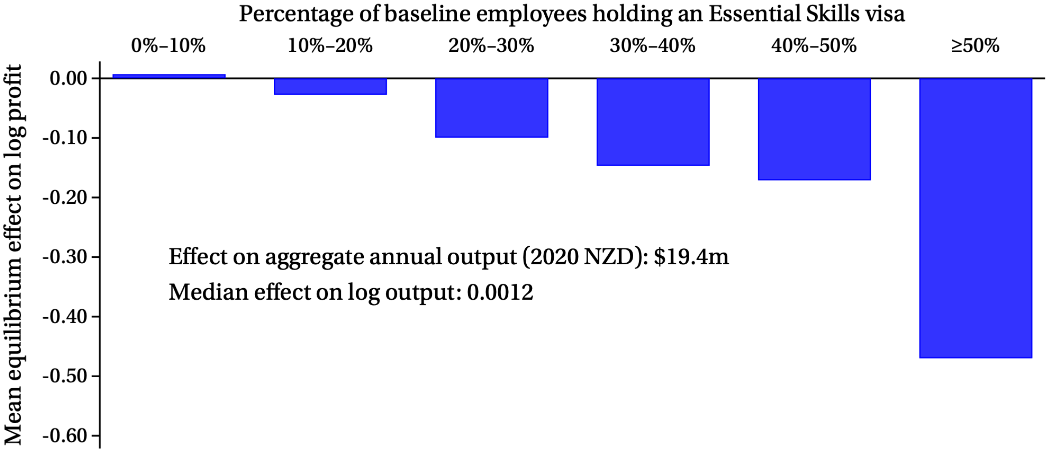
The equilibrium effect of allowing migrants to work at any firm



The equilibrium effect of allowing migrants to work at any firm



The equilibrium effect of allowing migrants to work at any firm



How restricting migrants' job options affects welfare

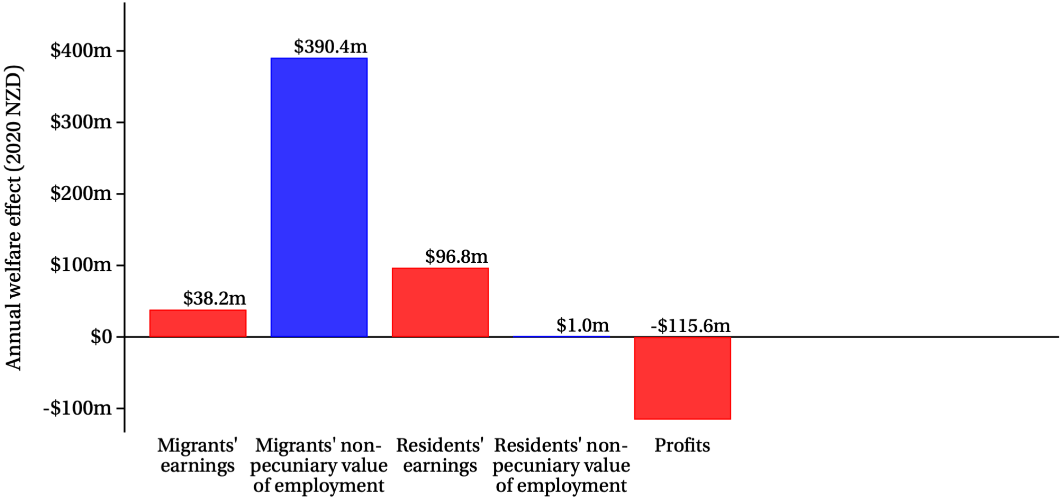
Let WTP_i denote i's money-metric welfare gain from the counterfactual equilibrium w', f', in which migrants can work at any firm:

$$u_i\left(w'_{o_i,f'_i} - WTP_i,\ f'_i\right) = u_i\left(w_{o_i,f_i},\ f_i\right),$$

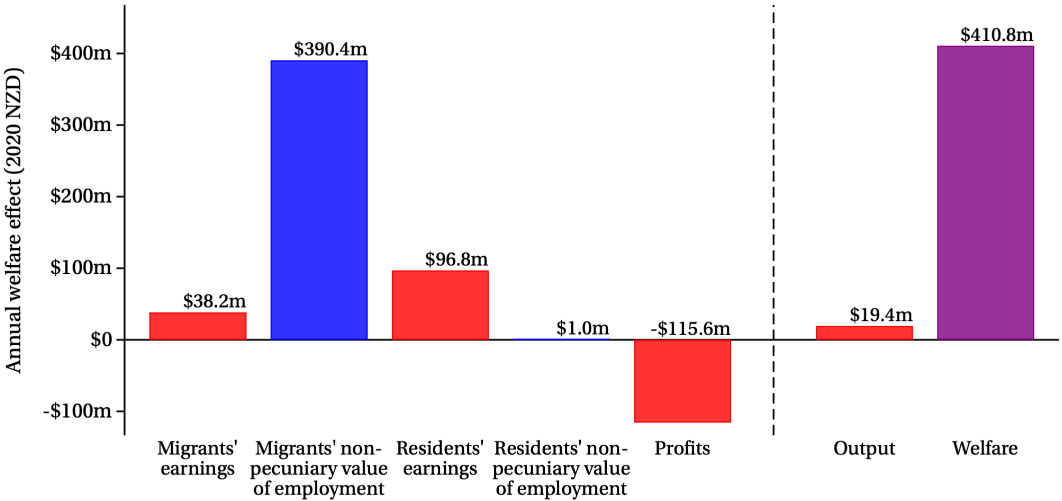
which we can decompose into

- an earnings effect $w'_{o_i,f'_i} - w_{o_i,f_i}$, and
- a non-penuniary effect $WTP_i - \left(w'_{o_i,f'_i} - w_{o_i,f_i}\right)$.

How restricting migrants' job options affects welfare



How restricting migrants' job options affects welfare



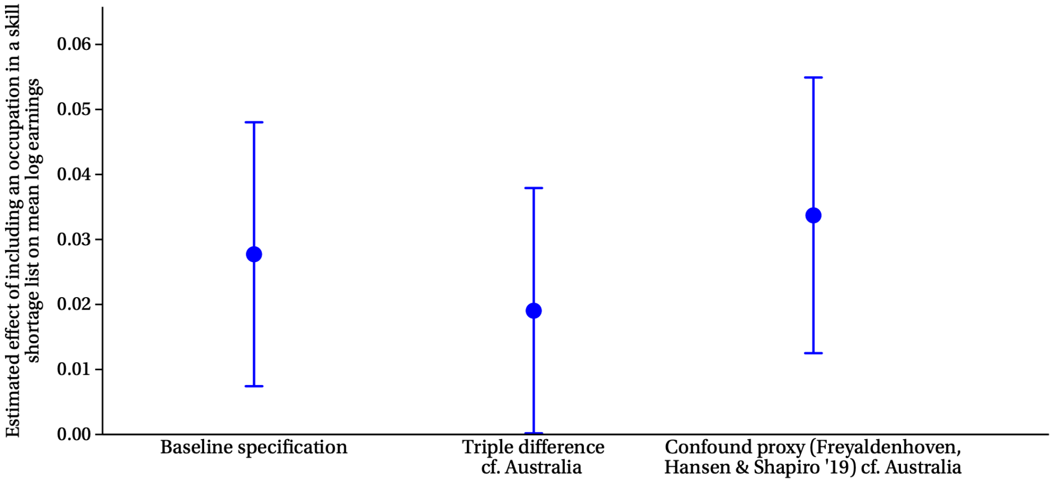
Restricting migrants’ job options affects everyone’s wages

Firms don’t *specifically* discriminate against migrants,

But firms do account for migrants’ weaker job options when setting everyone’s wages.

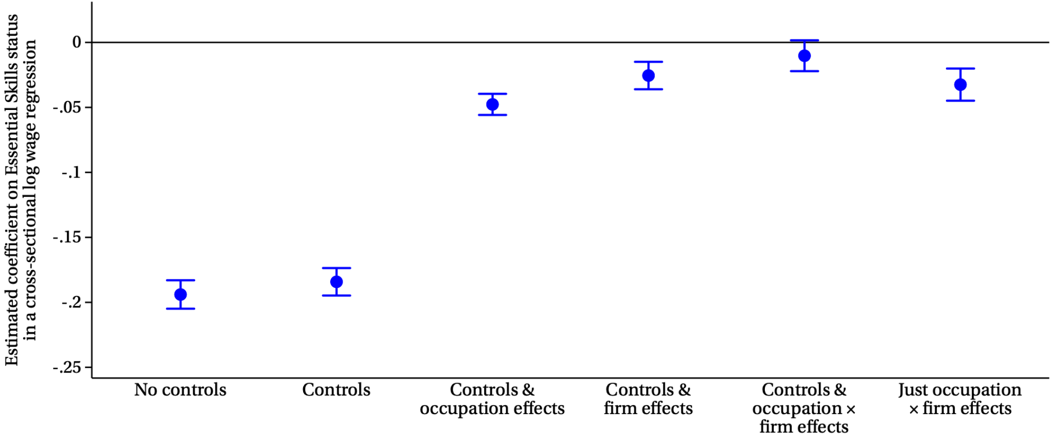
Restricting migrant’s job options reduces both their wages and the wages of their colleagues.

Using Australian data as a placebo outcome



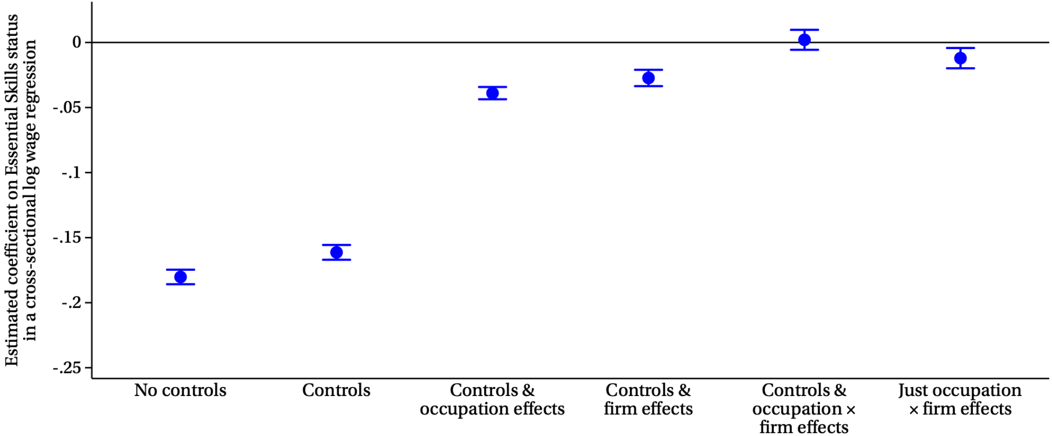
Back.

Migrants earn less than other workers... but only because of their jobs



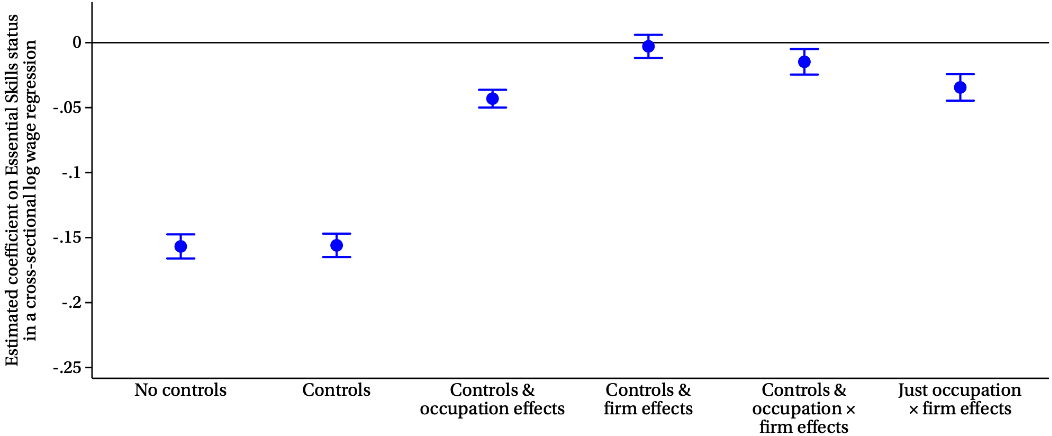
Sample: full-time employees with a unique firm in the 12 months before the 2013 Census. Back.

Migrants earn less than other workers... but only because of their jobs



Sample: full-time employees with a unique firm in the 6 months before the 2018 Census. Back.

Migrants earn less than other workers... but only because of their jobs



Sample: full-time employees with a unique firm in the 6 months before the 2013 Census. Back.

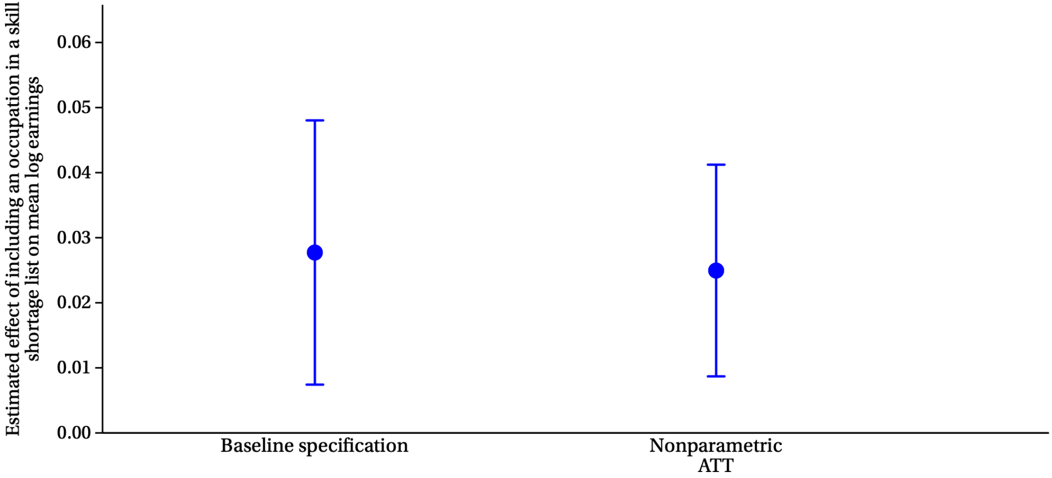
Accounting for treatment effect heterogeneity

A nonparametric ATT estimate *a la* de Chaisemartin & D'Haultfoeuille (2022).

- Assume that dynamic effects have stabilized after 2 years.
- Calculate a simple difference-in-difference estimate for each occupation added to or removed from a skill-shortage list, after 2 years of unchanged skill-shortage status, using each available control occupation and up to 36 post-treatment months.
- Average across control occupations, post-treatment months, and treatment occupations.

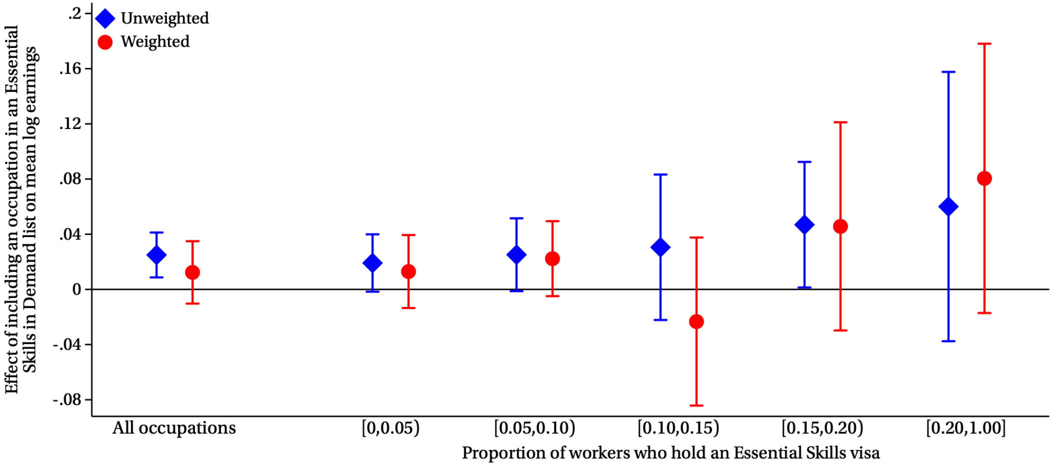
Accounting for treatment effect heterogeneity

A nonparametric ATT estimate *a la* de Chaisemartin & D'Haultfoeuille (2022).



Accounting for treatment effect heterogeneity

A nonparametric ATT estimate *a la* de Chaisemartin & D'Haultfoeuille (2022).



Identifying effects for job-stayers

Consider the potential outcomes framework for worker i in period $t \in \{0, 1\}$:

$$Y_{it} = Y_{it}(W_i, M_i),$$

- Y_{it} denotes log earnings,
- W_i denotes being a lottery winner,
- M_i denotes moving jobs, which itself depends on the lottery: $M_i = M_i(W_i)$.

Identifying effects for job-stayers

Consider the potential outcomes framework for worker i in period $t \in \{0,1\}$:

$$Y_{it} = Y_{it}(W_i, M_i),$$

- Y_{it} denotes log earnings,
- W_i denotes being a lottery winner,
- M_i denotes moving jobs, which itself depends on the lottery: $M_i = M_i(W_i)$.

Assume that the lottery, and the opportunity to switch jobs, occurs in period 1:

$$Y_{i0}(0,0) = Y_{i,0}(1,0) = Y_{i,0}(0,1) = Y_{i,0}(1,1).$$

Identifying effects for job-stayers

Consider the potential outcomes framework for worker i in period $t \in \{0, 1\}$:

$$Y_{it} = Y_{it}(W_i, M_i),$$

- Y_{it} denotes log earnings,
- W_i denotes being a lottery winner,
- M_i denotes moving jobs, which itself depends on the lottery: $M_i = M_i(W_i)$.

Assume that the lottery, and the opportunity to switch jobs, occurs in period 1:

$$Y_{i0}(0,0) = Y_{i,0}(1,0) = Y_{i,0}(0,1) = Y_{i,0}(1,1).$$

We hope to identify the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{i1}(1,0) - Y_{i1}(0,0) \mid M_i(1) = 0\right].$$

Identifying effects for job-stayers

We hope to identify the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{i1}(1,0) - Y_{i1}(0,0) \mid M_i(1) = 0\right].$$

Assumption 1: The lottery is random: $W_i \perp M_i(\cdot), Y_{i0}(\cdot,\cdot), Y_{i1}(\cdot,\cdot)$.
Assumption 2: Lottery losers never switch jobs: $\forall i : M_i(0) = 0$.

Identifying effects for job-stayers

We hope to identify the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{i1}(1,0) - Y_{i1}(0,0) \mid M_i(1) = 0\right].$$

Assumption 1: The lottery is random: $W_i \perp M_i(\cdot), Y_{i0}(\cdot,\cdot), Y_{i1}(\cdot,\cdot)$.
Assumption 2: Lottery losers never switch jobs: $\forall i : M_i(0) = 0$.

$$\therefore \qquad \underbrace{\mathbb{E}\left[Y_{i1}(1,0) \mid M_i(1) = 0\right]}_{\text{Earnings for treated job-stayers}}$$

Identifying effects for job-stayers

We hope to identify the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{i1}(1,0) - Y_{i1}(0,0) \mid M_i(1) = 0\right].$$

Assumption 1: The lottery is random: $W_i \perp M_i(\cdot), Y_{i0}(\cdot,\cdot), Y_{i1}(\cdot,\cdot)$.
Assumption 2: Lottery losers never switch jobs: $\forall\, i : M_i(0) = 0$.

$$\therefore \qquad \underbrace{\mathbb{E}\left[Y_{i1}(1,0) \mid M_i(1) = 0\right]}_{\text{Earnings for treated job-stayers}} = \underbrace{\mathbb{E}\left[Y_{i1} \mid M_i = 0, W_i = 1\right]}_{\text{This is observed}}.$$

Identifying effects for job-stayers

We hope to identify the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{i1}(1,0) - Y_{i1}(0,0) \mid M_i(1) = 0\right].$$

Assumption 1: The lottery is random: $W_i \perp M_i(\cdot), Y_{i0}(\cdot,\cdot), Y_{i1}(\cdot,\cdot)$.
Assumption 2: Lottery losers never switch jobs: $\forall\, i : M_i(0) = 0$.

$$\therefore \qquad \underbrace{\mathbb{E}\left[Y_{i1}(1,0) \mid M_i(1) = 0\right]}_{\text{Earnings for treated job-stayers}} = \underbrace{\mathbb{E}\left[Y_{i1} \mid M_i = 0, W_i = 1\right]}_{\text{This is observed}}.$$

Remaining job: identify average counterfactual earnings for job-stayers:

$$\mathbb{E}\left[Y_{i1}(0,0) \mid W_i(1) = 0\right].$$

Identifying effects for job-stayers

We hope to identify the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{i1}(1,0) - Y_{i1}(0,0) \mid M_i(1) = 0\right].$$

Remaining job: identify $\mathbb{E}\left[Y_{i1}(0,0) \mid W_i(1) = 0\right]$.

Assumption 1: The lottery is random: $W_i \perp M_i(\cdot), Y_{i0}(\cdot,\cdot), Y_{i1}(\cdot,\cdot)$.
Assumption 2: Lottery losers never switch jobs: $\forall i : M_i(0) = 0$.

Identifying effects for job-stayers

We hope to identify the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{i1}(1,0) - Y_{i1}(0,0) \mid M_i(1) = 0\right].$$

Remaining job: identify $\mathbb{E}\left[Y_{i1}(0,0) \mid W_i(1) = 0\right]$.

Assumption 1: The lottery is random: $W_i \perp M_i(\cdot), Y_{i0}(\cdot,\cdot), Y_{i1}(\cdot,\cdot)$.
Assumption 2: Lottery losers never switch jobs: $\forall i : M_i(0) = 0$.
$\therefore$ We identify the DGP of $Y_{it}(0,0)$ from lottery losers:

$$F_{Y_{i1}(0,0)}\left(y_1 \,\middle|\, Y_{i0}(0,0) = y_0\right) = F_{Y_{i1}}\left(y_1 \,\middle|\, Y_{i0} = y_0, W_i = 0\right)$$

Identifying effects for job-stayers

We hope to identify the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{i1}(1,0) - Y_{i1}(0,0) \mid M_i(1) = 0\right].$$

Remaining job: identify $\mathbb{E}\left[Y_{i1}(0,0) \mid W_i(1) = 0\right]$.

Assumption 1: The lottery is random: $W_i \perp M_i(\cdot), Y_{i0}(\cdot,\cdot), Y_{i1}(\cdot,\cdot)$.

$$\therefore \quad \mathbb{P}\left[M_i(1) = 1 | Y_{i0}(0,0)\right] = \mathbb{P}\left[M_i(1) = 1 | Y_{i0}(0,0), W_i = 1\right]$$

Identifying effects for job-stayers

We hope to identify the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{i1}(1,0) - Y_{i1}(0,0) \mid M_i(1) = 0\right].$$

Remaining job: identify $\mathbb{E}\left[Y_{i1}(0,0) \mid W_i(1) = 0\right]$.

Assumption 3: The job-switching decision is Markovian in counterfactual earnings:

$$M_i(1) \perp Y_{i0}(0,0) \mid Y_{i1}(0,0).$$

Identifying effects for job-stayers

We hope to identify the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{i1}(1,0) - Y_{i1}(0,0) \mid M_i(1) = 0\right].$$

Remaining job: identify $\mathbb{E}\left[Y_{i1}(0,0) \mid W_i(1) = 0\right]$.

Assumption 3: The job-switching decision is Markovian in counterfactual earnings:

$$M_i(1) \perp Y_{i0}(0,0) \mid Y_{i1}(0,0).$$

$$\begin{aligned} \therefore \quad & \mathbb{P}\left[M_i(1) = 1 \middle| Y_{i0}(0,0) = y_0\right] \\ & \qquad = \int \mathbb{P}\left[M_i(1) = 1 \middle| Y_{i1}(0,0) = y_1\right] dF_{Y_{i1}(0,0)}\left(y_1 \,\middle|\, Y_{i0}(0,0) = y_0\right) \end{aligned}$$

Identifying effects for job-stayers

We hope to identify the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{i1}(1,0) - Y_{i1}(0,0) \mid M_i(1) = 0\right].$$

Remaining job: identify $\mathbb{E}\left[Y_{i1}(0,0) \mid W_i(1) = 0\right]$.

With earlier results, we have the Fredholm integral equation of the first kind:

$$\begin{aligned}\mathbb{P}&\left[M_i(1) = 1 \middle| Y_{i0} = y_0, W_i = 1\right] \\ &= \int \mathbb{P}\left[M_i(1) = 1 \middle| Y_{i1}(0,0) = y_1\right] dF_{Y_{i1}(0,0)}\left(y_1 \middle| Y_{i0} = y_0, W_i = 0\right).\end{aligned}$$

Identifying effects for job-stayers

We hope to identify the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{i1}(1,0) - Y_{i1}(0,0) \mid M_i(1) = 0\right].$$

Remaining job: identify $\mathbb{E}\left[Y_{i1}(0,0) \mid W_i(1) = 0\right]$.

With earlier results, we have the Fredholm integral equation of the first kind:

$$\begin{aligned}
&\mathbb{P}\left[M_i(1) = 1 \middle| Y_{i0} = y_0, W_i = 1\right] \\
&\qquad = \int \mathbb{P}\left[M_i(1) = 1 \middle| Y_{i1}(0,0) = y_1\right] dF_{Y_{i1}(0,0)}\left(y_1 \,\middle|\, Y_{i0} = y_0, W_i = 0\right).
\end{aligned}$$

Under *regularity and completeness conditions*, the integral equation can be solved for

$$\mathbb{P}\left[M_i(1) = 1 \middle| Y_{i1}(0,0) = y_1\right].$$

Identifying effects for job-stayers

We hope to identify the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{i1}(1,0) - Y_{i1}(0,0) \mid M_i(1) = 0\right].$$

Remaining job: identify $\mathbb{E}\left[Y_{i1}(0,0) \mid W_i(1) = 0\right]$.

Having identified $\mathbb{P}\left[M_i(1) = 1 \middle| Y_{i1}(0,0) = y_1\right]$, we can find $dF_{Y_{i1}(0,0)}\left(y_1 \middle| M_i(1) = 1\right)$ using Bayes' rule:

$$dF_{Y_{i1}(0,0)}\left(y_1 \middle| M_i(1) = 1\right) = \mathbb{P}\left[M_i(1) = 1 \middle| Y_{i1}(0,0) = y_1\right] \frac{dF_{Y_{i1}(0,0)}\left(y_1\right)}{\mathbb{P}\left[M_i(1) = 1\right]}$$

where

- $dF_{Y_{i1}(0,0)}$ can be identified from lottery losers;
- $\mathbb{P}\left[M_i(1) = 1\right]$ can be identified from lottery winners.

Identifying effects for job-stayers

We hope to identify the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{i1}(1,0) - Y_{i1}(0,0) \mid M_i(1) = 0\right].$$

Proposition: The average treatment effect for job-stayers is identified from the joint distribution of earnings, moving indicators and lottery-winning indicators.

Back.

Estimating effects for job-stayers

We hope to estimate the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{it}(1,0) - Y_{it}(0,0) \mid M_{it}(1) = 0\right].$$

Estimating effects for job-stayers

We hope to estimate the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{it}(1,0) - Y_{it}(0,0) \mid M_{it}(1) = 0\right].$$

We impose the monotonicity assumption: $\forall i, t : M_{it}(1) \geq M_{it}(0)$.

- We observe $\mathbb{E}[Y_{it}(1,0) \mid M_{it}(1) = 0] = \mathbb{E}[Y_{it} \mid W_{it} = 1, M_{it} = 0]$.

Estimating effects for job-stayers

We hope to estimate the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{it}(1,0) - Y_{it}(0,0) \mid M_{it}(1) = 0\right].$$

Let $b(i)$ denote i's lottery. We estimate $\mathbb{E}\left[Y_{it}(0,0) \mid S_{it}(1) = 0\right]$ assuming:

- Job-moving is probit in $W_i, Y_{i,t}(0,0)$, with a lottery effect:

$$\mathbb{P}\left[M_{i,t} = 1 \mid W_i, \left(Y_{i,s}(0,0)\right)_{s \le t}, M_{i,t-1} = 0\right] = \Phi\left(\beta_1 W_i + \beta_2 Y_{i,t}(0,0) + \beta_3 W_i Y_{i,t}(0,0) + \delta_{b(i),t}\right);$$

Estimating effects for job-stayers

We hope to estimate the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{it}(1,0) - Y_{it}(0,0) \mid M_{it}(1) = 0\right].$$

Let $b(i)$ denote i's lottery. We estimate $\mathbb{E}\left[Y_{it}(0,0) \mid S_{it}(1) = 0\right]$ assuming:

- Job-moving is probit in $W_i, Y_{i,t}(0,0)$, with a lottery effect:

$$\mathbb{P}\left[M_{i,t} = 1 \mid W_i, \left(Y_{i,s}(0,0)\right)_{s \le t}, M_{i,t-1} = 0\right] = \Phi\left(\beta_1 W_i + \beta_2 Y_{i,t}(0,0) + \beta_3 W_i Y_{i,t}(0,0) + \delta_{b(i),t}\right);$$

- Counterfactual earnings $Y_{i,t}(0,0)$ are AR(1), with another lottery effect:

$$Y_{i,t}(0,0) = \alpha Y_{i,t-1}(0,0) + \gamma_{b(i),t} + \epsilon_{it}; \quad \epsilon_{it} \sim N(0, \sigma_\epsilon);$$

Estimating effects for job-stayers

We hope to estimate the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{it}(1,0) - Y_{it}(0,0) \mid M_{it}(1) = 0\right].$$

Let $b(i)$ denote i's lottery. We estimate $\mathbb{E}\left[Y_{it}(0,0) \mid S_{it}(1) = 0\right]$ assuming:

- Job-moving is probit in $W_i, Y_{i,t}(0,0)$, with a lottery effect:

$$\mathbb{P}\left[M_{i,t} = 1 \mid W_i, \left(Y_{i,s}(0,0)\right)_{s \le t}, M_{i,t-1} = 0\right] = \Phi\left(\beta_1 W_i + \beta_2 Y_{i,t}(0,0) + \beta_3 W_i Y_{i,t}(0,0) + \delta_{b(i),t}\right);$$

- Counterfactual earnings $Y_{i,t}(0,0)$ are AR(1), with another lottery effect:

$$Y_{i,t}(0,0) = \alpha Y_{i,t-1}(0,0) + \gamma_{b(i),t} + \epsilon_{it}; \quad \epsilon_{it} \sim N(0, \sigma_\epsilon);$$

- Lottery effects are joint-normal:

$$\delta_b, \gamma_b \sim N\left(\mu_{\delta\gamma}, \Sigma\right).$$

Estimating effects for job-stayers

We hope to estimate the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{it}(1,0) - Y_{it}(0,0) \mid M_{it}(1) = 0\right].$$

We calculate our estimator using a Gibbs sampler algorithm with state

$$\left[\{m_{it}\}, \left\{Y_{i,t}(0,0)\right\}, \beta, \delta, \alpha, \gamma, \sigma_\delta, \sigma_\gamma, \sigma_\epsilon\right],$$

where m_{it} is the Probit latent variable:

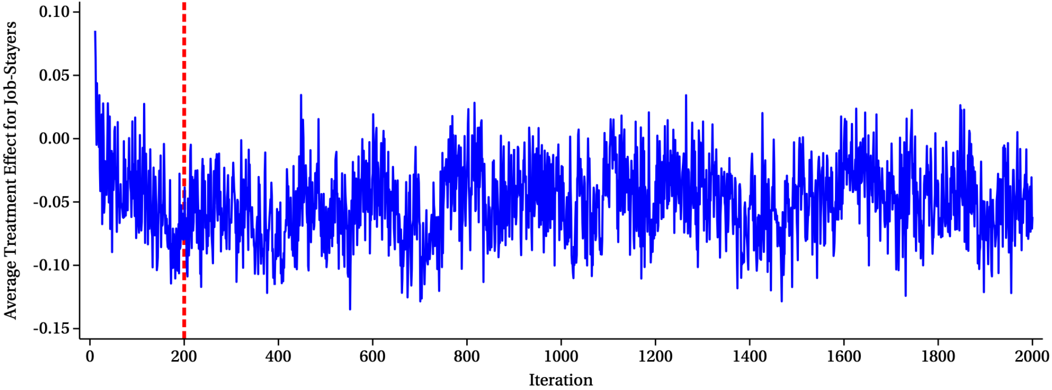
$$M_{it} = 1 \iff m_{it} \geq 0.$$

We impose uninformative conjugate priors on the hyper-parameters.

Estimating effects for job-stayers

We hope to estimate the **average treatment effect for job-stayers**:

$$\mathbb{E}\left[Y_{it}(1,0) - Y_{it}(0,0) \mid M_{it}(1) = 0\right].$$



Note: the first ten iterations are omitted from the plot. Back.

A novel algorithm for nested extreme value random variables

We are interested in drawing random variables with CDF:

$$\mathbb{P}\left[\left(X_j\right)_{j\in\mathbf{J}} \leq \left(x_j\right)_{j\in\mathbf{J}}\right] = \exp\left(\sum_{C\in\mathbf{C}}\left(\sum_{j\in C}\exp\left(\frac{-x_j}{\lambda}\right)\right)^{\lambda}\right),$$

where $\mathbf{C}$ is a partition on $\mathbf{J}$. Both $\mathbf{J}$ and $\mathbf{C}$ may be large.

Per Cardell '97: $X_j = \zeta_{C(j)} + (1-\sigma)\epsilon_j$, where $C(j)$ is the nest containing j, and both X_j and ϵ_j have marginal standard-Gumbel distributions.

By the Convolution Theorem, ζ_C has characteristic function

$$\phi_\zeta(t) = \frac{\Gamma(1-it)}{\Gamma(1-i(1-\sigma)t)},$$ where Γ is the gamma function and i is the imaginary unit.

By the Fourier inversion theorem, the pdf of ζ is given by $f_\zeta(x) = \frac{1}{2\pi}\int_0^\infty e^{-tx}\phi_\zeta(t)dt$.

A novel algorithm for nested extreme value random variables

We are interested in drawing random variables with CDF:

$$\mathbb{P}\left[\left(X_j\right)_{j\in\mathbf{J}} \le \left(x_j\right)_{j\in\mathbf{J}}\right] = \exp\left(\sum_{C\in\mathbf{C}}\left(\sum_{j\in C}\exp\left(\frac{-x_j}{\lambda}\right)\right)^{\lambda}\right),$$

where $\mathbf{C}$ is a partition on $\mathbf{J}$. Both $\mathbf{J}$ and $\mathbf{C}$ may be large.

Algorithm:

1. Approximate $f_\zeta(x) = \frac{1}{2\pi}\int_0^\infty e^{-tx}\phi_\zeta(t)dt$ numerically.
2. Draw ζ_C using inverse transform sampling.
3. Draw ϵ_j from a standard Gumbel distribution.
4. Form $X_j = \zeta_{C(j)} + (1-\sigma)\epsilon_j$.

Back.

Measuring the amenity value of employment at a firm

We infer $\xi_{f,o,x,t}$ using the labor supply of residents:

$$\xi_{f,o,x,t} = \log \sigma^{resident}_{f,o,x,t|c_f} - \tau \log(w_{f,o,t}) + D_{c_f,o,x,t},$$

When no type-x residents are observed, amenities must be imputed. We assume that amenities are joint-normal across types, and impute using (an approximation of) the posterior mode.

1. Calculate the empirical covariance of type-*NZ* and type-*abroad* amenities across firm-by-occupations at which both are observed $\implies$ a $N\left(\mu^{\xi}_{f,o,x,t}, s^{\xi}_{f,o,x,t}\right)$ prior.
2. The log posterior for $\tilde{\xi}_{f,o,x,t}$, given that $\sigma^{resident}_{f,o,x,t|c_f} = 0$ is

$$C + n_{x,c_f,t} \log\left(\frac{\sum_{f' \in \mathbf{F}_{c,o,t} \setminus f} \exp\left(\tau \log(w_{f',o,t}) + \tilde{\xi}_{f',o,x,t}\right)}{\sum_{f' \in \mathbf{F}_{c,o,t}} \exp\left(\tau \log(w_{f',o,t}) + \tilde{\xi}_{f',o,x,t}\right)}\right) + \frac{\left(\tilde{\xi}_{f,o,x,t} - \mu^{\xi}_{f,o,x,t}\right)^2}{2 s^{\xi}_{f,o,x,t}{}^2},$$

where $n_{x,c,t}$ is the number of type-x workers in location c.

Measuring the amenity value of employment at a firm

3. Taking a first-order condition for $\tilde{\xi}_{f,o,x,t}$ implies

$$-n_{x,c,t}\left(\frac{\exp\left(\tau\log(w_{f,o,t})+\tilde{\xi}_{f,o,x,t}\right)}{\sum_{f'\in\mathbf{F}_{c,o,t}\setminus f}\exp\left(\tau\log(w_{f',o,t})+\tilde{\xi}_{f',o,x,t}\right)}\right)-\frac{\left(\tilde{\xi}_{f,o,x,t}-\mu^{\xi}_{f,o,x,t}\right)}{{s^{\xi}_{f,o,x,t}}^{2}}=0.$$

4. Evaluated at $\tilde{\xi}_{f',o,x,t}\approx\mu^{\xi}_{f',o,x,t}$, yields the approximate solution

$$\tilde{\xi}_{f,o,x,t}=\mu^{\xi}_{f,o,x,t}-{s^{\xi}_{f,o,x,t}}^{2}n_{x,c,t}\left(\frac{\exp\left(\tau\log(w_{f,o,t})+\mu^{\xi}_{f,o,x,t}\right)}{\sum_{f'\in\mathbf{F}_{c,o,t}\setminus f}\exp\left(\tau\log(w_{f',o,t})+\mu^{\xi}_{f',o,x,t}\right)}\right).$$

Back.