

# How Restricting Migrants' Job Options Affects Both Migrants and Residents

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These results are not official statistics. They have been created for research purposes from the Integrated Data Infrastructure (IDI) which is carefully managed by Stats NZ. For more information about the IDI please visit <https://www.stats.govt.nz/integrated-data/>. The results are based in part on tax data supplied by Inland Revenue to Stats NZ under the Tax Administration Act 1994 for statistical purposes. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the data's ability to support Inland Revenue's core operational requirements. Access to the data used in this study was provided by Stats NZ under conditions designed to give effect to the security and confidentiality provisions of the Data and Statistics Act 2022. The results presented in this study are the work of the author, not Stats NZ or individual data suppliers.

# 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.**

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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 6%.
- ▶ Most residents are unaffected — but 2.5% 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 & Santarossa '23; Bloesch, Larsen & Taska '22; Hall & Krueger '12; Roussille & Scuderi 24; Rubens & Delabastita '24).

We study the effect of outside options **randomized** at the **individual level**.

## 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**  $\Rightarrow$  lower labor supply elasticity  
 $\Rightarrow$  **lower wages for all workers.**

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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.
- ▶ 38% have at least a degree (vs. 32% overall).

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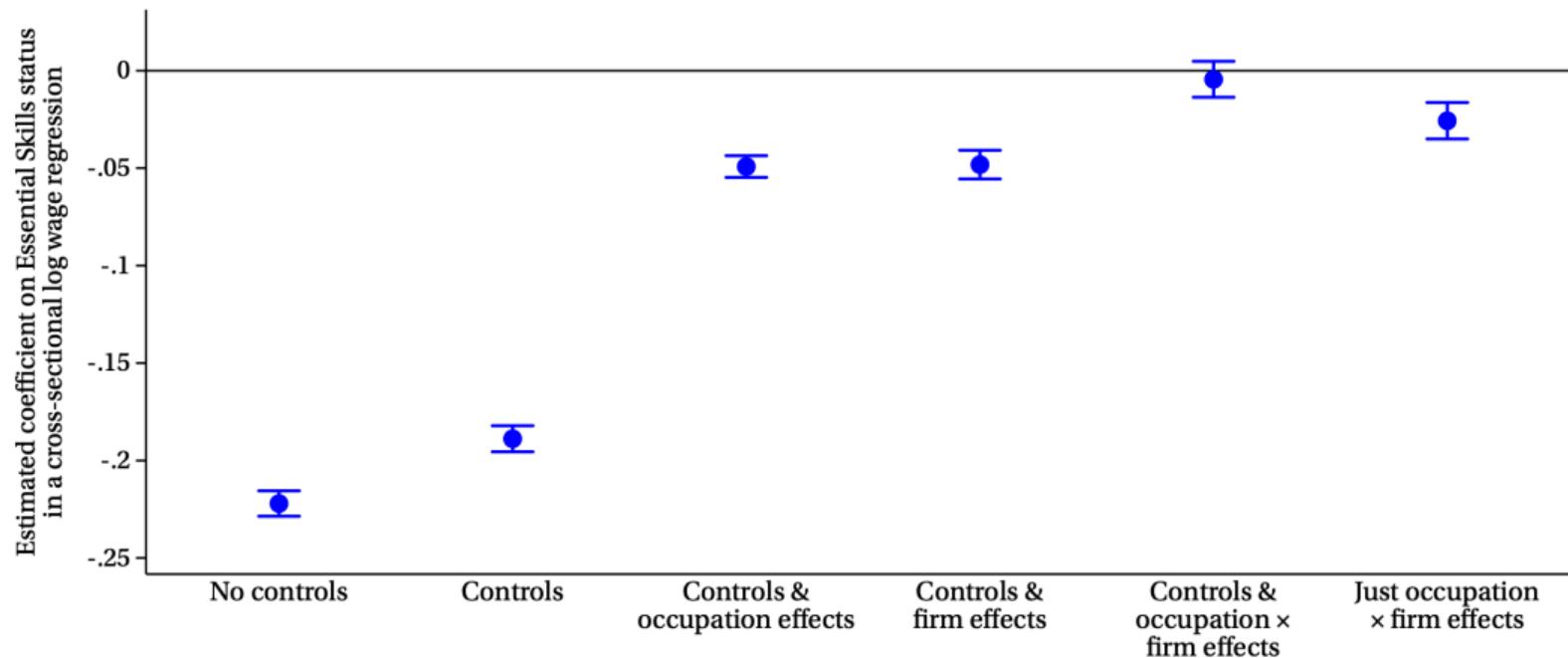
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# Migrants earn less than other workers...



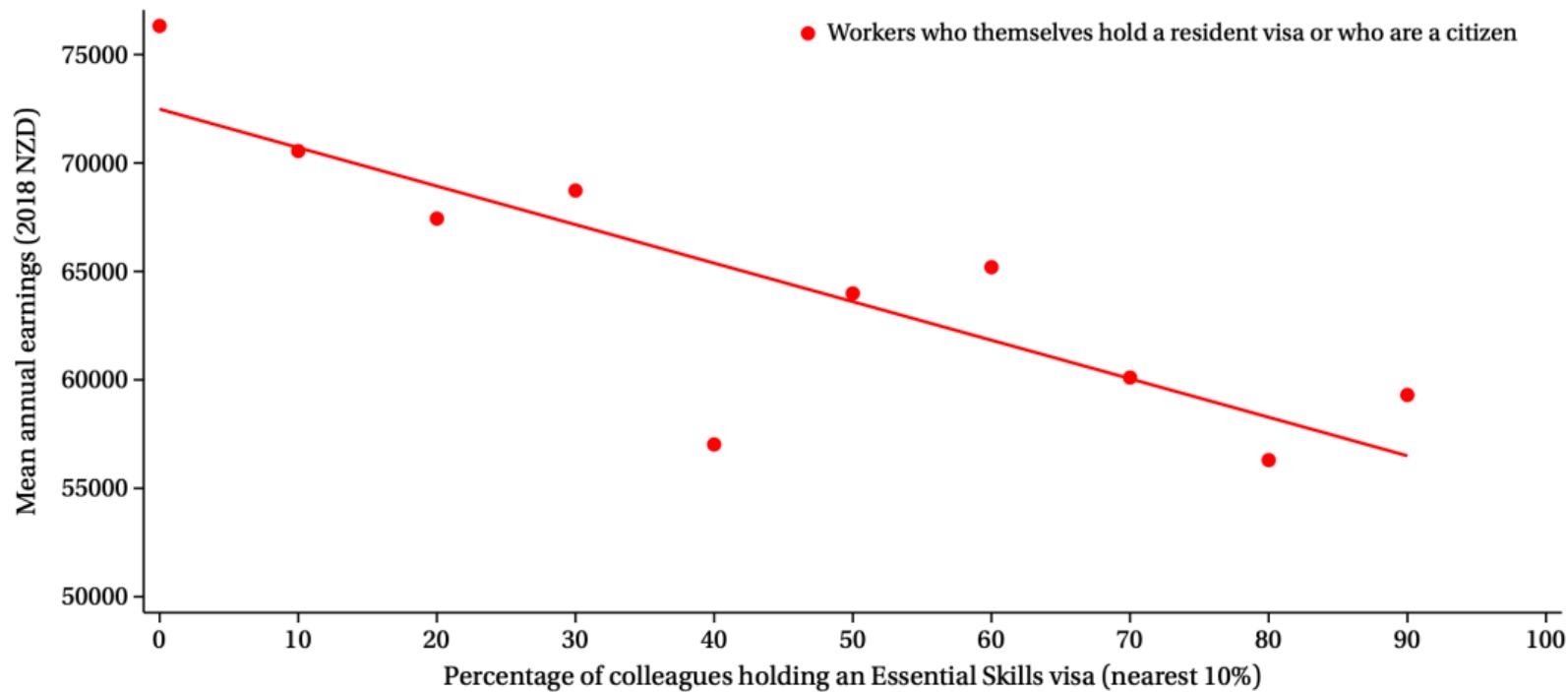
Sample: full-time employees with a unique firm in the 12 months before the 2018 Census. [Other samples](#).

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



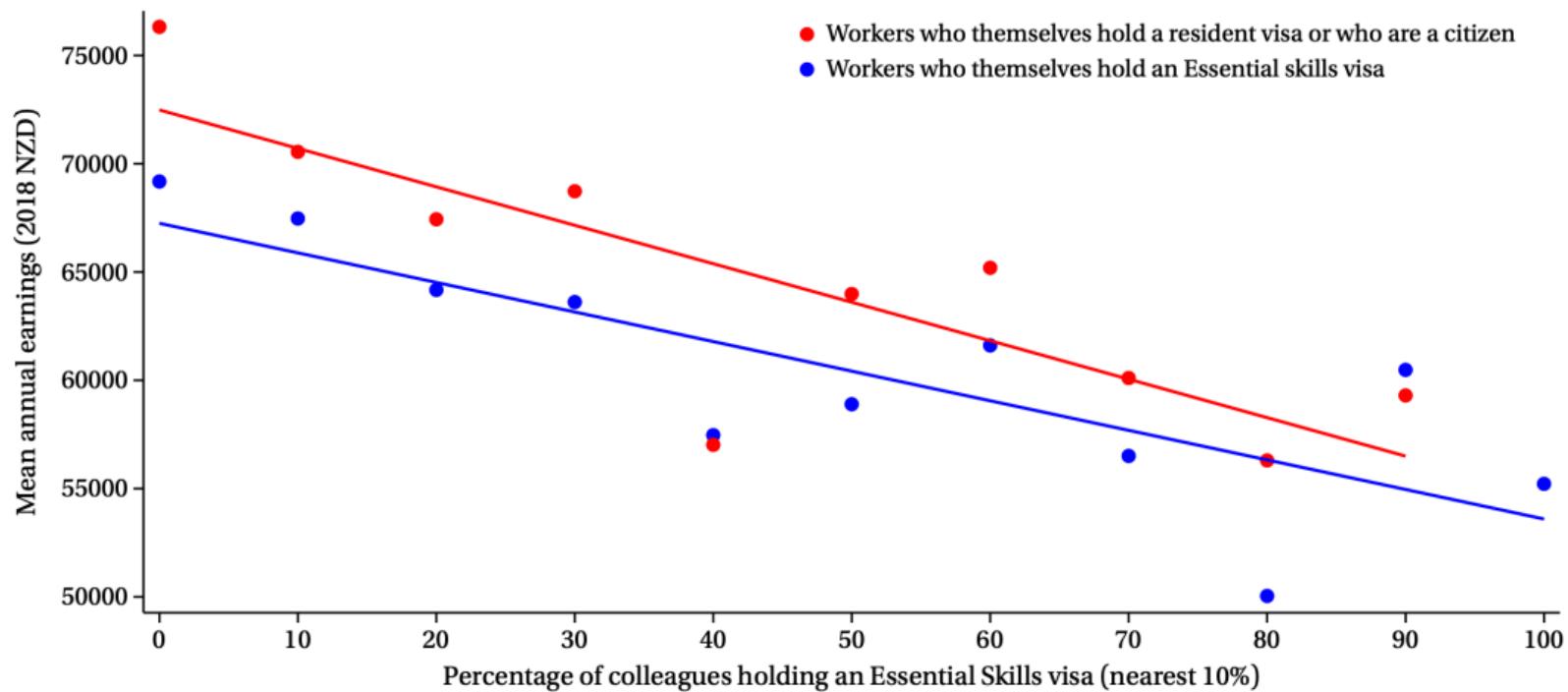
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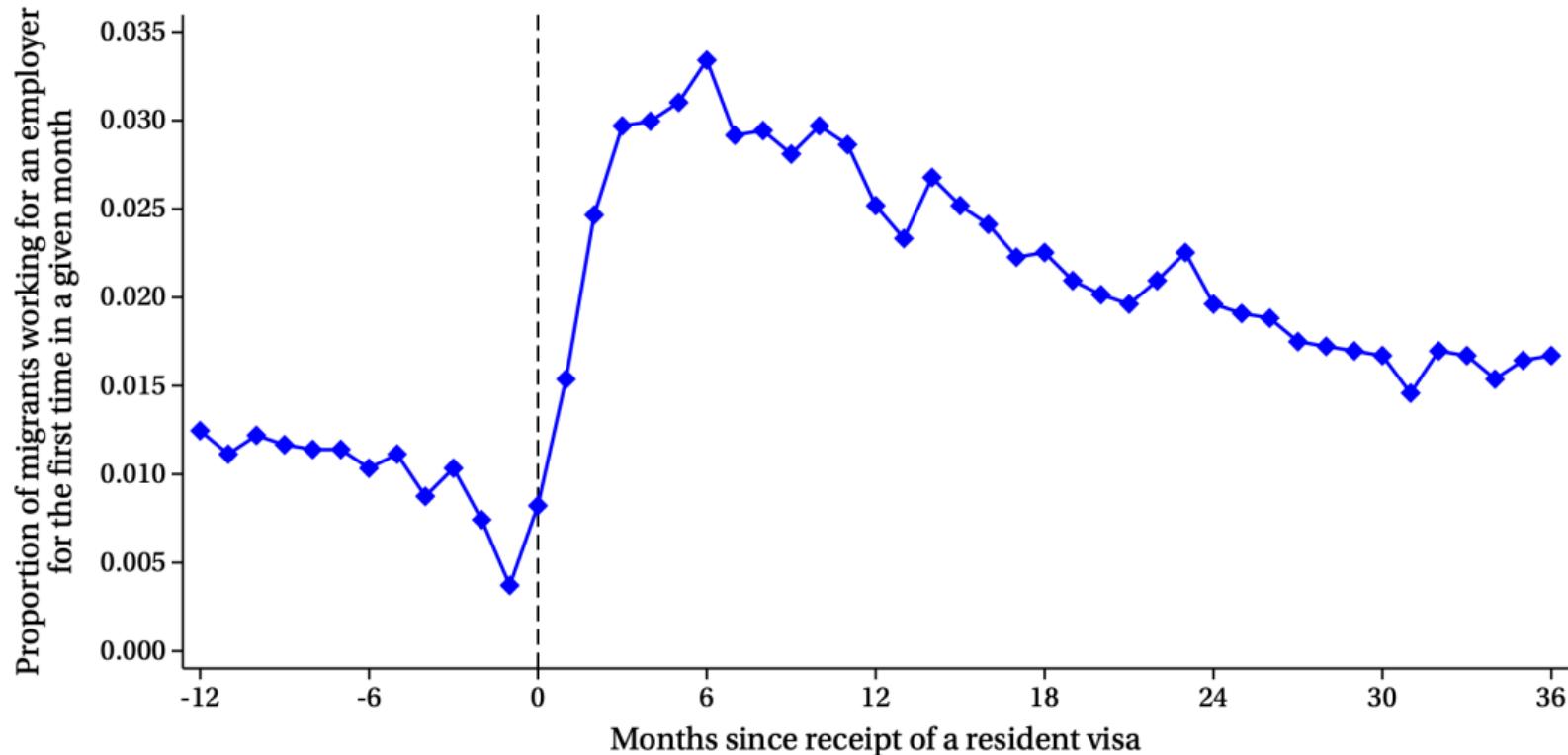
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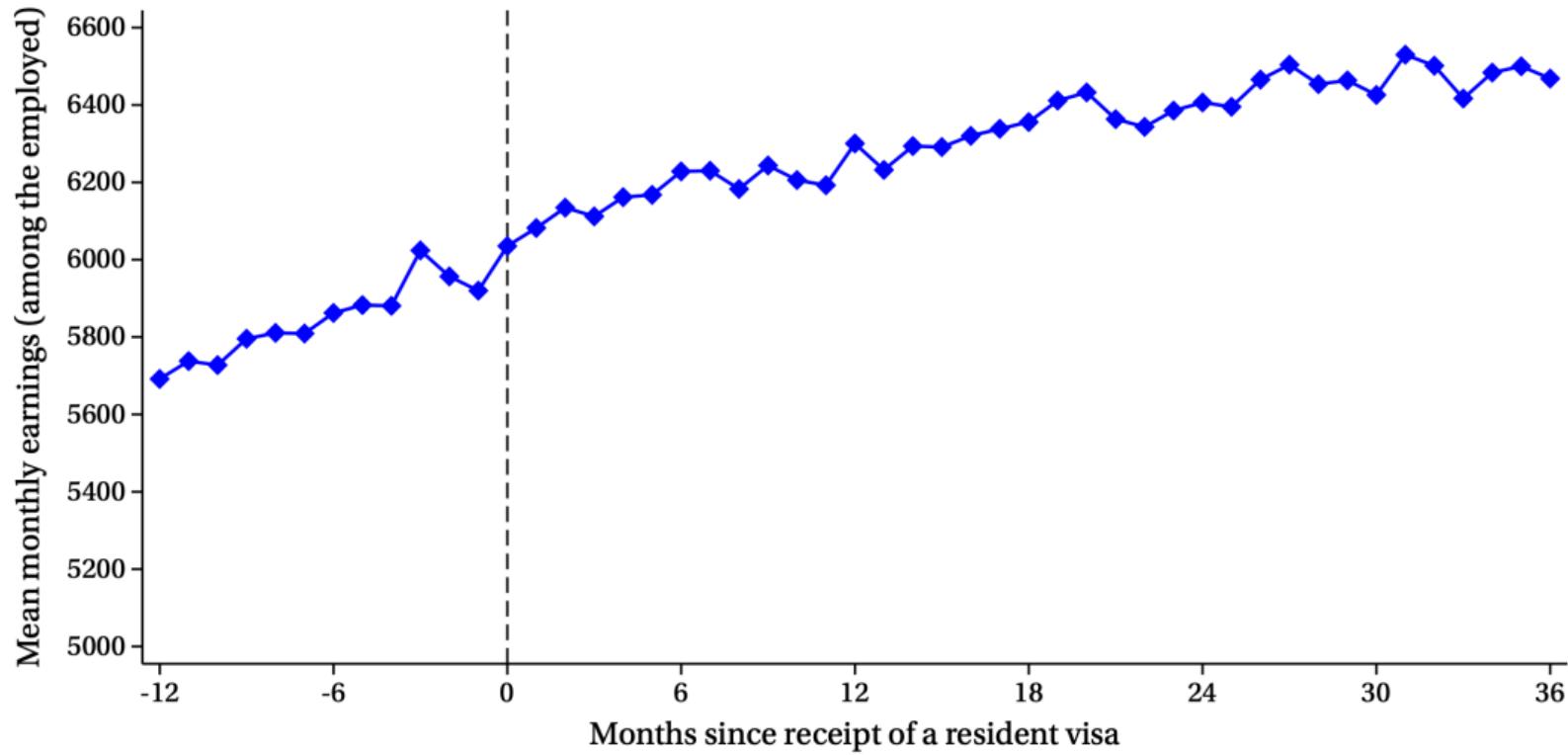
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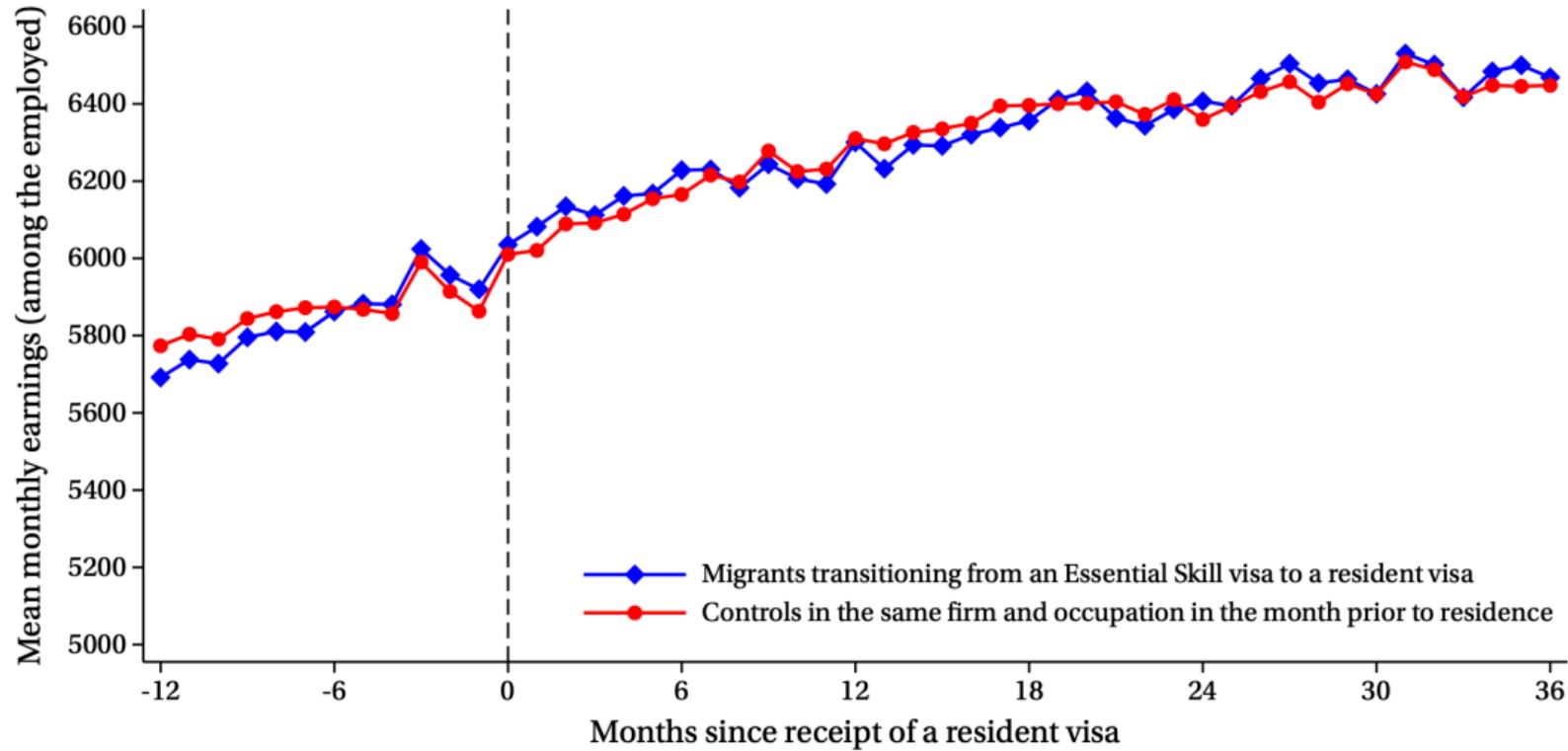
# The Essential Skills visa restricts migrants' job options...



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



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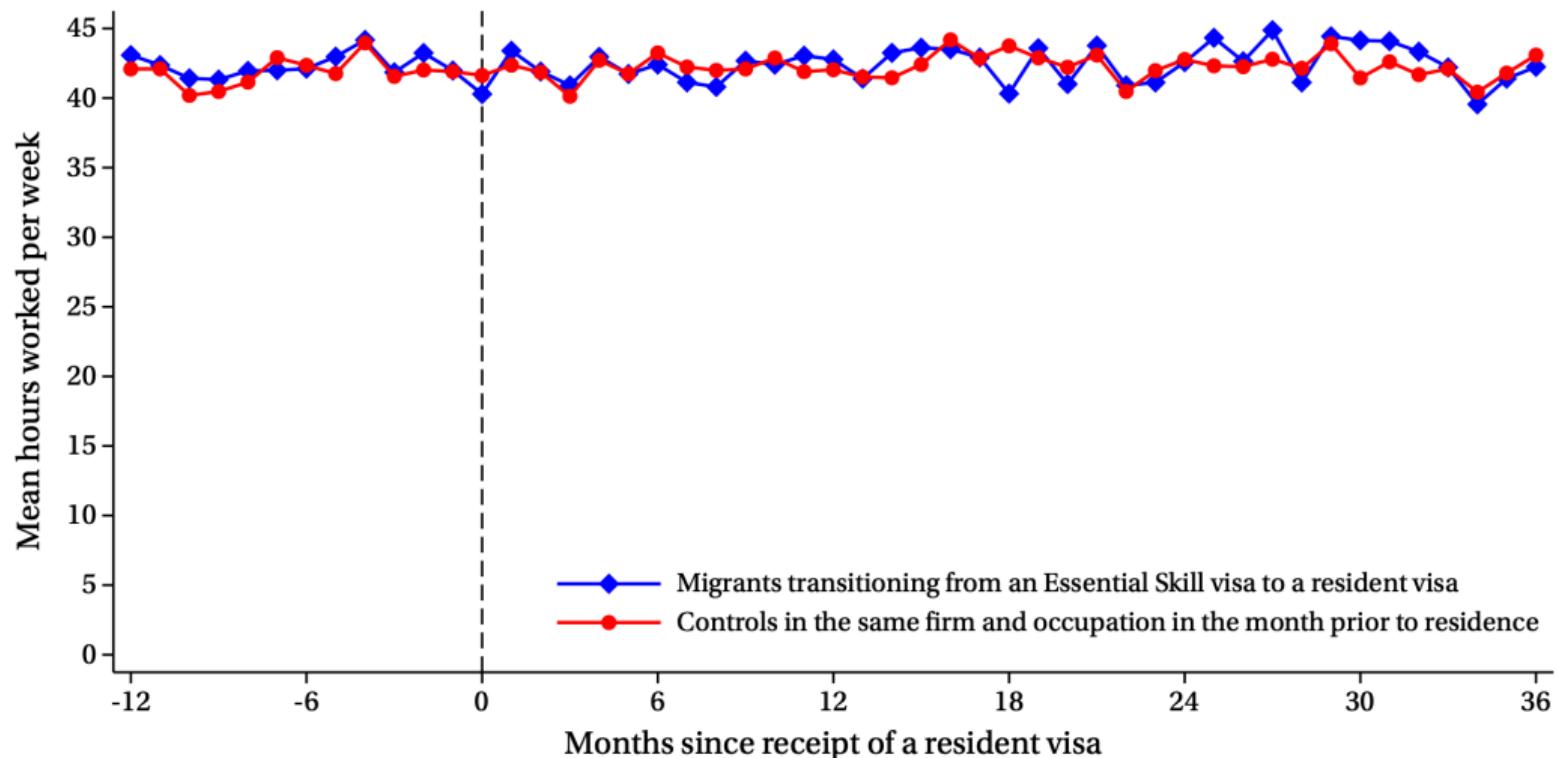


## An individual migrant's job restriction does not affect their wage

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



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Estimates by occupation.

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

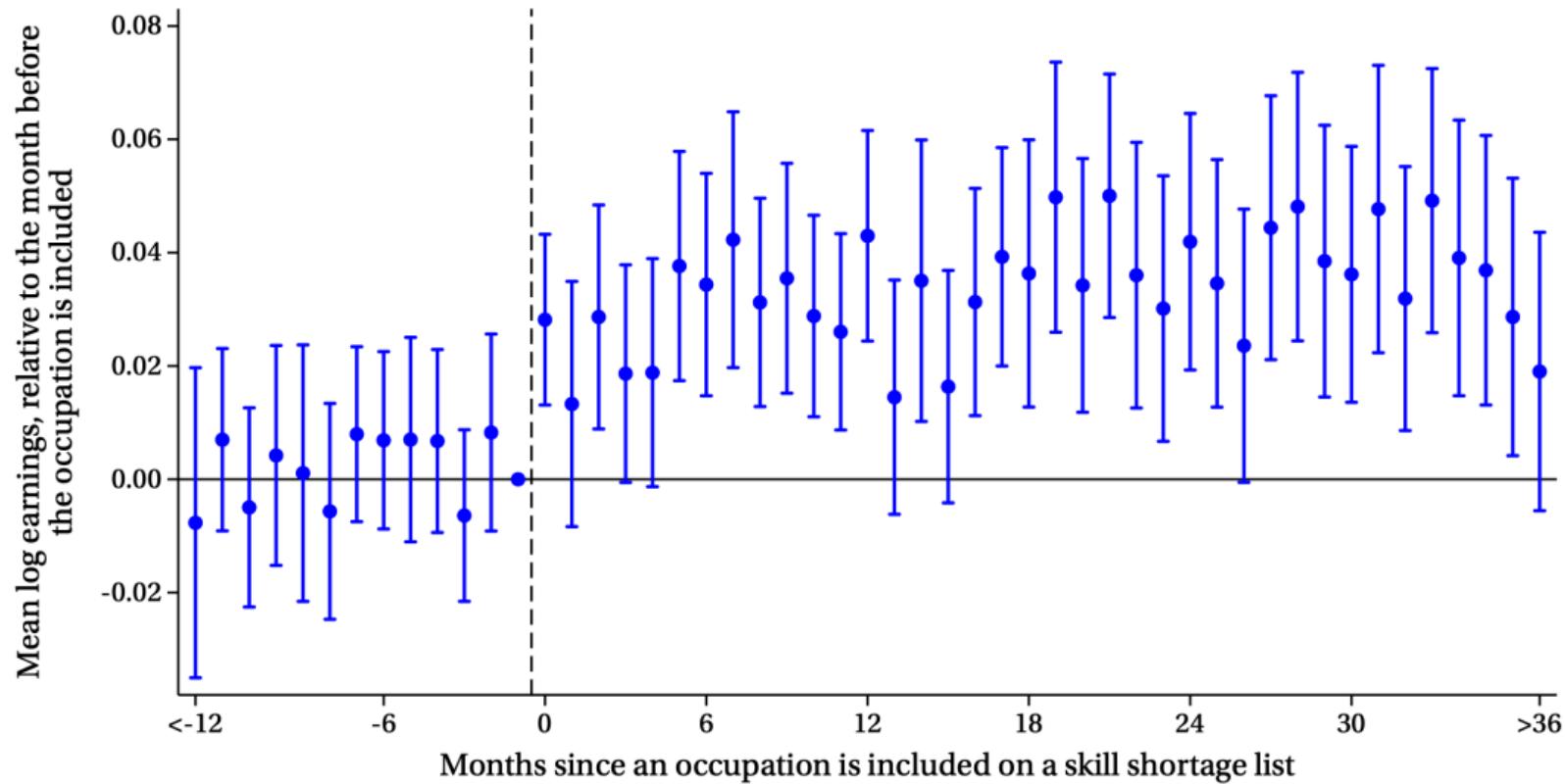
For **occupations on an 'Essential Skills in Demand' list:**

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

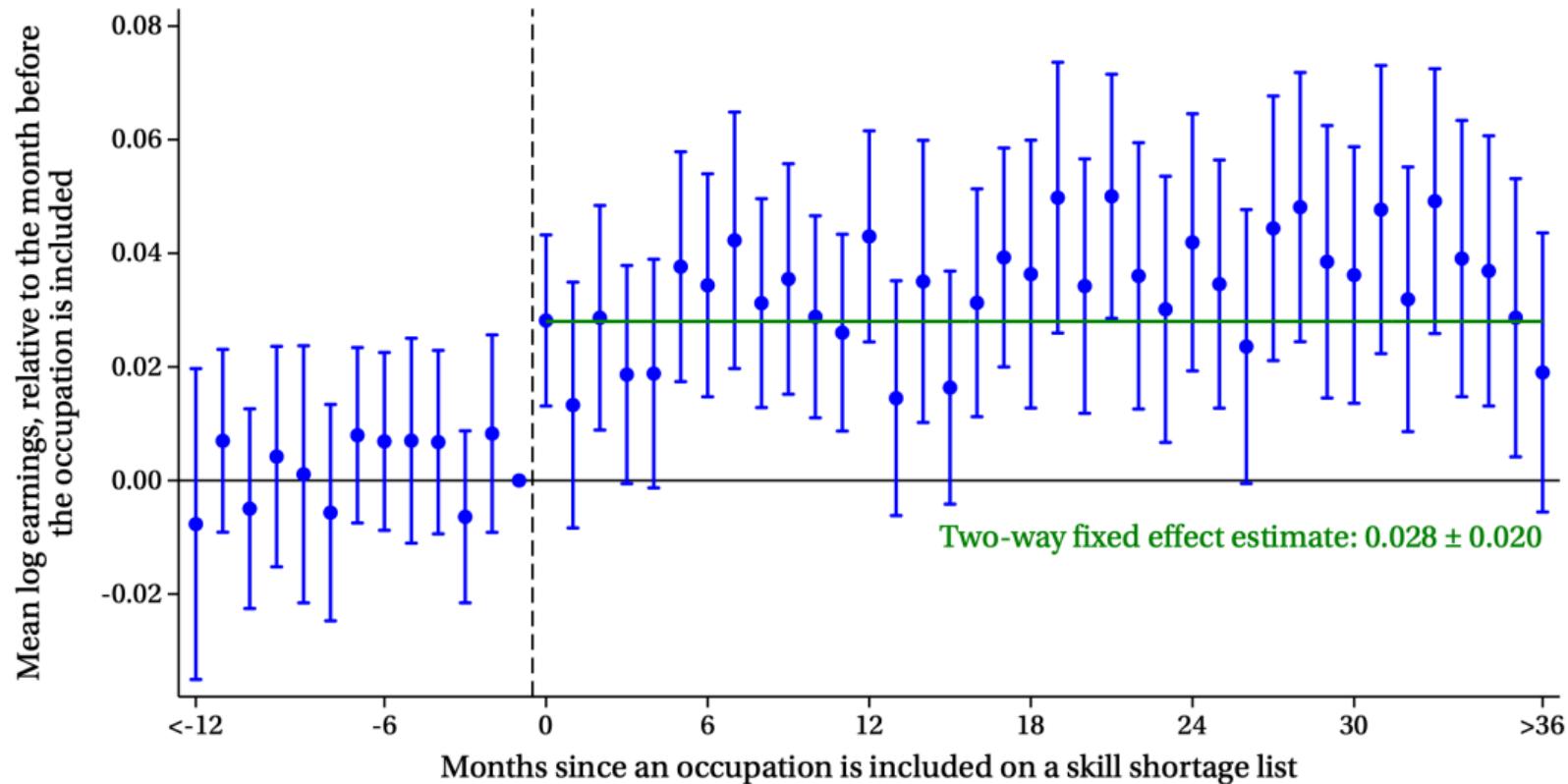
Occupations were added and removed from these lists regularly, often for reasons orthogonal to demand (e.g. occupation size).

**We ask how wages change when an occupation is listed.**

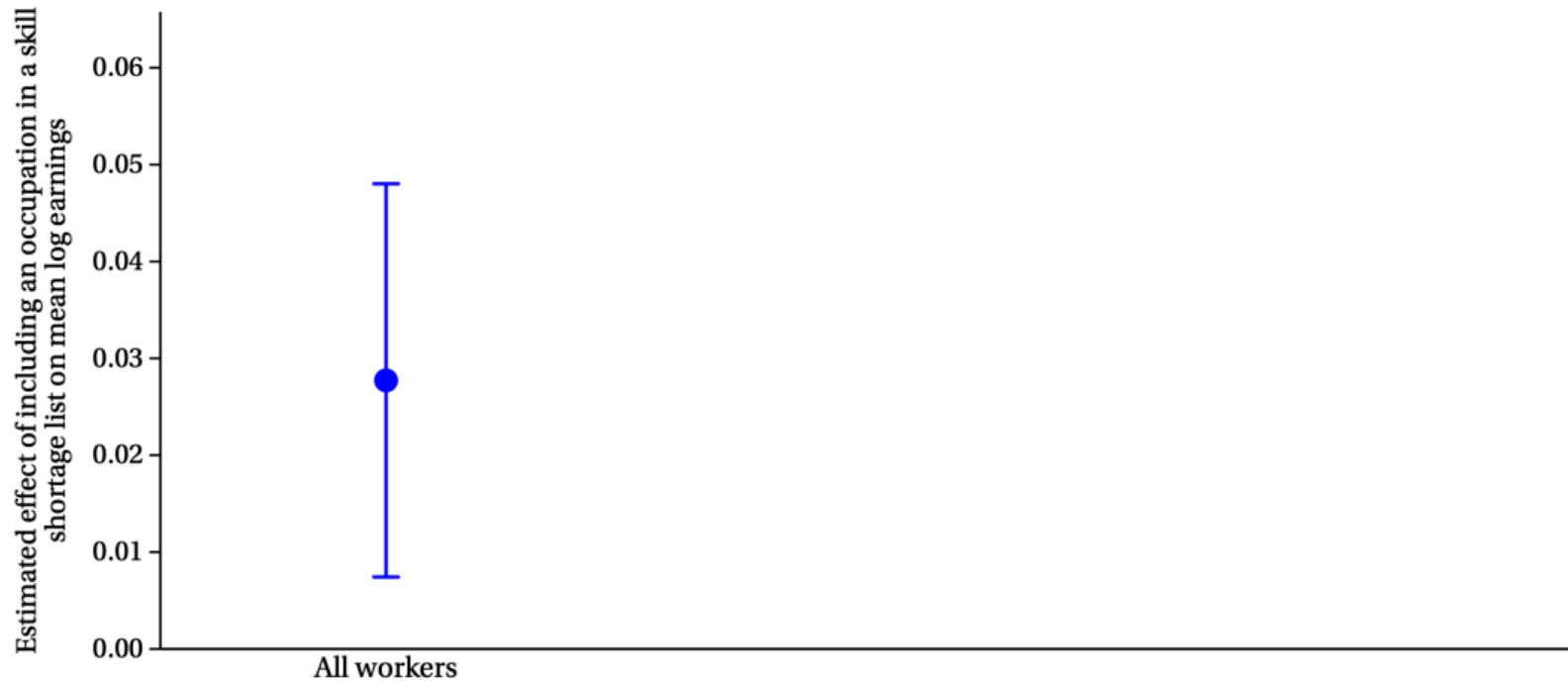
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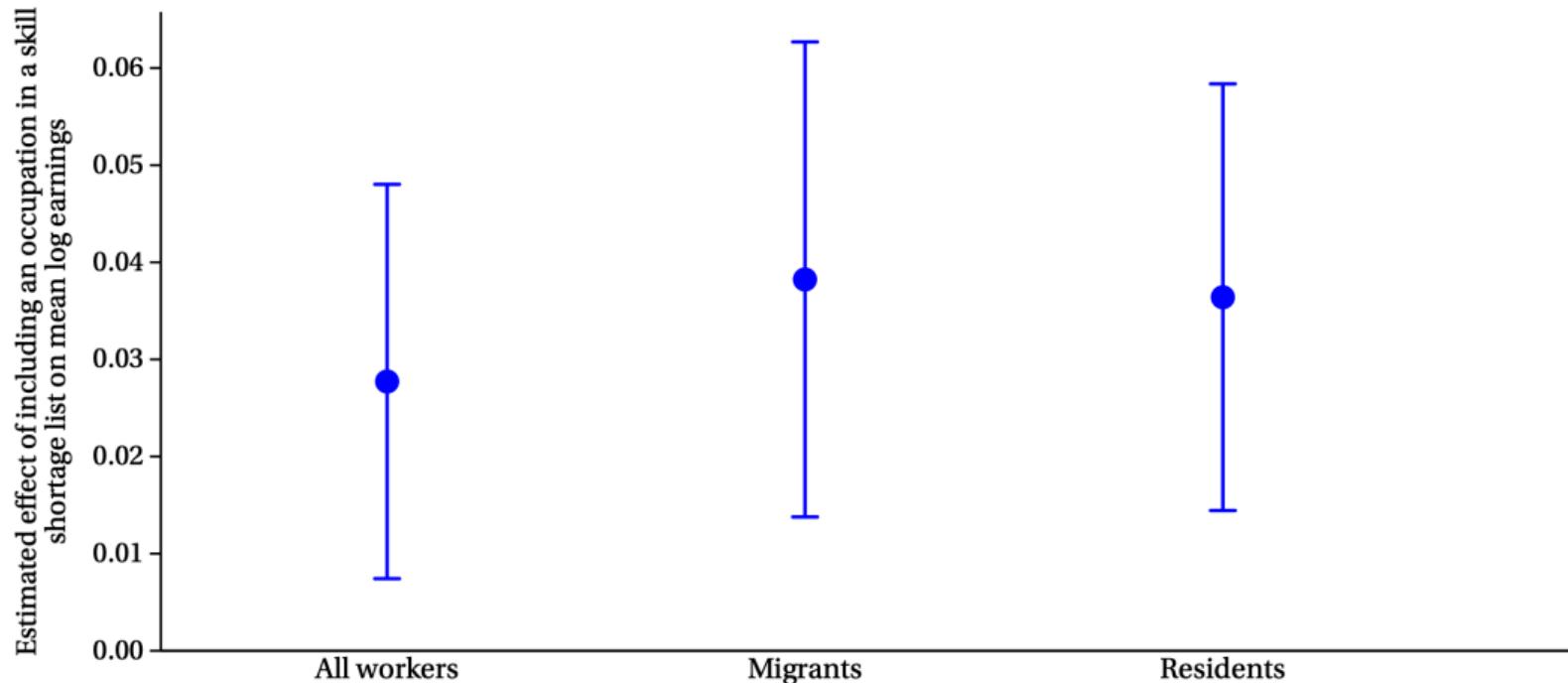
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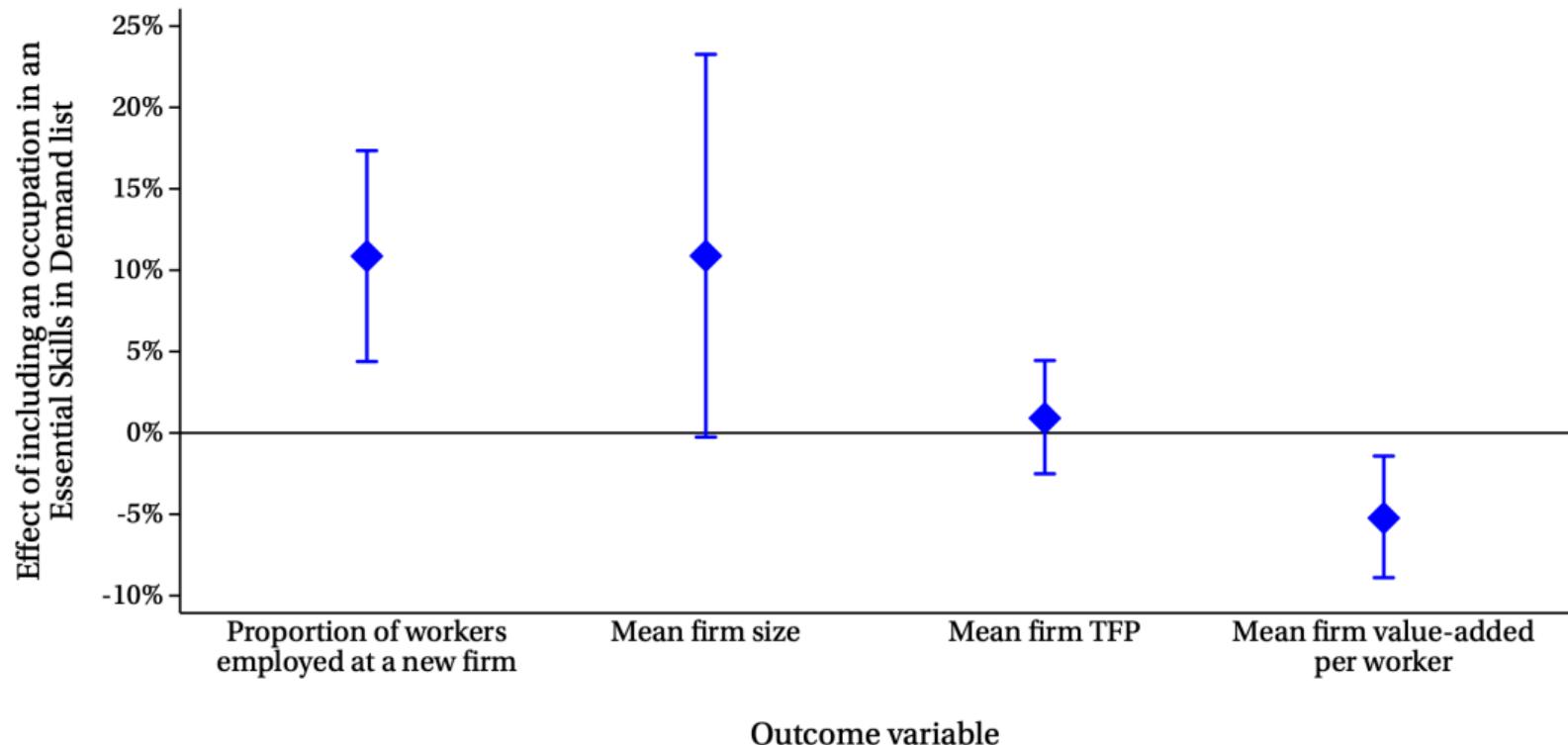
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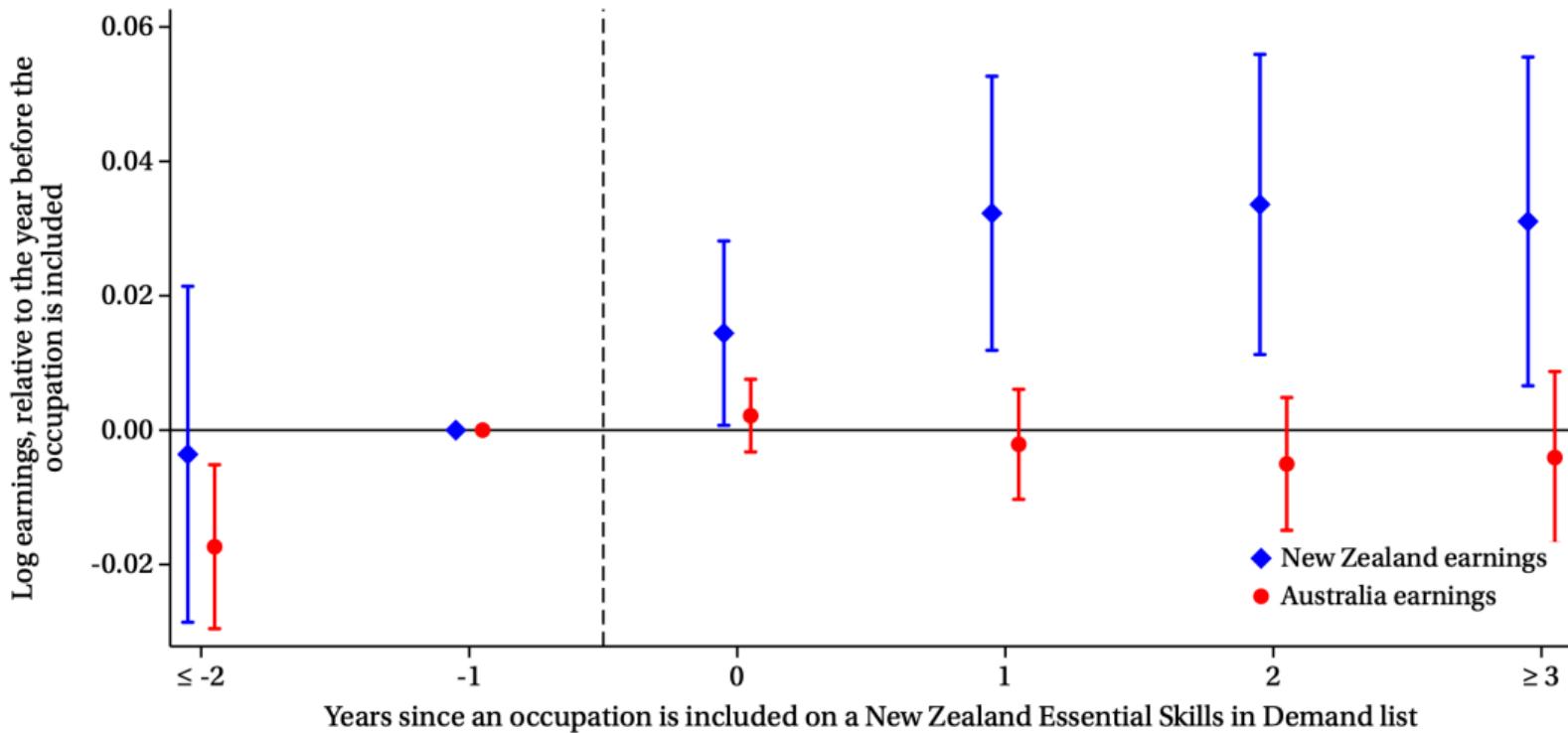
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# Why does strengthening migrants' job options increase wages?



# Using Australian data as a placebo outcome



Point estimate.

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## 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?
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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.

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

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

- ▶ If  $i$  is a *resident*:  $\mathbf{F}_{i,t} = \mathbf{F}_{o_{i,t}}$ ;
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A **type-x** worker has **nested-logit preferences** over firms  $f$  in locations  $c_f$  with wages  $w$ :

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

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Firms have **CES production functions**:

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

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

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

## Structural model: identification strategy

**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
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**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.

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Given a candidate  $\tau_0, \lambda_0 \dots$

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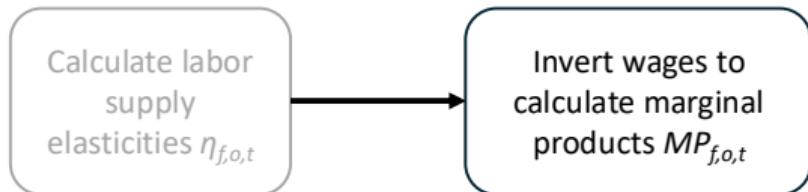
Calculate labor  
supply  
elasticities  $\eta_{f,o,t}$

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

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

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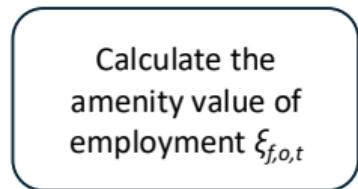
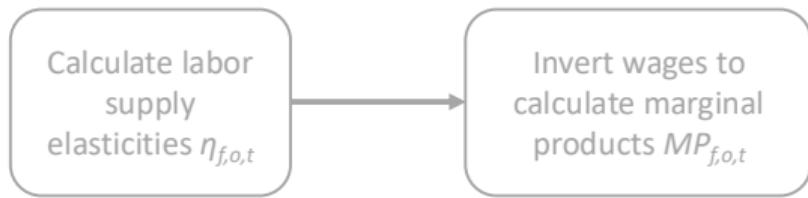
Given a candidate  $\tau_0, \lambda_0 \dots$



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

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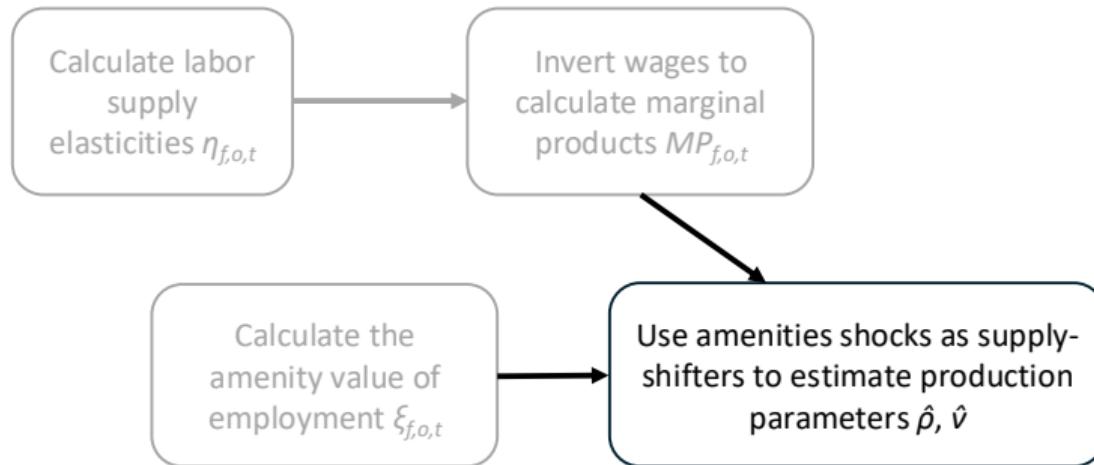
Given a candidate  $\tau_0, \lambda_0 \dots$



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

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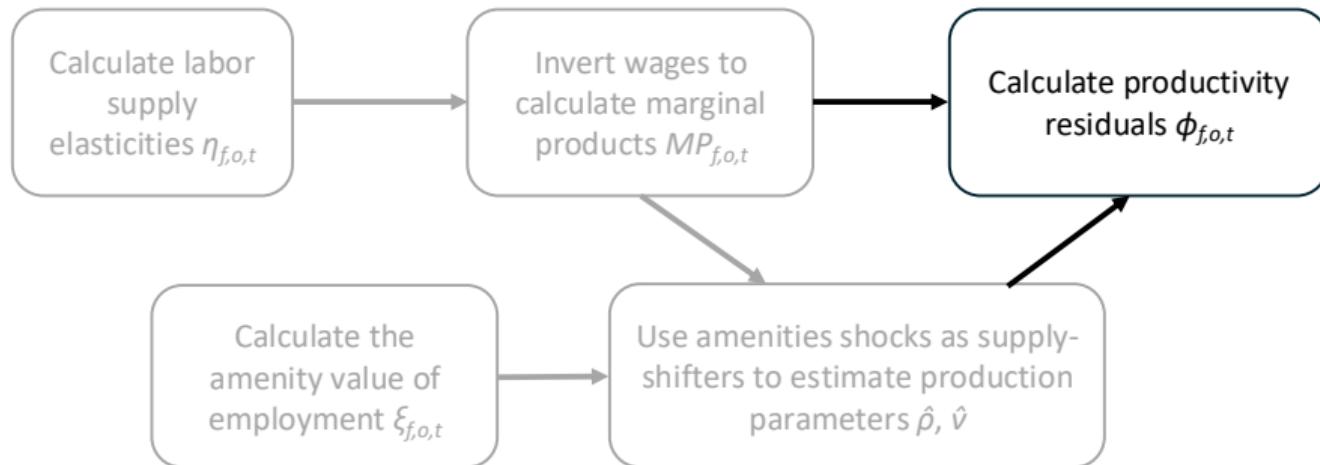


$$\Delta \log MP_{f,o,t} = (\rho - 1) \Delta \log L_{f,o,t} + \left( \frac{\nu - \rho}{\nu} \right) \Delta \log \tilde{L}_{f,t} + \Delta \phi_{f,o,t}$$

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

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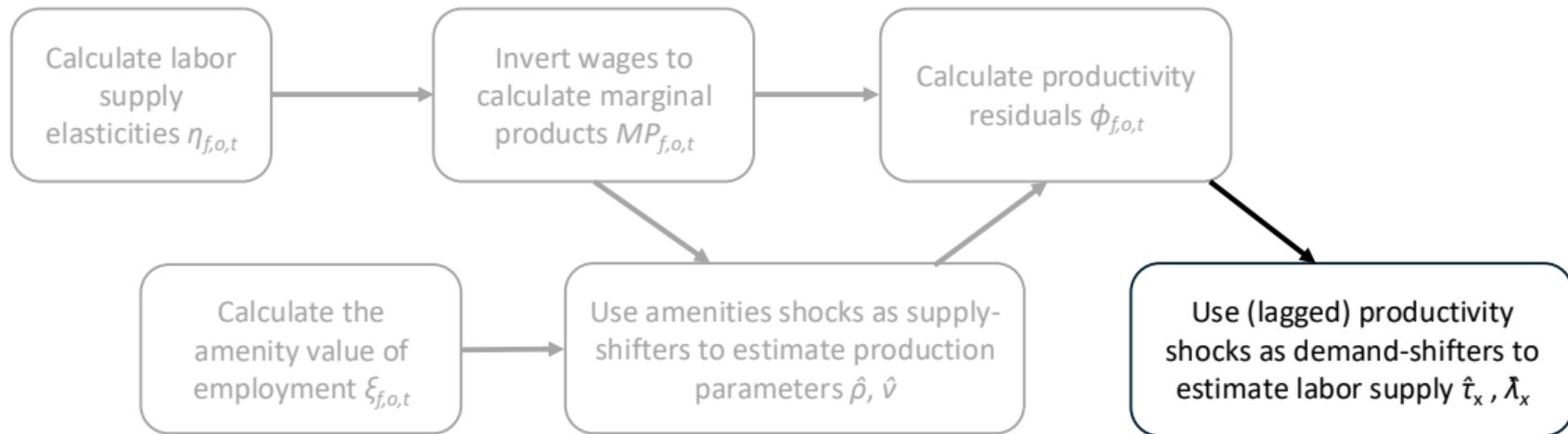
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$$\log MP_{f,o,t} = \frac{\rho \log \nu}{\nu} + (\rho - 1) \log L_{f,o,t} + \left( \frac{\nu - \rho}{\nu} \right) \log \tilde{L}_{f,t} + \phi_{f,o,t}$$

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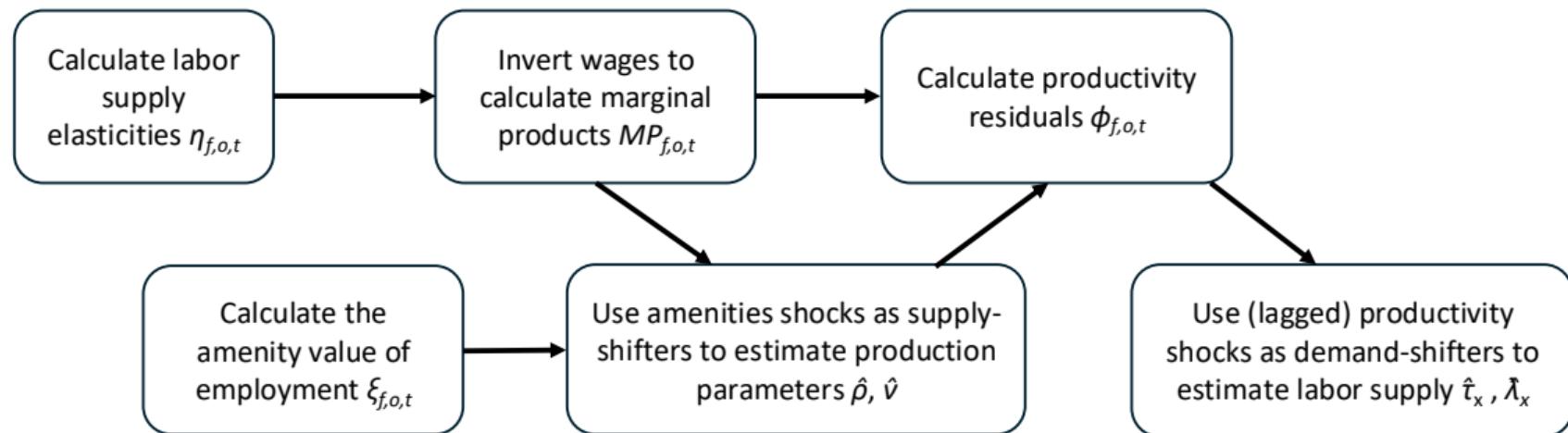


$$\Delta \log N_{f,o,x,t}^{\text{resident}} = \hat{\tau}_x \Delta \log w_{f,o,t} + \text{Constant}_{x,c_f,t} + \Delta \xi_{f,o,x,t}$$

$$\Delta \log N_{c,o,x,t}^{\text{resident}} = \hat{\lambda}_x \Delta \log \left( \sum_{f \in \mathbf{F}_{c,o,t}} e^{\tau_0^0 \log w_{f,o,t} + \hat{\xi}_{f,o,x,t}} \right) + \text{Constant}_{o,x,t} + \Delta \bar{\xi}_{c,o,x,t}$$

# Structural model: a fixed-point estimator

Given a candidate  $\tau_0, \lambda_0 \dots$



Our estimate is the fixed point  $\hat{\tau} = \tau_0, \hat{\lambda} = \lambda_0$

Conduct inference with an equivalent GMM representation, clustering by firm and occupation

## 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.

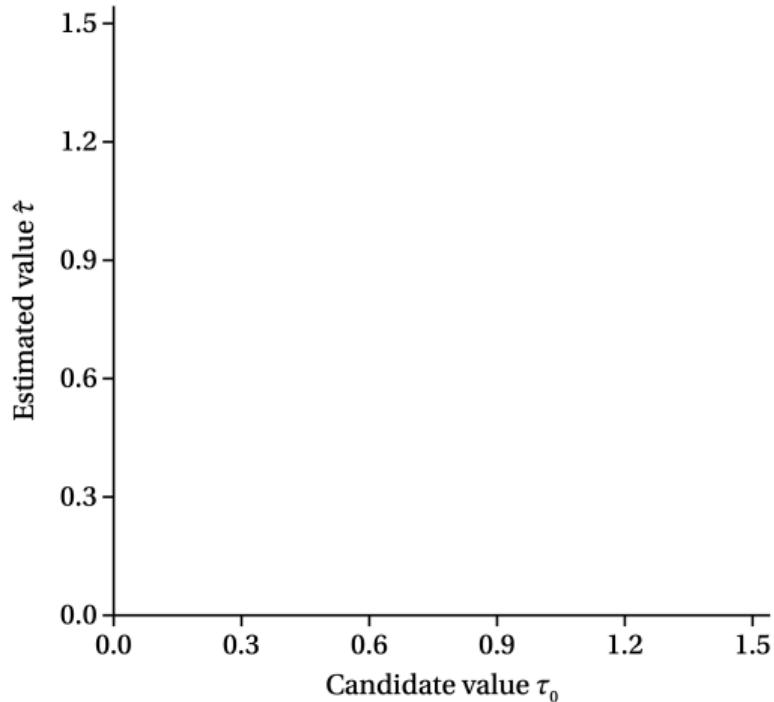
**Locations:** Functional urban areas.

**Firms:** Enterprise × location.

## Structural model: a fixed point estimator

First, assume  $\tau_x$  and  $\lambda_x$  are constant across types.

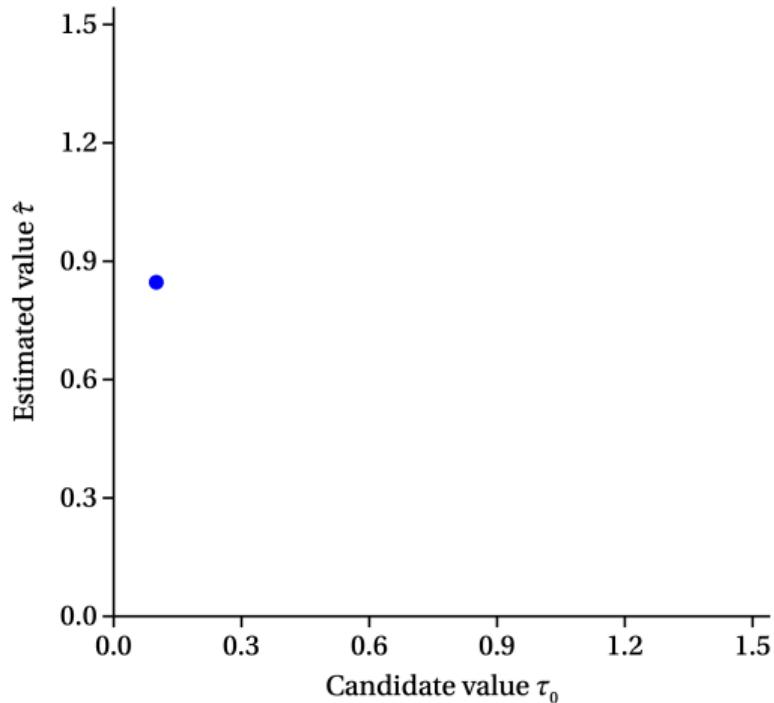
$\lambda_0$	$\tau_0$	$\hat{\rho}$	$\hat{v}$	$\hat{\tau}$	$\hat{\lambda}$
0.13	0.1	0.989	0.996		



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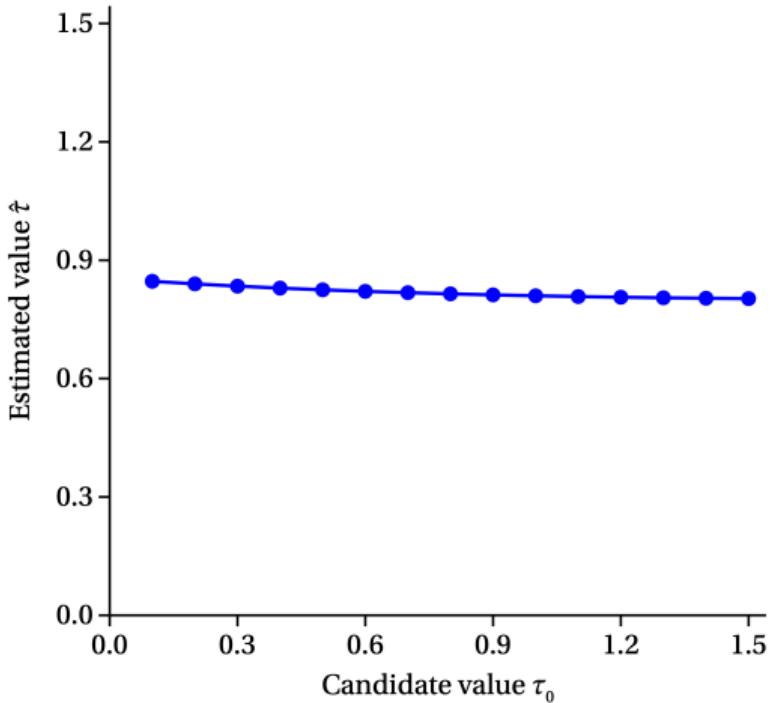
$\lambda_0$	$\tau_0$	$\hat{\rho}$	$\hat{v}$	$\hat{\tau}$	$\hat{\lambda}$
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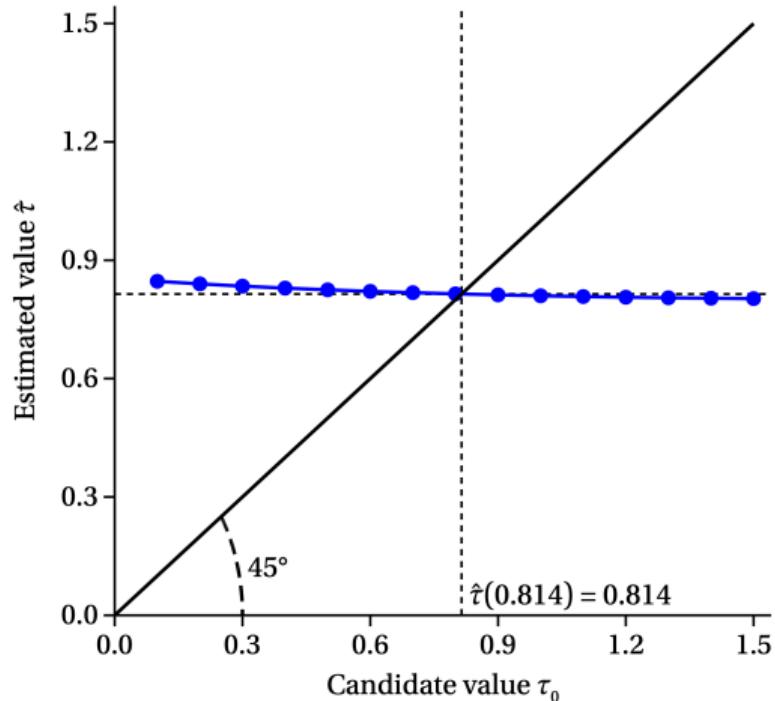
$\lambda_0$	$\tau_0$	$\hat{\rho}$	$\hat{v}$	$\hat{\tau}$	$\hat{\lambda}$
0.13	0.1	0.989	0.996	0.847	0.140
0.13	0.2	0.980	0.988	0.840	0.139
0.13	0.3	0.970	0.980	0.834	0.137
0.13	0.4	0.960	0.972	0.829	0.136
0.13	0.5	0.951	0.965	0.825	0.134
0.13	0.6	0.941	0.957	0.821	0.133
0.13	0.7	0.931	0.949	0.818	0.132
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



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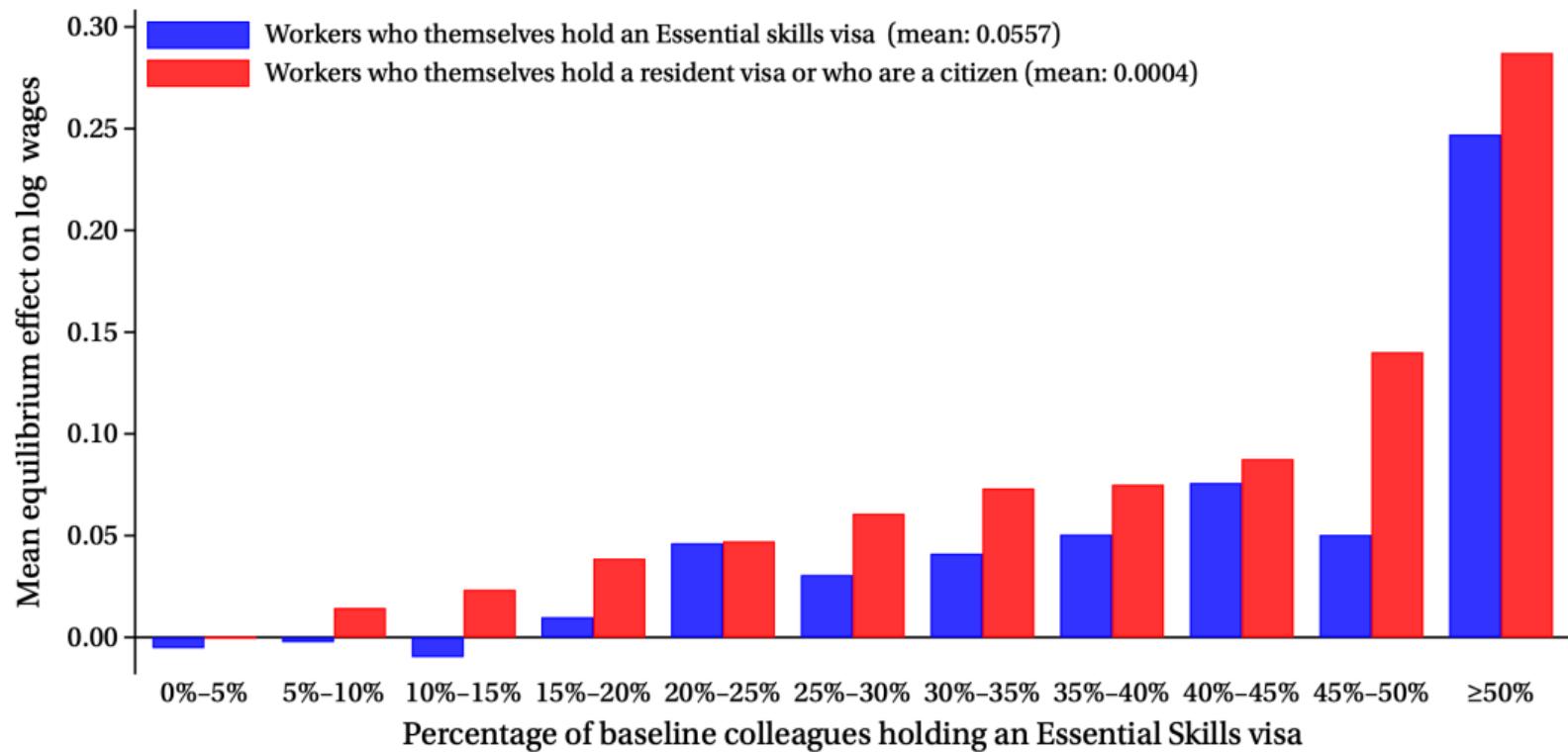
# Structural model: estimates

	Homogeneous coefficients	Heterogeneous coefficients	
		NZ-born	foreign-born
<b>Labor supply estimates</b>			
$\tau$ (labor supply elasticity for an atomistic firm)	0.814 [0.197]	0.845 [0.208]	0.751 [0.183]
$\lambda$ (workers' willingness substitute across space)	0.131 [0.008]	0.118 [0.008]	0.153 [0.010]
<b>Production function estimates</b>			
$\rho$ (firms' ability to substitute across occupations)	0.919 [0.019]	0.919 [0.019]	
$\nu$ (returns to scale)	0.940 [0.014]	0.940 [0.014]	

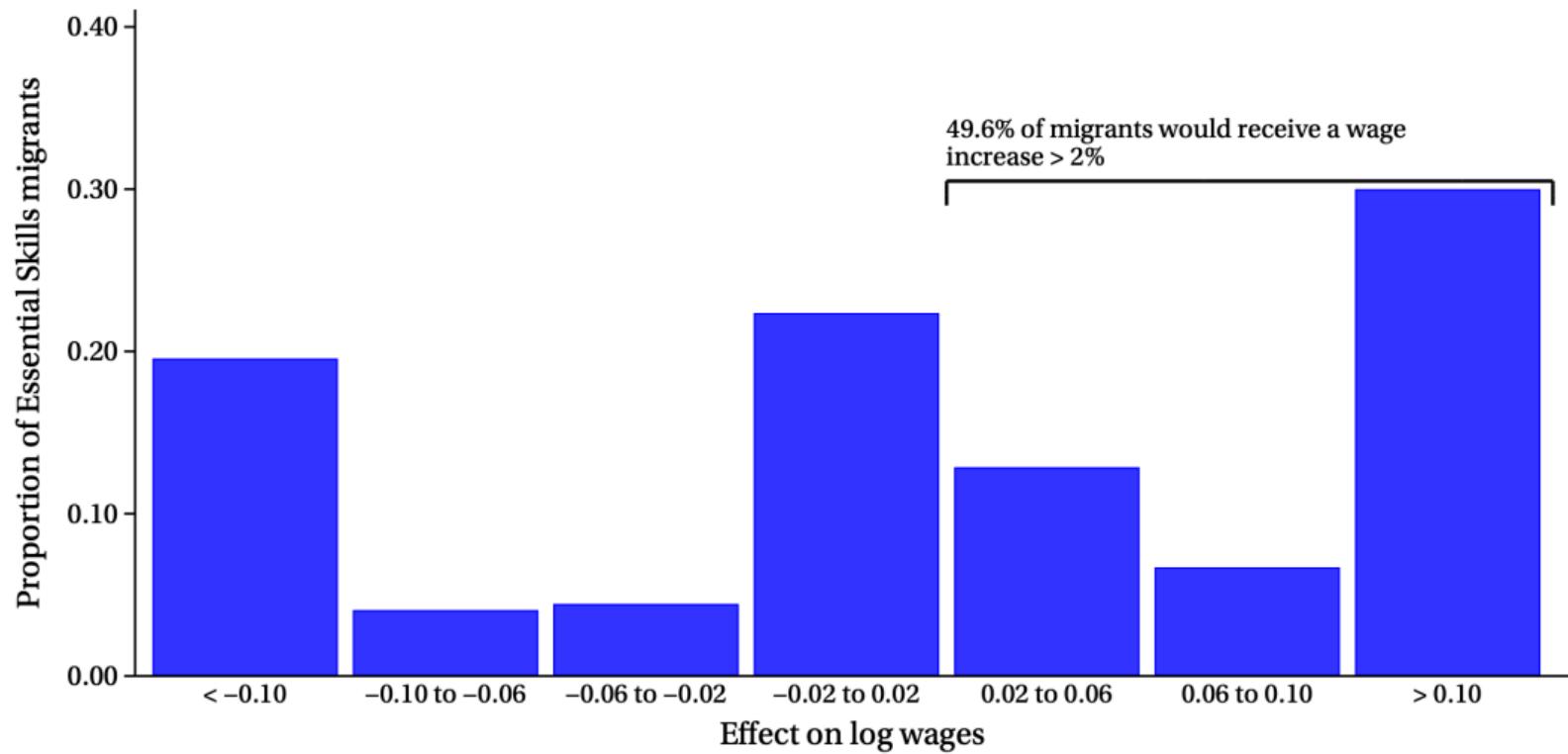
# The equilibrium effect of allowing migrants to work at any firm

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.**

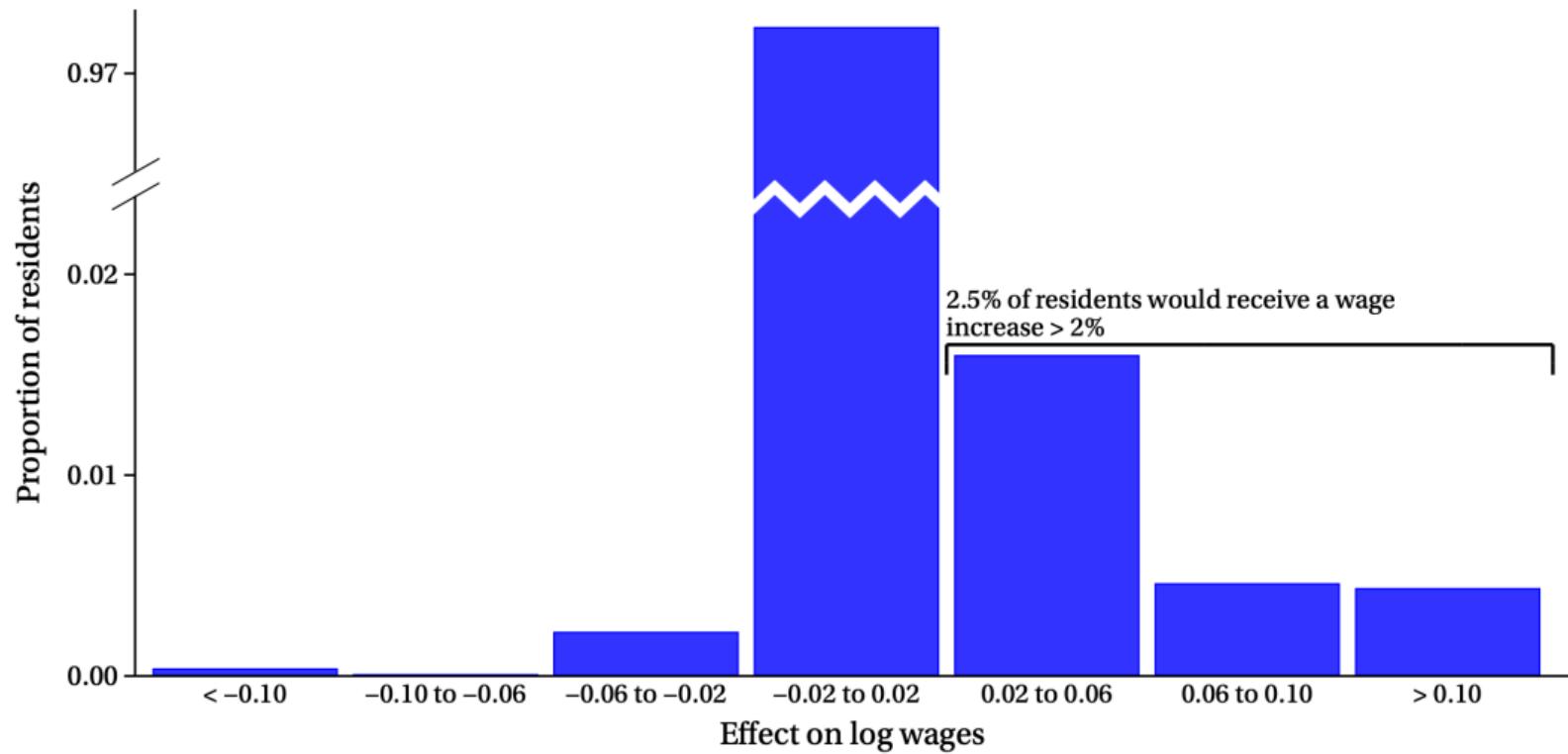
# The equilibrium effect of allowing migrants to work at any firm



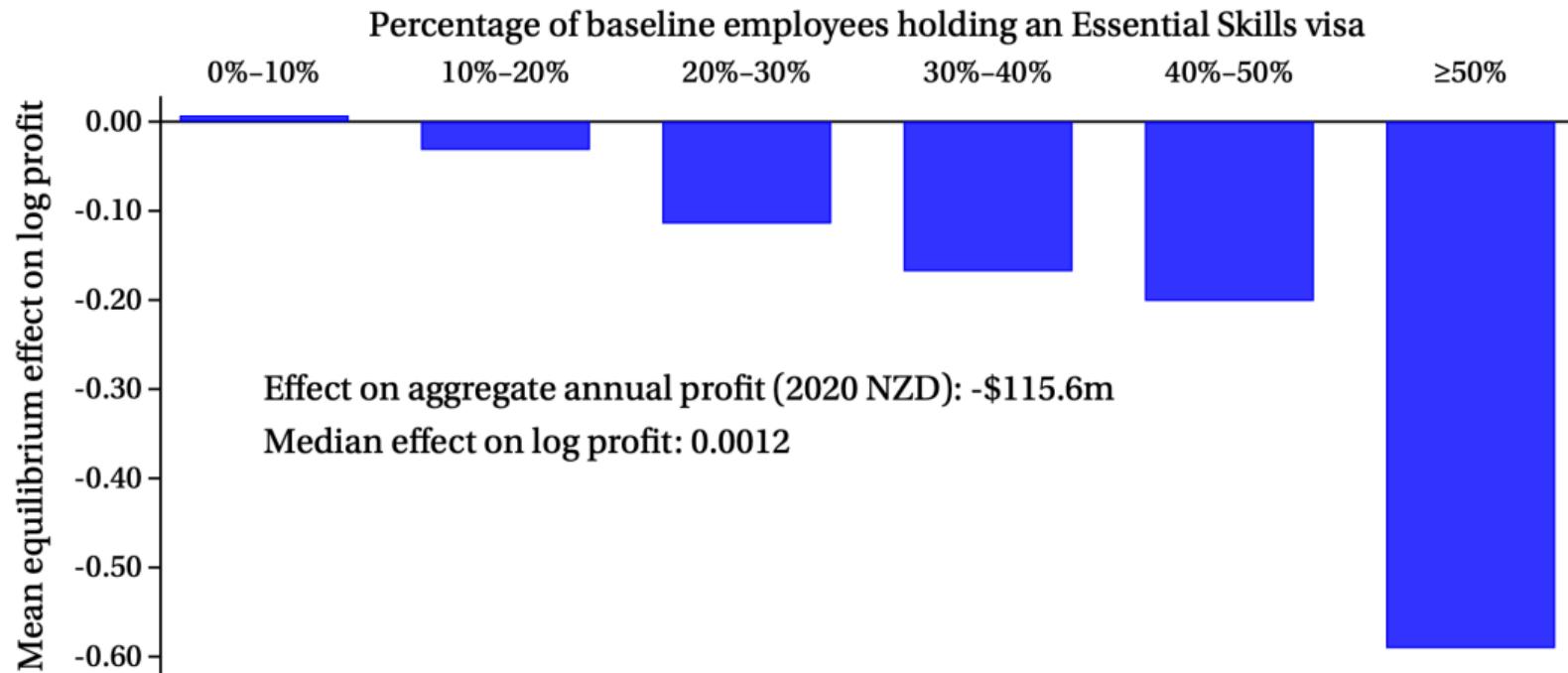
# The equilibrium effect of allowing migrants to work at any firm



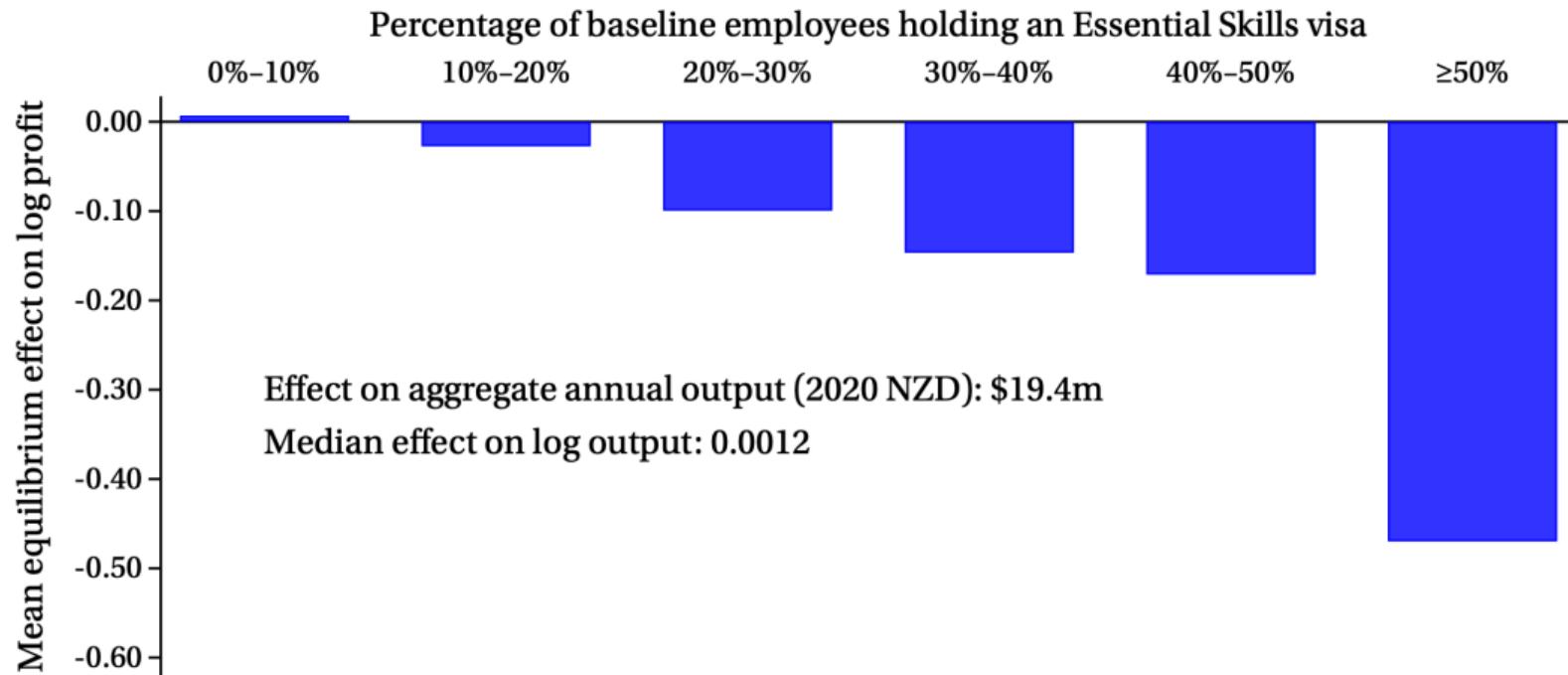
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## How restricting migrants' job options affects welfare

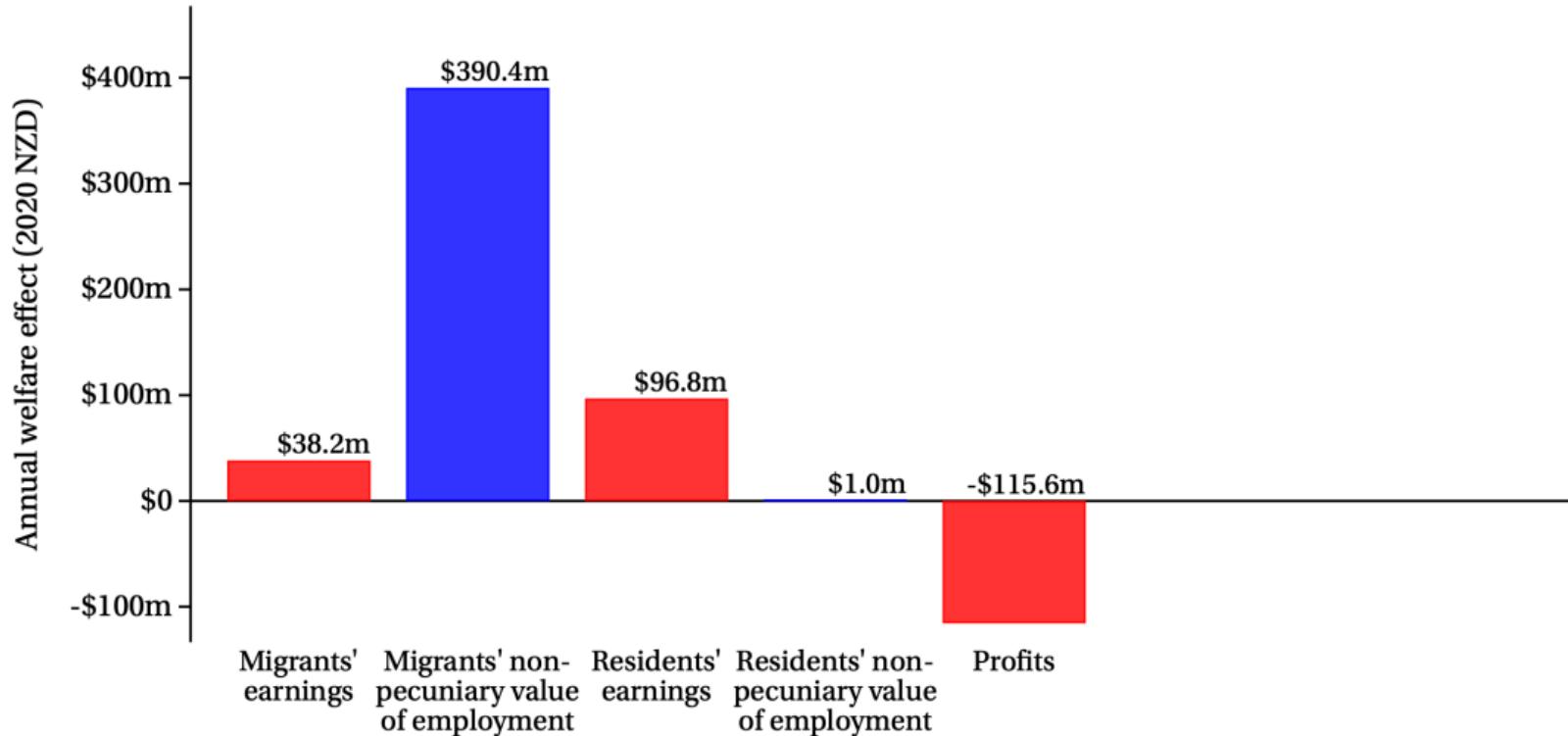
Let  $WTP_i$  denote  $i$ 's money-metric welfare gain from the counterfactual equilibrium  $w', f'$ , in which migrants can work at any firm:

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

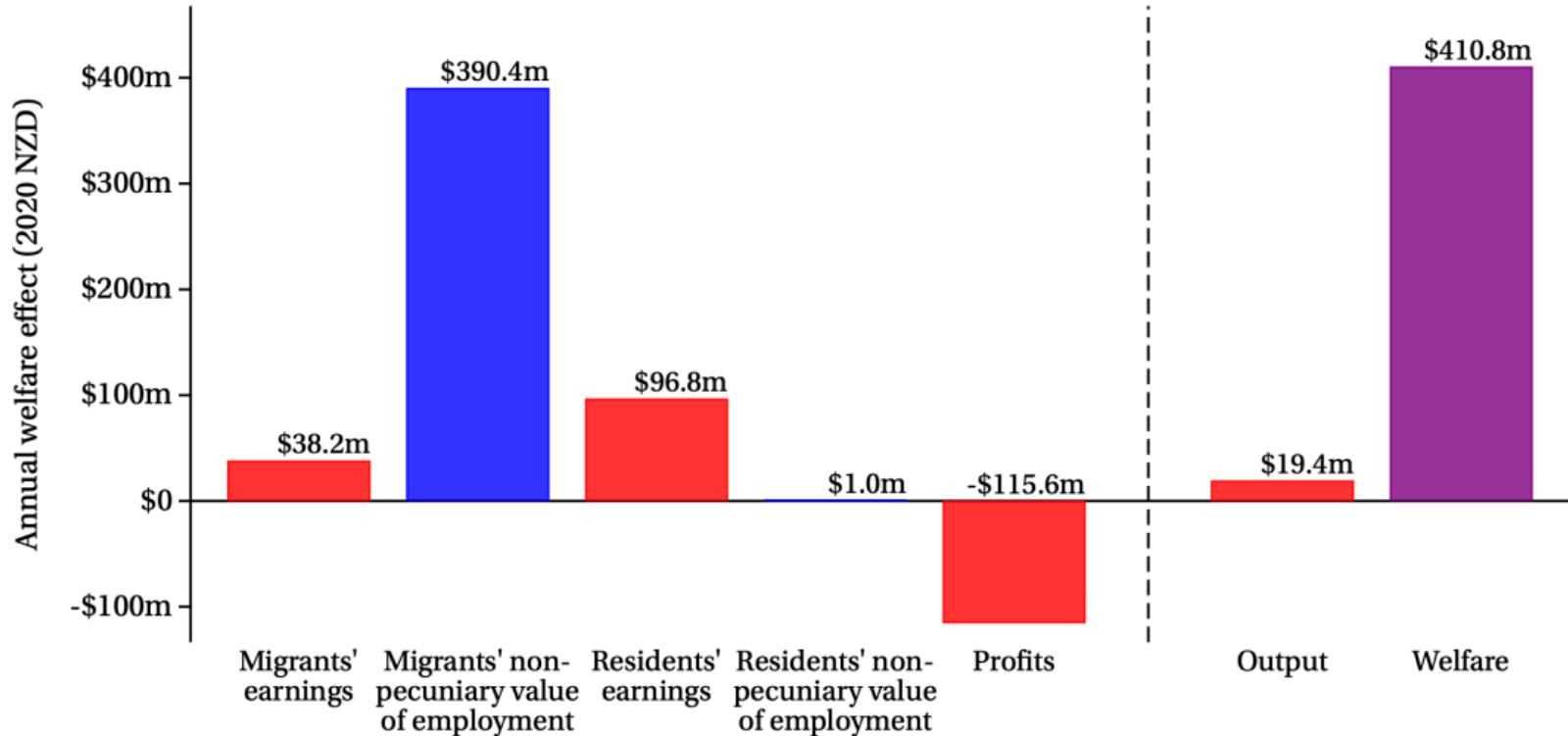
which we can decompose into

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

# How restricting migrants' job options affects welfare



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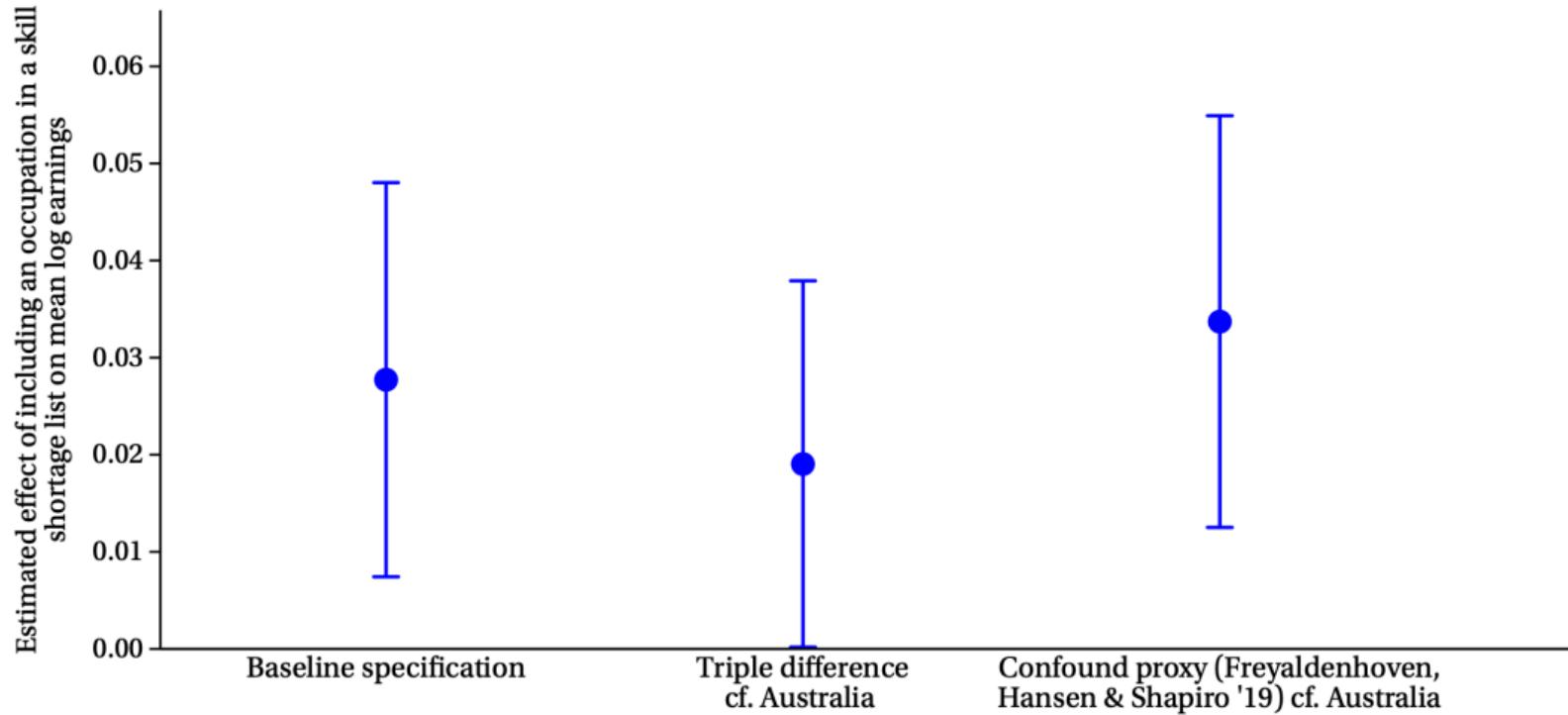
## Restricting migrants' job options affects everyone's wages

Firms don't *specifically* discriminate against migrants,

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

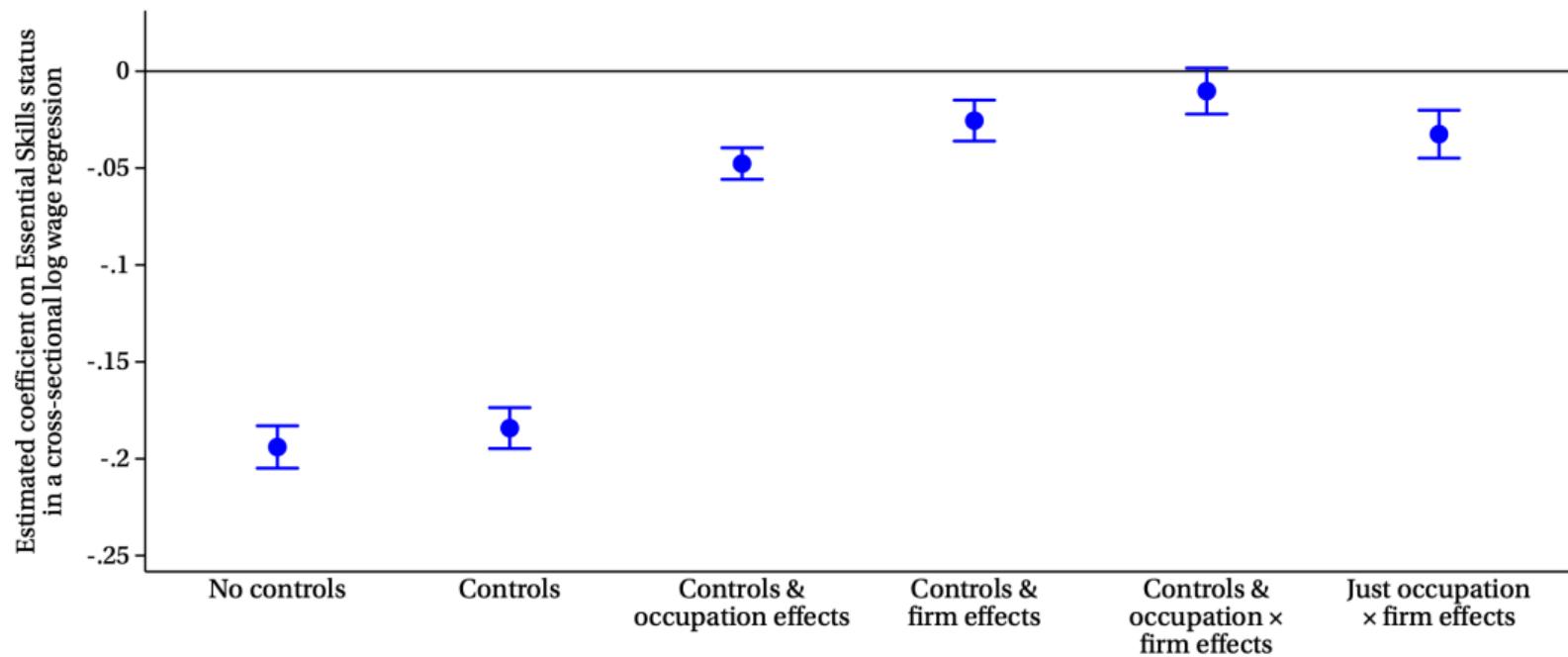
**Restricting migrant's job options reduces both their wages and the wages of their colleagues.**

# Using Australian data as a placebo outcome



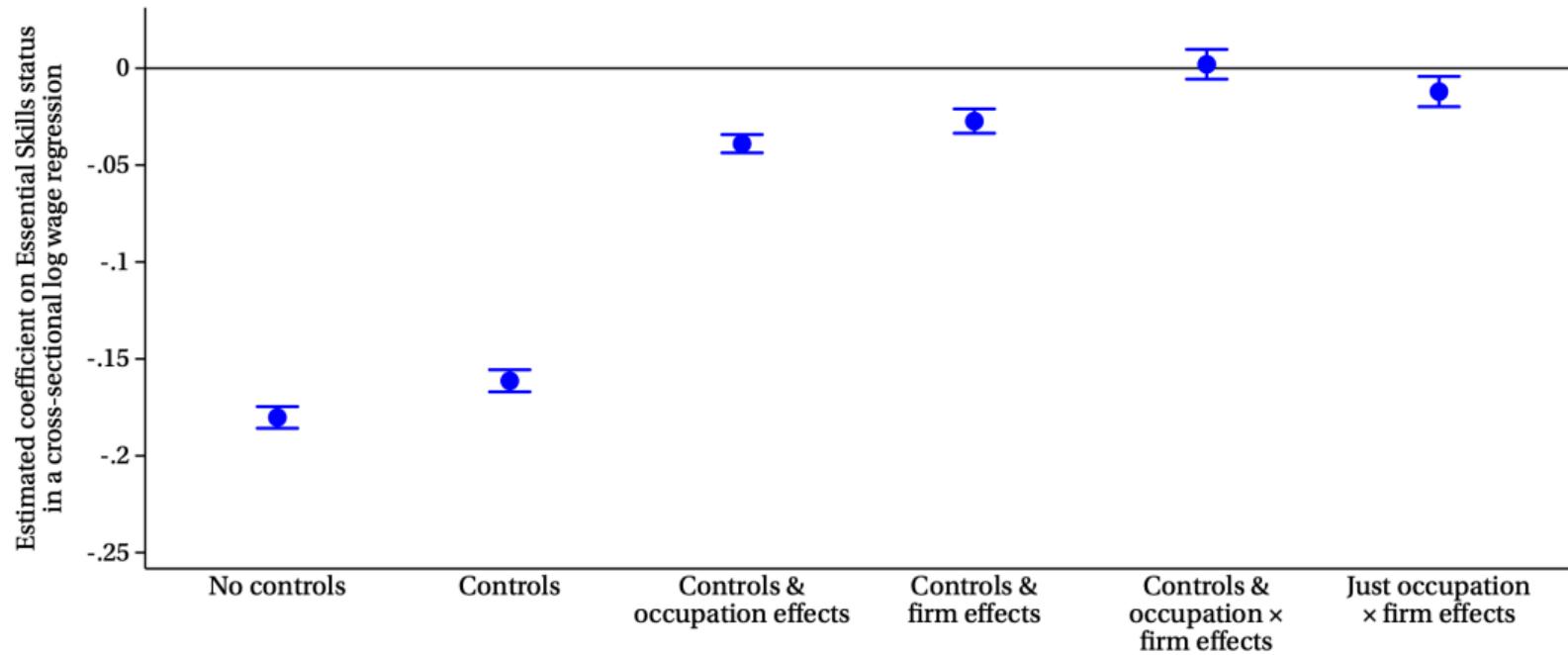
Back.

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



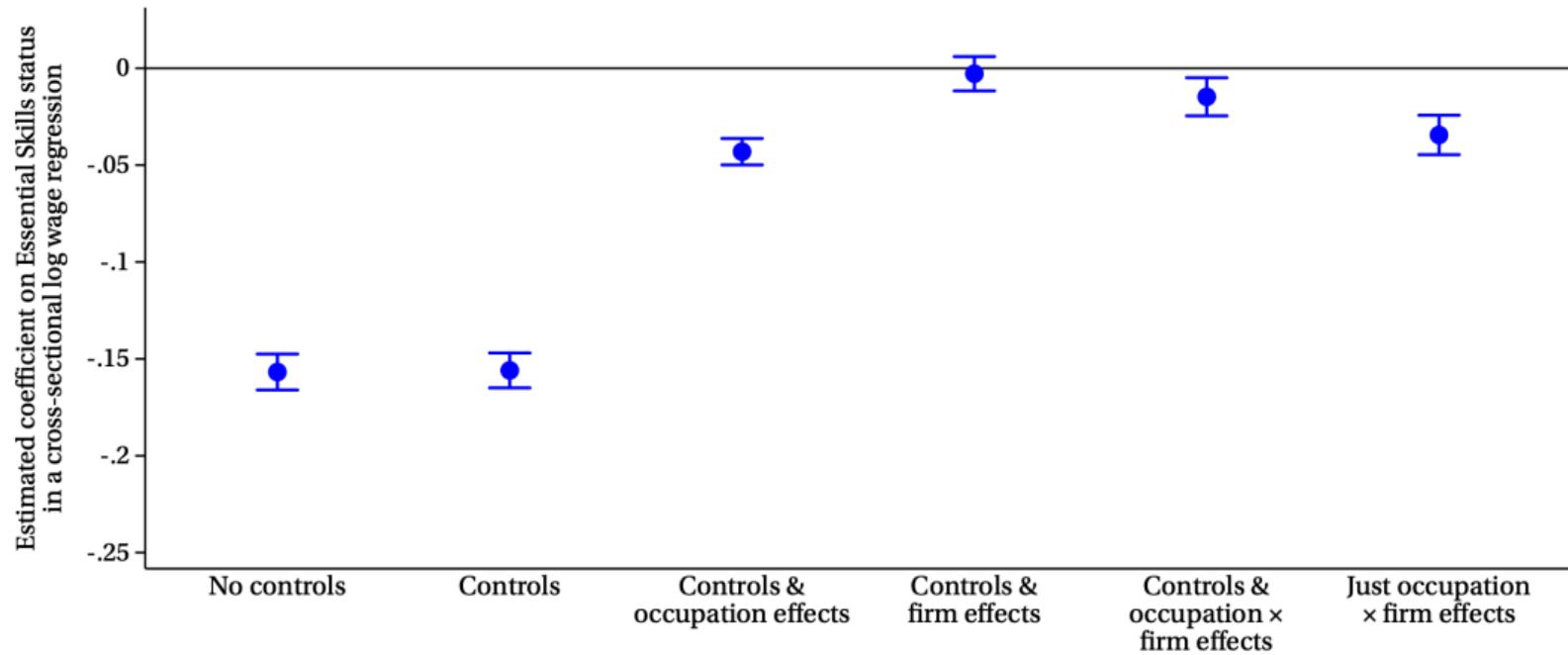
Sample: full-time employees with a unique firm in the 12 months before the 2013 Census. [Back](#).

# 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](#).

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Sample: full-time employees with a unique firm in the 6 months before the 2013 Census. [Back](#).

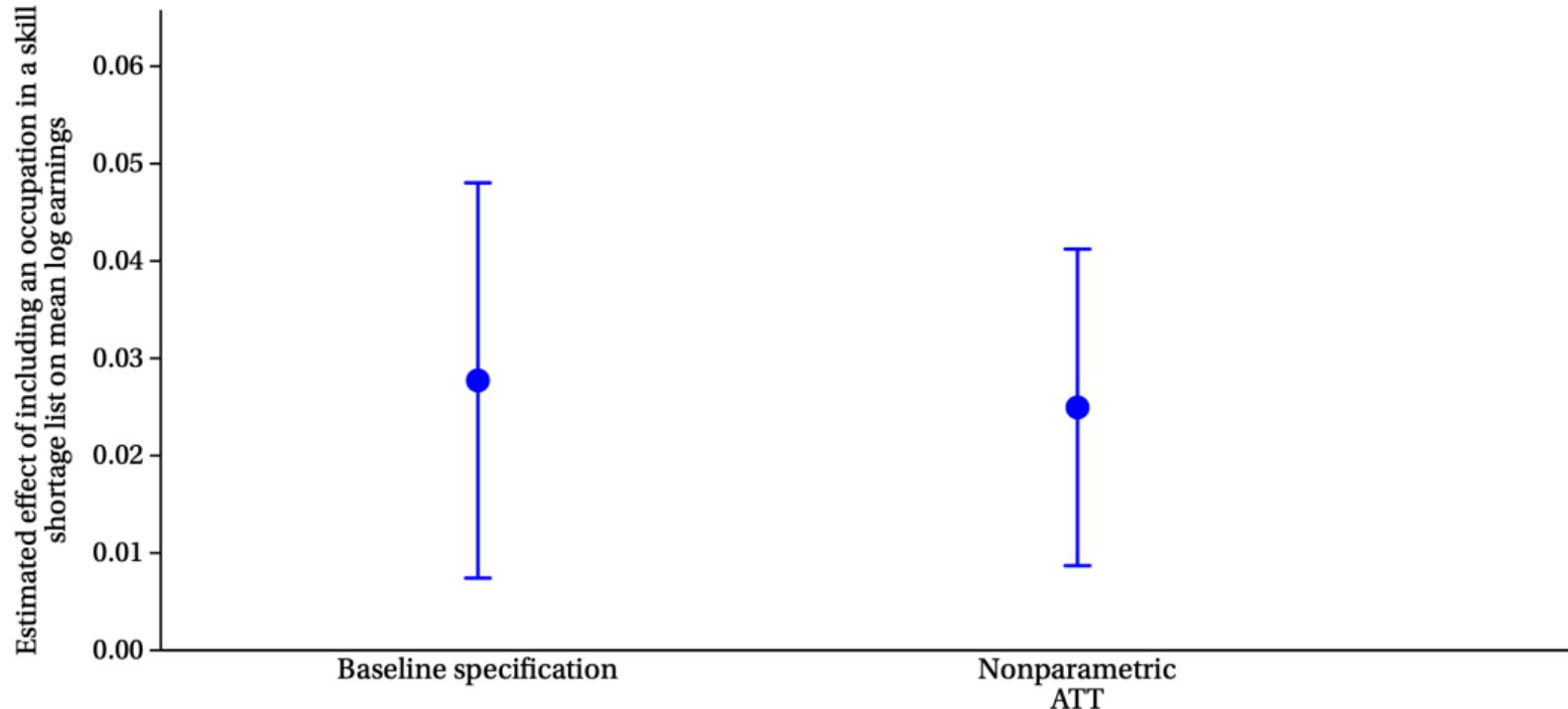
# Accounting for treatment effect heterogeneity

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.

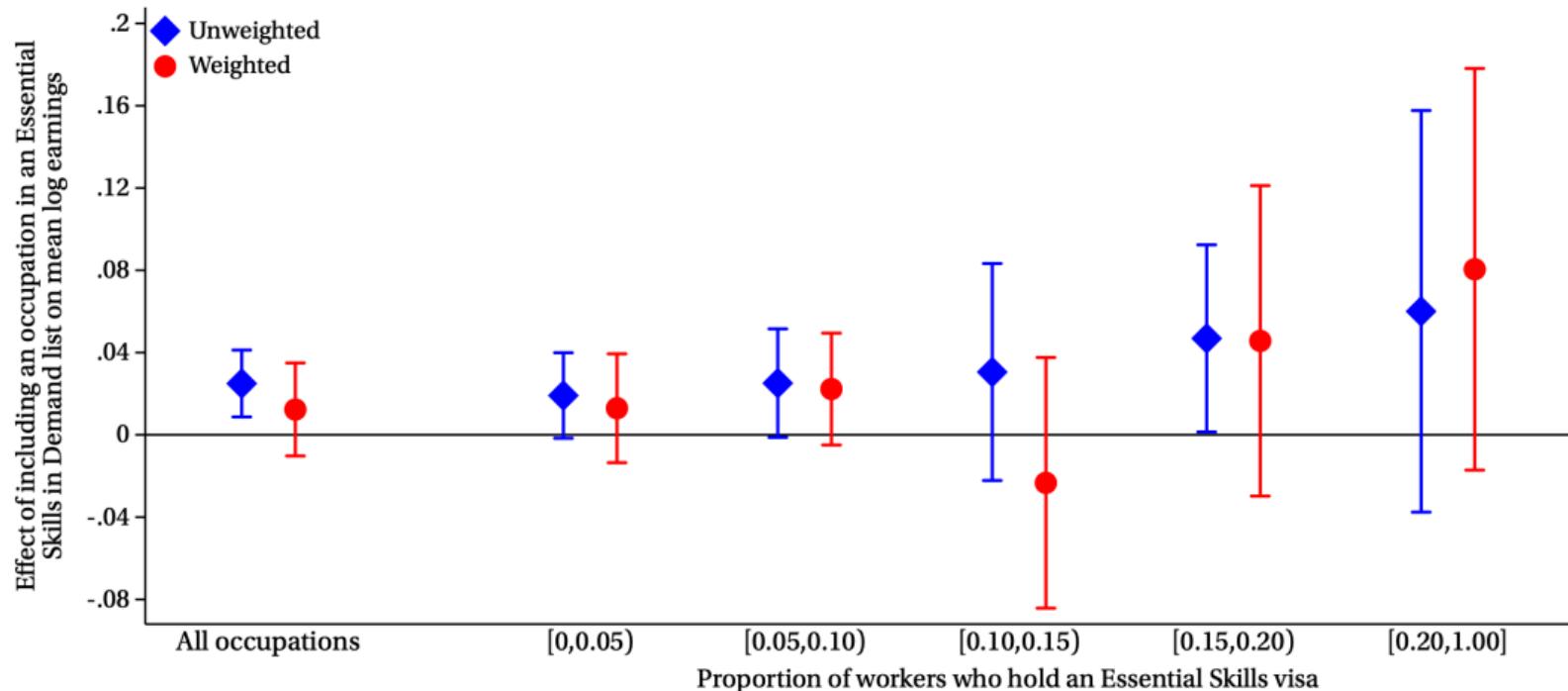
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# Identifying effects for job-stayers

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:  $M_i = M_i(W_i)$ .

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

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

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

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∴ We identify the DGP of  $Y_{it}(0, 0)$  from lottery losers:

$$F_{Y_{i1}(0, 0)}(y_1 \mid Y_{i0}(0, 0) = y_0) = F_{Y_{i1}}(y_1 \mid Y_{i0} = y_0, W_i = 0)$$

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

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

$$\mathbb{P}[M_i(1) = 1 \mid Y_{i1}(0, 0) = y_1].$$

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

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

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

where

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

# Identifying effects for job-stayers

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**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**:

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

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

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

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

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

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

- 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**:

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

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

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

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

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- Lottery effects are joint-normal:

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

## Estimating effects for job-stayers

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

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

We calculate our estimator using a Gibbs sampler algorithm with state

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

where  $m_{it}$  is the Probit latent variable:

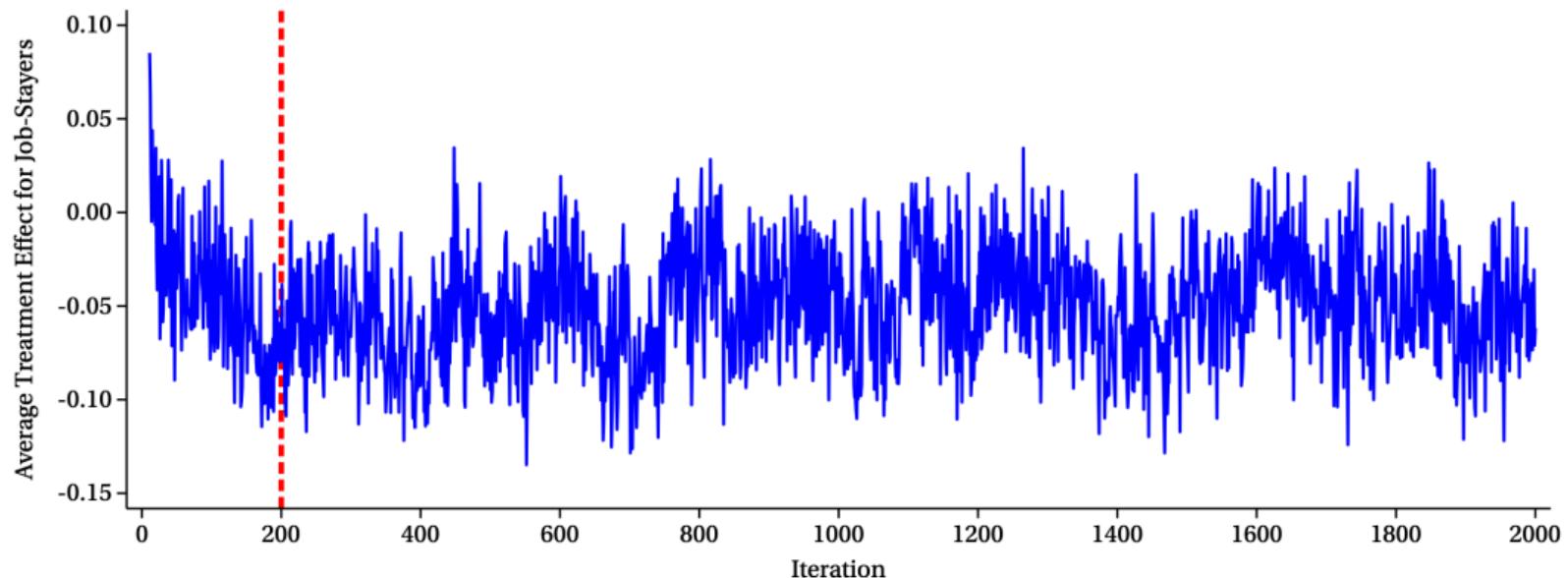
$$M_{it} = 1 \iff m_{it} \geq 0.$$

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**:

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



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:

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

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  $\epsilon_j$  have marginal standard-Gumbel distributions.

By the Convolution Theorem,  $\zeta_C$  has characteristic function

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

By the Fourier inversion theorem, the pdf of  $\zeta$  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:

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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  $\zeta_C$  using inverse transform sampling.
3. Draw  $\epsilon_j$  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:

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

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  $\Rightarrow$  a  $N(\mu_{f,o,x,t}^\xi, s_{f,o,x,t}^\xi)$  prior.
2. The log posterior for  $\tilde{\xi}_{f,o,x,t}$ , given that  $\sigma_{f,o,x,t|c_f}^{\text{resident}} = 0$  is

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

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

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

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

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

Back.

# The Pacific lottery visas

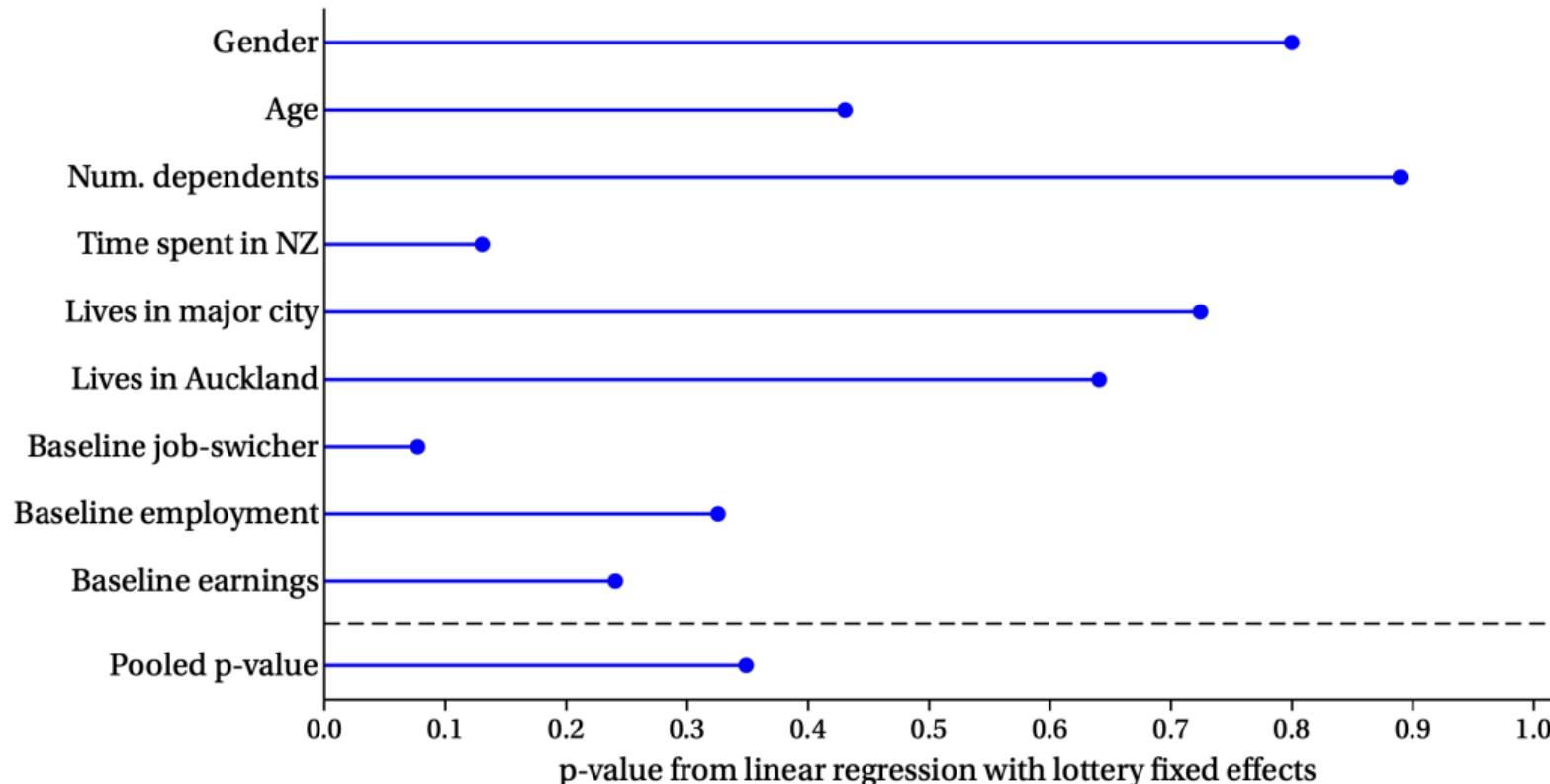
The **Pacific Access Category Resident Visa** and the **Samoan Quota Resident Visa** are New Zealand resident visas allocated by a **random lottery**.

- ▶ 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.

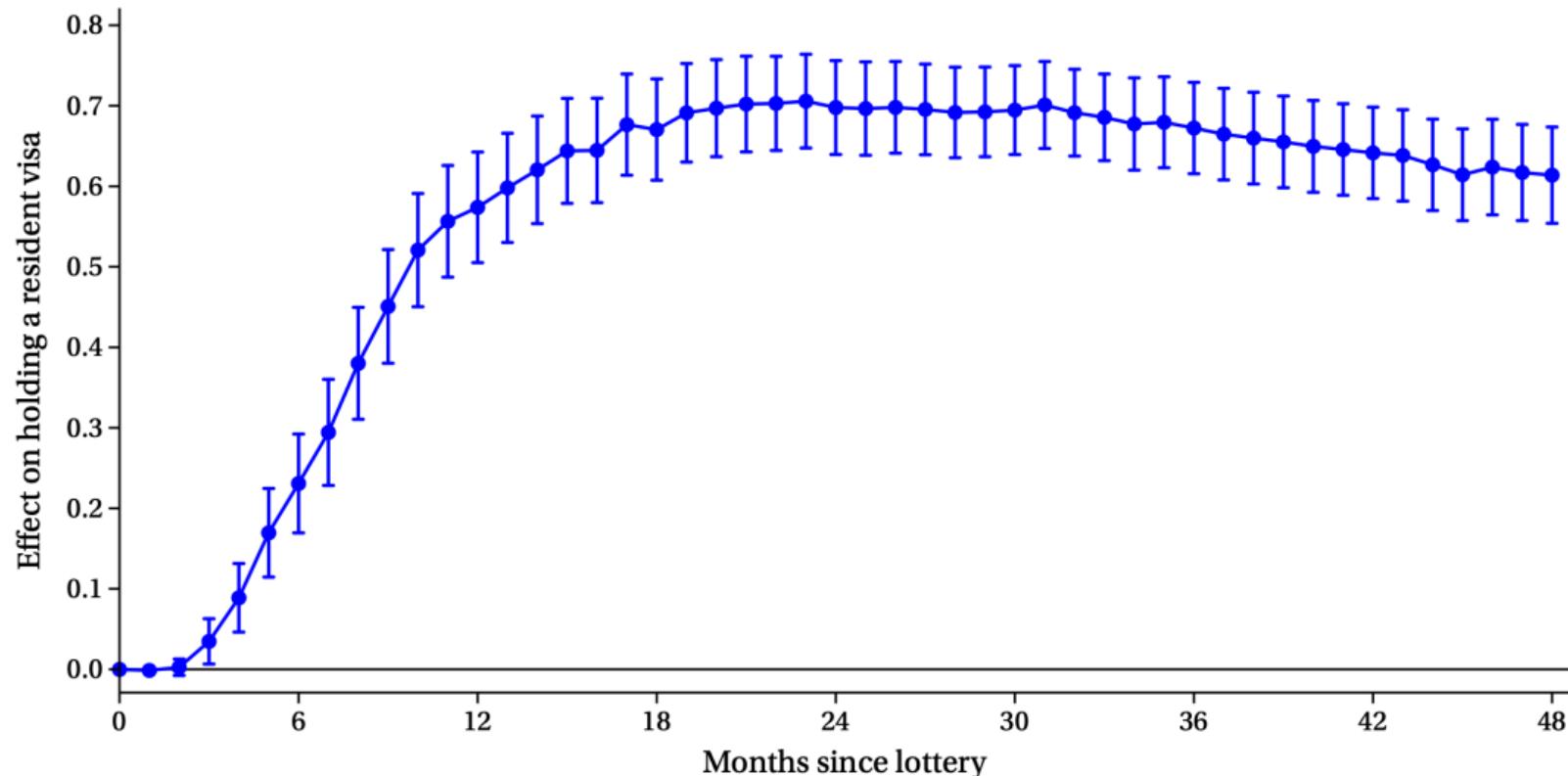
We study those 6501 lottery entries from 3891 individuals who

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

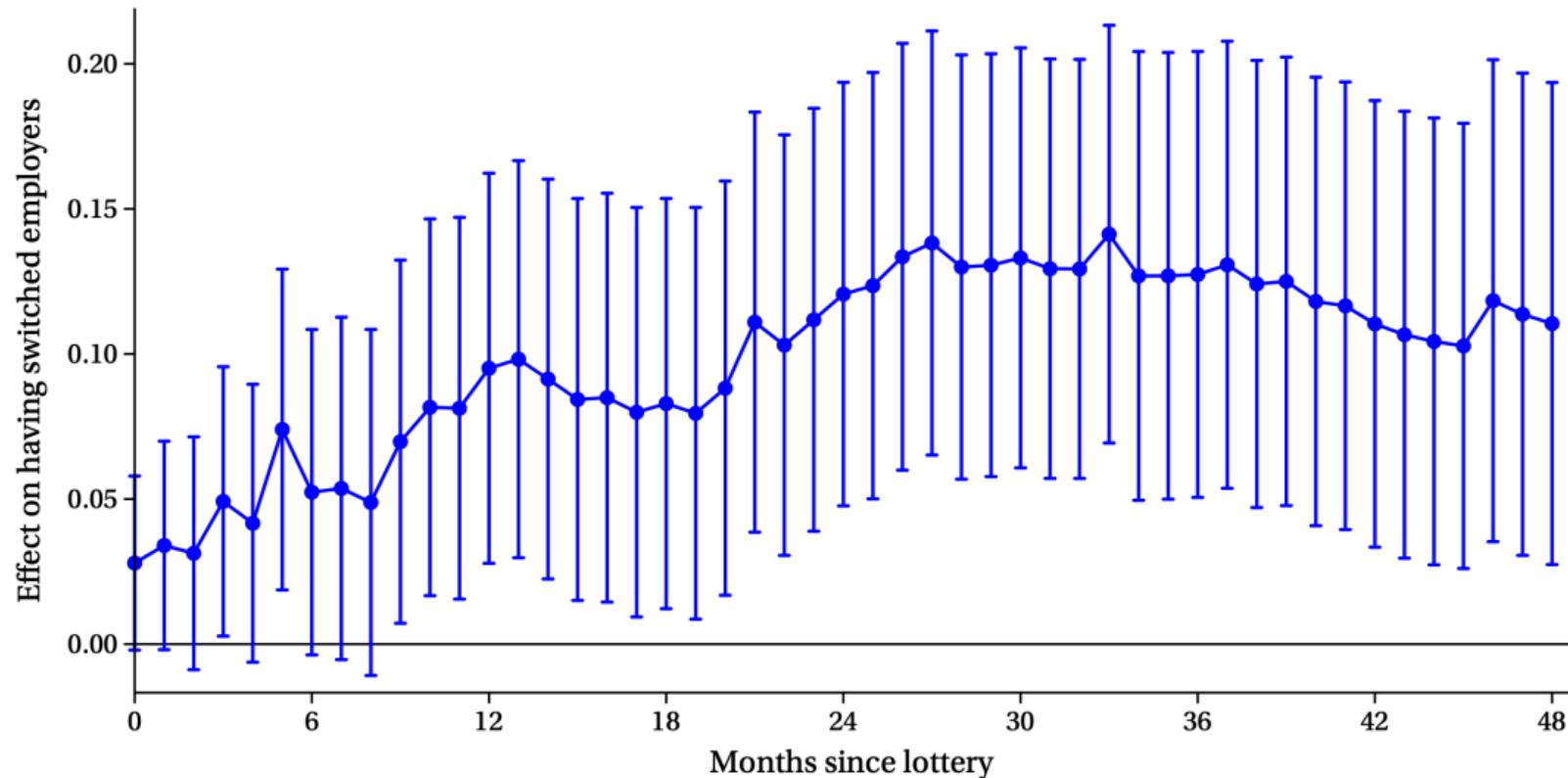
# Lottery winners are similar to lottery losers



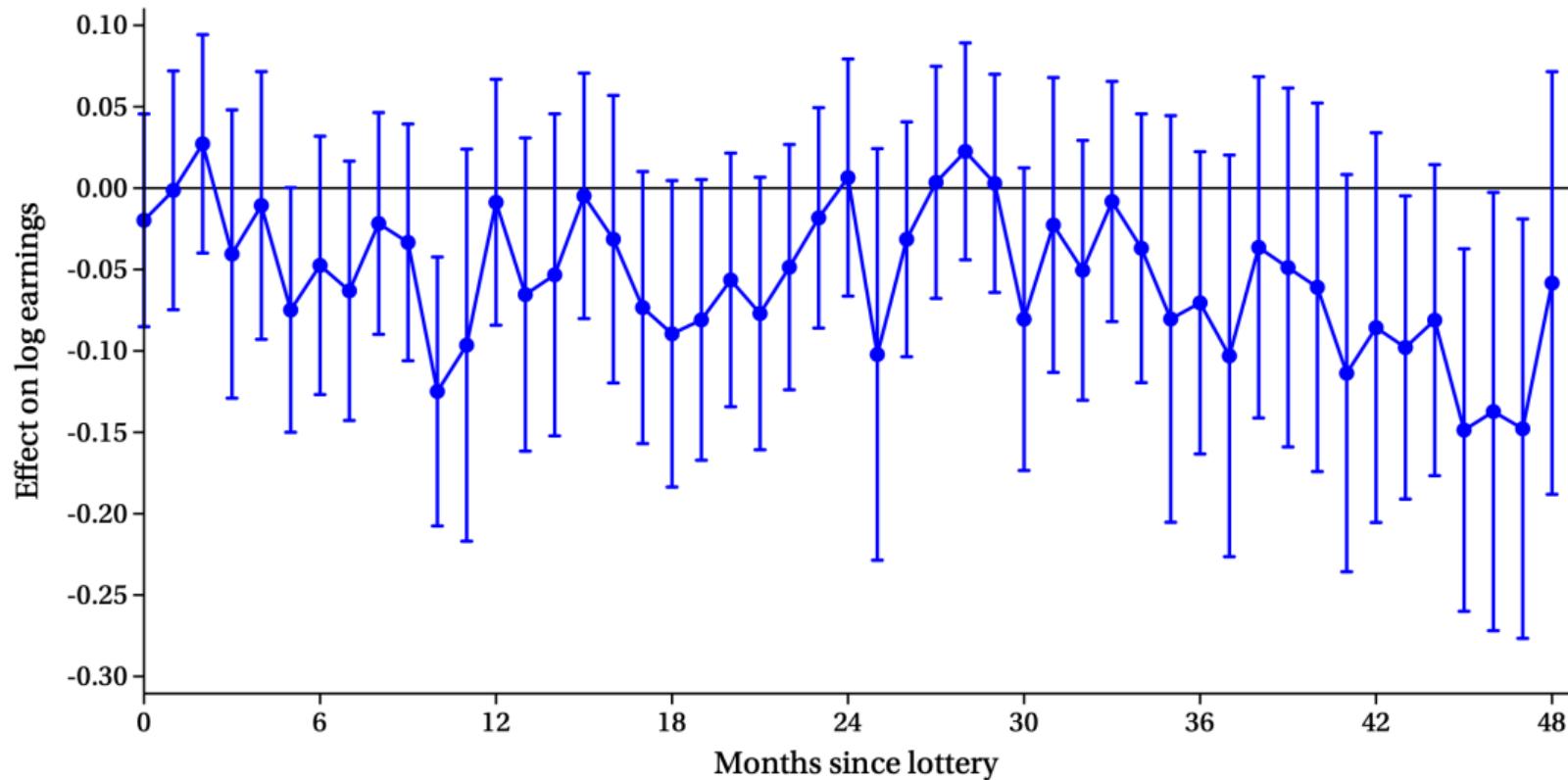
# Lottery winners are much more likely to obtain resident visas



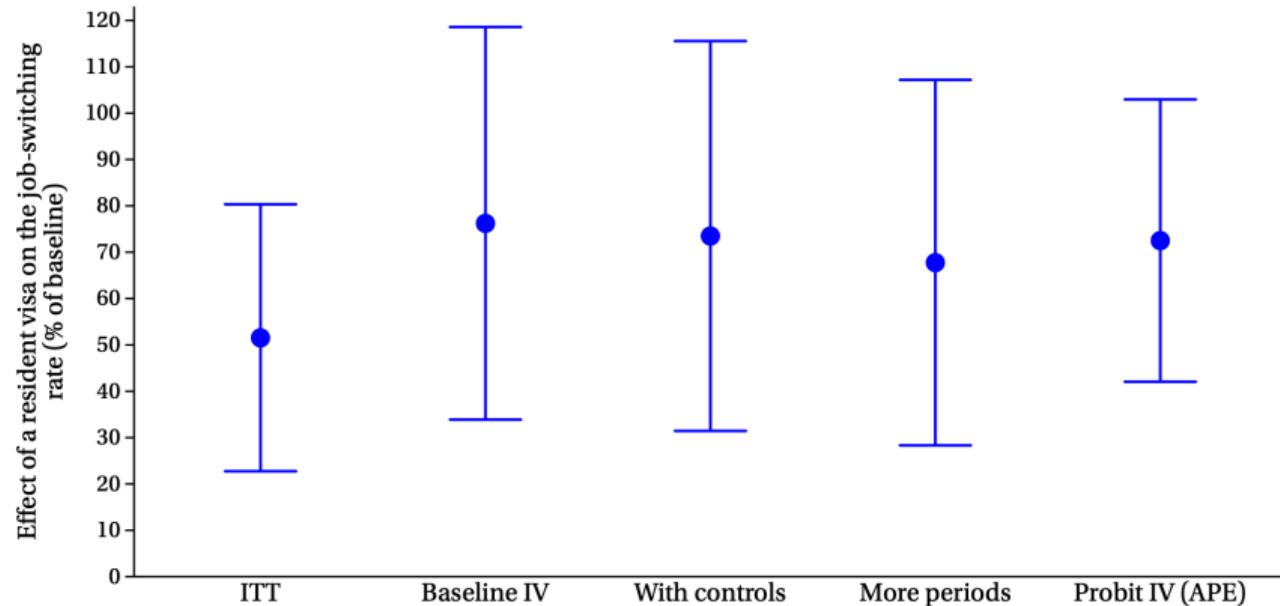
Lottery winners are more likely to switch jobs...



... but earn no more than lottery losers

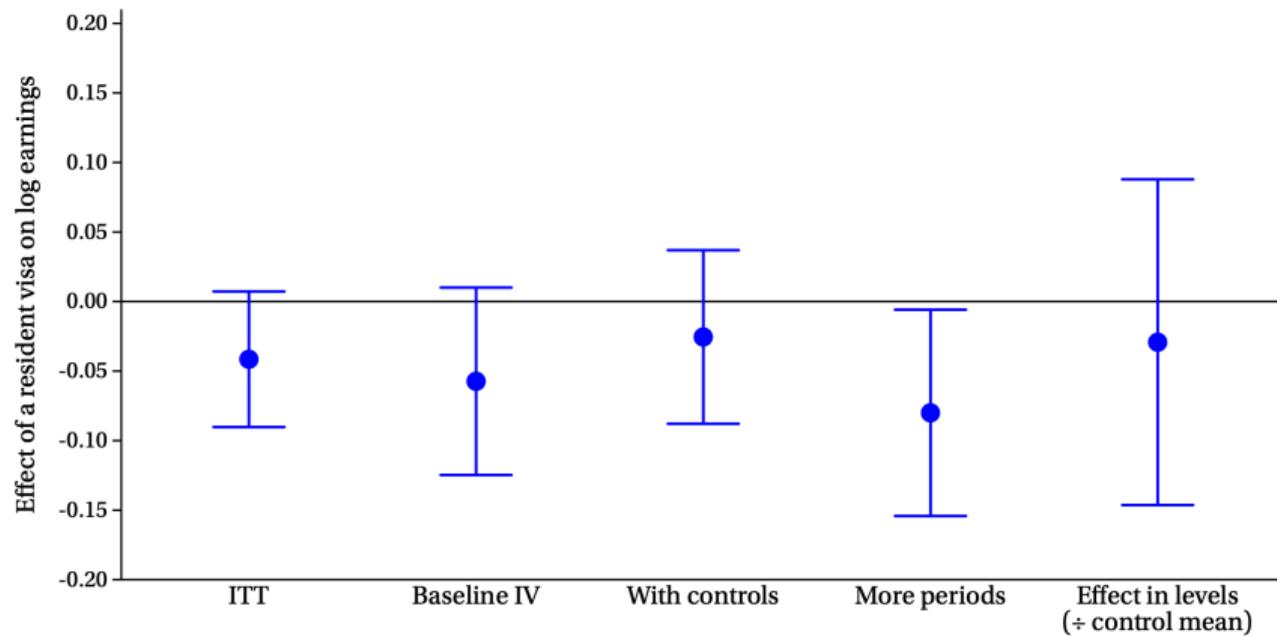


# IV estimates of the effect of a resident visa



Back.

# IV estimates of the effect of a resident visa



Back.

## 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  $M_{i,t} = M_{i,t}(W_i)$ :

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

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

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

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

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

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

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

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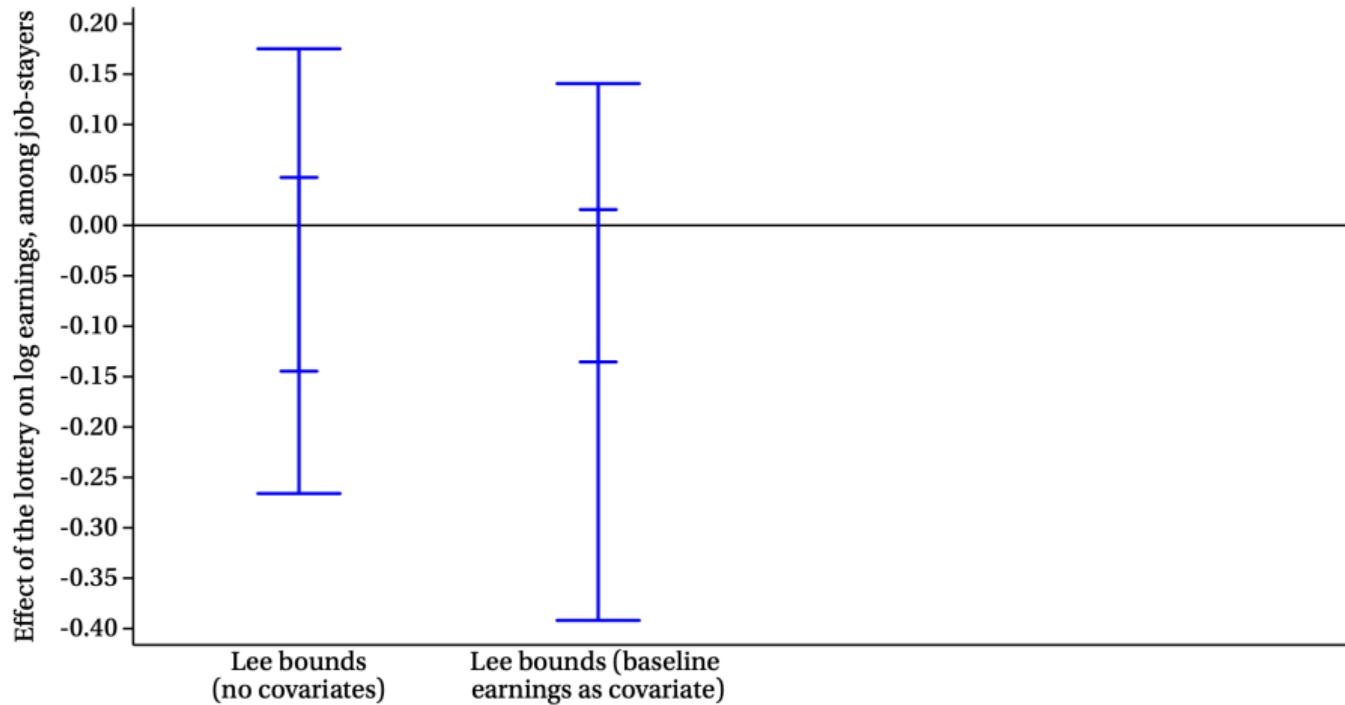
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Approach 1: Set-identify by dropping the highest or lowest  $Y_{i,t}$  among lottery losers (Lee '09).

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



Back.

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

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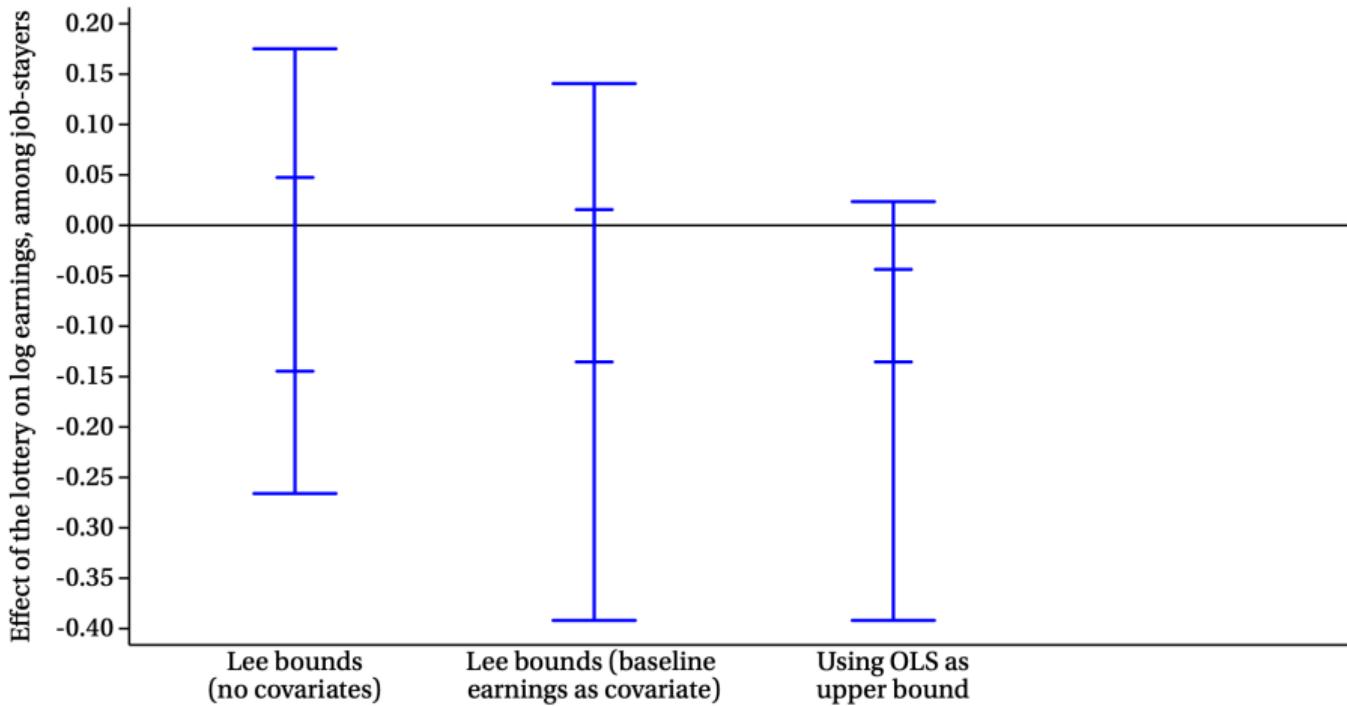
Approach 2: Sharpen the upper bound under the assumption that

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

which implies that OLS is upwards-biased.

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

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Back.

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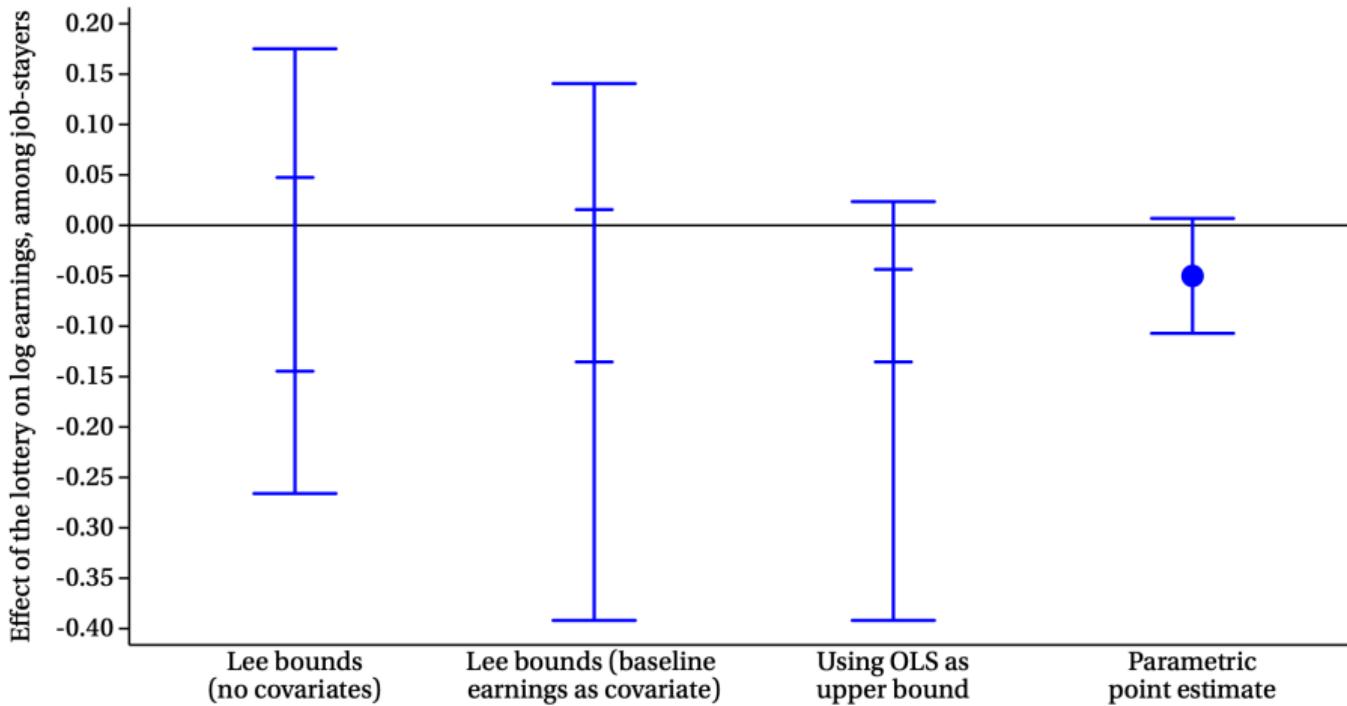
Approach 3: Point-identify by modeling the decision to move.

*Key assumption:* job-switching is Markovian in counterfactual earnings

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

.  
∴ 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?



Back.

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

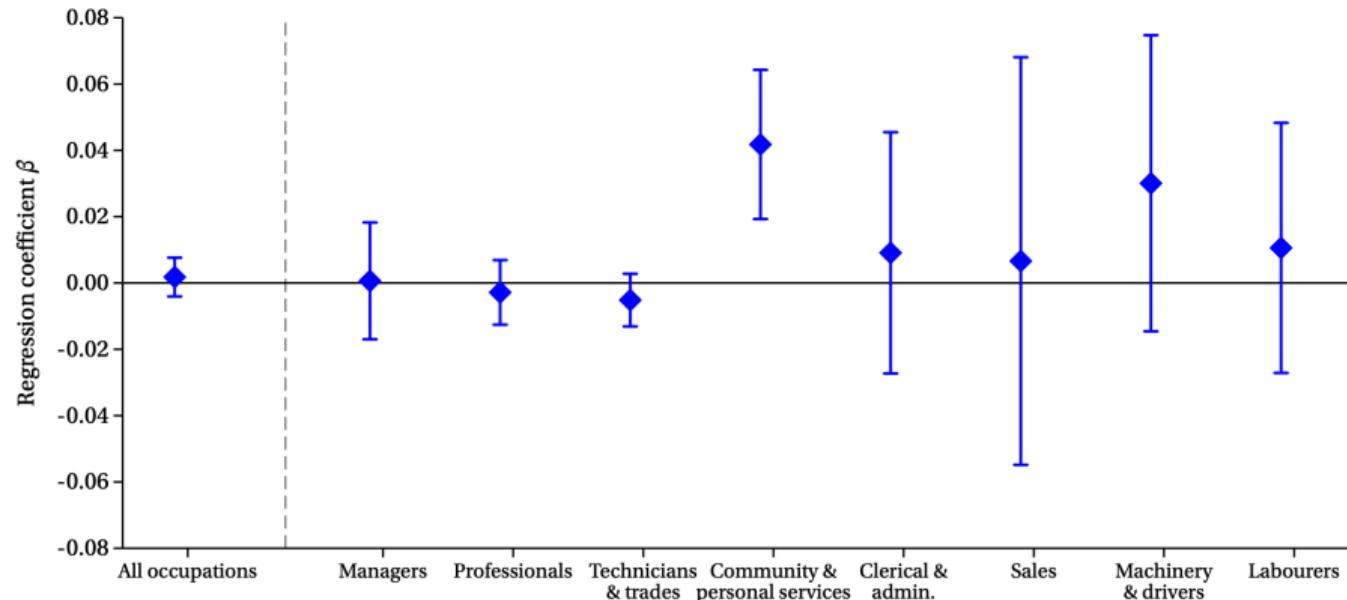
$$\log(\text{earnings}_{i,t}) - \log(\text{control earnings}_{i,t}) = \beta + \delta \left( \log(\text{earnings}_{i,-1}) - \log(\text{control earnings}_{i,-1}) \right) + e_{i,t}$$



Back.

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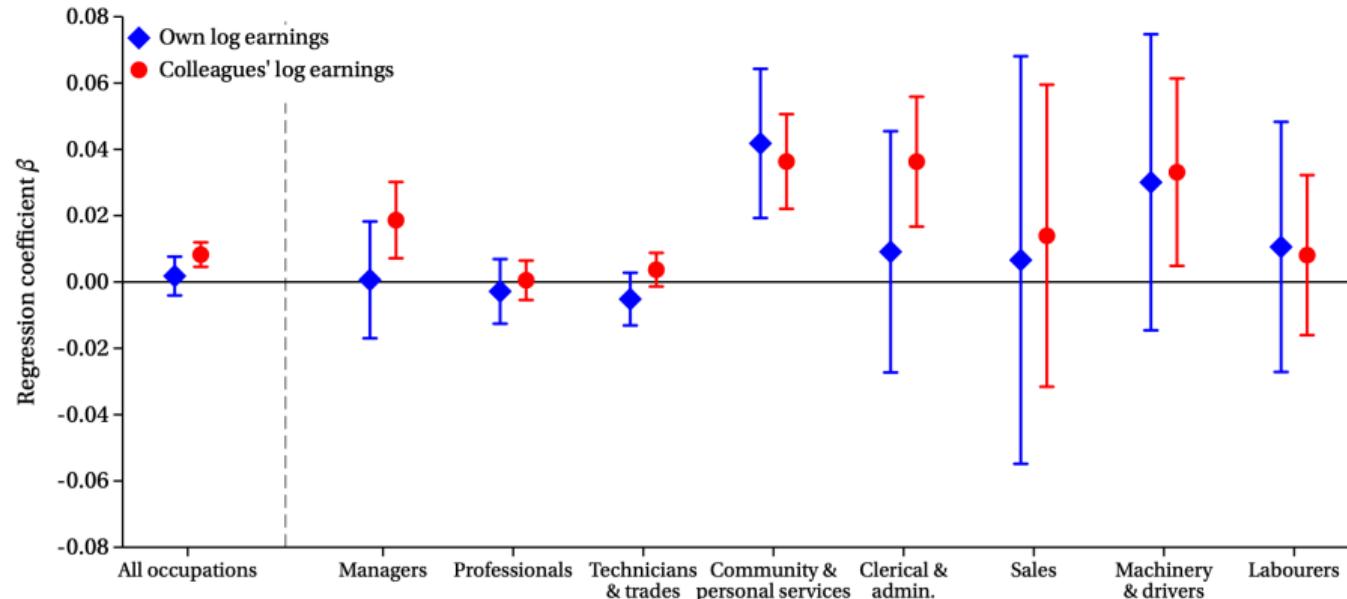
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Back.

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Back.