How Restricting Migrants' Job Options Affects Both Migrants and Residents

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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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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.**

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 2.7% have their wage decreased by $\geq$ 1.5%.
- The restrictions decrease aggregate welfare by 30% of migrants' baseline earnings — 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; 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 both a labor supply system, and firm-specific 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 2020.
- 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 visa specified an employer: **Essential Skills migrants could only switch employers if they obtained a new visa.**

The Essential Skills visa was limited to employers 'demonstrably unable to recruit New Zealanders'.

- 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).

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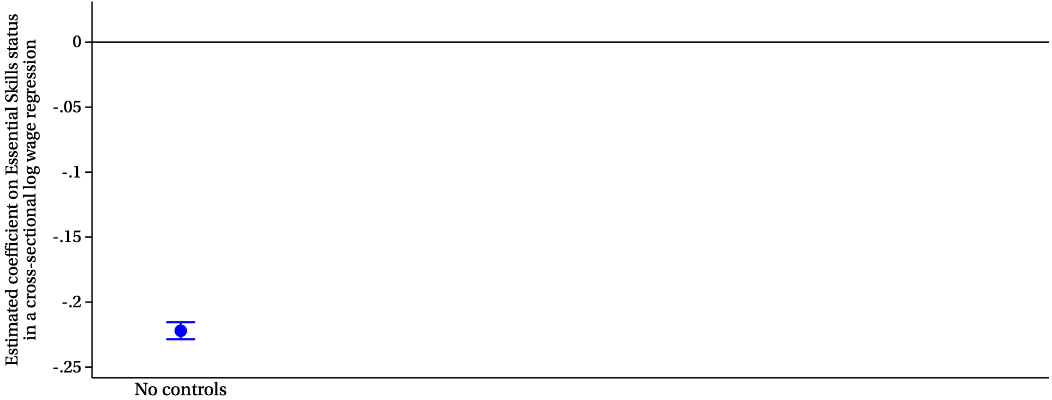

Sample: full-time employees with a unique firm in the 12 months before the 2018 Census. Other samples.

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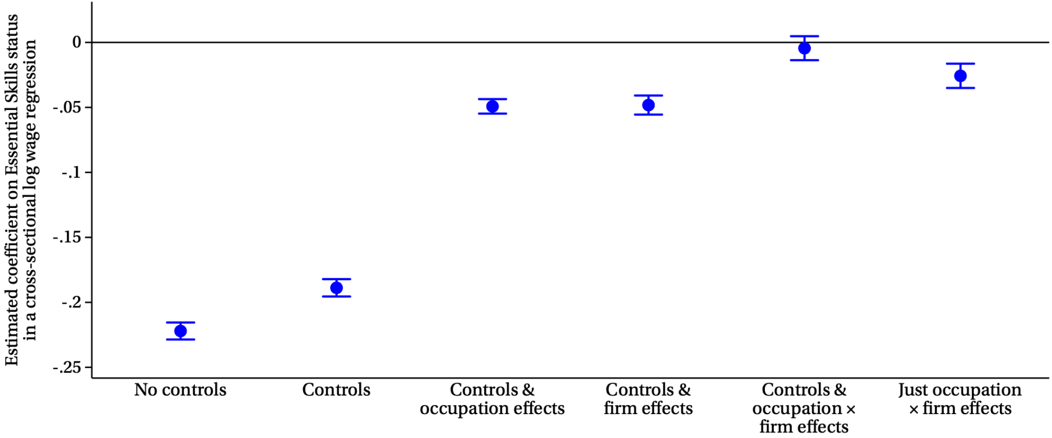

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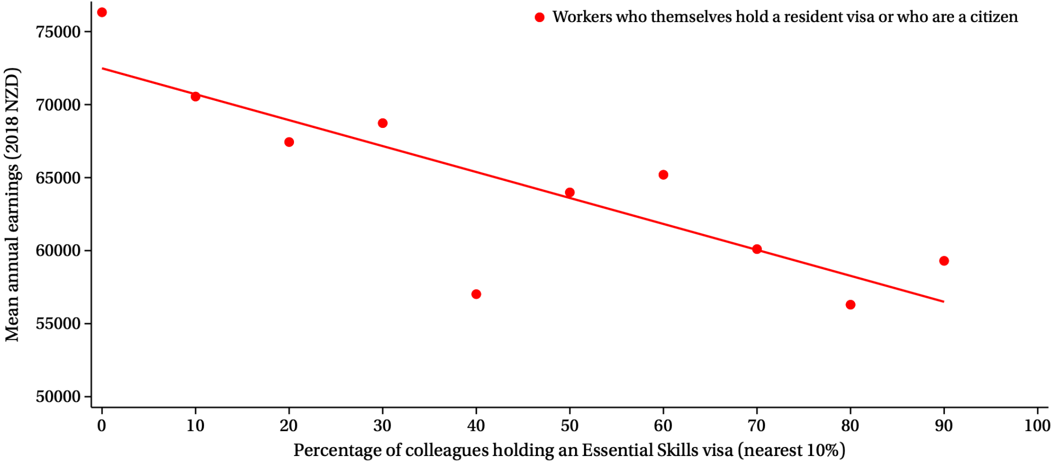

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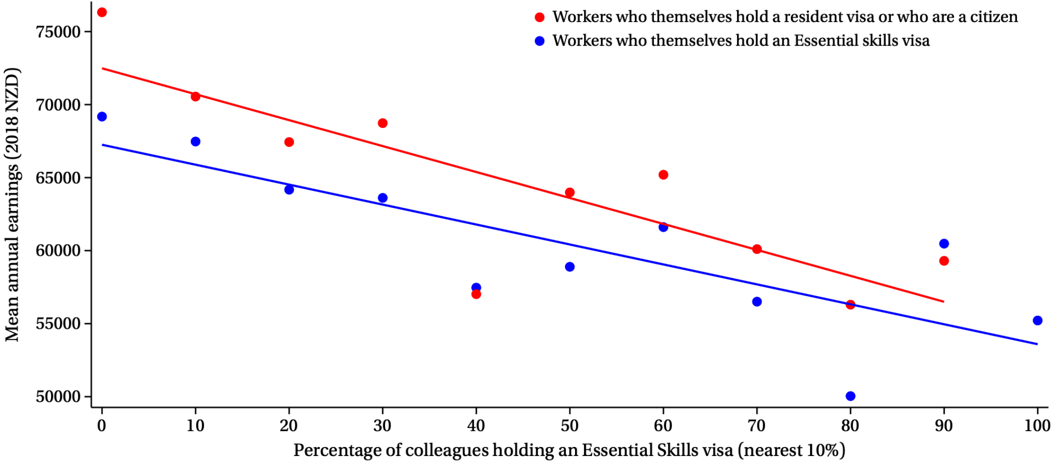

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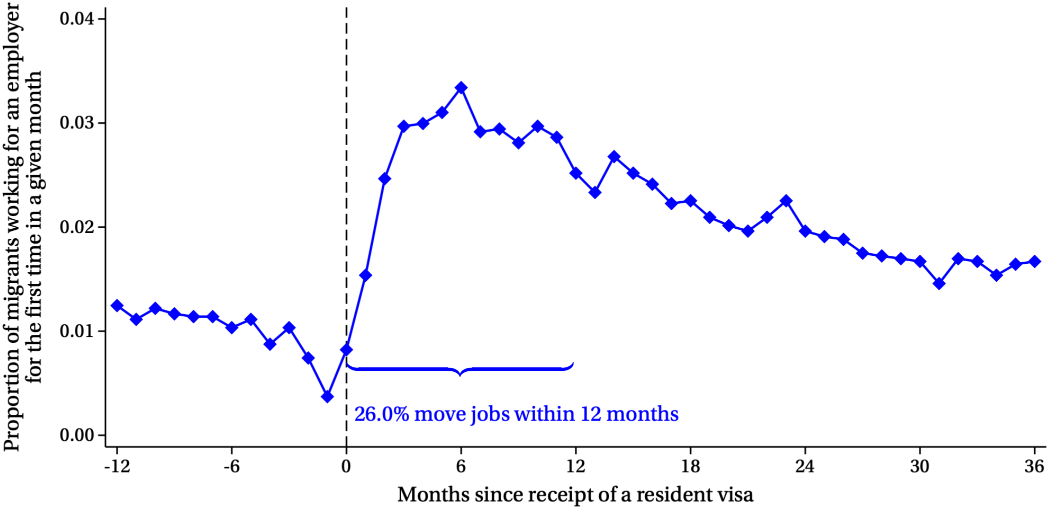
The Essential Skills visa restricts migrants' job options...



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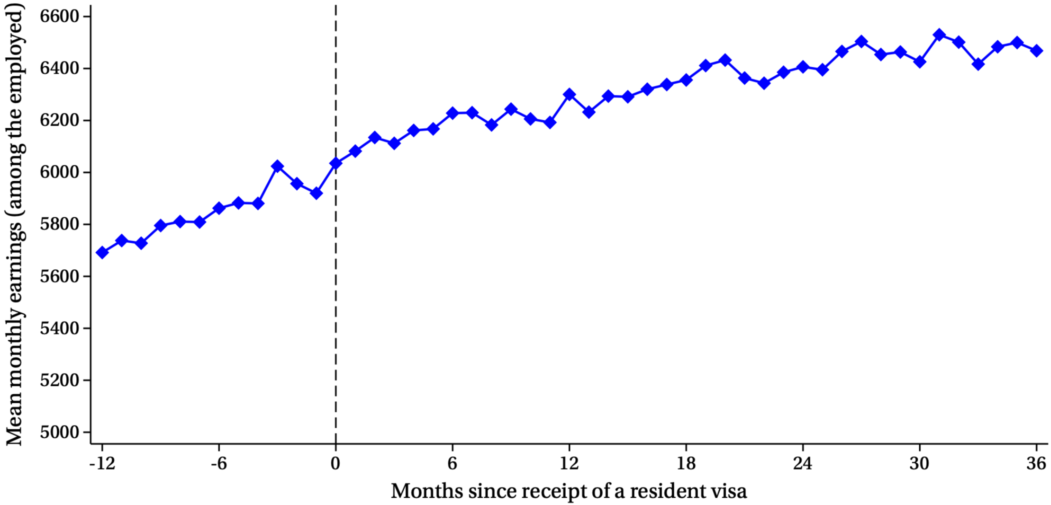

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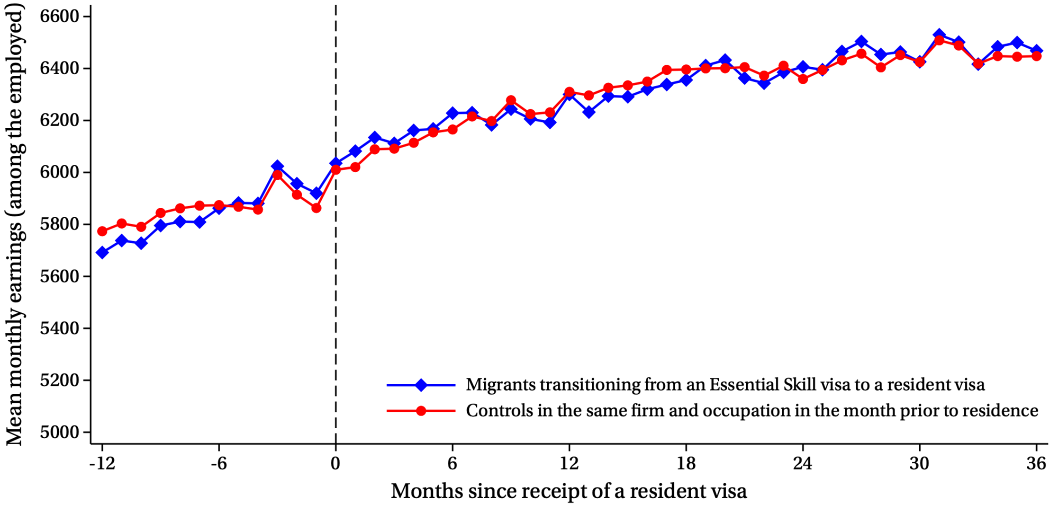

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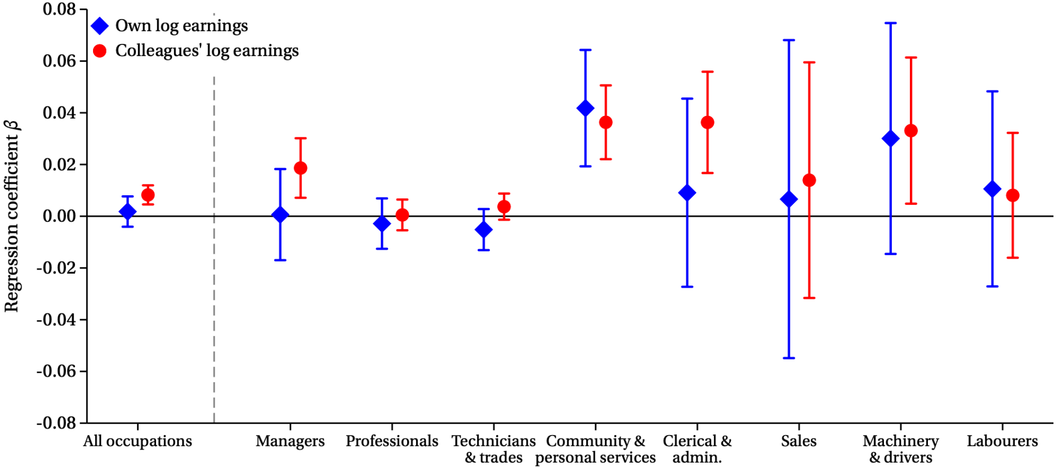
$$\log(\text{earnings}_{i,t}) - \log(\text{control earnings}_{i,t}) = \beta + \delta\Big(\log(\text{earnings}_{i,-1}) - \log(\text{control earnings}_{i,-1})\Big) + e_{i,t}$$

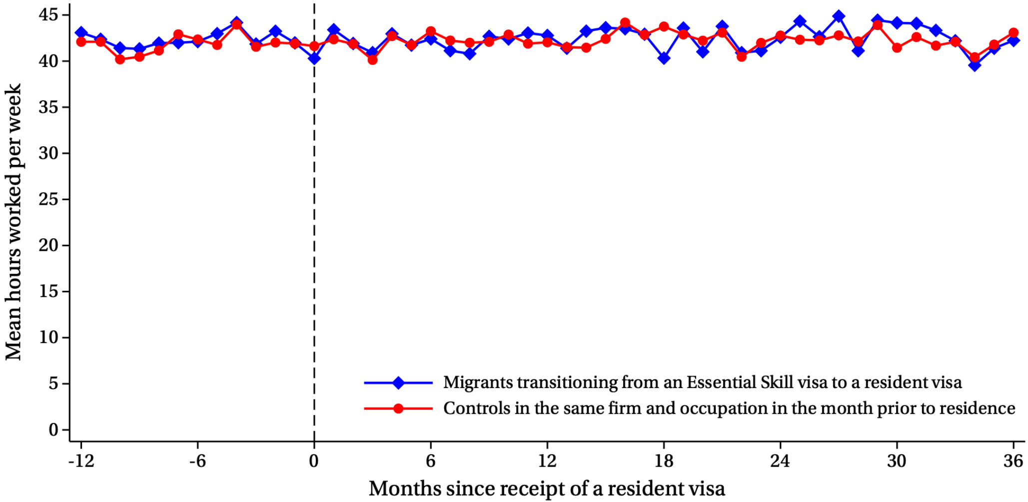


An individual migrant's job restriction does not affect their wage

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



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- Solution: *Study entrants into visa lotteries.*

The Pacific lottery visas

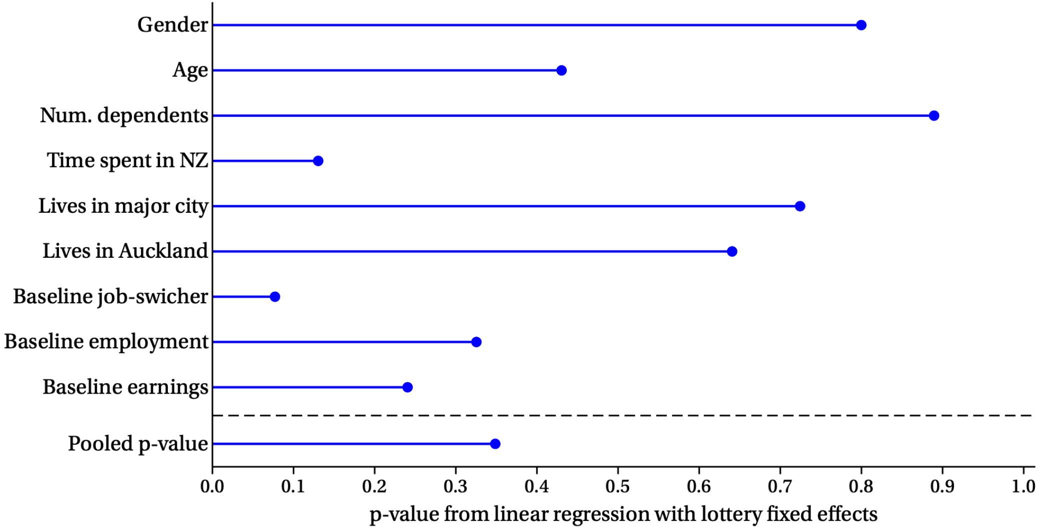
The **Pacific Access Category Resident Visa** and the **Samoan Quota Resident Visa** are New Zealand resident visas allocated by a **random lottery**.

- Holders can stay in New Zealand indefinitely, and **work for any employer willing to employ them.**
- 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.

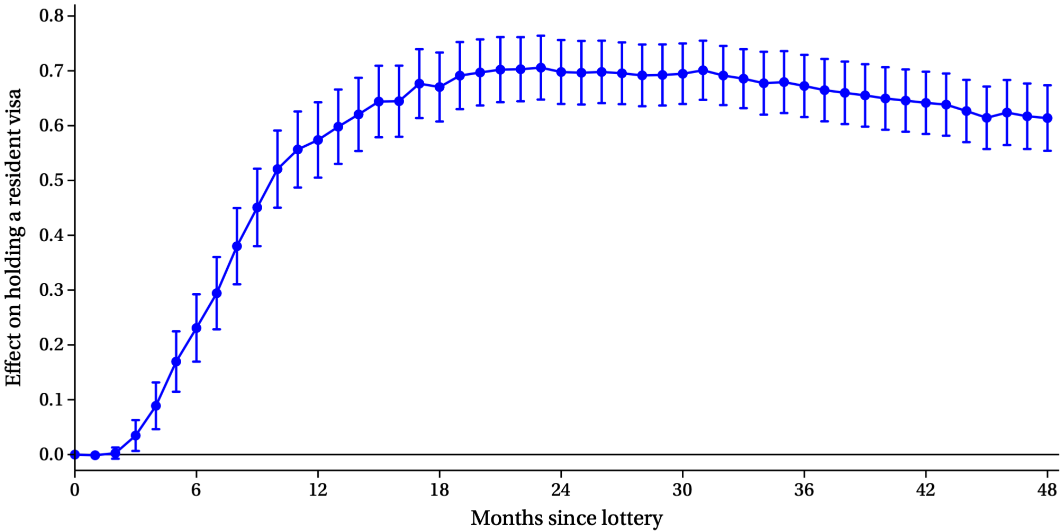
We study those 6501 lottery entries from 3891 individuals who

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

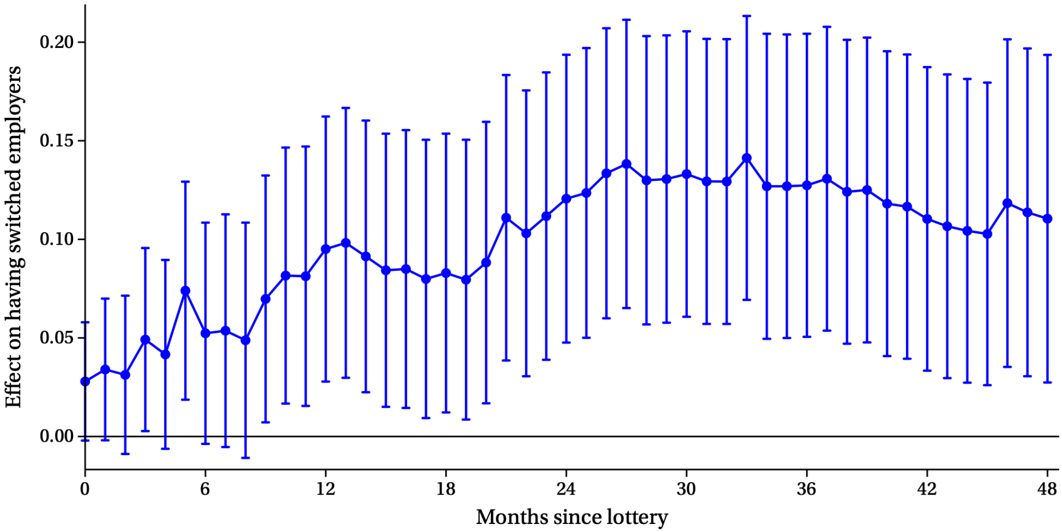
Lottery winners are similar to lottery losers



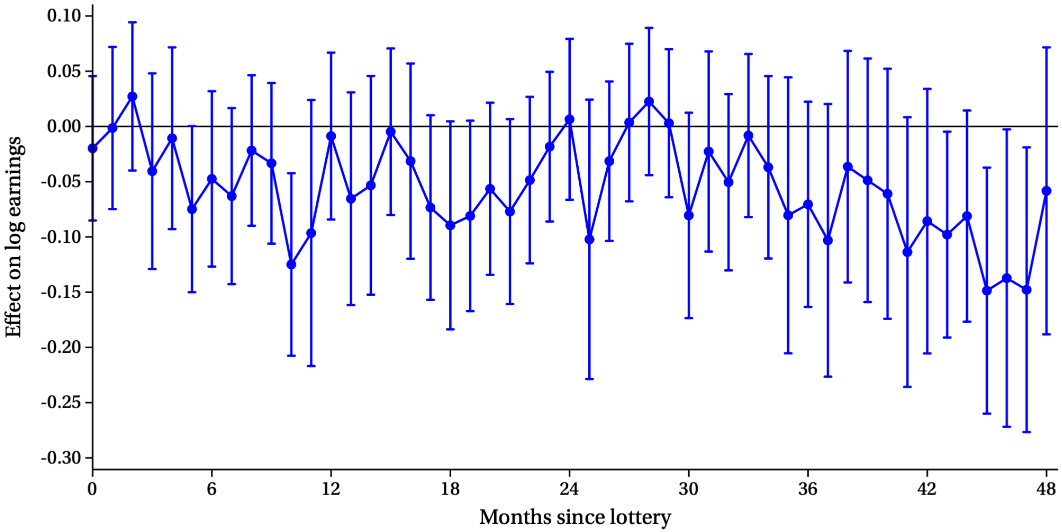
Lottery winners are much more likely to obtain resident visas



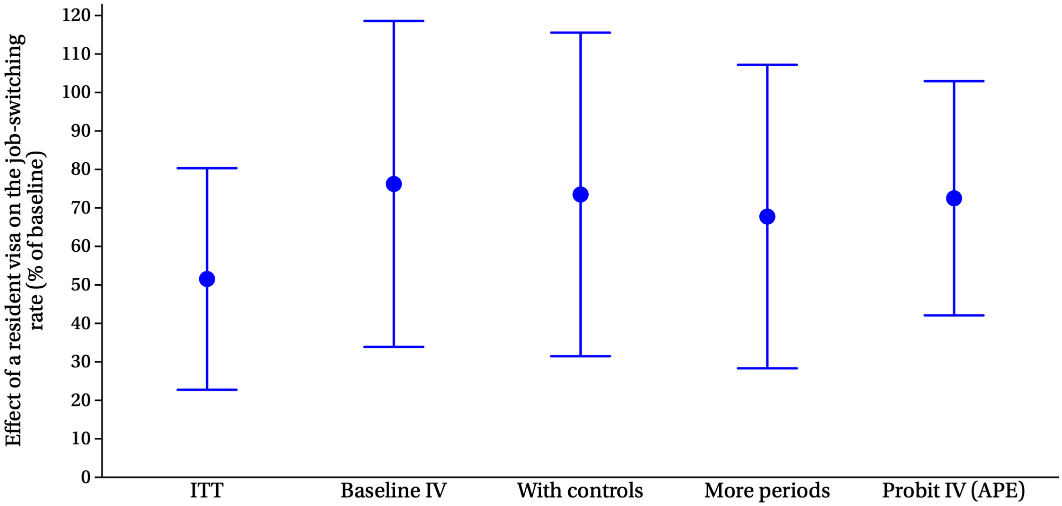
Lottery winners are more likely to switch jobs...



... but earn no more than lottery losers



IV estimates of the effect of a resident visa



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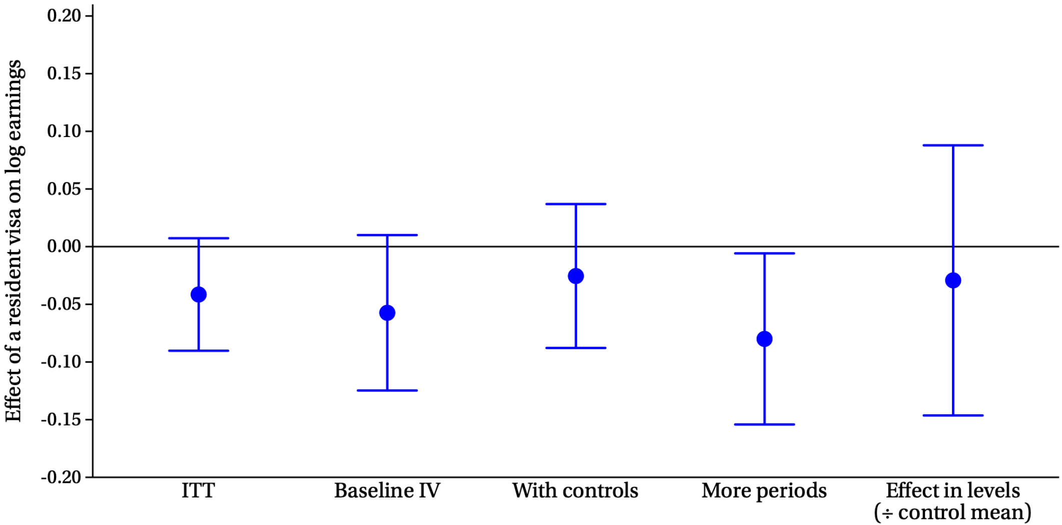

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Concern 2: Workers apply for residence in anticipation of **worker-specific** shocks.

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

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- 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?

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

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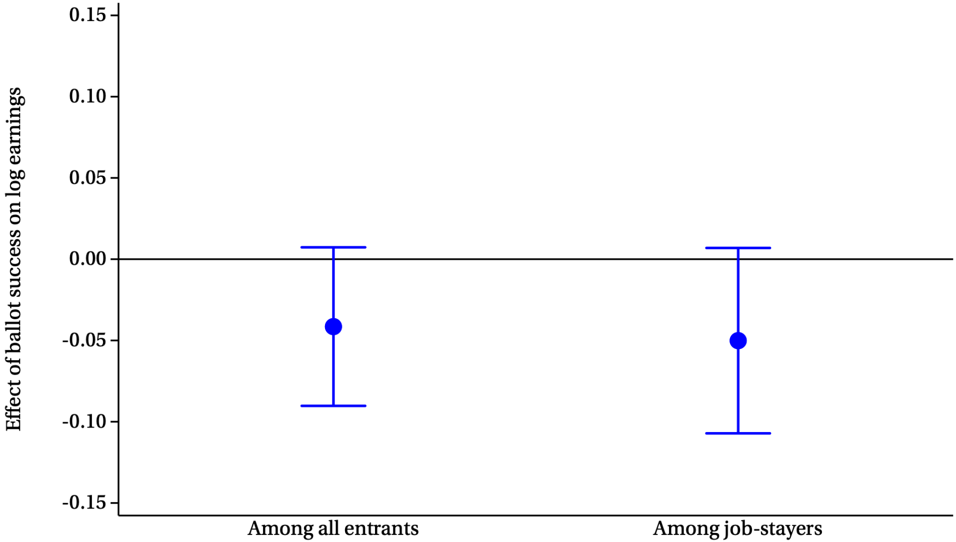
Identification details. Estimation details.

Winning the lottery does not increase job-stayers' earnings



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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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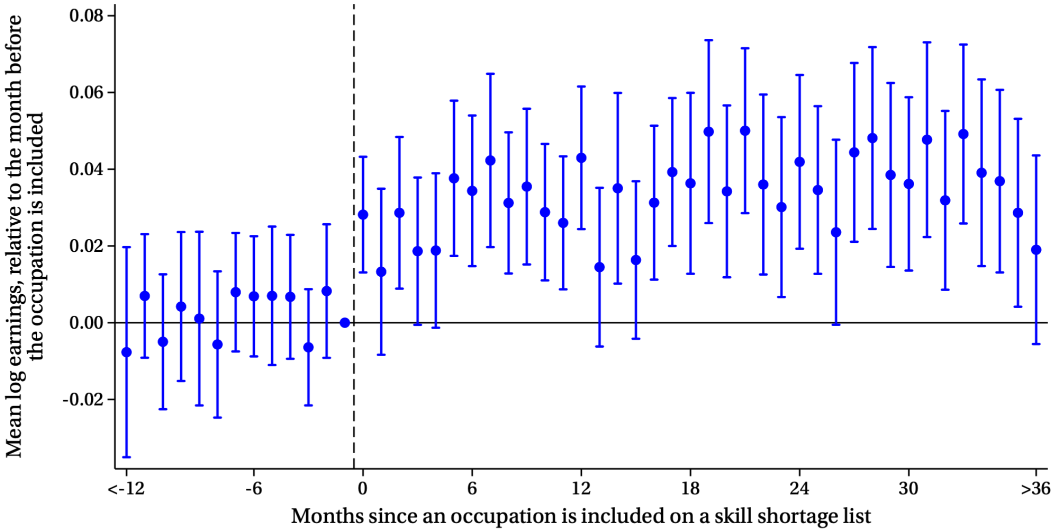

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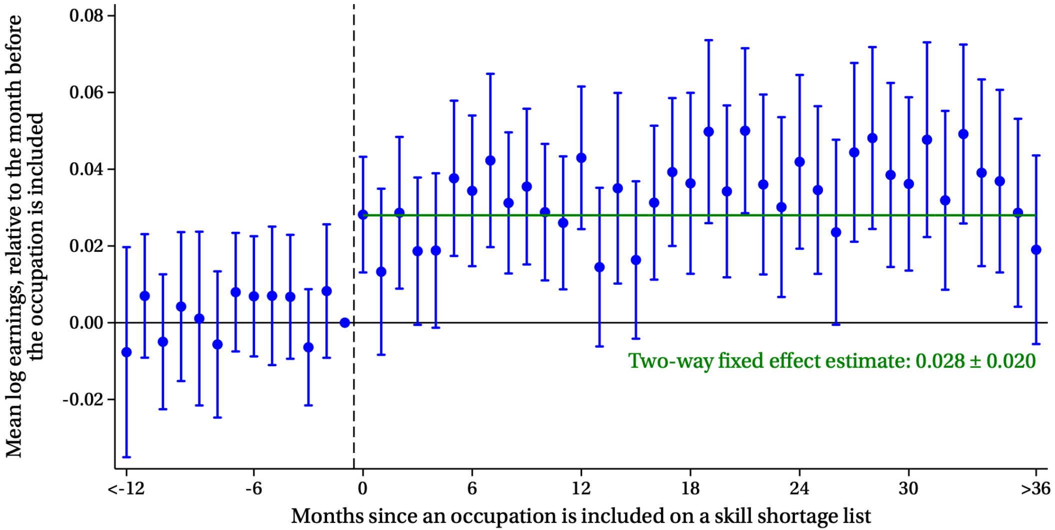

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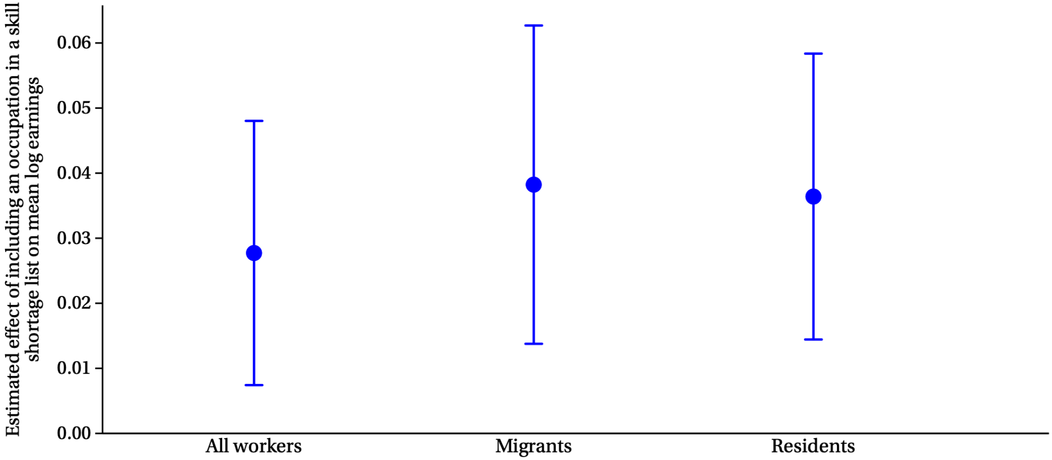

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- Solution 1: Add controls.

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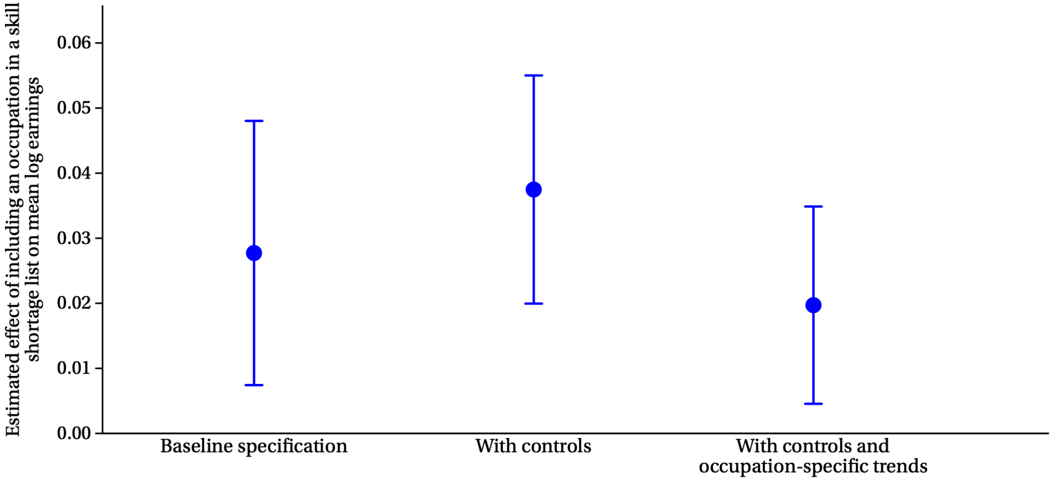
Controls: employer value-added, employer's number of employees.



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Concern 1: Occupations might be listed in anticipation of future demand shocks.

- Solution 1: Add controls.
- Solution 2: Proxy for an unobserved confounder using Australian data.

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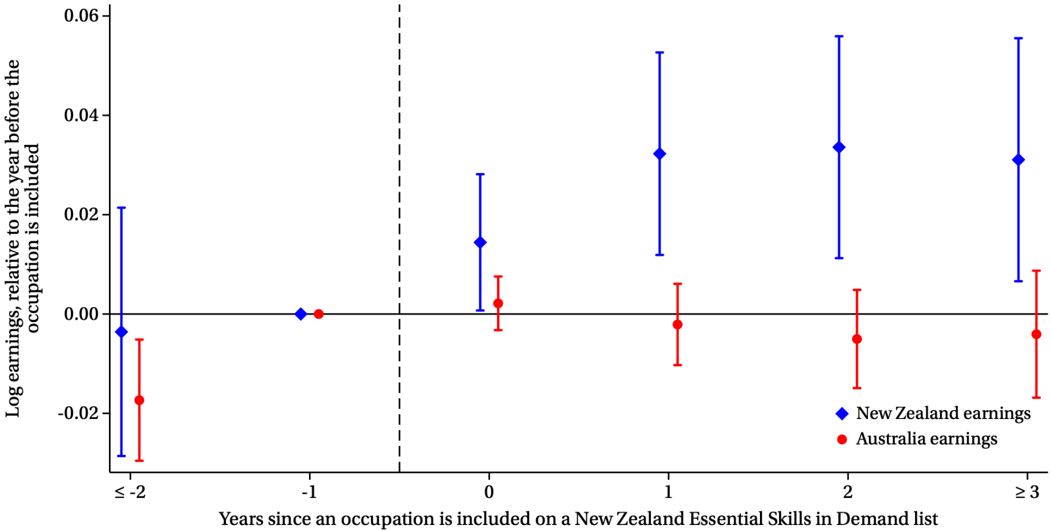

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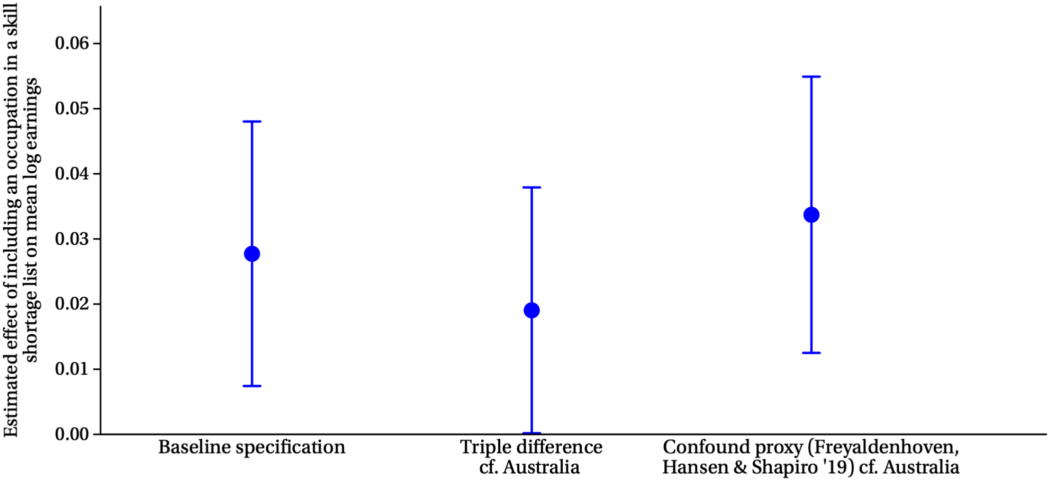

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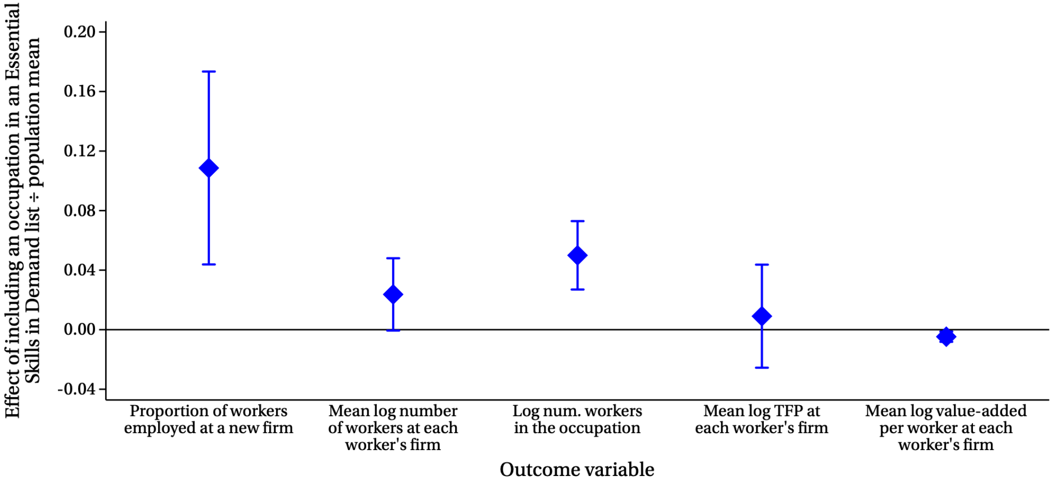
Concern 2: The two-way fixed effect estimand need not be a convex combination of treatment effects.

- Solution: Estimate an ATT *a la* de Chaisemartin & D'Haultfoeuille (2022).

Why does strengthening migrants' job options increase wages?



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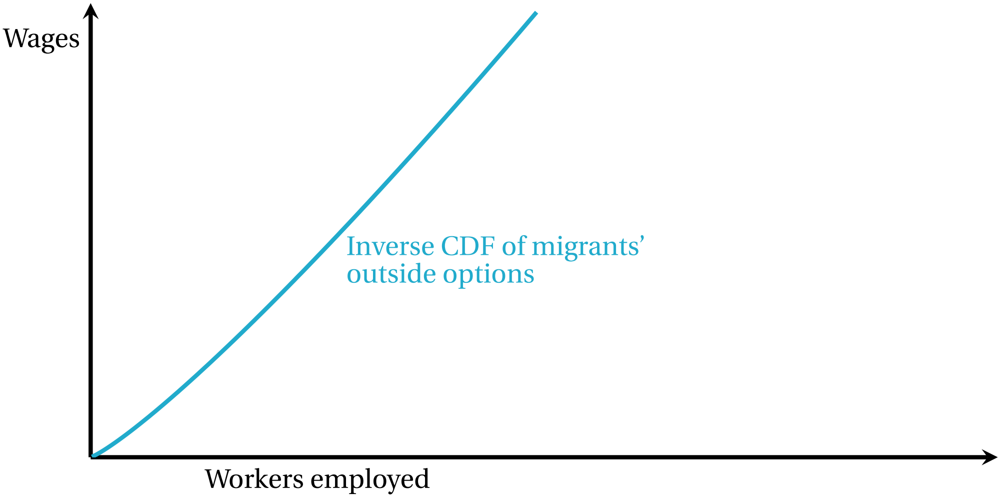

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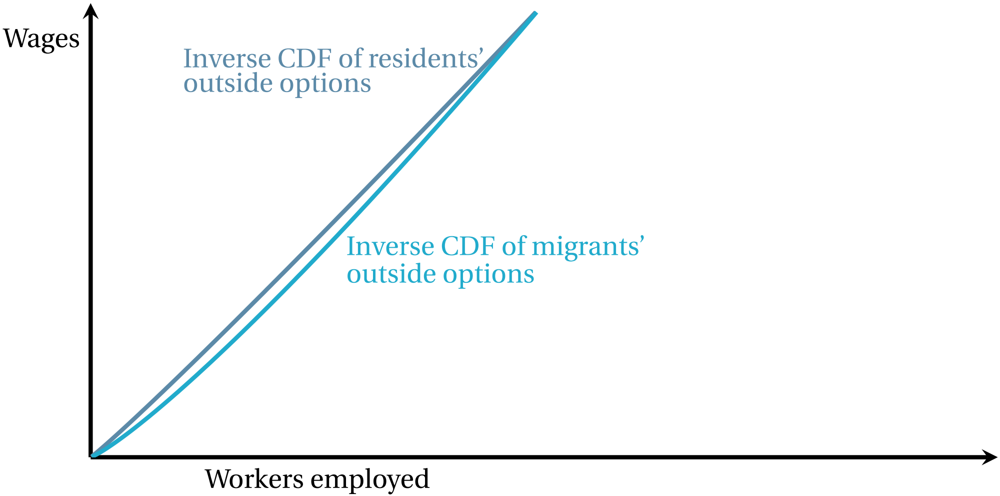

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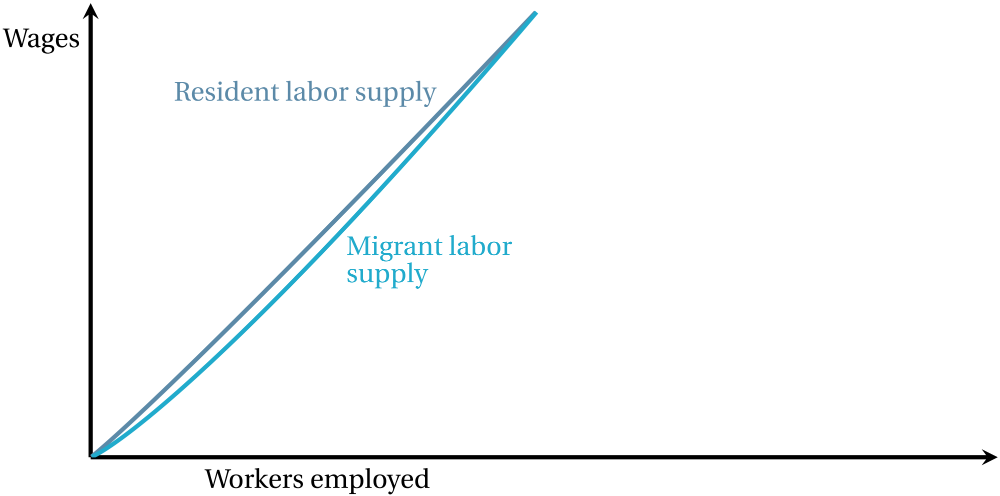

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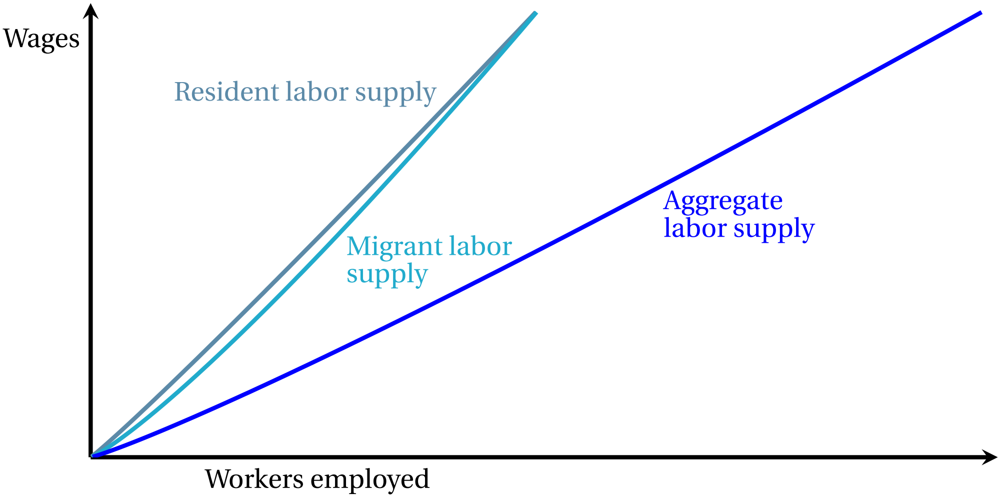

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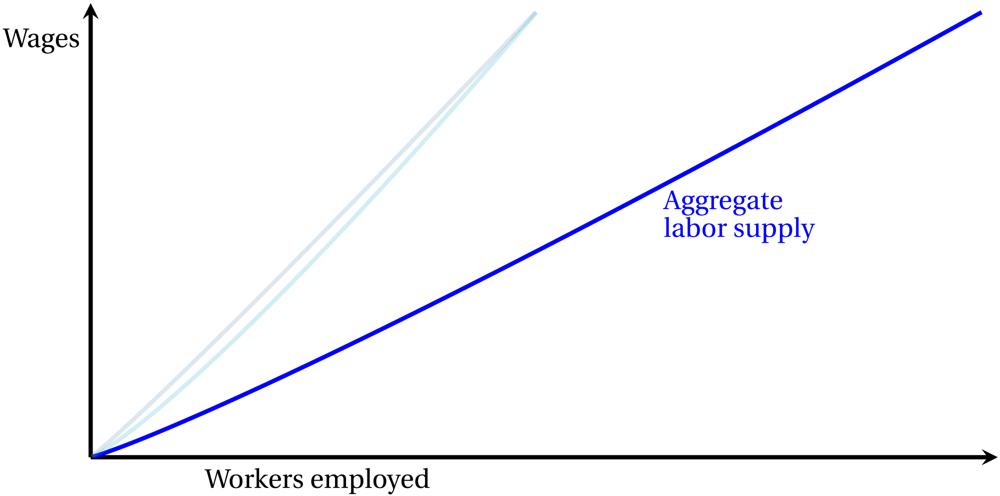

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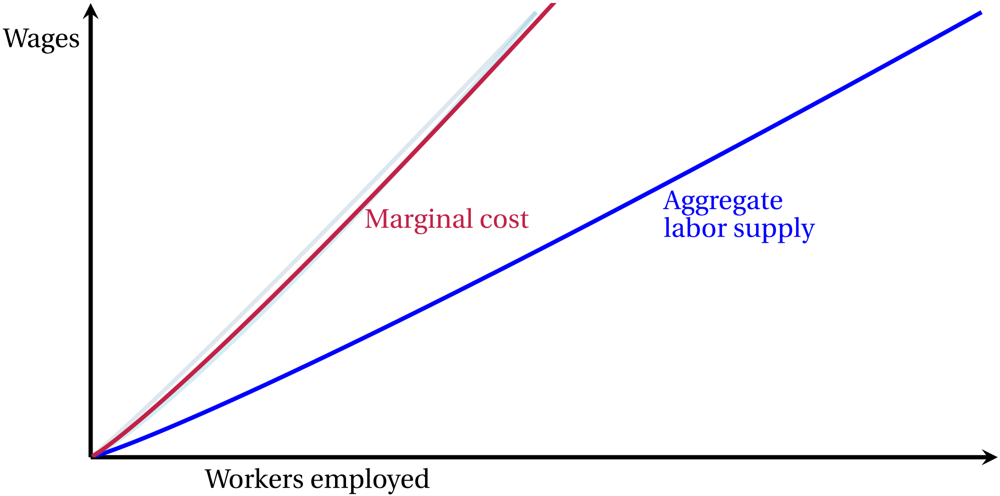

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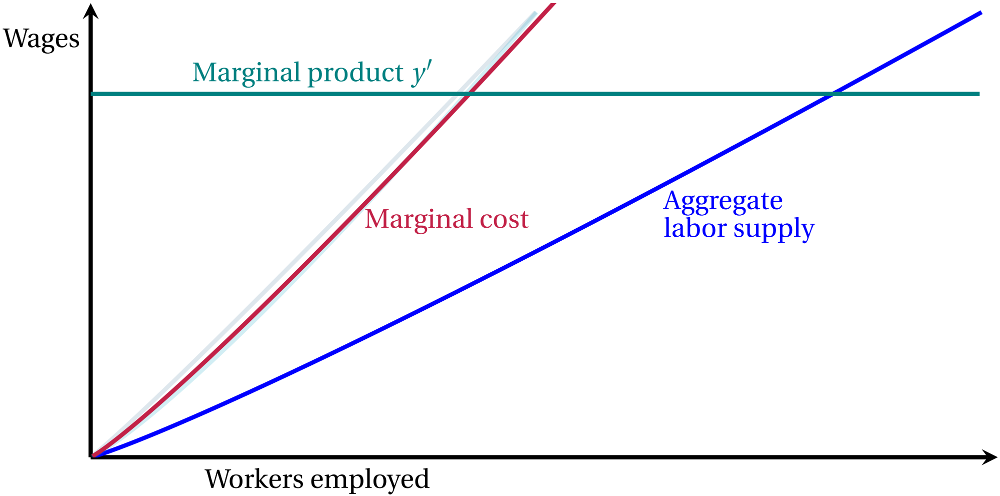

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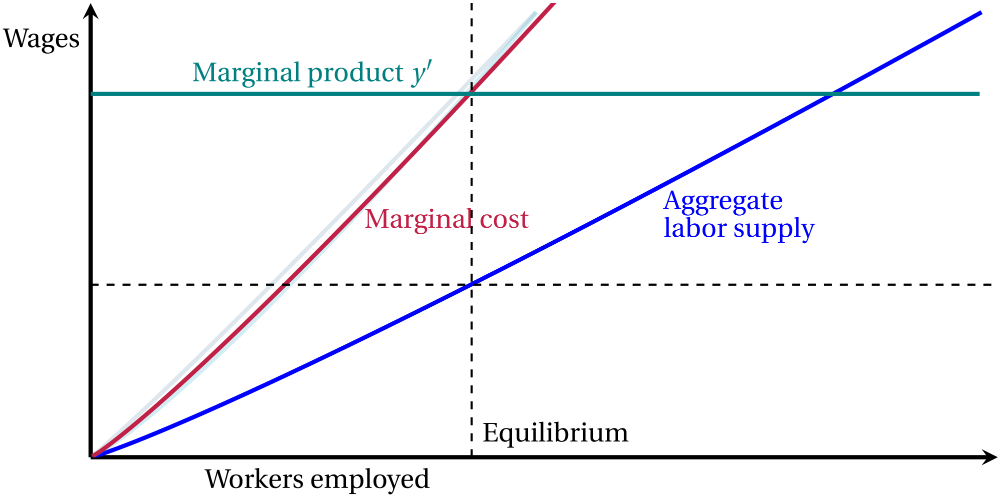

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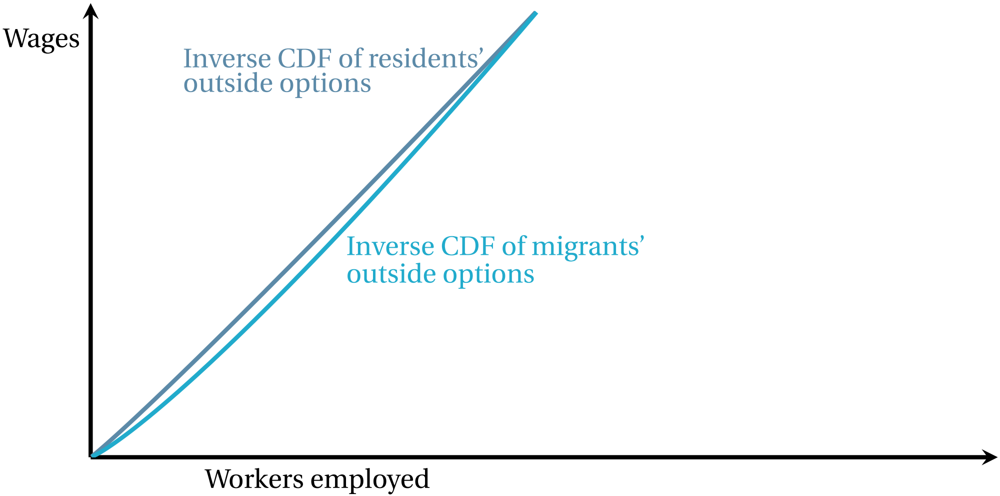

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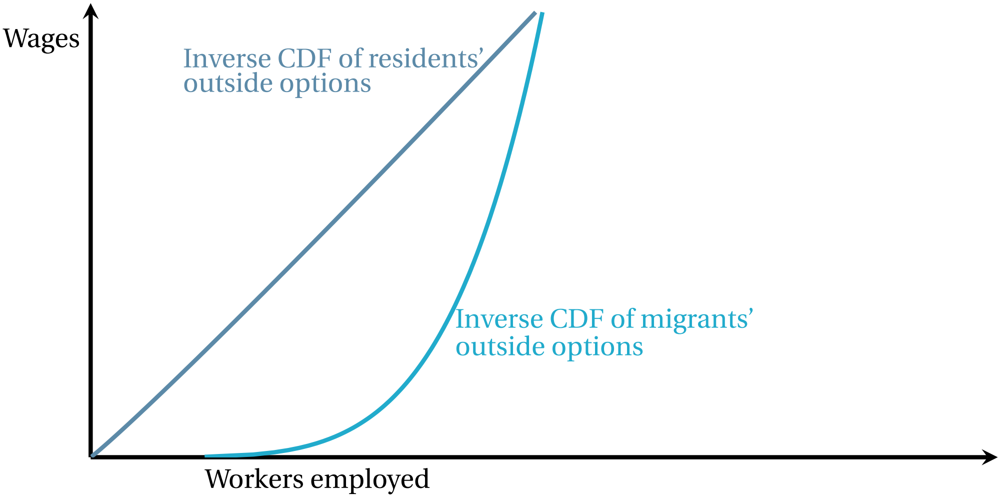

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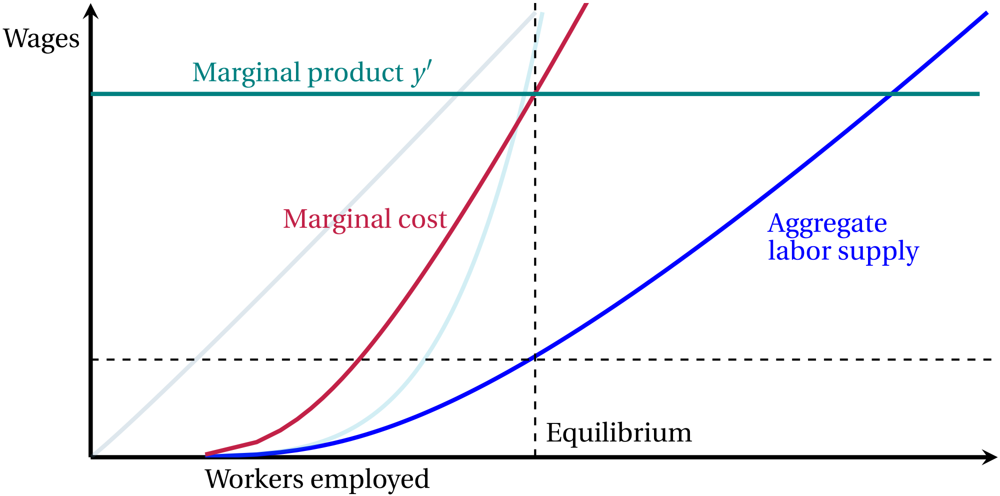
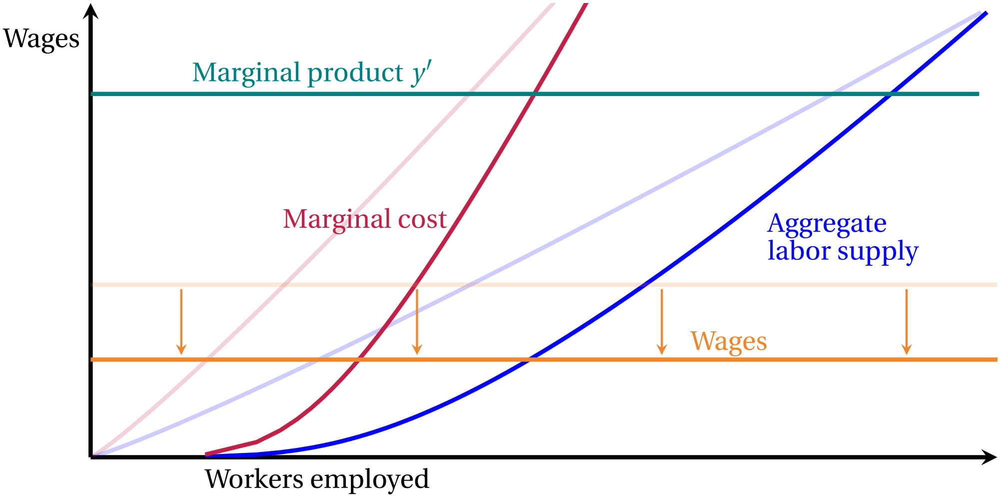


Restricting migrants' jobs reduces posted wages



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 substitute across 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 substitute across 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.
- (This is why we don't estimate a search model.)

Structural model: primitives

Perfect information, partial equilibrium. Two periods, but decision-making is static.

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

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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

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

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*: $\mathbf{F}_{i,t} = \mathbf{F}_{o_i,t}^{migrant} \subseteq \mathbf{F}_{o_i,t}$.

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

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

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Firms have **CES production functions**:

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

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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: calculating structural residuals

Given a candidate parameter vector τ, λ, ρ, ν:

1. Use Berry '94 inversion to calculate the **location and firm amenity values** $\bar{\xi}_{c,o,x,t}, \xi_{f,o,x,t}$ given observed employment levels, wages and the parameters τ, λ.

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4. Calculate the **marginal product of labor for each occupation at each firm** by inverting the markdown equation, given wages and the labor supply elasticities $\eta_{f,o,t}$.

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4. Calculate the **marginal product of labor for each occupation at each firm** by inverting the markdown equation, given wages and the labor supply elasticities $\eta_{f,o,t}$.
5. Use these marginal products, observed employment levels, and the production parameters ρ, ν **to calculate productivity residuals** $\phi_{f,o,t}$.

Explicit form for structural residuals.

Structural model: data

Sample: Paid employees with a unique firm during the three months prior to the 2013 and 2018 censuses.

Wages: The log wage in an occupation-by-firm is the mean log earnings less mean log hours.

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

Locations: Functional urban areas.

Firms: Enterprise × location.

Structural model: moment conditions

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

- productivity shocks $\Delta\phi_{f,o,t}$, and
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- Unobserved worker productivity generates measurement error in wages.
- Measurement error in wages introduces a spurious correlation.

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- Measurement error in wages introduces a spurious correlation.

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

Explicit form for moment conditions.

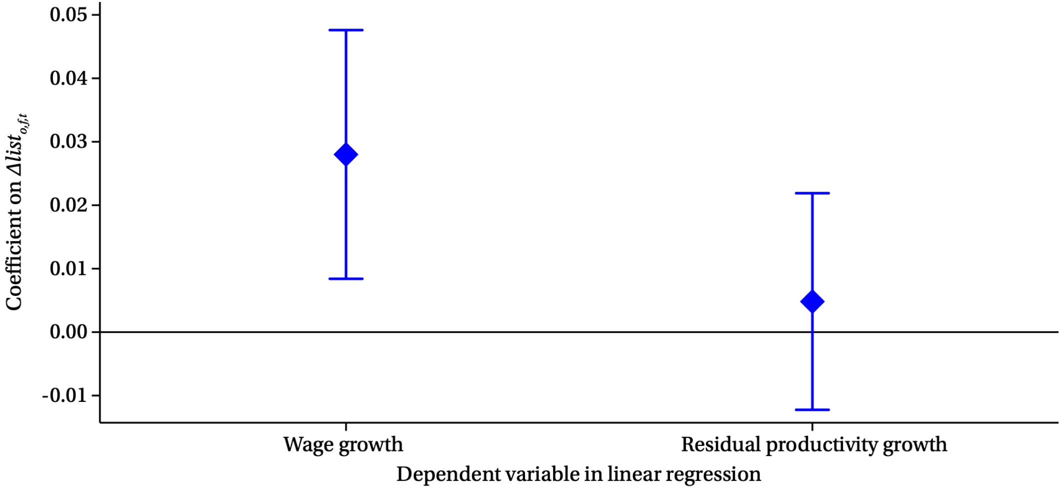
Structural model: estimates

	Baseline spec.
$\boldsymbol{\tau}$ (atomistic labor supply)	3.446
	[0.544]
$\boldsymbol{\lambda}$ (workers substitute across space)	0.483
	[0.242]
$\boldsymbol{\rho}$ (firms substitute across occs.)	0.970
	[0.026]
$\boldsymbol{\nu}$ (returns to scale)	0.541
	[0.097]

Structural model: estimates

	Baseline spec.	Richer demog.	Randomize workers	Coefficients by sector			Ignore hours
$\boldsymbol{\tau}$ (atomistic labor supply)	3.446	3.547	3.564			3.356	3.314
	[0.544]	[0.614]	[0.614]			[0.537]	[0.544]
$\boldsymbol{\lambda}$ (workers substitute across space)	0.483	0.513	0.682			0.463	0.456
	[0.242]	[0.305]	[0.294]			[0.225]	[0.216]
				Primary	Manuf.	Services	
$\boldsymbol{\rho}$ (firms substitute across occs.)	0.970	0.963	0.919	1.023	0.930	0.975	0.969
	[0.026]	[0.029]	[0.032]	[0.080]	[0.046]	[0.029]	[0.026]
$\boldsymbol{\nu}$ (returns to scale)	0.541	0.536	0.473	0.822	0.541	0.547	0.550
	[0.097]	[0.089]	[0.093]	[0.132]	[0.178]	[0.101]	[0.092]

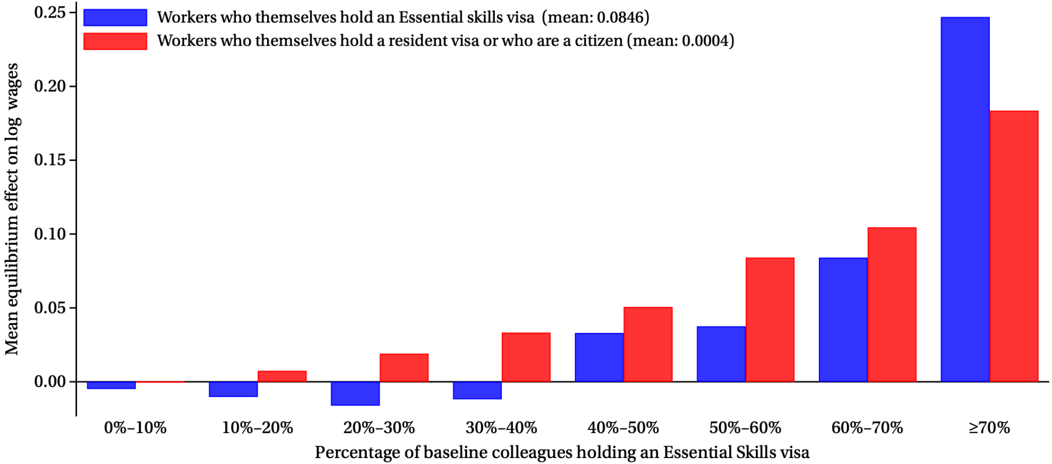
Structural model: over-identification



The equilibrium effect of allowing migrants to work at any firm

1. Use only 2018 cross-section, assume constant worker productivity.
2. Calculate TFP and labor-augmenting 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



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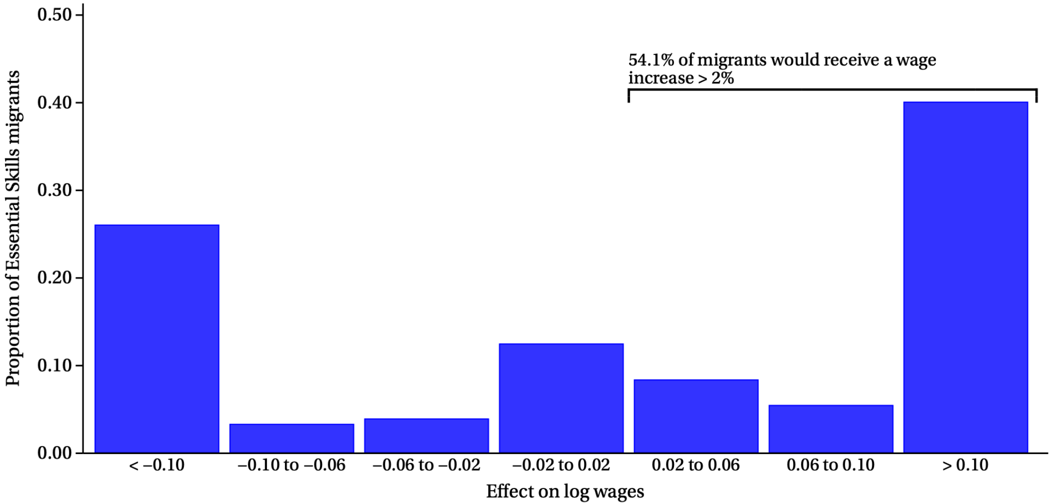

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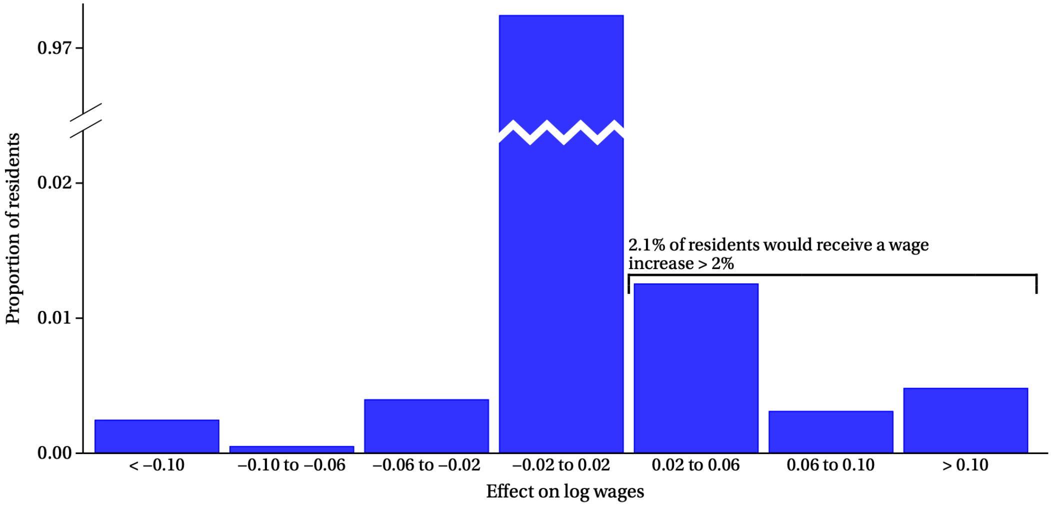

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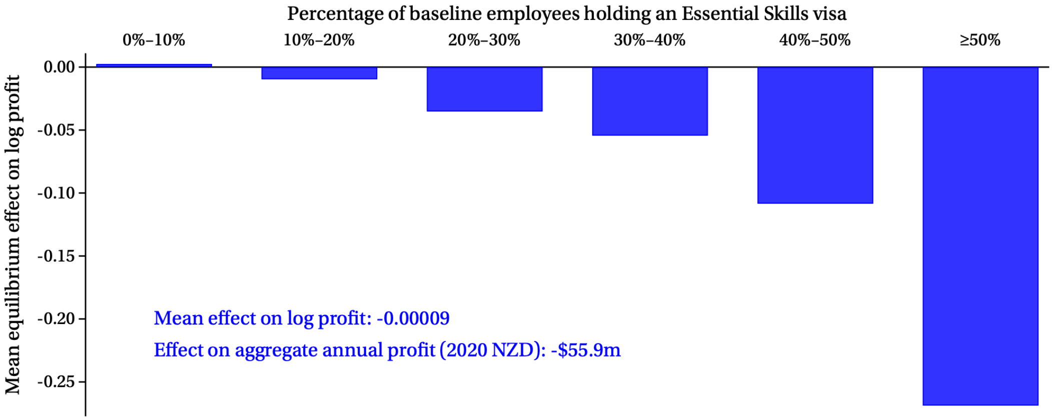

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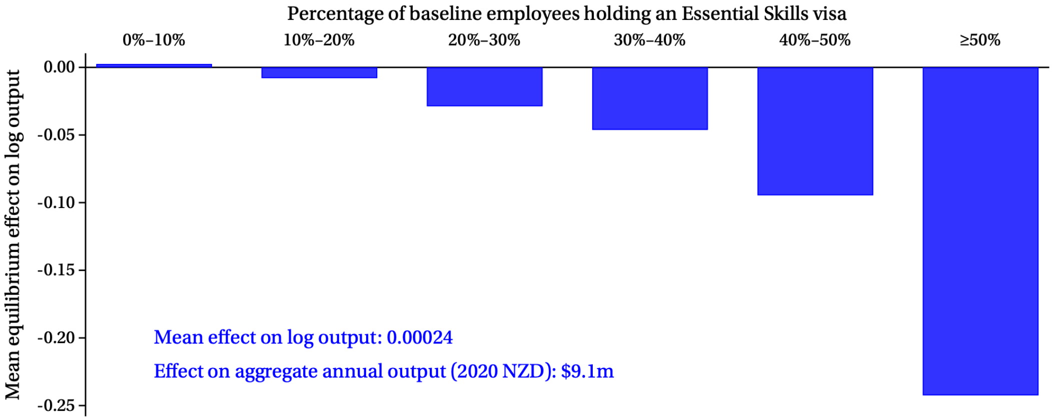


How restricting migrants' job options affects welfare

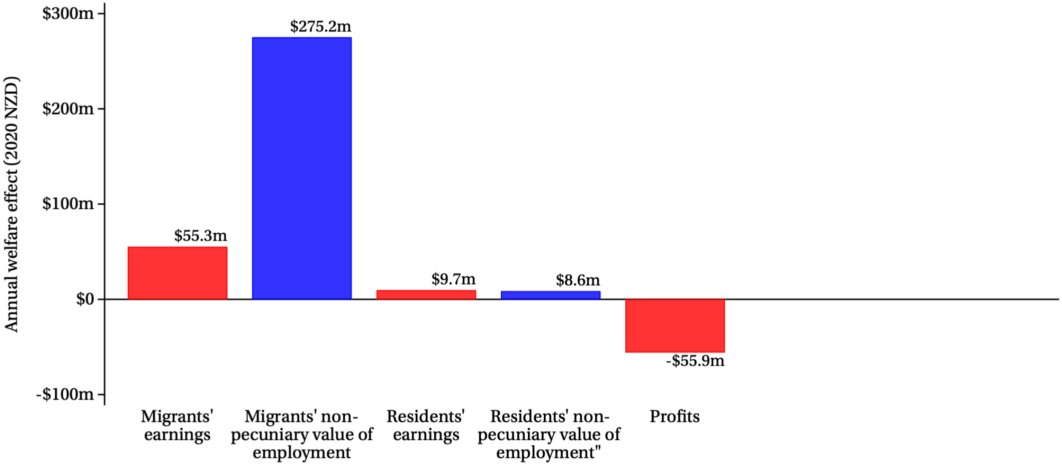
Let WTP_i denote i's money-metric welfare gain from the counterfactual equilibrium w', f', in which migrants can work at any firm:

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

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



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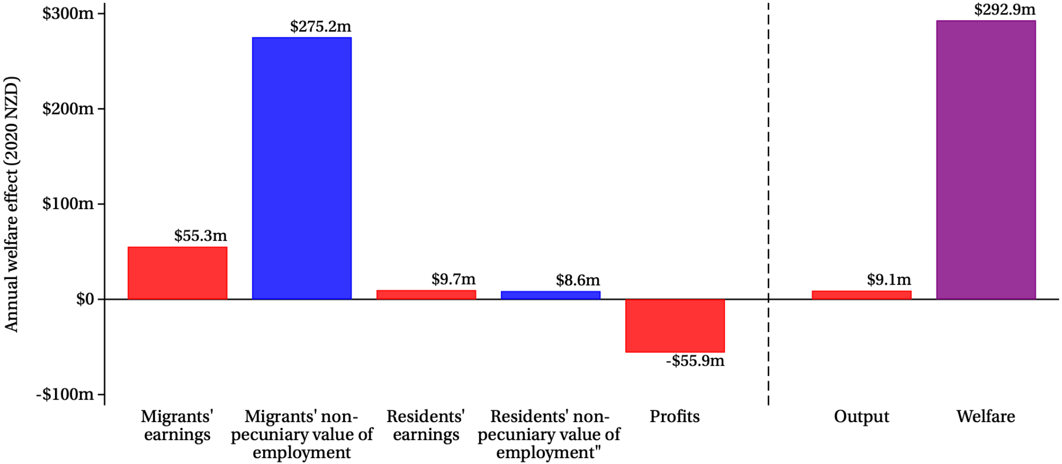


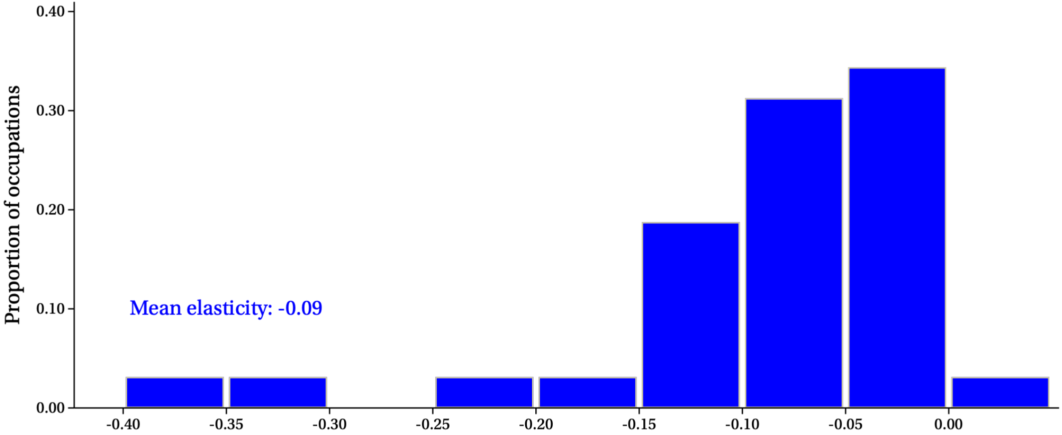
Restricting migrants’ job options affects everyone’s wages

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.

Does restricting migrants' job options protect residents from immigration?



$$\frac{\text{change in residents' mean log wage, given a 5\% increase in the number of migrants}}{\text{change in the log number of workers, given a 5\% increase in the number of migrants}}.$$

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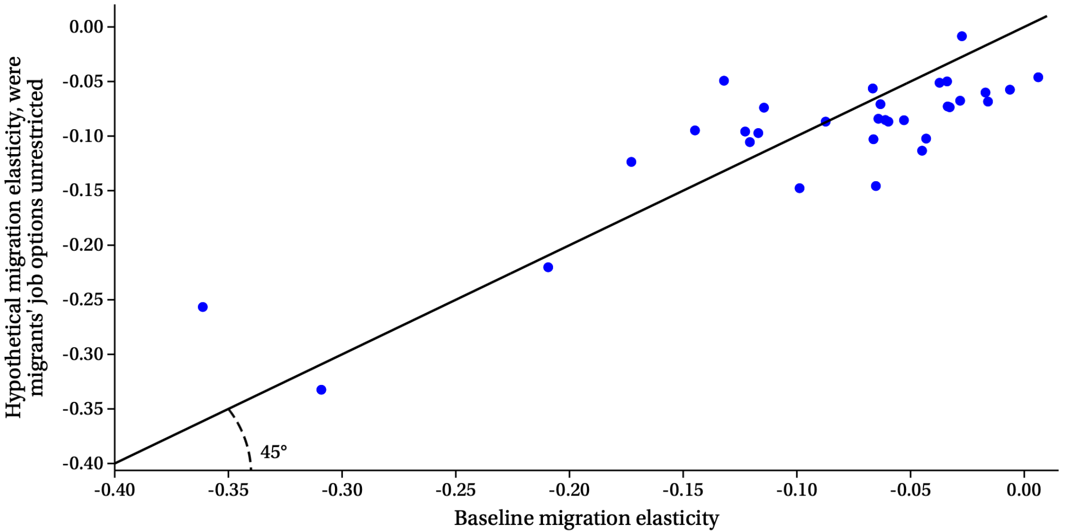

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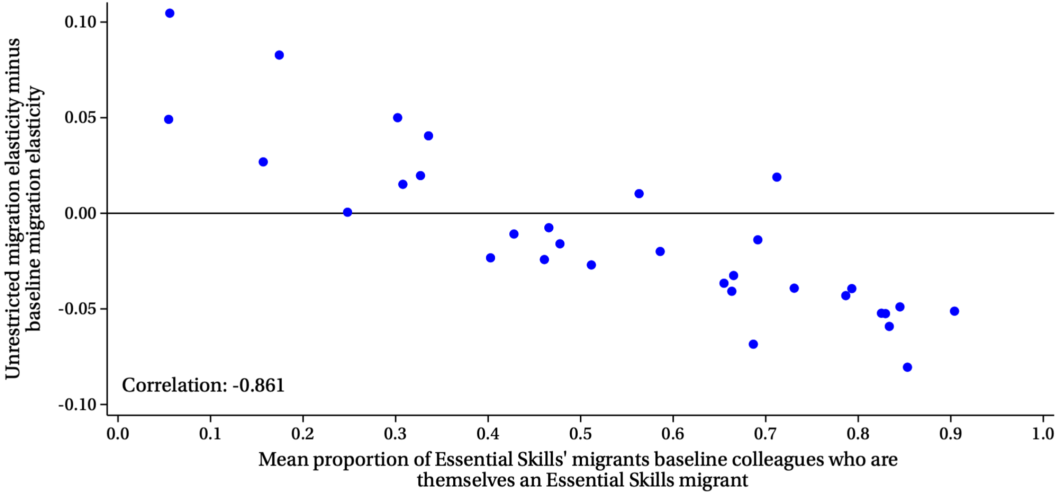
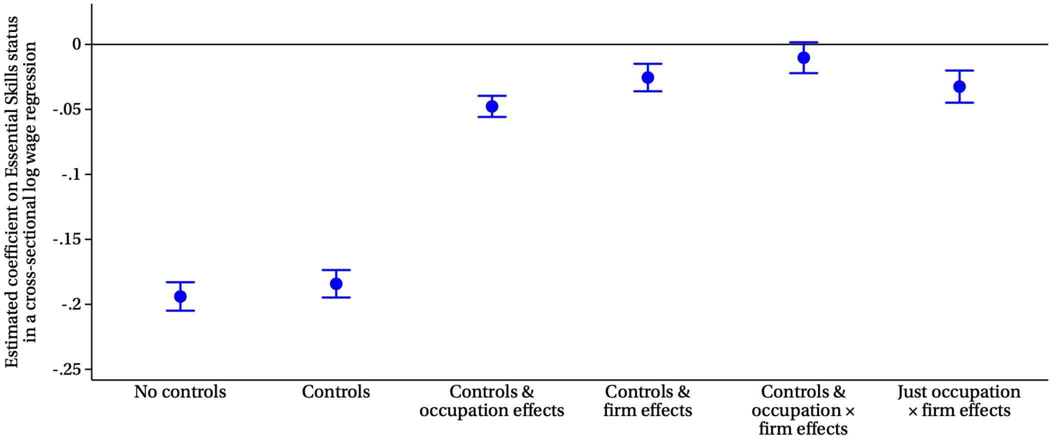


Migrants earn less than other workers... but only because of their jobs



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

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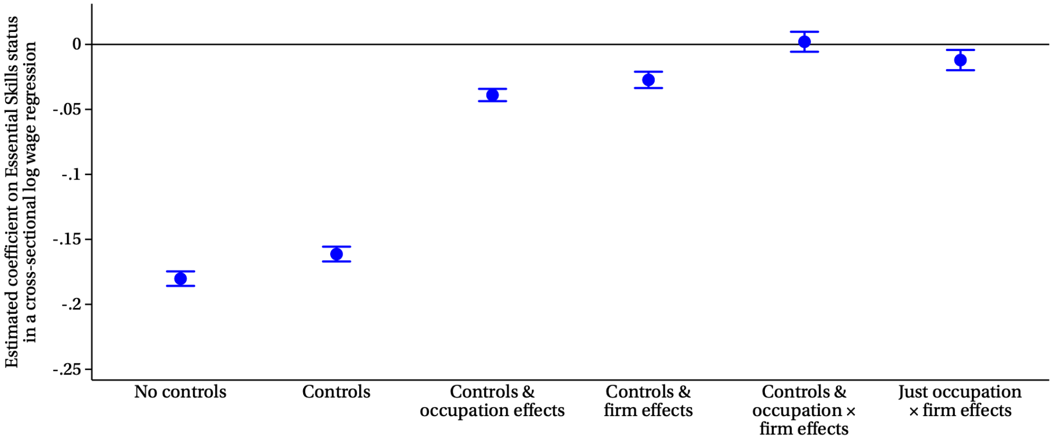

Sample: full-time employees with a unique firm in the 6 months before the 2018 Census. Back.

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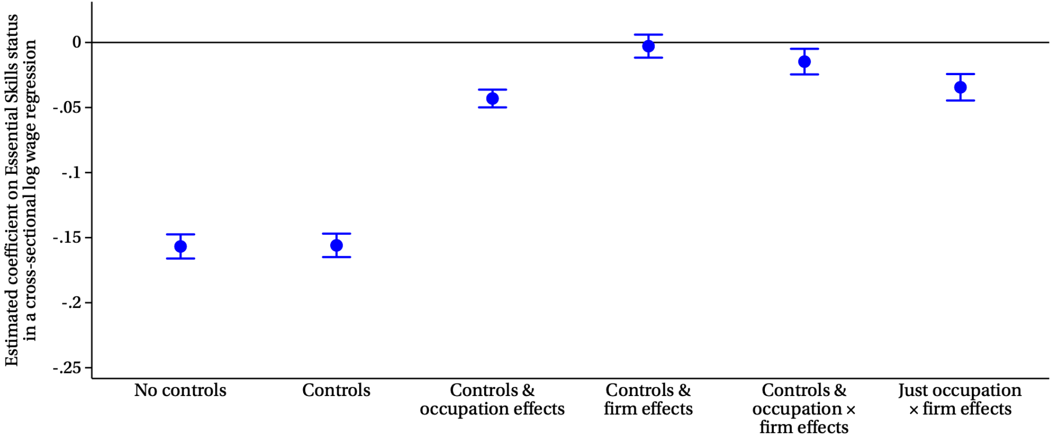

Sample: full-time employees with a unique firm in the 6 months before the 2013 Census. Back.

Accounting for treatment effect heterogeneity

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

- 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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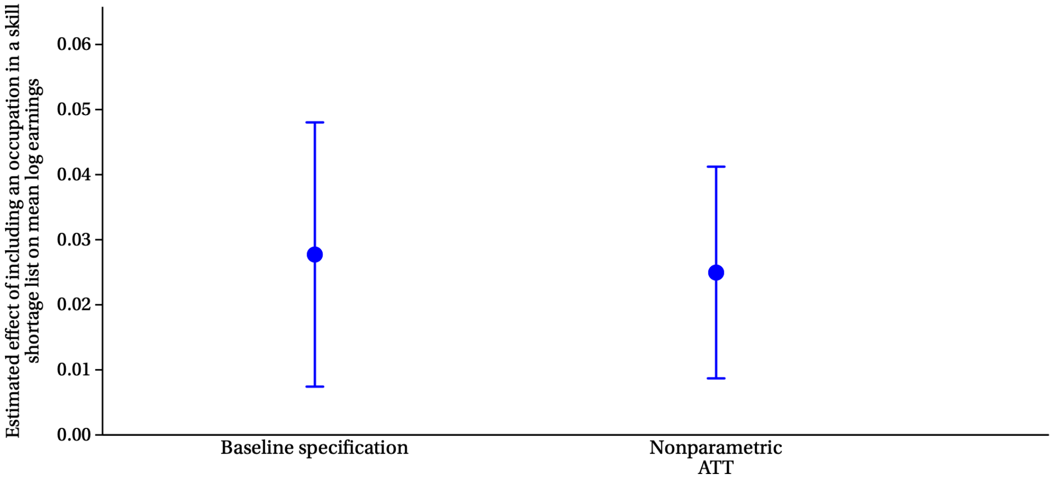

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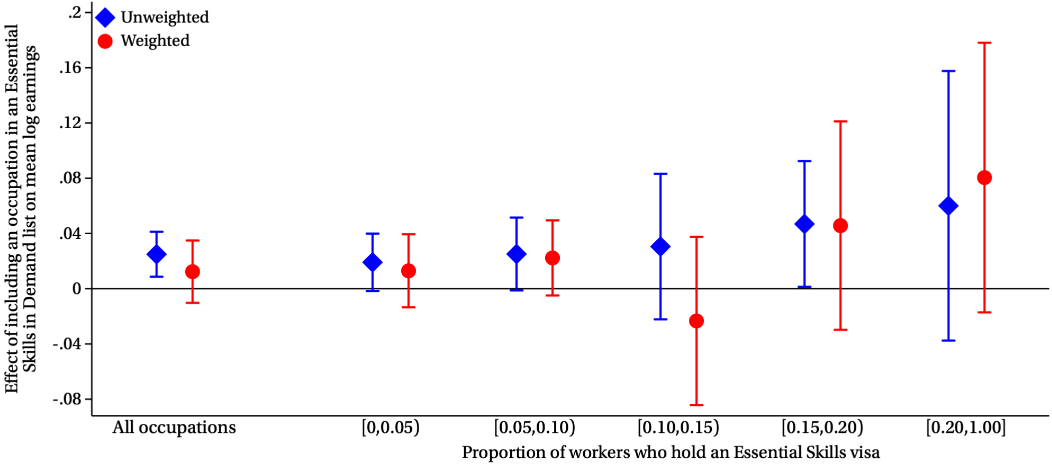

Identifying effects for job-stayers

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

$$Y_{it} = Y_{it}(L_{it}, S_{it}),$$

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

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$$\forall i : L_{i0} = S_{i0} = 0.$$

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

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

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

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

If counterfactual earnings were constant over time, we could simply look at lottery-winning job-stayers' initial earnings.

- They aren't, so nonparametric identification requires further assumptions.

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

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

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

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

Identifying effects for job-stayers

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

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

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

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

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

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Assumption 4: The null space of the kernel $dF_{Y_{i1}(0,0)}\left(y_1 \mid Y_{i0}(0,0) = y_0\right)$ is 0:

$$\int f\left(y_1\right) dF_{Y_{i1}(0,0)}\left(y_1 \mid Y_{i0}(0,0) = y_0\right) = 0 \implies f\left(y_1\right) = 0.$$

Identifying effects for job-stayers

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

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

Assumption 4: The null space of the kernel $dF_{Y_{i1}(0,0)}\left(y_1 \,\middle|\, Y_{i0}(0,0) = y_0\right)$ is 0.

$\therefore$ The integral equation can be solved for $\mathbb{P}\left[S_{i1}(1) = 1 \middle| Y_{i1}(0,0) = y_1\right]$.

Identifying effects for job-stayers

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

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

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

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

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

where, again invoking assumptions 1 and 2, $dF_{Y_{i1}(0,0)}$ can be identified from lottery losers and $\mathbb{P}\left[S_{i1}(1) = 1\right]$ can be identified from lottery winners.

Identifying effects for job-stayers

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

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

Proposition: Given Assumptions 1-4, the average treatment effect for job-stayers is identified.

Back.

Estimating effects for job-stayers

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

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

Our setting has additional complications:

- Our data spans more than 2 periods.
- Winning the lottery is only random *conditional on the lottery entered.*
- Lottery winners can switch firms.

Estimating effects for job-stayers

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

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

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

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

Estimating effects for job-stayers

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

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

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

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

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

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- 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

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

- 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 identify the **average treatment effect for job-stayers**:

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

We calculate our estimator using a Gibbs sampler algorithm with state

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

where w_{it} is the Probit latent variable:

$$S_{it} = 1 \iff w_{it} \geq 0.$$

We impose inverse gamma priors on the variance terms $\sigma_\delta, \sigma_\gamma, \sigma_\epsilon$ and normal priors on the remaining hyper-parameters.

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

$\phi_\zeta(t) = \dfrac{\Gamma(1-it)}{\Gamma(1-i(1-\sigma)t)}$, 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:

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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 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.

Explicit forms for structural residuals

Supply elasticities

$$\eta^{status}_{f,o,x,t} = \tau\left(1-(1-\lambda)\sigma^{status}_{f,o,x,t|c_f} - \lambda\sigma^{status}_{f,o,x,t}\right).$$

$$\eta_{f,o,t} = \sum_{x\in\mathbf{X}}\left(\sigma_{x,resident|f,o,t}\eta^{resident}_{f,o,x,t} + \sigma_{x,migrant|f,o,t}\eta^{migrant}_{f,o,x,t}\right).$$

The amenity value of employment.

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

The amenity value of living in a location.

$$\bar{\xi}_{c,o,x,t} = \frac{1}{\lambda}\log\sigma^{resident}_{c,o,x,t} - \log\left(\sum_{f\in\mathbf{F}_{c,o,t}}\exp\left(\tau\log(w_{f,o,t}) + \xi_{f,o,x,t}\right)\right) + D_{o,x,t}.$$

Back.

Explicit forms for structural residuals

Labor-augmenting productivity.

$$\phi_{f,o,t} = \log w_{f,o,t} + \log\left(1 + \frac{1}{\eta_{f,o,t}}\right) + (1-\rho)\log L_{o,f,t} - \left(\frac{\rho}{\nu}\right)\log \nu$$
$$+ \left(\frac{\rho - \nu}{\nu}\right)\log\left(\sum_{o' \in \mathbf{O}_{f,t}} \exp\left(\log w_{f,o',t} + \log\left(1 + \frac{1}{\eta_{f,o',t}}\right) + \log L_{o',f,t}\right)\right). \tag{1}$$

Back.

Explicit forms for moment conditions

Between split-samples:

- Amenity shocks are orthogonal to baseline residual productivity:

$$\Delta\hat{\xi}^{s}_{f,o,NZ,t} \perp \hat{\phi}^{-s}_{f,o,t-1} \mid o, c(f).$$

- Productivity shocks are orthogonal to firm-level amenity shocks:

$$\Delta\hat{\xi}^{s}_{f,o,NZ,t} \perp \Delta\hat{\phi}^{-s}_{f,o,t} \mid o, c(f).$$

- Productivity shocks are orthogonal to market-level amenity shocks:

$$\Delta\bar{\xi}^{s}_{c_f,o,NZ,t} \perp \Delta\hat{\phi}^{-s}_{f,o,t} \mid o.$$

Explicit forms for moment conditions

We construct a instrument to shift firm-level 'aggregate labor' $\log\left(\sum_{o\in\mathbf{O}_{f,t}} e^{\phi_{f,o,t}+\rho\log l_{f,o,t}}\right)$.

- Form the firm-by-occupation amenity shocks $\tilde{\xi}^s_{f,o,NZ}$ by residualizing $\Delta\hat{\xi}^s_{f,o,NZ,t}$ on a location-by-occupation-by-sample fixed effect.
- Form the firm-level aggregate amenity shock

$$\check{\xi}^s_{f,NZ,t} \equiv \log\left(\sum_{o\in\mathbf{O}_{f,t}} e^{\hat{\phi}^s_{f,o,t}+\rho\tilde{\xi}^s_{f,o,NZ}}\right).$$

- This aggregate amenity shock is also orthogonal to productivity shocks (between split-samples):

$$\check{\xi}^s_{f,NZ,t} \perp \Delta\hat{\phi}^{-s}_{f,o,t}.$$

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.